Automatic Repair of Real Bugs: An Experience Report on the Defects4J Dataset

Thomas Durieux, † Matias Martinez, † Martin Monperrus, † Romain Sommerard, † Jifeng Xuan ‡
† INRIA & University of Lille, France
‡ Wuhan University, China

Abstract—Automatic software repair aims to reduce human effort for fixing bugs. Various automatic repair approaches have emerged in recent years. In this paper, we report on an experiment on automatically repairing 224 bugs of a real-world and publicly available bug dataset, Defects4J. We investigate the results of three repair methods, GenProg (repair via random search), Kali (repair via exhaustive search), and Nopol (repair via constraint based search). We conduct our investigation with five research questions: fixability, patch correctness, ill-defined bugs, performance, and fault localizability. Our implementations of GenProg, Kali, and Nopol fix together 41 out of 224 (18%) bugs with 59 different patches. This can be viewed as a baseline for future usage of Defects4J for automatic repair research. In addition, manual analysis of sampling 42 of 59 generated patches shows that only 8 patches are undoubtedly correct. This is a novel piece of evidence that there is large room for improvement in the area of test suite based repair.

I. INTRODUCTION

Automatic software repair aims to reduce human effort for fixing bugs, in particular by generating appropriate patches. Test suite based repair has emerged in recent years; it consists in synthesizing a patch that passes a given test suite [24]. Such a patch conforms to the program specifications that are expressed in the test suite. In test suite based repair, human developers may eventually check the synthesized patch to decide its acceptance.

Automatic repair is a dynamic research field. GenProg by Le Goues et al. [24], a pioneering approach, transforms a program into an Abstract Syntax Tree (AST) and uses genetic programming techniques to search for the patch. Subsequent work explores different ideas, from the patterns of patches [22] to the use of Satisfiability Modulo Theories (SMT) in patch synthesis [35].

Along the way, various challenges and pitfalls of automatic software repair have been discovered and discussed. Le Goues et al. [23] outlined open research challenges of automatic repair and questioned the real-world practicality. Qi et al. [40] examined the actual effectiveness of genetic programming and showed that a random search strategy outperforms GenProg’s genetic programming strategy on 23 out of 24 bugs. In our previous work [32], we have discussed the problem statement and evaluation of automatic repair. From a disagreement with previous work [22], we have studied the criteria for performing sound and conclusive evaluations. Recent work by Qi et al. [41] examines the experimental configurations of the GenProg series of experiments [24] and RSRepair [40]. They find that only 2 out of 55 patches by GenProg are actually semantically correct (beyond passing a test suite). A recent research field, such as automatic repair, needs both creative techniques and well-designed evaluations.

In this paper, we present results of an evaluation experiment to deepen the strengths and weaknesses of automatic repair. The experiment consists of running three different repair approaches (GenProg [24], Kali [41], and Nopol [12]) on the Defects4J dataset [20]. Defects4J is a database of real-world Java bugs that are collected from open-source projects and are structured in a semantic way so as to support controlled experiments. Our experiment aims to answer two main Research Questions (RQs): RQ1. Can the bugs of the Defects4J dataset be fixed with state-of-the-art automatic repair techniques? RQ2. Are the generated patches correct, if any?

Answering those questions is essential to consolidate the field of automatic repair. First, all previous evaluations of automatic repair techniques were made on a bug dataset that was specifically built for the evaluation of those techniques. In other words, authors of the technique and authors of its corresponding evaluation dataset were the same. This increases many potential biases due to the cherry-picking data. On the contrary, we are not authors of the Defects4J dataset. We simply take Defects4J as it is and try to repair bugs in Defects4J. Second, a key concern behind test suite based repair is whether test suites are acceptable to drive the generation of correct patches. This question has been raised many times since the inception of the field and is still a hot question, such as Qi et al.’s recent results [40]. By answering RQ2 with manual analysis, we can contribute to the debate with novel empirical insights from large programs.

In addition, our experiment enables us to gain novel knowledge on the presence of ill-defined bugs in Defects4J (RQ3), on the execution time of automatic repair (RQ4), and on the importance of fault localization in the repair process (RQ5). Our experiment considers 224 bugs that are spread over 231K lines of code and 12K test cases in total. We ran the experiment for over 17 days of computational time on Grid’5000 [7], a large-scale grid for scientific experiments. Our main findings are as follows.

Answer to RQ1. The Defects4J dataset contains automatically repairable bugs. Our implementations of GenProg, Kali, and Nopol fix together 41 of 224 (18%) bugs with 59 different
Fig. 1. Overview of test suite based repair. Automatic repair takes a buggy program and its test suite as input; the output is the patch that passes the whole test suite if any.

A. Test Suite Based Repair

Test suite based repair generates a patch according to failing test cases. Different kinds of techniques can be used, such as genetic programming search in GenProg \cite{24} and SMT based program synthesis in SemFix \cite{35}. Often, before patch generation, a fault localization method is applied to rank the statements according to their suspiciousness. The intuition is that the patch generation technique is more likely to be successful on suspicious statements.

B. Kinds of Search in Repair

In essence, automatic repair is a search problem, which consists in looking for a patch among a large search space of potential code modifications. We roughly divide existing approaches into three categories of search: random search, exhaustive search, and constraint based search. We use this division to show the features of existing repair approaches. Note that the goal of such division is not to obtain a clear or systematic boundary of repair approaches. Table I lists examples in each category. Section VII will present other related approaches.

### Table I. Categories of Existing Approaches to Test Suite Based Repair.

| Category                     | Existing approaches |
|------------------------------|---------------------|
| Random search                | Arcuri & Yao \cite{5}, GenProg \cite{24}, Par \cite{22}, RSRepair \cite{40}, Martinez & Monperrus \cite{29} |
| Exhaustive search            | DeRoy & Wong \cite{11}, Kali \cite{41} |
| Constraint based search      | SemFix \cite{35}, Nopol \cite{12}, DirectFix \cite{31} |

Answer to RQ2. Our manual analysis of sampling 42 of 59 generated patches shows that 8/42 are correct, 26/42 incorrect, and 8/42 require a domain expertise, which we do not have. The incorrect patches tend to overfit the data that are used in test cases. This is a novel piece of evidence that either the current test suites are too weak or the current automatic repair techniques are too dumb.

Answer to RQ3, RQ4, and RQ5. We show that 1) Defects4J contains weakly specified bugs (RQ3); 2) the process of searching for a patch is a matter of minutes and not days (RQ4); and 3) the choice of fault localization ranking metrics has little impact on this bug dataset (RQ5). For sake of open science, our code and experimental data are publicly available in Github \cite{2}.

The remainder of this paper is organized as follows. Section II provides the background of test suite based repair and the dataset. Section III presents our experimental methodology. Section IV details answer to five research questions. Section V studies three generated patches in details. Section VI discusses potential threats to the validity and Section VII presents the related work. Section VIII concludes this paper and proposes future work.

II. BACKGROUND

In this paper, we consider one kind of automatic repair called test suite based repair. We now give the corresponding background and present the dataset that we use in our experiment.
moval. Once the search space based on modification operators is small enough, an exhaustive search can be applied.

Constraint based search uses some kinds of constraints (e.g., SAT or SMT) to find a patch. For instance, Nopol [12] targets bugs in IF statements: buggy IF conditions and missing preconditions. For an IF condition, an expected value is reasoned by angelic location mining. Then Nopol synthesizes program components, such as operators, variable values, and object-oriented features (like pre-defined methods or whether an object is null), to form a final patch. Contrary to random search, constraint based search is mostly deterministic.

C. The Defects4J Dataset

Defects4J by Just et al. [20] is a bug database that consists of 357 real-world bugs from five widely-used open-source Java projects. Bugs in Defects4J are organized in a unified structure that abstracts over programs, test cases, and patches.

Defects4J provides reproducible real software bugs and enables controlled studies in software testing research (e.g., [26, 21]). To our knowledge, Defects4J is the largest open database of well-organized real-world bugs. In our work, we use four out of five projects in our experiments, i.e., Commons Lang, JFreeChart, Commons Math, and Joda-Time. An exceptional project is Closure Compiler. Test cases in Closure Compiler are organized with scripts rather than JUnit files. We discard Closure Compiler in our experiment due to its incompatible test cases. Table II presents the details of bugs in Defects4J.

| Project         | #Bugs | Source KLoC | Test KLoC | #Test cases |
|-----------------|-------|-------------|----------|-------------|
| Commons Lang    | 65    | 22          | 6        | 2,245       |
| JFreeChart      | 26    | 96          | 50       | 2,205       |
| Commons Math    | 106   | 85          | 19       | 3,602       |
| Joda-Time       | 27    | 28          | 53       | 4,130       |
| Total           | 224   | 231         | 128      | 12,182      |

III. METHODOLOGY

We present an experimental methodology to assess the effectiveness of different automatic repair approaches on the real-world bugs of Defects4J. The protocol supports the analysis of five dimensions of automatic repair: fixability, patch correctness, ill-defined bugs, performance and fault localizability. We first list the five Research Questions (RQs) of our work; then we describe the research protocol of our experiment; finally, we present the implementation details.

A. Research Questions

1) RQ1. Fixability: Which bugs of Defects4J can be automatically repaired? How many bugs can be repaired by each approach?

2) RQ2. Patch correctness: Which bug fixes are semantically correct (beyond passing the test suite)?

A patch that passes the whole test suite may not be exactly the same as the patch written by developers. It may be syntactically different yet semantically equivalent; it may also be not correct when the test suite is not well-designed. The term “correct” denotes that a patch is exactly the same or equivalent to the patch that is written by developers. To answer this question, we sample a number of bugs that are automatically repaired (i.e., with generated patches) and manually examine these sampled patches.

3) RQ3. Ill-defined bugs: Which bugs in Defects4J are not sufficiently specified by the test suite? How many bugs should be discarded for the study of automatic repair?

In test suite based repair, a synthesized patch is highly dependent on the quality of the test suite. A patch generated without sufficiently high test coverage or sufficiently strong assertions may threaten the actual repair effectiveness. We answer this question by investigating bugs that should be discarded.

4) RQ4. Performance (execution time): How long is the execution time for each repair approach on one bug?

It is time-consuming to manually repair a bug. Test suite based repair automates the process of patch generation. To conduct a quantitative analysis on the performance of automatic repair, we evaluate the execution time of each repair approach.

5) RQ5. Fault localizability: Are standard techniques of spectrum-based fault localization effective to localize the buggy statements of the bugs of Defects4J?

Spectrum-based fault localization is a straightforward technique for ranking potential buggy statements. We evaluate the fault localizability on bugs in Defects4J with existing fault localization techniques.

B. Protocol

We run three repair algorithms (described in Section III-B1) on the Defects4J dataset (Section III-B2). Since the experiment requires a large amount of computation, we run it on a grid (Section III-B3). We then manually analyze a sample of synthesized patches (Section III-B4). Important implementation information for future replication will be shown in Section III-C.

1) Repair Algorithms Under Comparison: In this work, we select three repair approaches. The basic selection criterion is that it is able to repair Java code: GenProg [24], Kali [41], and Nopol [12]. However, to our knowledge, existing repair approaches are neither publicly available nor developed for Java. Nopol comes from our previous work [12]. We have re-implemented GenProg [24] and Kali [41] by ourselves. We
select GenProg since it can be considered as a baseline in the field and is a point of comparison in the related literature. Nopol is a constraint based repair approach, developed by our group, and represents a different family of repair techniques (constraint as opposed to random search). Kali has recently been proposed and performs an exhaustive search. To sum up, the three selected repair approaches represent the three families of approaches mentioned in Section I-B. In this paper, we do not evaluate other existing repair approaches. We leave such evaluation as future work. For sake of open research, all three systems are made publicly available on Github.

2) Dataset: Software testing and debugging research benefits from open datasets and benchmarks of real-world bugs [13]. For instance, a widely-studied dataset in testing, SIR[7] has provided an open and fair platform for testing research. In this paper, we use the bugs of Defects4J, which are extracted from Java projects. Table II gives the main descriptive statistics of this dataset. The main strength of Defects4J is to be semantically structured. One can ask the Defects4J backend for a given bug ID and its corresponding manual patch. To extract bug data from Defects4J and to facilitate the experiment, we wrote wrapper scripts to support the fully automated execution of the repair experiments. To our knowledge, Defects4J is the largest open dataset of real-world Java bugs.

3) Large Scale Execution: We assess three repair approaches on 224 bugs. One repair attempt may take hours to be completed. Hence, we need a large amount of computation power. Consequently, we deploy our experiment in Grid’5000, a grid for high performance computing [7]. In our experiment, we manually set the computing nodes in Grid’5000 in the experiment to the same hardware architecture. This avoid potential biases of the time cost measurement. All the experiments are deployed in the Lille site of Grid’5000 (located in Lille, France). The cluster management mechanism of Grid’5000 assists our experiments to be reproducible both in fixability and in time cost. For each repair approach, we set the timeout to two hours per bug.

4) Manual Analysis: To examine whether a generated patch is correct (the same or equivalent to the patch that is written by developers), we manually check a set of sampled patches. The reason is that such manual analysis is time consuming. In our work, we only sample 42 (71%) patches (from 59 generated patches) and leverage the sampled result to illustrate the equivalence between patches. This represents more than four full days of work. To our knowledge, only Qi et al. [41] have performed a similar manual assessment of patch synthesized with automatic repair.

C. Implementation

The three considered repair approaches, GenProg, Kali, and Nopol, are implemented in Java. All implementations are built on top of Spoon, a library for analyzing and transforming Java code [37] (Version 4.1). The fault localization technique in each repair approach is implemented on top of GZoltar. GZoltar[8] is a library of Java fault localization. The implementation of Nopol can be found in our previous paper [12]. For GenProg and Kali, we carefully implemented the approaches according to the corresponding literature and figured out the uncertain parts. All implementation decisions can be consulted in the source code that is publicly available [2].

1) GenProg Implementation: Our implementation of GenProg is on top of an evolutionary repair framework, Astor [28]. Astor has 8.7K lines of Java code while Nopol has 25K lines of Java code. Astor is publicly available at GitHub.

The evolutionary algorithm embedded in GenProg starts by defining a population of programs. The algorithm evolves the population during a number of generations. In each generation, variants in the population are modified, evaluated, and selected to next generation. GenProg in our implementation works at the level of statements.

2) Kali Implementation: The implementation of Kali is also built within the Astor framework. It is a simplification of the original Kali in [41]. In particular, we consider one out of three Kali’s operators: statement removal. The implementation navigates the suspicious statements that are obtained by fault localization. Then, for each of statements in descending order of suspicious values, Kali removes the statement, compiles the resulting program, and executes the test suite over the modified program (if compiling succeeds). Finally, the patch is returned if all test cases are passed.

IV. EMPIRICAL RESULTS

We present and discuss our answers to five research questions that motivate this work. The total execution of the experiment costs 17.07 days.

A. Fixability

RQ1. Which bugs can be automatically repaired? How many bugs can be repaired by each approach in comparison?

The three automatic repair approaches in this experiment are able to together fix 41 bugs of the Defects4J dataset. GenProg finds a patch for 16 bugs; Kali successfully fixes 9 bugs; and Nopol synthesizes a condition that makes the test suite passing for 34 bugs. Table III shows the bug identifiers, for which at least one patch is found. Each line corresponds to one bug in Defects4J and each column denotes the fixability of one repair approach. For instance, Bug M2 from Commons Math has been automatically fixed by GenProg and Kali.

As shown in Table III in two projects, Commons Lang and JFreeChart, all the bugs are fixed by Nopol while GenProg and Kali contribute zero patches. A possible reason is that the program of Commons Lang and JFreeChart is more complex than that of Commons Math; both GenProg and Kali cannot handle such a complex search space. All the three repair approaches under comparison have not fixed any bug in Joda-Time. A major reason is that our computing resource is not enough to handle Joda-Time due to its complex program structure and the large amount of test cases. Our implementations receive the errors of OutOfMemoryError and StackOverflowError during execution.

Fig. 2 shows the intersections between the fixed bugs among the three repair approaches. Nopol can fix 25 bugs that
TABLE III. RESULTS ON THE FIXABILITY OF 224 BUGS IN DEFECTS4J WITH THREE REPAIR APPROACHES. IN TOTAL, THE THREE REPAIR APPROACHES CAN REPAIR 41 BUGS (18%).

| Project | Bug Id | GenProg | Kali | Nopol |
|---------|--------|---------|------|-------|
|         |        | Fixed   | Fixed| Fixed |
|         |        |         | Fixed|       |
| Commons Lang | L44 | -       | -    | Fixed |
|             | L46   | -       | -    |       |
|             | L51   | -       | -    | Fixed |
|             | L55   | -       | -    | Fixed |
|             | L58   | -       | -    | Fixed |
| JFreeChart | C5    | -       | -    | Fixed |
|            | C9    | -       | -    | Fixed |
|            | C13   | -       | -    | Fixed |
|            | C17   | -       | -    | Fixed |
|            | C21   | -       | -    | Fixed |
|            | C25   | -       | -    | Fixed |
| Commons Math | M2   | Fixed   | Fixed| -     |
|             | M8    | Fixed   | Fixed| -     |
|             | M32   | -       | -    | Fixed |
|             | M33   | -       | -    | Fixed |
|             | M40   | Fixed   | -    | Fixed |
|             | M41   | -       | -    | Fixed |
|             | M42   | -       | -    | Fixed |
|             | M44   | Fixed   | -    | -     |
|             | M49   | Fixed   | Fixed| Fixed |
|             | M50   | Fixed   | Fixed| Fixed |
|             | M57   | -       | -    | Fixed |
|             | M58   | -       | -    | Fixed |
|             | M64   | Fixed   | -    | -     |
|             | M69   | -       | -    | Fixed |
|             | M70   | Fixed   | -    | -     |
|             | M73   | Fixed   | -    | Fixed |
|             | M78   | Fixed   | Fixed| Fixed |
|             | M79   | -       | -    | Fixed |
|             | M80   | Fixed   | Fixed| Fixed |
|             | M81   | Fixed   | Fixed| Fixed |
|             | M82   | Fixed   | Fixed| Fixed |
|             | M84   | Fixed   | -    | -     |
|             | M85   | Fixed   | Fixed| Fixed |
|             | M87   | -       | -    | Fixed |
|             | M88   | -       | -    | Fixed |
|             | M95   | Fixed   | -    | -     |
|             | M97   | -       | -    | Fixed |
|             | M99   | -       | -    | Fixed |
|             | M104  | -       | -    | Fixed |
|             | M105  | -       | -    | Fixed |
| Total      | 41 (18%) | 16 (7%) | 9 (4%) | 34 (15%) |

Table shows the results of this manual analysis. For each patch, one of the authors (called thereafter an “analyst”) analyzed its correctness, readability, and difficulty (the difficulty of validating the correctness). To perform the assessment, the correctness of a patch can be correct, incorrect, or unknown; the readability can be easy, medium, or hard; the difficulty can be easy, medium, hard, or expert. By “expert”, we mean a patch is hard to validate due to the required expertise in domain knowledge. Note that results in Table may be fallible due to the subjective nature of the assessment. However, all patches as

To our knowledge, those results are the very first automatic repair baseline on the Defects4J benchmark. Recall that they are done with an open-science ethics, all the implementations, experimental code, and results are available on Github [2]. Future research in automatic repair may try to fix more bugs than our work. The experiment in our paper can be used to facilitate the comparison by other researchers.

Neither GenProg nor Kali could repair. All the fixed bugs by Kali can be fixed by GenProg or Nopol. For seven bugs, all three repair approaches can generate a patch to pass the test suite.

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FIG. 2. Venn diagram that illustrates the bugs commonly fixed by different repair approaches. All fixed bugs by Kali are also fixed by GenProg or Nopol.

**Answer to RQ1.** In Defects4J, 41 out of 224 bugs can be fixed by one approach of GenProg, Kali, and Nopol. Nopol can fix the largest number of bugs (34 bugs). All the fixed bugs by Kali can be fixed by GenProg or Nopol.

**B. Patch Correctness**

**RQ2.** Which bug fixes are semantically correct (beyond passing the test suite)?

We manually evaluate the correctness of generated patches by three repair approaches. A generated patch is correct if this patch is the same to the manually-written patch by developers or the patch is semantically equivalent to the manual patch. A generated patch is incorrect if no semantically equivalence is met (even the test suite passes).

Recall the history of automatic repair research, it has been hypothesized that a pitfall of test suite based repair: a test suite cannot completely express the program specifications, so it is hazardous to drive the synthesis of a correct patch with a test suite. This comment has been made during conference talks and is common in peer reviews. However, only recent work by Qi et al. [41] invests many resources to manually analyze the previously-generated patches by test suite based repair. They found that the vast majority of patches by GenProg are incorrect. It is necessary to replicate their findings. We also suggest that following work in automatic repair conducts (or partially conducts) manual examination of patches.

To answer the question of patch correctness, we have manually analyzed a sample of fixed bugs. We cannot analyze all the 59 generated patches since analyzing one patch requires a period between a couple of minutes and several hours of work, depending on the correctness and the complexity of the synthesized patch. On one hand, a patch that is identical to the one written by developers is obviously true; on the other hand, several patches require a domain expertise that none of the authors has. In our work, we sample 42 (71%) of 59 generated patches to conduct manual analysis.

Table shows the results of this manual analysis. For each patch, one of the authors (called thereafter an “analyst”) analyzed its correctness, readability, and difficulty (the difficulty of validating the correctness). To perform the assessment, the correctness of a patch can be correct, incorrect, or unknown; the readability can be easy, medium, or hard; the difficulty can be easy, medium, hard, or expert. By “expert”, we mean a patch is hard to validate due to the required expertise in domain knowledge. Note that results in Table may be fallible due to the subjective nature of the assessment. However, all patches as
As shown in Table IV, 8 out of 42 analyzed patches are correct and 26 are incorrect. Meanwhile, for the other 8 patches, it is not possible to clearly validate the correctness, due to the lack of domain expertise (labeled as unknown). Section V will present three case studies of generated patches via manual analysis. Among the 8 correct patches, GenProg, Kali, and Nopol contribute to 4, 1, and 3 patches, respectively. All the correct patches by Nopol come from the project Commons Lang; correct patches by GenProg and Kali come from Commons Math since they do not fix any bugs in other projects. For the incorrect patches, the main reasons are as follows. First, all three approaches are able to remove some code (pure removal for Kali, replacement for GenProg, precondition addition for Nopol). The corresponding patches simply exploit some under-specification and remove the faulty but otherwise not used behavior. This goes along the line of Qi et al.’s results [41]. When the expected behavior seems to be well-specified (according to our understanding of the domain), the incorrect patches tend to overfit to the test data. For instance, if a failing test case handles a $2 \times 2$ matrix, the patch may use such test data to incorrectly force the patch to be suitable only for matrices with the size of $2 \times 2$.

Among 42 analyzed patches, 29 patches are identified as easy to read and understand; 12 and 17 patches are identified as easy and medium for validating the correctness of patches. For the difficulty of patch validation, 13 patches are labeled as hard or expert. This result shows it is hard and time consuming to conduct the validation of patches.

Overall, our experimental results confirm the conclusion of Qi et al. [41]: most patches found by test suite based repair are incorrect. This confirmation is two-sided. First, both results by Qi et al. and by us show the same conclusion, but come from different bug benchmarks. Second, the finding holds for different systems: while Qi et al.’s results were made on GenProg (a random search approach), the same finding holds for Nopol and Kali (a constraint based repair approach and an exhaustive search approach).

This leads to two pieces of future work. First, test case generation and test suite amplification may be able to reduce the risk that the synthesized patches overfit the test case data. Second, we imagine that different repair algorithms may be more or less subject to overfitting.

Answer to RQ2. Based on manual examination of patch correctness, we find out that only 8 out of 42 generated patches are semantically correct. There exist large room for improving the applicability of test suite based repair.

C. Ill-defined bugs

RQ3. Which bugs in Defects4j are not sufficiently specified by the test suite? How many bugs should be discarded for the study of automatic repair?

As shown in Section IV-A, the repair approach, Kali, can fix nine bugs, including seven bugs that are fixed by both GenProg and Nopol. Among these nine generated patches, we find out that eight patches are problematic. In each of the eight generated patches by Kali, one statement is removed to eliminate the failing program behavior, instead of making it correct. This kind of patches shows that the corresponding test suite is too weak to specify the expected program behaviors. The assertions that specify the expected behavior of the removed statement and the surrounding code are inexistent or too weak.

One exception among nine patches by Kali is the patch of Bug M50. As shown in Section IV-B, the patch of Bug M50 is correct. That is, the statement removal is expected by the test suite.

Table V shows the nine bugs that are suggested to be removed or not from the dataset with respect to automatic
repair. Note that there may still exist other weakly specified bugs, which were not detected by our Kali implementation.

Answer to RQ3. Based on the fixed bugs by Kali, we suggest discarding eight bugs of Commons Math from the Defects4J dataset for automatic repair experiments. The reason for this removal is that the buggy code is neither well covered nor well specified by the test suite.

D. Performance

RQ4. How long is the execution time for each repair approach on one bug?

For real applicability in industry, automatic repair approaches must execute fast enough. By “fast enough”, we mean an acceptable time period, which depends on the usage scenario of automatic repair and on the hardware. Generally, it is acceptable to fix one bug within several hours. The experiments in this paper run on a grid where most of nodes have comparable characteristics. Typically, we use machines with Intel Xeon X3440 Quad-core processor and 15GB RAM.

For sake of space, the complete performance cannot be presented in this paper but can be consulted online [2]. For a repaired bug, its patch is typically found within minutes (e.g., 10 minutes for Bug L44). The execution timeout for repairing one bug is set to two hours. That is, the patch generation will be aborted if the repair approach runs over two hours.

Table VI shows the time cost of patch generation in hours. It is acceptable, comparing with the time of manual repair by developers. The average time cost for three approaches is less than one hour.

Table VII shows the time cost of patch generation in hours. For a repaired bug, its patch is typically found within minutes (e.g., 10 minutes for Bug L44). The execution timeout for repairing one bug is set to two hours. That is, the patch generation will be aborted if the repair approach runs over two hours.

Answer to RQ4. The time cost of executing a repair approach for one bug is acceptable. Both the median value and the average value of time cost are about one hour.

Answer to RQ5. Typical techniques of spectrum-based fault localization are useful to identify buggy statements for automatic repair; meanwhile, buggy statements in several bugs are hard to be localized with classical fault localization ranking metrics.

TABLE V. BUGS THAT ARE VERY WEAKLY SPECIFIED

| Project          | Bug ID | Status        |
|------------------|--------|---------------|
| Commons Math     | M2, M8, M49, M78, M80, M81, M82, M85, M50 | To be discarded |

| Project          | Bug ID | Status        |
|------------------|--------|---------------|
| Commons Math     | M2, M8, M49, M78, M80, M81, M82, M85, M50 | To be discarded |

TABLE VI. TIME COST OF PATCH GENERATION (IN HOURS)

| Time cost | GenProg | Kali | Nopol |
|-----------|---------|------|-------|
| Min       | 0.0075  | 0.0050 | 0.0050 |
| Median    | 1.0269  | 0.0169 | 0.0161 |
| Max       | 1.3075  | 0.8572 | 0.9019 |
| Average   | 0.9608  | 0.0881 | 0.0831 |
| Total     | 165.2792 | 18.9003 | 22.6353 |

TABLE VII. SEVEN RANKING METRICS OF FAULT LOCALIZATION TECHNIQUES IN COMPARISON

| Ranking metric | Definition                                                                 |
|----------------|-----------------------------------------------------------------------------|
| Tarantula [13] | \( \frac{n_f}{n_f + n_p} \)                                                |
| Jaccard [3]   | \( \frac{n_f}{n_f + n_p} \)                                                |
| Naish1 [42]   | \( \begin{cases} -1 & \text{if } e_f > 0 \\ n_p & \text{if } e_f = 0 \end{cases} \) |
| Naish2 [42]   | \( \frac{n_f}{n_f + n_p + 1} \)                                            |
| Ochiai [5]    | \( \frac{e_f}{\sqrt{(e_f + e_p)(e_f + n_f)}} \)                              |
| Ample [2]     | \( \frac{f_f}{n_f + n_p + 1} \)                                            |
| GP13 [15]     | \( \frac{e_f}{n_f + n_p + 1} \)                                            |

E. Fault Localizability

RQ5. Are standard techniques of spectrum-based fault localization effective to localize the buggy statements of the bugs of Defects4J?

As shown in Section II-A, test suite based repair requires a general mechanism to order suspicious statements before generating a patch. Fault localization aims to rank candidate statements based on the likelihood of containing bug; then developers could manual check and analyze the ranked statements [19], [4]. To answer our question of fault localizability, we empirically explore the results of seven typical techniques of spectrum based fault localization on the bugs in Defects4J.

Table VIII presents the average and median ranks of buggy statements of 224 real-world bugs in Defects4J. Considering the median value of ranks of buggy statements, Jaccard obtains the best medians in three out of four projects. In general, there is no major differences for the median rank. Only Naish1 is clearly worse. On this bug dataset, the choice of the fault localization metric is not a crucial impact. The average fault localization performance reads differently. Ochiai achieves the best followed by Tarantula and Naish2. The difference between median and average is the sensitivity to outliers (average is very sensitive to outliers). This means that Ochiai tends to smooth the outliers. The very large difference between the median and the average indicates that there exist several bugs, which are hard to be identified with spectrum-based fault localization.

Answer to RQ5. Typical techniques of spectrum based fault localization are useful to identify buggy statements for automatic repair; meanwhile, buggy statements in several bugs are hard to be localized with classical fault localization ranking metrics.

TABLE VIII. AVERAGE AND MEDIAN RANKS OF BUGGY STATEMENTS

| Project          | Ranking metric | Average rank | Median rank |
|------------------|----------------|--------------|-------------|
| Commons Math     | Tarantula [13] | 13.50        | 13.50       |
|                 | Jaccard [3]    | 13.50        | 13.50       |
|                 | Naish1 [42]    | 13.50        | 13.50       |
|                 | Naish2 [42]    | 13.50        | 13.50       |
|                 | Ochiai [5]     | 13.50        | 13.50       |
|                 | Ample [2]      | 13.50        | 13.50       |
|                 | GP13 [15]      | 13.50        | 13.50       |

V. CASE STUDIES

In this section, we present three case studies of generated patches by GenProg, Kali, and Nopol, respectively. These case studies will show evidence as follows.
TABLE VIII. RANKS OF BUGGY STATEMENTS IN FAULT LOCALIZATION ON SEVEN RANKING METRICS. A LOWER RANK INDICATES A BETTER FAULT LOCALIZATION TECHNIQUE.

| Subject program   | Ample    | Jaccard | Ochiai | Naish1 | Gp13 | Naish2 | Tarantula |
|-------------------|----------|---------|--------|--------|------|--------|-----------|
| Commons Lang      | Median   | 11.5    | 11     | 12     | 13   | 10     | 10        | 11        | Average  | 219.65 | 197.07 | 147.80  | 223.10  | 199.30 | 104.67 | 201.45    |
|                   | Median   | 8       | 8      | 8      | 22   | 8      | 8         | 6         | Average  | 898.15 | 216.84 | 904.57  | 322.47  | 210.57 | 233.63 |
| JFreeChart        | Median   | 15      | 13     | 16     | 43   | 15     | 15        | 13        | Average  | 322.03 | 51.79  | 52.90   | 82.17   | 61.20  | 565.88 | 691.29    |
|                   | Median   | 22      | 15     | 15     | 108  | 22     | 22        | 15        | Average  | 880.41 | 692    | 326.17  | 936     | 725.52 | 563.88 | 691.29    |
| Commons Math      | Median   | 15      | 13     | 16     | 43   | 15     | 15        | 13        | Average  | 322.03 | 51.79  | 52.90   | 82.17   | 61.20  | 565.88 | 691.29    |
|                   | Median   | 22      | 15     | 15     | 108  | 22     | 22        | 15        | Average  | 880.41 | 692    | 326.17  | 936     | 725.52 | 563.88 | 691.29    |
| Joda-Time         | Median   | 15      | 13     | 16     | 43   | 15     | 15        | 13        | Average  | 322.03 | 51.79  | 52.90   | 82.17   | 61.20  | 565.88 | 691.29    |
|                   | Median   | 22      | 15     | 15     | 108  | 22     | 22        | 15        | Average  | 880.41 | 692    | 326.17  | 936     | 725.52 | 563.88 | 691.29    |

To fix Bug M70, GenProg generates a patch by replacing the method call by another one, which is picked elsewhere in the same class. This bug cannot be fixed by either Kali or Nopol. Kali only removes statements; Nopol only handles bugs that are related to IF conditions.

A. Case Study of M70, Bug that is Only Fixed by GenProg

GenProg [29] updates a given buggy program with genetic programming. In this section, we present a case study of Bug M70, which is fixed by GenProg, but fails to be fixed by Kali and Nopol.

Bug M70 in Commons Math is about univariate real function analysis. Fig. 3 presents the buggy method of Bug M70. This buggy method contains only one statement, a method call to an overloaded method. The buggy method call only uses two of four available parameters. In order to perform the correct calculation, the method has to introduce the parameter UnivariateRealFunction f (at Line 1) to the method call. Both the manually-written patch and the patch by GenProg add the parameter f to the method call (at Line 5). This generated patch is considered correct since the patch by GenProg is the same as that by developers.

To fix Bug M70, GenProg generates a patch by replacing the method call by another one, which is picked elsewhere in the same class. This bug cannot be fixed by either Kali or Nopol. Kali only removes statements; Nopol only handles bugs that are related to IF conditions.

B. Case Study of M8, Bug that is Incorrectly Fixed by Kali and GenProg

Kali [41] removes a candidate statement to pass the test suite. In this section, we present a case study of Bug M8, which is fixed by Kali as well as GenProg, but fails to be fixed by Nopol.

Bug M8[10] in Commons Math, is about the failure to create an array of a random sample from a discrete distribution. Listing 4 shows an excerpt of the buggy code and the corresponding manual and synthesized fixes (from class DiscreteDistribution<T>). The method sample receives the expected number sampleSize of random values and returns an array of the type T[].

The bug is due to an exception thrown at line 11 during the assignment to out[i]. The method Array.newInstance(class, int) requires a class of a data type as the first parameter. The bug of M8 occurs when a) the first parameter is of type T1, which is a sub-class of T and b) one of the samples is an object which is of type T2, which is a sub-class of T, but not of type T1. Due to the incompatibility of types T1 and T2,
void stop() {
    if (this.runningState != STATE_RUNNING
        && this.runningState != STATE_SUSPENDED) {
        throw new IllegalStateException(...);
    }
}

// MANUAL FIX:
// if (this.runningState == STATE_RUNNING)
// NOPOL FIX:
// if (stopTime < StopWatch.STATE_RUNNING)
stopTime = System.currentTimeMillis();
this.runningState = STATE_STOPPED;
}

Fig. 5. Code snippet of Bug L55. The manually-written patch is shown in the MANUAL FIX comment at Lines 6 and 7 while the patch by Nopol is shown in the NOPOL FIX at Lines 8 and 9. The patch by Nopol is semantically equivalent to the manually-written patch by developers.

an ArrayStoreException is thrown when this object is assigned to the array.

In the manual patch, developers change the array type in its declaration (from T[] to Object[]) and the way the array is instantiated. The patch generated by Kali simply removes the statement, which assigns sample() to the array. As consequence, method sample never throws an exception but returns an empty array (only containing null values). This patch passes the failing test case and the full test suite as well. The reason of this is that the test case has only one assertion: it asserts that the array size is equal to 1. There is no assertion on the content of the returned array. However, despite passing the test suite, the patch is clearly incorrect. This bug is not well specified by the test suite. This example makes us suggest discarding Bug M8 from Defects4J in automated repair; this kind of bugs should not be used for the evaluation of test suite based repair. For this bug, GenProg can also generate a patch by replacing the assignment by a side-effect free statement. Nopol cannot handle this bug since the bug does not involve a conditional statement.

C. Case Study of L55, Bug that is Fixed by Nopol, Equivalent to the Manual Patch

Nopol [12] focuses on condition-related bugs. Nopol collects runtime data to synthesize a condition patch: correcting the original condition or adding a precondition for a statement. In this section, we present a case study of Bug L55, which is only fixed by Nopol, but fails to be fixed by GenProg and Kali.

Bug L55 in Commons Lang relates a utility class for timing. The bug appears when the user stops a suspended timer: the stop time saved by the suspend action is overwritten by the stop action. Fig. 5 presents the buggy method of Bug L55. In order to solve this problem, the assignment at Line 10 has to be done only if the timer state is running.

As shown in Fig. 5, the manually-written patch by the developer adds a precondition before the assignment at Line 10 and it checks that the current timer state is running (at Line 7). The patch by Nopol is different from the manually-written one. The Nopol patch compares the stop time variable to a integer constant (at Line 9), which is pre-defined in the program class and equals to 1. In fact, when the timer is running, the stop time variable is equals to −1; when it is suspended, the stop time variable contains the stop time in millisecond. Consequently, both preconditions by developers and by Nopol are equivalent and correct. Despite being equivalent, the manual patch remains more understandable. This bug is neither fixed by GenProg nor Kali. To our knowledge, Nopol is the only approach that contains a strategy of adding preconditions to original statements, which does not exist in GenProg or Kali.

Summary. In this section, we have presented detailed case studies of three generated patches for three real-world bugs of Defects4J. Our case studies show that automatic repair approaches is able to fix real bugs. However, the weaknesses of some test suites may result in incorrect patches.

VI. THREATS TO VALIDITY

We now discuss threats to the validity of our findings.

No comparison by tuning test suites. A threat to the external validity experiment is that the test suites we consider are large and in high quality. Existing work [35], [40] experiment with sampled subsets of test cases to study the impact of test suites on fixability and performance. We agree that the impact of the number and quality of test cases is important to automatic repair. In this paper, we have not analyzed the impact of the number of test cases; instead, we focus on comparing the repair effectiveness and the execution time for three repair algorithms. Further analysis of the impact of test cases is one of our future work.

Implementations of GenProg and Kali. In our work, three repair approaches are evaluated on real-world bugs. Among these three approaches, Nopol is designed and proposed by ourselves; the other two, GenProg and Kali, are implemented according to their related papers. Although we have tried our best to understand and implement these two approaches, there still exists a threat that our implementations are not exactly the same as the original proposed ones. Since both GenProg and Kali are not publicly available, the implementation by ourselves is the only way to conduct the comparison.

No fixed bugs for the project Joda-Time. In our experiment, we use bugs from four projects in Defects4J as dataset. Among these four projects, Joda-Time does not contain any automatically fixed bugs. As mentioned in Section IV-A, the program scale and complexity of Joda-Time are higher than those in the other three projects. This fact suggests that the scale of the repaired bugs in this experiment may still not be representative of typical real-world bugs and test suites. We will further explore the reasons behind the unfixed bugs in Joda-Time.

Bias of assessing the correctness, readability, and difficulty. In our work, each patch in Table IV-A is validated by an analyst, i.e., one of the authors. An analyst manually identifies the correctness of a patch and labels the related readability and difficulty. However, it may happen that the analyst opinion is not in accord with the true status of the patches. In our experiment, due to the time-consuming work, we did not let more than one analyst validate the patch. We share our results online to let readers have a preliminary idea of the difficulty of our analysis work and the correctness of generated patches (see Section IV-A).
VII. RELATED WORK

We present the work related to this research in three categories, real-world bug datasets, repair approaches, and reflection on automatic repair.

A. Real-World Datasets of Bugs

The academic community has already developed many methods for finding and fixing bugs. Researchers employ real-world bug data to evaluate their methods and to analyze problems in practice. Do et al. [13] propose a controlled experimentation platform for testing techniques. Their dataset is included in SIR database, which provides widely-used testbeds in debugging and test suite optimization.

Dallmeier et al. [10] propose iBug, a benchmark for bug localization obtained by extracting historical bug data. BugBench by Lu et al. [27] and BegBunch by Cifuentes et al. [8] are two benchmarks that have been built to evaluate bug detection tools. The PROMISE repository [1] is a collection of datasets in various fields of software engineering. This repository is one of the largest database for software research data.

In this experience report, we employ Defects4J by Just et al. [20] to evaluate software repair. This database includes well-organized programs, bugs, and their test suites. The bug data in Defects4J has been extracted from the recent history of five widely-used Java projects. To our knowledge, our experience report is the first work that evaluates automatic repair techniques via Defects4J.

B. Test Suite Based Repair Approaches

As mentioned in Section II-B test suite based repair can be roughly divided into three categories according to the strategy of searching for patches.

Random search. The idea of applying evolutionary optimization to repair derives from Arcuri & Yao [5]. Their work applies co-evolutionary computation to automatically generate bug fixes. GenProg by Le Goues et al. [24] applies genetic programming to the AST of a buggy program and generates patches by adding, deleting, or replacing AST nodes. PAR by Kim et al. [22] leverages patch patterns learned from human-written patches to find readable patches. RSRRepair by Qi et al. [40] uses random search instead of genetic programming. This work shows that random search is more efficient in finding patches than genetic programming. Their follow-up work [39] further leverages test case prioritization to reduce the cost of patch generation. Recent work by Martinez & Monperrus [30] mines repair models from manually-written patches to reduce the search space of new patches.

Exhaustive search. Debroy & Wong [11] propose a mutation-based repair method inspired from mutation testing. This work combines fault localization with program mutation to exhaustively explore a space of possible patches. Kali by Qi et al. [41] has recently been proposed to examine the fixability power of simple actions, such as statement removal. This work examines previous results reported by GenProg [24] and RSRRepair [40]. They show that only 2 out of 55 generated patches by GenProg and 2 out of 24 generated patches by RSRRepair are correct; other reported patches are incorrect due to experimental configuration and semantic issues.

C. Reflection on Automatic Repair

Automatic repair is considered a challenging endeavor. We present existing work that reflects on the foundations of automatic repair. Fry et al. [15] conduct a study of machine-generated patches based on 150 participants and 32 real-world defects. Their work shows that machine-generated patches are slightly less maintainable than human-written ones. Tao et al. [43] conduct a study for assisting human debugging with machine-generated patches. Barr et al. [6] examine the plastic surgery hypothesis of genetic-programming based repair. Their work shows that patches can be reconstituted from existing code; meanwhile, Martinez et al. [30] investigate the redundancy assumptions in automatic repair.

Monperrus [32] discusses the problem statement of automatic repair and its evaluation criteria. To explore the process of finding bug fixes, Murphy-Hill et al. [33] design a qualitative interview with 40 industrial engineers and a survey with 326 engineers. Their work presents how developers navigate the potential fixes to decide the final patch. Zhong & Su [46] conduct a case study on over 9,000 real-world patches and summarize 15 findings in two key ingredients of automatic repair: fault localization and faulty code fix.

VIII. CONCLUSION

We present an experience report of a large scale evaluation of automatic repair approaches. Our experiment was conducted with three typical repair approaches on 224 bugs in the Defects4J dataset. We find out that only 41 out of 224 bugs can be fixed by the state-of-the-art test suite based repair approaches; among three approaches under comparison, Nopol performs the best and is able to fix 34 bugs. Our findings based on five research questions show that there exist large room for improvement in automatic repair.

In future work, we plan to implement and compare more repair approaches to further study the limitations and drawbacks of automatic repair techniques. Meanwhile, we want to perform a detailed analysis to explore the reasons behind unfixed bugs in our experiment. We hope that understanding the reasons behind the unfixed bugs could seed new and creative repair algorithms.

All experimental results are publicly available at http://github.com/Spirals-Team/defects4j-repair/
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