A General Framework to Identify Software Components from Execution Data

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Abstract: Restructuring an object-oriented software system into a component-based one allows for a better understanding of the software system and facilitates its future maintenance. A component-based architecture structures a software system in terms of components and interactions where each component refers to a set of classes. In reverse engineering, identifying components is crucial and challenging for recovering the component-based architecture. In this paper, we propose a general framework to facilitate the identification of components from software execution data. This framework is instantiated for various community detection algorithms, e.g., the Newman's spectral algorithm, Louvain algorithm, and smart local moving algorithm. The proposed framework has been implemented in the open source (Pro)cess (M)ining toolkit *ProM*. Using a set of software execution data containing around 1.000.000 method calls generated from four real-life software systems, we evaluated the quality of components identified by different community detection algorithms. The empirical evaluation results demonstrate that our approach can identify components with high quality, and the identified components can be further used to facilitate future software architecture recovery tasks.

1 INTRODUCTION

The maintenance and evolution of software systems have become a research focus in software engineering community (Mancoridis et al., 1999). Architectures of these systems can be used as guidance to help understand and facilitate the future maintenance (Liu et al., 2018d). However, complete and up-to-date software architecture descriptions rarely exist (Lindvall and Muthig, 2008). Software architectures that normally include components and interactions can be reconstructed from low-level data, such as source code, and execution data.

During the execution of software systems, tremendous amounts of execution data can be recorded. By exploiting these data, one can reconstruct a software architecture. To this end, we need to identify components from the execution data. For object-oriented software systems, a component is extracted as a set of classes that provide a number of functions for other components. In this paper, we propose a general framework to identify components from software execution data by applying various community detection algorithms. Community detection is one of the most useful techniques for complex networks analysis with an aim to identify communities. A software system can be viewed as a complex network of classes, in which the component identification problem can be naturally regarded as the community detection problem with modularity maximization.

More concretely, we first construct a class interaction graph by exploiting the software execution data that provides rich information on how classes interact with each other. Then, different community detection algorithms are applied to partition the class interaction graph into a set of sub-graphs. Classes that are grouped in the same sub-graph form a component. Next, a set of quality criteria are defined to evaluate the quality of the identified components from different perspectives. Our framework definition is generic and can be instantiated and extended to support various community detection algorithms. To validate the proposed approach, we developed two plug-ins in the *ProM* toolkit [1], which support both the identification and the evaluation process.

The main contributions of this paper include:

- a general framework to support the identification and quality evaluation of components from software execution data and its instantiation by five community detection algorithms. Different from

[1]http://www.promtools.org/

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existing graph partitioning-based algorithms, our approach does not require users to specify the number of clusters in advance; and

- two plug-ins in the *ProM* toolkit. This allows other researchers reproducing our experiments and comparing their approaches.

Section 2 presents some related work. Section 3 defines preliminaries. Section 4 presents the main approach. Section 5 introduces the tool support. In Section 6, we present the experimental evaluation. Finally, Section 7 concludes the paper.

2 RELATED WORK

Generally speaking, the identification of components can be achieved by clustering classes. Table 1 summarizes some typical component identification approaches for object-oriented software systems by considering the required type of input (i.e., source code, development documents, execution data), the type of identification techniques (e.g., graph clustering/partition, genetic algorithm, etc.), the parameter settings, and tool support availability. Note that ✓/✗ means that the tool is introduced in the paper but is not available online or does not work any more.

According to Table 1, these approaches are classified into three categories based on their required input artifacts: (1) *development documents-based* approaches that take the sequence diagram, class diagram and use case diagram as input; (2) *source code-based* approaches that take the source code as input and consider structural connections among classes; and (3) *execution data-based* approaches that take software execution data as input. The output of these approaches are component configurations, i.e., how classes are grouped to form components. Our work fits into the third category.

Because software development documents are typical either incomplete or out-of-date, the applicability of the development documents-based approaches is quite limited. For components, the idea is to group together classes that contribute to the same function. Source code-based approaches use the dependencies among classes that are extracted from the source code by static analysis techniques. However, classes in the source code may have in some cases a wider scope than the functional scope. In addition, they are not applicable anymore if the source code is not available (e.g., in case of legacy software systems). Another way to determine which class contributes to which function (component) is to execute the software system with individual functions. The execution data-based approaches help limit the analysis of dependency only to the space covered by the application execution. However, existing execution data-based approaches suffer from the following limitations that may restrict the applicability:

- **Requirement for User Input Parameters.** Existing approaches require users to specify a group of parameters (e.g., the number/size of components) as input. However, a reasonable parameter setting is very difficult for users that are not familiar with the approach. If parameters are not set properly, the underlying approaches may perform badly.
- **Lack of a Clearly Defined Systematic Methodology.** A systematic methodology defines clearly the required input, the techniques, the resulted output and the evaluation criteria of the approach to solve a general research challenge. Existing execution data-based approaches do not explicitly define such a complete methodology. This limits the applicability and extensibility of existing approaches in the large.
- **Lack of Tool Support.** The usability of an approach heavily relies on its tool availability. Existing dynamic component identification approaches do not provide usable tools that implement their techniques. This unavailability prohibits other researchers to reproduce the experiment and compare their approaches.

3 PRELIMINARIES

Let $\mathcal{U}_M$ be the method call universe, $\mathcal{U}_N$ be the method universe, $\mathcal{U}_C$ be the universe of classes, $\mathcal{U}_O$ be the object universe where objects are instances of classes. To relate these universes, we introduce the following notations: For any $m \in \mathcal{U}_M$, $\widehat{m} \in \mathcal{U}_N$ is the method of which m is an instance. For any $o \in \mathcal{U}_O$, $\widehat{o} \in \mathcal{U}_C$ is the class of o.

A method call is the basic unit of software execution data (Liu et al., 2016; Liu et al., 2018d; Liu et al., 2018a; Liu et al., 2018c; Liu et al., 2018b; Leemans and Liu, 2017; Qi et al., 2018). The method call and its attributes are defined as follows:

Definition 1. ***(Method Call, Attribute)*** *For any $m \in \mathcal{U}_M$, the following standard attributes are defined:*

- $\eta : \mathcal{U}_M \to \mathcal{U}_O$ *is a mapping from method calls to objects such that for each method call $m \in \mathcal{U}_M$, $\eta(m)$ is the object containing the instance of the method $\widehat{m}$.*
- $c : \mathcal{U}_M \to \mathcal{U}_M \cup \{\perp\}$ *is the calling relation among method calls. For any $m_i, m_j \in \mathcal{U}_M$, $c(m_i) = m_j$*

Table 1: Summary of Existing Component Identification Approaches.

Reference	Required Input Artifacts	Techniques	Parameter Requirement	Tool Availability
(Lee et al., 2001)	development documents	graph clustering	✓	✗
(Kim and Chang, 2004)	development documents	use case clustering	✓	✓/✗
(Hasheminejad and Jalili, 2015)	development documents	evolutionary algorithm	✓	✗
(Washizaki and Fukazawa, 2005)	source code	class relation clustering	✓	✓/✗
(Kebir et al., 2012)	source code	hierarchical clustering genetic algorithm	✓	✗
(Cui and Chae, 2011)	source code	hierarchical clustering	✓	✓/✗
(Luo et al., 2004)	source code	graph clustering graph iterative analysis	✓	✗
(Chiricota et al., 2003)	source code	graph clustering	✓	✗
(Mancoridis et al., 1999)	source code	graph partition	✓	✓/✗
(Qin et al., 2009)	execution data	hyper-graph clustering	✓	✗
(Allier et al., 2009)	execution data	concept lattices	✓	✗
(Allier et al., 2010)	execution data	genetic algorithm	✓	✗

means that m_i is called by m_j, and we name m_i as the callee and m_j as the caller. For $m \in \mathscr{U}_M$, if $c(m) = \perp$, then $\widehat{m}$ is a main method.

Definition 2. ***(Software Execution Data)*** *$SD \subseteq \mathscr{U}_M$ is the software execution data.*

According to Definition 2, the software execution data are defined as a finite set of method calls.

4 COMPONENT IDENTIFICATION

The input of our approach is software execution data, which can be obtained by instrumenting and monitoring software execution. In Section 4.1, we first give an overview of the identification framework. Then, we present the instantiation of the framework with details in Sections 4.2-4.4.

4.1 Approach Overview

An approach overview is described in the following:

- ***Class Interaction Graph Construction.*** Starting from the software execution data, we construct a class interaction graph (*CIG*) where a node represents a class and an edge represents a calling relation among the two classes.
- ***Component Identification.*** By taking the constructed *CIG* as input, we partition it into a set of sub-graphs using existing community detection algorithms. Classes that are grouped in the same sub-graph form components.
- ***Quality Evaluation of the Identified Components.*** After identifying a set of components, we evaluate the quality of the identified components against the original *CIG*.

4.2 Class Interaction Graph Construction

Given the software execution data, we first construct the *CIG* according to the following definition.

Definition 3. ***(Class Interaction Graph)*** *Let SD be the execution data of a piece of software. $G = (V, E)$ is defined as the Class Interaction Graph (CIG) of SD such that:*

- $V = \{v \in \mathscr{U}_C | \exists m \in SD : \widehat{\eta(m)} = v \vee \widehat{\eta(c(m))} = v\}$;
- $E = \{(v_i, v_j) \in V \times V | \exists m \in SD : \widehat{\eta(m)} = v_i \wedge \widehat{\eta(c(m))} = v_j\}$.

According to Definition 3, a *CIG* contains (1) a set of classes, i.e. vertices; and (2) a set of calling relations among them, i.e., edges. Note that the calling relations among classes are obtained from method calls, e.g., if m_1 calls m_2 we have a calling relation saying the class of m_1 calls the class of m_2. Different from existing software call graphs that are defined on top of the method calling relation in the source code (Qu et al., 2015), the *CIG* id defined on the class calling relations from the execution data.

4.3 Component Identification

After constructing a *CIG*, we introduce how to identify components out of the *CIG*. Essentially, the component identification is a division of the vertices of *CIG* into a finite set of non-overlapping groups as defined in the following:

Definition 4. ***(Component Identification)*** *Let SD be the software execution data and $G = (V, E)$ be its CIG. $CS \subseteq \mathcal{P}(V)$ is defined as the identified component set based on certain approach such that:*

- $\bigcup_{C \in CS} C = V$; *and*

- $\forall C_1, C_2 \in CS$, *we have* $C_1 \cap C_2 = \emptyset$, *i.e., classes of different components do not overlap.*

Definition 4 gives the general idea of component identification by explicitly defining the input and output, based on which we can see that the identification does not allow overlaps among components. Note that this definition can be instantiated by any graph clustering or community detection techniques.

In the following, we instantiate the component identification framework by five state-of-the-art community detection algorithms: (1) the Newman's spectral algorithm (Newman, 2006) and its MVM refinement (Schaffter, 2014); (2) Louvain algorithm (Blondel et al., 2008) and multi-level refinement (Rotta and Noack, 2011); and (3) Smart local moving algorithm (Waltman and Van Eck, 2013).

1) Newman's spectral algorithm and moving vertex method refinement. Newman's spectral algorithm aims to determine whether there exists any natural division of the vertices in a graph/network into nonoverlapping groups/modules, where these groups/modules may be of any size. This is addressed by defining a quantity called modularity Q to evaluate the division of a set of vertices into modules. Q is defined as follows: $Q = Fe - EFe$ where Fe represents fraction of edges falling within modules and EFe represents expected fraction of such edges in randomized graphs.

To further improve the quality of group structures inferred using the Newman's spectral algorithm, a refinement technique, called Moving Vertex Method (MVM) is introduced in (Schaffter, 2014). MVM works independently on top of the detection results obtained by the Newman's spectral algorithm. It tries to move nodes from one community to another community and checks the effect of the modification on Q. The modification that leads to the largest increase in Q is accepted. For more explanations of the MVM technique refinement, the reader is referred to (Newman, 2006) and (Schaffter, 2014).

2) Louvain algorithm and multi-level refinement. The Louvain algorithm starts with each node in a network belonging to its own community, i.e., each component consists of one node only. Then, the algorithm uses the *local moving heuristic* to obtain an improved community structure. The idea of *local moving heuristic* is to repeatedly move individual nodes from one community to another in such a way that each node movement results in a modularity increase. Hence, individual nodes are moved from one community to another until no further increase in modularity can be achieved. At this point, a reduced network where each node refers to a community in the original network is constructed. The Louvain algorithm proceeds by assigning each node in the reduced network to its own singleton community. Next, the local moving heuristic is applied to the reduced network in the same way as was done for the original network. The algorithm continues until a network is obtained that cannot be reduced further. An extension of the Louvain algorithm with multi-level refinement is introduced in (Rotta and Noack, 2011). The refinement improves solutions found by the Louvain algorithm in such a way that they become locally optimal with respect to individual node movements.

3) Smart local moving algorithm. The smart local moving (SLM) algorithm starts with each node in a network being its own community and it iterates over all communities in the present community structure. For each community, a sub-network is constructed which is a copy of the original network that includes only the nodes belonging to a specific community of interest. The SLM algorithm then uses the local moving heuristic to identify communities in the sub-network. Each node in the sub-network is first assigned to its own singleton community, and then local moving heuristic is applied. After a community structure has been obtained for each sub-network, the SLM algorithm constructs a reduced network. In the reduced network, each node corresponds to a community in one of the sub-networks. The SLM algorithm then performs an initial assignment of the nodes to communities in the reduced network in such a way that nodes corresponding to communities in the same sub-network are assigned to the same community. The previous steps start over again for the reduced network until a network is obtained that cannot be reduced any more.

4.4 Quality Metrics

This section introduces a group of quality metrics to help evaluate the components identified by different community detection techniques.

1) Size and Counting.

To give a general overview of the identified components, we first introduce the following metrics:

- The number of identified components (NoC) from the execution data of a software system.
- The average size of identified components (AoC), i.e., the average number of classes that each component involves.
- The ratio of single class components (RSC). RSC means the number of classes in single class components divided by the total number of classes.
- The ratio of largest component (RLC). RLC represents the number of classes in the largest component divided by the total number of classes.

- The ratio of intermediate components (RIC). RIC represents the number of classes in the intermediate components divided by the total number of classes. Note that RICs refer to components that neither contains one class nor be the largest ones.

According to (Cui and Chae, 2011), components with very large number of classes (high RLC) or very small number of classes (high RSC) cannot be regarded as good components. An ideal distribution is a normal distribution where quite many components have reasonable size (high RIC). Hence, we should try to avoid the case of too many single class components as well as a single very large one.

2) Coupling. In component-based software systems, coupling represents how tightly one component interacts with the others. The coupling metric between two components is defined as the ratio of the number of edges connecting them to the maximal number of edges that connect all their vertices.

Let $G = (V, E)$ be a *CIG* and *CS* be the identified components. For any $C_1, C_2 \in CS$, we have:

$$coupl(C_1, C_2) = \frac{|CouEdge|}{|C_1| \times |C_2|} \tag{1}$$

where $CouEdge = E \cap ((C_1 \times C_2) \cup (C_2 \times C_1))$ represents the set of edges that connecting components C_1 and C_2. Then, the coupling metric of all components is defined as follows:

$$Coupling(CS) = \frac{\sum_{1 \le i < j \le |CS|} coupl(C_i, C_j)}{|CS| \times (|CS| - 1)} \tag{2}$$

3) Cohesion. In component-based software systems, cohesion represents how tightly classes in the same component are associated. The cohesion metric of a component is defined as the ratio of the number of its edges to the maximal number of edges that can connect all its vertices (the number of edges in the complete graph on the set of vertices).

For any $C \in CS$, its cohesion metric is defined as:

$$cohes(C) = \frac{|CohEdge(C)|}{|C| \times (|C| - 1)} \tag{3}$$

where $CohEdge(C) = E \cap (C \times C)$ represents the set of edges that are contained in C. Then, the cohesion metric of all components is defined as follows:

$$Cohesion(CS) = \frac{\sum_{C \in CS} cohes(C)}{|CS|} \tag{4}$$

4) Modularity Quality. The cohesion and coupling metrics measure the quality of the identification results from two opposite perspectives. A well-organized component-based architecture should be highly cohesive and loosely coupled.

Table 2: Number and Size of Identified Components.

	Lexi 0.1.1		JHotDraw 5.1		JUnit 3.7		JGraphx 3.5.1	
	NoC	AoC	NoC	AoC	NoC	AoC	NoC	AoC
NSA	20	3.4	13	7.1	9	5.2	11	5.6
NSA-R	3	22.3	5	18.6	4	10.2	1	62
SLM	5	13.6	6	15.5	5	9.4	5	12.4
LA	5	13.6	6	15.5	5	9.4	5	12.4
LA-R	5	13.6	7	13.3	5	9.4	5	12.4
Base	5	13.6	7	13.3	3	15.6	9	6.9

Modularity Quality (MQ) aims to reward the creation of highly cohesive components and to penalize excessive coupling among them. It is formally defined as follows:

$$MQ(CS) = Cohesion(CS) - Coupling(CS) \tag{5}$$

MQ lies in the $[-1, 1]$ interval and a higher *MQ* value normally means a better architecture quality.

5 IMPLEMENTATION IN PROM

The open-source (Pro)cess (M)ining framework *ProM 6*[2] provides a completely plugable environment for process mining and related topics. It can be extended by adding plug-ins, and currently, more than 1600 plug-ins are included.

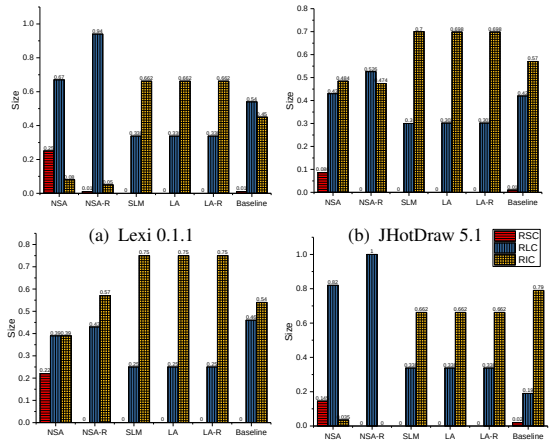
The component identification and quality evaluation approaches have been implemented as two plug-ins in our *ProM 6* package[3]. The first one, called *Integrated Component Identification Framework*, takes as input the software execution data, and returns the component configuration file that describes which classes belong to which components. Note that this plugin currently supports all community detection algorithms introduced in Section 4.3. The second plugin, called *Quality Measure of Component Identification*, takes (1) the software execution data and (2) component configuration as input, and returns the quality metrics (e.g., size and modularity values) of the identification component configuration. All experimental results in the following discussions are based on these two tools.

6 EXPERIMENTAL EVALUATION

Then, we evaluate our approaches using four open-source software systems.

[2]http://www.promtools.org/

[3]https://svn.win.tue.nl/repos/prom/Packages/SoftwareProcessMining/



(a) Lexi 0.1.1 (b) JHotDraw 5.1

(c) JUnit 3.7 (d) JGraphx 3.5.1

Figure 1: Size Comparison.

6.1 Subject Software Systems and Execution Data

For our experiments, we use the execution data that are collected from four open-source software systems. More specifically, *Lexi 0.1.1* [4] is a Java-based open-source word processor. Its main function is to create documents, edit texts, save files, etc. The format of exported files are compatible with Microsoft word. *JHotDraw 5.1*[5] is a GUI framework for technical and structured 2D Graphics. Its design relies heavily on some well-known GoF design patterns. *JUnit 3.7*[6] is a simple framework to write repeatable tests for java programs. It is an instance of the xUnit architecture for unit testing frameworks. *JGraphx 3.5.1*[7] is an open-source family of libraries that provide features aimed at applications that display interactive diagrams and graphs.

Note that the execution data of *Lexi 0.1.1*, *JGraphx 3.5.1*, and *JHotDraw 5.1* are collected by monitoring typical execution scenarios of the software systems. For example, a typical scenario of the *JHotDraw 5.1* is: launch JHotDraw, draw two rectangles, select and align the two rectangles, color them as blue, and close JHotDraw. For the *JUnit 3.7*, we monitor the execution of the project test suite with 259 independent tests provided in the *MapperXML*[8] release. Table 3 shows the detailed statistics of the data execution, including the number of packages/-classes/methods that are loaded during execution and the number of method calls analyzed.

[4]http://essere.disco.unimib.it/svn/DPB/Lexi%20v0.1.1%20alpha/

[5]http://www.inf.fu-berlin.de/lehre/WS99/java/swing/JHotDraw5.1/

[6]http://essere.disco.unimib.it/svn/DPB/JUnit%20v3.7/

[7]https://jgraph.github.io/mxgraph/

[8]http://essere.disco.unimib.it/svn/DPB/MapperXML%20v1.9.7/

Table 3: Statistics of Subject Software Execution Data.

Software	#Packages	#Classes	#Methods	#Method Calls
Lexi 0.1.1	5	68	263	20344
JHotDraw 5.1	7	93	549	583423
JUnit 3.7	3	47	213	363948
JGraphx 3.5.1	9	62	695	74842

6.2 Identification Approaches

Five component identification approaches are evaluated with respect to a baseline. The first approach identifies components by the Newman's spectral algorithm (denoted as *NSA*). The second approach identifies components by Newman's spectral algorithm with MVM refinement (denoted as *NSA-R*). The third one creates a component based on smart local moving algorithm (denoted as *SLM*). The forth approach identifies components by the Louvain algorithm (denoted as *LA*). Finally, the last one identifies components by the Louvain algorithm with multi-level refinement (denoted as *LA-R*).

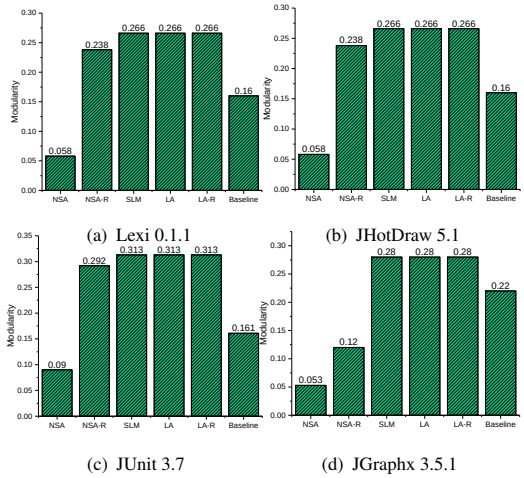
To evaluate the quality of identified components, we compare them with a baseline. The packages that are defined in the source code are assumed as components manually classified by software developers in the design stage, and are used as the baseline in the following experiments.

6.3 Evaluation Results

In this section, we evaluate the quality of the components identified by different approaches as well as the baseline. More specifically, we first identify components for the four software systems using *NSA*, *NSA-R*, *SLM*, *LA* and *LA-R*. Afterwards, the quality of components is measured and compared in terms of size and modularity metrics that are defined in Section 4.4. In addition, the time performance of different approaches are also compared.

The number of identified components (NoC) and the average size of components (AoC) for the four open-source software systems based on *NSA*, *NSA-R*, *SLM*, *LA*, *LA-R*, and the baseline are shown in Table 2. Note that the AoC value decreases as the NoC value increases for each software system. This is because the AoC is computed as the total number of classes divided by NoC. In general, the NoC/AoC values of *NSA-R*, *SLM*, *LA* and *LA-R* are similar with the baseline while the NoC/AoC value of *NSA* is much higher than others, i.e., too much components are identified by *NSA* for each software system.

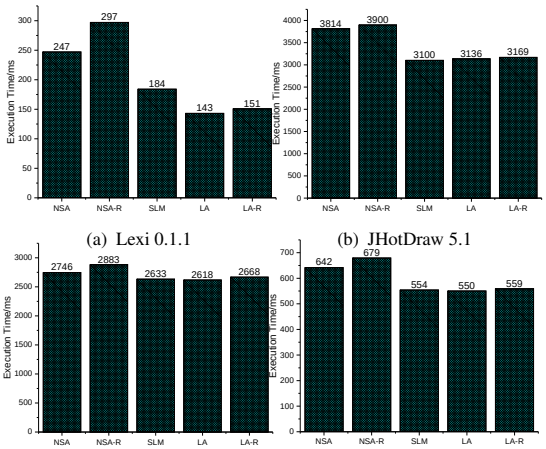
Fig. 1 shows the size metric evaluation results for *Lexi 0.1.1*, *JHotDraw 5.1*, *JUnit 3.7* and *JGraphx 3.5.1* based on *NSA*, *NSA-R*, *SLM*, *LA*, *LA-R*, and the



(a) Lexi 0.1.1 (b) JHotDraw 5.1

(c) JUnit 3.7 (d) JGraphx 3.5.1

Figure 2: Modularity Comparison.



(a) Lexi 0.1.1 (b) JHotDraw 5.1

(c) JUnit 3.7 (d) JGraphx 3.5.1

Figure 3: Time Performance Comparison.

baseline. Normally, a higher RIC (or low RSC and RLC) value indicates that the identified components are more well-organized than those with lower RIC (or high RSC and RLC) values. Generally speaking, the RIC values of *SLM*, *LA* and *LA-R* are much higher than those of *NSA* and *NSA-R* as well as the baseline. As for the *SLM*, *LA* and *LA-R*, they have almost the same results. This can be explained by the fact that all these three approaches are based on the local moving heuristic. Different from this general conclusion, there are some exceptions. Considering for example the *JGraphx 3.5.1*. The RIC value of the baseline is much higher than those of *SLM*, *LA* and *LA-R*. This indicates that the package structure of the *JGraphx 3.5.1* is better-organized than those of other software.

Fig. 2 shows the evaluation results in terms of the *MQ* for the four software systems. This metric measures the quality of the identified components from an architectural point of view. A higher *MQ* value normally indicates that the identified components lead to a better software architecture quality than those with lower *MQ* values. Generally speaking, the *MQ* values of *SLM*, *LA* and *LA-R* are much higher than those of *NSA* and *NSA-R* as well as the baseline. In addition, *NSA-R* always performs better than *NSA* for the four software systems. The rationale behind is that *NSA-R* refines the results of *NSA* with the aim to improve the overall modularity.

Fig. 3 shows the time performance comparison results in terms of milliseconds for the four software systems. An approach with a lower performance value indicates that it is more efficient than that with a higher value. Generally speaking, *SLM*, *LA* and *LA-R* are more efficient than *NSA* and *NSA-R* according to Fig. 3. As for *LA* and *LA-R*, *LA* is always more efficient than *LA-R* because *LA-R* requires a further refinement step on top of the results of *LA*.

In summary, compared with *NSA*, *NSA-R*, *SLM* and *LA*, *LA-R* can efficiently (from a performance point of view) identify components with high *MQ* values, which can help reconstruct the software architecture with better quality. Based on the experimental evaluation, we recommend to apply the *LA-R* to identify components for architecture recovery from software execution data.

7 CONCLUSION

By exploiting tremendous amounts of software execution data, we can identify a set of components for a given software system. Our proposed approaches have been implemented in the ProM toolkit and its advantage and usability were demonstrated by applying them to a set of software execution data generated from four different real-life software systems.

This paper provides a concrete step to reconstruct the architecture from software execution data by identifying a set of components. If the execution data does not cover certain part of the software, our approach fails to identify interaction between classes. In this scenario, combination of the static analysis techniques (i.e., source code) and dynamic analysis techniques (i.e., execution data) is desired. Another future challenge is to discover how components interact with each other via interfaces as well as reconstructing the overall software architecture. In addition, we will conduct an empirical evaluation to compare the quality of the recovered architectural models using different component identification techniques (e.g., (Allier et al., 2009; Qin et al., 2009)) and interface identification techniques (e.g., (Liu et al., 2018a)).

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