Fitness Workout for Fat Interfaces: Be Slim, Clean, and Flexible

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Abstract-A class that provides a fat interface violates the interface segregation principle, which states that the clients of the class should not be coupled with methods that they do not need. Coping with this problem involves extracting interfaces that satisfy the needs of the clients. In this paper, we envision an interface extraction method that serves a combination of four principles: (1) fitness, as the extracted interfaces have to fit the needs of the clients, (2) clarity, as the interfaces should not be cluttered with duplicated methods declarations due to the clients' similar needs, (3) *flexibility*, as it should be easy to maintain the extracted interfaces to cope with client changes, without affecting parts of the software that are not concerned by the changes, and (4) practicality, as the interface extraction should account for practical issues like the number of extracted interfaces, domain/developer specific constraints on what to include in the interfaces, etc. Our preliminary results show that it is feasible to extract interfaces by respecting the aforementioned principles. Moreover, our results reveal a number of open issues around the trading between fitness, clarity, flexibility and practicality.

Index Terms—Refactoring, interface segregation, extract interface

I. INTRODUCTION

Fat interfaces & interface segregation. In the Object-Oriented paradigm, the *interface segregation principle* states that the clients of a class should not be forced to depend upon methods that they do not use [1]. Empirical studies highlighted the practical benefits of the interface segregation principle [2] and empirical evidence showed that its violation leads to time consuming, costly, and error-prone maintenance [3]. A class provides a *fat interface* if its clients use subsets of the class' instance methods [4]. Classes with fat interfaces violate the interface segregation principle.

Problem. Dealing with classes that provide fat interfaces amounts to employing the *Extract Interface* refactoring [5]. The rationale behind this refactoring is to define a set of interfaces that satisfy the needs of the clients' of a given class. Although this seems a simple idea, in practice interface extraction is not an easy problem because it involves a number of conflicting concerns that the developer must take into account. More specifically:

- We have to extract interfaces that *fit* the needs of the clients (i.e., they provide the methods invoked by the clients).
- As the clients' needs are typically similar, the extracted interfaces become cluttered with duplicated method declarations. Hence, we must maintain the conceptual *clarity* of the extracted interfaces.

- Software evolves over time; new clients may be added, clients may be removed, the methods invoked by the clients may change. We must extract *flexible* interfaces that can be seamlessly maintained to cope with such changes, without affecting parts of the software that are not concerned by the changes.
- We must consider further *practical issues*, like the number of interfaces that are extracted, which should be reasonable, domain or developer specific concerns that impose constraints on what to include (resp. exclude) in (resp. from) a particular interface, etc.

State of the art: In well known IDEs, like Eclipse¹, Netbeans², and IntelliJ IDEA³, a developer extracts interfaces for a particular class by manually selecting the methods to be included in the extracted interfaces. Then, the IDEs provide automated means that modify the clients of the class towards using the extracted interfaces. The method proposed in [6] starts from a class that provides a fat interface and automatically extracts interfaces that fit the needs of the clients. However, the clarity of the interfaces is not considered. Specifically, if the clients use similar subsets of methods, the extracted interfaces are overlapping. In [7] and [8], the extraction of interfaces is handled as a search-based problem. These approaches start from a class that provides a fat interface and extract a set of interfaces based on the way that the fat interface is used by the clients. The extraction process tries to maximize the degree to which the interfaces fit the needs of the clients, while minimizing the number of extracted interfaces; [7] employs agglomerative clustering, while [8] relies on genetic algorithm. Hence, [7] and [8] do not guarantee that the extracted interfaces would fit the needs of the clients. The other problem with [7] and [8] is rigidity⁴, in the sense that the extracted interfaces cannot be incrementally updated to cope with client additions, removals, or updates. On the contrary, to deal with such changes, the interface extraction should start all over again with different input (i.e., the changed clients) and output (i.e., the extracted interfaces). Using an entirely new set of interfaces produced by the interface extraction process, requires changing all the clients of the class.

¹eclipse.org/

²netbeans.org

³jetbrains.com/idea/

⁴In general, we say that a software system is rigid if it is hard to change because every change affects too many parts of the system [1].

Contribution. We believe that the interface extraction problem should be handled with a fresh and broader look that considers the fitness, clarity, and flexibility of the extracted interfaces, along with, practical issues like the number of extracted interfaces, domain/developer specific constraints and so on. In this paper, we propose an interface extraction method, which starts from a class that provides a fat interface and produces a hierarchy of interfaces that has the following properties:

- *Fitness*: For each client there is an interface that provides exactly the methods the client needs.
- *Clarity*: The extracted interfaces are exempt from duplicated methods declarations due to the clients' similar needs. At the same time, the interfaces highlight the similarity between the clients' needs via generalization relations, which form the hierarchical structure of the extracted interfaces.
- *Flexibility*: The extracted hierarchy of interfaces can be incrementally updated to cope with client changes, without affecting parts that are not concerned by the changes.
- Practicality: The number of extracted interfaces is reasonable typically quite lower than the number of clients.

To assess the effectiveness and the practicality of the proposed method we report the preliminary results of an empirical study, performed over six open-source projects. Our results show that it is feasible to extract fit, clean, and flexible hierarchies that consist of a resonable number of interfaces, with respect to the number of clients a class has. Moreover, our results reveal a number of open issues when trading between fitness, clarity, flexibility and practicality.

II. APPROACH

In this section, we briefly sketch the main concepts of the proposed method.

Fitness. For a given class c that provides a fat interface and the set of clients C that use c, the proposed method extracts a flexible hierarchy of interfaces \mathcal{I} . Initially, the method iterates over the set of the clients C that use c. For each client, it constructs an interface that declares exactly the methods used by the client.

To illustrate the interface extraction method we employ a real world example that involves the RunNotifier class⁵ of the JUnit testing framework. RunNotifier is a key element of JUnit's notification mechanism that allows listeners to receive feedback about the progress of tests. RunNotifier has a fat interface that declares 11 methods. The class has 12 clients $c_1, c_2, \ldots c_{12}$ that use different subsets of the class' methods. Consequently, the initialization phase of the extraction method produces 12 interfaces $i_1, i_2, \ldots i_{12}$ that fit the needs of $c_1, c_2, \ldots c_{12}$, respectively. The initial interfaces are refined in the next phases of the proposed approach as discussed below. For simplicity reasons in our example, we

focus on a subset of the extracted interfaces that is given in Figure 1(a).

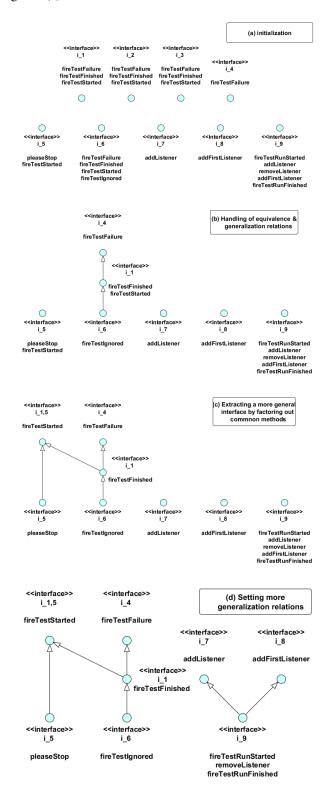


Fig. 1. Illustrating example: Hierarchy of interfaces for the ${\tt RunNotifier}$ class.

Clarity. The initial distribution of methods to interfaces

⁵junit.sourceforge.net/javadoc/org/junit/runner/notification/RunNotifier.html

ensures that the extracted interfaces satisfy the needs of the clients. Nevertheless, if clients have similar needs, the extracted interfaces may be overlapping, or even equivalent. The proposed method proceeds with an iterative process that improves the clarity of the interfaces. Each iteration, looks for the most similar pair of interfaces, i_1^{max} , i_2^{max} . To measure interface similarity, we employ the Jaccard similarity coefficient [9], i.e., the similarity between i_1^{max} , i_2^{max} , is the cardinality of the intersection of the methods declared in the interfaces, divided by the cardinality of the union of the methods declared in the interfaces. Then, clarity is improved as follows:

- Dealing with equivalence between i_1^{max} , i_2^{max} : If i_1^{max} and i_2^{max} provide the same methods⁶, only one of the two interfaces is retained.
- Setting a generalization relation between i_1^{max} , i_2^{max} : If the set of methods provided⁷ by i_1^{max} is a subset of the methods provided by i_2^{max} , the method declarations of i_1^{max} are removed from i_2^{max} and i_2^{max} becomes an extension of i_1^{max} . The case where i_2^{max} is more general than i_1^{max} is treated in the same way.
- Extracting of a more general interface for i_1^{max} , i_2^{max} : If there is no equivalence or generalization relation between i_1^{max} and i_2^{max} , a more general interface, $i_{1,2}^{max}$, is extracted. In particular, $i_{1,2}^{max}$ declares the methods that are common in i_1^{max} and i_2^{max} . Following, generalization relations are set between $i_{1,2}^{max}$, i_1^{max} and $i_{1,2}^{max}$, i_2^{max} . Specifically, the common method declarations are removed from i_1^{max} and i_2^{max} ; i_1^{max} and i_2^{max} become extensions of $i_{1,2}^{max}$.

In our example, the first two iterations (Figure 1(b)) discard i_2 and i_3 because they are equivalent with i_1 . In the third iteration the most similar pair of interfaces is i_1 , i_6 . The methods provided by i_1 are a subset of the methods provided by i_6 . Hence, a generalization relation is detected and i_6 becomes an extension of i_1 . Similarly, in the fourth iteration, a generalization relation. The most similar pair of interfaces is i_1, i_5 . None of these interfaces is a generalization of the other. Therefore, a more general interface $i_{1,5}$, is extracted. The interface contains the fireTestStarted method that is common in i_1 and i_5 ; i_1 and i_5 , become extensions of $i_{1,5}$. Finally, Figure 1(d) depicts two more generalization relations, set in the last two iterations; the first one between i_9 and i_7 , and the second one between i_9 and i_8 .

Flexibility. Fitness and clarity, enable flexibility, i.e., dealing with changes to clients without affecting parts of the software that are not concerned by the changes.

More specifically, given the hierarchy of interfaces \mathcal{I} that is extracted for a class c, there are 3 main evolution scenarios concerning the clients of c: addition of new clients, deletion of clients, and update of the clients' needs. Let \mathcal{A} , \mathcal{D} and \mathcal{U}

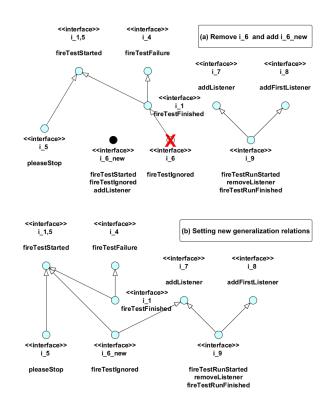


Fig. 2. Illustrating example: Incremental update of the hierarchy.

denote the sets of clients that are added, deleted, and updated, respectively. Then, the incremental update of \mathcal{I} , with respect to \mathcal{A} , \mathcal{D} and \mathcal{U} takes place as follows:

- Based on the set of deleted clients \mathcal{D} , update \mathcal{I} by removing interfaces that are no longer useful, i.e., interfaces that do not serve any client.
- Client updates are handled as client deletions followed by additions of new clients. Hence, \mathcal{I} is further modified by removing the interfaces that had been extracted for the updated clients \mathcal{U} .
- Extract interfaces for A∪U: (1) add to I, interfaces that fit the needs of the added and the updated clients; (2) improve the clarity of I.

In our example scenario, suppose that the needs of client c_6 change. To deal with this situation we remove i_6 from the hierarchy that is given in Figure 1(d). Then, an interface i_6^{new} that satisfies the new needs of client c_6 is added in the hierarchy (Figure 2(a)). Finally, two generalization relations are established, one between i_6^{new} and $i_{1,5}$, and another between i_6^{new} and i_7 (Figure 2(b)).

III. STATUS & EMERGING RESULTS

As a proof of concept for the proposed method we developed an Eclipse plugin. The plugin uses the Eclipse AST facility to gather information (method declarations, method invocations, etc.) about the classes of a given Java project. Based on this information, it extracts interfaces by applying the proposed method to classes with fat interfaces. At this

⁶We assume that two methods are equal if the method prototypes are the same, by definition in Java interfaces.

 $^{^{7}}$ We use the term *provided* to refer to the union of (a) the methods declared in an interface and (b) the methods inherited from other interfaces.

TABLE I CASE STUDIES.

Case Study	# of Classes with fat interfaces	URL
JUnit	44	junit.org
Concordion	15	www.concordion.org
JavaML	23	java-ml.sourceforge.net
JAGA	28	www.jaga.org/
JHotDraw	45	sourceforge.net/projects/jhotdraw
BlueJ	151	www.bluej.org

stage, the prototype does not directly refactor the code of the classes. However, to facilitate the work of the developer, it generates UML diagrams that specify the extracted interfaces and their relations.

We performed a study over six open-source projects (Table I) : we used two testing frameworks, JUnit v4.6 and Concordion v1.4.2; JavaML v0.1.7 that offers a collection of machine learning algorithms; JAGA v1.0 that provides a suite of genetic algorithms; JHotDraw v7.0.6, an extensible drawing tool that is based on design patterns; BlueJ v3.1.4, a popular Java development environment designed for beginners. In the case studies the number of classes with fat interfaces ranged from 15 to 151. The average number of method declarations for the classes, varied from 7.88 to 18.55, while the average number of clients, ranged from 6.25 to 11.88.

Fitness, clarity, and flexibility. Fitness and clarity are the key enablers of flexibility. Hence, the first issue of our study was to assess the proposed method with respect to these aspects. To this end, we measured the *decoupling degree* (DD) that is achieved for the clients C of a class c, when using the interfaces that are extracted for c. To measure the decoupling degree for a client $c_j \in C$, when using an interface i_{c_j} extracted for c, instead of using c, we employ the Actual Context Distance (ACD) introduced by Steimann [6]: $ACD(i_{c_i}, c) =$ number of c methods – number of i_{c_j} methods. The rationale number of c methods behind ACD is that the class provides methods that the client does not need, while the interface provides exactly the methods that the client needs. Hence, the difference between the number of the class' methods and the number of the interface's methods reflects the amount of decoupling that is achieved. Then, the decoupling degree that is achieved for the clients of c is: $DD = avg_{c_i \in C}ACD(i_{c_i}, c)$. Moreover, we measured the number of duplicated method declarations that have been eliminated from the interfaces that we extracted for the classes of the case studies.

Figure 3 gives the distribution of the decoupling degree achieved for the case studies. The average decoupling degree that we obtained was quite high, ranging from 69.97% (in the case of JavaML) to 80.96% (in the case of JHotDraw). In all case studies, we further observed *a positive correlation* between the number of methods, declared by a class, and the decoupling degree that is obtained for the clients of the class. To statistically validate this observation, we calculated the Spearman correlation coefficient, ρ , for these variables, along with the corresponding p-values (Table II). All the ρ

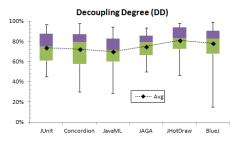


Fig. 3. Distribution of the decoupling degree achieved for the case studies.

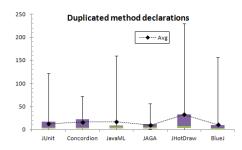


Fig. 4. Distribution of duplicated methods for the case studies.

values are positive, indicating that there is indeed a positive correlation between the variables. Moreover, the values are close to 1, indicating a strong correlation.

Figure 4, gives the distribution of the number of duplicated methods that have been eliminated. Overall, the average number of duplicated method declarations that have been eliminated varied quite a lot, from 9.32 (in the case of JAGA) to 32.56 (in the case of JHotDraw). In all case studies, we also observed a positive correlation between the number of duplicated methods that have been eliminated and the number of clients a class has. Due to lack of space we omit these findings.

Practicality. The second issue of the study was *to assess the price that we have to pay for fitness, clarity, and flexibility.* To address this issue, we measured the number of interfaces that are extracted for the examined classes. The detailed results that we obtained are given in Figure 5. For each case study, a scatter plot relates the number of extracted interfaces for each class, with the number of the class' clients. Each scatter plot further depicts a solid line that corresponds to the *identity*

 TABLE II

 Spearman correlation between methods & decoupling degree.

Case Study	ρ	Sample size	p-value
JUnit	0.86	44	3.26E-14
Concordion	0.80	15	1.13E-04
JavaML	0.83	23	1.92E-07
JAGA	0.91	28	1.65E-12
JHotDraw	0.83	45	5.95E-13
BlueJ	0.86	151	5.17E-47

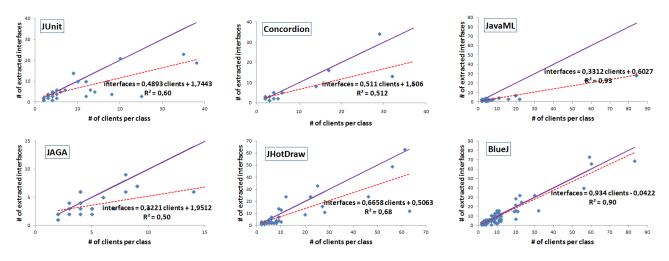


Fig. 5. Extracted interfaces, with respect to the number of clients.

function (i.e., number of interfaces = number of clients). All points that lie below the solid line correspond to classes for which the number of extracted interfaces is less than the number of clients. With the exception of BlueJ, the main observation that comes out from the results is that *typically* the number of interfaces that are extracted for a class is less than the number of clients that depend on the class. Even in the case of BlueJ, for most classes the number of extracted interfaces is less than, or equal, to the number of clients. To get more insight concerning the relation between the number of extracted interfaces and the number of clients, we further performed a linear regression analysis, which indicated a linear relation between the number of clients that use a class and the number of interfaces that are extracted for the class. For most cases, the regression coefficients that we obtained are medium-low (e.g., 0.48 in JUnit, 0.32 in JAGA, 0.33 in JavaML), which again shows that the number of extracted interfaces is usually lower than the number of clients. For BlueJ, the regression coefficient is close to, but still less than 1.

IV. NEXT STEPS

To sum up, our preliminary results ascertain that *it is feasible to extract fit, clean, and flexible hierarchies of interfaces, which consist of a reasonable number of interfaces, with respect to the number of clients a class has.*

Nevertheless, especially from the perspective of trading between fitness, clarity, flexibility, and practicality, there is still room for further research. In particular, extracting interfaces for every class that provides a fat interface may still clutter a particular software with a large number of interfaces. At the same time, there may be classes with fat interfaces, for which the extraction of interfaces that fit exactly the needs of the clients does not make much sense, or interfaces for which a degree of unclarity may be bearable, reasonable, or even desirable due to certain domain or developer specific concerns. An automated interface extraction approach must account for such issues that can emerge in real-world situations. Hence, a first objective of our future research agenda is to enhance the proposed approach with means that would allow the developers to focus the interface extraction method to the right classes by analyzing potential tradeoffs between the interface extraction benefits and costs. A second objective of our future research agenda is to enhance the proposed approach with means that would allow to customize the interface extraction process with domain and developer specific constraints (e.g., preferences/limits for the desired number of interfaces, methods per interface).

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