Spectrum-based Software Fault Localization: A Survey of Techniques, Advances, and Challenges

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Abstract

Despite being one of the most basic tasks in software development, debugging is still performed in a mostly manual way, leading to high cost and low performance. To address this problem, researchers have studied promising approaches, such as Spectrum-based Fault Localization (SFL) techniques, which pinpoint program elements more likely to contain faults. This survey discusses the state-of-the-art of SFL, including the different techniques that have been proposed, the type and number of faults they address, the types of spectra they use, the programs they utilize in their validation, the testing data that support them, and their use at industrial settings. Notwithstanding the advances, there are still challenges for the industry to adopt these techniques, which we analyze in this paper. SFL techniques should propose new ways to generate reduced sets of suspicious entities, combine different spectra to fine-tune the fault localization ability, use strategies to collect fine-grained coverage levels from suspicious coarser levels for balancing execution costs and output precision, and propose new techniques to cope with multiple-fault programs. Moreover, additional user studies are needed to understand better how SFL techniques can be used in practice. We conclude by presenting a concept map about topics and challenges for future research in SFL.

Keywords: Fault localization, spectrum-based, coverage-based, debugging, survey.

1 Introduction

Program faults are an inevitable consequence of writing code. Faults occur for various reasons: typing errors, misunderstanding software requirements, wrong values assigned to variables, or absence of code to cope with some unpredicted condition. During the testing phase or in the field, a fault is revealed when a program presents an unexpected behavior (known as failure). Once a failure occurs, the two-step debugging process begins. First, a developer inspects the code to locate the failure’s cause. Second, s/he fixes the fault.

Fault localization is a costly activity in the software development process. Testing and debugging can account for up to 75% of development costs. In practice, fault localization is performed manually; developers observe failing test cases and then search the source code for faults. They use their knowledge of the code to investigate excerpts that may be faulty. The most frequent debugging

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practices include inserting print statements and breakpoints, checking the stack trace, and verifying failing test cases. Since these manual processes can be expensive and ad-hoc [67], approaches that automate fault localization are valuable for software development cost reduction.

Several techniques for automating fault localization have been proposed in the last decades [7, 66, 147, 166, 117]. These techniques use testing data to suggest which program entities, such as statements, predicates, definition-use associations, and call functions [117], are more likely to be faulty. Using fault localization results, developers can inspect the code to search for bugs guided by a set of suspicious entities.

1.1 Motivation and scope

This survey’s main scope is to analyze fault localization techniques that use dynamic information from test execution, known as Spectrum-based Fault Localization (SFL) or Coverage-based Fault Localization. These techniques have achieved significant results when compared to other fault localization techniques and often present low overhead costs.

Despite the growing number of available SFL techniques, they are still unknown to practitioners. Many factors explain this. In general, SFL techniques have been evaluated using a set of known programs. In most cases, they are small and contain a single fault by version. In practice, though, developers tackle large programs with an unknown number of faults. To complicate things, these bugs may interact and produce different failures depending on the failing test case. User studies in which developers debug real faulty programs with the support of SFL techniques could shed light on such techniques’ effectiveness and efficiency, but they are scarce. As a consequence, the existing SFL techniques are rarely used to automate software companies’ debugging processes [111].

This survey presents a comprehensive view of state-of-the-art SFL techniques proposed from 2005 to October 2017. It describes the most recent advances and challenges, which includes: approaches and testing data used by SFL techniques; the number and characteristics of faults; benchmark programs used in experiments; costs of SFL techniques; new ways to provide fault localization results to developers; and practical use of SFL techniques.

We discuss and summarize features, limitations, and challenges, indicating future directions for improving SFL. The techniques are classified according to their debugging support strategies and relevance to the main topics. We also present a concept map [108] of the SFL area, addressing the relationships among topics, their roles, and challenges for future research. We believe the information in this survey is useful to both researchers interested in understanding and improving fault localization techniques, especially Spectrum-based Fault Localization, and practitioners interested in improving their debugging processes.

The remainder of this paper is organized as follows. Section 2 presents an overview of the fault localization area, including its history, and the terminology used in the area. We describe the scope, criteria to select relevant papers for this survey and the main topics regarding fault localization in Section 3. In Section 4 we present different fault localization approaches, focusing on spectrum-based techniques. Section 5 shows the different spectra used by SFL techniques. Concerns regarding faults are shown in Section 6. The programs used to evaluate the techniques are presented in Section 7. Section 8 shows the concerns related to the use of testing information in fault localization. The practical use of fault localization is presented in Section 9. We discuss main challenges and future directions in Section 10. Related works are shown in Section 11. Finally, we draw our conclusions in Section 12.
2 Concepts and seminal studies

In this section, we define the main terms used by fault localization studies and present a historical overview of seminal works.

2.1 Terminology

Due to the diversity of studies on fault localization, several terms have been used to define similar concepts. In what follows, we clarify terms and synonyms used in the studies addressed in the survey.

Faults, errors, and failures

Faults, errors, and failures represent three stages in the execution of a program during which an unexpected behavior occurs. The IEEE Standard 610.12 [60] defines fault, error, and failure as follows. Fault is an incorrect step, process, or data definition in a computer program. A fault is inserted by a developer who wrote the program. A fault is also called bug or defect.

Error is a tricky term, which is also sometimes used to refer to a fault, failure, or mistake. In its particular sense, an error is a difference between a computed value and the correct value [60]. The term is often used to indicate an incorrect state during program execution. Thus, an error occurs when an executed fault changes the program state. Other terms used to express error are infection and anomaly.

Failure describes a system’s inability to perform its function at the expected requirements [60]. A failure is observed as an unexpected output, which occurs when an error in a program state leads to a wrong output. A synonym for failure is unexpected behavior. Crashes are failures that interrupt program executions and thus have an apparent behavior. Mistakes are human actions that produce faults [60].

Real and seeded faults

The literature on fault localization refers to two categories of faults. Seeded faults are those intentionally inserted for monitoring detection [60]. Faults can be manually inserted for experimental purposes, or by using mutation testing [38]. Fault seeding is also known as fault injection. Conversely, real faults are those that naturally occur during software development.

Ranking metrics

Ranking metrics are used in fault localization to calculate the likelihood that program entities will be faulty. The studies on fault localization use different terms to refer to ranking metrics: technique, risk evaluation formula, metric, heuristic, ranking heuristic, coefficient, and similarity coefficient.

Program entity

A program entity is a part of a program. It comprises any granularity of a program, from a statement to a subprogram. Program entities include statements, blocks, branches, predicates, definition-use associations, components, functions, program elements, and program units.
Spectrum-based fault localization

Program spectra [118], also known as code coverage, can be defined as a set of program entities covered during test execution [117]. Spectrum-based fault localization uses information from program entities executed by test cases to indicate entities more likely to be faulty. There are several synonyms of program spectrum used in the literature, such as code coverage, testing data, dynamic information, execution trace, execution path, path profile, and execution profile.

Suspicious program entities

Program entities more likely to contain faults are called suspicious, suspected, candidate, and faulty elements.

2.2 A Brief History of Debugging Techniques

Unfortunately, developing programs without making mistakes is nearly impossible. Therefore, debugging is an inherent programming activity. The use of the word bug originates in Thomas Edison’s time. It was used to indicate flaws in engineering systems [72]. In the late 1940s, the Mark II computer at Harvard University suddenly stopped. Technicians found that a dead moth had shorted out some of the computer’s circuits, and taped the bug into the machine’s logbook [72]. The term debug was then associated with the activities of finding and fixing program faults. According to Araki et al. [11], the most primitive debugging practice entails inserting print statements in the code to verify the state of variables.

Despite advances, in practice fault localization has changed little over time. Most of the techniques used by developers today were proposed in the 1960s [6], and earlier debugging tools originate from the late 1950s [46]. Some examples are Gilmore’s debugging tool (called TX-O Direct Input Utility System) [49], FLex Interrogation Tape (FLIT) [129], and DEC (Digital Equipment Corporation) Debugging Tape (DDT) [77]. The TX-O Direct Input Utility System influenced subsequent, more sophisticated debugging tools. It was based on the idea of moving the debugging program to the computer’s memory, making it possible to verify and modify registers during the execution. As the first tool to implement the concept of a breakpoint, FLIT also allows modifying the program during its execution. DDT evolved from FLIT for the PDP-1 computer. Another advance in the 1960s debugging tools was the conditional breakpoint, which permits a breakpoint’s execution only when it reaches some specific condition. The first tools to provide code tracing were those for high-level languages, such as debugging tools for Lisp and Prolog. Beyond code tracing, debugging tools for high-level languages do not present any additional features compared to those for assembly [46]. Indeed, the debugging tools used in industrial settings today do not differ much from the above-described techniques.

Nevertheless, several techniques have been proposed for automating debugging, most of them for fault localization. Balzer presented a tool called EXtendable Debugging and Monitoring System (EXDAMS) [14], which was one of the first tools to allow either backward or forward navigation through the code. Its visualization provides control-flow and data-flow information using graphics, such as a tree structure of the execution at some point of interest. The execution data was stored in a history tape. However, EXDAMS did not use this information to suggest statements more likely to contain bugs, which would help developers in fault localization. Nagy and Pennebaker proposed one of the earliest techniques to automatically identify bugs by comparing successive versions of a program, considering that the changes in code are bug corrections [99]. Thus, their technique provides bug patterns to aid debugging.
Some previous techniques tried to understand a program’s whole behavior. These techniques depend on correct specifications of programs, which in practice are very difficult to obtain. Adam and Laurent proposed a tool called LAURA [4]. The tool receives a program model represented by graphs. To identify faults, LAURA makes program transformations to compare the original program with the program model. Johnson and Soloway proposed a tool called PROgram UnderSTanding (PROUST) [65], which receives programming plans, the intentions that a developer has to write the code, and a program. PROUST has a knowledge base of programming plans that it compares to the input plan’s goals. PROUST then generates a diagnostic output of bugs found in the code, including an explanation of mistakes causing the bugs.

Assertions are another strategy used to automate debugging. Fairley proposed a debugging tool called Assembly Language Assertion Drive Debugging INterpreter (ALADDIN) [47], which uses breakpoint assertions instead of breakpoint locations. The breakpoint assertion is executed when a wrong value occurs in the program state at a certain point. Assertions can be helpful for detecting errors in some circumstances, especially for functions that calculate values or must contain a certain number of elements. However, it is not always possible to use assertions to detect all incorrect program behaviors, which may be infeasible for large and complex programs.

Shapiro proposed two algorithms to detect incorrect program procedures [125]: one for deterministic programs, and another for non-deterministic programs. These algorithms ask an oracle if the output for a given input to a procedure is correct, repeating the process for the following program execution procedures. The first procedure with an incorrect output is the incorrect procedure. The algorithms proposed by Shapiro [125] suppose that developers perform the role of the oracle for each executed procedure, which may be an error-prone and time-consuming activity for long-running and large programs. The author suggests that a possible way to automate the oracle is to accumulate a knowledge database of developers’ answers. Fritzson et al. implements such an idea using category partition testing [48].

Korel proposed a tool called Program Error-Locating Assistant System (PELAS)—the first fault localization technique based on program dependence [75]. PELAS asks developers about a behavior’s correctness and uses the answer to indicate possible fault locations. Program dependence data is used to guide the developer navigation in searching possible fault sites. The author states that the backtracking reasoning used (based on program dependence) is an abstraction of experienced developers’ intuitive processes. PELAS can narrow the amount of code a developer must verify.

Program slicing, a technique based on program static information, was proposed by Weiser [139]. The technique generates subsets of a program, called slices, which contain the expected program behavior. Thus, a developer focuses his/her attention on a reduced part of a program. Program slicing can be used for debugging, or to change the code, depending on the specification of program elements or variables of interest, called slicing criterion. A slice is composed of elements that relate to such a criterion. Korel and Laski proposed dynamic slicing to reduce slice size [76]. Dynamic slices are composed of only executed statements. Although dynamic slicing reduces the amount of code to be inspected, the remaining code is still excessive, which makes it impractical.

The use of testing data for fault localization has grown over the last few decades. Collofello and Cousins proposed the first fault localization technique that uses paths executed by tests to indicate faulty sites [25]. They used ten ranking metrics to calculate the likelihood that program elements will be faulty, wherein a program element is a decision-to-decision path (DD-path)—the code chunk between two predicates. The technique uses a set of DD-paths from passing test cases, and DD-paths from a single failing test case, to indicate DD-paths likely to contain faults. Agrawal et al. proposed execution dices for fault localization [7]. An execution dice is a set of program basic blocks formed by the difference between two dynamic slices—one from a failing test case and the other one from a passing test case. Even reducing the amount of code returned, the dices still contain a large number
of blocks for inspection.

Other approaches were proposed in the early 2000s. Jones et al. present a technique called Tarantula that uses a homonym ranking metric to calculate statements’ suspiciousness \[66\]. The suspiciousness values are calculated according to the frequency of the statements in passing and failing test cases. These statements are classified and shown in a graphic visualization form, using different colors according to their suspiciousness values. Zeller applied the Delta Debugging (DD) algorithm to find causes of failures that occur during execution, using the difference in program states (variables and values) between one passing and one failing run \[166\]. These differences are reduced to obtain a minimal set that causes the failure. Such a subset is deemed the failure’s cause. DD differs from other works by using program states instead of program elements.

Some techniques proposed for fault localization use information from static analysis. These techniques are independent of testing and can be used to inspect all paths in a program. Static analysis advantageously assures that a program is fault-free by exploring all its possible interactions. However, the performance of these techniques is tied to formal proofs of program correctness. Such proofs are infeasible in practice, even for small general purpose programs. Wotawa et al. used Model-Based Diagnosis (MBD), which was originally used for electronic digital circuits, for debugging software faults \[147\]. MBD generates a logical model from the source code and uses logical reasoning to obtain a minimal set of statements that explain the existing faults. Hovemeyer and Pugh proposed a tool that uses bug patterns from Java to locate bugs automatically \[57\]. The tool statically analyzes a program to search for bug patterns; they proposed fifty bug patterns. The technique generates a list of warnings (statements that might be faulty). Rutar et al. discuss tools that use static analysis to automatically locate bugs \[122\].

In this brief historical overview, we described many different approaches to improve the localization of program faults. However, print statements and symbolic debuggers are prevalent in practice. What is the reason for such a state of affairs in debugging? Primarily, many of the techniques do not scale to programs developed in industry. Another reason is that the techniques are not assessed in situ; that is, in real debugging situations. Parnin and Orso showed that the developer behavior might differ from that expected by the proponents of localization technique \[111\].

The rest of this survey is dedicated to Spectrum-based Fault localization. SFL utilizes testing data to highlight suspicious pieces of code. By using data already collected during testing, SFL tends to have lower overhead in comparison to other debugging techniques. We discuss the more relevant results and challenges to industry adoption of SFL in the following sections.

### 3 Selection of studies and scope

This survey presents a comprehensive overview focused on techniques that use SFL. We searched for studies published from 2005 to October 2017 in the following digital libraries: ACM Digital Library, IEEE Xplore Digital Library, SpringerLink, and SciVerse Scopus - Elsevier.

The studies included in this survey were published in journals and conferences with acknowledged quality. We combined database searches with backward snowballing \[61\] to expand the search for relevant results. We selected studies that proposed new techniques to perform fault localization based on program spectrum data. Only works that carried out an experimental evaluation of the proposed technique were included. We also considered studies that compare existing fault localization techniques, that propose improvements to program spectra data (e.g., testing information), and that assess practical use of SFL techniques. When available, only the extended versions of the papers were analyzed.

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1. Explain means components that are logically related to faulty behaviors.
We selected papers after reading the title and abstract of all studies returned. In doubtful cases, other sections of the papers were read to decide whether they should be included. Selected papers were read in full. For the backward snowballing process, we first selected papers based on the description of such works from source papers. Then, we applied the same criteria to select the most relevant studies.

We classified the papers regarding the research topics and challenges that characterize these studies. Figure 1 shows the taxonomy that represents the main challenges addressed in this survey, which were classified into the following major topics: SFL Techniques, Spectra, Faults, Programs, Testing data, and Practical use. Most of the studies intersect more than one topic. For each topic, we present studies that present the most distinguishable contributions. Sections 4 to 9 present the studies according to the topics presented above.

4 Spectrum-based Fault Localization techniques

Spectrum-based Fault Localization techniques propose several strategies to pinpoint faulty program entities. Most of them rank suspicious entities by using ranking metrics or statistical techniques. Artificial intelligence approaches are also used for fault localization. Other SFL techniques are based on execution models that indicate suspicious entities by comparing passing and failing executions. Some studies combine previous techniques, while others compare the effectiveness of several techniques.

There are SFL techniques that make use of other program analysis information, like program dependencies, execution graphs, and clustering of program entities. In this section, we present SFL techniques, exploring the strategies mentioned above to improve fault localization.

4.1 Metric-based techniques

Metric-based techniques are those that use ranking metric formulas to pinpoint faulty program entities. Most of the SFL techniques use or propose ranking metrics to improve fault localization. To determine correlations between program entities and test case results, these ranking metrics use program spectrum information derived from testing as input. Each program entity receives a suspiciousness score that indicates how likely it is to be faulty. The rationale is that program entities frequently executed in failing test cases are more suspicious. Thus, the frequency in which entities are executed in failing and passing test cases is analyzed to calculate its suspiciousness score. There are ranking metrics specifically created for fault localization, and other metrics were adapted from areas such as molecular biology. Some studies perform experiments comparing ranking metrics.
Works that propose or use ranking metrics are presented hereafter.

**Tarantula** [66] was one of the first techniques proposed for SFL. Its formula is shown in Table 1. For each program entity, Tarantula calculates the frequency in which a program entity is executed in all failing test cases, divided by the frequency in which this program entity is executed in all failing and passing test cases. Tarantula has been used in several studies. Jones et al. use Tarantula to calculate the suspiciousness score of statements for their parallel debugging technique [67] (see Subsection 6.1). Ali et al. use Tarantula to evaluate characteristics that can influence fault localization techniques [8]. Furthermore, Tarantula has been used as a benchmark by several other techniques [142, 151]. Table 1 shows some of the main ranking metrics used for SFL. We use the following nomenclature in Table 1: \( c_{ef} \) indicates the number of times a program entity \((c)\) is executed \((e)\) in failing test cases \((f)\), \( c_{nf} \) is the number of times a program entity is not executed \((n)\) in failing test cases, \( c_{ep} \) is the number of times a program entity is executed by passing test cases \((p)\) and \( c_{np} \) represents the number of times a program entity is not executed by passing test cases.

Some studies propose ranking metrics similar to Tarantula for techniques that use other coverage types. Masri uses a Tarantula-like ranking metric for the DIFA coverage [94] (see Section 5). This ranking metric is combined with another that considers only the percentage of executions in failing test cases. The final suspiciousness score averages the two. Wang et al. use a ranking metric similar to Tarantula for basic blocks [137]. Chung et al. propose a ranking metric for predicates that is also similar to Tarantula [24].

In addition to Tarantula, other techniques based on similarity formulas have been proposed in the last years. Abreu et al. propose using Ochiai and Jaccard similarity coefficients as fault localization ranking metrics [1]. Ochiai was originally used in molecular biology, and Jaccard was used by Chen et al. to indicate faulty components in distributed applications [21]. The results of Abreu et al. [1] show that both Ochiai and Jaccard outperform Tarantula on fault localization effectiveness. From these results, several works have used Ochiai [124, 42]. Jaccard was not used on its own by any study presented in this survey. However, it was used in studies that compare the performance of several ranking metrics [103, 151, 92]. Ochiai and Jaccard do not take into account program entities that are not executed in passing test cases \((c_{np})\). Thus, these ranking metrics assign more discriminative suspiciousness values for the well-ranked entities than those suspiciousness values assigned by Tarantula. The ranking metric Zoltar proposed by González [50] is a variation of Jaccard. Its formula increases, even more, the suspiciousness of program entities that are more frequently executed in failing test cases. Zoltar was developed to detect errors in

<table>
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<th>Ranking metric</th>
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<tr>
<td>Tarantula</td>
<td>( \frac{c_{ef}}{c_{ef} + c_{nf} + c_{np}} )</td>
<td>Ochiai</td>
<td>( \sqrt{(c_{ef} + c_{nf})(c_{ef} + c_{ep})} )</td>
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<tr>
<td>Jaccard</td>
<td>( \frac{c_{ef}}{c_{ef} + c_{nf} + c_{ep}} )</td>
<td>Zoltar</td>
<td>( \frac{c_{ef}}{c_{ef} + c_{nf} + c_{np} + 10000} \cdot \frac{c_{nf}}{c_{ep}} )</td>
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<td>( O^p )</td>
<td>( c_{ef} ) - ( \frac{c_{ep}}{c_{ef} + c_{np} + 1} )</td>
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<td>( -1 ) if ( c_{nf} &gt; 0 ), otherwise ( c_{np} )</td>
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<td>Kulczynski2</td>
<td>( \frac{1}{2} \left( \frac{c_{ef}}{c_{ef} + c_{nf}} + \frac{c_{ef}}{c_{ef} + c_{ep}} \right) )</td>
<td>McCon</td>
<td>( \frac{c_{nf} - c_{np} - c_{nf}c_{ep}}{(c_{ef} + c_{nf})(c_{ef} + c_{ep})} )</td>
</tr>
<tr>
<td>DStar</td>
<td>( \frac{c_{ef}}{c_{nf} + c_{cp}} )</td>
<td>Minus</td>
<td>( \frac{c_{ef}}{c_{ef} + c_{cp}} - \frac{c_{nf}}{c_{nf} + c_{cp} + 1} - \frac{c_{np}}{c_{np} + c_{cp}} )</td>
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Xu et al. propose a Tarantula-like ranking metric called Minus KBC (MKBC) for their KBC coverage [153] (see Section 5). The difference is that MKBC subtracts the percentage that a KBC is not executed in failing test cases, and divides by the percentage that such KBC is not executed for all executions (see Table 1). This complementary frequency is called noise; it decreases the importance of non-execution in the analysis.

Naish et al. propose two new ranking metrics optimized for single-fault programs, called O and $O^p$ [104]. Assuming the existence of a single fault, only statements that are executed in all failing test cases are fault candidates. Kulczynski2 (from Artificial Intelligence) and McCon (from studies of plankton communities) are ranking metrics that have presented better results for programs with two simultaneous faults [102]. Wong et al. presented a technique called DStar [144], which is a modified version of the Kulczynski ranking metric. The idea behind DStar is that the execution trace of each statement through test cases can be viewed as an execution pattern. Thus, the similarity between statements more frequently executed by failing test cases can pinpoint the faulty ones.

Other techniques propose different strategies in conjunction with ranking metrics. Jeffrey et al. presented a technique that replaces values of statements in failing executions [62]. If a failing execution then passes, such statement is classified between the most suspicious. The technique uses values observed in a statement from all executions, and only one value for each statement is replaced per execution. Naish et al. presented an approach that assigns different weights to statements in failing test cases according to the number of statements in an execution [102]. The lower the number of commands, the greater the chance that one of them will be faulty.

Xie et al. proposed a technique that forms two groups of statements: one with statements that the failing test cases executed at least once, and another with statements that these test cases did not execute [150]. The first group’s statements receive suspiciousness scores. Bandyopadhay and Ghosh proposed a technique that assigns different weights for test cases according to the similarity of a passing and a failing test case [16]. The more similar a passing test case is, the higher its weight. The rationale is that a fault is more distinguishable since that there are few differences between the failing and the passing test cases.

4.2 Statistics-based techniques

Statistical techniques have also been applied in fault localization, and are used in the same manner as metric-based techniques. However, each statistical technique uniquely deals with testing information. Liblit et al. proposed using conditional probability to evaluate predicates during program executions for fault localization [85]. Predicates that are evaluated only as true in failing executions are deemed as more suspicious. They calculate the probability that a predicate $p$ with value true causes a failure ($\text{Failure}(p)$), and the probability that an execution of $p$ causes the failure ($\text{Context}(p)$). The difference between such values (Importance) indicates the suspiciousness of each predicate. Liu et al. proposed a statistical fault localization technique called SOBER [87] that considers the results of predicates evaluated as true multiple times per execution for several executions. They used Bernoulli distribution to model each predicate’s result for each execution. Then, conditional probability for passing and failing executions is used to calculate a predicate’s bug relevance.

Nainar et al. proposed the idea of complex predicates as bug predictors for fault localization [100]. Complex predicates are formed by two predicates that are evaluated in each execution using boolean function operations (conjunction and disjunction). They argued that combinations of predicates can enhance fault localization when the predicates that form the complex predicates are
already good bug predictors. Baah et al. studied the use of causal inference for fault localization [13], aiming to enhance fault localization by isolating causal effects that occur between program entities in a program dependence graph. This isolation can improve the values assigned to faulty entities by reducing noise caused by other program elements in the presence of failures. They used causal graphs concepts to identify entities that are independent in a program dependence graph. They also proposed a linear regression model to calculate the causal effect of statements on failures.

Zhang et al. proposed a technique for using a non-parametric statistical model for fault localization [177]. They observed that the distribution of predicates during executions is non-normal (see Section 5). To calculate the suspiciousness of predicates, they consider the difference between the probability density function of a random variable of passing test cases and a failing test case. Wong et al. use a crosstab-based technique for fault localization [145]. The chi-square test was used to calculate the null hypothesis that an execution is independent of the coverage of a statement. Chi-square is applied to deal with categorical variables; in this work, such values are the test case results (pass and fail), and the presence of a statement in an execution (executed or not). Thus, they measured the dependency between an execution and a statement.

Zhang et al. used maximum likelihood estimation and linear regression to tune in SFL lists [174]. They used previously known lists and bug positions, assuming a symmetric distribution of bug positions in such lists. Thus, they estimated a position to adjust the lists. Xue and Namin applied the odds ratio to SFL [156]. The odds ratio is a statistical technique often used in classification and text mining problems. The odds ratio measures the strength or the weakness of a variable (a statement executed or not executed) associated with an event (a passing or a failing test case). Xu et al. proposed the use of probabilistic cause-effect graphs (PCEG), which is obtained using program dependence graph of failing test cases [152]. The technique applies PCEG (a Bayesian network variation) to calculate the probability of statements to be faulty. The most suspicious statements are those more strongly connected to other suspicious statements.

4.3 Artificial intelligence-based techniques

Artificial Intelligence (AI) techniques have been applied for fault localization, using program spectrum data as input for classifying suspicious program elements. Liu et al. proposed a technique that uses graph mining and support vector machines (SVM) for fault localization [86]. Program executions are represented as behavior graphs. Each node of a behavior graph is an executed function. The graphs are labeled with their execution result. Graph mining is applied to discover frequent subgraphs, which are features used to classify the graphs. SVM is applied to classify incorrect and correct executions. Thus, a sequence of bug-relevant functions is presented for a developer’s inspection. Nessa et al. applied N-gram analysis, from Data Mining, for fault localization [106]. The technique generates N-grams, subsequences of statements, from program spectra. The technique uses Association Rule Mining to calculate the conditional probability that each N-gram relates to faulty executions. A list of the most suspicious statements is obtained from the most suspicious N-grams.

The technique proposed by Murtaza et al. [97] uses a decision tree as a heuristic to indicate the origin of a fault. The technique identifies patterns of function calls related to the fault. Wong et al. developed a Radial Basis Function neural network (RBF-NN) for fault localization [143]. The RBF-NN is modeled as statements representing the input neurons. Thus, the neural network acts as a ranking metric, in which the neural network individually evaluates each statement to determine its suspiciousness. Lucia et al. assessed the use of association measures for fault localization [91]. They

2 We are considering Artificial Intelligence as a broader area, which includes Data Mining and Machine Learning techniques.
evaluated 20 association measures commonly used in data mining and statistics, such as Yule-Q, Yule-Y, and odds ratio. They modeled the problem as the strength of association between each entity’s execution (and non-execution) and failures. Two association measures had a performance comparable to Ochiai: information gain and cosine. However, none of these association measures resulted in significant improvements for SFL.

Roychowdhury and Khurshid proposed a technique based on Feature Selection from Machine Learning [121]. They used two well-known methods, RELIEF and RELIEF-F, to classify statements according to their relevant potential to be faulty. The coverage matrix obtained from the test execution is applied to RELIEF and RELIEF-F. Each executed statement is considered a feature, and each coverage of a certain test case is a sample. Thus, the technique captures the diversity of these statements’ behaviors as they relate to bug execution. Zhang and Zhang applied Markov Logic Network from machine learning to fault localization [169]. They modeled the problem by considering dynamic information (program spectra), static information (control-flow and data-flow dependence), and prior bug knowledge (locations of similar bugs found in the past). The technique is developed for single-bug programs.

4.4 Execution models

Another strategy used by SFL techniques is to build execution models from test executions. Such models represent patterns of failing and/or passing executions. Execution models are used to identify entities that meet or flee from an expected pattern. There are also models represented by graphs of execution. Wang and Roychoudhury proposed a technique that generates a passing run from a failing run [135]. The technique consists of toggling the results of branches in the failing run until obtaining a passing run. The outcome is a list of branches that were modified in the passing run. The toggling process starts on the last branch executed, and more branches are incrementally toggled until a passing run is located. A developer must check whether the generated run is correct. Zhang et al. also proposed a technique that toggles branches of a failing run to generate a passing one [171]. However, only one predicate is toggled per execution. The process starts on the last executed predicate and can be applied backward in all the following predicates until generating a passing run.

The technique proposed by Zhang et al., called Capture Propagation [176], performs the propagation of suspicious values between related code blocks using graph models. The technique generates two mean edge profiles, one for all passing test cases, and another for all failing test cases. These profiles are used to obtain the suspiciousness for each edge. A propagation ratio of an edge is calculated according to the number of edges that enter in a successor block. Finally, the suspiciousness value of the predecessor block is obtained from the sum of the propagation ratio of all successor blocks for which the predecessor block has an edge. The technique presented by Mariani et al. [93], detailed in Section 5, uses a behavior model of method calls from passing test cases. This model is compared with interactions from failing test cases to indicate suspicious interactions. Liu et al. proposed a technique in which the model is composed of messages from objects within the same class [89].

Wan et al. proposed a behavioral model that is constructed using two different coverage types: objects of an OO program and calls occurred inside each object [134]. A model is a sequence of objects and calls in execution traces of failing and passing test cases. The model contains two levels: the objects, and its internal calls. Two values from each entity are used to compose a suspicious value: coverage and violation. The violation means that entities from failing executions that are not present in the model are more suspicious, and entities which are present in the model from passing executions are less suspicious. Dandan et al. proposed a probabilistic model of state dependency
for fault localization [28]. State dependency relates to predicate statement, which can be true or false. The technique calculates the probability that a predicate is true or false in passing and failing executions. Two probability models are generated: one for passing executions, and another for failing executions. The probability of control dependent statements is based on the probability of their parent statements. The suspiciousness value for each statement is then calculated using the models’ probability values, and the outcome is a list of the most suspicious statements.

Laghari et al. proposed a technique that indicates methods more likely to be faulty [79]. The technique uses information from integration testing, capturing patterns of method calls for each executed method through the use of closed itemset mining algorithm. These methods are ranked according to the highest score of its patterns.

4.5 Program dependence-based techniques

In their attempts to highlight faulty code excerpts, some techniques use additional program analysis information to highlight faulty code excerpts, such as program dependence data, program slicing, and assignment of weights to differentiate program entities. The technique proposed by Zhang et al. (see Subsection 4.4) considers the influence between nodes and related edges from a control-flow graph to assign weights for code blocks [176]. Zhao et al. propose a technique for calculating the suspiciousness of edges in a control-flow graph [178]. This value is used to obtain a weighted coverage for each edge that considers the distribution of the control-flow for passing and failing test cases. The suspiciousness of each block is then calculated using the passing and failing weighted coverages for each block through a Tarantula-like metric.

Yu et al. propose a technique that uses an Ochiai-like metric to calculate the similarity of control and data dynamic dependences [163]. This similarity indicates the correlation between these dependences and an incorrect program behavior. The final suspiciousness scores are obtained by considering the maximum value between the suspiciousness of control and data dependences for each statement. Zhao et al. proposed a technique that uses the influence of edges (branches) in an execution to obtain a list of suspicious blocks [179]. First, they calculate the suspiciousness of edges. Afterwards, they calculate the fault proneness of each edge using the total nodes that in in the successor node and total nodes that out from the predecessor node. The approach indirectly uses the dependencies between basic blocks to measure the importance of predecessor blocks in their successor blocks.

For their work on fault localization for field failures, Jin and Orso proposed three strategies to reduce the number of entities (branches) presented for fault localization [64]: (1) filtering, which excludes entities at three levels: those executed only by passing executions, branches executed for both passing and failing executions, and branches that have other control dependent branches; (2) profiling, which computes the suspiciousness of program entities by considering the number of times an entity is executed in each execution for all executions; and (3) grouping, which groups entities that belong to the same code region and have the same suspiciousness values. These strategies can in most cases pinpoint the faulty entities in the first picks.

Li et al. proposed a technique that uses information from program structure to improve fault localization [84]. They consider that some structures can influence their statements, making them more susceptible to be wrongly classified by SFL techniques. For example, a faulty statement in a main class can be underestimated because it is always executed by both failing and passing runs. Conversely, a non-faulty statement in a catch block can be overestimated because it is only executed by failing runs.

Some studies use program slicing because of their ability to hold faulty statements in their resultant subsets. However, slicing-based techniques must propose strategies for reducing the amount of
Zhang et al. evaluated three variations of dynamic slicing for fault localization [170]: data slicing, full slicing, and relevant slicing. Regarding the amount of information returned, relevant slices are larger than full slices, which are in turn larger than data slices. The results show that, although data slices returned a reduced amount of statements, in several cases the fault statement was not returned. Full slicing returned a large number of statements, with the faulty statement in most cases among them. Relevant slicing returned a slightly larger amount of statements than full slicing, but the faulty statement was always present. Wong and Qi proposed a technique that uses execution slices and inter-block data dependency for fault localization [141]. The technique first computes a dice from one failing and one passing execution. If the fault is not in the dice, inter-block data dependency from the failing test case is used to add more information. If the amount of code after adding such data dependencies is excessive, the technique uses the distinct blocks presented in another passing execution, with respect to the previous passing execution, to generate another dice.

Alves et al. used dynamic slicing and change impact analysis to reduce the number of statements in the ranking lists provided by fault localization techniques [10]. Three techniques were proposed to obtain this reduction: T1, which ranks only statements that appear in the dynamic slice; T2, which applies a change impact analysis before the dynamic slicing and considers all statements in the dynamic slice; T3, which is similar to T2, but with only changed statements ranked. Tian, et al. proposed a technique that calculates suspiciousness of predicates using SFL [132]. F-score is used to assign values that indicate the likelihood that predicates will be faulty. From a predicate, the technique generates control-flow and data-flow information on demand for each predicate by constructing a procedure dependence graph (PDG) for the procedure that includes the predicate. Next, backward and forward slices from this PDG are obtained.

Ju et al. proposed a technique that combines full slices from failing executions with execution slices from passing executions [69]. These slices are merged using intersection to obtain a hybrid slice. Wen et al. proposed a technique that combines SFL and program slicing [140]; it removes all program elements that do not belong to any failing executions slices. To calculate the suspiciousness of the remaining elements, they consider the execution frequency of each element in each test case and the contribution of an element in a test case. The contribution is the percentage in which an element is executed, considering all executed elements. Neelofar et al. combines dynamic and static analysis for fault localization [105]. They categorize statements in several categories (e.g., assignment, control, function call). These categories are used to weight suspiciousness scores obtained using SFL.

### 4.6 Combination of SFL techniques

The many techniques based on ranking metrics led to studies that combine different approaches to improve fault localization. Debroy and Wong used Tarantula, Ochiai, and Wong3 to propose a consensus technique, using the concept of rank aggregation, specifically Borda’s method, to combine statements classified with different values by each previous technique [35]. Ju et al. proposed a new ranking metric called \( \text{HSS} \) [69]. They combined two ranking metrics, \( O_p \) and Russel&Rao, by multiplying them to calculate the suspiciousness of program entities. Xie et al. showed both \( O_p \) and Russel&Rao to be better-performing ranking metrics [151] (see Subsection 4.7).

Other studies use AI to create or combine previous techniques. Yoo built several ranking metrics using Genetic Programming (GP) [162]. The GP operators used to create such ranking metrics were simple arithmetic operations: addition, subtraction, multiplication, division, and square root operation. To measure how well a ranking metric classifies faults, they used the EXAM score evaluation metric (see Subsection 9.1) as the fitness function. Six out of 30 ranking metrics created using GP outperformed other ranking metrics used for comparison. Cai and Xu proposed a technique that
uses suspiciousness lists from previous ranking metrics \[20\]. The lists of 28 ranking metrics were used as input. The technique uses a \textit{k-means} algorithm to cluster the statements, using the ranking position obtained by each ranking metric as features of the statements.

The technique proposed by \cite{Le} combines SFL (Tarantula) and Information Retrieval-based fault localization (IRFL) \cite{82}. IRFL uses bug reports to generate suspiciousness lists \cite{123}. Their technique combines program elements from failing test cases with related suspicious words from the bug reports. The results are present at method level.

### 4.7 Comparison of metric-based techniques

While some studies use several metric-based techniques to evaluate their proposed techniques, others compare techniques to identify which are more effective. \cite{Naish} use 33 ranking metrics, including their metrics \(O^p\) and \(O\), which were proposed for single-fault programs \cite{104}. The ranking metrics \(O, O^p, \text{Wong3}, \text{Zoltar},\) and \(\text{Ochiai}\) were more efficient in most cases. They also show that several ranking metrics are equivalent, producing the same ranking lists. \cite{Debroy} show the equivalence between different ranking metrics by comparing and simplifying their formulas \cite{34}. These ranking metrics (e.g., Jaccard, Ochiai, Sorensen-Dice) classify program entities in the same relative position in their ranking lists. Thus, one can avoid using equivalent ranking metrics in future work.

\cite{Xie} performed a theoretical comparison between 30 ranking metrics used in fault localization \cite{151}. To make this comparison, they grouped statements classified by the ranking metrics according to statements with respective higher, equal, and lower scores than the faulty statement. They identified six groups of equivalent ranking metrics, and seven ranking metrics that lack equivalent metrics. They also showed that five ranking metrics (\(O, O^p, \text{Wong1}, \text{Russel} \& \text{Rao}, \text{and Binary}\) perform hierarchically better than others for two single-fault sample programs. \cite{Le} evaluated the study of \cite{Xie} using well-studied programs, showing that the theoretical comparison does not hold for such programs \cite{80}. \cite{Ju} extended the work of \cite{Xie} to evaluate multiple faults \cite{68}.

\cite{Ma} compared seven ranking metrics for SFL \cite{92}. To model the comparison, they proposed a \textit{Vector Table Model} that represents the possible state of each statement for any program. They assumed that a program has a single fault. The results show that \(O, O^p, D^E(J), D^E(C)\) are equivalent. These metrics outperform \text{Wong1} and also outperform Jaccard and Kulczynski1 (which are equivalent). \(D^E(J)\) and \(D^E(C)\) were proposed by \cite{Naish}. \cite{Kim} carried out another ranking metric comparison, classifying 32 ranking metrics using clustering \cite{73}. The similarity was measured using the normalized suspiciousness values of such ranking metrics to compare their effectiveness, and the metrics were clustered in three groups of equivalent ranking metrics. They pointed out that these groups have complementary characteristics, each of which has its weaknesses and strengths.

Ranking metrics have also presented divergent results regarding programs with real and seeded faults. The study of \cite{Pearson} shows that the Metalaxis \cite{110} and \(O^p\) ranking metrics perform better for seeded faults, while DStar and Ochiai performed better for real faults. Thus, several factors should be considered when using ranking metrics, since their performance may vary on different study settings.

### 5 Program spectra

Program spectra can represent different levels of program structures, from fine-grained to coarser excerpts. The different coverage types include statements, blocks, predicates, function or method
calls, and spectra proposed in the studies. Also, some studies combine different coverage levels.

5.1 Types of spectra

The program entities most commonly used by SFL techniques are statements. The examination of statements may lead a programmer directly to the faulty site. However, a large number of statements may need to be examined before the faulty statement is found. Several works have used statements as their program entity investigation level [67, 150, 80]. Other works used block coverage [141, 176, 157].

Predicates are statements such as branches, return values, and scalar-pairs [85]. Guo et al. use predicate coverage to compare one failing execution to all passing executions, and then to identify the most similar passing execution [51]. This similarity is measured by comparing the results of predicates (true or false) and their execution order. The technique generates a report composed of predicates that were executed only by the failing execution. Naish et al. propose a technique that generates predicate information from statement coverage to perform fault localization [103]. The authors show that predicate coverage provides more information about the execution, such as execution results and control-flow data, than statement coverage. Zhang et al. perform a statistical study of the distribution behavior of predicates that are relevant to the occurrence of failures [175]. In their experiments, about 40% of predicates lack normal distribution. Chilimbi et al. proposed a technique that uses path profiles (intra-procedural code segments) and conditional probability to identify paths that are more likely to be faulty [23]. Their results showed that paths are more precise than predicates for pinpointing faults.

Dallmeier et al. used method call sequences in their technique [27]. The method call sequences that income and outcome in an object are summarized to represent a sequence set per class. Classes whose sequence sets differ from one failing run to several passing runs are more suspicious of being faulty. In this work, the authors observed that incoming calls are more likely to contain faults than outgoing calls. Laghari et al. proposed an SFL technique that also produces suspiciousness lists at class level [78]. Mariani et al. present a technique that gathers information about interactions (sequences of method calls) between software components [93]. The technique generates an interaction model of passing test cases. This model is compared to interactions from failing test cases to indicate suspicious method calls. Other works also used method call coverages [161, 31].

New coverage types have been proposed for fault localization. Santelices et al. compared the performance of different coverages—statement, branch, and dua [124]. They showed that different faults are best located by different coverage types. Three approaches were proposed combining such coverages. One of them (avg-SBD), which calculates the average suspiciousness values of statement, branch, and dua [124]. They showed that different faults are best located by different coverage types. Three approaches were proposed combining such coverages. One of them (avg-SBD), which calculates the average suspiciousness values of statement, branch, and dua coverages, achieved better results. In this same study, the authors used a technique that infers an approximation of dua coverage (dua approx) using branch coverage data, which demands lower execution costs. Yilmaz et al. proposed a technique based on the concept of time spectra [161]. The technique collects the execution times of methods in passing runs to build a behavior model for each method. Methods executed in failing runs that deviate from the model are considered more suspected. As time is an aggregate value, it can also represent sequences of events.

Masri uses a coverage named Dynamic Information Flow Analysis (DIFA) for fault localization [94]. DIFA is composed of interactions performed in an execution, including data and control dependences from statements and variables. These interactions are known as information flow profiles. Xu et al. present the coverage Key Block Chains (KBC) [153]. Each KBC is composed of...

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3 A scalar-pair is a relationship between a variable assignment and another same-typed variable or constant

4 Components in this study of Mariani et al. [93] are independent programs used by other programs.
only one predicate whose execution result is true, known as an atomic predicate. Thus, a KBC may have several sizes, according to the code blocks that are executed until a predicate is evaluated as true. Papadakis and Le Traon use mutants as a new type of coverage for fault localization [110]. They calculate the suspiciousness of mutated versions using Ochiai. Next, they map the mutants for the statements using the location in which they were inserted.

Strategies to reduce coverage data gathered can also contribute to enhancing fault localization. Perez et al. propose a technique that reduces the amount of code coverage information by choosing the granularity of the inspected elements that are collected [113]. Only the most suspect elements in a coarser level are collected at a more fine-grained level. The proposed strategy reduces the average execution time for performing fault localization. The technique presented by Wang and Liu performs multiple predicate switching to find predicates that are critical for revealing faults [136]. To avoid exponential growth due to the number of predicates, they first apply Ochiai to reduce the number of predicates on the switching phase.

6 Faults

In practice, a developer does not know how many bugs a program has; it may contain single or multiple faults. Simultaneous faults may change the execution behavior, causing interferences in the test results and affecting the performance of SFL techniques. There are different types of faults, which can present varied characteristics, also impacting in SFL techniques’ suspiciousness lists. We present these concerns regarding faults below.

6.1 Multiple faults

Most Spectrum-based Fault Localization techniques are assessed using programs with single faults. However, a few techniques were proposed specifically for programs with single faults [3, 104, 169]. Most techniques that were assessed using single-fault programs do not specify such a limitation. For experimental purposes, in which the faults are already known, it is acceptable to suppose that a program has only one fault. However, it is impossible to foresee how many faults a program has in industrial settings. Concerning this, SFL techniques started to be evaluated in programs with multiple faults. The following techniques were proposed addressing multiple faults or using multiple faults in their evaluation.

To deal with multiple faults, Zheng et al. used a bi-clustering process to classify predicates and failing runs [181]: they calculated the conditional probability of predicates related to failing runs. The selected predicates were applied in a collective voting process, in which each failing run votes for its favorite predicate. This voting process is iterative, aiming to identify strong relationships between predicates and failing runs.

Another strategy is to identify similar failing test cases. Jones et al. introduced a technique to parallelize debugging for multiple faults by grouping failing test cases that are most similar to a particular fault [67]. They use agglomerative hierarchical clustering to obtain these groups, called fault focusing clusters. DiGiuseppe and Jones investigated factors that can affect failure clustering [39]. They show that execution profiles and test case outputs can be accurately used for failure clustering. They also verified that failures whose profiles and outputs differ due to the presence of multiple faults can impair the failure clustering process. Such failures may be pre-processed to improve failure clustering. In the following study [40], DiGiuseppe and Jones presented a failure clustering technique that uses semantic information from source code to improve the failure clustering process.
Liu et al. compared six failure proximity techniques [88]. These techniques are used to classify failure reports that are related to the same bugs. A failure proximity technique extracts a failure’s signature and uses a function to calculate the distance from other failures to group them as related to the same fault. Högerle et al. investigated factors that impact debugging in parallel for multiple faults [55]. They highlight the infeasibility to obtain pure failure clusters. Such clusters should contain entities and failing test cases entirely related to each fault. One trade-off is obtaining clusters that share program entities, causing what they called bug race. Bug race means that faults can be present in more than one cluster. Another trade-off is obtaining clusters that share tests instead of program entities. Bug races are avoided in this case, but some clusters may have no faulty program entities.

The work proposed by Dean et al. uses linear programming to locate multiple faults [32]. The technique returns a set of statements that explain all failing test cases. For the experiments, the single-fault versions of the Space and Siemens suite were joined to create a version with all faults per program. Naish et al. conducted experiments with several ranking metrics in programs with one and two faults per version [102]. The results show that some ranking metrics were more effective for programs with two faults, while others were more effective for single-fault programs (see Subsection 4.1).

Steimann and Bertschler proposed a technique that uses only failing test cases, assuming that in each of them there is at least one program entity (method) that explains the fault [127]. All entities in these test cases have the same probability of being faulty. All possible combinations of methods through the test cases are verified, and only combinations that can explain the fault are kept. Some entities can be more present than others in the remaining explanations. Thus, the entities are classified according to their frequencies in the explanations.

Abreu et al. proposed a technique for multiple faults called Zoltar-M [3]. The authors used MBD (Model-based Diagnosis) along with program spectra information to obtain groups of statements that relate to the existing faults. The MBD is constructed under logical propositions from the results of the dynamic execution information. Yu et al. presented a technique for distinguishing test cases that fail due to single faults from those that fail due to multiple faults [165]. The technique creates test sets composed of one failing test case and all passing test cases. Then, they calculated the distance between a failing test case and its most similar passing test case. With the presence of multiple faults, tests with large distances are more likely related.

SFL techniques that cope with multiple faults often add more complexity to the fault localization process in order to isolate such faults. Conversely, the study of Perez et al. investigated bug fixing commits from 72 open source projects, showing that 82.5% of the commits have a single fault [113]. This fact may alleviate the need for more complex techniques to deal with multiple faults. However, unknown faults may exist in such commits.

6.2 Fault interference

The occurrence of multiple faults may impair fault localization results, which led to concerns about interferences between simultaneous faults. Debroy and Wong showed that simultaneous faults can cause interferences in which some faults hide the incorrect behavior of other faults [33]. Conversely, some faults can help to manifest failures related to other faults. The experiments performed showed an incidence of fault interference in 67% of the assessed programs.

Xue and Namin studied the impact of multiple faults on five fault localization techniques [157]. They showed that fault interference can reduce fault localization effectiveness by 20% using Ochiai. They also demonstrated improved fault localization effectiveness in around 30% of the cases. Regarding the ranking metrics used, they observed that some of them, like Tarantula and Ochiai,
poorly performed as the number of faults increased. The ranking metrics Chi-Square and Odds Ratio exhibited no difference in their performance as the number of faults increased.

DiGiuseppe and Jones investigated the influence of multiple faults on the performance of SFL techniques [42]. The results showed that the presence of multiple faults has little impact (a decrease in 2% of effectiveness) on the performance of SFL techniques to find the first fault. The fault localization effectiveness of the other faults (beyond the first fault) is impaired as the number of faults grows. They also showed that the suspiciousness scores of faults tend to decrease as the number of faults increases. There were cases of improved effectiveness and other cases in which some faults became unlocalizable. They also verified that fault interference occurred in 80% of the assessed programs.

6.3 Fault classification

Few studies have addressed the impact of fault types on their techniques. Santelices et al. argue that different coverages can contribute to locating distinct fault types, but do not present any relationship between the proposed coverages and the fault types that such coverages locate better [124]. Guo et al. assessed their technique in the presence of three types of faults: branch faults, assignment faults, and code omission [51].

Faults by code omission are generally difficult to locate [176, 154, 151]. Zhang et al. proposed a technique to deal with faults caused by code omission [172]. They used the concept of implicit dependence to identify indirect dependencies between the use of a variable and a previous conditional statement.

There are few works that show how the proposed techniques deal with specific faults. Masri described the faults used in their experiments and analyzed the influence of these faults’ characteristics on his technique [94]. Burger and Zeller also described the types of faults used in experiments and discussed their impact on the new technique [19]. Zhang et al. used a fault classification defined by Durães and Madeira [44] to verify the frequency of these faults in real programs [177].

Debroy et al. pointed out another type of fault that relates to single faults spread over more than one statement [37], which is also known as multi-statement faults. Lucia et al. examined 374 faults from three real systems to understand when faults are localizable [90]. By localizable, they meant faults present in one or several lines of code in a nearby region, which is the general assumption of fault localization techniques. They manually inspected all faults, finding that 30% of such faults occur in a single line, while around 10% of the faults spread to more than 25 lines each. Less than 45% of these faults appear in a single method, and less than 75% take place in a single file. Pearson et al. observed that, from the real faults from the Defects4J database [70] (see Section 7), 76% are composed of multi-line statements, and 30% are related to code omission [112]. There are also 3% of the faults in non-executable code (e.g., variable declaration), which are not covered by SFL techniques. Keller et al. found that only 88 of 350 bugs from the AspectJ program (see Section 7) may be identifiable using SFL [71]. Besides the cases of misclassified bugs, bugs related to concurrency and environment (e.g., hardware constraints) are difficult to reproduce. Approaches to automatically classify faults, such as proposed by Thung et al. [131], can be helpful for evaluating SFL techniques in the presence of different fault types.

7 Programs

Several programs have been used to assess SFL techniques; some are program suites composed of small programs often used as benchmarks, whereas others are medium and large programs. Most
of them are open source programs included in software testing repositories, such as the Software-artifact Infrastructure Repository (SIR) [43]. SIR contains C and Java programs prepared for experimental use, including seeded and real faults, and scripts to automate the execution of controlled experiments.

Next, we present a description of programs used as benchmarks by the SFL techniques. We also describe their characteristics, such as size and number of faults.

### 7.1 Description of the main programs

Several programs have frequently been used to carry out fault localization experiments. Among them are Siemens suite [59], Unix suite, Space, flex, gcc, grep, gzip, make, and NanoXML. Table 2 shows a description of benchmarks often used in the studies, the average number of lines of code (LOC) per version, number of faults for all versions, number of versions, and the average number of test cases per version. The Siemens suite and Unix suite data show the average of their programs. The number of LOC, faults, versions, and test cases may vary throughout the studies.

<table>
<thead>
<tr>
<th>Program</th>
<th>Description</th>
<th>LOC</th>
<th>Faults</th>
<th>Versions</th>
<th>Test cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Siemens suite</td>
<td>7 programs</td>
<td>483</td>
<td>19</td>
<td>1</td>
<td>3,115</td>
</tr>
<tr>
<td>Unix suite</td>
<td>10 programs</td>
<td>261</td>
<td>17</td>
<td>17</td>
<td>401</td>
</tr>
<tr>
<td>Space</td>
<td>Satellite antenna controller</td>
<td>6,200</td>
<td>38</td>
<td>1</td>
<td>13,585</td>
</tr>
<tr>
<td>flex</td>
<td>Lexical analyzer</td>
<td>10,459</td>
<td>21</td>
<td>6</td>
<td>567</td>
</tr>
<tr>
<td>grep</td>
<td>Search for patterns in files</td>
<td>10,068</td>
<td>18</td>
<td>6</td>
<td>470</td>
</tr>
<tr>
<td>gzip</td>
<td>Data compressor</td>
<td>5,680</td>
<td>28</td>
<td>6</td>
<td>211</td>
</tr>
<tr>
<td>make</td>
<td>Build manager</td>
<td>35,545</td>
<td>19</td>
<td>6</td>
<td>793</td>
</tr>
<tr>
<td>NanoXML</td>
<td>XML Parser</td>
<td>7,646</td>
<td>32</td>
<td>5</td>
<td>216</td>
</tr>
<tr>
<td>Ant</td>
<td>Build manager</td>
<td>80,500</td>
<td>18</td>
<td>11</td>
<td>871</td>
</tr>
<tr>
<td>gcc</td>
<td>C compiler</td>
<td>95,218</td>
<td>5</td>
<td>1</td>
<td>9,495</td>
</tr>
<tr>
<td>XML-security</td>
<td>Encrypter</td>
<td>16,500</td>
<td>52</td>
<td>3</td>
<td>94</td>
</tr>
<tr>
<td>JFreeChart</td>
<td>Chart library</td>
<td>96K</td>
<td>26</td>
<td>–</td>
<td>2,205</td>
</tr>
<tr>
<td>Closure Compiler</td>
<td>JavaScript compiler</td>
<td>90K</td>
<td>133</td>
<td>–</td>
<td>7,927</td>
</tr>
<tr>
<td>Commons Math</td>
<td>Math library</td>
<td>85K</td>
<td>106</td>
<td>–</td>
<td>3,602</td>
</tr>
<tr>
<td>Joda-Time</td>
<td>Date and time library</td>
<td>28K</td>
<td>27</td>
<td>–</td>
<td>4,130</td>
</tr>
<tr>
<td>Commons Lang</td>
<td>Text library</td>
<td>22K</td>
<td>65</td>
<td>–</td>
<td>2,245</td>
</tr>
<tr>
<td>Mockito</td>
<td>Mocking framework</td>
<td>11,838</td>
<td>38</td>
<td>–</td>
<td>1,854</td>
</tr>
</tbody>
</table>

The Siemens suite comprises seven small programs written in C: print_tokens, print_tokens2, replace, schedule, schedule2, tcas, and tot_info. Each program contains one fault per version and a test suite including thousands of test cases. The large test suites were created to achieve a high testing coverage. To simulate realistic faults, the faults were seeded for experimental purposes by ten people [59]. A large number of studies used Siemens suite in their experiments [51, 32, 28]. The Unix suite is a collection of Unix utilities written in C that are small in size and contain several faulty versions [43]. These programs are Cal, Checked, Col, Comm, Crypt, Look, Sort, Spline, Tr, and Uniq. The faults of Unix suite were seeded using mutation-based injection. Several works have used Unix suite to assess their techniques [142, 120].
Other medium and large-sized programs have been used for fault localization. Such programs provide more realistic scenarios for experiments, due to their sizes and different domain characteristics. The Space program, used in several studies, was developed by the European Space Agency. It contains 38 real faults discovered during the development. The test suite was created by Vokolos and Frankl [133] and the Aristotle Research Group [12], consisting of 13,585 test cases to guarantee that each branch is exercised by at least 30 test cases [67]. Flex, grep, gzip, and make are medium-sized Unix utilities also frequently used for experiments [88, 143]. NanoXML is an XML parser for Java with different versions used as benchmarks. The program has both real and seeded faults. Ant and XML-security are other Java programs used in SFL experiments [93, 31].

Other studies have added additional programs for use in experimentation. Ali et al. describe the process adopted to prepare the Concordance program for use in fault localization experiments [8]. They also argue that the hand-seeded faults of the Siemens suite may not be suitable to represent programs. The iBugs project [26] is a repository of bugs that contains 390 from three Java programs: AspectJ, Rhino, and JodaTime. Most of the faults belong to AspectJ (350), and each of the three programs contains more than 1,000 test cases. The bugs were identified in the programs’ repositories and have been used in fault localization research [90]. 258 of all bugs have an associated test case, which can be used for fault localization.

Also, Just et al. created a repository for testing research called Defects4J [70], which is currently composed of six large Java programs and 395 real faults. The faults were identified and extracted from the programs’ repositories. Defects4J has been used in several recent studies [83, 79, 112]. In Table 2, projects from JFreeChart to Commons Lang belong to the Defects4J repository. LOC (in KLOC) and Test cases columns contain the values reported by the authors [70]; for Mockito, which also belongs to Defects4J, we obtained LOC using the CLOC program for the latest version available in its repository. We also used this version to obtain the number of test cases. We do not have the numbers of versions of the Defects4J’s programs.

### 7.2 Size

A program’s size is often used to refer to it as a large (or real) program, or as a small one. There is no precise definition limit to determine a program as small, medium, or large in size. Zhang et al. consider flex, grep, gzip, and sed—programs that contain between 6.5 and 12.6 KLOC—as real-life medium-sized programs [176]. Other authors consider these programs as large in size [37, 8]. Space, with about 10 KLOC, is deemed a large and real program [102, 163]. Generally, we can assume that programs with more than 10 KLOC are large programs. Those programs containing between 2 and 10 KLOC are medium-sized programs, and programs with less than 2 KLOC are considered small programs.

We identified that most authors consider programs ‘real’ if they are applied to professional use, whereas ‘not real’ programs (called toy programs) are those used for experimental purposes or to perform small tasks, including operational system utilities [102, 177]. Real programs in this context also consider the existence of real program faults. We observed that the programs considered as medium and large in size by the studies in this survey can be assumed as real programs and the small programs as toy programs.

Some experiments with large programs used only a few parts of them. For the Gcc program, Wong et al. instrumented one sub-directory (gcc/cp) for their experiments [143]. Mariani et al. uses NanoXML (8 KLOC), Eclipse (17 MLOC), and Tomcat (300 KLOC), analyzing interactions occurred in subsets of such programs [93]. Thus, even experiments with programs that vary from millions to hundreds of thousands of lines of code may be criticized for their representativeness as large and real programs.
7.3 Number of faults

As discussed in Subsection 6.1, an important concern that should be investigated by SFL techniques is the presence of multiple faults. To achieve such a goal, programs used in the experiments must also have multiple faults. Moreover, some of these faults must change the output behavior of other faults to address the study of fault interferences.

The existing programs are generally composed of single faults. Researchers usually change the subject programs to generate multiple-fault versions for their experiments, yet these modifications can add biases to the evaluation and make experiments more difficult to reproduce. Jones et al. created 100 versions of Space, each of them containing from 1 to 8 faults, randomly combining the single-fault versions [67]. Abreu et al. also generated multiple-fault versions for gzip, Space, and sed in their experiments [3]. Several other works have used these random strategies to generate multiple faults [137, 42].

Other studies identified faults to carry out their multiple-fault experiments. Steimann and Bertschler claim that the number of available multiple-fault programs is quite limited [127]. In their experiments, they show an example with three simultaneous real faults from the program Apache Commons Codec. Wong et al. identified five existing faults of the Gcc compiler using the Bugzilla database. They merged these bugs to create a 5-bug version of Gcc for their experiments [143]. Identifying real occurrences of simultaneous faults is a time-consuming activity, but it can improve the evaluation of SFL techniques.

8 Testing data

The quality of testing data is pivotal for the performance of SFL techniques. Thus, refinements on test suites may impact fault localization performance. A desirable characteristic of test suites is the capacity to execute distinguishable parts of the code, which can improve the ability of SFL techniques to pinpoint faulty code more precisely. As large test suites can impact the execution costs of SFL techniques, test suites with reduced size are also desirable. In this section, we present several strategies that propose improvements in testing data for fault localization. Concerns regarding evaluation of testing data, coincidental correctness, and use of mutation testing for SFL are also discussed.

8.1 Test suite improvements

Some works have addressed ways to distinguish program entities between test cases to improve fault localization. Baudry et al. proposed a testing criterion called Dynamic Basic Block (DBB) [17], which is a group of statements that are executed by the same test cases. These statements always have the same suspiciousness, and are thereby indistinguishable: the greater the number of DBBs, the lesser the number of indistinguishable statements, and thus the better it is for fault localization. Hao et al. proposed three strategies to reduce test cases according to their capacity to execute different statements [54].

Other studies have evaluated the impacts of testing on fault localization and proposed new strategies to improve testing data. Abreu et al. observed the influence of test suite quality on SFL [1]. They varied the number of test cases that exercised faults between passing and failing test cases, and measured the fault localization effectiveness. As expected, having more failing test cases exercising faulty statements leads to better effectiveness. However, a limited number of failing test cases suffices. In their experiments, a value of six failing runs is optimal, and additional failing test cases do not affect effectiveness. Xuan and Monperrus proposed a technique for improving testing
data used by SFL techniques [155]. Given a failing test case with more than one assertion, they created one test case for each of these assertions. This aims to avoid situations in which an error occurring in a test case execution prevents the following assertions from being executed. After generating the atomic assertion failing test cases, they apply dynamic slicing to create a list of suspicious statements.

Test suite reduction strategies aim to reduce the number of test cases keeping the former coverage level. Thus, the execution cost to run the tests reduces, without impacting on the test suite’s quality. These strategies are especially suitable for regression testing. However, reduced test suite size may impact the effectiveness of SFL techniques. Yu et al. investigated the effects of test suite size reduction on fault localization [164]. They used ten test suite reduction strategies in four ranking metrics. The strategies hold the statement coverage and remove the test cases from different outputs (all test cases, only failing test cases, only passing test cases). Zhang et al. used category partition to prioritize test cases for fault localization [173]. Program spectra information is not needed for the prioritization—their technique chooses test cases with inputs farthest from the previously chosen ones, aiming to obtain a high coverage diversity to improve fault localization. Zhang et al. applied cloned failing test cases to improve fault localization [167]. Their idea was to balance the amount of failing and passing test cases.

The occurrence of coincidentally correct test cases and their impacts for fault localization have also been studied in the recent years. Coincidental correctness can impair SFL techniques by executing faulty entities as passing test cases, reducing their suspiciousness scores. Masri and Assi proposed a technique to identify coincidental correct test cases to improve fault localization [95]. They showed that coincidentally correct test cases (CC test cases) are common. They also show that coincidental correctness affects SFL techniques by classifying faulty entities with lesser suspiciousness scores. The proposed technique uses k-means clustering to classify test cases as CC or not. Bandyopadhyay and Ghosh extended the previous version of the work of Masri and Assi [95], including interactions with the developer to exclude false positive CC test cases [15]. They recalculate the list of remaining suspicious statements throughout the interactions. Other studies that deal with coincidental correctness for SFL have been proposed [158, 159].

Guo et al. proposed a technique to evaluate the correctness of test oracles [52]. Since humans act as oracles, evaluation mistakes can impair testing and debugging. Their approach considers that tests with similar execution traces likely produce identical results. Similar test cases that diverge are deemed suspicious.

### 8.2 Mutation testing

Mutation testing has been used to propose new SFL techniques. Nica et al. proposed a technique to reduce bug candidates by using constraint-based debugging [107]. First, statements that do not violate the constraints and that explain the failing test cases are deemed bug candidates. Second, the technique generates mutants for each bug candidate.Mutants that make the failing test cases pass are used to suggest possible faulty sites. Moon et al. proposed a technique that uses mutation to modify faulty and correct statements [96]. The rationale is that, if a mutant inserted in a faulty statement reduces the amount of failing test cases, then the faulty statement is more likely to be faulty. Conversely, a mutant inserted in a correct statement which generates more failing test cases is less likely to be faulty. Hong et al. proposed a similar approach for multilingual programs [56].

Mutation testing is also used to seed faults for experiments, and to suggest fixes for program repair [138, 36]. Ali et al. used mutation testing to generate faults and shown that these faults are similar to real faults [8].
9 Practical use

Spectrum-based Fault Localization’s goal is to help developers to find and fix faults. For practical use, one needs to understand whether the evaluation metrics that assess SFL techniques reflect what happens in development settings. Moreover, the techniques should be assessed by user studies to understand their role in the debugging activity.

In this section, we address concerns related to the practical use of SFL techniques. First, we present the metrics used to evaluate SFL techniques. We also present experiments with developers using SFL techniques in practice. Finally, we present the strategies proposed to enrich SFL techniques with contextual information.

9.1 Evaluation metrics

There are measures often used by studies to evaluate the performance of SFL techniques. Fault localization effectiveness is an effort measure which indicates how much code is inspected using an SFL technique. As most of the SFL techniques generate ranking lists, studies often use this approach or a variation of it.

The most commonly used metric is EXAM score [24, 104, 143]. This metric represents the developer’s effort to find a fault using a list of suspicious program entities. The EXAM score is measured as the relative position in which the faulty entity was ranked. It represents the percentage of entities that must be examined to find the fault. EXAM score was based on the metric score, proposed by Renieris and Reiss [117], which indicates the percentage of code that does not need to be examined until finding a fault. Essentially, EXAM score and score provide the same information in inversely proportional way. Several works also used score [51, 8, 180].

There are other metrics similar to EXAM score. Zhang et al. proposed a metric called p-score [177]. Expense [164] is a variation of EXAM score for programs with multiple faults: that is, the percentage of code verified before locating the first fault. To measure the total effort to locate faults for programs with multiple faults, Jones et al. propose another variation of EXAM score called total developer expense (D) [67], which is the sum of the EXAM score for all faults in a program. Another metric proposed in this work is critical expense to a failure-free program (FF), which measures the time to obtain a failure-free program. Assuming that developers work in parallel to fix the faults, and for each fault found the program is recompiled, FF is the sum of the maximum developer expense at each iteration.

Other metrics identified were precision and recall, used to measure the accuracy of fault localization techniques based on artificial intelligence. For the fault localization domain, precision generally means the percentage of entities classified by a technique as faults that are in fact faults. Recall is the percentage of faults correctly classified when considering all faults. Roychowdhury and Khurshid used a metric called Metric-Quality to evaluate a technique’s ability to rank the most important statements with higher values, and the least important statements with lower values [121].

Ranking lists commonly classify several program entities with the same suspiciousness scores. This fact impacts the evaluation of ranking metrics, which can vary widely. To deal with ties in ranking lists, Wong et al. measured the best and the worst cases for the score metric [142]. The best case considers the fault in the first position of the tied entities, while the worst case considers that the fault is in the last position. Xu et al. presented a study that shows that ties in SFL ranking lists are common [154]. They propose four tie-breaking strategies to deal with ranking list ties.

Moon et al. proposed an evaluation metric for fault localization based on information theory, called Locality Information Loss (LIL) [96]. LIL is used to calculate the difference between the true locality and the predicted locality of a fault. This metric can be applied to any technique that
generates ranking lists.

Techniques providing lists of suspicious elements often assume a perfect bug understanding [58], which supposes that the developer inspecting a list will immediately identify, understand, and fix the fault as soon as s/he reaches the faulty program element. However, this may not happen in practice, and the amount of examined code may increase. As pointed out by Parnin and Orso [111], the measurement of relative positions is quite imprecise. The absolute number of entities to be inspected before finding a bug can be a more accurate measure, regardless of the amount of LOC a program has. Liblit et al. measured the number of predicates their technique returned [85]. Hsu et al. evaluated their technique of bug signatures (see Subsection 9.3), measuring the absolute number of bug signatures that contain faults [58]. Other studies, most of them from recent years, have used the absolute number of inspected entities to evaluate their techniques [127, 81, 126, 31].

The evaluation metrics presented here are useful for comparing SFL techniques in experiments. However, user studies with developers allow us to verify whether these metrics are a good model of what happens in practice.

9.2 User studies

Despite the importance of understanding how SFL techniques can be used in practice, there are few studies that perform experiments with developers. Parnin and Orso carried out experiments with a group of developers using Tarantula [111]. The authors provided a list of suspicious statements for the developers using two programs, each of them containing a single fault. The results show that the developers take into account their knowledge of the code to search for the faults, and do not usually follow the classification order indicated by the SFL technique. Some other results were observed, including that the perfect bug detection did not occur in the experiment. The authors also verified that the position in which the faulty statement is classified had no significant impact on the ability of developers to find the bugs. The developers suggested improvements, such as the aggregation of the results by their classes or files, and the provision of input values used in test cases to enrich the debugging.

Perez and Abreu carried out an experiment with 40 developers to assess their technique for visualization of debugging information (GZoltar) [114]. The participants were master’s students with more than five years of experience in Java. Two groups were formed—control and experimental groups—with 20 students each using the same program and the same fault. The experimental group used GZoltar, and all participants were able to locate the bug in seven minutes on average. The control group used the Eclipse without GZoltar. Only 35% of its participants located the fault within the set time of 30 minutes. Perscheid et al. conducted a user study with eight developers to evaluate their program state navigation debugging tool [116]. All developers were undergraduate students with six years of experience. Four faults were debugged by each student, two using the default debugging tool, and two using the new tool. A time limit of fifteen minutes was assigned to each fault. In most cases, the developers found the faults using their approach. They also spent less time to find the same faults by using the new tool.

Kochhar et al. asked 386 software engineering practitioners about their expectations of issues regarding research in fault localization [74]. Most participants deemed research in fault localization as worthwhile. Regarding the preferred code granularity level, method was preferred by most of them, closely followed by statements and basic blocks. Almost all respondents are willing to adopt a fault localization tool that is trustworthy, scalable, and efficient (i.e., a tool that classifies a fault among the top-5 entities in most cases). Böhme et al. performed a study regarding the whole debugging process in which 12 professional developers were asked to manually debug 27 real bugs [18]. The authors built a benchmark called DBGbench, which includes fault locations, patches, and
debugging strategies provided by the participants. This benchmark can be used to evaluate fault localization techniques.

Two recent works replicate the study of Parnin and Orso [111]. Xie et al. evaluate the use of SFL with 207 undergraduate students and 17 faults [149]. The programs used are classic Computer Science algorithms, with at most 500 LOC. Their results show that SFL helped to locate faults only when such faults were ranked between the first positions. Moreover, SFL increased the time spent to locate bugs in most cases. They also show that the participants started the debugging activities with a brief overview of the code before using SFL. Xia et al. conducted a following study with 36 professional developers and 16 real faults from open source projects, showing that SFL improves both effectiveness and efficiency [148]. Most developers started the debugging tasks using the SFL lists before inspecting the code and the tests.

These studies have presented divergent results regarding the usefulness of SFL in practice. However, all studies resulted in at least some improvements for participants that used SFL, showing that these techniques can be useful in practice. More studies will help understand the current SFL techniques and develop new techniques useful in industrial settings.

9.3 Contextual information

SFL techniques have in general tried to precisely pinpoint the faulty site. Ranking lists often contain suspicious elements sorted only by their suspiciousness scores. As a result, elements from different code excerpts can be assigned with higher scores, which may lead to first picks that have no direct relationship among them—for example, statements that do not belong to a same method or class. In practice, when a developer searches for a bug, s/he tries to understand the conditions in which the bug occurs. Techniques have been proposed aiming to provide more information for fault localization. Contextual information in fault localization is associated with strategies that help developers understand bug causes [63].

Jiang and Su proposed one of the first techniques for contextualization in fault localization [63]. Their technique selects predicates likely to reveal faults using two machine learning techniques: Support Vector Machines (SVM) and Random Forest (RF). These predicates are correlated using a k-means clustering algorithm. Predicates with similar behaviors over the executions tend to be related. The faulty control-flow paths are constructed based on paths exercised by failing executions that traverse these predicates. The control-flow paths are composed of correlated predicates that provide a context for understanding faults.

Hsu et al. presented a technique that provides a list of subsequences of elements (branches) [58]. These subsequences are called bug signatures; each of them may contain one or more branches in their execution order. The technique first classifies the most suspicious branches. From failing traces, the amount of branches is reduced using a threshold value. They use a longest common subsequence algorithm to identify subsequences that are present in all failing executions. They are then ordered by their suspicious values. Cheng et al. extended the idea proposed by Hsu et al. [58] using graph mining to present a list of suspicious subgraphs [22]. Graphs of faulty and correct executions are generated to obtain significant subgraphs that differ in the executions. The subgraphs can be extracted at two code levels: blocks or methods.

Hao et al. proposed an interactive fault localization technique that follows the manual debugging routine [53]. The technique uses the developer’s estimation in the fault localization process. The technique recommends checkpoints based on the suspiciousness of statements. The developer’s feedback is used to update the suspiciousness of statements and choose the next checkpoint.

The technique proposed by Röbler et al. provides a list of correlated elements likely to be faulty [111]. It combines SFL with automated test generation, using one failing test case and generating
several test cases. Only branches and state predicates, called facts, executed in failing test runs are suspected as relevant to faults. Conditional probability is used to estimate the relevance of facts to explain a bug.

Information from source code and code structures are also used to provide contextual information. DiGiuseppe and Jones utilize semantic information for fault localization [41]: comments, class and method names, and keywords from the source code. The program is instrumented and the source code is parsed to extract the information. Terms from the source code are normalized and correlated with the program entities they belong to. A list of top terms is presented as an outcome. de Souza et al. use integration coverage (i.e., pairs of method calls) for SFL [31]. They provide two entity-levels to search for faults. The first level is a list of suspicious methods named roadmap. For each method, it is possible to inspect the most suspicious blocks that belong to it. Two filtering strategies are then used to limit the number of blocks to be checked for each method, avoiding the inspection of blocks with lesser suspiciousness scores.

Le et al. proposed a technique that evaluates the output of SFL techniques (ranking lists) to indicate when this output should be used by developers [81]. They used SVM to build an oracle that indicates whether SFL lists are reliable for inspection. They identified several features of programs to build the oracle, such as number of failing test cases and number of program elements with the same suspiciousness score.

Yi et al. proposed a technique that combines semantic and dynamic analysis to suggest fault explanations for regression testing [160]. Semantic analysis is applied to identify statements that cause an assertion to fail. Dynamic analysis is then used to identify code changes that retain the failing assertions. These code changes are reported as explanations. The technique presented by Elsaka and Memon extracts subsequences of statements from a set of failing executions [45]. These subsequences derive from common subsequence graphs and include variable values from the execution.

Sohn and Yoo use information of source code metrics along with ranking metrics for fault localization [126]. The code metrics used are related to fault proneness. They apply Genetic Programming and SVM to rank the most suspicious methods. Zhang et al. proposed the use of the PageRank algorithm [109] for SFL [168]. First, they classify failing tests according to their importance to reveal the faulty code. Tests that execute fewer methods are deemed more important. Second, they use static call graph information to verify methods that are connected with other more suspicious methods. PageRank is then used to calculate the most suspicious methods.

10 Discussion

In this section, we discuss the main features, results, and challenges of fault localization techniques presented in this survey. We follow the structure proposed in Figure 1 to organize the discussion.

10.1 Techniques

Several ranking metrics have been proposed for fault localization, which were created or adapted from other areas. Each has its specificity. Ochiai differs from Tarantula by taking into account the absence of a statement in failing runs. Jaccard differs from Tarantula by considering statements executed in passing test runs. Experiments have shown that Ochiai has presented higher effectiveness compared to other ranking metrics [1, 80, 151]. However, the effectiveness of the best ranking metrics is slightly better (e.g., around 1% less code to examine) in most cases, indicating that they provide similar results [104, 80]. This means that there is a “ranking metric barrier” for such approach. Can
we do better to distinguish suspiciousness values from the actual faulty elements? A possible way is to investigate whether ranking metrics present better results for different types of faults.

Statistics-based techniques have also been explored by SFL techniques, especially techniques using conditional probability. An important issue regarding spectra data is its non-normal distribution [177], which indicates that non-parametric techniques can be explored for fault localization.

Other ways to enhance fault localization explore program behavior; program dependence and artificial intelligence techniques have been used for this purpose. However, due to the high computational costs that are inherent to AI techniques, their results should be significantly better to compensate such costs. SFL techniques that use program dependence information often deal with large amounts of code. Thus, it is also necessary an extra effort to develop strategies to reduce information. Such strategies may impose high execution costs, especially for large programs. Moreover, SFL techniques based on both artificial intelligence and program dependence can be used to identify relationships in the internal structures of programs, helping to provide contextual information about existing faults. Further studies shall be proposed to provide better results.

Combining previous SFL techniques to propose new ones requires deep knowledge of the strengths and weaknesses of each technique through different program characteristics, which can help to understand new ways to improve fault localization.

10.2 Spectra

The choice of program spectra influences the performance of SFL techniques, impacting execution costs, data available to be analyzed, and outputs for inspection. Techniques that use coarser spectra data (e.g., method coverage) may have reduced execution costs, requiring less code instrumentation.

Although statement spectrum is more used, searching for faults through single statements may be difficult due to the absence of context that isolated statements provide for developers. To tackle this issue, grouping most suspicious statements from the same code regions can help to understand faults. Method spectra may help to bring context to comprehend faults since it is the lowest code level that contains the logic of a program. Methods were also chosen as the preferred code unit for debugging by developers [74]. However, developers will manually inspect these methods, which may increase the amount of code to be verified compared to statements. An increasing number of techniques have used method spectra [79, 126, 31, 168]. However, these studies have not yet been compared to them. Class spectra can also help in understanding faults, although classes generally contain a large amount of code.

Different spectra have been combined to improve fault localization [94, 124, 163, 83]. We note that data-flow information can improve fault localization techniques. However, the amount of collected data and the execution costs to process it are high compared to those based on control-flow. Maybe due to this fact, a few studies have explored the use of data-flow for SFL. Strategies to reduce execution costs to collect data-flow spectra can make these approaches more feasible for practical use [29, 30].

10.3 Faults

In controlled environments, it may be reasonable to carry out experiments with single-fault programs. However, SFL techniques must deal with an unknown number of faults to be adopted by practitioners. Most of the proposed SFL techniques have been assessed using single-fault programs. Several works have evaluated their performance for multiple faults as a complementary study. These studies carried out complete experiments for programs with single faults, and small experiments with multiple-fault programs [176, 143]. In some cases, experiments for multiple faults
use a reduced number of programs when compared to single-fault experiments. SFL techniques have been proposed to deal with multiple faults \[67, 32, 156\]. However, their performances have not been compared by these studies.

The absence of programs containing multiple faults makes it difficult to conduct experiments. The studies that perform experiments with multiple faults generate their multiple-fault versions by randomly merging single-fault versions \[67, 33, 102\]. This impairs the comparison between techniques, due to the different procedures used to create the benchmarks.

The presence of multiple faults has been shown to hamper fault localization effectiveness \[102\]. On the other hand, DiGiuseppe and Jones argued that multiple faults had a negligible impact on effectiveness since at least one of the faults is well ranked in most cases \[42\]. Their results show that SFL techniques had an average 2% decrease in effectiveness. For large programs, though, 2% of statements may represent a sizable amount of code for inspection. The existence of multiple faults can even increase fault localization effectiveness. When two or more faults cause failures on different test cases, which is expected for well-designed unit test cases, it is possible that at least one of these faults is well ranked, as occurred in the study by de Souza et al. \[31\].

Another important issue raised by recent studies is the interference between simultaneous faults \[33, 42\]. More studies are necessary to investigate the effects of fault interference on fault localization. Existing studies have already shown frequent interference among faults. One concern is that experiments with faults randomly spread across programs do not assure that the faults indeed interfere with each other, which may result in non-realistic multiple-fault programs.

The behavior of SFL techniques in the presence of different fault types is a rarely approached issue. Authors have reported their techniques’ difficulties in dealing with particular fault types. There are techniques that explicitly do not identify faults resulting from code omission \[94, 163\]. Other authors analyzed the behavior of their techniques for specific faults \[85, 93, 41\]. By assessing the performance of SFL techniques through different fault types, it is possible to understand strengths and weaknesses of such techniques and, thus, propose techniques that are more effective to cope with specific fault types. It is also possible to improve a technique that does not work well for a fault type or even combine techniques that are better for distinct fault types.

To deal with multi-statement faults, SFL techniques must be able to locate faults scattered across different code regions. The techniques must also provide hints (e.g., names of variables and/or classes) to help developers to locate non-executable statements or faulty sites that need additional code.

10.4 Programs

The use of small programs facilitates experiments. It also allows different studies to use the same subject programs to compare techniques. However, the prevalence of small programs or the use of the same benchmark programs in experiments impairs the assessment of SFL techniques. Thus, the use of several programs from different domains is needed for a comprehensive evaluation of SFL techniques.

As discussed in the previous subsection, programs do not contain multiple simultaneous faults. Thus, the creation of programs with multiple faults can contribute to experimentation in more realistic scenarios. However, creating benchmarks for controlled experimentation is expensive and difficult \[13\]. One way to create benchmarks is to identify faults in software repositories of open source programs, as done by Dallmeier and Zimmermann \[26\] and Just et al. \[70\]. This approach provides real faults for experimentation and facilitates reproduction of experiments. Another possible solution to reduce the effort in creating benchmarks is to seed faults by using mutation testing, which has been shown to be a good simulation of real faults \[8\]. Conversely, Pearson et al. showed
that SFL techniques present different results for seeded and real faults [112].

Notwithstanding the current existing benchmarks, new programs should be added to increase the diversity of domains and faults for experimentation. For example, most of the real programs currently used to evaluate SFL techniques are frameworks and libraries. End-user programs should also be assessed to better comprehend the performance of SFL. These new programs must also be available to other researchers to facilitate their use in future studies.

10.5 Testing data

Software testing is the main source of information for debugging. There are several ways to measure test quality. Testing requirements are used to guarantee that the code is widely tested, and most of the program elements are executed. Fault detection rate is a quality measure used to assess the ability of a test suite to reveal failures. Fault localization leads to another desired criterion for test suites: fault localization capability. This characteristic means that test suites should be able to distinguish program elements from their test cases.

A natural process for obtaining test suites with higher coverage is to increase their size. However, large test suites lead to greater computational costs to execute them. Test suite reduction strategies are then used to minimize the number of test cases without losing the ability to failure detection. Moreover, they are also expected to hold the distinctiveness of program elements throughout the test cases, i.e., the fault localization capability. Thus, test suite reduction techniques have to cope with a trade-off between reducing test size and keeping test cases distinguishable.

Future studies should devise new ways to measure the quality of testing data for fault localization. Test cases that cover a reduced amount of code excerpts may be useful to highlight the most suspicious ones. Conversely, individual test cases that cover a large code excerpts may impair fault localization by adding an excessive amount of program entities for each execution.

10.6 Practical use

Evaluation metrics used to measure SFL techniques are based on assumptions that in practice may not occur. Measuring fault localization performance by the relative position of a faulty entity in a ranking list can mislead the effort to find bugs. For example, if a technique returns the faulty entity within 1% of the most suspicious statements of a program with 100 KLOC, it may be necessary to inspect 1 KLOC to find the fault. This may be infeasible in practice. Developers tend to leave SFL lists if they do not find the fault among the first picks [111]. As pointed out by previous studies [111, 128], the techniques should focus on the absolute position, with the faulty statement among the first positions. Moreover, perfect bug detection (see Subsection 9.1) does not hold in practice, and thus the effort to find faults tends to increase.

The ranking lists provided by SFL techniques are based on suspiciousness scores and may be composed of entities with no direct relation to each other (e.g., statements that belong to distinct classes). This fact may impair the identification of faults. Thus, techniques that provide more information can help debuggers understand the conditions in which faults occur. Strategies have been proposed to tackle this problem, such as grouping related entities, exploring different code levels, adding source code information, or presenting subsequences of execution traces. Future approaches should explore new ways to reduce the amount of non-relevant information and to enrich the information provided to developers.

When developing fault localization techniques, we suppose several assumptions about the developers’ behavior while performing debugging tasks. However, without user studies, one cannot know whether these assumptions hold in practice. Thus, these studies are essential for identifying how the
techniques are used, to assess the developers’ fondness of SFL techniques, and to provide guidance on their use in industrial settings. Unfortunately, debugging user studies are still scarce and the few existing ones have presented divergent results. This may occur due to difficulties to obtain participants for user studies, especially professional developers, and samples that are statistically representative. Notwithstanding, new user studies are pivotal for understanding the feasibility of SFL adoption by practitioners.

Moreover, there is a lack of evaluations of SFL techniques in real development scenarios (e.g., case studies), which can bring findings to improve fault localization. Also, the current user studies had participants without previous knowledge of the code being debugged. Can SFL improve the debugging performance of developers inspecting their own code? Future studies should consider these concerns aiming to understand better the use of SFL in practice.

10.7 Concept map in Spectrum-based Fault Localization

Concept maps [108] are used to organize and represent knowledge. Based on the analysis process carried out throughout this survey, we created a concept map representing an overview of the main features and their relationships within the spectrum-based fault localization area, as shown in Figure 2.

Throughout this survey, we present and discuss several advances and difficulties of SFL studies. Figure 2 presents the multiple challenges that should be tackled to improve SFL for its main objective: to be used in real development settings. Through this concept map, researchers can identify their contributions to the area, the issues that a study address, how studies relate to each other, and future research topics. Several advances were obtained by studies over the period of this survey. We now summarize our discussions of this survey from the perspective of the concept map.

![Figure 2: Spectrum-based Fault Localization Concept map](image)

**Summary of advances and challenges**

SFL techniques have proposed several ranking metrics, and it seems that there is not a best ranking metric for all scenarios. Some of them achieve better results for different scenarios (e.g., single-
fault programs, real faults, specific programs). Studies that compared several ranking metrics have shown that some ranking metrics produce equivalent results. Moreover, the best ranking metrics have achieved small improvements in ranking the faulty program elements. Have we reached a limit for the improvement of such metrics? Future work may answer this question.

Although the prevalence of statements and branches as the most used program spectra for SFL, several recent studies have chosen methods as their program entities. However, only by changing the granularity level is not enough to understand whether a spectrum is better. Although method-level spectrum is less precise, it may be more comprehensive from the developers’ perspective, which can help to understand a bug context. Future studies should compare the use of different spectra for fault localization. Moreover, other spectra (e.g., data-flow) should be applied to better investigate their usefulness for fault localization. User studies are fundamental to evaluate such issues.

The SFL ranking lists are also prevalent in studies. However, other proposals have been presented to provide more context for debugging. The examples are small code execution paths and lists combining different spectra. How to provide significant information for fault localization and how developers use such information are open challenges.

SFL techniques deal with different types of faults, which can be more easy or difficult to locate. How the techniques behave through varied fault types is another open challenge. Faults by code omission have been shown by previous studies as a great challenge for SFL techniques. Moreover, interactions among faults have been investigated by a few studies and need more attention for a better comprehension of their impact on the performance of SFL. The characteristics of programs used to assess SFL techniques also impact on their performance and, thus, deserve future investigation. In practice, there are programs that differ from most of the benchmark programs used in SFL evaluations (e.g., small test suites, large methods, legacy code, multi-language programs).

Regarding evaluation metrics, recent studies have focused on the absolute number of program elements to inspect. Indeed, percentages of inspected code are only useful to compare SFL techniques but do not serve to evaluate how techniques will be used in practice since developers do not seem to be willing to inspect a large number of code excerpts.

Testing improvements have also been explored in recent years. These studies have shown that beyond code coverage, tests should cover distinguishable code excerpts to improve SFL effectiveness.

User studies with SFL are rare. However, most of them have been performed recently. Each of them has its own experimental design, insights, and limitations. More replications studies are needed to better comprehend how developers use SFL. Also, there is a need for studies in real development settings, with professional developers, which can bring new findings to understand the practical use of SFL.

Automating debugging is a complex challenge and SFL is a promising approach to locate faults. However, SFL is a process that involves: (1) choosing test cases and spectra; (2) calculating the suspiciousness of program elements; (3) understanding the strengths and weaknesses of an SFL technique through different characteristics of programs and their faults; (4) measuring SFL effectiveness; (5) proposing useful SFL outputs; and (6) assessing their practical use. By understanding and relating all these concerns, we can propose new ways to improve SFL.

11 Related work

Other studies were proposed to provide an overview of the fault localization area. The studies shown in Section 4.7 [104, 34, 151, 80] evaluated and compared the performance of several ranking metrics. Alipour conducted a survey on fault localization [9]. The author considered that the major fault localization approaches are program slicing, spectrum-based, statistical inference, delta debugging,
dynamic, and model checking. In his survey, only six studies of SFL techniques were addressed—most of the studies are related to model checking-based techniques. The author concludes that such techniques are far from practical use due to difficulties related to execution time and scalability for large programs. Beyond these concerns, model checking techniques usually require formal specifications of programs, which is difficult to obtain for most programs. Agarwal and Agrawal presented a literature review on fault localization, including studies from 2007 to 2013. They selected 30 papers from major Software Engineering journals and conferences. Most of the papers are focused on test suite improvements for fault localization and SFL techniques. The results are presented in a table describing studies’ characteristics and a description of the most frequent techniques and strategies in the area.

Wong et al. presented a fault localization survey addressing techniques from 1977 to November 2014. They classified the techniques in eight categories: program slicing, spectrum-based, statistics, program state, machine learning, data mining, model-based debugging, and additional techniques. Their survey also addresses fault localization tools developed by the presented studies.

Our survey differs from the previous ones by focusing on spectrum-based techniques from 2005 to October 2017, which includes the most recent work of the SFL research area; moreover, we discuss seminal works on automated debugging from the 1950s to 2004 through a historical overview.

Besides the database search, we applied a snowballing process to extend the searching for fault localization studies.

This survey also differs by addressing topics related to the practical adoption of SFL, such as user studies and techniques that provide additional contextual information, aiming to improve developer program comprehension. We understand that future research must focus on strategies to allow the use of SFL techniques in real settings. Moreover, we also included studies that focus on testing improvements and mutation-based techniques for fault localization. Another contribution of this survey is to propose a concept map positioning the main topics in the field as well as the relationships among them.

12 Conclusion

A great number of fault localization techniques have been proposed in the last decades. These techniques aim to pinpoint program entities that are likely to be faulty. Thus, developers can inspect these entities to find faults, reducing the time spent debugging.

This survey focuses on spectrum-based fault localization techniques, which have presented promising results. We address the main topics regarding SFL to provide a comprehensive overview of the research area: SFL techniques, spectra, faults, programs, testing data, and practical use.

Several advances have been achieved, while some challenges and limitations should be tackled to improve SFL techniques. Among the advances, recent techniques have carried out experiments with real programs. Other SFL techniques aimed at providing more information to improve fault localization. Moreover, more studies have focused on pinpointing the faults among the first picks of the suspiciousness lists.

There are several challenges that future studies should consider. New ways for exploring program spectrum information and new strategies for generating reduced sets of suspicious entities can contribute to improving the output results. Combining different spectra (e.g., data-flow and control-flow spectra) seems to fine-tune the fault localization ability of SFL techniques; however, sophisticated spectra are costly to collect. Strategies for collecting fine-grained coverage levels from suspicious coarser levels can help balance execution costs and output precision. New techniques that cope with multiple-fault programs are needed to support fault localization of real programs.
in which the number of faults is unknown. Large-size programs from diverse domains, containing
different fault types and multiple faults, will provide realistic scenarios for assessing SFL techniques.
More user studies will enable a better understanding of how fault localization techniques are used
in practice.

This survey also presents a concept map of SFL, representing the relationships between the main
topics and challenges for future research. By presenting the state-of-the-art of SFL techniques, we
hope this survey encourages the development of debugging techniques that end up adopted by
practitioners.

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