Abstract—Template-based program repair research is in need for a common ground to express fix patterns in a standard and reusable manner. We propose to build on the concept of generic patch (also known as semantic patch), which is widely used in the Linux community to automate code evolution. We advocate that generic patches could provide at the same time a unified representation and a specification for fix patterns. Generic patches are indeed formally defined, and there exists a robust, industry-adapted, and extensible engine that processes generic patches to perform control-flow code matching and automatically generates concrete patches based on the specified change operations.

In this paper, we present the design and implementation of a repair framework, FLEXIREPAIR, that explores generic patches as the core concept. In particular, we show how concretely generic patches can be inferred and applied in a pipeline of Automated Program Repair (APR). With FLEXIREPAIR, we address an urgent challenge in the template-based APR community to separate implementation details from actual scientific contributions by providing an open, transparent and flexible repair pipeline on top of which all advancements in terms of efficiency, efficacy and usability can be measured and assessed rigorously. Furthermore, because the underlying tools and concepts have already been accepted by a wide practitioner community, we expect FLEXIREPAIR’s adoption by industry to be facilitated. Preliminary experiments with a prototype FLEXIREPAIR on the IntroClass and CodeFlaws benchmarks suggest that it already constitutes a solid baseline with comparable performance to some of the state of the art.

Index Terms—Generic Patch, Fix Pattern, Fix Template, Program Repair.

I. INTRODUCTION

In the race for achieving the old software engineering dream of automating program repair, approaches that leverage fix patterns currently have the lead (in terms of how many benchmark bugs can be fixed) [1]. Unfortunately, despite the excitement of this momentum in the research community, practitioners expectations are not met and full integration in industrial settings remain anecdotal. Initial experimental attempts to large-scale application of automatic bug fixing suggest however that pattern-based patch generation fits the current practice of software engineering: At Facebook, Getafix [2] and SapFix [3] suggest fixes for in-house software by learning patterns using “hierarchical clustering to many thousands of past code changes that human engineers made, looking at both the change itself and also the context around the code change”. In the Linux open source ecosystem, the CocciNelle [4] code transformation engine, which builds on pattern-like specifications written by developers, has been leveraged to automatically generate over 6000 patches [5] that were accepted in the kernel code base. Besides repair, Ubisoft designed Clever [6] to detect risky commits at commit-time using patterns of programming mistakes from the code history.

Recently, Liu et al. [7] proposed to revisit the performance of automated program repair (APR), carefully searching to identify the pattern databases that were available in the literature. Their experience report suggests that researchers do not actually share a common definition of what constitutes a repair pattern: levels of abstraction vary significantly and their immediate exploitation is often impossible as a transferable ingredient. Koyuncu et al. [8] and Ueda et al. [9], in two independent works, pointed out that fix patterns should be made tractable (i.e., they should be a clearly identifiable artefact in the repair pipeline towards explaining the patch generation decisions) and editable (i.e., APR users should be enabled to intervene to correct these patterns manually to take into account project specificities). On top of these concerns, the full APR pipeline generally suffers from a lack of:

- **Practicality**: A large body of the literature in APR present approaches that target well curated benchmarks with several constraints (e.g., test cases are readily available for the identified bugs) which may not be the case in practice. Although recent works [10] have started to investigate the use of bug reports, their pipelines remain heavily driven by test suites (e.g., for validation).

- **Flexibility**: Regardless of the patch generation process (i.e., heuristic-based, constraint-based, or template-based following the taxonomy proposed in [11]), the available change transformations are generally limited to small mutations operators which are tightly embedded in the proposed algorithms. Seldom, an approach allows third party members in the community to readily edit and extend the list of possible code transformations.

- **Transparency**: The repair approaches suggest patch candidates from a search space. However, in most of the case, the origins of the patch candidates, i.e., how they are discovered, is missing. This intracetable remains a big obstacle for the transparency.

Overall, we note that on the road to automated program repair, the practitioner community is looking for techniques that can rapidly recommend patches that may be manually validated by developers. Indeed, these appear to be acceptable in various industrial settings so far. It may thus be worthwhile to drain some research effort into building an automatic patch
This paper. We present the core concept behind FLEXIREPAIR, a flexible, transparent and practical APR pipeline. We have initiated this FLEXIREPAIR and call for the community to commit on working on its building blocks for delivering a reliable tool support for practitioners in the context of program repair. FLEXIREPAIR is built on top of well-accepted software maintenance concepts in the Linux community, notably the concept of generic patch (more known as semantic patch in recall for the specification language: the Semantic Patch Language [12]). We use generic patch specification as the tractable notation for fix patterns. The main contributions of our work are as follows:

- We propose a critical review of template-based APR steps and suggest the design of a patch generation system around the concept of generic patch whose underlying definition and structure is borrowed from the Linux community toolbox.
- We initialize an open framework for program repair. The proposed pipeline, FLEXIREPAIR, transparently uses state of the art building blocks that can be customized.
- We evaluate the prototype pipeline, using available building blocks from the literature. Performance is measured with C program repair benchmarks.

II. RELATED WORK

Program repair at a glance. Patch generation is one of the key tasks in software maintenance since it is time consuming and tedious. If this task is automated, the cost and time of developers for maintenance will inevitably be reduced in a dramatic manner. To address this issue, many automated techniques have been proposed for program repair [11, 13]. Ultimately, program repair is about traversing a search space of patch candidates that are generated by applying change operators to the buggy program code. Depending on how a technique conducts the search and constructs the patches, it can be considered as heuristics-based [14, 15, 16, 17] or constraint-based [17, 18, 19] following the taxonomy proposed by Le Goues et al. [11]. If such a technique further leverages learning mechanisms to infer transformation patterns, or to build patch models or to even predict patches, it is considered as learning-aided [20, 21, 22].

In the last decade, most proposed techniques in the literature present repair pipelines where patch candidates are generated then validated against a program specification, generally a (weak) test suite. We refer to them as generate-and-validate test-suite based repair approaches and focus FLEXIREPAIR framework under this practical repair scheme. The generic programming-based approach proposed by Weimer et al. [16], as well as follow-up works, appeared only valid for hypothetical use cases. Nevertheless, in the last couple of years, two independent reports have illustrated the use of literature techniques in actual development flows: in the open source community, the Repairator project [23] has successfully demonstrated that automated repair engines can be reliable:

open source maintainers accepted and merged patches which were suggested by an APR bot. At the premises of Facebook, the SapFix repair system has been reported to be part of the continuous integration pipeline [3] while Getafix was used there at large scale [24].

Given fault localization information that pinpoints the code locations in the program that are the most likely to be buggy, test suite program repair approaches apply syntactic transformations to generate patches. Early techniques such as GenProg [25, 16] relied on simple mutation operators to drive the genetic evolution of the code. More widespread today are approaches that build on fix patterns [15] (also referred to as fix templates [26] or program transformation schemas [27]) learned from existing patches. Several APR systems [15, 28, 29, 26, 27, 8, 30, 31, 32, 33, 34] implement this strategy by using diverse sets of fix patterns obtained either via manual generation or automatic mining of bug fix datasets. Unfortunately, whether they are generated on-the-fly (e.g., with SimFix [14] and CapGen [34]) or stored in a database, fix patterns remain an elusive concept.

In our work, our aim is to establish generic patches specified via the Semantic patch language as the formal notation for abstracting and defining fix patterns.

Fix patterns inference for program repair. While the literature includes a large body of work on change patterns [35], [36], [37], and more generally on change redundancies [38], [39], [40], [41], [42], [43], [44], very few approaches have actually leveraged again their “discovered” patterns to instantiate repair patches.

Nevertheless, specific bug patterns have been mined to build fixing engines: Livshits and Zimmermann [45] discovered application-specific repair templates by using association rule mining on two Java projects while Hanam et al. [46] have developed the BugAID technique for discovering most prevalent repair templates in JavaScript.

DevReplay [9] is a recent static analysis tool that suggests source code changes based on a project’s git history. The proposed changes can be edited by users without requiring knowledge about the AST.

FixMiner [8] is an automated approach to mining relevant and actionable fix patterns based on an iterative clustering strategy applied to atomic changes within patches. The goal of FixMiner is to infer separate and reusable fix patterns that can be leveraged in other patch generation systems. This approach provides an appealing building block in the context of the FLEXIREPAIR framework. Unfortunately, its patterns are also not immediately actionable; they must be manually integrated into a repair engine, which require a tedious an error-prone hard-coding of bug-fixing patterns. Additionally, FixMiner patterns do not contain any code token information: they have holes. The donor code should be searched before generating a concrete patch, which may lead to various nonsensical patches. FixMiner currently supports only Java and it does not provide any end-to-end traceability (i.e. we do not know from where the pattern has been inferred).
We borrow some ideas from the FixMiner approach for computing patch similarity towards inferring patterns. In particular, we find their rich AST edit script to be appealing for building the prototype implementation of FlexiRepair.

**Generic patches in the literature.** There have been some work addressing the problem of considering a set of patches and attempting to find a “generic patch” that summarizes the change that is common across the patches. Chawathe et al. proposed a seminal method to detect changes to structured information based on an ordered tree and its updated version [47]. The goal was to derive a compact description of the changes with the notion of minimum cost edit script which has been used in the recent ChangeDistiller and GumTree tools. Spdiff [48], [49] was then a promising approach that considered inferred change patterns from a set of patches. It was however found to scale poorly to a large number of patches, and to have constraints in producing ready-to-use tools. Spdiff [48], [49] was then a promising approach that considered inferred change patterns from a set of patches. It was however found to scale poorly to a large number of patches, and to have constraints in producing ready-to-use patterns that can be used (e.g., by the Coccinelle matching and transformation engine [12]). Recently, Serrano et al. [50] proposed Spinfer as a tool-supported approach to ease large-scale changes across many source files in Linux by suggesting transformation rules to developers, inferred automatically from a collection of examples.

Spinfer builds on the notion of “generic patch” (also referred to as “semantic patch”), which Linux developers are already familiar with, thanks to the wide adoption of the Coccinelle [4] transformation engine and the associated Semantic Patch Language. We will rely on this building block for the inference of fix patterns in the prototype version of FlexiRepair.

### III. The FlexiRepair Framework

FlexiRepair builds on the momentum of template-based program repair, which has been shown successful in fixing a variety of bugs in APR benchmarks. To date these approaches are among the most effective (in terms of the number of benchmark bugs that are fixed) repair tools in the literature. Relevant approaches in the literature (e.g., TBar [7], AVATAR [31], CapGen [54], SimFiX [14]) are often provided in a monolithic tooling which prevents extension, adaptation and even application on real-world code bases beyond those targeted by initial experimental validations.

**In this work, we propose to initiate a community-wide effort to build a flexible, transparent and practical framework for template-based program repair to (1) enable better assessment of research advancements, and (2) facilitate adoption of APR by software maintainers.**

FlexiRepair is carefully designed to ensuring that its users have control over important steps of the patch generation process. In particular, we consider the following critical questions:

1. **Where should we mine repair transformations?** Template-based program repair systems, whether they leverage specifically pre-defined mutation operators, infer code transformations on-the-fly or rely on offline-inferred fix patterns, they generally build on data of existing code bases (preferably with a large history of code changes). If the source of mining is not appropriate (e.g., limited recurrent changes or changes associated to domain-specific bugs), the mined patterns may be irrelevant for the program that is targeted for repair.

2. **How are fix patterns inferred?** A challenge that has been highlighted in two recent independent studies [8], [9] is that fix patterns discussed in the APR community are largely intractable artefacts. If the underlying fix patterns cannot be manipulated (i.e., checked and edited) by practitioners, the adoption of the integrating APR tool will be largely hindered.

3. **How are patches generated?** Besides fault localization information which generally drives the selection of fix patterns, the application of code transformations generally follows various ad-hoc recipes and involve empirical design choices for fix pattern matching and donor code search. If these activities cannot be ensured to be deterministic, industry adoption of APR cannot be ensured.

### A. Execution steps of FlexiRepair

We propose to build an APR pipeline that addresses the issues raised in the aforementioned questions. Figure 1 illustrates an overview of the FlexiRepair.

The pipeline takes the code repositories that the maintainer judge to be relevant for learning code transformations as its input. This set of code repositories can be constituted by the single source code repository associated to the program under repair. Then, each of the questions formulated above are addressed by a major component involved in a specific step of the FlexiRepair pipeline:

- **Miner** analyzes the structural similarity between input repository patches and yields clusters that can be tuned by FlexiRepair users to take into account the recurrence level of code transformations that will be supported by the patch generation.
- **Inferrer** then abstracts fix patterns from each retained cluster and specifies it in a format that can be inspected (for relevance) and edited (to account for specific maintenance style requirements).
- **Generator** finally builds the concrete patches for the given buggy programs, after attempting to match fix patterns to the appropriate code locations (i.e., the likely buggy code locations).

Instead of re-inventing new algorithms and prototyping tools that would require extensive vetting before adoption, we propose to bootstrap the FlexiRepair pipeline by relying on tried-and-true technologies that software maintenance are already familiar with. Concretely, we have identified a code transformation tool that is part of the Linux kernel developer toolbox since 2008 and which is now increasingly used to automate large-scale changes in kernel code. This tool, Coccinelle [4] builds on a concept of semantic patch that allows developers to write transformation rules using a diff-like syntax. **In this work, we will use instead the term “generic patch” to refer to the specification of transformation rules that can be given as input to Coccinelle.** A generic patch is thus an abstraction that uses metavariables to represent...
common but unspecified subterms (e.g., any variable) and notation for reasoning about control flow paths.

Given the standing of Linux development practices in the software development community, the adoption of a tool such as Coccinelle, and its underlying concepts, is a strong signal that it fits with industry standards. We therefore propose to build the FLEXIREPAIR pipeline on top of the Coccinelle engine.

A fix pattern in FLEXIREPAIR is a generic patch that is specified using the specification language of Coccinelle, which is now integrated to the Linux development toolbox.

B. Overview of the SmPL Language

The Coccinelle tool is an example of public research effort that gained traction in industrial settings, thanks to support from the open source community. It was initially designed to document and automate collateral evolutions \(^4\) in the Linux kernel source code, but is now used in a variety of other code bases as an base engine for performing control-flow-based program searches and transformations in C code \(^5\). Coccinelle integrates a static analysis that is specified using control-flow sensitive concrete syntax matching rules, search (i.e., identifying code fragments that match a pattern) and transformations (i.e., generating patches following the fix pattern) are specified via the Semantic Patch language (SmPL) language, and executed by a dedicated transformation engine. Although the Linux community refers to the SmPL specifications as "semantic patches", we will refer to them in FLEXIREPAIR as "generic patches" to reflect the idea that they are abstract patterns that must be "concretized" into generated patches.

Although SmPL specifications can contain OCaml or Python code, allowing to perform arbitrary computations, in this work we focus on its pattern matching and code transformation capabilities. Listing 1 provides an example of generic patch (as an SmPL specification). The patch goal is:

1. to identify all code locations where there is an attempt to access a field of struct whose pointer has not been safely checked beforehand in the control flow. Indeed if the pointer (param) is NULL, the dereference would lead to a segmentation fault (and a crash in the case of an operating system code).
2. to produce a corrective patch (i.e., adding check and early return statement) at all places where such an unsafe dereference can take place.

The generic patch is constituted of a single rule named "unsafe_dereference" which defines five metavariables (lines 2-4): \(\overline{T}\) (type) which represents any data type; \(p\), which represents an arbitrary position in the source program; \(f_{n}\) (function name), \(pa_{r}{m}\) (parameter name) and \(f_{d}\) (data structure field name), which represent arbitrary identifiers. Metavariables are bounded by matching the code pattern against the source code. For example, the pattern fragment on line 6 \(\{(f_{n}(\ldots, T *pa_{r}{m}, 
\ldots))\}\) will cause \(f_{n}\) to be bounded to the name of a function in its definition, and cause \(pa_{r}{m}\) to be bounded to any pointer parameter name. The notation \(\forall p\) binds the position metavariable \(p\) to information about the position of the match of the preceding token. Once bounded, a metavariable must maintain the same value within the current control-flow path: thus, for example, the occurrences of \(pa_{r}{m}\) on lines 6-13 must all match the same expression. The fix pattern (lines 6-15) therefore consists of essentially C code, mixed with a few operators to raise the level of abstraction so that a single generic patch can apply to many code sites.

Listing 1: Example of generic patch

1) Sequences abstraction: The main abstraction operator provided by SmPL is ‘...', representing a sequence of terms. In line 6, '...' represents the remaining parameters of a function that appear before and after a given parameter is matched in the parameter list; in line 7, '...' represents the sequence of statements reachable from the begin of the definition of a function along any control-flow path. By default\(^6\) such a sequence is quantified over all paths (e.g., over all branches of a conditional block), but the annotation “exists”, next to the rule name, indicates that for this “unsafe_dereference” rule, the matching should be done even for one path. It is also possible to restrict the kinds of sequences that ‘...' can match using the keyword when. Lines 9-12 use when to indicate

\(^{1}\) This default behavior can also be explicitly stated using the “forall” annotation.
that there should be no reassignment of param nor any check on the validity of the param pointer value before reaching the dereference that consists in accessing a field fld in the corresponding data structure.

A SmPL rule only applies when it matches the code completely. Consider the example of buggy code in Listing 2. The rule unsafe_dereference matches the parameters of type struct person * on line 1 and the dereference on line 6 as it exists a control-flow path where the validity of pers is not checked. The metavariable fn (cf. Listing 1) is bound to the identifier get_age, and the metavariable param is bound to pers. The metavariable p is bound to various information about the position of the dereference, such as the file name, line number, character number (on the line).

```
int get_age(struct person *pers, char *context){
  int age=0;
  if (pers != NULL)
    age=pers->age;
  else
    age=pers->age_death - pers->age;
  return age;
}
```

Listing 2: Example of buggy code with an unsafe dereference

2) **Disjunctions and Nests:** Besides the ‘...’, SmPL provides disjunctions, \((pat_1 \mid ... \mid pat_n)\), and nests, \(<...pat...>\). A nest \(<...pat...>\) in SmPL matches a sequence of terms, like ‘...’. However, additionally, it can match zero or more occurrences of \(pat\) within the matched sequence. Another form of nest exists for matching one or more occurrences of \(pat\) within the matched sequence. By analogy to the \(+\) operator of regular expressions, this form is denoted \(<+...pat...+>\).

The examples discussed above illustrate the abstraction power that generic patches provide in the activity of propagating fixes. In the next section we present the steps for:

- **Regrouping patches** into clusters where bug fix code transformations are made with similar patterns.
- **Automatically generating generic patches** from clusters of patches in order to populate the repair template databases.
- **Performing patch generation** in practice given an identified buggy code location (even at a coarse granularity)

### C. Patch clustering

The goal of the Miner is to perform patch clustering, i.e., to group together the code changes that are representing a repeating code context and change operations. In order to convey the full syntactic and semantic meaning of the code change and to discover cluster of patches that are sharing a common representation, we leverage the rich AST edit script representation proposed by Koyuncu et al. [8].

A rich AST edit script, whose grammar is illustrated in Grammar 1, encodes the information about the AST node types in a change diff tree, the repair actions performed, the raw tokens involved as well as the parent-child relation among the nodes. We consider only code context and change operation presentation (cf. Figure 2) to detect similar changes and group them into clusters of similar code changes. The objective of this step is to ensure that we can reduce the noise in pattern inference, regrouping together patches that perform similar changes actions, and potentially filtering out cases where the redundancies of changes are limited.

Grammar 1: Notation of rich AST edit script

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**Example of buggy code with an unsafe dereference**

```c
int get_age(struct person *pers, char *context){
  int age=0;
  if (pers != NULL)
    age=pers->age;
  else
    age=pers->age_death - pers->age;
  return age;
}
```

Fig. 2: An example code context and change operation presentation.

### D. Generic Patch Inference

The goal of the INFERRER is to derive generic patches from the clusters of similar concrete patches that have been mined in the previous step. We build on a recent work by Serrano et al. [50] which showed that it is possible to automatically generate SmPL transformation rules by learning from examples. The approach considers both similarity among code fragments and among control flows associated to the changes to identify change patterns and specify transformation rules.

In practice, the idea is to abstract over common changes across the examples, incrementally extending a pattern until obtaining a rule that describes the complete change, respecting both control-flow and data-flow relationships between the fragments of the code. To that end, each patch in a cluster is used to reconstitute the before- and after-change files, then the INFERRER identifies sets of common removed or added terms across the examples, and further generalizes these terms in each set into a pattern that matches all of the terms in the set, and finally integrates these patterns into transformation rules that respect both control-flow and data constraints exhibited by the examples.

Figure 3 illustrates an example of inferred generic pattern. It encodes the information of how to transform code, the locations of where the pattern is inferred, as well as statistics on the recall (i.e., the percentage of expected changes in the examples that are obtained by applying the inferred generic patch), precision (i.e., the percentage of changes obtained by applying the inferred generic patch that are identical to the expected changes in the examples). We benefit in FLEXIREPAIR from the SmPL-specified generic patch notation which is close to C: it makes the patterns understandable to the user and even
allows the user to improve the script or adapt it to other uses, hence contributing to transparent schema of program repair where patterns are tractable.

```cpp
// Recall: 0.11, Precision: 1.00, Matching recall: 0.50
// Infered from: /MultiMarkdown-6/{prevFiles/
// prev_626381_73d644_Sources#libMultiMarkdown#aho-
// corasick.c,revFiles/626381_73d644_Sources#
// libMultiMarkdown#aho-corasick.c); ac_trip_search()
// Recall: 0.11, Precision: 1.00, Matching recall: 0.50
```

Fig. 3: An example of generic patch.

**E. Code Transformation with Generic Patches**

Given that we leverage the SmPL language to specify generic patches, code transformation is provided for free by the Coccinelle search and transformation engine. The engine takes as input a generic patch and a source code file that it parses. Then it performs a control-flow matching to identify code locations whose shape fit with the structure of the code structure targeted by the generic patch. Taking the metavariables values bounded at each matched code location, it then generates the necessary concrete patches. This engine thus provides two essential advantages over existing generate-and-validate repair pipelines:

- (1) there is no need for a fine-grained bug localization engine. A coarse-grained localization that points to buggy files can be leveraged. Thus, even IR-based bug localization tools which produce results at file level without requiring test cases can be relevant (as advocated by recent work [10]).
- (2) the search for donor code is facilitated by the use of metavariables in the generic patch, allowing for the transformation engine to infer and track tokens across the control-flow, and thus maximizing the chances of producing sensical patches (i.e., patches that at least make the program compile).

**IV. STUDY DESIGN**

We now overview some details of our experimental validation. The objective in this study is not to build a novel state of the art repair tool, but to rather offer a new perspective into a framework for template-based program repair with at its core the concept of generic patch for specifying fix patterns (aka fix templates). Before presenting the results, we discuss the dataset of code repositories that we build for mining similar patches and further inferring generic patches. Then, we present the benchmarks used to assess the overall performance of FLEXIREPAIR as a our prototype implementation. Finally we overview the implementation choices made for both the patch clustering and pattern inference steps.

**A. Subjects**

FLEXIREPAIR provides a flexible interface to its user, who can decide either to use a specific code repository to mine the fix patterns, or to use the pre-constructed fix pattern database shipped with the framework. To build this database we needed to first collect a large set of the code repositories with a long history of code changes.

The subjects that are included in our dataset are collected: i) by manual identification of popular C repositories from github, gitlab, savannah with a large code history and ii) systematically by leveraging the build activities in Travis CI. For the latter we refer to the data of Durieux et al. [51], which contains all the Travis CI jobs executed between 30 September 2018 and 22 January 2019 by 272 917 projects. From their dataset we identified 2 858 C repositories. We further curates this dataset based on the repository properties from github (i.e., commit count, watchers count, forks count etc.). Eventually we select the repositories i) that are not forks, ii) having at least 200 commits, iii) at least 10 watchers iv) and at least 10 forks. Our dataset eventually includes 351 repositories. Table [I] lists some of the major ones.

| repository | commitCount | watchers | forks |
|------------|-------------|----------|-------|
| xqemu/xqemu | 68836 | 462 | 49 |
| git/git | 59910 | 33398 | 19513 |
| greenplum-db/gpdb | 56052 | 4073 | 1171 |
| MonetDB/MonetDBLite-C | 54946 | 26 | 13 |
| panda-re/panda | 54869 | 1640 | 393 |

**B. Assessment Benchmarks**

We selected the Introclass [52] and Codeflaws [53] datasets to empirically assess FLEXIREPAIR.

The Introclass dataset is a benchmark of small C programs collected from classroom assignments of students. It includes 998 defects, 778 of them being associated with an instructor constructed black-box test suite and 845 being associated with a white-box test suite created using KLEE [54] (a symbolic execution tool that automatically generates tests).

Codeflaws benchmark consists of 3 902 defects collected from C programs developed during programming contests. The benchmark is associated with two sets of test-suites: i) a test suite given to repair tools for generating repair ii) a held-out test suite for validating the correctness of patches.

Table [II] lists some statistics about the benchmarks.

| Benchmark | # of Defects | Size of Test Suite I | Size of Test Suite II | LOCs |
|-----------|-------------|----------------------|----------------------|------|
| Codeflaws | 3902        | 2-8                  | 5-350                | 1-322|
| Introclass | 998        | 6-9                  | 6-10                | 13-24|

**C. Implementation Choices**

FLEXIREPAIR aims for flexibility and extensibility such that practitioners may tune parameters and adapt the framework to
their requirements. We recall that we have made the following parameter choices in the FLEXIREPAIR:

- Repository selection is made based on the C programs with a large commit history and which are actively used.
- Change size in a patch is limited to have at most 50 changed lines.
- Patch spread is limited such that each patch contains at most 3 hunks.
- Timeout for generic patch inference is set to 900 seconds for each patch cluster.

V. ASSESSMENT

We assess the prototype framework of FLEXIREPAIR via performing experiments that answer the following research questions.

A. Research Questions

RQ-1: To what extent can the application of MINER and INFERRER produce generic patches from the collected code repositories?

RQ-2: Where did FLEXIREPAIR find relevant redundant changes to mine the generic patches?

RQ-3: What is the repairability performance of FLEXIREPAIR?

RQ-4: What is the efficiency performance of FLEXIREPAIR?

VI. RESULTS

A. Generic Patch Inference Capability

We first assess the relevance of the patch clusters yielded by the MINER component of FLEXIREPAIR. Then, we look at the generic patches yielded by the INFERRER implementation.

MINER Assessment. Performance of MINER is evaluated through the clusters that it yields. The objective is to estimate whether it can find enough cases of recurrent changes within patches collected from project repositories to form clusters. A given patch cluster will contain all the patches having the similar code change hunks. Table III overviews the statistics of clusters yielded by MINER by taking as input the dataset of repositories presented in Section IV. The implementation choices presented in Section IV are also followed. Overall, 350,676 code hunks have been extracted. Among these hunks, we noticed that 110,949 (∼32%) are unique code hunk, and thus, they cannot be part of a cluster. For the remaining 239,727 code hunks (∼68%), there exists at least one other code hunk, among the 350,676 code hunks, which is identical. They can thus form clusters of more than one patch. Overall, among these 239,727 code hunks, we identified 31,310 patch clusters (i.e., the code hunks of each patch of a cluster are identical).

| Total # of hunks | # unique hunks | # hunks which can form a cluster of at least 2 patches | # clusters |
|------------------|----------------|-----------------------------------------------------|------------|
| 350,676          | 110,949        | 239,727                                             | 31,310     |

TABLE III: Statistics on Patch Clusters .

Figure 4 shows the size distribution of the patch clusters. A majority of clusters, i.e., 16,081 (∼51%), are formed by two recurrent code change hunks only. Conversely, 2394 (249+1,023+875+247, ∼7.6%) clusters contain at least 10 recurrent code change hunks.

Fig. 4: Distribution of the patch cluster sizes.

We further investigate how the cluster elements are spread across patches. To that end, we follow the categorization proposed by Koyuncu et al. [8].

- A vertical cluster is a cluster whose code change hunk is recurrent within a single patch. Such clusters are generally formed when we have patches that developers commit to perform a single type of change (e.g., change kmalloc call to kzalloc calls) across several code locations.
- An horizontal cluster is a cluster whose code change hunk is recurrent across several patches. Such clusters are formed when a code change (e.g., add a missing NULL check) is implemented by different developers for different code locations.

Table IV overviews the statistics of clusters yielded. Most of the clusters (24,230) are horizontal clusters. This suggests that the same code changes are often spread among different patches, any or all of which may be used to infer the common generic patch. The vertical clusters can also be useful for inferring generic patches: they represent large patches making the same changes at once at several locations (e.g., collateral evolutions in Linux are applied through vertical patches).

TABLE IV: Statistics on the inferred generic patches.

| # Clusters | # Patch | # Hunk | # Clusters | # Patch | # Hunk |
|------------|---------|--------|------------|---------|--------|
| 31,78      | 31,78   | 7,565  | 24,230     | 7,569   | 7,569  |

A generic patch can simultaneously be vertical (when it is associated to several changes in hunks of the same patch) and horizontal (when it appears as well within other patches).

RQ-1.1: MINER is practical. It is able to identify patch clusters (i.e., recurrent patch sets) of various sizes.

INFERRER Assessment. We assess the ability of INFERRER to analyses changes within patch clusters and derive a generic patch (i.e., abstract the relevant fix pattern and specify it with the SmPL notation). Our implementation uses SPINNER as a backend for matching control-flow similarities. Preliminary experiments revealed that the approach is sensitive to the noise among patches. We expect our INFERRER step to have provided homogeneous patch clusters.

Table V overviews some statistics on the inferred generic patches. From the 31,310 patch clusters obtained with MINER, INFERRER was able to successfully yield a generic patch for
20,467 (~65%) clusters. The remaining clusters (~35%) do not lead to any generic patch either because of the timeout value of 900 seconds set for analysing each patch cluster, or because they do not exhibit the necessary data or control-flow dependencies to satisfy any inference. Note that the initial generic patch inferred from a given cluster can contain several rules. We consider each transformation rule as a generic patch on its own. Eventually, we are left with 68,368 atomic generic patches (i.e., generic patches with a single transformation rule).

Note that in the middle column of Table VI we also report the number of code hunks that have been used to infer the generic patches. Overall, 125,483 (~52%) out of 239,727 code hunks contributed to a generic patch.

**TABLE V: Inferred Generic Patch statistics.**

|          | # Patch Clusters | # Code hunks | # "Atomic" Generic Patches |
|----------|------------------|--------------|----------------------------|
|          | 20,467           | 125,483      | 68,368                     |

Table VI lists five of the most frequently observed generic patches in our dataset. We further manually investigate these generic patches by checking the corresponding commits in the repositories in order to understand the nature of the changes described by the developers.

**TABLE VI: Frequently observed generic patches.**

| Frequency | generic patch |
|-----------|---------------|
| Hunk      | @lock_content_42_08 | identifier [4, 10]; |
| Function  | -expression E1, E2, E3; |
| File      | _structure resource +10; |
| Patch     | - 10 = platform_get_resource[E1, |
| Project   | _IORESOURCE_MEM, E2]; |
|           | - E3+10 = devm_ioremap_resource[E2+10]; |
|           | - E3+10 = devm_platform_ioremap_resource[E1, |
|           | E2]; |
| Hunk      | @expr_stmt_4_32 | expression E0; |
| Function  | -free[E0]; |
| File      | + FREE_AND_NULL[E0]; |
| Patch     | return[E0]; |
| Project   | return[E0]; |
| Hunk      | @lock_content_12_208 | expression E0; |
| Function  | E0; |
| File      | + free[E0]; |
| Patch     | - E0 = NULL; |
| Project   | + FREE_AND_NULL[E0]; |
| Hunk      | @lock_content_18_38 | expression E2, E1, E0; |
| Function  | E0; |
| File      | _memory_region_init_ram[E0, NULL, E1, E2, & |
| Patch     | _error_abort; |
| Project   | _mstate_register_mem_global[E0]; |
|           | + memory_region_alloc_system_memory[E0, |
|           | NULL, E1, E2]; |
| Hunk      | @stmt_stmt_8_8 | binary operator B1 = {== ,&& }; |
| Function  | expression E0, E2; |
| File      | E0; |
| Patch     | if[B0 B1 E2]; |
| Project   | if[B2 B1 E0]; |

We discover that two generic patches (generic patches #1 and #3 in Table VI) have been generated from patches that were actually automatically generated to automate some evolutions at large scale across Linux: the relevant commit logs even mention the Coccielline tool being used.

The second generic patch (id expr_stmt_4_32), is spread among 14 projects (as we can see in the Frequency column of Table VI) and the associated comments are often described with "Fix coding style" (indeed, the generic patch simply removes brackets). The generic patch @lock_content_18_3 is inferred from 3 different projects. This generic patch fixes a memory mapping issue. Finally, the generic patch if_stmt_8_8 switches the order of the expressions in the condition of the if statement, to alter the control flow. A corresponding commit log summarizes this behaviour as "Put CONFIG first in if(). This may fix build failures with EAC3 disabled and is more consistent".

To conclude this RQ, we check from which repositories the generic patches have been inferred. Table VII lists the Top-10 projects which contributed to the pattern inference. We note that all of these projects have large code histories. Overall, from the 351 repositories used to mine the clusters and infer the generic patterns, 301 contributed to pattern inference. It is possible that the remaining 50 projects do not contribute because of the filtering constraints imposed in our implementation choices, or simply because the do not contain enough recurrent code change context from we generic patches can be inferred.

**TABLE VII: Top-10 projects contributed to pattern inference.**

| projects   | occurrences |
|------------|-------------|
| freebsd    | 11812       |
| linux      | 11419       |
| qemu       | 9907        |
| wireshark  | 9337        |
| php-src    | 7187        |
| xqemu      | 7090        |
| vlc        | 6288        |
| panda      | 5249        |
| gik        | 4740        |
| FFmpeg     | 4325        |

**RQ.1.2: INFERRER successfully yields generic patches for a large number of clusters: some generic patches are summarized patterns of changes that spread across several projects.**

**B. Generic Patch traceability**

We investigate potential relationships between the distributions of code change locations and the performance of pattern inference, in order to estimate the adequate locations for optimizing the search of generic patches.

Generic patches are inferred from hunks in a cluster. Note that, in a cluster, when the code context and change operation of several hunks are syntactically identical we consider them as a single same hunk in this research question. Figure 5 shows the distribution of the generic patches in terms the number of hunks that were used to infer them. Overall, from the 68,368 inferred generic patches, 40,529 (~60%) is inferred from a single hunk.

![Fig. 5: Distribution of the generic patches in hunks.](image-url)
action, but we do not consider the similarity among tokens. On the other hand, our current implementation of Inferrer\textsuperscript{2} considers also the similarity of the tokens involved in the change to track a pattern: if the tokens involved in the set of patches can be abstracted in a single metavariable then a single transformation rule can be formed. Otherwise, the generic patch will include multiple transformation rules, each including specific tokens (e.g., specific method names). Figure 6 illustrates a concrete example of such case. For both of the code examples, Miner produces the same AST rich edit script (cf. representation in Fig. 2) leading them to be placed in the same cluster. However, since they differ in terms of the tokens used (different method names and different parameters), Inferrer creates two distinct transformation rules.

Fig. 6: An example of patches sharing the same cluster but having distinct generic patches.

Note that distributions of generic patches in terms of number of functions and functions also follow the same long tail shape: for example, we observed that \( \approx 85\% = \frac{176}{686} \) of the patterns are inferred from a single function. We postulate that the distribution of locations can be used as an heuristic for prioritizing pattern selection in program (cf. RQ-4 for more insights).

RQ-2: Generic patches present a long tail distribution in terms of the number of code locations that were involved in their inference. Flexirepair further provides traceability links to diagnose the code changes set that share similar transformations leading to a fix pattern.

C. Repairability

We assess whether the inferred generic patches can be used to automate generation of patches for real bugs. More specifically, we perform two program repair experiments by using the generic patches generated by Inferrer as the main input ingredients. Introclass and Codeflaws are leveraged for benchmarking.

Table VIII illustrates the comparative results in terms of numbers of plausible patches (i.e., that make the program pass all the test cases) for the black-box and white-box test suites. Among the selected 764 defects in Introclass, Flexirepair can generate plausible patches for 186 defects using the black-box test suite and 261 plausible patches using the white-box test suite. Overall, we generate plausible patches for 288 defects of Introclass when both scenarios are combined. We compare the repair performance of Flexirepair against 3 state-of-the-art APR tools which have been evaluated. With the white-box test suite, Flexirepair ranks second in terms of number of generated plausible patches, and third with the black-box scenario. It is noteworthy that Flexirepair fixes significantly more bugs than other APR tools in some projects such as checksum, grade, and syllables.

| Pattern     | #Patches | #Defects |
|-------------|----------|----------|
| Expression E0, E1; | 83 | 14 |
| - scanf("%s", E0); - gets(E0); | 45 | 10 |
| Expression E0, E1, E2; | 7 | 6 |
| - for(E0 = E1; E0 < E2; E0++) | 9 | 1 |

TABLE VIII: Number of Introclass bugs fixed by APR tools.

| Project | Flexirepair WB | GenProg WB | TriAutoRepair WB | AE WB |
|---------|----------------|------------|------------------|-------|
| checksum | 23 | 23 | 3 | 8 |
| digits | 37 | 8 | 99 | 30 |
| grade | 12 | 8 | 3 | 2 |
| median | 44 | 27 | 63 | 108 |
| smallest | 75 | 56 | 118 | 120 |
| syllables | 70 | 64 | 6 | 19 |

Total | 261 | 186 | 292 | 287 |
212 | 247 | 166 | 139 |

Table IX lists example generic patches relevant for fixing Introclass defects. The first generic patch is an example of a fix pattern that matches several locations: it substitutes the \( C \) standard library function scanf() with gets(). According to documentation, scanf() reads input until it encounters whitespace, newline or End Of File (EOF), whereas gets() reads input until it encounters newline or End Of File (EOF). We notice that gets() does not stop reading input when it encounters whitespace, but instead it takes whitespace as a string, avoiding bugs. The other listed patterns are mostly related to control logic (i.e., wrong operator usage, boundary checks etc.) in if and for statements.

TABLE IX: Selected generic patches fixing Introclass defects.

| Pattern     | #Defects |
|-------------|----------|
| Expression E0, E1; | 83 |
| - scanf("%s", E0); - gets(E0); | 45 |
| Expression E0, E1, E2; | 7 |
| - for(E0 = E1; E0 < E2; E0++) | 9 |

Our second experiment is performed on the Codeflaws benchmark. For this experiment, we limit the number of generic patches to Top-10000 based on their frequency in code hunks. Flexirepair can generate plausible patches for 83 defects using the test-suite I. 20 of those 83 defects have been validated to be correctly fixed using the test-suite II. We compare the repair performance of Flexirepair against 5 state-of-the-art APR tools as illustrated in Table X. There is an

| Project | Flexirepair | Angelix | Prophet | SPR | GenProg | CoCoNet |
|---------|-------------|---------|---------|-----|---------|---------|
| Total | 2083 | 318591 | 801389 | 283273 | 1255369143 | 423716 |

1 In each column, we provide \( x/y \) numbers: \( x \) is the number of correctly fixed bugs; \( y \) is the number of bugs for which a plausible patch is generated by the APR tool. The data about Angelix, Prophet, SPR, and GenProg are extracted from the experimental results reported by CoCoNet. 2

Our second experiment is performed on the Codeflaws benchmark. For this experiment, we limit the number of generic patches to Top-10000 based on their frequency in code hunks. Flexirepair can generate plausible patches for 83 defects using the test-suite I. 20 of those 83 defects have been validated to be correctly fixed using the test-suite II. We compare the repair performance of Flexirepair against 5 state-of-the-art APR tools as illustrated in Table X. There is an
important performance gap between FLEXIREPAIR and other state-of-the-art APR tools. We postulate that the limitation on the number of generic patches had a significant negative impact. Finding a good balance between efficiency (i.e., the search space must not explode by considering all possibilities) and effectiveness can be considered as an engineering detail. We discuss this in the following research question.

**RQ-3:** Note that we do not seek to outperform existing APR tools with our prototype implementation building on the generic patch specifications. Instead, we propose baseline performance for future research in template-based program repair that uses the proposed unified representation of fix patterns. Nevertheless, we note that the baseline is competitive with some state of the art on IntroClass benchmark.

**D. Efficiency**

We assess efficiency of repair in terms of Number of Patch Candidates (NPC) generated before the first plausible patch is found. NPC represent the invalid patches that an APR tool has consumed resources to test. NPC score has been advocated as a less biased metric of performance compared to execution time [11, 60, 61]. Our evaluation on the IntroClass benchmark distinguishes two categories:

1. **Nonsensical patches** are patches which cannot even make the patched buggy program successfully compile [12, 59].
2. **In-plausible patches** are patches which let the patched buggy program successfully compile, but fail to pass some test cases in the available test suite.

Figure 7 shows the distribution of the position of the first plausible patch when considering all sensical patches (i.e., patches that let the program compile). The median of the position for the black-box scenario is 23, and 31 for the white-box scenario. These represent NPC scores when considering only in-plausible patches.

**Fig. 7:** NPC of sensical patches.

Figure 8 shows the distribution of the position of the first plausible patch counting all the patches, i.e., including nonsensical patches). We note that the mean value of NPC in the black-box scenario is 41,626 and in the white-box scenario 31,587. Such high values indicate that the baseline tool applies first some generic patches that lead to nonsensical patches. Recall that, we select generic patches to apply first based on their frequency in code hunks in FLEXIREPAIR. This result therefore suggests that other selection strategies could improve the overall results, and are thus worth to be explored extensively as future work.

We investigate a first simple strategy of generic patch selection for repair based on its recurrence in the mining dataset measured in terms of functions, files, patches, projects whose hunks contributed to the pattern abstraction. We experiment with all five cases and focus exclusively on white-box scenario.

**Fig. 8:** NPC of all patches.

Figure 9 shows the corresponding distribution NPCs excluding the nonsensical patches. The strategy where the selection is driven by the frequencies of the generic patches among the projects yields the best results: when we prioritize generic patches inferred from a large number of projects, the NPC score is lower.

**Fig. 9:** NPC of sensical patches for various selection strategies.

**Fig. 10:** NPC of all patches for various selection strategies.

**RQ-4:** We note that the efficiency of FLEXIREPAIR could be improved by better prioritizing generic patches. We show that because of the traceability in pattern inference, we are able to leverage frequency information to improve the efficiency score by halving the NPC.

**VII. Conclusion**

We have presented FLEXIREPAIR, an open framework for template-based program repair where we build on the concept of generic patch to define a unified representation/notation for specifying fix patterns (aka templates). We show that generic patches are powerful for expressing fix patterns in a transparent and flexible way. FLEXIREPAIR thus offers means, with a baseline, to measure and assess repair new contributions in template-based program repair (e.g., pattern inference, heuristics of candidate search, etc.). We evaluate the repair performance of a prototype implementation on the
IntroClass and CodeFlaws benchmarks and we show that our baseline provides comparable performance to the state of the art. We open source FlexiRepair’s code and release all data of this study to facilitate replication and encourage further research in this direction: [https://github.com/FlexiRepair](https://github.com/FlexiRepair)

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