Leveraging Fuzzy System to Reduce Uncertainty of Decision Making in Software Engineering Automation

Yueke Zhang
Southwest University
zyueek@gmail.com

Yu Huang
Vanderbilt University
yu.huang@vanderbilt.edu

ABSTRACT

Decision making in automated GI-based software engineering tasks can significantly affect the performance of the system. However, modern SE usually presents high uncertainty in such decision making process due to the existence of multiple solutions that reply on heuristics. We propose to apply the theory of ***Fuzzy System*** to obtain a final decision with lower uncertainty and higher accuracy. We also demonstrate a motivating example and discuss the challenges and opportunities for applying fuzzy system to SE tasks.

KEYWORDS

decision making, uncertainty, fuzzy system, SE automation

1 INTRODUCTION

Modern software engineering (SE) benefits from automation techniques, which can efficiently reduce developer burden. For example, fault localization (FL) techniques provide recommendations to locate buggy lines; automated program repair (APR), which involves FL, fixes bugs automatically; AI models automatically perform downstream tasks in SE. Many such automation techniques rely on assumptions or heuristics rather than provable theories. For example, spectrum-based fault localization (e.g., Tarantula [1]) assumes that the likelihood (i.e., suspiciousness) of a line containing a bug is associated with the number of passing or failing test runs; APR leverages the idea that randomly changing the program can eventually make it pass all test cases. As a result, there are multiple algorithms and tools using different interpretations and tuning decisions. For instance, there are already over 40 spectrum-based FL tools alone, each of which emphasizes different aspects of the FL assumptions [3]. As a result, each tool entails some degree of uncertainty — there does not exist a *best* solution. In this paper, we propose the following research problem in SE: ***can we address the uncertainty in decision making in automated software engineering tasks***? Similarly, when multiple techniques targeting the same problem provide different solutions, how should we make the final decision?

Meanwhile, the operation research community has developed theories to quantify uncertainty in decision making processes: **Fuzzy System** [5]. The theory of Fuzzy System delivers a final optimal decision by modeling imperfect observations, ambiguities, and uncertainty from multiple individual *sources* of domain knowledge (e.g., output from an FL tool), and then applying a fusion algorithm to integrate the sources. Based on the the format of the decision making problem (e.g., if it is a binary decision problem or attribute-value decision problem), there are multiple approaches including *fuzzy set theory*, *evidence theory*, and *rough set theory*, to model the uncertainty using different mathematical approaches. Finally, we can fuse the modeled uncertainty among multiple sources (e.g., using the Dempster Combination Rule (DCR) [7]) to present a single final output containing lower uncertainty and higher confidence (loosely, fusion attempts to maximize certainty in the best aspects of each source of information). As shown in Section 2, decision making processes in SE can benefit from such approaches.

Though fuzzy system is still a new concept in SE, it has been applied to certain computer science domains. For example, it has been used to reduce semantic ambiguity in Natural Language Processing [8], detect phishing attacks in security research [6], and to enhance template matching [4].

In this paper, we propose to apply the theory of fuzzy system to GI-based SE tasks (e.g., fault localization in APR). We leverage three main insights: (1) The majority of algorithms in programming automation are heuristic-based, which present different recommendations that are difficult to compare. Such differences raise uncertainty in decision making, which contribute to overall system performance. (2) Fuzzy-based approach can efficiently fuse multiple sources of information that present different findings. (3) The output of algorithms in GI-based SE tasks can be applied to fuzzy system with minimal modification. We anticipate that applying the theory of fuzzy system can improve the accuracy of certain processes in GI-assisted tasks by providing decisions with less uncertainty. Below, we discuss a motivating example in which we demonstrate improved fault localization accuracy by fusing multiple FL algorithms. We also discuss potential challenges, solutions, and opportunities for using fuzzy based method in automated SE.

2 MOTIVATING EXAMPLE

We use the fault localization process in APR as an example to introduce how fuzzy based method can be used to reduce uncertainty in the decision making for faulty lines. This example also shows that fuzzy system provides a final decision based on all individual decision makers (i.e., different FL algorithms) but with a higher overall accuracy.

As shown in Table 1, we apply three popular FL algorithms (i.e., Ochiai, Ample, and Zoltar) to a 9261-line snippet in the `Math` library from the Defect4j dataset and fuse the suspiciousness/rankings to present a final FL result. `Math` contains 85k lines of code and 106 snippets with bugs (each snippet comes with a test suite to expose the bugs). The three spectrum-based FL algorithms assign different suspiciousness rankings (in the example, the suspiciousness scores are normalized within each FL method for fair comparison and fusion in fuzzy system). Using fuzzy system, for each FL, we treat it as an individual decision maker and use the suspiciousness score as the probability P of bug existence in a line of code, and use $1 - p$ to model the uncertainty of this decision. Then using the

GECCO '22 Companion, July 9–13, 2022, Boston, MA, USA
2022. ACM ISBN 978-1-4503-9268-6/22/07…$15.00
https://doi.org/10.1145/3520304.3533991

Table 1: A motivating example showing the uncertainty from three popular fault localization algorithms: *Ochiai*, *Ample*, and *Zoltar*, and how fuzzy system improves the final decision. Column 3–5 presents the normalized suspiciousness scores and the ranking (in parenthesis, among 9261 total LoC) of each line of code in this partial snippet from each of the three FL algorithms. The right-most column "Fuzzy" shows the final suspiciousness scores and ranking for each line using the proposed fuzzy-based approach which fuses the results from Column 3–5. The *Exam Score* displays the overall performance of all the FL approaches. The proposed fuzzy system based approach achieves a better exam score (a lower exam score indicates better hit accuracy).

Red lines indicate buggy code in this snippet.

Line #	Line of Code	Ochiai	Ample	Zoltar	Fuzzy
1	`currentEvent.stepAccepted(eventT, eventY);`	0.75 (113)	0.48 (366)	0.53 (124)	0.94 (124)
2	`isLastStep = currentEvent.stop();`	0.75 (122)	0.48 (362)	0.53 (114)	0.94 (126)
3	`for (final StepHandler handler : stepHandlers) {`	0.75 (121)	0.48 (370)	0.53 (121)	0.94 (131)
4	`handler.handleStep(interpolator, isLastStep);}`	1.00 (13)	0.54 (187)	1.00 (13)	1.00 (6)
5	`if (isLastStep) {`	0.75 (95)	0.48 (390)	0.53 (95)	0.94 (105)
6	`System.arraycopy(eventY, 0, y, 0, y.length);`	0 (8283)	0.08 (7518)	0 (8283)	0.08 (7531)
7	`for (final EventState remaining : occuringEvents) {`	0 (8293)	0.08 (7519)	0 (8293)	0.08 (7529)
8	`remaining.stepAccepted(eventT, eventY); }`	0 (8269)	0.01 (7750)	0 (8269)	0.01 (7761)
	Exam Score	0.41	0.39	0.41	**0.38**

Dempester-Shafer combination rule, we fuse the suspiciousness decisions and present the final suspiciousness score/ranking, as shown in Column "Fuzzy". With fuzzy system, the suspiciousness scores of all buggy lines have increased (note that there are many other lines in the code snippet we cannot show due to space limit), and the rankings are improved overall among the buggy lines. We also present the exam score in the table, which shows that the fuzzy based method has a better overall performance than all three individual FL algorithms.

3 CHALLENGES AND OPPORTUNITIES

We identify and discuss three main challenges for applying fuzzy system to SE tasks: modeling, computational overhead, and evaluation. We also discuss the potential solutions and opportunities.

Modeling. We identify the main challenge as modeling the uncertainty in the decision making process of SE tasks. In operation research, this modeling process is called *fuzzification*, which is the process of converting a real world problem to fuzzy system expression. We need to measure the uncertainty with domain knowledge (e.g., suspiciousness score in FL). In a fuzzy approach, a division criterion is also required to deal with ambiguous decisions.

Computational Overhead. In most scenarios, such as the motivating example, the Dempster Combination Rule is used to fuse individual sources, which is a linear formula with respect to the number of sources being fused. While the computation associated with DCR-based fusion is negligible, it may still be costly to compute all of the different sources needing fusion. In the case of our FL example, we must compute all of the suspiciousness scores using each technique before we can fuse the results to pick the best choice—this may require substantial computational resources.

Evaluation. In traditional fuzzy system applications, two main evaluation methods are applied: (1) gold standard, where labeled correct decisions are provided to evaluate the accuracy of fuzzy system; (2) expertise-based evaluation, where we must rely on evaluations from experts (instead of labels). In the latter evaluation method, human studies are usually required. Such evaluations can be naturally adopted in the applications of fuzzy system in SE tasks.

Though there are challenges for applying fuzzy based method to SE tasks, it provides a great opportunity to address the issue of uncertainty in decision making process in SE. Researchers in SE have tried to combine different (but hard to compare) SE techniques to seek for a overall better solution for certain tasks, but they have only been able to randomly test different combinations of methods and provide heuristics for such combinations [2]. Fuzzy system can provide a theory-based solution that improves the overall accuracy of decision making. Furthermore, fuzzy system also has the potentials to address the uncertainty issue in the human factor studies in SE (e.g., any process that relies on human ratings).

4 CONCLUSION

We propose to adopt the theory of fuzzy system from operation research to automated GI-based tasks to address the problem of uncertainty issue in decision making processes. We highlight the potential of using fuzzy system to improve the overall performance of SE tasks (e.g., FL) and discuss the challenges, solutions and opportunities of applying fuzzy system to a wider range of SE tasks.

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