Abstract—Most automatic program repair techniques rely on test cases to specify correct program behavior. Due to test cases' frequently incomplete coverage of desired behavior, however, patches often overfit and fail to generalize to broader requirements. Moreover, in the absence of perfectly correct outputs, methods to promote higher patch quality, such as merging together several patches or a human evaluating patch recommendations, benefit from having access to a diverse set of patches, making patch diversity a potentially useful trait. We evaluate the correctness and diversity of patches generated by GenProg and an invariant-based diversity-enhancing extension described in our prior work. We find no evidence that promoting diversity changes the correctness of patches in a positive or negative direction. Using invariant- and test case generation-driven metrics for measuring semantic diversity, we find no observed semantic differences between patches for most bugs, regardless of the repair technique used.

I. INTRODUCTION

Software bugs are troublesome: a study of software bugs in 2017 found that just 606 known bugs affected half of the population and $1.7 trillion USD of assets [1]. They are also cumbersome for programmers, who spend, on average, approximately half of their time diagnosing and squashing bugs [2]. Efforts in automated program repair attempt to alleviate these societal and developmental costs by automating the bug repair process. Most program repair tools require the user to input a program and a set of test cases, which specify desired program behavior. Test cases, however, frequently fail to fully cover the actual specifications of a program. Consequently, program repair techniques frequently produce incorrect patches that overfit to the provided test suite and fail to generalize to broader requirements not explicitly specified in the provided tests [3]–[6]. Producing correct patches that adhere to broader, implicit specifications is thus a desideratum of program repair techniques.

Inconsistency in the quality of patches generated by automated program repair tools can perhaps be alleviated with, among other means, a human in the loop judging patches and/or by combining information from patches to produce a superior patch [7]. In both cases, providing a set of diverse patches may be useful. For the human in the loop adjudicating patches, a diversity of patches means a diversity of options to choose from. For the approach of merging patches into a better patch, a diversity of patches means a diversity of information to merge together. Producing diverse patches may thus also be desirable for these applications.

We thus evaluate patch correctness and diversity for two program repair techniques: GenProg [8], a search-based program repair technique based on genetic programming, and an invariant-driven diversity-promoting repair technique derived from GenProg and described in our prior work [9]. To evaluate patch correctness, we use held-out tests, a practice previously used in evaluating program repair tools [5], [6]. To evaluate patch diversity, we use semantic diversity metrics based on inferred invariants [9] and automatic test case generation tools [7].

This paper’s main contributions are:

• An evaluation of patch correctness for GenProg [8] and our diversity-promoting repair technique [9].
• An evaluation of patch diversity using both invariant-based [9] and test generation-based [7] semantic diversity for GenProg and our diversity-promoting repair technique.

II. BACKGROUND

A. GenProg and Attempts at Improvement

GenProg [8] is a search-based automated program repair technique. GenProg accepts, as input, a faulty program’s source code, failing test cases (negative tests) that demonstrate the fault, and passing test cases (positive tests) that demonstrate desirable program behavior to preserve. To produce a bug patch, GenProg treats bug repair as an optimization problem: which patch(es) in the space of possible patches passes as many test cases as possible? The globally optimal solutions are patches that pass all test cases, which GenProg assumes to be correct. GenProg solves this optimization problem using genetic programming. To traverse the space of patches, GenProg mutates and recombines code at the statement level, creating a population of variant programs, or candidate patches. In contrast to approaches that randomly traverse the space of patches, such as TrpAutoRepair [10], GenProg guides the traversal by observing the number of test cases that each candidate patch passes. For each candidate patch, GenProg computes a fitness score equal to a weighted sum of the number of positive and negative patches that the candidate patch passes. Candidate patches with higher fitness are more likely to reproduce through further mutation and recombination, and their offspring will carry the code edits of the parent candidate patch, unless if negated by further code edits.
GenProg’s reliance on test cases as a measurement of program correctness makes the approach vulnerable to overfitting, where GenProg constructs a patch that conforms to the test suite, but breaks other implicit software requirements not covered by the provided tests. The weakness of test cases as a specification for program behavior is not specific to GenProg; the problem is common among program repair techniques that rely on test cases as a metric of program correctness. Qi et al. [3] found that almost all repairs produced by GenProg, AE [11], and RSRepair [12]—techniques which depend on test cases to specify desired behavior—are incorrect. They also find that many patches introduce undesirable effects, such as deleting functionality or introducing security vulnerabilities. Other studies, which we discuss in more detail in Section V, have also found a high proportion of incorrect patches among various program repair techniques [4]–[6].

Moreover, GenProg’s test case-based fitness function should, in theory, identify and favor partial solutions that have also found a high proportion of incorrect patches among various program repair techniques [4]–[6].

The fitness function’s inability to differentiate between candidate patches undermines GenProg’s ability to compose more complex patches. Despite being capable of constructing multi-edit repairs, much of GenProg’s patches actually reduce down to single-edit repairs [3]. A potential explanation of test cases’ weakness at discriminating candidate patches may lie in the binary nature of test cases. Test cases generally only pass or fail, and generally do not provide indications of partial correctness. As a result, test cases lack granularity in the semantic information they provide, and a test case-based fitness function would thus also be not granular. Thus, a test suite might determine different patches with differing levels of partial correctness to be equally incorrect.

Our previous work [9] attempts to improve on GenProg’s search strategy by incorporating additional semantic information from inferred invariants. Using semantic information derived from invariants, we determine which patches appear to be more semantically unique and diverse, which we favor for selection and further exploration. By leveraging added semantic information to diversify the search of the repair space, we sought to discourage the search process from being trapped in locally optimal fitness values, which are undesirable in genetic algorithms [15]. Moreover, producing multiple semantically diverse patches may be desirable for patch recommendation systems, where a human in the loop may choose between several semantically diverse patches, or for combining multiple low quality patches into a higher quality patch [7]. We describe the approach’s method of measuring and promoting semantic diversity in [11–18]. An evaluation on a refactored subset of IntroClassJava [16] reveals that while our prior work was able to successfully diversify the search for a repair and better differentiate between candidate patches, we had no statistically significant evidence of an improvement in repair efficiency or success.

There exist other previous efforts to incorporate more semantic information to improve GenProg’s search process. Fast et al. [17] attempts to learn correlations between invariant behavior and program success or failure. Their approach uses known patches for a bug to train a linear model that maps the behavior of invariants and test cases to fitness values. de Souza et al. [13] uses dynamic analysis to track changes in variable values at pre-determined source code checkpoints. They produce a checkpoints metric based on these changes, which they incorporate into the fitness function.

B. Daikon and Invariant-Based Semantic Diversity

Daikon [18] is a dynamic analysis tool that infers likely program invariants. Program invariants are properties which hold true at indicated program locations. Given a program and a method to execute the program (such as test cases), Daikon collects execution traces and analyzes which invariants, as described by a grammar, are statistically likely to be true for the program, as evidenced by program values in the collected trace.

Our previous work [9] introduces a measurement of semantic difference based on inferred invariants in the context of program repair. Given a set of likely invariants inferred from the original faulty program, we construct an invariant profile—a string representation of the reachability and truth of the set of invariants in a program—for each candidate patch. We construct this invariant profile by instrumenting candidate patches to detect whether each invariant is reached and ever violated during program execution, with the results recorded separately for executions of positive and negative tests. The semantic distance between two programs is the Hamming distance between the two programs’ string-based invariant profiles. The semantic diversity of a program within a population of programs is the semantic distance between the program and the rest of the population, which we compute by summing the semantic distance between the program and each other program in the population. We promote semantic diversity by using our semantic diversity metric as an optimization objective along with test cases.

C. EvoSuite and Test Generation-Based Semantic Diversity

EvoSuite [19] is a search-based automatic test case generation tool for Java programs. Given a Java bytecode program, EvoSuite produces JUnit tests [20]. To generate tests, EvoSuite uses a combination of mutation analysis and concolic execution to produce and evolve a test suite that maximizes code coverage. Mutating the program simulates the introduction of faults, and EvoSuite uses genetic programming to create tests that detect these mutations, with concolic execution activated after a preset number of generations.

Soto [7] proposes a measurement for semantic distance based on the output of test case generators. Given two programs $P$ and $Q$ to compare, Soto uses EvoSuite to generate
test suites $T_P$ and $T_Q$ and merges them to produce $T_P \cup T_Q$. To describe the semantics of $P$ and $Q$, Soto evaluates each program on the merged test suite $T_P \cup T_Q$ to produce a string-based report. The semantic distance between $P$ and $Q$ is the Hamming distance between the two programs’ reports, normalized by the length of the reports ($|T_P \cup T_Q|$).

### III. Analysis

We evaluate the correctness and semantic diversity of patches generated by GenProg [8] and the program repair approach described by our prior work [9]. We address the following research questions:

**RQ1: Does promoting semantic diversity using invariants change the correctness of repairs generated?**

Since both repair approaches rely on test cases to specify desired program behavior, both techniques risk creating patches that overfit to the provided tests and fail to generalize to broader, implicit requirements. Previous evaluation of GenProg found that many of its repairs are, in fact, incorrect due to weak test suites [3]. Promoting semantic diversity may inadvertently encourage an accumulation of negative, fault-creating edits that test cases might fail to detect, since these edits may result in a change in invariant-observed semantic behavior and thus be favored. Conversely, if truly correct patches are sparser in semantic space than falsely correct patches, then broadening and diversifying the search throughout semantic space might result in a higher chance of encountering truly correct repairs. We thus investigate patch correctness for both repair techniques.

**RQ2: Does promoting semantic diversity using invariants change the semantic diversity of repairs generated?**

By encouraging a broad and diverse search through semantic space, we hypothesize that our previously described approach would produce semantically diverse patches. A diverse set of patches may be useful for applications with a human in the loop, such as patch recommendation systems, or for combining multiple patches into a better patch [7]. We thus evaluate patch diversity for both repair techniques.

To evaluate our research questions, we use the modified version of IntroClassJava [15] created for our prior work [9]. IntroClassJava is a derivative of IntroClass [21], a set of buggy programs written by students in an introductory programming class. Every IntroClassJava bug comes with a set of black-box tests and white-box tests. Black-box tests derive from the program’s specifications and are written manually by the class’s instructor. White-box tests derive from generating tests using KLEE [22], a symbolic execution-based test generator, on a C reference implementation, with manually written tests to cover branches that KLEE cannot generate a test for. We use white-box tests as input to GenProg and our diversity-promoting repair technique, and we use black-box tests as a held-out test suite to evaluate the correctness of patches generated by both techniques as part of RQ1. Note that this evaluation setup differs from the setup used in evaluating our prior work [9], where we inputted both white-box and black-box tests to both repair techniques.

We discard any patches found during the initialization process of either technique, as GenProg and our diversity-promoting technique differ only after the initialization process, where selective pressure begins to shape the search for a repair. As a result, both techniques traverses the search space identically during initialization, and any patches found during initialization do not illustrate the differences in behavior of the two techniques. Therefore, we exclude such patches from analysis.

For our preliminary experiments described here, we use four bugs from the six bugs successfully repaired by either repair technique in our prior work [9]. We use a subset of our previously repaired bugs—which pass all white-box and black-box tests—in order to guarantee that there exists at least one “correct” patch that passes both sets of tests within the search space of the techniques. Out of the six bugs, we exclude smallest-af81-000 as the bug does not have any failing white-box tests, and we exclude smallest-8839-002 as both techniques found patches exclusively during the initialization process in our testing. We thus use the four remaining bugs.

For both techniques, we use the append, replace, and delete mutation operators, one-point crossover, tournament selection with a tournament size of $k = 2$, a population size of 40, and a limit of 10 generations. We repeat each experiment with random seeds 0–9 inclusive. We conduct our experiments on a computer with the following specifications: Ubuntu Server 16.04 LTS, 4x Intel Xeon E7-4820, 128 GB of RAM, and 2 TB of magnetic hard disk storage.

#### A. Evaluation of RQ1: Patch Correctness

We evaluate patch correctness by testing each patch against its held-out black-box tests. Table 1 provides the proportion of “correct” patches generated by each technique. The proportion of patches that the black-box tests deem correct are almost identical for both techniques. A two-sided Fisher’s exact test reveals no statistically significant evidence ($p > 0.05$) of a difference in the number of correct and incorrect patches generated by both techniques. Moreover, most bugs demonstrate all-or-nothing behavior, where almost all repairs generated by

| Bug           | Number of “Correct” Patches | GenProg | Ding et al. |
|---------------|-------------------------------|---------|-------------|
| digits-0cdf-006 | 1 / 6                         | 1 / 7   |
| digits-0cdf-007 | 4 / 4                         | 4 / 4   |
| digits-8b50-000 | 0 / 7                         | 0 / 7   |
| digits-d120-001 | 7 / 8                         | 8 / 8   |
| **Total**     | **12 / 25**                   | **13 / 26** |
TABLE II: Average semantic diversity of patches generated by each repair technique, measured by both inferred invariants [2] and EvoSuite-generated tests [7].

| Bug             | Mean Semantic Diversity |
|-----------------|-------------------------|
|                 | Invariant-Based | EvoSuite-Based |
|                 | GenProg | Ding et al. | GenProg | Ding et al. |
| digits-0cdf-006 | 0       | 0           | 0       | 0           |
| digits-0cdf-007 | 0       | 0           | 0       | 0           |
| digits-5b50-000 | 0       | 0           | 0.5     | 0.08        |
| digits-d120-001 | 0       | 0           | 0       | 0           |

either technique are correct or incorrect, suggesting that the strength of test suites takes precedence over the search strategy in producing correct patches.

B. Evaluation of RQ2: Patch Diversity

We evaluate patch diversity using both invariant-based and test generation-based metrics of semantic diversity. To measure invariant-based diversity, we treated the set of repairs for a particular bug as a population and used the metric for invariant-based semantic diversity described in our prior work [2]. To measure test generation-based semantic diversity, we used the metric for semantic distance described by Soto [7], and summed the semantic distance between a patch and every other patch for a particular bug to compute a patch’s semantic diversity. Table II provides the average semantic diversity of patches generated by both techniques. For both techniques and almost all bugs, neither metric for semantic diversity discerned any semantic difference between any patches for a particular bug.

The semantic indistinguishability of patches suggests either a lack of patch diversity or weakness in the two metrics of semantic distance. We intend to conduct a manual patch analysis to investigate patch semantics and determine the cause of indistinguishability in future work.

IV. THREATS TO VALIDITY

A. Test Case Weakness

Using held-out test cases to evaluate patch correctness poses the risk of a patch overfitting to both the white-box and black-box tests. While patches deemed correct by the held-out tests may still be incorrect, using held-out tests nevertheless allows us to determine whether patches generalize to requirements not specified in the inputted tests but evaluated in the held-out tests. Manual correctness analysis and formal verification may provide stronger evidence of correctness.

B. Sample Size

Our early results evaluate only four bugs and 51 patches. The four bugs are chosen as test subjects as there exist known patches within the search space that are correct with respect to both white-box and black-box tests. We propose to broaden our evaluation to more software bugs in future work.

C. Bug Benchmark

We use a subset of IntroClassJava [16] programs as a benchmark for evaluation. These buggy programs are small (< 30 LOC) and are written by introductory programming students as part of class assignments, rather than by professional software engineers as a part of real-world software. Moreover, the bugs' test suites were designed to have very high specification coverage (with black-box tests) or branch coverage (with white-box tests) [21], which is not always true in real-world software. Evaluating IntroClassJava programs and their bugs does not simulate an application of program repair on industrially-sized software. We propose to evaluate patch correctness and diversity on benchmark datasets containing larger, real-world programs, such as Defects4J [23] or Bugs.Jar [24].

V. RELATED WORK

This section discusses other prior efforts in evaluating patch quality. We are not aware of prior efforts in evaluating patch diversity at the time of writing.

Qi et al. [3] evaluates the correctness of patches generated by the search-based program repair tools GenProg [8], AE [11], and RSRRepair [12]. They find that the vast majority of patches generated by these tools are incorrect. When they write additional test cases to expose the errors found and input them into GenProg to better guide the search, GenProg was unable to find any patches. They also found that most patches generated by all three techniques are semantically reducible to functionality deletion and often introduce undesired effects, such as security flaws or loss of functionality.

Martinez et al. [4] evaluates the correctness of patches that GenProg generates for the Defects4J benchmark, a set of real-world Java bugs in open source software. Manual analysis reveals that a large majority of patches were incorrect.

Smith et al. [5] evaluates the correctness of patches generated by the search-based program repair tools GenProg [8] and TrpAutoRepair [10], as well as compare the correctness of tool-generated patches to patches written by novice student programmers. They use IntroClass as a benchmark and also use held-out tests to evaluate patch correctness in a manner similar to our evaluation. They find that a large majority of patches are incorrect based on the held-out tests, but also that there’s no statistically significant difference between the correctness rate of tool and novice human-generated tests.

Le et al. [6] evaluates the correctness of patches generated by semantics-based program repair techniques, which use symbolic execution and program synthesis, rather than a search through the space of possible patches, to generate a repair. They evaluate the semantics-based repair tool Angelix [25] and variations of the tool with different synthesis engines [26] on the IntroClass [21] and Codeflaws [27] benchmarks, both of which supply two separate test suites per bug. Similar to our evaluation of patch correctness, they use one of the two independent test suites as held-out tests for evaluating patch correctness. They find that a large majority of patches generated by all techniques are incorrect based on the held-out
tests, revealing that the problem of patch overfitting extends to semantic-based repair techniques as well.

Xin and Reiss [28] proposes DiffTGen, a technique for evaluating patch correctness by generating test cases based on differences in program syntax between a buggy program and its patch. If running these generated tests produces different output, the difference is sent to an oracle (a human in their evaluation) for correctness analysis. DiffTGen identified 49.4% of overfitting patches generated by various program repair techniques. Their tool can also enhance automated program repair techniques by augmenting test suites with additional generated tests.

VI. CONCLUSION

Our initial results do not suggest evidence of diversity promotion causing an increase or decrease in patch correctness. We moreover find that our metrics for semantic diversity were unable to distinguish between patches for almost every bug, regardless of repair technique used. We propose to further investigate the cause of semantic patch indistinguishability with further analyses, including manual analysis. Moreover, we intend to broaden the scope of bugs for investigation, including real-world bugs in larger, industrially-sized software.

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