

Impact Analysis of Configuration Changes for Test Case Selection

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Abstract— Testing configurable systems, which are becoming prevalent, is expensive due to the large number of configurations and test cases. Existing approaches reduce this expense by selecting or prioritizing configurations. However, these approaches redundantly run the full test suite for the selected configurations. To address this redundancy, we propose a test case selection approach by analyzing the impact of configuration changes with static program slicing. Given an existing test suite T used for testing a system S under a configuration C , our approach decides for each t in T if t has to be used for testing S under a different configuration C' . We have evaluated our approach on a large industrial system within ABB with promising results.

Keywords- configuration testing; test case selection; program slicing; static impact analysis

I. INTRODUCTION

User configurable software systems — systems that can be customized through a set of options by the user — are becoming increasingly prevalent. When these systems are used with different configurations, for the same operations, the systems may behave differently as different parts of the system source code may be executed. As a result, new faults may be revealed [6][17][26]. For example, a conflict between IE7 and the Google toolbar was reported by many users in 2006: users of the IE7 browser suffered from the problem of losing the “Open in New Tab” option in the right-click menu [29]. To solve this problem, the users had to disable or uninstall the Google toolbar. With different configurations (i.e., with Google toolbar enabled or disabled), the system, IE7, behaves differently with the same operation (right clicking on a link). From a testing perspective, if IE7 was tested with the Google toolbar disabled, this incompatibility (hence, a fault) would not be detected. But, if IE7 was tested with the Google toolbar enabled, the fault would be detected.

Therefore, a configurable system should be retested when the system is running with a new, previously untested configuration. Configuration testing can be expensive because configurable systems usually have a large number of possible configurations and test cases. To reduce this expense, one can select (or prioritize) configurations from all possible configurations and select test cases for the selected configurations from an existing test suite. Configuration selection (prioritization) and test case selection are in fact two different dimensions of configuration-aware testing. Approaches exist for selecting [5][19] or prioritizing [17]

configurations. However, these approaches run the full test suite for each of the selected configurations. This causes redundant testing, as different test cases can have exactly the same behavior or coverage with different configurations with no increase in the fault detection capability.

To address this problem, we propose an approach for selecting test cases for the pre-selected configurations of a system. Our approach assumes that a test suite already exists for the system under test and that there are no changes made to the system source code when testing with different configurations. To formalize, let an existing test suite T be used for testing a system S under a configuration C . Our goal of test case selection is to decide for each $t \in T$, if t has to be used for testing S under a different configuration C' . Our study results show that on average, only 20% of the test cases were enough to test a large system developed at ABB, when a configuration under test changes. Considering that large systems usually test hundreds or even thousands of configurations, our approach will lead to substantial savings.

A test case selection approach is *safe* if it always selects a test case $t \in T$ whenever the parts of the system source code executed by t are different under C and C' (i.e., the dynamic code coverage of t in S is different under C and C') [22]. However, in practice, the coverage data of t under C' is unavailable unless we rerun the full test suite T under C' . Therefore, our approach statically approximates, while being conservative, the parts of source code where t executes differently in S under C and C' . Specifically, by analyzing the impact of configuration changes (i.e., the differences between C and C' mapped to the source code) through static *program slicing* [24], our approach selects test cases in T which covered parts of the source code that are statically impacted by the configuration changes. Our study results demonstrate that our static approximation of the dynamic coverage can lead to a safe test case selection. Moreover, unlike most coverage-based test case selection approaches [21][22], which only consider control flow, our approach considers both control and data flow for test case selection. Hence, our approach may select additional useful test cases.

The rest of the paper is organized as follows. In Section II, we describe our approach of test case selection with an illustrative example. In Section III, we describe the implementation of our approach. In Section IV, we present a study to evaluate our approach. In Section V, we present the results of our study. In Section VI, we discuss the limitations and threats to validity of our approach. In Section VII, we discuss the related literature. Finally, in Section VIII, we conclude and identify areas for further research.

II. APPROACH

In this section, we describe our test case selection approach. In Section A, we describe the concept of configurable systems with an illustrative example. In Section B, we define the notations used to describe our approach. In Section C, we define the problem addressed by our approach. In Section D, we provide an overview of our approach. In Section E, we describe our approach in detail using the example we present in Section A. In Sections F-H, we discuss several considerations related to our approach such as the safety criterion of our approach and the opportunities for time savings with the static analysis used in our approach.

A. Configurable Systems

A configurable system has various configurable *options* that control the system's execution. The specific execution of the system depends on the actual *values* supplied for these options. For example, *vim* is an open source editor which is configurable. In *vim*, if the value ON is assigned to one of the *vim*'s configurable options, `more`, *vim* pauses listing a file when the whole screen is filled. If OFF is assigned to `more`, *vim* continues listing a file until finished.

Given a configurable system, let us denote the set of m configurable options by $P = \{P_1, P_2, P_3, \dots, P_m\}$. A particular assignment of values to each configurable option forms a *configuration instance* (henceforth, we use the term configuration and configuration instance interchangeably). For each P_i , let P_i^C represent the value assigned to P_i in configuration C . Hence, the configuration instance C can be represented by the set $\{P_1^C, P_2^C, \dots, P_m^C\}$. An example configurable system, denoted by S , is shown in Figure 2, along with two test cases $T = \{t_0, t_1\}$. S executes three functions (f_1 , f_2 , and f_3) with two configurable options $P = \{P_1, P_2\}$. Figure 1 shows two configurations $C = \{OFF, OFF\}$ and $C' = \{ON, OFF\}$ that are pre-selected for testing S . When S is tested under configuration C , t_0 executes f_2 . When S is tested under configuration C' , t_0 executes f_1 instead. Our example illustrates that a given test case for a configurable system can have different coverage with different configurations.

Configuration C	Configuration C'
P_1 : OFF	P_1 : ON
P_2 : OFF	P_2 : OFF

Figure 1 Pre-selected configurations for testing S

B. Notations

Let $T = \{t_1, t_2, \dots, t_n\}$ be an existing test suite with n test cases used for testing a configurable system S with m configurable options. Let $C = \{P_1^C, P_2^C, \dots, P_m^C\}$ and $C' = \{P_1^{C'}, P_2^{C'}, \dots, P_m^{C'}\}$ be two configurations selected for testing S .

Let $\Delta(C, C')$ denote the set of options whose values are different between C and C' (henceforth, we use Δ to refer to $\Delta(C, C')$). By definition, $\Delta = \{P_i \mid P_i^C \neq P_i^{C'}, i \in [1, m]\}$.

A given configuration option, P_i , can be mapped to its corresponding variables in the source code (see Section IV.B for details). Let $imp(P_i)$ represent the code in S that is statically impacted by the variables corresponding to P_i . Let $imp(\Delta)$ represent the code that is statically impacted by the variables corresponding to options in Δ . Specifically, let imp^f (imp^s) be a set of functions (statements) that are impacted. Let $cov(C, t_i)$ represent the code that t_i executes when S is tested under C . Specifically, let $cov^f(C, t_i)$ ($cov^s(C, t_i)$) be the functions (statements) that t_i covers.

C. Problem Definition

If S is tested with test suite T under C , the problem addressed by our approach is to select $T' \subseteq T$, to test S under C' . In other words, the problem is to determine for each $t_i \in T$, if t_i belongs to T' .

```

1: S(int x){
2:   #if P1           // P1 = ON
3:     if (x == 0)    // test case t0 executes
4:       f1();
5:     if (x == 1)    // test case t1 executes
6:       f3(-29);
7:   #else           // P1 = OFF
8:     if (x == 0)
9:       f2();
10:    if (x == 1)
11:      f3(25);
12:   #endif
13: }
14:
15: void f1(){
16:   printf("Executed only when P1 is ON.");
17: }
18:
19: void f2(){
20:   printf("Executed only when P1 is OFF.");
21: }
22:
23: void f3(int x){
24:   printf("This statement is not controlled
25:         by P1.");
26:   if (x < 0)
27:     printf("This statement is executed
28:           only when P1 is ON.");
29: }

```

Test case t_0 : $S(0)$
Test case t_1 : $S(1)$

Figure 2 An example configurable system with two test cases

D. Overview

The essential goal of testing S under a new configuration C' is to execute the code in S that has not been covered when S is tested under the old configuration C . To achieve this goal, a test case should be selected if it covers different code when executed under C' that is not covered by the same test case when executed under C . Formally, t_i should be selected if the set difference, $cov(C', t_i) - cov(C, t_i) \neq \emptyset$. However, the dynamic $cov(C', t_i)$ is unavailable in practice unless we rerun the full test suite T under C' . Given that t_i and the source code of S are unchanged, the different coverage of t_i in S under C' can only be caused by the

configuration changes. Hence, our approach conservatively approximates the dynamic coverage difference (i.e., $cov(C', t_i) - cov(C, t_i)$), which is not available in practice, using static impact of configuration changes. Accordingly, our approach selects t_i for testing S under configuration C' if t_i covers, under configuration C , parts of the source code that are impacted by the configuration changes (Δ). Formally, our approach selects t_i if $cov(C, t_i) \cap imp(\Delta) \neq \emptyset$. Code coverage can be measured at different granularities, such as statement, block, or function. Our approach uses function-level granularity because a function is typically considered as a unit in testing. Hence, our approach selects t_i for testing S under C' if

$$cov^f(C, t_i) \cap imp^f(\Delta) \neq \emptyset \quad (1)$$

E. Details

Our approach involves four steps as shown in Figure 3: (1) computing configuration differences between C and C' , (2) computing the functions impacted in S by the configuration differences, (3) computing the function coverage for each test case t_i in T when S is tested under C dynamically, and (4) selecting t_i based on Equation (1).

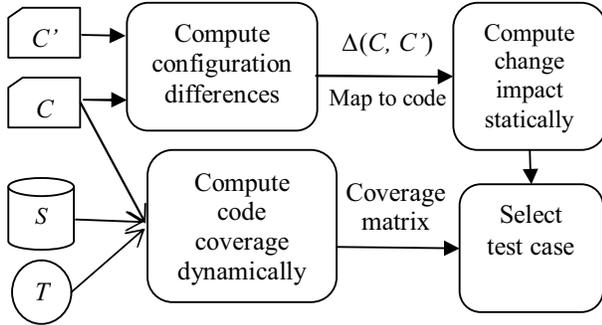


Figure 3 Our approach of test case selection

Next, we describe these steps with the example configurable system S shown in Figure 2.

1) Computing Configuration Differences (Δ)

For each option P_i ($i \in [1, m]$), our approach compares $P_i^{C'}$ with P_i^C : if they are different, P_i is included in set Δ . In our example, $m=2$ and $\Delta = \{P_1\}$.

2) Computing Configuration Change Impact ($imp^f(\Delta)$)

For each $P_i \in \Delta$, our approach maps P_i to its corresponding variable(s) in the source code (see Section IV.B for details) and then computes $imp^f(P_i)$. By combining all impact sets,

$$imp^f(\Delta) = \bigcup_{P_i \in \Delta} imp^f(P_i) \quad (2)$$

In our example, $imp^f(\Delta) = imp^f(\{P_1\}) = \{f_1, f_2, f_3\}$, since P_1 impacts f_1, f_2 , and f_3 .

3) Computing Code Coverage

While executing T under C , our approach computes $cov^f(C, t_i)$ for each $t_i \in T$. The left half of TABLE I shows the resulting function coverage matrix. Value 1 (0) represents that a function is covered (not covered) by a test case under a specific configuration. In our example, $cov^f(C, t_0) = \{f_2\}$ and $cov^f(C, t_1) = \{f_3\}$.

4) Selecting Test Cases

According to Equation (1), our approach selects t_0 since $cov^f(C, t_0) \cap imp^f(\Delta) = \{f_2\} \neq \emptyset$. For the same reason, t_1 is also selected.

TABLE I FUNCTION COVERAGE MATRICES UNDER C AND C'

	C		C'	
	t_0	t_1	t_0	t_1
f_1	0	0	1	0
f_2	1	0	0	0
f_3	0	1	0	1

TABLE II STATEMENT COVERAGE MATRICES UNDER C AND C'

	C		C'	
	t_0	t_1	t_0	t_1
f_1	0	0	16	0
f_2	20	0	0	0
f_3	0	24	0	24,25,26

F. Safety Criterion of Our Approach

Our test case selection approach is safe if it selects all test cases in T that have different coverage in S under C and C' . But the dynamic coverage difference for t_i , i.e., $(cov(C, t_i) - cov(C', t_i)) \cup (cov(C', t_i) - cov(C, t_i))$, which we denote by $\langle cov(C, t_i) - cov(C', t_i) \rangle$, is unavailable in practice. Hence, as discussed in Section D, a full recall of the dynamic coverage difference by the static configuration change impact is a necessary and sufficient condition for the safety of our approach. Specifically, the *safety criterion* can be described as follows. For each t_i , the code which is statically impacted by configuration changes must contain the code that is covered by t_i under C' but not by t_i under C and vice versa. Formally,

$$imp(\Delta) \supseteq \langle cov(C, t_i) - cov(C', t_i) \rangle, t_i \in T \quad (3)$$

or

$$imp(\Delta) \supseteq \bigcup_{t_i \in T} \langle cov(C, t_i) - cov(C', t_i) \rangle \quad (4)$$

For the LHS of Equation (4), $imp(\Delta)$ is computed with Equation (2) at the function granularity. Next, we discuss how the granularity used for measuring coverage affects the RHS of Equation (4), and hence, the accuracy of the safety criterion.

First, we consider the case where coverage is measured at the function granularity. The function coverage matrices for S under C and C' with $T = \{t_0, t_1\}$ are shown in TABLE I. From this table, $\langle cov^f(C, t_0) - cov^f(C', t_0) \rangle = \{f_1, f_2\}$ and $\langle cov^f(C, t_1) - cov^f(C', t_1) \rangle = \emptyset$. According to Equation (4), the safety criterion is $imp^f(\Delta) \supseteq \{f_1, f_2\}$. However, this criterion is not accurate since f_3 should also be included in the RHS of Equation (4). In our example, t_1 covers f_3 under both C and C' , but at the statement level, it executes more statements in f_3 when tested under C' . This difference is not captured when the coverage is measured at the function granularity.

Next, we consider the case where coverage is measured at the statement granularity. The statement coverage matrices

for S under C and C' with $T=\{t_0, t_1\}$ are shown in TABLE II. Each entry represents the line numbers covered by a particular test case in a particular function. The bold font numbers indicate that t_1 covers no statements of f_1 but covers statement 24 of f_3 . From this table, $\langle cov^s(C, t_0) - cov^s(C', t_0) \rangle = \{16, 20\}$, which belongs to functions f_1 and f_2 ; and $\langle cov^s(C, t_1) - cov^s(C', t_1) \rangle = \{25, 26\}$, which belongs to f_3 . According to Equation (4), the safety criterion is $imp(\Delta) \supseteq \{f_1, f_2, f_3\}$, which accurately captures the coverage differences. In Section IV, we present an empirical study that verifies the safety of our approach.

Although coverage measured at the statement-level granularity is appropriate for the safety analysis of our test selection approach, our approach measures coverage at the function-level as defined in Equation (1), because coverage measured at finer granularities (e.g., statement-level) incurs more cost, while coverage measured at coarser granularities (e.g., file-level) leads to imprecision, and hence, too many false positives in test selection. A function-level granularity makes a trade-off between cost and precision.

G. Static Analysis Used by Our Approach

Theoretically, we expect that the impact set generated with expensive static analysis settings should have better recall of dynamic coverage differences compared to the impact set generated with less expensive static analysis settings. As discussed in Section F, the recall of the dynamic coverage differences by the static impact decides the safety of our approach. Hence, by default, our approach uses the most expensive static analysis settings available. However, the time overhead may be prohibitive with expensive static analysis settings, especially for larger systems. In Section IV, we present a study comparing the impact sets generated with different static analysis settings.

H. Computing Impact of Multiple Option Changes

Besides considering less expensive static analysis settings to lower the cost of our approach, we also explore other opportunities to save the time incurred by the static analysis. Let $\Delta = \{P_{ch1}, \dots, P_{chk}\} \subseteq P$ ($1 \leq k \leq m$), where $P_{ch1} \dots P_{chk}$ denote k options that change between C and C' . When the change involves multiple option changes ($k > 1$), we compute $imp(\Delta)$ as the union of impact of each option in Δ (Equation (2)). We call this the *union* method. Alternatively, we may merge variables corresponding to each option in Δ as one single input to static analysis. Our approach then computes the impact of all changes at once. We call this the *multi-select* method. Compared to the union method, the multi-select method may largely reduce the redundant overhead of rerunning static analysis for each option change. The union method invokes the analysis multiple times but the multi-select method invokes the analysis only once. However, the multi-select method may be used only if it is a conservative approximation of the union method for computing the impact, formally,

$$imp(P_{ch1} + \dots + P_{chk}) \supseteq \bigcup_{i=1}^k imp(P_{chi}).$$

In Section IV, we present a study comparing the impact sets generated by the *union* method and *multi-select* method.

III. IMPLEMENTATION

Our approach employs a static analysis tool, *CodeSurfer* [28], for computing configuration change impact. *CodeSurfer* uses forward program slicing to compute $imp(P_i)$. Forward slicing, required for computing the impact sets, depends on several static analysis parameters such as pointer analysis, context/flow sensitivity, non-local analysis, and slicing dependency analysis.

TABLE III STATIC ANALYSIS SETTINGS USED IN OUR EXPERIMENTS

	<i>H</i>	<i>L</i>	<i>H_cd</i>	<i>H_dd</i>	<i>L_cd</i>	<i>L_dd</i>
<i>non-locals</i>	<i>yes</i>	<i>no</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
<i>dependencies</i>	<i>both</i>	<i>both</i>	<i>cd</i>	<i>dd</i>	<i>cd</i>	<i>dd</i>

We did several experiments to determine that the static analysis parameters non-local analysis and slicing dependency analysis had the most significant impact on the time and safety of our test selection approach. Hence, in our experiments, we do not consider other static analysis parameters and conservatively use the most expensive value available for them (for example, for pointer analysis, we always uses the Andersen’s algorithm [1]).

The non-locals of a function include all the global variables and indirectly accessed variables used or modified by a function. With *CodeSurfer*, the non-local analysis (in short, *non-locals*) is configurable and can be shut off. There are three options for slicing dependency analysis (in short, *dependencies*): control-dependence only (*cd*), data-dependence only (*dd*), and both (*both*). Depending on the option, the forward slicing follows control-dependence edges only, data-dependence edges only, or both edges. With two choices for *non-locals* (*yes/no*) and three for *dependencies* (*cd/dd/both*), there are six static analysis settings (set of static analysis parameters) altogether, as shown in TABLE III (*H* and *L* represent *H_both* and *L_both* respectively). These different settings decide the expense of our static analysis. For example, setting *H* is the most expensive, while *L_cd* and *L_dd* are the least expensive.

IV. STUDY

In this section, we present a study to examine the safety of our test case selection approach on *make* [30]. We also present a study on a large industrial system developed at ABB, to explore several opportunities to reduce the time taken by the static analysis used by our approach. We have the following research questions:

- RQ1. Is our approach safe for test case selection when using the most expensive static analysis settings?
- RQ2. What percentage of functions is impacted by a configurable option change? Hence, what percentage of testing cost can our approach potentially save?

- RQ3. How do the impact sets generated with less expensive static analysis settings compare with those generated by the most expensive static analysis settings?
- RQ4. How do the impact sets computed by the *multi-select* and the *union* method compare?

A. Study Subjects

We study the safety of our approach on *make* [30], an open source program written in C. *make* is a widely popular and general purpose tool used to compile programs. The source code for *make* (version 3.78.1) is available at the GNU website [30]. There are about 15,000 uncommented lines of code in the source code of this version.

We also apply our approach to a core component (called *ABB1* hereafter) of a large real-time embedded software system developed at ABB. *ABB1* consists of 1.18 MLOC written in C/C++. It contains 20,432 functions across 58 modules. Each module defines a subsystem that implements different functionalities of the system.

In some configurable systems such as *make* and *vim*, each configurable option is mapped to a unique global variable, which is used throughout the system. Different from these systems, *ABB1* stores the values of its configurable options in a database. When an option is to be used, its value is retrieved from the database and assigned to a locally defined variable. Therefore, a configuration option in *ABB1* may map to multiple variables in the system. Specifically, there are 129 configurable options used in *ABB1*, distributed among 394 variables. Some options map to only one variable while others map to multiple variables ranging from 2 to 37. Code coverage data is unavailable for *ABB1* (we discuss this issue in Section VI.B).

B. Study of the Safety of Our Approach

By default, our approach uses the most expensive static analysis settings available with *CodeSufEr*. Based on Equation (4), we examine the safety of our approach by comparing $imp^f(\Delta)$ with $\langle cov^s(C, t_i) - cov^s(C', t_i) \rangle$. The whole process of our safety study is broken into multiple steps: (1) creating configurations and test cases, (2) executing test cases under different configurations, (3) computing change impact, $imp^f(\Delta)$, with static analysis, (4) computing code coverage differences, $\langle cov^s(C, t_i) - cov^s(C', t_i) \rangle$, and (5) comparing change impact with code coverage differences. Each step is described next.

1) Creating configurations and test cases

The test suite for *make* was obtained from the Software Infrastructure Repository (SIR) [7]. This test suite has been previously studied in a related research [16]. We modified the test suite by separating out test cases with configurable options, leaving behind 540 test cases in the test suite. We also select 12 configurable options and create seven configuration instances using a commonly used sampling approach [6][17].

2) Executing test cases

We run 540 test cases under each configuration on a GNU/Linux machine. We instrument the code using *gcov* [30], run the tests, and record the statement coverage data as defined in Section II.F and shown in TABLE II. Recall that though our test case selection approach measures coverage at the function granularity, for our study of safety, the coverage is measured at the statement granularity (see Section II.F).

```

1: struct command_switch
2: {
3:     int c;        /* The switch character. */
4:     enum         /* Type of the value. */
5:     {
6:         flag,
7:         flag_off,
8:         string,
9:         positive_int,
10:        floating,
11:        ignore
12:    } type;
13:
14:    char *value_ptr; /* Pointer to the
15:                    value-holding variable. */
16:    unsigned int env:1;
17:    unsigned int toenv:1;
18:    unsigned int no_makefile:1;
19:
20:    char *noarg_value; /* Pointer to value
21:                      used if no argument is given. */
22:    char *default_value; /* Pointer to
23:                        default value. */
24:
25:    char *long_name; /*Long option name. */
26:    char *argdesc;
27:    char *description;
28: };
29:
30: /* The table of command switches. */
31: static const struct command_switch
32: switches[] =
33: {
34:     ...
35:     ...
50:    {'s', flag, (char *) &silent_flag, 1, 1,
36:     0, 0, 0, "silent", 0, ("Don't echo
37:     commands")},
38:     ...
39:     ...
40: }

```

Figure 4 Data structure and values of options for *make*

3) Computing configuration change impact

There are seven configurations, resulting in 21 pairs of different configurations. For each pair, we first identify the differences (i.e., Δ) between configurations in that pair. Next, we map the options in Δ to their corresponding variables in the source code. Our mapping process for *make* is illustrated as follows.

Figure 4 shows the *main.c* file of *make* (some comments and lines are omitted for clarity). Lines 1 to 27 define a data structure, *command_switch*, which is used for holding configuration option information for *make*. The first member in the data structure, *c*, holds the character

(symbol) of the option (Line 3). The third member, `value_ptr`, is used to hold the value of the option (Line 14). Rest of the code from Line 30 onwards defines a concrete object of this structure, `switches`, which is an array containing multiple options. Each item in the `switch` array represents an option. For example, `s` is an option (defined in Line 50) that determines if the various compile commands are echoed when `make` compiles a program. The value of this option is held in the variable `silent_flag`. Hence, we regard `silent_flag` as the corresponding variable in the source code for option `s`. Following the same procedure, every option in Δ is mapped to its corresponding variable in the source code. By running *CodeSurfer* with H setting on each option in Δ , we get $imp^f(\Delta)$ (Equation (2)).

4) Computing coverage difference

For each configuration, there is a corresponding statement coverage matrix (see TABLE II for an example) generated from `gcov`. For each pair of configurations, we compute $\langle cov^s(C, t_i) - cov^s(C', t_i) \rangle$ for each test case t_i .

5) Safety of our approach

For each pair of configurations, we compare $imp^f(\Delta)$ with the union of all $\langle cov^s(C, t_i) - cov^s(C', t_i) \rangle$ where $i \in [1, 540]$.

C. Study on *ABBI*

For the research questions related to the study of *ABBI*, RQ2-RQ4, the dependent variable is measured as the percentage of the functions impacted in *ABBI*.

In *ABBI*, there are 129 configurable options distributed among 394 variables. Our static analysis module takes each variable as an input and analyzes it with six settings (defined in Section III): H , H_{cd} , H_{dd} , L , L_{cd} , and L_{dd} . These settings come from the combination of two independent variables: I_1 (H , L) and I_2 (cd , dd , $both$). *CodeSurfer* generates 2364 (394×6) impact sets in total. Each impact set consists of the impacted lines, impacted functions, and the number of impacted lines and functions.

For RQ2, we calculate the percentage of the functions that is impacted by a single configurable option change, with the H setting. We group the impact sets by configurable options. For each option, we count the total number of impacted functions across all variables and calculate the percentage over all 20432 functions in *ABBI*.

For RQ3, our goal is to compare the impact sets generated with less expensive static analysis settings and the most expensive static analysis setting possible. As described in the beginning of this section, there are six impact sets generated by *CodeSurfer* corresponding to six setting combinations of I_1 and I_2 . For each impact set, we calculate the percentage of impacted functions for each variable. We compare these impact sets with respect to I_1 and I_2 .

For RQ4, the independent variable is the method of calculating impact of multiple option changes, which can either be the *union* method or the *multi-select* method (defined in Section II.H). Particularly, we examine

configuration changes that involve only two changed options between C and C' . We study changes involving only a pair of option changes as any changes with three or more option changes can be seen as multiple pairs of option changes. With 129 options in *ABBI*, there are over 8000 pairs of options. Since the computation with *union* or *multi-select* method is independent of the options being computed, it suffices to study a random selection of option pairs. Hence, we randomly select 10 pairs, (P_1^i, P_2^i) ($i \in [1, 10]$). For each pair i , let $\{a_{1i}, a_{2i}, \dots, a_{pi}\}$ and $\{b_{1i}, b_{2i}, \dots, b_{qi}\}$ represent variables mapped from P_1^i and P_2^i , respectively. The numbers of the variables for each option (denoted as p and q) in a pair are shown in TABLE IV. For each pair, *CodeSurfer* generates $imp(a_{1i}+a_{2i}+\dots+a_{pi}+b_{1i}+b_{2i}+\dots+b_{qi})$ by the *multi-select* method and $(\bigcup_{k=1}^p imp(a_{ki})) \cup (\bigcup_{k=1}^q imp(b_{ki}))$ by the *union* method. By default, *CodeSurfer* uses the most expensive H setting for both methods.

TABLE IV NUMBER OF VARIABLES CORRESPONDING TO EACH OPTION IN THE SELECTED OPTION PAIRS

pair i	1	2	3	4	5	6	7	8	9	10
p	1	1	2	1	1	9	1	1	1	5
q	1	1	1	2	6	1	6	1	2	1

V. RESULTS

In this section, we present the results of our study with respect to each research question, presented in Section IV. All *impact* is measured in terms of the *percentage of impacted functions*.

A. RQ1: Safety of Our Approach

For RHS of Equation (4), our approach runs the test suite T (540 test cases) under each configuration, with `gcov` to collect statement coverage, $cov^s(T, C_i)$, $i \in [1, 7]$. For each pair of configurations C and C' ($C, C' \in \{C_i\}$, $i \in [1, 7]$ and $C \neq C'$), we compute the functions whose code coverage is different in C and C' , are shown in TABLE V. The number ranges from 0 to 101. As for the LHS of Equation (4), the number of impacted functions computed by our static analysis ($imp^f(\Delta)$) is 294 for all pairs.

TABLE V NUMBER OF FUNCTIONS OF DIFFERENT COVERAGE

C_1, C_2	91	C_2, C_4	82	C_3, C_7	97
C_1, C_3	99	C_2, C_5	9	C_4, C_5	90
C_1, C_4	43	C_2, C_6	10	C_4, C_6	90
C_1, C_5	99	C_2, C_7	101	C_4, C_7	55
C_1, C_6	99	C_3, C_4	90	C_5, C_6	1
C_1, C_7	23	C_3, C_5	0	C_5, C_7	97
C_2, C_3	9	C_3, C_6	1	C_6, C_7	97

We compare the sets of functions whose code coverage is different in C and C' , with the impact sets. In 9 among 21 cases, $imp^f(\Delta) \supseteq \bigcup_{t_i \in T} \langle cov^s(C, t_i) - cov^s(C', t_i) \rangle$, that is, satisfying the safety criterion. Other cases all share the same exception: there are only two functions that belong

to $\cup_{t_i \in T} < cov^s(C, t_i) - cov^s(C', t_i) >$ but not in $imp^f(\Delta)$. The first one is the function `perorr_with_name`. However, `perorr_with_name` calls function `error`, which is contained in $imp^f(\Delta)$. Our approach will select all test cases that cover `error`, and the test cases covering `perorr_with_name` are only a subset of them. In other words, our approach will not miss any test case that covers `perorr_with_name`. The second function is the function `fatal`. Let F be a set of functions that call `fatal`, then `fatal` can only be covered by test cases that cover functions in F . In our study, all functions that call `fatal` are contained in $imp^f(\Delta)$. Our approach will select all test cases that cover functions in F , which contains all test cases that may cover `fatal`. Hence, the fact that functions `perorr_with_name` and `fatal` are not contained in $imp^f(\Delta)$ does not affect the test case selection safety of our approach. In summary, we have empirically confirmed that the impacted functions computed by our static analysis are a conservative approximation of coverage differences, and hence our test case selection approach is expected to be safe.

Moreover, the set of impacted functions computed statically is larger than the set of functions in the dynamic coverage difference. This may be because that our static analysis considers both control and data flow, while the dynamic coverage data only considers the control flow.

B. RQ2: Impact of Configuration Changes

To address RQ2, we examine the impact of changing a single configurable option. Figure 5 shows a box plot for the change impact for all 129 options. Changes to most of the options only impact less than 10% of all the functions in *ABBI*. The largest impact by an option change is no more than 20% of all the functions. In *ABBI*, the test cases are evenly distributed among the units (functions) that are tested. In other words, each function under test is tested by almost the same number of test cases. Given this even distribution of test cases, our results indicate that only about 20% of the test cases may have to be selected for *ABBI* if a configurable option changes. Considering that large systems usually have hundreds or even thousands of configurations to test, our approach will lead to substantial savings.

C. RQ3: Impact Sets and the Expense of Static Analysis

In RQ3, we examine whether our approach computes significantly smaller impact with less expensive static analysis settings (i.e., less expensive settings of I_1 and I_2), compared to that with the highest setting. TABLE VI shows the statistics for the impact computed by our approach with six different settings. At a first glance, it appears that the impact sets computed by *CodeSurfer* with the less expensive settings are much smaller than that with the higher setting. For example, the average (mean) impact is 3.318% with H , and only 0.686%, 0.005%, and 0.046% with L , H_cd , and H_dd respectively.

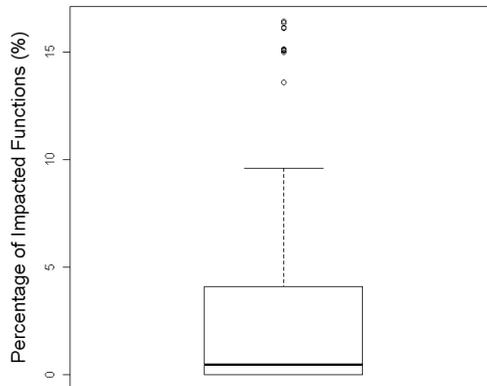


Figure 5 Impact computed with setting H (per option)

We examine if the differences in the values in different impact sets are statistically significant. In other words, we examine if setting I_1 and/or I_2 has statistically significant effect on the impact results. We apply a *two-factor ANOVA test* [12] on all our impact results. TABLE VII shows our results. The first column lists each individual setting followed by the interaction between the settings denoted by “ $I_1 \times I_2$ ”. The last column shows the probability of the null hypothesis: *there is no significant effect of this setting (or of the interaction between settings)*. The probability of $I_1 \times I_2$ is smaller than 2.2×10^{-16} (shown in bold font), which is smaller than a typical α level of 0.05. This indicates that we should reject the null hypothesis and accept the alternative hypothesis: *there is a significant interaction between I_1 and I_2* . Due to this significant interaction, we are unable to examine the *main effects* of each setting; instead, we examine their *simple effects* [12].

TABLE VI IMPACT (%) COMPUTED WITH VARIOUS SETTINGS

	L	L_cd	L_dd	H	H_cd	H_dd
max	13.590	0.005	0.049	16.450	0.005	8.374
3 rd qtr.	0.661	0.005	0.020	4.126	0.005	0.020
mean	0.686	0.005	0.014	3.318	0.005	0.046
median	0.230	0.005	0.015	0.499	0.005	0.015
1 st qtr.	0.015	0.005	0.005	0.025	0.005	0.005
min	0.005	0.005	0.005	0.005	0.005	0.005

TABLE VII ANOVA TEST RESULTS FOR RQ2

	Degree of Freedom	F value	Probability (>F)
I_1	1	94.76	$< 2.2 \times 10^{-16}$
I_2	2	210.52	$< 2.2 \times 10^{-16}$
$I_1 \times I_2$	2	91.45	$< 2.2 \times 10^{-16}$

1) Simple Effects of I_1 : H vs. L

First, we examine the effect of I_1 . Figure 6 shows the box plots comparing the impact computed with different settings of I_1 (H and L), for all variables, grouped by I_2 . The figure shows that for the “*both*” setting of I_2 (left box plots), impact computed with the H setting is a superset of the impact

computed with the L setting. For the “ cd ” and “ dd ” settings of I_2 (middle and right box plots), the impact computed with H and L are similar. We also apply a t -test [12] on the impact set of the first group (i.e., “ $both$ ” setting of I_2). The result indicates that the difference is statistically significant. Based on this examination, if we choose setting “ $both$ ” for I_2 , *CodeSurfer* with less expensive settings of I_1 (i.e., L) will compute impact sets that are significantly smaller.

2) Simple Effects of I_2 : both vs. cd vs. dd

Next, we examine the effect of I_2 . Figure 7 shows the box plots comparing the impact computed with different settings of I_2 (cd , dd , and $both$), for all variables, grouped by I_1 . Our results show that impact sets with “ $both$ ” are significantly larger than those with “ cd ” and “ dd ”, both for H (left box plots) and L (right box plots). We also apply a t -test on the impact sets of both groups. The results are consistent with what we observed from the figure. Based on our study, less expensive setting of I_2 (i.e., cd or dd) will compute impact sets that are significantly smaller.

3) Summary

From our analysis of both I_1 and I_2 , to compute the impact of configuration changes for *ABBI*, less expensive static analysis settings result in significantly smaller impact. As a result, it appears that from the perspective of test selection safety, it is better for *CodeSurfer* to be run with H setting, since the settings of both I_1 and I_2 can result in significantly different impact sets. However, if the resource constraints only allow *CodeSurfer* to be run with a less expensive setting, among all other five choices (H_{cd} , H_{dd} , L , L_{cd} , and L_{dd}), L will result in impact that has better recall of the coverage differences. This indicates that considering both control and data dependencies may be more important than nonlocal analysis for the safety of test case selection when using less expensive settings.

D. RQ4: Multi-select vs. Union Method

TABLE VIII shows the number of impacted functions computed by the *union* and the *multi-select* methods for the 10 pairs of configurable options. While seven impact sets are identical, for the remaining three, impact sets computed by the *union* method are smaller compared to that computed by the *multi-select* method.

TABLE VIII NUMBER OF IMPACTED FUNCTIONS COMPUTED BY DIFFERENT METHODS

pair	1	2	3	4	5
Union	97	2199	2108	6	3063
Multi-select	97	2284	2193	6	3063
pair	6	7	8	9	10
Union	297	3060	2108	3060	274
Multi-select	297	3060	2193	3060	274

Our results also show that for each pair, the impacted functions computed by the *union* method is a subset of the impacted functions computed by the *multi-select* method. This indicates that it is safe to calculate the impact of multiple option changes with the *multi-select* method

instead of the *union* method. The *multi-select* method incurs lesser time overhead with no significant loss in safety.

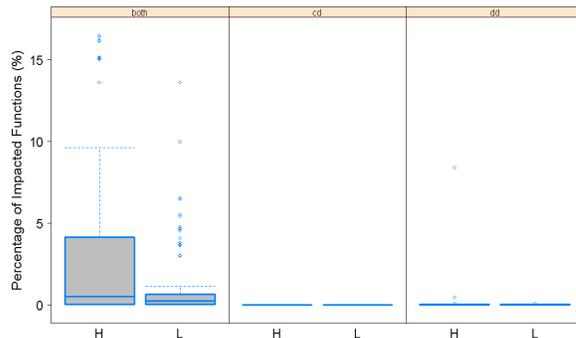


Figure 6 Impact by different setting of I_1 (grouped by I_2)

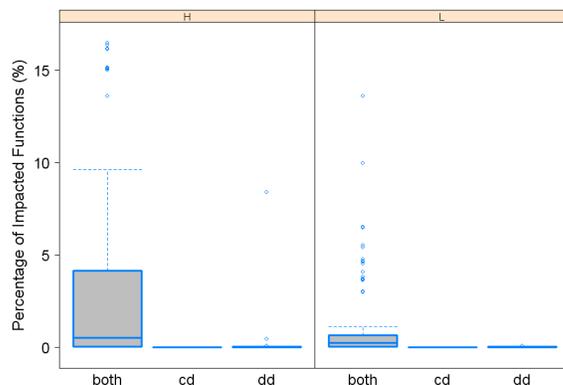


Figure 7 Impact by different setting of I_2 (grouped by I_1)

VI. DISCUSSION

In this section, we discuss the limitations and threats to validity related to our approach.

A. Configuration Mappings

We have examined the safety of our approach with an empirical study on *make*. However, we should notice that the safety is also dependent on the correctness and completeness of the mappings between configurable options and their corresponding variables in the source code. In *make*, the mapping of configurable options to variables in source code is straightforward. However, in complex systems, it is often difficult to accurately map configurable options to the variables in the source code. The accurate mapping requires a thorough understanding of the system specifications and a good communication with the system developers. The configuration of *ABBI* is complex and the mappings between each option and its variables were manually derived. We have carefully read through the configuration specification and the comments in source code that describe how configuration options are defined, loaded, and used in the system. But we might have still missed some options and their corresponding variables.

B. Applicability and Generality

The study of different static analysis settings help us decide if we can save cost by choosing less expensive static setting without losing significant impact. However, the correlation between the static analysis expense and the size of impact set is system dependent, because different systems define and implement configurations differently. Therefore, our results may not generalize to other systems. Furthermore, though the static analysis with lower settings of both I_1 and I_2 result in significantly smaller impact sets compared to that with the highest setting, it does not necessarily mean that the selections based on lower settings are unsafe. We will investigate the interplay between static analysis and safety as a part of our future work.

1) Test Case Selection without Coverage Data

For some systems, the function coverage data ($cov(T,C)$) might not be available. For such systems, either the testing was done without the coverage tool or the coverage tool was not compatible with the third-party applications used by the system. In such cases, some approximations may be used for the function coverage data. For example, in *ABB1*, test cases were created for testing different functionalities of the system. Hence, we can map each test case to the functionalities that it tests. Furthermore, particular system functionality is implemented in one or more functions. Hence, we can also map the functionality to its functions. Given the mappings between test cases and functionalities, and between functionalities and functions, we can approximate the set of functions that are “covered” by a particular test case even when the actual function coverage information is unavailable.

VII. RELATED WORK

In this section, we introduce related literature on test case selection, configurable system testing, and impact analysis of configuration changes.

A. Test Case Selection

In traditional regression testing, given an initial version of a system S and a test suite T , a subset of tests T' has to be selected from T to test a new version S' (due to source code changes) of S . *Ad-hoc* selection approaches [10] are not safe because they may miss some test cases that reveal faults in the modified program. *Safe* test case selection approaches [21] select *all* test cases in the original test suite, which can reveal faults in the modified program. Rothermel et al. present a safe regression test selection approach [22] based on analyzing the Control Flow Graphs (CFG) of S and S' .

Our approach is complementary to traditional regression testing approaches. While regression testing approaches select test cases between multiple versions of a system (when the code changes), our approach selects test cases for testing a single version of a system (no code changes) under different configurations.

B. Testing Configurable Systems

As introduced in Section I, configuration selection (prioritization) and test case selection for the selected configurations are two different dimensions of testing configurable systems. To our best knowledge, existing approaches [5][17][19] only deal with the first dimension, i.e., configuration selection and prioritization. In contrast, our approach deals with the second dimension, i.e., test case selection for the pre-selected configurations.

Combinatorial Interaction Testing (CIT) [4] is commonly used for sampling configurations. Many studies [6][11] examine the effectiveness of CIT to model configurations and the impact of configurations on testing. Moreover, Reisner et al. [19] show that most code can be covered if a system is tested by sampling its configurations by considering lower levels of interactions between options.

Approaches for regression testing of configurable systems [9][26][27] study the issue of improving the effectiveness of configuration sampling for testing a new version of system. Qu et al. [17] study the impact of configurations across multiple versions of a system and prioritize configurations to improve early fault detection.

Product lines are commonly regarded as configurable systems. Scheidemann [24] proposed an approach to select a small set of vehicle configurations for product verification, such that the successful verification of this small set implies the correctness of the entire product family.

However, none the aforementioned approaches deal with selecting test cases for testing a system under sampled or prioritized configurations.

Recently, Nanda et al. [14] proposed an approach to support regression testing of systems that exhibit frequent changes in non-code parts of the system. They focus on changes to databases and simple configuration files. However, their approach focuses on a simple model of property files, and hence, cannot handle complex configurations. In comparison, our approach handles different types of configurations by mapping configurable options to the corresponding variables in the source code. Moreover, as our approach analyzes the configuration changes on source code through conservative static program slicing, our impact results can lead to a safe test selection.

C. Impact Analysis of Configuration Changes

Dor et al. [8] investigate the impact of configuration changes in an *ERP* system through program slicing [24]. The impact information is then used by the system’s customers and maintainers to understand the change and select the right values for the configuration options. However, their approach does not handle test case selection. Also, their impact analysis tool was specifically designed for *ERP* systems, and hence, their approach is not generically applicable to other types of systems. In contrast, our approach is not limited to any particular type of systems.

Robinson and White [18] propose an approach and develop a tool, *Firewall*, to analyze the impact of

configuration changes for selecting test cases. Their approach only identifies local impact which is one calling level away from the change. But in fact, as evidenced by our empirical study (presented in Section V.C), configuration impact usually propagates globally beyond one calling level, across different functions, files, and modules. Therefore, their test case selection based on local impact is not safe.

VIII. CONCLUSIONS

In this paper, we proposed an approach to select test cases when configuration under test changes. Our approach uses the dynamic coverage data of the test suite under previously tested configuration and the static impact of configuration differences for selecting test cases. Our results demonstrate that our approach is safe. Our results also indicate that only about 20% of test cases need to be selected for *ABB1* when a configuration under test changes, thereby reducing the testing cost. As a part of future work, we will study the different static analysis settings [2] and test-selection safety tradeoffs that might be possible with our approach. We will also explore how configuration selection and test case selection for the selected configurations can be combined.

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REFERENCES

- [1] L. O. Andersen. Program analysis and specialization for the C programming language. PhD thesis. DIKU University of Copenhagen, 1994.
- [2] M. Acharya and B. Robinson. Practical change impact analysis based on static program slicing for industrial software systems. *International Conference on Software Engineering (ICSE)*, 2011, pp. 746-755.
- [3] R. S. Arnold. Software Change Impact Analysis. *IEEE Computer Society Press*, 1996.
- [4] D. M. Cohen, S. R. Dalal, M. L. Fredman, and G. C. Patton. The AETG system: an approach to testing based on combinatorial design. *IEEE Transactions on Software Engineering (TSE)*, 23(7), 1997, pp. 437-444.
- [5] M. B. Cohen, M.B. Dwyer, and J. Shi, Constructing interaction test suites for highly-configurable systems in the presence of constraints: A greedy approach, *IEEE Transactions on Software Engineering (TSE)*, 34(5), 2008, pp. 633-650.
- [6] M. B. Cohen, J. Snyder, and G. Rothermel. Testing across configurations: Implications for combinatorial testing. *ACM SIGSOFT Software Engineering Notes*, 2006, pp. 1-9.
- [7] H. Do, S. G. Elbaum, and G. Rothermel. Supporting controlled experimentation with testing techniques: An infrastructure and its potential impact. *Empirical Software Engineering: An International Journal*, 10(4), 2005, pp. 405-435.
- [8] N. Dor, T. Lev-Ami, S. Litvak, M. Sagiv, and D. Weiss. Customization change impact analysis for ERP professionals via program slicing. *International symposium on Software Testing and Analysis (ISSTA)*, 2008, pp. 97-108.
- [9] S. Fouche, M. B. Cohen, and A. Porter. Towards incremental adaptive covering arrays. *Symposium on the Foundations of Software Engineering (FSE)*, 2007, pp. 557-560.
- [10] T. L. Graves, M. J. Harrold, J.-M. Kim, A. Porter, and G. Rothermel. An empirical study of regression test selection techniques. *IEEE Transactions on Software Engineering (TSE)*, 10(2), 2001, pp. 184-208.
- [11] D. Kuhn, D. R. Wallace, and A. M. Gallo. Software fault interactions and implications for software testing. *IEEE Transactions on Software Engineering (TSE)*, 30(6), 2004, pp. 418-421.
- [12] R. O. Kuehl. Design of Experiments: Statistical Principles of Research Design and Analysis. Brooks/Cole, 2000.
- [13] M. Nita and D. Notkin. White-box approaches for improved testing and analysis of configurable software systems. *International Conference on Software Engineering (ICSE)*, 2009, pp. 307-310.
- [14] A. Nanda, S. Mani, S. Sinha, M.J. Harrold, and A. Orso. Regression testing in the presence of non-code changes. *International Conference on Software Testing (ICST)*, 2011, pp. 21-30.
- [15] A. Orso, T. Apiwattanapong, J. Law, G. Rothermel, and M. J. Harrold. An empirical comparison of dynamic impact analysis algorithms. *International Conference on Software Engineering (ICSE)*, 2004, pp. 491-500.
- [16] X. Qu, M. B. Cohen, and K. M. Woolf. Combinatorial interaction regression testing: a study of test case generation and prioritization. *IEEE International Conference on Software Maintenance (ICSM)*, 2007, pp. 255-264.
- [17] X. Qu, M.B. Cohen, and G. Rothermel. Configuration-aware regression testing: an empirical study of sampling and prioritization. *International Symposium on Software Testing and Analysis (ISSTA)*, 2008, pp. 75-85.
- [18] B. Robinson and L. White. Testing of user-configurable software systems using Firewalls. *International Symposium on Software Reliability Engineering (ISSRE)*, 2008, pp. 177-186.
- [19] E. Reisner, C. Song, K-K. Ma, J. S. Foster, and A. Porter. Using symbolic evaluation to understand behavior in configurable software systems. *International Conference on Software Engineering (ICSE)*, 2010, pp. 445-454.
- [20] G. Rothermel, R. Untch, C. Chu, and M. J. Harrold. Prioritizing test cases for regression testing. *IEEE Transactions on Software Engineering (TSE)*, 27(10), 2001, pp. 929-948.
- [21] G. Rothermel and M. J. Harrold. Analyzing regression test selection techniques. *IEEE Transactions on Software Engineering (TSE)*, 22(8), 1996, pp. 529-551.
- [22] G. Rothermel and M. J. Harrold. Empirical studies of a safe regression test selection technique. *IEEE Transactions on Software Engineering (TSE)*, 24(6), 1998, pp. 401-419.
- [23] X. Ren, F. Shah, F. Tip, B. G. Ryder, and O. Chesley. Chianti: A tool for change impact analysis of Java programs. *ACM SIGPLAN Conference on Object-oriented Programming, Systems, Languages, and Applications (OOPSLA)*, 2004, pp. 432-448.
- [24] K.D. Scheidemann. Optimizing the Selection of representative configurations in verification of evolving product lines of distributed embedded systems. *Software Product Line Conference (SPLC)*, 2006, pp.75-84.
- [25] M. Weiser. Program slicing. *International Conference on Software Engineering (ICSE)*, 1981, pp. 439-449.
- [26] C. Yilmaz, M. B. Cohen, and A. Porter. Covering arrays for efficient fault characterization in complex configuration spaces. *IEEE Transactions on Software Engineering (TSE)*, 31(1), 2006, pp. 20-34.
- [27] I.-C. Yoon, A. Sussman, A. Memon, and A. Porter. Effective and scalable software compatibility testing. *International symposium on Software Testing and Analysis (ISSTA)*, 2008, pp. 63-74.
- [28] *CodeSurfer*. GrammaTech Inc. <http://www.grammatech.com/products/codesurfer>
- [29] B. Moolenaar. Lavasoft support forums. <http://www.lavasoftsupport.com>
- [30] Free Software Foundation. *gccov*. <http://gcc.gnu.org/onlinedocs/gcc/Gcov.html>, 2007.
- [31] GNU *make*. <http://www.gnu.org/software/make/>