Automatic Program Repair by Fixing Contracts*

Yu Pei, Carlo A. Furia, Martin Nordio, and Bertrand Meyer

Chair of Software Engineering, ETH Zurich, Switzerland
firstname.lastname@inf.ethz.ch

Abstract. While most debugging techniques focus on patching implementations, there are bugs whose most appropriate corrections consist in fixing the specification to prevent invalid executions—such as to define the correct input domain of a function. In this paper, we present a fully automatic technique that fixes bugs by proposing changes to contracts (simple executable specification elements such as pre- and postconditions). The technique relies on dynamic analysis to understand the source of buggy behavior, to infer changes to the contracts that emend the bugs, and to validate the changes against general usage. We have implemented the technique in a tool called SpecFix, which works on programs written in Eiffel, and evaluated it on 44 bugs found in standard data-structure libraries. Manual analysis by human programmers found that SpecFix suggested repairs that are deployable for 25% of the faults; in most cases, these contract repairs were preferred over fixes for the same bugs that change the implementation.

1 Introduction

A software *bug* is the manifestation of a discrepancy between specification and implementation: program behavior (implementation) deviates from expectations (specification). Correcting a bug may thus require changing implementation, specification, or both. In fact, there is a significant number of bugs [3] whose most appropriate correction is changing the specification to rectify the expectations about what the implementation ought to do. For example, a function `max` computing the maximum value of a set of integers is undefined if the set is empty; we could change `max`'s implementation to return a special value when called on an empty set, but the best thing to do is disallowing such calls altogether by specifying them invalid. However, since specifications are often informal or implicit at best, debugging techniques normally modify implementations rather than specifications. In particular, fully automatic fixing—which has made substantial progress in recent years [21,20,13] (see Section 5 for more references)—has focused on suggesting repairs to implementations, thus failing to provide the best corrections in cases where the ultimate source of failure is incorrect specification.

This paper presents a fully automatic technique that fixes bugs by rectifying specifications. Our technique targets programs with *contracts*—simple specification elements in the form of executable assertions. A program execution that violates some contract reveals a bug; to fix it, the technique suggests changes to the contracts that prevent the violation from being triggered. We have prototyped the technique in a tool called

* Work partially supported by ERC grant CME/291389; by SNF grants LSAT/200020-134974 and ASII/200021-134976; and by Hasler-Stiftung grant #2327.

SpecFix, which works on programs with contracts written in Eiffel. SpecFix is completely automatic: its only required input are programs with simple contracts. In an experimental evaluation, we applied SpecFix to 44 bugs of Eiffel's standard data-structure libraries. SpecFix suggested repairs for 42 of these bugs; more significant, 11 of the bug repairs are genuine corrections of quality sufficient to be deployable. A small trial with human programmers confirmed this assessment and often found the fixes produced by SpecFix preferable to fixes for the same bugs that modified the implementation rather than the contracts.

Fixing contracts relies on extracting specification elements based on the actual behavior of the implementation. This is superficially similar to the problem of *inferring* (or mining) specifications—a well-established research area that produced numerous landmark results (e.g., [4,8]; see Section 5 for more references). While SpecFix uses inference techniques as one of its components, suggesting changes to an existing specification to correct a bug is more delicate business than just inferring specifications. Changing contracts is changing the design of an API as experienced by its clients. In the example of `max`, adding a precondition that requires that the set be non empty makes all client code of `max` responsible for satisfying the requirement upon calling `max`. Therefore, we must make sure that the suggested contract changes have a limited impact on a potentially infinite number of clients.

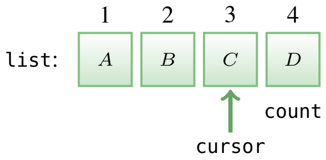
The SpecFix technique presented in this paper uses a combination of heuristics to validate possible specification fixes with respect to their impact on client code. It discards fixes that invalidate previously passing test cases; to avoid overfitting, it runs every candidate fix through a regression testing session that generates (completely automatically, using our testing framework AutoTest) new executions; and it ranks all fixes that pass regression by preferring those that are the least restrictive. The empirical evaluation in Section 4 indicates that these heuristics work well in practice for the bugs we considered. Notably, there is a significant fraction of bugs whose appropriate fix is a change to the specification; in those cases, SpecFix can often generate useful fixes.

Section 2 demonstrates the idea of fixing specifications by means of an actual example from the standard Eiffel implementation of array-based circular lists. Section 3 presents the technique implemented in SpecFix, starting with an overview of its components (Figure 3) followed by a detailed description of each of them. For brevity, we use the name "SpecFix" to denote both the fixing technique presented in this paper and its prototype implementation. The evaluation in Section 4 presents experiments where we applied SpecFix to 44 faults in standard data-structure libraries. Section 5 discusses the essential related work; and Section 6 concludes and outlines future work.

2 SpecFix in Action

Let us briefly demonstrate how SpecFix works using an example from the experimental evaluation of Section 4. The example targets a bug of routine (method) `duplicate` in class `CIRCULAR`, which is the standard Eiffel library implementation of circular array-based lists.

To understand the bug, Figure 1 illustrates a few details of `CIRCULAR`'s API. Lists are numbered from index 1 to index `count` (an attribute denoting the list length), and include an internal cursor that may point to any element of the list. Routine duplicate takes a single integer argument n, which denotes the number of elements to be copied; called on a list object list, it returns a new instance of CIRCULAR with at most n elements copied from list starting from the position pointed to by cursor. Since we are dealing with circular lists, the copy wraps over to the first element. For example, calling duplicate (3) on the list in Figure 1a returns a fresh list with elements $\langle C, D, A\rangle$ in this order.



(a) A circular list of class CIRCULAR: the internal cursor points to the element C at index 3.

```
1  class CIRCULAR [G]
2
3    make (m: INTEGER)
4       require  m ≥ 1
5       do ... end
6
7    duplicate (n: INTEGER): CIRCULAR [G]
8       do
9          create Result.make (count)
10         ...
11      end
12
13   count: INTEGER    -- Length of list
```

(b) Some implementation details of CIRCULAR.

Fig. 1: Example and some API details of circular lists in Eiffel.

The implementation of duplicate is straightforward: it creates a fresh CIRCULAR object **Result** (line 9 in Figure 1b); it iteratively copies n elements from the current list into **Result**; and it finally returns the list attached to **Result**. The call to the creation procedure (constructor) make on line 9 allocates space for a list with count elements; this is certainly sufficient, since **Result** cannot contain more elements than the list that is duplicated. However, CIRCULAR's creation procedure make includes a precondition (line 4 in Figure 1b) that only allows allocating lists with space for at least one element (**require** m ≥ 1). This sets off a bug when duplicate is called on an empty list: count is 0, and hence the call on line 9 triggers a violation of make's precondition. Testing tools such as AutoTest detect this bug automatically by providing a concrete test case that exposes the discrepancy between implementation and specification.

How should we fix this bug? Figure 2 shows three different possible repairs, all of which we can generate completely automatically. An obvious choice is patching duplicate's implementation as shown in Figure 2a: if count is 0 when duplicate is invoked, allocate **Result** with space for *one* element; this satisfies make's precondition in all cases. Our AutoFix tool [20,17] targets fixes of *implementations* and in fact suggests the patch in Figure 2a.

The fix that changes the implementation is acceptable, since it makes duplicate run correctly, but it is not entirely satisfactory: CIRCULAR's implementation looks perfectly adequate, whereas the ultimate source of failure seems to be incorrect or inadequate *specification*. A straightforward fix is then adding a precondition to duplicate that on-

```
make (m: INTEGER)
  require  m ≥ 1

duplicate (n: INTEGER):
      CIRCULAR [G]

  do
   if count > 0 then
      create Result.make (count)
    else
      create Result.make (1)
    end
```

(a) Patching the implementation.

```
make (m: INTEGER)
  require  m ≥ 1

duplicate (n: INTEGER):
      CIRCULAR [G]
  require count > 0
  do

    create Result.make (count)
```

(b) Strengthening the specification.

```
make (m: INTEGER)
  require  m ≥ 0

duplicate (n: INTEGER):
      CIRCULAR [G]

  do

    create Result.make (count)
```

(c) Weakening the specification.

Fig. 2: Three different fixes for the bug of Figure 1. Changed or added lines are highlighted.

ly allows calling it on non-empty lists. Figure 2b shows such a fix, which *strengthens* duplicate's precondition thus invalidating the test case exposing the bug. The strengthening fix has the advantage of being textually simpler than the implementation fix, and hence also probably simpler for programmers to understand. However, both fixes in Figures 2a and 2b are partial, in that they remove the source of faulty behavior in duplicate but they do not prevent similar faults—deriving from calling make with m = 0—from happening. A more critical issue with the specification-strengthening fix in Figure 2b is that it may break clients of CIRCULAR that rely on the previous weaker precondition.[1] There are cases—such as when computing the maximum of an empty list—where strengthening produces the most appropriate fixes; in the running example, however, strengthening arguably is not the optimal strategy.

A look at make's implementation (not shown in Figure 1b) would reveal that the creation procedure's precondition $m \geq 1$ is unnecessarily restrictive, since the routine body works as expected also when executed with m = 0. This suggests a fix that *weakens* make's precondition as shown in Figure 2c. This is arguably the most appropriate correction to the bug of duplicate: it is very simple, it fixes the specific bug as well as similar ones originating in creating an empty list, and it does not invalidate any clients of CIRCULAR's API. The SpecFix tool described in this paper generates both specification fixes in Figures 2b and 2c but ranks the weakening fix higher than the strengthening one. More generally, SpecFix outputs specification-strengthening fixes only when they do not introduce bugs in available tests, and it always prefers the least restrictive fixes among those that are applicable.

3 How SpecFix Works

SpecFix works completely automatically: its only input is an Eiffel program annotated with simple contracts (pre- and postconditions and class invariants) which constitute its

[1] Note that this strengthening does not introduce new bugs; it just shifts the responsibility for the fault from duplicate to its clients.

specification. After going through the steps described in the rest of this section, SpecFix's final output is a list of fix suggestions for the bugs in the input program.

Figure 3 gives an overview of the components of the SpecFix technique. SpecFix is based on dynamic analysis, and hence it characterizes correct and incorrect behavior by means of passing and failing *test cases* (Sections 3.1 and 3.2). To provide full automation, we use the random testing framework AutoTest to generate the tests used by SpecFix. The core of the *fix generation* algorithm applies two complementary strategies (Section 3.3): weaken (i.e., relax) a violated contract if it is needlessly restrictive; or strengthen an existing contract to rule out failure-inducing inputs. SpecFix produces *candidate fixes* using both strategies, possibly in combination (Section 3.4). To determine whether the weaker or stronger contracts remove all faulty behavior in the program, SpecFix runs candidate fixes through a *validation* phase (Section 3.5) based on all available tests. To avoid overfitting, some tests are generated initially but used only in the validation phase (and not directly to generate fixes). If multiple fixes for the same fault survive the validation phase, SpecFix outputs them to the user *ordered* according to the strength of their new contracts: weaker contracts are more widely applicable, and hence are ranked higher than more restrictive stronger contracts (Section 3.5).

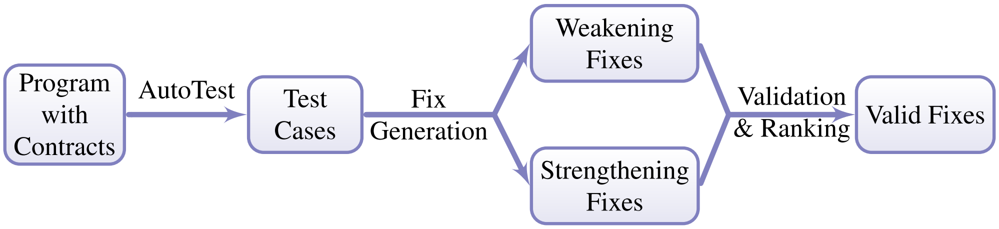


Fig. 3: An overview of how SpecFix works. Running AutoTest on an input Eiffel program with contracts produces a collection of test cases that characterize correct and incorrect behavior. With the goal of correcting faulty behavior, the fix generation algorithm builds candidate fixes using two strategies: weakening and strengthening the existing contracts. The candidate fixes enter a validation phase where they must pass all valid test cases; valid fixes are ranked—the weaker the new contracts the higher the ranking—and presented as output.

3.1 Test Cases

A *test case* (or just "test") t consists of a call of some routine r with actual arguments $a_1, \ldots, a_n$ on a target object a_0, written $t : a_0.r(a_1, \ldots, a_m)$; we refer to r as t's *outermost* routine. For instance, if `list` is the list of Figure 1a and `emp` is an instance of empty `CIRCULAR` list, `list.duplicate`(3) and `emp.duplicate`(1) are two tests.

Let $\mathcal{S}$ be a set of program states. The execution of a test t starts with routine r's body executing from an initial state $s_0 \in \mathcal{S}$. In general, r's body may call another routine r_1 from a state s_1, which in turn calls another r_2 from a state s_2, and so on until the test terminates.[2] Therefore, a test t uniquely defines a *trace* ρ_t as the sequence

$$\rho_t \quad = \quad s_0\, r_0\, s_1\, r_1\, \cdots\, s_{n-1}\, r_{n-1}\, s_n\, r_n \tag{1}$$

of state snapshots when nested routines are called or return. Precisely, for $j = 0, \ldots, n$, a pair $s_j r_j$ denotes either that routine r_j begins execution from state s_j, that is s_j is the *pre-state* of a nested call; or that routine r_j returns to the caller from state s_j, that is s_j is the *post-state* of a nested call. Since t is a call to r at the outermost level, $r_0 = r$; call traces ignore intermediate states other than pre- and post-states. The sequence

$$\kappa_t \;=\; r_0\, r_1\, \cdots\, r_{n-1}\, r_n \tag{2}$$

containing only routine names in ρ_t is the *call sequence* determined by t. For example, the test `emp.duplicate`(1) determines the trace x_0 `duplicate` x_1 `make` where x_0 is the initial state and x_1 is the state when calling `make` on line 9 in Figure 1b; the test terminates then with a contract violation. The other test `list.duplicate`(3) determines the trace y_0 `duplicate` y_1 `make` y_2 `make` y_3 `duplicate` where y_0 is the initial state, y_1 is the state when calling `make`, y_2 is the state when `make` returns, and y_3 is the state when `duplicate` and the whole test terminates.

In SpecFix, we generate test cases automatically using AutoTest—Eiffel's random test generator. Using AutoTest makes SpecFix a completely automatic technique: the only required input is a collection of buggy routines. However, if manually-written test cases are available, they can also be supplied to SpecFix to supplement the automatically generated tests; the extra input may improve the quality of the final output.

3.2 Contracts, Correctness, and Faults

Contracts are simple specification elements made of assertions including preconditions (**`require`**), postconditions (**`ensure`**), and class invariants (**`invariant`**). We denote by P_r and Q_r the pre- and postcondition of a routine r. In this work, we focus on changing pre- and postconditions only; thus, we use the term *specification* to collectively denote pre- and postconditions, and use the terms "specification" and "contracts" as synonyms.

Given an assertion A (pre- or postcondition) and a program state $s \in \mathcal{S}$, we say that A *holds* at s (or, equivalently, that s satisfies A) if A evaluates to **`True`** under state s; if this is the case, we write $s \models A$. Since contracts are executable, we can evaluate any assertion at any program state reached during a concrete execution.

Contracts provide an operational criterion to classify test cases into invalid, passing, and failing. A test case t is *valid* if the initial state s_0 of the trace ρ_t is such that it satisfies r's precondition, that is $s_0 \models P_r$; otherwise t is *invalid*. An invalid test case for routine r does not tell us anything about r's correctness, since every invocation of r should satisfy r's precondition to be acceptable. A valid test case t is *passing* if, for every $j = 1, \ldots, n$, state s_j in t's trace ρ_t satisfies the following: if s_j is the pre-state of a call to r_j then $s_j \models P_{r_j}$; and if s_j is the post-state of a call to r_j then $s_j \models Q_{r_j}$. In words, every nested call performed during the computation of r starts

[2] To avoid dealing with nonterminating programs, we forcibly terminate tests that are still running after a timeout.

in a state that satisfies the called routine's precondition and terminates in a state that satisfies the called routine's postcondition when it returns. A valid test case is *failing* if it is not passing, that is if it eventually reaches a state that violates some pre- or postcondition; the violation terminates test case execution. The test `list.duplicate`(3) is passing because the call to `duplicate` terminates without violating any contract (and produces the correct result). The other test `emp.duplicate`(1) is valid but failing: the nested call to `make` does not satisfy `make`'s precondition `m` ≥ 1 on line 4 in Figure 1b because `count` = $0 < 1$ in an empty list.

A failing test case t reveals a *fault* (informally called bug in the introduction) in routine r, namely a discrepancy between implementation and specification (the violated contract). Conversely, a passing test case documents a legitimate usage of routine r with respect to its specification. Two failing test cases t_1, t_2 identify the *same fault* if their call sequences κ_1, κ_2 are the same (and hence they violate the same assertion).

3.3 Weakening vs. Strengthening

Let t be a failing test case with trace ρ_t as in (1); $r = r_0$ is the outermost routine of t, and r_n is the routine whose contract violation triggers the fault. Assuming the implementation of all routines $r_0, \ldots, r_n$ is correct, we should change the contracts of $r_0, r_1, \ldots, r_n$ to fix the fault exposed by t. There are two ways to do that:

Strengthening: strengthen r's precondition to disallow t's input. Strengthening makes t invalid and thus prevents the call sequence that led to the violation of r_n's contract.

Weakening: weaken r_n's contract to allow t's execution to continue past r_n. If the execution can continue without triggering other errors, weakening makes t passing.

If applicable, weakening is in principle preferable to strengthening, because the former does not risk breaking clients by introducing more stringent conditions for correctly calling r. Strengthening is, however, always applicable, whereas weakening may not work if r_n's correct execution depends on the weakened contract. Even in the cases where weakening makes t passing without triggering any new fault, it may be that the absence of new faults is just a result of the rest of the specification being inaccurate or incomplete. For example, weakening the precondition of a function `max` to work on lists of any size (including empty lists) may not trigger any faults simply because `max` has no postcondition, and hence there is no automatic way of finding out that the value returned for empty lists is inconsistent.

In practice, SpecFix prefers the least restrictive fixes (i.e., weakening) but always tries both weakening and strengthening in combination. Another observation is that strengthening only the outermost routine's precondition often is too *ad hoc*, since it corresponds to a partial change of API assumptions which may be inconsistent with the way other routines are used. Therefore, SpecFix tries to collectively strengthen all routines $r_0, \ldots, r_{n-1}$ to disallow fault-inducing input at every call site. Indeed, the experiments of Section 4 show that strengthening leads to many useful and correct fixes in practice.

3.4 Fix Generation

A run of SpecFix targets a specific fault of some routine r. This is characterized by a set $\mathcal{F}_r$ of failing test cases all of which have r as outermost routine and identify the same fault—the violation of contract A_n (pre- or postcondition) of routine r_n. To characterize correct behavior, SpecFix also inputs a set $\mathcal{P}_r$ of passing test cases which have r as outermost routine. Based on this, SpecFix builds a set Φ of candidate fixes through the following steps, illustrated on the running example.

Build weakening assertions Ω for r_n. Let $\widetilde{r}_n$ be r_n with A_n relaxed to **`True`**. Generate fresh sets $\widetilde{\mathcal{P}}$ and $\widetilde{\mathcal{F}}$ of passing and failing test cases for $\widetilde{r}_n$. Based on them, determine the sets $\mathcal{I}^{\widetilde{\mathcal{P}}}$ and $\mathcal{I}^{\widetilde{\mathcal{F}}}$ of dynamic *invariants* respectively holding in all passing tests $\widetilde{\mathcal{P}}$ and in all failing tests $\widetilde{\mathcal{F}}$ (Section 3.6 describes the dynamic invariant detection process). Let $\Omega = \{\omega \mid \omega \in \mathcal{I}^{\widetilde{\mathcal{P}}}$ and $\neg\omega \in \mathcal{I}^{\widetilde{\mathcal{F}}}\}$ be a set of weakening assertions, which characterize the minimal requirements for a test of $\widetilde{r}_n$ to be passing and not failing. In the example, `make` works without errors when $\texttt{m} \geq 0$, whereas it fails when $\texttt{m} < 0$; thus $\Omega = \{\texttt{m} \geq 0\}$.

Build weakening fixes W. For each $\omega \in \Omega \cup \{\textbf{\texttt{False}}\}$, build the weakening fix f obtained by replacing A_n with $A_n \vee w$ in r_n. Add f to the set W of weakening fixes. Adding **`False`** to Ω determines a dummy fix which is used to build purely strengthening fixes in the next step. In the example, W contains a weakening fix f_w corresponding to the one in Figure 2c, and a dummy fix f_0 where `make`'s precondition has been "weakened" with **`False`** (hence it is unchanged).

Validate weakening fixes. For each $f \in W$, if f passes all tests in $\mathcal{P}_r \cup \mathcal{F}_r$ then add f to the set Φ of candidate fixes without modifications, and remove it from W. In the example, f_w passes validation and is added to Φ. f_0 is instead the unchanged program in Figure 1b, and hence it stays in W.

Build strengthening assertions Σ_k for r_k. For each $f \in W$ that did not pass validation, determine the sets $\mathcal{I}_k^{\mathcal{P}}$ and $\mathcal{I}_k^{\mathcal{F}}$ of dynamic *invariants* currently holding in all pre-states of the calls to r_k respectively in the passing tests $\mathcal{P}_r$ and in the failing tests $\mathcal{F}_r$; k ranges over the subset of $\{0, \ldots, n-1\}$ for which s_k is a pre-state ($s_k r_k$ appears in the traces). Let $\Sigma_k = \{\sigma \mid \sigma \in \mathcal{I}_k^{\mathcal{P}}$ and $\neg\sigma \in \mathcal{I}_k^{\mathcal{F}}\}$ be the corresponding sets of strengthening assertions, which characterize the minimal additional requirements for a test to pass through r_k without failing. In the example, `duplicate` correctly calls `make` precisely when $\texttt{count} > 0$; thus, $\Sigma_0 = \{\texttt{count} > 0\}$.

Build strengthening fixes. For each combination $\langle \sigma_0, \ldots, \sigma_{n-1} \rangle \subseteq \Sigma_0 \times \cdots \times \Sigma_{n-1}$ of strengthening assertions, build the strengthening fix ϕ obtained by replacing each precondition P_{r_k} of routine r_k with $P_{r_k} \wedge \sigma_k$, for all applicable k. Add ϕ to the set Φ of candidate fixes. In the example, the dummy fix f_0 is turned into a valid fix ϕ_0 by strengthening `duplicate`'s precondition as $\texttt{count} > 0$.

Candidates. The output of the fix generation phase is a set Φ of fix candidates. The candidates are filtered and ranked as explained in the following section.

3.5 Fix Validation and Ranking

Validation. The purpose of the *validation* phase is to ascertain which of the candidate fixes in Φ remove the fault under analysis. To this end, SpecFix runs every fix candidate

$f \in \Phi$ through all available tests for r; f is *valid* if it still passes all originally passing tests, and it also passes all originally failing tests that have not become invalid.

The dual risk of unsoundness for validation based on a finite number of test cases is *overfitting*: a fix may pass validation but be unusable in a general context, because it introduces specification changes that harm usages of the API different from those exercised by the test cases used to generate the fix. To reduce the risk of overfitting, SpecFix uses only half of the originally generated test cases to generate the candidate fixes. Then, the validation phase uses *all* available tests for the routine under analysis, not only those in $\mathcal{P}_r$ and $\mathcal{F}_r$ used to generate fixes. This increases the likelihood that the validated fixes are applicable beyond the specific cases that drove fix generation.

Ranking. Not all valid fixes are equally desirable: all else being equal, we prefer those that introduce the least changes to the specification, and that make invalid the fewest test cases. SpecFix ranks valid fixes to reflect these criteria, and only reports the top five fixes for each fault. This approach is a good compromise between the contrasting needs of exposing programmers to a limited number of fixes—which they have to understand and validate—and of retaining fixes that fall behind in the ranking even if they are of high quality, due to the imperfect precision of the ranking heuristics.

The ranking heuristics is based on two elements: number of invalidated tests and the strength of the new contracts. A fix f consists of a collection $\langle A_0, \dots, A_n \rangle$ of new contracts for the routines $r_0, \dots, r_n$; each A_0 is either a pre- or a postcondition and may be weaker, stronger, or unchanged with respect to the original program. Given two valid fixes f_1, f_2, let A_k^1, A_k^2 be their new contracts for the same routine r_k. We say that A_k^1 is *not stronger than* A_k^2, written $A_k^1 \preceq A_k^2$, if A_k^1 holds whenever A_k^2 holds; precisely, we determine strength based on executing all available tests for r: $A_k^1 \preceq A_k^2$ iff every test that is valid for A_k^1 (i.e., a test that leads to executions where A_k^1 is evaluated and holds) is also valid for A_k^2 (i.e., A_k^2 is evaluated and holds). This generalizes to an ordering between fixes by lexicographic generalization of $\preceq$ on tuples $\langle A_0, \dots, A_n \rangle$. The ordering is partial because the sets of valid test cases for f_1 and for f_2 may be non-comparable. The final ranking orders fixes according to the $\preceq$ relation and, for incomparable fixes, ranks higher those that determine the higher number of valid (and hence passing) tests.

In the running example, the weakening fix in Figure 2c ranks higher than the strengthening fix in Figure 2b: all test cases with `count` > 0 are equivalent for the t-wo fixes, but the test cases with `count` = 0 are valid only for the weakening fix.

3.6 Dynamic Invariants and State Abstraction

SpecFix infers invariants at program states dynamically by observing the behavior during concrete executions. Dynamic invariant inference (see Section 5) has become a standard technique of dynamic analysis. Using the notation of Section 3.1, we can define an invariant at the entry of routine r_k as an assertion I such that $s_k \models I$ for every test t whose trace ρ_t includes the snapshot $s_k\, r_k$ where s_k is a pre-state; the invariant at routine exit is defined similarly with respect to post-states.

Invariant inference in SpecFix must cater to the specific needs of fixing contracts. To this end, we abstract the concrete program state by a number of predicates that include public queries (i.e., routines or attributes giving a value characterizing object state) as well as any subexpressions of the available contracts. For lack of space, we discuss some (straightforward) details in the Appendix.

4 Experimental Evaluation

We performed a preliminary evaluation of the behavior of SpecFix by applying it to 44 bugs of production software. The overall goal of the evaluation is corroborating the expectation that, for bugs whose "most appropriate" correction is fixing the specification, SpecFix can produce repair suggestions of good quality. A more detailed evaluation taking into account aspects such as robustness and readability of the produced fixes belongs to future work.

4.1 Experimental Setup

We selected 10 of the most widely used data-structure classes of the EiffelBase (rev. 92914) and Gobo (rev. 91005) libraries—the two major Eiffel standard libraries. While these are the same classes used in the experimental evaluation of AutoFix [20], we did not attempt a direct comparison for different reasons. First, some of the bugs used in AutoFix have been fixed in the latest library versions, and hence they are not reproducible. Second, running SpecFix on the very same input as AutoFix would limit the generalizability of the evaluation results; instead, we want to evaluate the behavior of SpecFix in standard conditions and avoid overfitting.

All the experiments ran on a Windows 7 machine with a 2.6 GHz Intel 4-core CPU and 16 GB of memory. We ran AutoTest for one hour on each of the 10 classes in Table 4. This automatic testing session found 44 unique faults consisting of pre- or postcondition violations. We ran SpecFix on each of these faults individually, using half of the test cases (generated for each fault in the one-hour session) to generate the fixes and the other half in the validation phase (Section 3.5). The right-hand side of Table 4 reports, for each class, the total number of test cases used by SpecFix, and the total time for testing (the initial one-hour sessions plus additional calls to AutoTest to generate tests for relaxed routines used to infer the weakening assertions Ω, as described in Section 3.4) and fixing. The average figures *per fault* are: 106.4 minutes of testing time and 7.2 minutes of fixing time (minimum: 4.1 minutes, maximum: 30 minutes, median 6.2 minutes). The testing time dominates since AutoTest operates randomly and thus generates many test cases that will not be used (such as passing tests of routines without faults).

4.2 Results

Evaluating the effectiveness of repairs that modify contracts is a somewhat subtle issue, since it ultimately involves what is a design choice: changing API specification. Related work on automatic repair (see Section 5) has rarely, if ever,[4] assessed the quality and

[3] Shortened to `CIRCULAR` in Section 2.

[4] The only exception we are aware of is [13].

CLASS	LOC	#R	#P	#Q	#C	#F	#$\mathcal{P}$	#$\mathcal{F}$	$\mathcal{T}_t$	$\mathcal{T}_f$
ACTIVE_LIST	2165	139	91	121	25	2	212	210	240	23
ARRAY	1474	101	70	110	10	9	850	555	900	72
ARRAYED_CIRCULAR[3]	1907	133	80	92	23	3	320	234	360	17
ARRAYED_SET	2346	146	118	131	26	6	554	432	720	34
DS_ARRAYED_LIST	2862	168	219	173	15	3	132	89	240	15
DS_HASH_SET	3159	171	154	140	20	1	14	60	120	5
DS_LINKED_LIST	3497	162	207	166	13	3	360	25	360	25
LINKED_LIST	1995	109	70	91	23	0	–	–	60	–
LINKED_SET	2347	122	99	101	26	4	416	70	480	22
TWO_WAY_SORTED_SET	2856	141	118	118	31	13	1260	655	1260	106
TOTAL	24608	1392	1226	1243	212	44	4118	2330	4680	319

Table 4: Classes used in the experiments; for each class we report: lines of code LOC, number #R of routines, number #P of assertions in preconditions, number #Q of assertions in postconditions, and number #C of assertions in the class invariant. In the right-hand side, we report the number #F of faults targeted by the experiments, the total number of test cases (passing #$\mathcal{P}$ and #$\mathcal{F}$ failing) used by SpecFix, the $\mathcal{T}_t$ minutes spent running AutoTest on routines of the class, and the $\mathcal{T}_f$ minutes spent running SpecFix (net of testing time) on faults of the class.

acceptability for human programmers of the produced fixes beyond running standard regression test suites. To this end, in previous work [20,17] we introduced the notions of *valid* and *proper* fix: any fix that passes all the available tests is valid (and hence every fix output by SpecFix is valid), but only those that manual inspection reveals to satisfactorily remove the real source of failure without introducing other bugs are classified as *proper*.

We use the same classification criterion in the evaluation of fixes produced by SpecFix: Table 5 lists the total number of faults for which SpecFix generated valid or proper fixes (and ranked them in the top 5 positions: we ignore fixes that rank lower).

For 25% of the faults, SpecFix produced fixes that manual inspection revealed to satisfactorily remove the real source of failure.

TYPE OF FAULT	#F	VALID	PROPER	VALID FIXES				PROPER FIXES			
				ALL	WEAK	STRONG	BOTH	ALL	WEAK	STRONG	BOTH
Precondition violation	22	22	7	77	23	30	24	13	1	12	0
Postcondition violation	22	20	4	71	56	13	2	7	3	4	0
TOTAL	44	42	11	148	79	43	26	20	4	16	0

Table 5: Fixes built by SpecFix. For each TYPE of fault, the left-hand side of the table reports the number #F of faults of that type input to SpecFix, and for how many of those faults SpecFix built (at least one) VALID or PROPER fixes. The right-hand side reports the total number of *fixes* produced in each category; the same fault may have multiple valid or proper fixes. Columns ALL list all fixes in each category, followed by a breakdown into purely weakening (WEAK), purely strengthening (STRONG), and mixed (involving BOTH strengthening of some contract and weakening of some other).

The percentage of proper fixes (25% of faults) is similar to that obtained in the work with AutoFix; but the high percentage of valid fixes (over 90%) requires some explanation. Obtaining valid contract fixes is easy if only poor-quality tests are available. One can always strengthen preconditions to invalidate failing test cases (or, conversely, weaken failing postconditions to trivially pass tests): since SpecFix validates fixes based on the available test cases, which in turn are only as good as the contracts of the class (beyond those directly targeted by the fix), such straightforward fixes yield valid repairs for classes equipped with very weak and incomplete contracts. This does not mean that such fixes are always improper; in fact, 80% of all proper fixes strengthen preconditions: it is only when it is combined with very poor specification (especially class invariants) that fixing may lead to improper fixes. Furthermore, despite being not directly deployable, the valid but improper fixes produced by SpecFix are still very valuable as debugging aids, since they clearly highlight the failure-inducing inputs.

Acceptability trial. In order to get more confidence in the capability of SpecFix to produce proper, acceptable fixes from a programmer's perspective, we conducted a small trial involving 4 PhD students (henceforth, the "subjects") in our group. The 4 subjects were quite familiar with the Eiffel language and its standard libraries, but had not been involved in the work on SpecFix or AutoFix. To keep the workload small, we randomly selected only 8 out of the 11 faults for which SpecFix produced proper fixes, and submitted them to the subjects: for each fault, we produced one failing test case (randomly picked among those produced by AutoTest) and up to 3 fixes produced by SpecFix. In order to compare the acceptability of specification and implementation fixes, we also included up to 2 proper implementation fixes for each of 5 faults (out of 8) produced using AutoFix. For each fault, the subjects: (1) declared which fixes they considered acceptable (i.e., they "correct the fault while not introducing new faults", as in our definition of "proper"); and (2) ordered the fixes in decreasing order of quality.

The Appendix reports the results of the trial in some detail. The highlights: all subjects but one agreed with our assessment of proper fixes; the subjects unanimously preferred a contract fix over an implementation fix for 3 of the 5 faults that had both kinds of fix. The subject who disagreed about proper fixes still agreed that the contract fixes for 6 out of 8 faults are proper. With the proviso that its small scale does not warrant arbitrary generalizations, the trial demonstrates substantial agreement with our assessment of proper fixes; and suggests that, if a fault can be fixed with a contract fix, SpecFix has a chance of building a high-quality one.

Programmers found most proper fixes produced by SpecFix acceptable and often preferable to fixes for the same bugs that change the implementation.

4.3 Limitations and Threats to Validity

Limitations. The main limitation to the applicability of SpecFix is that it requires contracts. On the one hand, it requires a language where contracts are expressible; this is an obvious consequence of the technique's goals and is not severely restrictive since many languages support some form of notation for contracts (e.g., JML for Java and CodeContracts for C#). On the other hand, SpecFix works well only on classes that come already equipped with *some* contracts of decent quality. Class invariants (which

SpecFix does not change but only assumes) are particularly useful to ensure that the test cases generated represent reasonable usage, so that validation (Section 3.5) is precise. Despite being often weak and largely incomplete, the kinds of contracts Eiffel programmer write have been sufficient to get good experimental results; but in future work we will investigate how SpecFix performance improves if it is given more expressive contracts [18].

Threats to validity. The most significant threat to *external* validity—concerning the generalizability of our experimental results—comes from limiting the experiments to data-structure classes. This is a limitation partly inherited from the usage of AutoTest to generate test cases; AutoTest is meant for unit testing and hence works more easily with classes with a clearly defined interface such as data structures. In future work, we plan to experiment with other kinds of program (as we already did successfully with AutoFix [17]) and possibly with manually-written test cases. Another threat comes from the small number of subjects used in the trial (Section 6). We acknowledge that the trial only gives a preliminary assessment, and more user studies are needed to ensure generalizability.

Threats to *internal* validity—concerning the proper execution of our experiments—include repeatability. Since SpecFix uses AutoTest to generate test cases, and the performance of AutoTest is affected by chance, different runs may yield different results. Based on our previous extensive experience with using AutoTest's test cases for dynamic analysis [18,17,19,20], we expect AutoTest behavior to be predictable over the testing time allotted in our experiments; therefore, this threat is unlikely to be significant. Since SpecFix produces many valid but not proper fixes, an issue is how much effort is required to identify the improper fixes. While we have no hard evidence about this, even improper fixes succinctly characterize the failure-inducing inputs, and hence they are still useful as debugging aids. Furthermore, contract fixes are normally quite simple, arguably easier to read than implementation fixes; all subjects in the trial spent on average around two minutes to classify each contract fix, which seems to indicate an acceptable overhead.

5 Related Work

SpecFix is a novel technique in the recently emerging area of automatic program repair, whose most important contributions we briefly review below. Dynamic invariant inference is one of the specific techniques used in SpecFix; we also discuss fundamental related work in this area.

Automatic program repair. Source-code repair aims to remove buggy behavior from a program by changing its implementation. GenProg [21] is one of the first and most successful techniques for source-code repair. It uses genetic programming to mutate a faulty program into one that satisfies a given set of test cases. GenProg has been evaluated [14] using various open-source programs, showing that it can produce many non-trivial fixes. GenProg works on programs without annotations; however, it requires a regression test suite as part of its input.

Other work has applied different techniques to the problem of source-code repair, with the goal of improving the applicability and acceptability of the produced repairs;

for example, by deploying machine-learning techniques [12,2,13], constraint-based approaches [10,16], and finite-state abstractions [7]. These techniques also normally require a regression test suite as part of their input.

In previous work, we developed AutoFix [20,17], an automatic tool that suggests fixes of implementations written in Eiffel and annotated with simple contracts. Contracts dispense with the need for a regression test suite, as one can be generated as needed through automatic testing. SpecFix's technique can be seen as the dual to AutoFix's: the latter assumes contracts correct to fix implementations, whereas the former assumes implementations correct to fix contracts.

Invariant inference. Invariant inference techniques learn assertions that hold for a given implementation. These techniques are naturally classified in *static* and *dynamic*. Static techniques analyze the source code to infer specification elements. Since inferring all but the simplest classes of properties is undecidable, static techniques are usually sound but incomplete. Abstract interpretation is a fundamental framework for static invariant inference [4], which has been applied in many different contexts.

SpecFix relies instead on *dynamic* techniques for invariant inference. These summarize properties that are invariant over multiple runs of a program; their advantage over static techniques is that dynamic approaches do not require a sophisticated analytical framework and are applicable to the whole programming language: they work on anything that can be executed. While dynamic techniques provide no guarantees of soundness or completeness, they work quite well in practice. Dynamic invariant inference has been pioneered by the Daikon tool [8]. Daikon uses a pre-defined set of templates describing common relations among program variables. Much work has been done to extend and improve the Daikon approach; for example to support object-oriented features [5], and to infer complex and often complete postconditions [19]. The dynamic approach has also been applied to other kinds of specifications such as finite-state behavioral specifications [1,22,6,15] and algebraic specifications [9,11].

6 Conclusions and Future Work

We presented a technique that fixes programming bugs by rectifying *specifications* in the form of simple contracts (pre- and postconditions). The technique is completely automatic and can produce fixes that strengthen the original specification (and hence prevent buggy behavior from being triggered) as well as fixes that weaken it (and hence allow more executions); whenever both types of fix are applicable, it prefers the latter because less restrictive. In an experimental evaluation, we ran SpecFix on 44 bugs of Eiffel standard data-structure libraries. An evaluation by human programmers indicates that SpecFix produced fixes of quality sufficient to be deployed for 25% of the bugs.

We now have complementary techniques to fix bugs either by changing the implementation (such as in our previous work on AutoFix [20,17]) or by changing the specification (using SpecFix presented in this paper). Therefore, the main goal of future work is to apply both fixing approaches in combination, and in particular to develop automatic heuristics to decide whether the "best" fix for a given bug involves changing implementation, specification, or both.

Availability. The SpecFix source code, and all data and results cited in this article, are available at: `http://se.inf.ethz.ch/research/autofix/specfix.html`.

Acknowledgments. Thanks to Alexey Kolesnichenko, Nadia Polikarpova, Andrey Rusakov, and Julian Tschannen for participating in the trial (Section 4.2).

References

1. Ammons, G., Bodík, R., Larus, J.R.: Mining specifications. In: POPL. pp. 4–16 (2002)
2. Arcuri, A.: Evolutionary repair of faulty software. Applied Soft Computing 11(4), 3494–3514 (2011)
3. Ciupa, I., Pretschner, A., Oriol, M., Leitner, A., Meyer, B.: On the number and nature of faults found by random testing. Softw. Test., Verif. Reliab. 21(1), 3–28 (2011)
4. Cousot, P., Halbwachs, N.: Automatic discovery of linear restraints among variables of a program. In: POPL. pp. 84–96 (1978)
5. Csallner, C., Smaragdakis, Y.: Dynamically discovering likely interface invariants. In: ICSE. pp. 861–864 (2006)
6. Dallmeier, V., Lindig, C., Wasylkowski, A., Zeller, A.: Mining object behavior with ADABU. In: WODA. pp. 17–24 (2006)
7. Dallmeier, V., Zeller, A., Meyer, B.: Generating fixes from object behavior anomalies. In: ASE. pp. 550–554. IEEE (2009)
8. Ernst, M.D., Cockrell, J., Griswold, W.G., Notkin, D.: Dynamically discovering likely program invariants to support program evolution. IEEE TSE 27(2), 99–123 (2001)
9. Ghezzi, C., Mocci, A., Monga, M.: Synthesizing intensional behavior models by graph transformation. In: ICSE. pp. 430–440 (2009)
10. Gopinath, D., Malik, M.Z., Khurshid, S.: Specification-based program repair using SAT. In: TACAS. LNCS, vol. 6605, pp. 173–188. Springer (2011)
11. Henkel, J., Reichenbach, C., Diwan, A.: Discovering documentation for Java container classes. IEEE TSE 33(8), 526–543 (2007)
12. Jeffrey, D., Feng, M., Gupta, N., Gupta, R.: BugFix: a learning-based tool to assist developers in fixing bugs. In: ICPC. pp. 70–79. IEEE (2009)
13. Kim, D., Nam, J., Song, J., Kim, S.: Automatic patch generation learned from human-written patches. In: ICSE. pp. 802–811. IEEE (2013)
14. Le Goues, C., Dewey-Vogt, M., Forrest, S., Weimer, W.: A systematic study of automated program repair: Fixing 55 out of 105 bugs for $8 each. In: ICSE. pp. 3–13. IEEE (2012)
15. Lorenzoli, D., Mariani, L., Pezzè, M.: Automatic generation of software behavioral models. In: ICSE. pp. 501–510 (2008)
16. Nguyen, H.D.T., Qi, D., Roychoudhury, A., Chandra, S.: SemFix: program repair via semantic analysis. In: ICSE. pp. 772–781. IEEE (2013)
17. Pei, Y., Wei, Y., Furia, C.A., Nordio, M., Meyer, B.: Code-based automated program fixing. In: ASE. pp. 392–395. ACM (2011)
18. Polikarpova, N., Furia, C.A., Pei, Y., Wei, Y., Meyer, B.: What good are strong specifications? In: ICSE. pp. 257–266. ACM (2013)
19. Wei, Y., Furia, C.A., Kazmin, N., Meyer, B.: Inferring better contracts. In: ICSE. pp. 191–200. ACM (2011)
20. Wei, Y., Pei, Y., Furia, C.A., Silva, L.S., Buchholz, S., Meyer, B., Zeller, A.: Automated fixing of programs with contracts. In: ISSTA. pp. 61–72. ACM (2010)
21. Weimer, W., Nguyen, T., Le Goues, C., Forrest, S.: Automatically finding patches using genetic programming. In: ICSE. pp. 364–374. IEEE (2009)
22. Xie, T., Martin, E., Yuan, H.: Automatic extraction of abstract-object-state machines from unit-test executions. In: ICSE. pp. 835–838. IEEE (2006)

A Dynamic Invariants and State Abstraction (Section 3.6)

SpecFix abstracts the concrete program state by a number of predicates that include public queries (i.e., routines or attributes giving a value characterizing object state) as well as any subexpressions of the available contracts. Roughly, a set E of state expressions is built as follows:

$$E \ ::= \ b \mid \neg b \mid b_1 \wedge b_2 \mid b_1 \vee b_2 \mid n_1 < n_2 \mid n_1 = n_2 \mid n_1 \neq n_2 \mid r_1 = r_2 \mid r_1 \neq r_2 \,,$$

where b ranges over the set of Boolean expressions (public Boolean queries, visible Boolean arguments, and Boolean subexpressions of visible expressions including contracts, the Boolean constants **`True`** and **`False`**, as well as any recursively defined element of E); n ranges over the set of integer expressions (similarly defined); and r ranges over the set of reference expressions. E defines an abstraction on the concrete state; invariants are expressed in terms of elements of E that hold in all executions.

B Acceptability Trial (Section 4.2): Detailed Results

Table 6 summarizes the results of the acceptability trial (described in Section 4.2): for each subject S_x and fault F_y, a "c" represents a contract fix (produced by SpecFix) and an "i" an implementation fix (produced by AutoFix); the order represents the one expressed in task (2) of the trial; multiple fixes judged of equally good quality are grouped in braces. Underlined fixes correspond to those judged acceptable in task (1) of the trial. For example, the entry $\{\underline{i}\,\underline{i}\}\,\underline{c}\,c$ in row S_4, column F_5 means that subject S_4 judged the two implementation fixes of fault F_5 acceptable and of equivalent quality, better than one contract fix (still acceptable), and better still than another contract fix (unacceptable).

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
S_1	$\underline{c}\,\underline{i}$	$\{\underline{c}\,\underline{c}\}\,\underline{i}\,\underline{i}$	$\underline{c}\,\underline{c}\,\underline{i}\,c$	$\underline{i}\,\underline{c}\,\{i\,c\}$	$\{\underline{i}\,\underline{i}\}\,\underline{c}\,c$	$\underline{c}\,\underline{c}$	$\underline{c}\,\underline{c}$	$\underline{c}\,c$
S_2	$\underline{c}\,\underline{i}$	$\underline{c}\,\{c\,i\,i\}$	$\underline{c}\,\underline{c}\,\{i\,c\}$	$\underline{i}\,\underline{c}\,\{i\,c\}$	$\underline{c}\,\underline{i}\,\{c\,i\}$	$\underline{c}\,\underline{c}$	$\underline{c}\,c$	$\underline{c}\,c$
S_3	$\underline{c}\,\underline{i}$	$\underline{c}\,\underline{c}\,\{i\,i\}$	$\underline{c}\,\{c\,i\,c\}$	$\underline{c}\,\underline{i}\,\underline{i}\,c$	$\underline{i}\,\underline{i}\,\{c\,c\}$	$\underline{c}\,c$	$\underline{c}\,c$	$\{c\,c\}$
S_4	$\underline{c}\,\underline{i}$	$\underline{c}\,\underline{c}\,\underline{i}\,\underline{i}$	$\underline{c}\,\underline{i}\,\underline{c}\,c$	$\underline{c}\,\underline{i}\,\{i\,c\}$	$\{\underline{i}\,\underline{i}\}\,\underline{c}\,c$	$\underline{c}\,\underline{c}$	$\{\underline{c}\,\underline{c}\}$	$\underline{c}\,\underline{c}$

Table 6: Results of the trial.

The disagreement of subject S_3 about which faults are proper targets two faults which are worth discussing in more detail because they are indicative of the expectations of different programmers. Fault F_8 affects routine `subtract` in class `TWO_WAY_SORTED_SET`: `s.subtract(t)` removes from set `s` all elements in set `t`, but it does not work correctly if `s` and `t` are references to the same object. One repair produced by SpecFix strengthens `subtract`'s precondition to disallow the case `s = t`; the other three subjects thought that the case of `s` and `t` aliased is special and hence can be handled separately, whereas S_3 maintained that a proper fix should work correctly also when `s = t`. The other fault F_5 affects routine `prune_first` of class `DS_ARRAYED_LIST`: `l.prune_first` removes the first element of list `l`, but it does not work if `l` is empty.

SpecFix suggested to strengthen the routine's precondition to `count` >0; S_3 expected a proper fix to do nothing when `l` is empty, whereas the other subjects thought that removing the "first" element makes sense only if the first element exists. In both cases, how the routines should behave on corner cases is a somewhat subjective matter. Anyway, all the subject agreed that even improper strengthening fixes are useful to understand a fault's source and manually fix them. For F_5 and F_8 which we just described, the inferred preconditions clearly outline the case in which the routines do not work; changing the implementation to cover those cases as well becomes straightforward.