Test Selection via Mining Common Operational Models

Wujie Zheng
Department of Computer Science & Engineering
The Chinese University of Hong Kong
wjzheng@cse.cuhk.edu.hk

Michael R. Lyu
Department of Computer Science & Engineering
The Chinese University of Hong Kong
lyu@cse.cuhk.edu.hk

Tao Xie
Department of Computer Science
North Carolina State University
xie@csc.ncsu.edu

ABSTRACT

In automated testing, especially test generation in the absence of specifications, a large amount of manual effort is spent on test-result inspection. Test selection helps to reduce this effort by selecting a small subset of tests that are likely to reveal faults. A promising test-selection approach is to dynamically mine operational models as potential test oracles and then select tests that violate them. Existing work adopting this approach mines operational models based on dynamic invariant detection. In this paper, we propose to mine common operational models, which are often but not always true in all observed traces, from a (potentially large) set of unverified tests. Specifically, our approach collects branch coverage and data value bounds at runtime and then mines implication relationships between branches and constraints of data values as potential operational models after running all the tests. Our approach then selects tests that violate the mined common operational models for result inspection. We have evaluated our approach on a set of programs, compared with previous code-coverage-based, clustering-based, dynamic-invariant-based, and random selection approaches. The experimental results show that our approach can more effectively reduce the number of tests for result inspection while revealing most of the faults.

Categories and Subject Descriptors

D.2.5 [**Software Engineering**]: Testing and Debugging

General Terms

Reliability, Experimentation

Keywords

Software testing, Test selection

1. INTRODUCTION

It is labor-intensive to manually generate a large set of test inputs and verify their outputs. Recently, there have been various practical approaches on automatic test-input generation [23, 25, 26, 27]. However, test-result inspection still remains a largely manual task. Given *a priori* specification, developers can reduce this manual effort by selecting test inputs (in short as *tests*) using specification coverage criteria [4]. But it is uncommon to have *a priori* specification in practice. Sometimes developers may use general test oracles based on memory monitoring tools such as Valgrind [20]. But these oracles are limited in checking specific kinds of faults. It is highly demanded to develop practical test-selection techniques, which can select a small subset of tests that are likely to reveal faults.

A promising test-selection approach is to dynamically mine operational models as potential test oracles and then select tests that violate them. Existing approaches such as Jov [28] and Eclat [22] mine dynamic invariants using Daikon [8] from a set of manually written passing unit tests whose results are verified with manually written assertions. Due to nontrivial effort for writing the assertions, the number of these existing passing unit tests is often limited. Therefore, the mined dynamic invariants could be noisy and thus many model violations could be false positives. The operational difference approach [12] starts with an empty test suite and repeatedly adds new tests if they violate the invariants mined from the previously selected tests. As the number of previously selected tests is also limited, this approach faces the same problem of producing many false positives. DIDUCE [10] mines operational models from normal execution of long-running applications and relaxes the models gradually. At the beginning of a program run, many presumed operational models may be violated and a violation that reveals a fault can be overwhelmed by the false-positive noise.

In this paper, we propose to mine common operational models, which are often but not always true in all observed traces, from a (potentially large) set of unverified tests. A program that is not of poor quality should pass most of the tests. So the common operational models mined from a large set of unverified tests may be similar to the true operational models and their violations are likely to reveal faults. By using the information of all the unverified tests at hand, our approach can avoid the noise caused by a small number of data samples, without requiring a large set of verified tests. As a common operational model is not always true over the whole set of tests, the type of Daikon inference techniques does not work anymore. Alternatively, we may generate and collect all the potential models at runtime (instead of immediately discarding any violated potential models) and

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```
1    not_text = (! (always_text | out_quiet)
               && memchr(bufbeg,'\0', buflim-bufbeg));
2    done_on_match += not_text;
3    out_quiet += not_text;
4    for (;;)
5    {
6        ...
7        nlines += grepbuf (beg, lim);
8        ...
9        if (nlines && done_on_match && !out_invert)
10           goto finish_grep;
11       ...
12   }
13   finish_grep:
     /* missing code: done_on_match -= not_text;
                      out_quiet -= not_text; */
14   if ((not_text & ~out_quiet) && nlines != 0)
15       printf(_("Binary file %s matches\n"),filename);
```

Figure 1: Faulty code of the *grep* program

evaluate them after running all the tests. However, such an approach can incur high runtime overhead if Daikon-like operational models, which are in a large number, are used.

To mine common operational models efficiently, we propose an approach based on mining control rules and data rules. A control rule is an implication relationship between branches, and a data rule is an implicit constraint of the variable values. Specifically, our approach collects branch coverage and data value bounds at runtime using the Cooperative Bug Isolation (CBI) tools [17]. Our approach then mines control rules and data rules as potential operational models after running all the tests. The likelihood of a common operational model to be a true oracle is evaluated using the concept of confidence, i.e., the ratio of the number of tests that satisfy the model over the number of tests that satisfy or violate the model. When a model's confidence is not equal to 1, the higher the model's confidence is, the more suspicious its violations are in revealing a fault. Finally, our approach selects a small subset of tests that violate the mined common operational models for result inspection.

To illustrate what a common operational model may look like and how its violation is useful for indicating faults, we present an example in Figure 1. The example is a faulty version of *grep* 2.3, which is downloaded from the Software Infrastructure Repository (SIR) [1]. *grep* is a GNU utility that searches the input files for lines containing a match to a given pattern list. When *grep* finds a match in a line of a text file, it copies the line to the standard output. But if the input file is a binary file, it normally[1] outputs either a one-line message saying that a binary file matches, or no message if there is no match. Furthermore, given the option "–quiet", *grep* should not write anything to the standard output.

In Line 1, `always_text` is 0 by default, `out_quiet` is 0 when the option "–quiet" is not specified, `memchr(bufbeg,'0',buflim-bufbeg)` returns a non-null pointer if the input is a binary file. In Line 3, `out_quiet` should be set to be positive if `not_text` is 1, so as to suppress the normal outputs of matchings. In Line 7, `nlines` records the number of found matches. Finally, in Line 14, the program checks whether the input is a binary file, the "–quiet" option is not specified, and there are some matches found. If so, the program should output a one-line message saying that a binary file matches. However, since `out_quiet` may be changed in Line 3, the checking in Line 13 may not work as expected. When the input is a binary file, the "–quiet" option is not specified, and there are some matches found, the checking in Line 14 is expected to return true. In this case, `out_quiet` is originally 0 and then is changed to be 1 in Line 3. Without restoring the original value of `out_quiet`, the checking in Line 14 returns false and no message would be output. Because returning no message is not the desired result, we call the test a failing test.

Without knowing the fault *a priori*, how can we identify such a test to be a suspicious one among a large number of tests? Our insight is that we may get some guidance from the (unverified) executions of the program. We run the *grep* programs on 809 tests that are also downloaded from SIR. Among the 809 tests, 667 tests cover the branch that `nlines` is true (Line 9), among which only 8 tests cover the branch that `memchr(bufbeg,'0',buflim-bufbeg)` is true (Line 1). Therefore, we can uncover a common operational model from the executions: "`nlines` > 0 is ever true $\Rightarrow$ `memchr(bufbeg,'0',buflim-bufbeg)` is never true (in a test)". Although this model is not always true, it reflects the fact that we search more often in a text file than in a binary file, and a binary file is less likely to contain a match to a given pattern. The violations of this model are corner cases that may require special handling. Yet such corner cases are often neglected by programmers or their handling is too tedious to be fault free. Therefore, it is valuable to check the result of a test that violates the model, i.e., satisfying "`nlines` > 0 is ever true $\wedge$ `memchr(bufbeg,'0',buflim-bufbeg)` is ever true". We then find the selected test to be a failing test that reveals the fault.

This paper makes the following main contributions[2]:

- We propose to mine common operational models, which are often but not always true in all observed traces, from a (potentially large) set of unverified tests. Such common operational models capture typical behaviors of the unverified tests and their violations are likely to reveal faults.
- We propose two kinds of common operational models, including implication relationships between branches and constraints of data values. These two kinds of common operational models are indicative of many faults and they can be mined from execution traces that consist of only branch coverage and data value bounds.
- We conduct a comprehensive experimental study of the effectiveness and efficiency of our approach, compared with previous code-coverage-based, clustering-based, dynamic-invariant-based, and random selection approaches.

The rest of the paper is organized as follows. Section 2 presents the proposed approach to mine common operational models. Section 3 presents the test selection approach. Section 4 describes the empirical studies and results. Section 5 reviews related work. Section 6 concludes the work with future directions.

[1] By default, binary files are not treated as text files

[2] An earlier version of this work was presented in ICSE NIER 2009 as a 4-page paper [30]. This work extends the NIER paper in two main aspects. First, we enrich the common operational models with data rules, which are complementary to our previous control rules. Second, we evaluate both the effectiveness and efficiency of our approach, compared with the existing approaches besides random selection.

2. MINING COMMON OPERATIONAL MODELS

In this section, we propose two kinds of common operational models that are potentially fault-revealing, including control rules and data rules. A control rule is an implication relationship between branches. A data rule is an implicit constraint of the variable values. We mine common operational models from all the unverified tests. A program that is not of poor quality should pass most of the tests. Therefore, the common operational models mined from a set of unverified tests may be similar to the real models in passing tests.

2.1 Control Rules

Many faults can be revealed only when specific control paths are executed. Such control paths may have special branch combinations that the programmers do not expect. Therefore, we can mine common relationships between branches and isolate their violations as suspicious tests.

Given a branch condition C, let us denote its then-branch and else-branch as C=true and C=false. In a loop, a branch may be executed multiple times. We use two branch predicates C_t and C_f to denote that the branch C=true is ever covered (satisfied) and C=false is ever covered, respectively. Correspondingly, $\neg C_t$ means that C=true is never covered and $\neg C_f$ means that C=false is never covered. Note that $\neg C_t$ is not equivalent to C_f. It is possible that one of them is true and the other is false. The evaluations of a branch predicate x may be implied by other predicates. To model such implication relationships, we consider two kinds of rules $y \Rightarrow x$ and $y \Rightarrow \neg x$, where y is another branch predicate. We call $y \Rightarrow x$ and $y \Rightarrow \neg x$ control rules.

```
1    bool   Non_Crossing_Biased_Climb()
2    {
3        ...
4        upward_preferred = Inhibit_Biased_Climb()
                            >=Down_Separation;
                            /* >= should be > */
5        if(upward_preferred)
6            ...
7    }
8    bool   Non_Crossing_Biased_Descend()
9    {
10       ...
11       upward_preferred = Inhibit_Biased_Climb()
                            >Down_Separation;
12       if(upward_preferred)
13           ...
14   }
```

Figure 2: Faulty code of the tcas program

We have shown an example of the rule $y \Rightarrow \neg x$ in Figure 1. Here we show an example of the rule $y \Rightarrow x$ in Figure 2. The example program is a faulty version of the tcas program, which is an altitude separation controller, in the *Siemens* suite [15]. In Line 4, a > operator is wrongly implemented as $\geq$. Let x and y be two branch predicates for denoting that the branch `upward_preferred=true` in Line 12 is ever covered and the branch `upward_preferred=true` in Line 5 is ever covered, respectively. Running 1608 tests on the program, we can find that y is true in 514 tests, among which x is true 478 times. Therefore, we can uncover a common operational model "$y \Rightarrow x$". This model reflects the real assumption of the programmers. Its violations cause errors that may finally become observable failures.

There may be a large number of control rules. We are interested only in the control rules that are likely to be true oracles and are violated by some tests. To evaluate the likelihood of a control rule to be a true oracle, we use the concept of confidence. The confidence of $y \Rightarrow x$ is defined as the ratio of the number of tests that satisfy $y \wedge x$ over the number of tests that satisfy y. The confidence of $y \Rightarrow \neg x$ is defined as the ratio of the number of tests that satisfy $y \wedge \neg x$ over the number of tests that satisfy y. If a rule's confidence is 1, it can be omitted since there is no violation of this rule. Our approach then selects a subset of rules with high confidences. More specifically, for each predicate x, our approach selects the most confident rule $y \Rightarrow x$ and the most confident rule $y \Rightarrow !x$. Another possible way is to select the rules whose confidences are higher than a preset threshold, whose value may be application-dependent.

2.2 Data Rules

The values of a variable may have some implicit constraints. A failure may require or result in suspicious data values, i.e., violating the value constraints. Therefore, we can mine implicit constraints of variable values and isolate their violations as suspicious tests.

Given a variable V, we use V_{max} and V_{min} to denote the maximum value and minimum value ever assigned to V in a test. The values of a variable may be within an expected range. To model such potential constraints of variable values, we consider two kinds of rules $V_{max} \leq c_1$ and $V_{min} \geq c_2$, where c_1 and c_2 are constants (different variables have different c_1 and c_2). We call $V_{max} \leq c_1$ and $V_{min} \geq c_2$ data rules.

Unlike control rules, data rules have some parameters c_1 and c_2 to be determined. Let us first consider the rule $V_{max} \leq c_1$. Assume V_{max} follows the normal distribution. We can get the estimations of the mean value μ_1 and the standard deviation σ_1 based on the values of V_{max} in the observed but unverified tests. We would like to select a c_1 such that there is a high probability, say 0.9, that V_{max} is no more than c_1. Let $Z = (V_{max} - \mu_1)/\sigma_1$, then Z follows the standard normal distribution, i.e., having a mean of 0 and a standard deviation of 1. The problem $Prob(V_{max} \leq c_1) = 0.9$ is equivalent to the problem $Prob(Z \leq (c_1 - \mu_1)/\sigma_1) = 0.9$. Querying the cumulative probabilities of the standard normal table [2], we can get the solution $(c_1 - \mu_1)/\sigma_1 = 1.28$, i.e., $c_1 = 1.28 * \sigma_1 + \mu_1$. For example, if the set of values of V_{max} is {1,2,3,4,5}, we can estimate $\mu_1 = 3$ and $\sigma_1 = 1.58$. We then have $c_1 = 5.02$. There is no violation of the rule $V_{max} \leq c_1$. Alternatively, if the set of values of V_{max} is {1,2,3,4,10}, we can estimate $\mu_1 = 4$ and $\sigma_1 = 3.54$. We then have $c_1 = 8.53$. There is a violation of the rule $V_{max} \leq c_1$. Similarly, we would like to select a c_2 such that there is a high probability, say 0.9, that V_{min} is no less than c_2. We can get $c_2 = -1.28 * \sigma_2 + \mu_2$, where μ_2 and σ_2 are the mean value and the standard deviation of V_{min}.

Figure 3 shows an example of the data rule $V_{max} \leq c_1$. The example program is a faulty version of the print_tokens program, which is a lexical analyzer, in the *Siemens* suite [15]. In the loop, `token_ind` is increased by 1 each time. When `next_st` $= 30$, `token_ind` should be reset to 0, which is wrongly

```
1   while(!token_found)
2   {
3       if(token_ind<80)
4       {
5           token_str[token_ind++] = ch;
6           next_st = next_state(cu_state,ch);
7       }
8       ...
9       switch(next_st)
10      {
11          ...
12          case 30:
13              skip(tstream_ptr->ch_stream);
14              next_st = 0;
                /* missing code: token_ind = 0; */
15              break;
16      }
17  }
```

Figure 3: Faulty code of the print_tokens program

omitted. The omission of this assignment may make `token_ind` get unusually large values. Running the program on 4130 tests, the assignment of `token_ind` in Line 5 is executed in 4070 tests. Its maximum value has a mean value of 11 and a standard deviation of 13. So we can get a data rule $V_{max} \leq c_1 = 1.28 * \sigma_1 + \mu_1 = 28$, where V is `token_ind` in Line 5. Violations of this model may be caused by an omission fault and indicate failures.

To evaluate the likelihood of a data rule to be a true oracle, we also use the concept of confidence. The confidence of $V_{max} \leq c_1$ is defined as the ratio of the number of tests that satisfy $V_{max} \leq c_1$ over the number of tests where V is ever assigned. The confidence of $V_{min} \geq c_2$ is defined as the ratio of the number of tests that satisfy $V_{min} \geq c_2$ over the number of tests where V is ever assigned. If a rule's confidence is 1, it can be omitted since there is no violation of this rule.

3. TEST SELECTION

Given a set of control rules and data rules, selecting all the tests that violate any of the rules may result in a large subset of the tests. Instead, our approach selects only a small subset of the tests that violate all these rules at least once, in a way that the most confident rules are violated by the selected tests first. Since the control rules and the data rules have different definitions of the confidence, we deal with them separately. The process of test selection based on the control rules is as follows. Initially, the set of selected tests is empty. Our approach sorts the control rules in descending order of confidence. From the top to bottom, if a rule is not violated by any of the previously selected tests, our approach randomly selects a test that violates the rule. Finally, in a greedy way each of the control rules is violated by the selected tests. Our approach also selects a subset of tests that violate all the data rules in the similar way. We merge together the selected tests based on the control rules and those based on the data rules as the final subset of selected tests.

4. EMPIRICAL STUDIES

In this section, we present a set of empirical studies to evaluate the effectiveness of our approach in test selection. In particular, we investigate three main research questions:

- RQ1: Can our approach select a small subset of tests that have high fault-detection capability? What is the effectiveness of violating different kinds of rules?
- RQ2: How does our approach compare with the existing approaches, including the code-coverage-based, clustering-based, and dynamic-invariant-based approaches?
- RQ3: What is the efficiency of our approach?

We next describe the subjects and measurements. We then present the results of our approach in test selection, compared with the existing approaches. The detailed results of our evaluation are available at `https://sites.google.com/site/asergrp/projects/testselect/`.

4.1 Subject programs

We have implemented the proposed approach and applied it to select tests in three subjects, including the *Siemens* suite [15], the *Space* program [24], and the *grep* program. All the three subjects are downloaded from the Subject Infrastructure Repository [1]. The first two subjects were also used in previous study of dynamic-invariant-based test selection [12].

The first subject is the *Siemens* suite [15], which was created by *Siemens* researchers. The *Siemens* researchers created 132 faulty versions of 7 programs that range in size from 170 to 540 lines. The *Siemens* researchers generated tests automatically from test-specification scripts, then augmented those tests with manually-constructed white-box tests such that each exercisable coverage unit was covered by at least 30 test cases. The numbers of tests range from 1052 to 5542. There are 130 faults that can be detected by the test suite in our environment.

The second subject is the *Space* program [24], which interprets Array Definition Language inputs. The *Space* program was developed at the European Space Agency. It has 9564 lines of C code. The test suite of *Space* contains 13585 test cases, where 10000 were randomly generated and the remainder were added to cover every statement or branch at least 30 times. There are 38 faults, among which 34 faults can be detected by the test suite in our environment.

The third subject is the *grep* program, which is a GNU utility that searches the input files for lines containing a match to a given pattern list. It has 13358 lines of C code. There are 809 test cases, which were generated based on informal specifications and then augmented to increase statement coverage [1]. There are five original versions of the *grep* program, each of which was seeded by a number of faults. In our environment, there are in total 20 faults that can be detected by the test suite.

The characteristic of the subject programs is shown in Table 1. In these subjects, there are many trivial faults that fail on more than 5% of the tests. Such faults are less likely to be seen in practical setting. To better evaluate the potential effectiveness of test selection approaches in practice, we conduct additional experiments on only the nontrivial faults.

4.2 Measurement

To evaluate the effectiveness of an approach in test selection, we use two metrics. The first metric is the size of the selected test suite, i.e., the number of the selected tests. This metric indicates the amount of human effort required to

Table 1: Characteristic of the subjects

Program	LOC	Test Cases	Faulty Versions	Failed Tests (Avg.)	Faulty Versions (Nontrivial)	Failed Tests (Nontrivial)	Program Description
print_tokens	539	4130	7	69	7	69	lexical analyzer
print_tokens2	489	4115	10	224	4	109	lexical analyzer
replace	507	5542	31	106	29	93	pattern replacement
schedule	397	2650	9	88	6	21	priority scheduler
schedule2	299	2710	9	33	9	33	priority scheduler
tcas	174	1608	41	39	36	28	altitude separation
tot_info	398	1052	23	83	11	24	information measure
Siemens suite	404	3115	130	92	102	54	–
Space	9564	13585	34	2111	17	164	ADL interpreter
grep	13358	809	20	177	9	12	pattern matching

check the results of the selected tests. The second metric is the percentage of faults that can be detected by the selected tests. A set of tests are said to detect a fault if the faulty program fails on one or more of the tests. We would like to reveal as many faults as possible. A good test-selection algorithm should select a small number of tests that can reveal most of the faults.

4.3 Results

Figures 4 and 5 show the results of our approach and the existing test selection approaches, including the code-coverage-based, clustering-based, and dynamic-invariant-based approaches. The x-axis is the number of selected tests and the y-axis is the percentage of faults revealed by the selected tests. We also present the results of random selection as the comparison baseline. Because the three subjects are quite different in the program size and the original test suite size, we present the results in these three subjects separately. Tables 2, 3, 4, and 5 show some of the detailed results, including the number of selected tests and the percentage of revealed faults in each subject program. To reduce the potential effect of random noise, we run all of the experiments 50 times and then report the averaged results.

4.3.1 Effectiveness of Our Approach

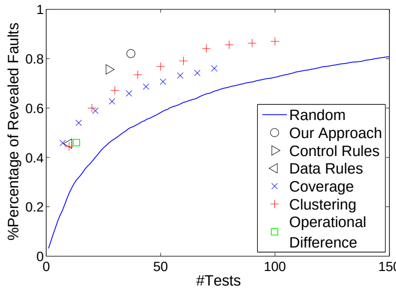
We observe that our approach is effective in reducing the number of tests while revealing most of the faults. In the *Siemens* suite (all faults), our approach selects only 37 tests for the programs on average, which can still reveal 82% of the faults. In the *Space* and the *grep* programs (all faults), our approach selects 345 and 219 tests on average, which can reveal 100% and 97% of the faults, respectively. We note that randomly selecting the same number of tests as our approach can also reveal 52%, 89% and 90% of the faults in these subjects. This result is due to two main factors: (1) many trivial faults can be easily revealed and (2) the probability of finding no failures of a fault decreases exponentially with the number of selected tests. Checking the results in nontrivial faults, we can see that our approach is still effective while the effectiveness of random selection decreases much. For example, in the *Siemens* suite (nontrivial faults), our approach selects only 37 tests for the programs on average, which can still reveal 80% of the faults. Randomly selecting the same number of tests can reveal only 41% of the faults.

We also evaluate the effects of the two kinds of common operational models that we proposed, i.e., control rules and data rules, separately. The results are plotted in Figures 4 and 5, and shown in Tables 2 and 4. We observe that both these two kinds of rules are helpful in revealing faults. Among them, covering violations of control rules can detect more faults than covering violations of data rules, but also requires much more tests. The data rules are better for some programs such as tot_info, which is an information measure program that deals with data tables. In summary, these two kinds of rules are complementary to each other as they reflect different aspects of program behaviors. When combined together, they are able to help select quite a good subset of tests.

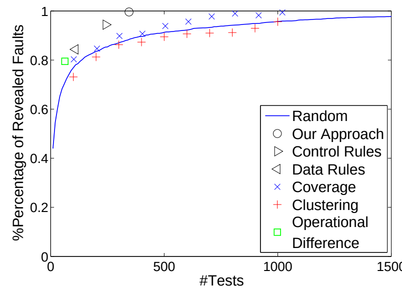
4.3.2 Comparison with the Code-coverage-based Approach

We compare our approach with the code-coverage-based approach. The code-coverage-based approach attempts to cover as many program elements of a given type as the original test suite with as few test cases as possible [16]. Selecting a minimal-size, coverage-maximizing subset of a test suite is an instance of the set-cover problem, which is often solved using a greedy approximation algorithm. On each of its iterations, the greedy algorithm selects the test that covers the largest number of elements not covered by the previously selected tests. This approach is based on the assumption that many software faults and their caused failures can be revealed simply by exercising such elements, regardless of other factors. To evaluate the potential capability of finding more faults using the code-coverage-based approach, we also extend the basic code-coverage-based approach by increasing the number of times each program element should be covered. We say a program element is covered k times if there are k different tests that cover it. We use the branch coverage and we experiment with k from 1 to 10. The results are plotted in Figures 4 and 5, and shown in Tables 3 and 5.

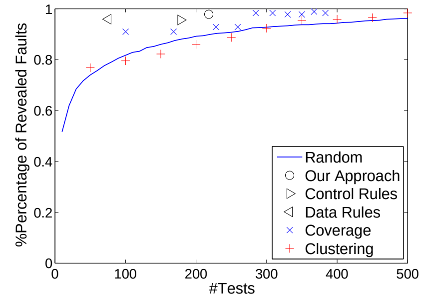
We observe that the basic code-coverage-based approach, in which each branch is covered at least once, is good in selecting a small subset of tests that can reveal many faults. However, it misses many other faults, e.g., it misses more than half of the faults in the *Siemens* suite. Our approach can select a test suite with a much higher fault-revealing capability, and the number of selected tests is only a few times larger than that of the basic code-coverage-based approach.



(a) Results for the *Siemens* suite

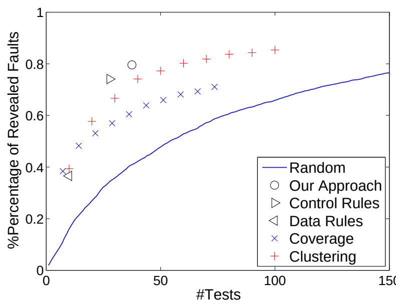


(b) Results for the *Space* program

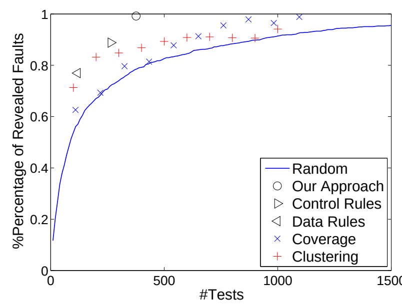


(c) Results for the *grep* program

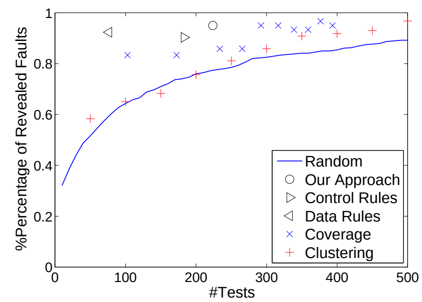
Figure 4: Results of all the faults



(a) Results for the *Siemens* suite



(b) Results for the *Space* program



(c) Results for the *grep* program

Figure 5: Results of the nontrivial faults

Table 2: Results of our approach on all the faults

Program	Original Test Suite		Our Approach		Control Rules		Data Rules	
	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults
print_tokens	4130	100	25	89	17	88	8	50
print_tokens2	4115	100	41	100	30	100	10	61
replace	5542	100	75	80	60	73	16	37
schedule	2650	100	31	86	24	70	7	49
schedule2	2710	100	32	62	24	61	9	25
tcas	1608	100	26	74	15	68	12	23
tot_info	1052	100	29	84	21	71	9	74
Siemens suite	3115	100	**37**	**82**	27	76	10	46
Space	13585	100	**345**	**100**	242	94	109	84
grep	809	100	**218**	**98**	178	96	75	96

Table 3: Results of other approaches on all the faults

Program	Original Test Suite		Random Selection		Code-coverage-based Approach (k=1)		Clustering-based Approach		Operational Difference	
	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults
print_tokens	4130	100	37	39	6	61	40	84	9	37
print_tokens2	4115	100	37	78	4	90	40	100	6	51
replace	5542	100	37	45	12	33	40	57	18	45
schedule	2650	100	37	48	7	26	40	60	10	33
schedule2	2710	100	37	34	5	26	40	47	13	30
tcas	1608	100	37	46	11	31	40	84	26	55
tot_info	1052	100	37	75	5	53	40	82	9	72
Siemens suite	3115	100	**37**	**52**	**7**	**46**	**40**	**73**	**13**	**46**
Space	13585	100	**345**	**89**	**102**	**80**	**400**	**87**	**63**	**80**
grep	809	100	**219**	**90**	**100**	**91**	**250**	**89**	-	-

Table 4: **Results of our approach on nontrivial faults**

Program	Original Test Suite		Our Approach		Control Rules		Data Rules	
	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults
print_tokens	4130	100	25	89	17	88	8	50
print_tokens2	4115	100	42	100	32	100	10	38
replace	5542	100	75	78	60	71	16	35
schedule	2650	100	32	87	25	84	7	35
schedule2	2710	100	32	62	24	61	9	25
tcas	1608	100	26	72	15	65	12	18
tot_info	1052	100	30	69	21	50	9	55
Siemens suite	3115	100	**37**	**80**	28	74	10	37
Space	13585	100	**376**	**99**	265	89	118	77
grep	809	100	**224**	**95**	183	90	76	92

Table 5: **Results of other approaches on nontrivial faults**

Program	Original Test Suite		Random Selection		Code-coverage-based Approach (k=1)		Clustering-based Approach	
	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults	#Tests	%Faults
print_tokens	4130	100	37	39	6	61	40	84
print_tokens2	4115	100	37	54	5	76	40	100
replace	5542	100	37	42	12	32	40	60
schedule	2650	100	37	26	7	26	40	80
schedule2	2710	100	37	34	5	26	40	47
tcas	1608	100	37	40	11	25	40	82
tot_info	1052	100	37	51	5	23	40	67
Siemens suite	3115	100	**37**	**41**	**7**	**38**	**40**	**74**
Space	13585	100	**376**	**79**	**110**	**63**	**400**	**87**
grep	809	100	**225**	**77**	**103**	**83**	**250**	**81**

Increasing the number of the times that each branch should be covered helps reveal more faults, but is less cost-effective than our approach. Sometimes increasing k may decrease the percentage of revealed faults. Such an observation is due to that the smallest subset of tests that covers each program element at least k times may not be a subset of the smallest subset of tests that covers each program element at least k+1 times.

4.3.3 *Comparison with the Clustering-based Approach*

We next compare the results of our approach with the results of the clustering-based approach [5]. The clustering-based approach uses agglomerative hierarchical clustering to cluster the tests, and then selects one test from each cluster. The main assumption of the clustering-based approach is that a significant number of failures are isolated in clusters of small size. Besides one-per-cluster sampling, there are other possible sampling schemes that aim at finding more failing tests for each fault [6]. As our concern is to increase the likelihood of finding at least one failing test for each fault, we do not compare our approach with these other sampling schemes. We use the binary branch profiles for clustering. We do not use the variable-value profiles since a variable may not be observed in all the tests. We experiment with 10 different values of the number of the clusters. The values are 10 to 100, 100 to 1000, and 50 to 500 in the *Siemens* suite, the *Space* program, and the *grep* program, respectively. We select these values based on the program sizes and the numbers of tests selected by the code-coverage-based approach. The results are plotted in Figures 4 and 5, and shown in Tables 3 and 5.

We observe that the clustering-based approach performs better than random selection in the *Siemens* suite (all faults), the *Siemens* suite (nontrivial faults), and the *Space* program (nontrivial faults), but not better than random selection in the other experiments. There are two main reasons for such results. First, there is a large number of tests in the *Siemens* and the *Space* program. The tests could be highly redundant, especially for the common execution paths. The clustering-based approach may then help to cover more different execution paths. However, there are not a large number of tests in the *grep* program, and these tests are not redundant. In this case, the clustering-based approach may not help cover more different execution paths or isolate the most suspicious tests. Second, there are many trivial faults in the *Space* program and the *grep* program, which may violate the assumption of the clustering-based approach that a significant number of failures are isolated in clusters of small size. Our approach can isolate tests that are suspicious in some program elements. It is more stable in different cases and is better than the clustering-based approach in general.

4.3.4 *Comparison with the Dynamic-Invariant-based Approach*

Finally, we compare our approach with the dynamic-invariant-based approach. Harder et al. [12] proposed the operational difference approach to select tests based on Daikon. It starts with an empty test suite and repeatedly adds new tests if they violate the invariants of the previously selected tests. To control the number of tests, the algorithm terminates when n (n=50 in their experiments) consecutive tests are considered and rejected. They also conducted experiments

Table 6: Efficiency of Our Approach (*seconds*)

Program	LOC	#Tests	Our Approach	Coverage	Clustering
print_tokens	539	4130	1.4	0.4	366.2
print_tokens2	489	4115	5.4	0.7	82.5
replace	507	5542	7.8	1.0	390
schedule	397	2650	1.0	0.2	65.1
schedule2	299	2710	1.3	0.2	93.8
tcas	174	1608	0.7	0.1	38.8
tot_info	398	1052	0.8	0.1	14.7
Siemens suite	400	3115	2.6	0.4	150.2
Space	9564	13585	598.8	5.4	1364
grep	13358	809	92.9	4.9	6.8

on the *Siemens* suite and the *Space* program that we used[3]. We adopt the experimental results from their original paper directly, which are shown in Table 3 and plotted in Figure 4. No result of the operational difference approach in the *grep* program or on the nontrivial faults is available (Daikon cannot be scalable to deal with the *grep* program and therefore poses barriers for us to re-implement and apply the operational difference approach on the *grep* program).

We observe that the operational difference approach performs similarly to the basic code-coverage-based approach. It works well in selecting a small subset of tests that can reveal many faults. However, it misses many other faults at the same time. The operational difference approach may be able to reveal more faults if the termination condition is removed. However, it may then select much more tests due to the false positives in the detected invariants. By using the information of all the unverified tests at hand, our approach can reduce the noise of mined operational models and thus select a reasonably sized subset of tests that can reveal most of the faults.

4.3.5 Efficiency

To evaluate the efficiency of our approach, we measure the time cost of our approach on the three subjects, compared with that of the basic code-coverage-based approach and that of the clustering-based approach. The result is shown in Table 6.

Among the three approaches, the basic code-coverage-based approach is the fastest. It takes at most a few seconds in each of the subject programs. The clustering-based approach is fast in the *grep* program but is not fast in other programs. Basically, the more tests there are, the longer time the clustering-based approach takes. However, there is no clear polynomial relationships between the time cost and the number of tests. The time cost of the clustering approach can be greatly affected by the distribution of the tests. Our approach is fast in the *Siemens* suite and takes reasonable time in the *Space* program and the *grep* program. More specifically, our approach takes about 10 minutes in the *Space* program, which contains about 9564 lines of code and 13,585 tests. However, our approach may not be efficient enough for large programs with large test suites. The main cost of our approach is the time of mining the control rules, which is proportional to the number of tests and to the square of the number of branches. For a large program with 100,000 lines of code and a large test suite that has 13,585 tests, our approach may take about 20 hours. In this case, a possible improvement is to mine only the control rules between the branches in the same modules. We can then greatly reduce the number of candidate control rules and thus the time cost of our approach.

[3] In their experiments, they only have 30 faulty versions for the replace program (31 in our experiments). But this difference can be negligible.

4.3.6 Summary and Discussions

Our results suggest the following observations:

- Our approach is effective in reducing the number of tests while revealing most of the faults. Control rules and data rules are complementary to each other as they reflect different aspects of program behaviors.

- Our approach can select a test suite with a much higher fault-revealing capability than those of the code-coverage-based approach and the dynamic-invariant-based approach, and is more robust and cost-effective than the clustering-based approach. But we note that there are some issues to be considered. The code-coverage-based approach may reveal more faults if more complex coverage profiles are used, which however are more difficult to collect. The clustering-based approach is more flexible for selecting different numbers of tests.

- Our approach takes reasonable time for small to medium sized programs with large test suites. However, it may not be efficient enough for large programs with large test suites. This issue may be alleviated by mining only the control rules between the branches in the same modules. We need to conduct further experiments to investigate this technique.

4.4 Threats to Validity

The threats to external validity primarily include the degree to which the subject programs, faults, and test cases are representative of true practice. The *Siemens* programs are small and the *Space* program is of medium size. Most of the faulty versions involve simple, one or two-line manually seeded faults. Moreover, the tests are manually or randomly generated, while in automated testing, a number of test generation approaches generate tests systematically. These threats could be reduced by more experiments on wider types of subjects with systematically generated tests in future work. The threats to internal validity include the fact that different approaches select different numbers of tests. This fact may make the comparison of fault-revealing effectiveness bias to the approaches that select larger number of tests. To reduce this bias, we present the results of random selection as the baseline. We also evaluate the fault-revealing capabilities of other approaches with different numbers of selected tests.

5. RELATED WORK

In this section, we describe existing work in test selection, which can be classified into five main categories.

Black-box Test Selection. There exist a number of black-box approaches for test selection. In partition testing [19], a test input domain is divided into subdomains based on some criteria, and then developers can select one or more representative inputs from each subdomain. Our approach partitions the tests based on mining common software behaviors, without requiring any knowledge of input domains. When *a priori* specifications are provided for a program, Chang and Richardson [4] used specification coverage criteria to select a candidate set of test cases that exercise new aspects of the specification. Our approach does not require *a priori* specifications.

Code-coverage-based Test Selection. Various kinds of code coverage criteria have been proposed for test selection, such as control-flow testing criteria [14] and data-flow testing criteria [9]. Hutchins et al. [15] reported an experimental study investigating the effectiveness of control-flow and data-flow testing criteria. Their results suggested that test sets achieving high code coverage levels usually showed significantly better fault-detection capability than randomly chosen test sets of the same size. However, the results also indicated that 100% code coverage alone is not a reliable indicator of the effectiveness of a test set. Leon et al. [16] evaluated the effectiveness of complex information flow criteria, which model indirect control/data dependencies between instructions or objects, for test selection. Their results suggested that test sets maximizing complex information flow criteria revealed more faults than test sets maximizing block coverage with substantial additional cost, and in some subjects the profiles could not be generated due to memory constraints. Our approach is based on low overhead profiles, such as branch coverage and data value bounds. Yet our approach can reveal most of the faults by mining and violating implication relationships between branches and constraints of data values.

Clustering-based Test Selection. Dickinson et al. [5] used clustering analysis to partition executions based on structural profiles, and employed sampling techniques to select executions from clusters for result inspection. They further proposed a failure-pursuit sampling approach [6] to enhance the efficiency in finding failures. Moreover, Leon et al. [16] evaluated the effectiveness of clustering analysis based on complex information flow criteria. Their results suggested that the effectiveness of the clustering analysis did not depend strongly on the type of used profiling. Our approach selects tests using the principle of anomaly detection instead of sampling. In addition, our approach also mines common operational models that may guide result inspection.

Behavioral-model-based Test Selection. There are many approaches that build software behavioral models and then classify failures using both failing and passing tests. Haran et al. [11] built behavior models of failures in-house using random forests, so as to help classify remotely-collected execution data. Michail and Xie [18] collected bug and "not bug" reports that consist of event histories from GUI application users. They then built a distance weighted nearest neighbor learner to help users avoid bugs in GUI applications. Bowring et al. [3] classified program executions based on Markov models. They trained the models incrementally in an active-learning paradigm to help test-plan development.

There are also many approaches that mine behavioral models based on dynamic invariant detection for test selection. Hangal and Lam [10] developed DIDUCE that extracts operational models dynamically from long-running program executions. DIDUCE reports all detected violations at runtime and gradually relaxes invariants to allow for new behavior. Harder et al. [12] proposed the operational difference approach to select tests based on Daikon. Their approach repeatedly adds new tests if they violate the invariants of the previously selected tests. Xie and Notkin [28] developed an operational violation approach called Jov for unit-test selection and generation. They mined operational models using Daikon from a set of manually written passing unit tests and selected automatically generated test inputs that violated the operational models. Pacheco and Ernst [22] developed a similar tool named Eclat, which further distinguishes illegal and fault-revealing inputs with some strategies. Due to the limited number of existing passing tests or previously selected tests, the mined dynamic invariants of these approaches could be noisy and thus many model violations could be false positives. Differently, our approach mines common operational models based on a (potentially large) set of unverified tests to reduce the noise.

Xie and Notkin [29] developed an approach for automatically identifying special and common unit tests based on algebraic models. Their approach selects a test as a special test if the test exercises a certain program behavior that is not exhibited by most other tests. Although our approach shares a similar rationale with their approach, our approach mines operational models instead of algebraic models, which are applicable only in object-oriented unit testing.

Regression Test Selection. There has been a lot of work to select, prioritize, or minimize the test cases in a regression test suite [7, 13, 21, 24]. Orso et al. [21] present a technique for Java programs that selects every test case in a regression test suite that may behave differently in the original and modified versions of the software, and yet scales to large systems. Rothermel et al. [24] and Elbaum et al. [7] evaluate a set of prioritization techniques for regression testing, focusing on the goal of increasing the likelihood of revealing faults earlier in the testing process. Hus and Orso [13] propose a test-suite minimization framework based on integer linear programming. Their approach can get optimal solutions for various minimization problems that involve any number of criteria. Although these techniques also select/prioritize a small number of tests that are likely to reveal (regression) faults, they are based on code changes and historical testing information, and have other objectives such as reducing the time of running test cases. Our work focuses on reducing the effort of result inspection in initial testing when test oracles are not available.

6. CONCLUSIONS AND FUTURE WORK

We have proposed an approach for test selection without *a priori* specifications. We propose to mine common operational models, which are often but not always true in all observed traces, from a set of unverified tests. Specifically, we collect branch coverage and data value bounds at runtime and then mine implication relationships between branches and constraints of data values as common operational models after running all the tests. We then select tests that violate all these common operational models greedily. We have evaluated our approach on the *Siemens* suite, the *Space* program, and the *grep* program, compared with code-coverage-based, clustering-based, and dynamic-invariant-based approaches. The experimental results show that our approach can select a test suite with a much higher fault-revealing capability than those of the code-coverage-based approach and the dynamic-invariant-based approach, and is more robust and cost-effective than the clustering-based approach.

We plan to pursue several future directions for improving our approach. First, we plan to combine our approach with automatic test generation tools. Our current experiments are based on existing test suites whose tests are manually or randomly generated. It is valuable to investigate how our approach can work on automatically generated test sets. Second, we plan to conduct experiments on large programs with large test suites. Our current implementation may not be efficient enough for such cases. We would like to evaluate some possible improvements, such as mining only the control rules between the branches in the same modules. Third, we plan to propose common operational models for specific applications based on domain knowledge.

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