Revisiting ssFix for Better Program Repair

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Abstract—A branch of automated program repair (APR) techniques look at finding and reusing existing code for bug repair. ssFix is one of such techniques that is syntactic search-based: it searches a code database for code fragments that are syntactically similar to the bug context and reuses such retrieved code fragments to produce patches. Using such a syntactic approach, ssFix is relatively lightweight and was shown to outperform many other APR techniques. In this paper, we investigate the true effectiveness of ssFix, we conducted multiple experiments to validate ssFix’s built-upon assumption (i.e., to see whether it is often possible to reuse existing code for bug repair) and evaluate its code search and code reuse approaches. Our results show that while the basic idea of ssFix, i.e., reusing existing code for bug repair, is promising, the approaches ssFix uses are not the best and can be significantly improved. We proposed a new repair technique sharpFix which follows ssFix’s basic idea but differs in the code search and reuse approaches used. We evaluated sharpFix and ssFix on two bug datasets: Defects4J and Bugs.jar-ELIXIR. The results confirm that sharpFix is an improvement over ssFix. For the Defects4J dataset, sharpFix successfully repaired a total of 36 bugs and outperformed many existing repair techniques in repairing more bugs. For the Bugs.jar-ELIXIR dataset, we compared sharpFix, ssFix, and four other APR techniques, and found that sharpFix has the best repair performance. In essence, the paper shows how effective a syntactic search-based approach can be and what techniques should be used for such an approach.

I. INTRODUCTION

Automated program repair (APR) [1] can significantly save people time and effort by repairing a bug automatically. Given a faulty program and a fault-exposing test suite, a typical APR technique automatically modifies the faulty program to produce a patched program that passes the test suite. Over the past decade, many APR techniques [2]–[21] have been developed. They look at using different approaches to do bug repair. One major problem faced by current APR techniques is the search space problem [22]. An APR technique often needs to define a huge search space of patches to support repairing different types of bugs. However, searching for a correct patch in such a huge search space is often difficult [22].

To address the problem, one idea is to reuse existing code from existing programs. By doing so, a repair technique can avoid generating a large amount of artificial code to possibly avoid the search space explosion. The recent APR technique ssFix [16] was built upon the idea. It performs syntactic code search to find existing code fragments from the local faulty program and an external code repository that are similar to the bug context and reuse those code fragments to produce patches for bug repair. ssFix leverages the syntactic differences between any retrieved code fragment and the bug context to produce patches. For a code fragment that is similar to the bug context, the differences are small, and the search space is therefore reduced. Experimental results from [16] showed that ssFix is lightweight and relatively effective: it generated valid patches for 20 bugs in the Defects4J dataset [23] with the median running time for generating a patch being only about 11 minutes, and it outperformed five other APR techniques [2], [7]–[9], [13].

Though ssFix seems like a promising technique, we do not know much about its repair potential for two reasons: First, ssFix is built upon the assumption that existing programs contain the fix ingredients (the statements/expressions needed for producing a correct patch). However, we do not really know how often the assumption holds in practice. Second, assuming the fix ingredients do exist in existing programs, we do not know whether ssFix uses the best approaches for finding and reusing these fix ingredients for repair.

In this paper, we conducted multiple experiments on the Defects4J bug dataset [23] to (1) test the fix-ingredient-assumption, i.e., to investigate whether the fix ingredients for bug repair often exist and to (2) evaluate ssFix’s abilities in finding and reusing the fix ingredients for bug repair. For (1), we first defined the fix ingredient for a bug in the context of automated program repair (Section II-A) and then performed syntactic code search to check whether the fix ingredient exists in the local faulty program or in any non-local programs in a code repository (Section II-B). For (2), we conducted multiple experiments (Section III) looking at (a) whether ssFix can effectively retrieve the existing fix ingredients, (b) whether ssFix can effectively reuse the fix ingredients it retrieved to do bug repair, and (c) whether ssFix can do effective repair possibly with the fault being accurately located.

Our results showed that (1) the idea of reusing existing code for bug repair is promising (Section II-B3) and (2) the approaches used by ssFix for code search and code reuse however can be improved significantly (Sections III-B and III-C). Based on our experimental observations, we developed a new repair technique sharpFix which follows ssFix’s basic idea but uses improved approaches for code search and reuse. sharpFix improves ssFix’s code search by using different code search methods for retrieving code fragments from the local faulty program and from the non-local programs in the code repository.
repository. For patch generation, sharpFix goes through the same steps used by ssFix: code translation, code matching (component matching in [16]), and modification. Each step however is different and improved. The improved approaches used by sharpFix let it correctly repair 36 Defects4J bugs in total and outperform ssFix in correctly repairing 14 more bugs. We further evaluated sharpFix, ssFix, and four existing APR techniques: jGenProg [24], jKali [24], Nopol (version 2015) [25], and HDRepair [26] on another dataset: Bugs.jar-ELIXIR [15] which contains 127 real Java bugs. The results show that sharpFix outperformed all these techniques and again confirm that existing code that it looks at often contains the fix ingredient needed for producing a correct patch. It is important to know whether assumption holds in practice to understand whether a search-based repair technique is truly effective. We conducted an experiment to test the assumption, i.e., to investigate how often the fix ingredient for bug repair exists. For our experiment, we looked at simple patches. For a simple patch, all the fixing changes are made within either an expression or a primitive statement which contains no children statements. In the context of automated bug repair, we defined six types of fix ingredients for a simple patch. For each bug in the Defects4J dataset whose patch is simple, we identified the fix ingredient and checked whether it exists in the code database we used. We did not look at more complex patches. To deal with a complex patch, one may apply our method by first dividing the patch into simple patches and then searching for the fix ingredient for each. This corresponds to a natural way of producing a complex patch: it is not likely to produce the component (simple) patches all at once but one by one.

There are existing studies that also test the fix ingredient assumption: Some of the studies [27], [28] looked at whether the fix ingredient exists at the level of code lines. A fix ingredient however does not have to be an entire code line to be reused for bug repair (we will show this with an example later). The others [29], [30] do not actually fit our context. For example, Martinez et al. [30] studied whether the fix ingredient exists in a program’s previous versions which a repair technique like ssFix often does not look at for repair.

A. Defining the Fix Ingredient

Some simple definitions can be either too general or too constrained. As an example, the correct (developer) patch for the Defects4J bug Math_83 changes the buggy if-condition from \( \text{fa} \ast \text{fb} > 0.0 \) to \( \text{fa} \ast \text{fb} > 0.0 \). A fix ingredient defined as the exact changed expression is too general: we can find lots of code fragments containing \( > \), but very few of them can possibly be useful for repair. A fix ingredient defined as the changed line can be constrained since it requires the correct expression to appear as an if-condition. A fix ingredient defined as the changed statement is too program-specific and thus too constrained.

In the context of automated bug repair, we looked at using six types of modifications (M0-M5 as shown below) used by existing APR techniques [2], [10], [13], [16], [31] to model a general repair modification. For each type of modification, we defined the corresponding fix ingredient. If the fix ingredient can be found within a code fragment that is reasonably small, then it is possible for a repair technique to effectively reuse the fix ingredient to produce a correct patch.

- **M0**: Combining a Boolean condition with another Boolean condition using \( \& \) or \( | | \) (e.g., \( \text{if (c0)} \{ \ldots \} \rightarrow \text{if (c0 | | c1)} \{ \ldots \} \))
- **M1**: Changing an expression (as a non-if-condition) to another expression (also as a non-if-condition) (e.g., \( e0 \rightarrow e1 \))
- **M2**: Changing an if-condition to another if-condition (e.g., \( \text{if (c0)} \{ \ldots \} \rightarrow \text{if (c1)} \{ \ldots \} \))
- **M3**: Adding an if-condition for one or more statements (e.g., \( s \rightarrow \text{if (c)} \{ s \} \))
- **M4**: Replacing a statement with another statement (e.g., \( s0 \rightarrow s1 \))
- **M5**: Inserting a statement (e.g., \( s \rightarrow s0; \ s \))

The corresponding fix ingredients (FIs) are shown below.

- **F0**: The combined Boolean condition (\( c1 \) in M0’s example)
- **F1**: The parent statement/expression of the changed expression (the parent of \( e1 \) in M1’s example)
- **F2**: The changed if-condition (\( c1 \) in M2’s example)
- **F3**: The added if-condition (\( c \) in M3’s example)
- **F4**: The replaced statement (\( s1 \) in M4’s example)
- **F5**: The inserted statement (\( s0 \) in M5’s example)

For M0, M2, and M3, we use the combined, changed, and added if-conditions as the fix ingredients respectively. For M4 and M5, we use the replaced and inserted statements as the fix ingredients respectively. For M1, we do not simply use the changed expression (i.e, \( e1 \) in M1’s example) as the fix ingredient since the changed expression can be too small and thus be lack of context (consider \( e1 \) as a variable
argument of a method call). So instead, we use the parent statement/expression of the changed expression as the fix ingredient (in the abstract syntax tree, this is the parent node of the changed expression node).

For the Math_B5 example, we define the fix ingredient as the expression \(fa \cdot fb > 0.0\), and we successfully found the exact fix ingredient from the local faulty program in a loop statement: \(\{\ldots\} while((fa \cdot fb > 0.0) \&\& \ldots).\) For this bug, this is the only statement in the local program where \(fa \cdot fb > 0.0\) is contained.

B. Experiment for Testing the Fix Ingredient Assumption

1) Setup: Our experimental dataset is the Defects4J dataset (version 0.1.0) [23] which contains in total 357 real bugs. We manually identified 103 bugs whose developer patches (provided by the dataset) are simple. For each patch, we looked at the modification types in an sequential order from M0 to M5, identified the first type as which the patch can be classified, and then identified the fix ingredient. For experiment, we checked whether the fix ingredient exists in either the local faulty program or any non-local program in a code repository for which we used the DARPA MUSE code repository which consists of 66,341 Java projects (about 81GB).

2) Search Methodology: For each simple patch, we performed syntactic code search to check whether the identified fix ingredient can be found within the code database, i.e., the local faulty program plus all the programs in the code repository we used. In our definition, a fix ingredient can only be an expression or a statement. So we extracted every statement within every method in the code database, tokenized the fix ingredient and every extracted statement, and checked whether the fix ingredient’s tokens are a subsequence of any extracted statement’s tokens in either the exact or the parameterized form. For parameterization, we replaced program-specific (i.e., non-JDK) variables, types, and methods with special symbols: $v$ for variables, $t$ for types, and $m$ for methods.

To find a fix ingredient within the local faulty program, we exactly checked whether the fix ingredient’s tokens are a subsequence of any extracted statement’s tokens with and without parameterization. To find a fix ingredient within the code repository, we could do the same, but this can be very expensive: for each of the 103 bugs, we would have to iterate every statement in the large code repository. So instead, we indexed every statement in the code repository using ssFix (from https://github.com/qixin5/ssFix), and performed two steps: (1) we did ssFix’s code search using the fix ingredient’s enclosing statement as the query to have the top-500 statements retrieved and (2) we checked, for each retrieved statement, whether the fix ingredient’s tokens are a subsequence of the statement’s tokens. For code search within the repository, we filtered away any statement whose enclosing method’s signature is identical to the faulty method’s signature and whose enclosing package’s name is identical to the faulty method’s enclosing package’s name (as did in [16]). We did so to ignore any fix ingredients that are simply from any bug-fixed versions of the faulty program.

III. Analyzing ssFix

A. Some Background of ssFix

Given a faulty program, a fault-exposing test suite (which the program failed), and a code database which consists of the faulty program and a large code repository, ssFix goes through the following four stages to possibly produce a patched program that can pass the test suite. Such a patched program (or the patch) is called plausible.

1) Fault Localization: ssFix relies on an existing technique GZoltar [33] to identify a list of suspicious statements ranked from the most suspicious to the least. In the following stages, it looks at each statement independently to produce patches.

2) Code Search: Given a suspicious statement, ssFix produces a code chunk (called the target chunk, or the target) including the statement possibly with its local context and searches for code chunks (called the candidate chunks, or the candidates) in the code database that are syntax-related (structurally similar and conceptually related) to the target to be reused for bug repair. In later stages, ssFix
looks at reusing each candidate to produce patches for the target independently.

3) **Patch Generation**: Given a candidate being retrieved, ssFix first translates the candidate by renaming the variables, types, and methods used in the candidate and then produces a set of patches based on the syntactic differences between the target and the translated candidate. More specifically, ssFix matches the related statements and expressions between the two chunks and performs three types of modifications to produce patches based on the matching result.

4) **Patch Validation**: ssFix sorts the generated patches and then tests them to find the first plausible patch. For testing a patch, ssFix first applies the patch to the faulty program to get a patched program. It then checks whether the patched program can compile and can pass the test suite.

More details about ssFix can be found in [16]. In this paper, we call the last two stages **code reuse**.

### B. Evaluating ssFix’s Code Search

To evaluate ssFix’s code search ability, we looked at the 103 bugs used in Section II-B whose developer patches are simple. For each bug, we provided ssFix with the real faulty statement, ran its code search, and checked whether it can effectively retrieve any candidates that contain the fix ingredient that we identified earlier. We call a candidate (possibly after translation) that contains the fix ingredient in its exact form **promising**. Our results show that ssFix retrieved promising candidates within the top-500 results for 38 bugs.

1) **Experiment**: For each of the 103 bugs, we provided ssFix with the faulty statement, ran ssFix’s code search to retrieve a list of ranked candidates (as code chunks) from the code database, translated the candidates using ssFix’s code translation (otherwise it may not be able to reuse the fix ingredient for repair), and checked whether any retrieved candidate is promising, i.e., contains the exact fix ingredient.

The code database we used consists of the DARPA MUSE code repository (as used in Section II-B) as the external code repository and the same five projects used in [16] as the local programs. We filtered away candidates that are syntactically redundant and those that are simply from the bug-fixed versions. We looked at the top-500 candidates as the retrieval results.

2) **Result**: Figure 2 shows the numbers of promising candidates ssFix retrieved within the top-k results (with k being 50, 100, 200, and 500 respectively). Within the top-500 results, ssFix retrieved promising candidates for 38 bugs: it retrieved in total 61 candidates that contain the fix ingredients in the parameterized forms, among which, 38 candidates are promising, i.e., contain the exact fix ingredients after translation. In Section II-B3, we showed that for as many as 80 bugs, the fix ingredients in the parameterized forms exist. ssFix retrieved promising fix ingredients for 38/80=47.5% bugs.

Our results show that ssFix produced 25 plausible patches among which 23 are correct. It successfully reused 23/61=37.7% candidates for bug repair. Note that this is a lower bound because not all the candidates can be reasonably reused for repair. We found that the exact fix ingredients (without any translation) are contained in 38 candidates, and we expect ssFix to be able to reuse those fix ingredients in producing the correct patches. For the other 23 (61-38) candidates which only contain the fix ingredients in the parameterized forms, we manually determined whether they can be reasonably reused for bug repair. We identified only 3 such candidates (it may not be reasonable for a repair technique to translate an arbitrary, parameterized fix ingredient into the exact one to be reused for repair).

We analyzed the failures of ssFix in reusing the 18 (38+3-23) reasonable candidates for producing the correct patches. We found that 7 candidates are not ideal for repair. As one example, for the bug Cl119, ssFix retrieved a candidate containing the exact fix ingredient case Token.CATCH: as a statement to be inserted in the target for producing the correct patch. However, the fix ingredient is embedded in a big switch statement, and it is therefore difficult for ssFix to leverage the fix ingredient to do the correct repair. For the other failures, we found that ssFix yielded bad candidate translations for 3 cases, it created bad code matching results for 2 cases, and its modifications are not sophisticated enough for producing the correct patches for 6 cases. We identified the key shortcomings of ssFix in translation, code matching, and modification, and developed sharpFix for an improvement. More details can be found in Section IV-C.
TABLE I
THE RESULTS OF E0 (THE FULL REPAIR EXPERIMENT)

| Project (Defects4J) | Time (hr) | ShapFix | ssFix |
|---------------------|-----------|---------|-------|
|                      | Min       | Mean    | Max   |
|                      | Med       | Avg     |       |
|                      | HP        | PC      |       |
|                      | HP        | PC      |       |
| C                   | 11.5      | 11.6    | 11.6  |
| M                   | 18.7      | 19.2    | 20.7  |
| L                   | 18.9      | 21.3    | 25.1  |

We show the projects in their abbreviations: C is Commons lang. M is Commons Math. T is TextTimer and L is Commons Lang. HP and PC are the respective numbers of the plausible and correct patches generated.

D. Evaluating ssFix’s Repair

We conducted three experiments to evaluate ssFix’s repair abilities: one experiment (E0) to evaluate ssFix’s full repair ability and two more experiments (E1 & E2) to evaluate its partial repair abilities with the fault-located statement and method manually provided.

1) Experiment: For E0, we ran ssFix to repair all the 357 Defects4J bugs automatically. For E1, we manually identified 112 Defects4J bugs for repair. For each bug, the developer patch makes changes for a single statement, we manually identified the statement and provided ssFix with it as the faulty statement for bug repair. In the case where the developer patch inserts a statement, we identified its two adjacent statements (at most) in the inserted statement’s block, considered each adjacent statement as the faulty statement, ran ssFix to repair each, and used the better result. For E2, we manually identified 201 bugs. For each bug, the developer patch makes changes within only one method. We manually identified the method, ran ssFix’s fault localization to obtain a list of suspicious statements within it, and provided the list of statements to ssFix for repair. ssFix used the same code database used in Section V-B for bug repair. It ignored any candidates that are from the bug-fixed versions of the faulty programs. We set the maximum number of candidates used by ssFix for repairing each suspicious statement to be 200. We set the time budget and memory budget for repairing each bug as two hours and 8GB for all experiments. We ran all the experiments on a machine with 32 Intel-Xeon-2.6GHz CPUs and 128GB memory.

2) Results: The results of E0 are shown in Table I (see the right six columns). ssFix produced in total 69 plausible patches with the median and average times of producing a plausible patch being about 10 and 21 minutes respectively. Among the 69 patches, 22 are correct. We manually determined the correctness of a plausible patch by comparing it to the developer patch in the dataset and checking whether the two patches are semantics-equivalent. We explained for each correct patch why it is semantics-equivalent to the developer patch (see the link we provided at the end of Section V-B).

Our results of E1 show that ssFix produced 42 plausible patches among which 26 are correct. With the faulty statement known in advance, the median and average times for producing a plausible patch are 1.9 and 3 minutes. For the same 112 bugs in E0, the fully automatic repair experiment, ssFix produced plausible and correct patches for 38 and 21 bugs. With the faulty statement being accurately located, ssFix correctly repaired (26-21)/21=23.8% more bugs.

Our results of E2 show that ssFix produced 61 plausible patches among which 27 are correct. With the faulty method known in advance, the median and average times for producing a plausible patch are 3.5 and 13 minutes. For the same 201 bugs in E0, ssFix produced plausible and correct patches for 54 and 22 bugs. With the faulty method being accurately located, ssFix correctly repaired (27-22)/22=22.7% more bugs. Our results of E1 & E2 show that more accurate fault localization can significantly improve a technique’s repair ability.

IV. SHARPFIX

We identified possible weaknesses of ssFix’s approaches, and developed the new APR technique sharpFix as an improvement. We conducted similar experiments to evaluate sharpFix. The results demonstrated that compared to ssFix, sharpFix has better code search, code reuse, and repair abilities. In this section, we elaborate on how sharpFix works and show the experimental results we got.

A. Overview

Similar to ssFix, sharpFix is an APR technique that reuses existing code fragments from a code database for bug repair. It also goes through four stages: fault localization, code search, patch generation, and patch validation to possibly produce a plausible patch. sharpFix uses ssFix’s method to do fault localization. Its methods for code search and code reuse (i.e., patch generation and patch validation) however are different from ssFix’s. For code search, sharpFix uses different methods for searching candidates from the local faulty program and from the code repository and combines the results (i.e., the retrieved candidates) for reuse. For patch generation, sharpFix goes through the same steps used by ssFix: code translation, code matching, and modification, each step however is different. For patch validation, sharpFix’s method is identical to ssFix’s method except that sharpFix performs S6’s static resolving technique as an extra step to check the validity of a patch (e.g., whether it used an undeclared variable) before dynamically validating the patched program.

We use the Defects4J bug C4 (Figure 3) as an example to explain how sharpFix works. For this bug, the developer patch produced an if-condition (Line 1) to guard the three statements (Lines 2-4) to avoid a null-pointer exception. Though the repair is relatively easy, ssFix and many other existing techniques failed to produce the correct patch. sharpFix successfully produced the correct patch in about 9.7 minutes. For this bug, sharpFix’s fault localization identified the statement at Line 2 as top-suspicious statement for repair.

Note that the bugs used for E1 are not the same ones used in Section II-B. Here we looked for bugs for which we can identify single faulty statements. The developer patches for these bugs are not necessarily simple. We identified the statement as the first enclosing statement where a fixing change was made. If there are multiple such statements, we ignored the bug. ¹

sharpFix was built upon ssFix’s implementation available at https://github.com/qixin5/ssFix.

sharpFix is not specifically designed to repair null-pointer errors. A repair technique that targets on such errors (e.g., [35]) may work faster.

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from the top-50 results. We found that K5WMD overall yielded the best results. It retrieved 22 candidates containing the fix ingredients, though it is not significantly better than the other two methods. Compared to the second-best method K5WMD, K3WMD yielded the best result: it retrieved 22 candidates containing the fix ingredients from the top-500 results, though not significantly better than K5WMD (the best result).

More specifically, we re-ran ssFix’s the code search experiments in Section III-B1 using different sizes of code chunks: we created six code search methods K5WC1, K5WC2, K5WC3, K5WC4, K5WC5, and K5WMD that look at using code chunks containing one to five statements (K5WC1 to K5WC5), and the whole Java method (K5WMD). These search methods are equivalent to ssFix’s search method except that the used chunks are in different sizes. For each search method, we counted the number of bugs whose exact fix ingredients can be found from any retrieved candidate (with and without ssFix’s translation). We slightly changed the original measure to be used for lists.

Fig. 3. The Developer Patch for the C4 Bug

2) Methodology: In Section IV-B1 we showed that K3WMD and LCS1 yielded the best searching results for global and local code search respectively and that it is possible to combine the two to yield better results. Based on these findings, we developed sharpFix’s code search method which performs K3WMD and LCS1 to do code search separately and merges the results together to obtain a list of candidates to be reused for bug repair.

More specifically, given a suspicious statement $s$, sharpFix produces two code chunks: $tchunk_0$ which contains the enclosing method of $s$ and $tchunk_1$ which contains $s$ itself. Next it performs K3WMD using $tchunk_0$ as the query to obtain a list of ranked candidate code chunks $cchunks_0$ from the code repository and it performs LCS1 using $tchunk_1$ as the query to obtain a list of ranked candidate code chunks $cchunks_1$ from the local faulty program. For each $cchunk_0 \in cchunks_0$ which is actually a Java method, sharpFix does not simply use the whole method for code reuse but identifies small code fragments as single statements within the method that are

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1We additionally checked whether the exact fix ingredient can be found in the original untranslated candidate because it is possible for ssFix to yield a bad translation.

2We slightly changed the original measure to be used for lists.
likely to be relevant to s (and are thus useful for repair). To
obtain such code fragments, sharpFix first translates cchunk0
into rcchunk0 (using the translation method we will explain in
Section IV-C1), and uses LCS1 to identify two statements cs0
and cs1 in rcchunk0 that are most similar to s. Each of the
two statements is associated with the searching score of cchunk0.
Next sharpFix normalizes separately the searching scores of
(1) the statement candidates identified from cchunks0 and (2)
the candidates from cchunks1, merges the candidates together,
and ranks them by the normalized scores. This way, sharpFix
obtains a list of candidates (as statements) retrieved from both
the local faulty program and the code repository. For code
reuse, sharpFix looks at each candidate in the list to possibly
produce a plausible patch for the target which contains the
suspicious statement s only.

For our example shown in Figure 3 given the suspicious
statement (at Line 2) identified by fault localization, sharpFix
performed code search and retrieved a candidate (rank 105)
from the local faulty program that contains the single statement
shown at Line 2 in Figure 4.

3) Evaluation: We conducted an experiment similar to the
one used in Section III-B1 to evaluate sharpFix. For each of
the used 103 Defects4J bugs, we provided sharpFix with the
faulty statement, ran its code search, and checked whether
the fix ingredient was contained in the retrieved candidate
statements. As we did in Section III-B1, we filtered away
candidates that are syntactically redundant3 and those that are
simply from the bug-fixed versions, and we looked at the top-
500 retrieved candidates. For each candidate (that contains
a single statement), we performed sharpFix’s translation to
translate its enclosing method, and checked whether the exact
fix ingredient is contained in the translated statement, its two
neighbouring statements (which sharpFix uses for insertion),
and the enclosing if-condition when the enclosing statement
is an if-statement (sharpFix uses the enclosing if-condition to
produce a new if-statement for patch generation).

Figure 2 shows our results (see the red bars). We found
that sharpFix’s code search method is better than ssFix’s.
It retrieved promising candidates that contain the exact fix
ingredients for 39 bugs within the top-50 results and for 42
bugs within the top-500 results. Compared to ssFix’s code
search, though sharpFix’s code search retrieved only four more
promising candidates within the top-50 results, it retrieved 39
promising candidates within the top-500 results which are more
than all the promising candidates ssFix retrieved within the
top-500 results. Section II-B5 showed that the parameterized
fix ingredients exist for 80 bugs. sharpFix retrieved promising
fix ingredients for 42/80=52.5% bugs.

C. Code Reuse

We analyzed ssFix’s failures in its code reusing steps: code
translation, code matching, and modification in Section II-C
identified possible ways for improvement, and developed
sharpFix’s method for each step.

1) Code Translation: For code translation, ssFix first maps
identifiers in the candidate (or candidate identifiers) to the
related identifiers in the target (or target identifiers), and
then renames the candidate identifiers as the mapped target
identifiers to yield a translated candidate. We identified two
weaknesses of ssFix’s current method for mapping identifiers:
(1) ssFix only maps candidate identifiers to identifiers that are
used in the target. A candidate identifier can be related to an
identifier that is not used in the target but is accessible there;
and (2) ssFix identifies two identifiers as related only based
on matching the code patterns of their usage contexts. This can
be insufficient: Two identifiers can be highly related but their
usage contexts are not identical (though very similar). Identical
usage contexts may also not imply that the two identifiers
being compared are the most related.

Algorithm 1 Creating an Identifier Mapping
Input: tchunk, cchunk
Output: imap
1. imap = iddict ← empty
2. tids = collect all the non-JDK candidate identifiers (those appear in tchunk's method)
3. cids = collect all the non-JDK target identifiers (those appear in tchunk's method and appear in the declared
   fields and methods of tchunk's class)
4. for all cid ∈ cids do
5.   if ShortName(cid) then
6.     t = find the first tid ∈ tids whose name is equal to cid's name
7.     if t exists and is compatible with cid then
8.     imap.add(t, cid)
9. end
10. eumtid = get tchunk's enclosing method identifier
11. ecid = get tchunk's enclosing class identifier
12. if imap.containsKey(eumtid) && imap.containsKey(ecid) then
13.   imap.put(eumtid, ecid)
14. if EnumConstantIndex(eumtid) && imap.containsKey(EnumConstantIndex(eumtid)) then
15.   imaps = taxonomyContainsClass(eumtid) && imap.containsKey(Var) then
16.   imap.add(Var, imaps)
17. if len(imap) = 0 then
18.   return

To address the two problems, we developed a new algo-
Algorithm 1 used by sharpFix to create an identifier mapping.
Based on the created identifier mapping, sharpFix
renames each candidate identifier as its mapped target identi-
} if (r!=null) {
} result = r.getUpperBound();
}
based on not just their usage contexts but their string lengths, string equality, locations, and shared concepts (measured by the overlap of the extracted conceptual tokens).

As shown in Algorithm 1, sharpFix accepts the target chunk \texttt{tchunk} and the candidate chunk \texttt{cchunk} as input. As output, sharpFix creates an identifier mapping \texttt{imap}. sharpFix starts by collecting two lists of non-JDK identifiers \texttt{cids} and \texttt{tids} (Lines 2 & 3) which are actually identifier bindings (e.g., representing a variable declaration and its use). It first maps identifiers that share the same names which are not too short (Lines 4-8), next maps the method and class identifiers (Lines 9-16), next maps identifiers by their usage contexts (Line 17), and finally maps identifiers by the shared conceptual words extracted in their names (Lines 18-23). sharpFix uses ssFix’s method (from Section III-A(2) of [16]) for matching two identifiers’ usage contexts and for extracting conceptual words.

The translated version yielded by sharpFix for the candidate shown in Figure 4 is just as itself (sharpFix changed the candidate’s enclosing method’s name and the name of a method call that do not appear in the candidate and are not shown). For the variable identifier result in the candidate, sharpFix found an identifier in the target’s method that has the same name, mapped result to this identifier, and renamed result as itself. For the variable \( r \) in the candidate, sharpFix mapped it to the identifier \( r \) in the target based on their matched usage contexts (e.g., as both \( r \neq \text{null} \)). sharpFix did not map \texttt{getUpperBound} to any target identifier and thus did not change it (it did not map \texttt{getUpperBound} to \texttt{getAnnotations} since they only share a stop word \texttt{get}).

2) Code Matching: ssFix’s code matching method is based on matching rules and arbitrary thresholds. We found this makes ssFix’s code matching somewhat inflexible. For example, it does not allow two method calls to match unless the method names are identical which can sometimes hinder ssFix from repairing an incorrectly called method. sharpFix uses a new method to do code matching which uses simplified matching rules and no thresholds. It matches statements/expressions based on the extracted conceptual tokens and symbols, i.e., the LCS2 tokens shown in Section IV-B1. To do code matching, sharpFix accepts the target \texttt{tchunk} and the translated candidate \texttt{rcchunk} as input. As output, it produces a code mapping \texttt{cmap} that maps each statement/expression in \texttt{tchunk} to its matched statement/expression in \texttt{rcchunk}. To create such a mapping, sharpFix starts by collecting two lists of statements and expressions \texttt{tse} and \texttt{cse} from \texttt{tchunk} and \texttt{rcchunk} respectively (by visiting the ASTs in pre-order). The collected expressions are non-trivial and do not include identifiers, number constants, or any of the four types of literals: \texttt{boolean}, \texttt{null}, \texttt{character}, and \texttt{string}. For each statement/expression \texttt{tse} in \texttt{tse}, sharpFix finds a \texttt{cse} in \texttt{cse} that is compatible with \texttt{tse} and shares the most LCS2 tokens with \texttt{tse} (measured by the Dice Similarity) and maps \texttt{tse} to \texttt{cse}.

When two \texttt{ses} (statements/expressions) are both statements, they are compatible if they are both loops. Otherwise, they need to have the same statement type\(^{10}\) (e.g., both as return statements) to be compatible. When two \texttt{ses} are both expressions, they are compatible if their expression types are equal. When one \texttt{se} is a statement and the other is an expression, they are only compatible if the statement’s type is \texttt{VariableDeclarationStatement} and the expression’s type is either \texttt{Assignment} or \texttt{VariableDeclarationExpression}.

For the bug example, sharpFix maps the target statement at Line 2 in Figure 3 to the matched (also translated) candidate statement at Line 2 in Figure 2. The extracted tokens and the similarity calculation are shown below.

\[
\begin{align*}
\text{LCS2 Tokens from the Target Statement (12 in total):} & <\text{collection}, <\text{collect}, <\text{get}, <\text{getAnnotations}, <\text{get}, <\text{result}, <\text{result}> >, <\text{result}> >, <\text{result}> >, <\text{result}> > >, <\text{result}> >, <\text{get}>, <\text{get}>. \\
\text{LCS2 Tokens from the Candidate Statement (11 in total):} & <\text{result}, <\text{result}, <\text{result}, <\text{result}, <\text{result}> >, <\text{result}> >, <\text{get}>, <\text{get}>. \\
\text{Overlapped Tokens (7 in total):} & <\text{result}, <\text{result}, <\text{result}, <\text{result}> >, <\text{result}> > >, <\text{result}> >, <\text{result}> >, <\text{result}> >, <\text{result}> > >, <\text{result}> >, <\text{result}> >, <\text{result}> >, <\text{result}> > >, <\text{result}> >, <\text{result}> >. \\
\text{Dice Similarity:} & \frac{(2*7)}{(12+11)}=0.609
\end{align*}
\]

3) Modification: ssFix uses three types of modifications: replacement, insertion, and deletion to produce patches based on the matched and unmatched statements/expressions between the target and the translated candidate. We made sharpFix’s modification strategy more sophisticated by adding two more modifications: adding if-guard and method replacement. To produce patches using adding if-guard, sharpFix looks at a target statement \( s \) (which appears in the target) and its mapped candidate statement \( s' \) (which appears in the translated candidate). If the parent of \( s' \) is an if-statement with a condition \( c' \), sharpFix creates new if-statements with the condition \( c' \) to guard existing statements in the target (and possibly in its enclosing method). Currently, sharpFix selects two sets of statements to be guarded: (1) the target statement \( s \) itself and (2) \( s \) plus the following statements its block, and produces the corresponding patches. To produce a patch using the modification method replacement, sharpFix replaces the enclosing method of the target with the enclosing method of the translated candidate to possibly support making multiple changes in the scope of a method.

sharpFix uses the same method used by ssFix to do replacement. For insertion, sharpFix looks at the candidate statement \( s' \) (translated) to which the target statement \( s \) is mapped, identifies the adjacent statements of \( s' \) in its block: \( s_0' \) and \( s_1' \) (translated) that are before and after \( s' \), and inserts \( s_0' \) before \( s \) and \( s_1' \) after \( s \) to yield two patches. sharpFix does not use ssFix’s method to do insertion because the target and candidate chunks it looks at both contain only one statement. sharpFix does not use ssFix’s deletion because it was shown in [16] to be likely to produce defective patches.

For the bug example, sharpFix produces two patches using the modification adding if-guard. As one patch, sharpFix uses the if-condition \( r \neq \text{null} \) to guard the target statement (Line 2 in Figure 3) only. The patched program however fails to compile because variable \( c \) at Line 3 becomes undeclared. As the other patch, sharpFix uses the if-condition to guard

\(^{10}\) The type of a statement/expression is its corresponding node type in the abstract syntax tree that sharpFix builds using the Eclipse JDT library [36].
the target statement plus its following statements in the block. 
This is the correct patch shown in Figure 3.

4) Evaluation: sharpFix retrieved candidates that contain the parameterized fix ingredients for 59 bugs within the top-500 results. To evaluate sharpFix’s code reuse, we looked at the 59 bugs. For each bug, we provided sharpFix with the target and the retrieved candidate, and ran sharpFix’s patch generation and patch validation automatically. If sharpFix produced a plausible patch, we manually checked whether the patch is correct. Our results show that sharpFix produced 30 plausible patches which are all correct, and successfully reused 30/59=50.8% candidates for bug repair.

The exact fix ingredients (without any translation) are contained in 39 candidates, and we expect sharpFix to be able to reuse those fix ingredients in producing the correct patches. For the other 20 (59-39) candidates which only contain the fix ingredients in the parameterized forms, we identified only three candidates that can be reasonably reused for repair. We analyzed sharpFix’s failures in resizing the candidates for repairing the 12 (39+3-30) bugs and found that the candidates are not ideal for repairing 9 bugs (an example of such candidate can be found in Section III-C). To successfully reuse the candidates to repair the other 3 bugs, sharpFix’s modification needs to be more sophisticated. Though we can make sharpFix’s modification more sophisticated, doing so may not actually improve its overall repair performance (as suggested in [22]).

D. Repair

We also conducted the three experiments (E0, E1, and E2) used in Section III-D to evaluate sharpFix’s repair abilities. Table I shows the results of E0: the full repair experiment. sharpFix produced in total 89 plausible patches (for 89 bugs) among which 36 are correct. For E1 and E2, with the faulty statement and method known in advance, sharpFix produced correct patches for 34.5% and 19.4% more bugs respectively (compared to the results of E0).

V. EVALUATION

We evaluated sharpFix, ssFix, and four other repair techniques jGenProg [24], jKali [24], Nopol (version 2015) [25], and HDRepair [26] on a different bug dataset: Bugs.jar-ELIXIR [15] which is a sample of the Bugs.jar dataset [37] and contains 127 real bugs. Our results confirm that sharpFix is an improvement over ssFix and show that it outperformed the others in successfully repairing more bugs.

A. Setup

The Bugs.jar dataset [37] consists of 1,158 real Java bugs drawn from 8 open-source Java projects. The Bugs.jar-ELIXIR dataset [15] created by Saha et al. is a sample of the original dataset and contains 127 real bugs drawn from 7 of the 8 Java projects. For each of the 127 bugs, the bug-fixing change is local (within a hook). Although these bugs are relatively easy for repair (since their bug-fixing changes are local and are thus simple), we think they are still reasonable to be used for evaluating existing APR techniques since no existing APR technique has been shown to be good at repairing complex bugs through making complex, non-local fixes.

For evaluation, we ran sharpFix, ssFix, and all other techniques each to repair all the 127 bugs. The external code repository used by sharpFix and ssFix is the DARPA MUSE repository. ssFix uses the earliest versions of the 7 projects as the local projects. The time and memory budgets used by each technique for repairing a bug are two hours and 8GB. All the experiments were run on the same machine we used for the experiments shown in Sections III-D and IV-D. Given that jGenProg and HDRepair use randomness for patch generation, we ran each technique in three trials[11] to repair a bug. We did not compare sharpFix to many other repair techniques that are written for C (e.g., SearchRepair [6], CodePhage [38], Prophet [10], and Angelix [11]) or are not publicly available (e.g., PAR [4]) including ELIXIR [15].

B. Results

Table II shows the repairing results of sharpFix and ssFix for each of the 7 projects and for all of them. sharpFix has better repair performance than ssFix: it produced four more correct patches and was less prone to producing overfitting (plausible-but-incorrect) patches with the non-overfitting rate being 15/39=38.5%. Though sharpFix ran longer than ssFix did to produce a plausible patch, the running times are still comparable. For the five projects: ACC, CML, FLK, OAK, and MNG, our results show that sharpFix and ssFix are comparable but both have limited repair abilities. For MAT, sharpFix produced an additional correct patch but ran slower than ssFix. For WCT, sharpFix outperformed ssFix in correctly repairing 6 bugs that ssFix did not. We found that for five of the bugs: WCT-3098, WCT-3520, WCT-3845, WCT-4276, and WCT-5891, sharpFix found very effective candidates: for each such bug, it looked at no more than 8 candidates to yield the correct

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11Running jGenProg and HDRepair only in three trials might be insufficient to show the tools’ full abilities. However, we believe our results are sufficient to show that sharpFix outperforms these tools: it generated more than 10 correct patches in one trial than these tools did in three trials.
patch. For WCT-5686, sharpFix reused a candidate ranked 31th to produce the correct patch. ssFix failed to reuse any candidates to produce any plausible patches for four bugs: WCT-3098, WCT-3520, WCT-3845, and WCT-5686. For the other two bugs: WCT-4276 and WCT-5891, it only produced overfitting patches.

Table III shows the repairing results of all the six techniques. We found that compared to sharpFix and ssFix, the other four techniques have very limited repair abilities. They each can only produce correct patches for no more than one bug. jGenProg only looks at finding the fix ingredients as statements from the local faulty program. This type of repair constrains itself from finding useful fix ingredients that are expressions and are from non-local programs. jKali can only do deletions and is unable to produce many types of non-deletion patches. Nopol looks at producing if-condition-related patches but is prone to synthesizing if-conditions that are either too constrained or too loose. HDRule leverages mined bug-fixing changes to guide the search of a correct patch. However, according to our results, this type of guidance is not effective.

All the fix ingredients, retrieved candidates, and repair results are released and can be found at https://github.com/sharpFix18/sharpFix/tree/master/expt0.

C. Discussion

For all repair experiments, we determined the correctness of a plausible patch by manually comparing it to the developer patch available from the dataset (either Defects4J or Bugs.jar-ELIXIR). We took a relatively conservative approach for our manual comparing process and only considered a patch as correct if we found a semantics-preserving transformation between the generated patch and the developer patch. Since our manual process is conservative, the correctness of the patches that we identified as correct are clear. We released all such patches and provided reasons for why they are correct.

ELIXIR was not available when we performed our experiments, and we did not run it on the Bugs.jar-ELIXIR dataset for comparison. In [15], ELIXIR was shown to repair 22 bugs with correct patches generated (the times for generating these patches however were not given). For repair, ELIXIR leveraged bug reports for ranking the generated patches, and this was shown to be very effective: for the Defects4J bugs, ELIXIR generated 6/(26-6)=30% more patches using bug reports than it did without using bug reports. sharpFix did not leverage any bug report information for repair: such information is typically not available. Though sharpFix outperformed ELIXIR in generating 10 more correct patches for the Defects4J bugs, it generated 7 fewer correct patches for the Bugs.jar-ELIXIR bugs. It would be interesting to see how sharpFix works by leveraging the bug report information. It would also be interesting to compare the two techniques on other possible datasets. We leave these as future work.

VI. RELATED WORK

In this paper, we conducted an experiment testing the fix ingredient assumption. Our experiment is closely related to the studies by Barr et al. [27] and by Sumi et al. [28] which also investigate whether the fix ingredients exist in local and non-local programs. Different from our experiment, the two studies looked at the code line(s) as a fix ingredient and investigated what fraction of a fix ingredient (in terms of the code lines) for a bug-fixing change can be found from existing programs. Our experiment is also related to other studies that look at the repetitiveness of a fixing change (rather than the fix code) [29], the existence of fix ingredients in the program’s earlier versions [30], and code redundancy [39]-[41] in general.

sharpFix finds and reuses existing code fragments from the local faulty program and a code repository to do bug repair, and is an improved version of ssFix [16]. sharpFix is closely related to SearchRepair [6] and CodePhage [58] which also do code search to find existing code for bug repair. Different from sharpFix which performs syntactic code search, SearchRepair’s code search is based on symbolic execution and constraint-solving, and CodePhage’s code search is based on program execution. CSAR [42] is an improvement over SearchRepair. It performs string matching on constraints rather than doing constraint-solving to identify semantics-related code. sharpFix is also related to the recent technique SimFix [18] which leverages similar code to produce patches. Different from sharpFix, SimFix also leverages existing patches to build the search space and it only looks at the local program for finding similar code. The syntactic features that SimFix and sharpFix use for finding similar code are also different. GenProg [2], [43] is an early APR technique that reuses existing code to produce patches and is related to sharpFix. Different from sharpFix, GenProg only reuses statements from the local faulty program itself to produce patches. It does not directly find and reuse similar code but uses genetic algorithms to modify the program and produce patches.

sharpFix is related to many repair techniques that use genetic algorithms [2], [3], [43], random search [5], human-written templates [4], bug-fixing instances [9], [17], [44], program comparison [45], program synthesis [11], [12], [46]-[49], condition synthesis [8], [13], repair templates plus condition synthesis [31], modifications with patch ranking models [10], [15], [21], modifications based on monitored program states [14], learned transformations [50], [51], invariants [52], bug reports [53], statistical analysis [54], reference implementation [20], and non-test-suite specifications [55]-[57].

VII. CONCLUSION

In this paper, we conducted multiple experiments for analyzing ssFix, a syntactic search-based repair technique. We found the built-upon idea of ssFix (and other related techniques), i.e., reusing existing code for bug repair is promising. However, the approaches used by ssFix for code search and code reuse can be significantly improved. We developed a new repair technique sharpFix which uses improved approaches for code search and code reuse and demonstrated through experiments that it outperforms ssFix and four other repair techniques.
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