Efficient Leverage of Symbolic ATG Tools to Advanced Coverage Criteria

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Abstract—Automatic test data generation (ATG) is a major topic in software engineering. In this paper, we seek to bridge the gap between the coverage criteria supported by symbolic ATG tools and the most advanced coverage criteria found in the literature. We define a new testing criterion, label coverage, and prove it to be both expressive and amenable to efficient automation. We propose several innovative techniques resulting in an effective black-box support for label coverage, while a direct approach induces an exponential blow-up of the search space. Initial experiments show that ATG for label coverage can be achieved at a reasonable cost and that our optimisations yield very significant savings.

Keywords—Testing, symbolic execution, coverage criteria

I. INTRODUCTION

Context and problem. Automatic test data generation (ATG) is a major concern in software engineering and program analysis. Recent progress in automated theorem proving led to significant improvements of symbolic approaches for white-box ATG, such as Dynamic Symbolic Execution (DSE) [11], [32], [50]. Tools have been developed [4], [5], [6], [12], [33] and impressive case-studies have been carried out [5], [6], [14].

DSE follows mostly an exhaustive exploration of the path space of the program under test, covering all execution paths up to a given bound. While this “all-path coverage” criterion proves successful in some contexts, it is well known that the resulting test suite can still miss bugs related to data rather than control. Moreover, standard DSE does not support coverage objectives defined over artifacts not explicitly present in the source code, such as multiple-condition coverage.

On the other hand, many coverage criteria have been defined along the years [2], ranging from control-flow or data-flow criteria to mutations [9], input domain partitions and MCDC. But only very few of them are incorporated inside DSE tools, while they could efficiently guide test generation.

Goal. Our main objective is to bridge the gap between coverage criteria supported by symbolic ATG tools, especially DSE, and the most advanced coverage criteria found in the literature. Recent works aim at leveraging DSE to mutation testing [29], [30], [51] or improving DSE bug-detection abilities by making explicit run-time error conditions [7], [13], [17]. Interestingly, these approaches are mainly based on instrumentation and allow for black-box reuse of existing ATG tools. However, they come at a high price since they induce a blow-up of the path space and a significant overhead. We follow the same general line, emphasising black-box reuse as much as possible. However, we focus on two main points mostly left unaddressed: we want to characterize which kind of coverage criteria can be supported by DSE-like techniques, and we want to support them efficiently.

Approach. We define label coverage, a new testing criterion which appears to be both expressive and amenable to efficient automation. Especially, it turns out that DSE can be extended for label coverage with only a slight overhead. Labels are predicates attached to program instructions through a labelling function. A label is covered if a test execution reaches it and satisfies the predicate. This idea underlies former work on the subject [7], [13], [17], [31]. We generalize these results and propose ways of taming the potential blow-up. Especially, we introduce a tight instrumentation, where “tight” is made precise in the paper, and a strong coupling of DSE and label coverage named iterative label deletion. The combination results in an effective support for label coverage in DSE. Interestingly, both techniques can be implemented in black-box.

Contribution. Our main contributions are the following:

- We show that label coverage is expressive enough to faithfully emulate many standard coverage criteria, from decision or condition coverage to input domain coverage and a substantial subset of weak mutations (the side-effect free fragment, Theorem 2).
- We formally characterise the properties of direct instrumentation for label coverage. We show that the instrumentation is sound (w.r.t. label coverage) and leads to very efficient coverage score computation. However, it is very ineffective for any analysis working through path exploration, as it yields an exponential increase as well as a “complexification” of the path space (Theorem 5).
- We propose tight instrumentation and iterative label deletion as ways of taming this complexity blow-up. Tight instrumentation yields only a linear growth of the path space without any complexification (Theorem 7). Both techniques are orthogonal and allow for a significant speed-up. Moreover, they can both be implemented either through dedicated DSE algorithms or in a black-box manner.
• We have implemented these results inside a DSE tool [36]. Initial experiments on small benchmarks show that ATG for label coverage can be achieved at a reasonable cost w.r.t. the usual (all-path) DSE approach, while our optimisations yield very significant reductions of both search space and computation time compared to direct instrumentation.

As a whole, label coverage forms the basis of a very generic and convenient framework for test automation, providing a powerful specification mechanism for test objectives and featuring efficient integration into symbolic ATG techniques as well as cheap coverage score computation. Moreover, static analysis techniques can also be used directly on the instrumented programs in order to detect uncoverable labels, as was proposed for mutation testing [21].

This work bridges part of the gap between symbolic ATG techniques and coverage criteria. On the one hand, we show that DSE techniques can be cheaply extended to more advanced testing criteria, such as side-effect free weak mutations. On the other hand, we identify a large subclass of weak mutations amenable to efficient automation, both in terms of ATG and mutation score computation.

Outline. The remaining part of the paper is structured as follows. After presenting basic notation (Section II), we define labels and explore their expressiveness (Section III). We then focus on automation. The direct instrumentation is defined and studied (Section IV). Afterwards, we describe our own approach to label-based ATG (Section V) and first experiments are presented (Section VI). Finally, we sketch a highly automatized testing framework based on labels (Section VII), discuss related work (Section VIII) and give a conclusion (Section IX).

II. BACKGROUND

A. Notation

Given a program $P$ over a vector of input variables $V$ taking values in some domain $D$, a test data $t$ for $P$ is any valuation of $V$, i.e. $t \in D$. The execution of $P$ over $t$, denoted $P(t)$, is formalized as a path (or run) $\sigma \triangleq (loc_1, S_1) \ldots (loc_n, S_n)$, where the $loc_i$ denote control-locations (or control-points, or simply locations) of $P$ and the $S_i$ denote the successive internal states of $P$ ($\approx$ valuation of all global and local variables as well as memory-allocated structures) before the execution of each $loc_i$. A test data $t$ reaches a specific location $loc$ with internal state $S$, denoted $t \sim_P (loc, S)$, if $P(t)$ is of the form $\sigma_1 \cdot (loc, S) \cdot \sigma_2$. A test suite $TS$ is a finite set of test data.

Given a test objective $c$, we write $t \sim_P c$ if test data $t$ covers $c$. We extend the notation for a test suite $TS$ and a set of test objectives $C$, writing $TS \sim_P C$ when for any $c \in C$, there exists $t \in TS$ such that $t \sim_P c$.

The above definitions are generic and leave the exact definition of “covering” to the considered testing criterion. For example, test objectives derived from the Decision Coverage criterion are of the form $c \triangleq (loc, cond)$ or $c \triangleq (loc, ! cond)$, where cond is the condition of the branching instruction at location loc. Here, $t \sim_P c$ if $t$ reaches some $loc$ in $S$ where cond evaluates to true (resp. false) in $S$.

B. DSE in brief

We remind here a few basic facts about Symbolic Execution (SE) [18] and Dynamic Symbolic Execution (DSE) [11], [32], [36]. Let us consider a program under test $P$ with input variables $V$ over domain $D$ and a path $\sigma$ of $P$. The key insight of SE is that it is possible in many cases to compute a path predicate $\phi_\sigma$ for $\sigma$ such that for any input valuation $t \in D$, we have: $t$ satisfies $\phi_\sigma$ iff $P(t)$ covers $\sigma$. In practice, path predicates are often under-approximated and only the left-to-right implication holds, which is already fine for testing: SE outputs a set of pairs $(t_i, \sigma_i)$ such that each $t_i$ is ensured to cover the corresponding $\sigma_i$. Hence, SE is sound from a testing point of view. DSE enhances SE by interleaving concrete and symbolic executions. The dynamically collected information can help the symbolic step, for example by suggesting relevant approximations.

A simplified view of SE is depicted in Algorithm 1. While high level, it is sufficient to understand the rest of the paper. We assume that the set of paths of $P$, denoted $Paths(P)$, is finite. In practice, DSE tools enforce this assumption through a bound on path lengths. We assume the availability of a procedure for path predicate computation (with predicates in some theory $T$), as well as the availability of a solver taking a formula $\phi \in T$ and returning either $sat$ with a solution $t$ or $unsat$. All DSE tools rely on such procedures. The algorithm builds iteratively a test suite $TS$ by exploring all paths from $Paths(P)$.

Algorithm 1: Symbolic Execution algorithm

| Input: a program $P$ with finite set of paths $Paths(P)$ |
| Output: $TS$, a set of pairs $(t, \sigma)$ such that $P(t) \sim_P \sigma$ |
| 1 $TS := \emptyset$; |
| 2 $S_{paths} := Paths(P)$; |
| 3 while $S_{paths} \neq \emptyset$ do |
| 4 choose $\sigma \in S_{paths}$; $S_{paths} := S_{paths} \setminus \{\sigma\}$; |
| 5 compute path predicate $\phi_\sigma$ for $\sigma$; |
| 6 switch solve($\phi_\sigma$) do |
| 7 case $sat(t)$: $TS := TS \cup \{(t, \sigma)\}$; |
| 8 case $unsat$: skip ; |
| 9 endsw |
| 10 end |
| 11 return $TS$; |

The major issue here is that SE and DSE must in some ways explore all $Paths(P)$. Advanced tools explore this set lazily, yet they still have to crawl it. Therefore, the size of $Paths(P)$, denoted $|Paths(P)|$, is one of the two major bottlenecks of SE and DSE, the other one being the average cost of solving path predicates.

Bounded model checking (BMC) [8] is sensitive to the same parameters, as it amounts to building a large formula encompassing all paths up to a given length. Especially, more paths yield larger formulas with more $\lor$-operators.

III. LABEL COVERAGE

A. Definitions

Given a program $P$, a label $l$ is a pair $(loc, \phi)$ where loc is a location of $P$ and $\phi$ is a predicate obeying the following rules:

The above definitions are generic and leave the exact definition of “covering” to the considered testing criterion. For example, test objectives derived from the Decision Coverage criterion are of the form $c \triangleq (loc, cond)$ or $c \triangleq (loc, ! cond)$, where cond is the condition of the branching instruction at location loc. Here, $t \sim_P c$ if $t$ reaches some $loc$ in $S$ where cond evaluates to true (resp. false) in $S$. 

The major issue here is that SE and DSE must in some ways explore all $Paths(P)$. Advanced tools explore this set lazily, yet they still have to crawl it. Therefore, the size of $Paths(P)$, denoted $|Paths(P)|$, is one of the two major bottlenecks of SE and DSE, the other one being the average cost of solving path predicates.

Bounded model checking (BMC) [8] is sensitive to the same parameters, as it amounts to building a large formula encompassing all paths up to a given length. Especially, more paths yield larger formulas with more $\lor$-operators.
• $p$ contains only variables and expressions well-defined in $P$ at location $loc$;
• $p$ contains no side-effect expressions.

An annotated program is a pair $\langle P, L \rangle$ where $L$ is a set of labels defined over $P$. A test data $t$ covers $l \equiv (loc, \phi)$, denoted $t \sim_P l$, if $t$ covers some $(loc, S)$ with $S$ satisfying predicate $\phi$. The label coverage testing criterion will be denoted by $LC$.

For simplicity, we consider in the rest of the paper normalized programs, i.e., programs such that no side-effect occurs in any condition of a branching instruction. This is not a severe restriction since any (well-defined) program $P_1$ can be rewritten into a normalized program $P_2$, using intermediate variables to evaluate the side-effect prone conditions outside the branching instruction. For example, if $(x++ \leq y \&\& e==f)$ becomes $b = (x++ \leq y) \&\& (b \&\& e==f)$ or $\text{tmp} = x++; \text{if (tmp} \leq y \&\& e==f)$. Notice that similar transformations are automatically performed by the Cil library frequently used by DSE tools for C programs [32], [36].

B. Expressiveness of label coverage

We seek to characterize the power of the LC testing criterion. We prove in Theorem 1 and Theorem 2 that labels allow to simulate many standard testing criteria, including DC (decision coverage), MCC (multiple-condition coverage) and a large subset of WM (weak mutations). A key notion is that of labelling function. A labelling function $\psi$ maps a program $P$ into an annotated program $\langle P, L \rangle$. We write $LC_\psi$ to denote the coverage of labels defined by $\psi$.

**Definition 1:** A coverage criterion $C$ can be simulated by $LC$ if there exists a labelling function $\psi$ such that for any program $P$, a test suite $TS$ covers $C$ iff $TS$ covers $LC_\psi$.

We show first how $LC$ can simulate basic graph and logic coverage criteria. We consider the following coverage criteria: instruction coverage $IC$, decision coverage $DC$, (simple) condition coverage $CC$, decision-condition coverage $DCC$ and multiple-condition coverage $MCC$. The basic idea is to introduce in $P$ labels based on branching predicates and their atomic conditions. An example for $CC$ is depicted in Figure 1, where additional labels (right) enforce coverage of the two atomic conditions $x==y$ and $a<b$.

![Fig. 1. Simulating CC with labels](image)

**Theorem 1:** The coverage criteria $IC$, $DC$, $CC$, $DCC$ and $MCC$ can be simulated by $LC$.

**Proof:** We need to define a suitable labelling function for any of the considered coverage criteria. For $IC$, we choose the labelling function $\psi_{IC}(P)$ adding all labels of the form $(loc, true)$, where $loc$ is any location of $P$. Given a test suite $TS$, $TS \sim_P IC$ iff $TS$ can reach any $loc$ of $P$ iff $TS$ covers any $(loc, true)$ iff $TS \sim_P LC_\psi$. We conclude that $IC$ can be simulated by $LC$.

Other criteria are handled similarly. The labelling function $\psi_{DC}$ adds the set of all $(loc, \phi)$ and $(loc, \neg \phi)$, where $loc$ contains a conditional statement with condition $\phi$. The labelling function $\psi_{CC}$ adds the set of all $(loc, a_i)$ and $(loc, \neg a_i)$, where $loc$ contains a conditional statement whose atomic conditions are exactly the $a_i$. The labelling function $\psi_{DCC}$ adds the union of $\psi_{DC}$ and $\psi_{CC}$. The labelling function $\psi_{MCC}$ adds the set of all $(loc, \bigwedge_i a_i)$, where the $a_i$ are atomic conditions and $\bigwedge_i$ denotes either $a_i$ or $\neg a_i$.

**Weak mutations.** We now consider a more involved testing criterion, namely weak mutations. In mutation testing [9], test objectives consist of mutants, i.e., slight syntactic modifications of the program under test. In the strong mutation setting $M$, a mutant $M$ is covered (or killed) by a test data $t$ if the output of $P(t)$ differs from the output of $M(t)$. In the weak mutation setting WM [15], a mutant $M$ is covered by $t$, denoted $t \sim_P M$, if the internal states of $P(t)$ and $M(t)$ differ from each other right after the mutated location (cf. Figure 2). $M$ is a powerful testing criterion in practice [11], [25]. While less powerful in theory, WM appears to be almost equivalent to $M$ in practice [23].

![Fig. 2. Strong and weak mutations](image)

We show hereafter that a substantial part of WM can be simulated by $LC$. First we need a few more definitions. Mutation testing is parametrised by a set of mutation operators $O$. A mutation operator $op \in O$ is a function mapping a program $P$ into a finite set of well-defined programs (mutants), such that $P$ differs from each mutant $M$ in only one location (atomic mutation). We denote $WM_O$ the weak mutation criterion restricted to mutants created through operators in $O$. We consider that mutations can affect either a lhs value, an expression or a condition. This is a very generic model of mutations, encompassing all standard operators [2]. Finally, we restrict ourselves to mutation operators neither affecting nor introducing side-effect expressions (including calls to side-effect prone functions). We refer to such operators as side-effect free mutation operators.
Theorem 2: For any finite set \( O \) of side-effect free mutation operators, \( WM_O \) can be simulated by \( LC \).

Proof: For simplicity, let us consider first a single mutation operator \( op \in O \). The main idea is to introduce one label for each mutant created by \( op \). The label encodes the necessary and sufficient conditions to distinguish \( M \) from \( P \) once the modified location has been reached. This transformation is depicted in Figure 3. Let us consider a mutant \( M \) differing from \( P \) only at location \( loc \). We consider three cases, depending on the modification introduced by \( op \):

- \( \text{lhs} := \text{expr} \) becomes \( \text{lhs} := \text{expr}' \): we add label \( l \triangleq (loc, \text{expr} \neq \text{expr}') \). We must prove that \( t \sim_P M \) iff \( t \sim_P l \). Note that \( t \sim_P t \) iff \( t \) reaches \( loc \) with an internal state such that \( \text{expr} \) and \( \text{expr}' \) evaluate to different values. This is equivalent to say that \( P(t) \) and \( M(t) \) are in different internal states right after \( loc \), which corresponds by definition to \( t \sim_P M \).

- \( \text{if} (\text{cond}) \text{ then becomes if} (\text{cond}') \text{ then} \): we add label \( l \triangleq (loc, \text{cond} \oplus \text{cond}') \), where \( \oplus \) is the xor-operator. We follow the same line of reasoning as in the previous case. The \( \oplus \) operator ensures that \( P(t) \) and \( M(t) \) will not follow the same branching condition.

- \( \text{lhs} := \text{expr} \) becomes \( \text{lhs}' := \text{expr} \): we add label \( l \triangleq (loc, \alpha(\text{lhs}) \neq \alpha(\text{lhs}') \land (\text{lhs} \neq \text{expr} \lor \text{lhs}' \neq \text{expr})) \), where \( \alpha(x) \) denotes the memory location (\( \approx \) address) of \( x \), not its value. For example, in \( C \) the memory location is given by the \( \& \) operator. We follow the same line of reasoning as in the previous case. This case requires a little more explanation. In order to observe a difference between \( P(t) \) and \( M(t) \) right after the mutated location, we need first that \( \text{lhs}' \) and \( \text{lhs} \) refer to different memory locations (which is not always obvious in the case of aliasing expressions). Moreover, there are only two ways of noticing a difference: either the old value of \( \text{lhs} \) differs from \( \text{expr} \), then \( \text{lhs} \) will evaluate to different values in \( P(t) \) (equals to \( \text{expr} \)) and in \( M(t) \) (remains unchanged) just after the mutation, or the symmetric counterpart for \( \text{lhs}' \). This is exactly what \( l \) encodes.

By applying this technique for every mutant created by all considered mutation operators, we obtain the desired labelling function.

The subset of mutations we have been considering so far is limited to (1) atomic mutations and (2) side-effect free operators. The first restriction is not a major issue as atomic mutations have been proved to be almost as powerful as high-order mutations [7] [23]. The second restriction has two sides: (2.a) it forbids mutation operators introducing side-effects, for example mapping \( x \) to \( x++ \), and (2.b) it forbids to mutate a side-effect prone expression. Again, restriction (2.a) is not severe: on side-effect free programs, the side-effect free fragment of \( WM \) encompasses the ABS, ROR, AOR, COR and UOI operators [2], which have been experimentally shown mostly equivalent to much larger sets of operators [24], [35]. It is left as an open question to quantify more precisely what is lost with restriction (2.b). Anyway, the previous points show that while side-effect free \( WM \) is less powerful than full \( WM \), it is still a substantial subset.

Other criteria. Several other testing criteria commonly found in the literature can be emulated by labels. We focus here on Input Domain Coverage and Run-Time Error Coverage.

- Input Domain Coverage: assuming a partition of the input domain \( D \) of \( P \) given as disjoint predicates \( \phi_1, \ldots, \phi_k \), this criterion consists in considering one \( t_i \) for each \( \phi_i \). The corresponding labelling function adds all labels of the form \( (loc_0, \phi_j) \), where \( loc_0 \) is the entry point of \( P \). The approach is independent of the way the partition is obtained, covering both interface-based and functionality-based partitions [2].

- Run-Time Error Coverage: test objectives corresponding to run-time errors such as those implicitly searched for in active testing or assertion-based testing [7], [13], [17] can be easily captured by labels. These objectives include division by zero, out-of-bound array accesses or null-pointer dereference. Typically, any error-prone instruction at location \( loc \) with a precondition \( \phi_{\text{safe}} \) will be tagged by a label \( (loc, \neg \phi_{\text{safe}}) \).

Limits. The following criteria cannot be emulated through labels, at least with simple encoding: weak mutations with operators involving side-effects, criteria imposing constraints on paths rather than constraints on program locations (k-path coverage, data-flow criteria) and criteria relating different paths (strong mutations, MCDC). It is left as future work to study whether these limitations are strict or not.

IV. AUTOMATING LC: A FIRST ATTEMPT

Given an annotated program \( (P, L) \), we seek automatic methods: (1) to compute the \( LC \) score of a given test suite \( TS \), and (2) to derive a test set achieving high \( LC \)-coverage. We propose first a black-box approach, reusing standard automatic testing tools through a direct instrumentation of \( P \). This technique underlies previous works aiming at extending DSE coverage abilities [7], [13], [17], [31]. While it allows for cheap
LC score computation, it is far from efficient for ATG, mainly because of an exponential blow-up of the path space of the program.

A. Direct instrumentation

The direct instrumentation $P'$ for $⟨P, L⟩$ consists in inserting for each label $l ≡ (loc, \phi) \in L$ a new branching instruction $I$: `if ($\phi$) { }`; such that all instructions leading to $loc$ in $P$ are connected to $I$ in $P'$, and $I$ is connected to $loc$. The transformation is depicted in Figure 4. When different labels are attached to the same location, the new instructions are chained together in a sequence ultimately leading to $loc$.

![Figure 4. Direct instrumentation $P'$](image)

The direct instrumentation is sound with respect to LC in the following sense. Let us denote by NTD the set of test objectives over $P'$ requiring to cover all New Then-Decision introduced by the instrumentation. The following result holds.

**Theorem 3 (Soundness):** Given an annotated program $⟨P, L⟩$, its instrumented version $P'$ and a test suite $TS$, we have: $TS \sim_P LC$ iff $TS \sim_{P', NTD}$.

This is interesting for both LC score computation and ATG. Any ATG tool run on $P'$ will produce a test suite $TS$ covering LC for $P$ as soon as $TS$ covers all branches of interest in $P'$. Concerning score computation, a slightly modified version of the direct instrumentation, updating coverage information in the new then-branches, allows to compute LC score efficiently.

**Theorem 4:** Given an annotated program $⟨P, L⟩$, its instrumented version $P'$ and a test suite $TS$, then the LC score of $TS$ can be computed in time bounded by $|TS| \cdot \text{maxtime}(\{P'(t) | t \in TS\})$.

Interestingly, computing LC score can be done independently from $|L|$. Regarding coverage score computation, LC is much closer to DC (each test $t$ is executed only once) than it is to WM (each test $t$ is executed once per mutant). While efficient mutation score computation is a difficult issue in mutation testing, Theorem 4 together with Theorem 2 show that the side-effect free subset of WM supports efficient mutation score computation.

B. Drawbacks

So far, the direct instrumentation seems to perfectly suit our needs. Unfortunately, it is significantly inefficient for ATG. There are two main reasons for that.

- $P'$ is too complex: it exhibits much more behaviours than $P$, most of them being unduly complex for covering the labels we are targeting.
- DSE will naturally produce a $TS$ covering several times the same labels, which is useless since each label needs to be covered only once.

We formalize the first point hereafter. We consider two dimensions in which $P'$ is “too complex”: the size of the search space, denoted $|\text{Paths}(P')|$, and the shape of paths in $\text{Paths}(P')$. Let us call label constraints all additional branches $\phi$ and $\neg \phi$ introduced in $P'$ compared to $P$, and let us denote by $m$ the maximal number of labels per location in $P$. A single path $\sigma \in P$ may correspond to up to $2^m |\sigma|$ paths in $P'$, since each label of $P$ creates a branching in $P'$ and at most $m$ such branchings can be found at each step of $\sigma$. Note also that the paths $\sigma' \in P'$ corresponding to $\sigma \in P$ have length bounded by $m \cdot |\sigma|$. Therefore they can pass through up to $m \cdot |\sigma|$ label constraints, while (by definition) $\sigma$ does not pass through any label constraint. Theorem 5 summarises these results.

**Theorem 5 (Non-tightness):** Given an annotated program $⟨P, L⟩$ and its instrumented version $P'$, let us assume that $\text{Paths}(P)$ is bounded, that $k$ represents the maximal length of paths in $\text{Paths}(P)$ and that $m$ is the maximal number of labels per location in $P$. Then $\text{Paths}(P')$ is more complex than $\text{Paths}(P)$ in the following sense:

- $|\text{Paths}(P')|$ can be exponentially larger than $|\text{Paths}(P)|$ by a factor $2^m k$;
- any $\sigma' \in \text{Paths}(P')$ may carry up to $m \cdot k$ (positive or negative) label constraints.

Both aspects are problematic for a symbolic exploration of the search space: more paths means either more requests to a theorem prover (DSE) or a larger formula (BMC), and more constrained paths means more expensive requests.

V. EFFICIENT ATG FOR LC

We describe in this section two main ingredients in order to obtain efficient ATG for LC: (1) a tight instrumentation avoiding all drawbacks of the direct instrumentation, and (2) a strong coupling of label coverage and DSE through iterative label deletion.

A. Tight instrumentation

Given a label $l \equiv (loc, \phi)$, the key insights behind the tight instrumentation are the following:

- label constraint $\phi$ is useful only for covering $l$, and should not be propagated beyond that point;
- label constraint $\neg \phi$ is pointless w.r.t. covering $l$, and should not be enforced in any way.

Keeping these lines in mind, the instrumentation works as depicted in Figure 5 for each label $(loc, \phi)$, we introduce a
new instruction \texttt{if (nondet) \{assert(\phi); exit\};}

where \texttt{assert(\phi)} requires \phi to be verified, exit forces
the execution to stop and \texttt{nondet} is a non-deterministic
choice. In the resulting instrumented program \( P^* \) (Figure 5
right column), when an execution reaches \texttt{loc}, it gives rise
to two execution paths: the first one tries to cover the label
by asserting \( \phi \) and \texttt{stops right there}, the second one simply
follows its execution as \texttt{it would do in P}, neither \( \phi \) nor \( \neg \phi \)
being enforced.

![Fig. 5. Tight instrumentation \( P^* \)](image)

The tight instrumentation \( P^* \) is sound w.r.t. \texttt{LC}. Let us
denote by \texttt{NA} the test objective over \( P^* \) requiring to cover
all \texttt{New Assert} introduced by the instrumentation (with
condition evaluating to true). The following result holds.

\textbf{Theorem 6 (Soundness):} Given an annotated program
\( (P, L) \), its tight instrumentation \( P^* \) and a test suite \( TS \), we
have: \( TS \sim^p L \texttt{C} \) iff \( TS \sim^p P \cdot \texttt{NA} \).

Interestingly, the tight instrumentation does not show any
of the issues reported in Theorem 5. The underlying reasons
have been sketched at the beginning of Section V-A and are
depicted in Figure 6. A single execution path in \( P \) going
through \( n \) labels can give birth up to \( 2^n \) paths in \( P^* \) (left
column), while it can create only \( n+1 \) paths in \( P^* \) (right
column). Moreover, each path in \( P^* \) can go through at most
one single positive label constraint, while a path \( \sigma' \) in \( P^* \)
can carry up to \(|\sigma'| \) (positive or negative) label constraints. These
results are summarized in Theorem 6.

\textbf{Theorem 7 (Tightness):} Given an annotated program
\( (P, L) \) and its instrumented version \( P^* \), let us assume that
\( Paths(P) \) is bounded, that \( k \) represents the maximal length
of paths in \( Paths(P) \) and that \( m \) is the maximal number of
labels per location in \( P \). Then \( P^* \) is tight in the following
sense:

\begin{itemize}
  \item \( |Paths(P^*)| \) is linear in \( |Paths(P)| \) and \( m \cdot k \);
  \item any \( \sigma \in Paths(P^*) \) carries at most one label-
  constraint.
\end{itemize}

\textbf{Proof:} The main reasons behind this result directly follow
from the tight instrumentation, and have already been exposed
just before Theorem 7. We can be more precise: \( |Paths(P^*)| \)
is bounded by \( (m \cdot k+1) \cdot |Paths(P)| \).

\textbf{Theorem 7} implies that any path-based method conducted
over \( P^* \) will have a much easier task than over \( P' \), since \( P^* \)
contains exponentially less paths and those paths are simpler.
This is independent of the underlying verification technique
as long as it enumerates paths in some way, such as DSE or
BMC.

\subsection*{B. Iterative label deletion}

We focus now on the last issue pointed out in Section V-B.
Besides the dramatic complexity of the search space induced
by \( P' \), which is settled by \( P^* \), the remaining problem is that
a DSE procedure launched on \( P^* \) will try to cover all paths
from \( P^* \), while we are only interested in covering branches
corresponding to labels. Especially, a standard DSE may try
to cover many path prefixes ending in an already-covered
\texttt{assert(\phi)}. Whether they fail or not, these computations
will be redundant since the \texttt{LC}-soundness result of Theorem 6
requires that each new \texttt{assert} be covered only once.

\textbf{Iterative label deletion} (IDL) consists in (conceptually)
erasing a label constraint as soon as it is covered, so that it will
not affect the subsequent path search. IDL requires to modify
SE/DSE in the following way: each label \( l \) is equipped with a
boolean variable \( b_l \) set to true iff \( l \) has already been covered
during path exploration, and attempts to symbolically execute
paths leading to \( l \) continue as long as \( b_l \) is false.

We present DSE with IDL over annotated programs in
Algorithm 2 where modifications w.r.t. standard SE/DSE are
pointed out by (*) marks. We assume that \( Paths((P, L)) \) is
constructed in the following way: at each step, a run encountering
a label \( l \equiv (loc, \phi) \) can either choose to go through

![Fig. 6. Direct vs. tight instrumentation](image)
l (enforcing \( \phi \)) and continue, or bypass l (no constraint) and continue. The adaptation to \( P^* \) is described after.

Algorithm 2: Symbolic Execution with IDL

Input: an annotated program \((P, L)\) with finite set of paths \(\text{Paths}(P)\)

Output: \(TS\), a set of pairs \((t, \sigma)\) such that \(P(t) \sim_P \sigma\)

1. \(TS := \emptyset\);
2. \(S_{paths} := \text{Paths}(\langle P, L \rangle)\);
3. while \(S_{paths} \neq \emptyset\) do
   4. choose \(\sigma \in S_{paths}\); \(S_{paths} := S_{paths} \setminus \sigma\);
   5. compute \(\phi_{\sigma}\);
   6. switch \(\text{solv}(\phi_{\sigma})\) do
      7. case \text{sat}(t):
         8. \(TS := TS \cup \{(t, \sigma)\}\);
         9. (*): for all \(l\) covered by \(\sigma\), do \(b_l := 1\);
         10. (*): remove from \(S_{paths}\) all \(\sigma’\) going through a label \(l\) s.t. \(b_l = 1\);
      11. case \text{unsat}:
         12. skip;
   13. endsw
4. return \(TS\);

For integration in a realistic SE/DSE setting with dynamic exploration of path space, we distinguish two flavors of IDL:

- **IDL-1**: a label is marked as covered only when it belongs to a path prefix being successfully solved. This is a purely symbolic approach.
- **IDL-2**: a label is also marked when it is covered by a concrete execution, taking advantage of dynamic runs to delete several labels at once.

**Combining IDL with tight instrumentation.** Both variants of IDL can be combined with tight instrumentation either in a dedicated manner or in a black-box setting. Since dedicated implementations are straightforward, we focus hereafter on black-box implementations. An instrumentation enforcing IDL-1 over \(P^*\) is depicted in Figure 7. We follow the idea of adding extra boolean variables for coverage, denoted \(b_1\) where \(l\) is a label identifier. However, it is mandatory that the coverage information be global to the whole path search process and not bound to a single execution. It can be achieved by putting the coverage information in an external file, accessed and modified through operations \(\text{read}(b_1)\) and \(\text{set_covered}(b_1)\).

![Fig. 7. IDL-1 variant of tight instrumentation \(P^*\)](image)

Enforcing IDL-2 in a black-box setting requires a fine-grained control over the DSE procedure. We need to be able to query the DSE engine for the next generated test data. The procedure reuses the IDL-1 approach for path space exploration, but each new generated test data is also run on the *direct instrumentation* \(P^*\). Then all covered labels are marked in the coverage file of IDL-1 before the next test data is searched for. The technique is depicted in Figure 8 where TD stands for “test data”.

![Fig. 8. IDL-2 variant for DSE](image)

We denote by DSE* the DSE procedure enhanced with IDL-1 or IDL-2, and we consider only deterministic and sound DSE techniques. The following result holds.

**Theorem 8:** Given an annotated program \((P, L)\) and its tight instrumentation \(P^*\), then DSE*(\(P^*\)) covers as many labels as DSE(\(P^*\)) does.

**Proof:** The result comes from three facts. First, a label is discarded iff it is covered by an already generated test data \(t \in TS\). Second, labels act only as “observers” in \((P, L)\): they do not impact the execution, so they cannot enable or prevent the coverage of a particular test objective. It implies that paths from \(P\) are sufficient for reaching coverable labels (FACT 2). Third, by construction, the set of paths from \(P^*\) contains all paths from \(P\) (those without any label constraint) plus additional paths with label constraints (FACT 3). Therefore, deleting a label constraint in DSE*(\(P^*\)) cannot discard any of the original path from \(P\). Using FACT 2, we deduce that label deletion cannot make uncoverable an otherwise-coverable label. Note that the proof (and the theorem) does not hold for the direct instrumentation \(P^*\) since FACT 3 is false in that case.

VI. IMPLEMENTATION & EXPERIMENTS

A. Implementation

We have implemented tight instrumentation and iterative label deletion inside PATHCRAWLER [36]. The tool follows a standard DSE approach and targets safety-critical C programs, with a strong focus on relative completeness guarantees. For example, the underlying constraint solver deals precisely with modular arithmetic, bitwise operations, floats and multi-level pointer dereferences. The DSE engine relies on a simple DFS path search heuristics. On the other hand, the tool is highly optimised for programs with many infeasible paths. Aside from early detection of infeasible paths which is ensured by the “dynamic execution-driven” nature of DSE, optimisations include several levels of incremental solving for cheap detection of infeasible paths.

Our implementation follows the description of Section V. We adopt a grey-box approach rather than a full black-box approach because PATHCRAWLER does not offer yet the required
API for IDL-2 and does not support non-deterministic choice. We add a pathcrawler_label(bool) instruction, those native treatment implements tight instrumentation and IDL-2. The current search heuristics is mostly depth-first, but labels are handled as soon as possible.

B. Experiments

Preliminary experiments have been conducted in order to test the following properties: (i) the relative gain of our two optimisations w.r.t. direct instrumentation, (ii) the overhead of leveraging DSE to LC. Evaluating the practical feasibility of label-based DSE over large programs or its bug-finding power are left as future work. Note that the bug-finding power of the coverage criteria emulated through labels in Section III has already been extensively studied in the literature.

Protocol. We consider a few standard benchmark programs taken from related works [7, 31, 29], together with three types of labels simulating standard coverage criteria of increasing difficulty: CC, MCC and WM. For WM, our labels mimic mutations typically introduced by MuJava [19] for operators AOIU, AOR, COR and ROR [2]. We compare the following algorithms: $DSE(P)$ denotes the standard DSE on the standard program (witness), $DSE(P')$ denotes standard DSE on direct instrumentation, $DSE(P''')$ denotes standard DSE on tight instrumentation and $DSE^{*}(P'')$ denotes DSE with iterative label deletion run on tight instrumentation. Experiments are performed on a standard laptop (Intel Core2 Duo 2.40GHz, 4GB of RAM). Time out for solver is set to 1 min.

We record the following information: number of paths explored by the search, computation time and achieved coverage. The number of paths is a good measure for comparing the complexity of the different search spaces, and therefore to assess both the “cost” of leveraging DSE to labels and the benefits of our optimisations. Coverage score together with computation time indicate how practical label-based DSE is.

It must be highlighted that PATHCRAWLER does not stop until all feasible paths are explored. This strategy gives us a good estimation of the size of the path space, however in practice it would be wiser to implement a label-based stopping criteria. Hence, from a feasibility point of view, results reported here are too pessimistic.

Results. Results are summarized in Table 1. We can observe the following facts. First, the number of explored paths is always much greater in $DSE(P')$ than in $DSE^{*}(P'')$, with a factor between 4x and 50x on all examples but Tcas-cc and Tcas-mcc, where the difference is less than 1.5x. Actually, labels in those two programs lead mostly to infeasible paths, yielding no path explosion. Things are more mitigated for computation time, certainly because of PATHCRAWLER optimisations. Yet, $DSE(P')$ and $DSE^{*}(P'')$ are at worst mostly equivalent on the smallest examples (except for Trityp-cc), and $DSE^{*}(P'')$ can be up to 25x faster on the most demanding programs. Second, as expected, $DSE(P')$ stands between $DSE(P)$ and $DSE^{*}(P'')$ for the number of paths, and for computation time on the most demanding examples. Finally, compared with $DSE(P)$, $DSE^{*}(P'')$ yields at most a 3x growth of the search space and an overhead between 1.1x and 7x for computation time.

![Table 1. Experimental results for ATG](image)

Conclusion. These experiments confirm our formal predictions:

- our fully-optimised DSE performs significantly better on difficult programs than the direct instrumentation, both in terms of search space and computation time;
- the overhead w.r.t. standard DSE turns out to be always acceptable, even sometimes very low.

These preliminary results suggest that DSE can be efficiently leveraged to LC coverage thanks to our optimisations. Yet, additional experiments on real-size programs are required to confirm that point.

Finally, we can observe that the very significant reduction of the path space does not always translate into an equivalent reduction of computation time. Optimisations of DSE tools certainly play a role here. Indeed, several PATHCRAWLER optimisations may significantly accelerate usual DSE exploration for some programs.

VII. BEYOND TEST DATA GENERATION

Section III proves that LC is a powerful coverage criterion, encompassing many standard criteria and a large subset of weak mutations. Section V and Section VI demonstrate the feasibility of efficient ATG for LC, with a cost-effective integration in DSE. We also sketched in Section VI how to perform cheap LC score computation. Everything put together, labels form the basis of a very powerful framework for automatic testing, handling many different criteria in a uniform fashion. We describe such a view in Figure 9.
Starting from a program $P$ and a testing criterion $C$, a predefined labelling function $\psi_C$ creates the $C$-equivalent annotated program $(\tilde{P}, L)$ (Theorem 1 and Theorem 2). Then, we can perform automatic and efficient LC score computation and LC-based ATG through instrumentation (Theorem 4 and Theorem 6). Finally, static analysis techniques can be used on $P^*$ in order to detect uncoverable labels, i.e., labels $l \not\equiv (loc, \phi)$ for which there is no test data $t$ such that $t \sim_P l$. Static detection of uncoverable labels can help ATG tools by avoiding wasting time on infeasible objectives, as was observed in the case of mutation testing [16].

**VIII. RELATED WORK**

**Leveraging DSE to higher coverage criteria.** The need for enhancing DSE with better coverage criteria has already been pointed out in active testing (a.k.a assertion-based testing) [7], [13], [17] and in Mutation DSE [29],[30]. The present work generalizes these results and proposes ways of taming the potential blow-up, resulting in an effective support of advanced coverage criteria in DSE with only a small overhead.

Active testing targets run-time errors by adding explicit branches into the program. It is similar to the Run-Time Error Coverage criterion presented in Section II. Labels are a more general approach. Interestingly, the direct instrumentation $P'$ for this criterion is mostly equivalent to $P^*$ since additional branches can only trigger errors and stop the execution. Yet, active testing could benefit from the IDL optimisation. In that case only the IDL-1 flavour makes sense since an execution cannot cover two different run-time errors. Finally, since most test objectives are (hopefully!) uncoverable for Run-Time Error Coverage, some approaches aim at combining DSE with static detection of uncoverable targets [7]. These techniques and heuristics can be reused for labels, and should be useful when many labels are uncoverable.

Mutation-based DSE [29], [30], [31] is probably the work closest to ours. Following Offutt et al. [10], Papadakis et al. show that WM can be reduced to branch coverage through the use of a variant of Mutant Schemata [34]. This is pretty similar to the direct encoding $P^*$ mentioned here. They propose essentially two variations of DSE for mutation testing: a black-box approach [29] based on a direct encoding similar to our DSE($P'$) scheme, and a more ad hoc approach [29] preventing reuse of existing DSE tools but offering several optimisations. Papadakis et al. propose a variant of IDL, a dedicated search heuristic based on shortest paths [28] and an improvement of the direct encoding through the use of mutant identifiers (following exactly Mutant Schemata). On the one hand, it ensures that a given path cannot go through several different mutants, on the other hand there is still an exponential blow-up of the search space in the worst case, and IDL cannot cover more than one mutant at once.

We give a more generic view of the problem, identifying labels and annotated programs as the key concept underlying the approach. We also clearly identify the limits and hypotheses of the method by defining the side-effect free fragment of WM, proving soundness of direct instrumentation and providing a formalization of the path space “complexification” (Non-Tightness Theorem) induced by direct instrumentation. Most important, we propose the tight instrumentation which completely prevents complexification. Finally, our optimisations can be implemented in a pure black-box setting and we do not impose anything on the search heuristics, keeping room for future improvements.

**Labels and optimized DSE.** The label-specific optimisations described here can be freely mixed with other DSE optimisations. It is left as future work to explore which optimisations turn out to be the most effective for labels. As already stated, combining static discovery of uncoverable labels with DSE [7] could be useful for often-uncoverable labels, such as those generated for Run-Time Error Coverage or MCC. Another interesting idea is to adapt DSE search heuristics [37] by taking advantage of the dissimilarities between labels and branches, possibly getting inspiration from [28].

The IDL optimisation shows some similarities with Look-Ahead pruning (LA) [3]. Basically, LA takes advantage of (global) static analysis to prune path prefixes which cannot reach any uncovered branches (it could also be adapted for labels). On $P^*$, IDL-1 is a very specific (but cheap) case of LA while IDL-2 is not: LA will prune all “label paths” pruned by IDL-1 plus other normal paths leading only to already covered labels, while IDL-2 will prune several “label paths” at once thanks to dynamic analysis.

**Automation of mutation testing.** Mutation coverage [9], [25] has been established as a powerful criterion through several experimental studies [1], [25]. Yet, it is very difficult to automatize. Even mutation score computation is expensive in practice if not done wisely. Weak mutations [15] relax mutation coverage by abandoning the “propagation step”, making WM easier to compare with standard criteria and easier to test for. WM has been experimentally proved to be almost equivalent to strong mutations [23], and from a theoretical point of view WM subsumes many other criteria [26].

The few existing symbolic methods for mutation-based ATG are based on the encoding proposed by Offutt et al. and have already been discussed [10], [31], [30]. The Mutation Schemata technique [34] was originally developed in order to factorize the compilation costs of hundreds of similar mutants. Static analysis has been proposed for the “equivalent mutant detection” problem [21],[20] in a way similar to what is sketched in Section VII.
The side-effect free fragment of (atomic) WM presented in this paper seems to be a sweet spot of mutation testing: it is amenable to efficient automation and still very expressive. It is left as future work to identify if something essential is lost within this fragment. Finally, our encoding of WM into LC is orthogonal to and can be combined with some of the many techniques developed for efficient mutation testing, such as operator reduction [24], [35] or smart use of operators [16].

IX. CONCLUSION

We have defined label coverage, a new testing criterion which appears to be both expressive and amenable to efficient automation. Especially, we have shown that DSE can be extended for label coverage in a black-box manner with only a slight overhead, thanks to tight instrumentation and iterative label deletion. Experiments show that these two optimisations yield significant improvements.

This work bridges parts of the gap between symbolic ATG techniques and coverage criteria. On the one hand, we show that DSE techniques can be cheaply extended to support more advanced testing criteria, including side-effect free weak mutations. On the other hand, we identify a powerful criterion amenable to efficient automation, both in terms of AFG and coverage score computation.

Future work comprises better delimitation of the expressiveness of labels, designing DSE optimisations geared towards label coverage and carrying out more thorough experimental evaluations.

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