Empirical Investigation of the Impact of Accounting for Transitive Relationships on Lack-of-Cohesion Measurement

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Abstract: - The quality of a class in object oriented system has a great impact on the overall quality of the software. Class cohesion, which refers to the degree of relatedness of the class members, is an important quality aspect. A few of class cohesion metrics, which are proposed in the literature, empirically address the impact of accounting for transitive relations between class attributes and methods caused by method invocations. This paper provides an empirical evaluation for the impact of considering transitive relationships on class cohesion quantified by one of the most popular class cohesion metrics, referenced as Lack of Cohesion (LCOM). The metric is applied with and without considering transitive relations on classes of two open source Java applications and the results are statistically analyzed. The results provide an evidence that the ability of LCOM in precisely indicating class quality enhances when accounting for both direct and transitive relations in the LCOM measurement.

Key-Words: - object-oriented class, software quality, class cohesion metric, class cohesion, direct and transitive relations.

1. Introduction

To evaluate and improve the quality of an application during the development process, developers and managers use several metrics. These metrics estimate the quality of different software attributes, such as cohesion, coupling, and complexity. The cohesion of a module refers to the relatedness of the module components. A module that has high cohesion performs one basic function and cannot be split into separate modules easily. Highly cohesive modules are more understandable, modifiable, and maintainable [1]. Classes are the basic units in object-oriented systems. The members of a class are its attributes and methods. Therefore, class cohesion refers to the relatedness of the class members.

Several metrics are proposed in the literature to indicate class cohesion during high or low level design phases. Lack of Cohesion (LCOM) [3] is proposed by Chidamber and Kemerer, and it calculated as the number of method pairs that do not directly share attributes minus the number of method pairs that directly share attributes. Higher LCOM value indicates low cohesion and vice versa. LCOM is widely applied and theoretically and empirically compared to other metrics (e.g., [1, 2, 3, 12, 13, 14, 21]). In these empirical studies, the goodness of the metric in indicating cohesion is indirectly measured by statistically analyzing the relation between the cohesion values and the values of external software attributes such as the fault proneness of the class (i.e., the extent to which a class is prone to faults). Most of the reported empirical results show that LCOM is relatively weakly capable in predicting faulty classes. As a result, LCOM is suggested not to be a good cohesion indicator. Originally, LCOM accounts only for direct relations. That is, two methods are considered to be related if they directly use at least a common attribute. Directly using an attribute means that the attribute is explicitly referenced within the method. If a method m_1 calls another method m_2 and m_2 uses an attribute a, m_1 is not considered as directly referencing attribute a. Instead, in this case, m_1 is considered transitively referencing the attribute. The transitive referencing of an attribute is not considered in the original definition of LCOM. In this paper, we extend the definition of LCOM to account for transitive relations as well as the direct relations, and we refer to the extended metric as TLCOM (transitive LCOM). We perform an empirical study to support the validity of our extended metric. The empirical study is applied on classes of two open source Java systems that have available fault data repositories. The empirical study results show that accounting for transitive relations as well as direct relations, in the computation of LCOM, improves its goodness in predicting faulty class. This indirectly, indicates that our extension improves LCOM's goodness in indicating class cohesion.

This paper is organized as follows. Section 2 provides an overview of the class cohesion metrics proposed in literature. Section 3 proposes the extended LCOM metric. Section 4 illustrates an empirical case study and reports and discusses its results. Finally, Section 5 concludes and discusses future work.

2. Related Work

Researchers have proposed several class cohesion metrics in the literature. These metrics can be applicable based on high-level design (HLD) or low-level design (LLD) information. HLD class cohesion metrics rely on information related to class and method interfaces. The more numerous LLD class cohesion metrics require an

analysis of the algorithms used in the class methods (or the code itself if available) or access to highly precise method postconditions. Class cohesion metrics are based on the use or sharing of class attributes. For example, the LCOM metric counts the number of method pairs that do not share instance variables [15]. Chidamber and Kemerer [16] propose another version of the LCOM metric, which calculates the difference between the number of method pairs that do and do not share instance variables. Li and Henry [17] use an undirected graph that represents each method as a node and the sharing of at least one instance variable as an edge. They define lack-of-cohesion in methods as the number of connected components in the graph. The graph is extended in [18] by adding an edge between a pair of methods if one of them invokes the other. Hitz and Montazeri [18] introduce a connectivity metric to apply when the graph has one component. In addition, Henderson-Sellers [19] proposes a lack-of-cohesion in methods metric that considers the number of methods referencing each attribute.

Bieman and Kang [4] describe two class cohesion metrics, Tight Class Cohesion (TCC) and Loose Class Cohesion (LCC), to measure the relative number of directly connected pairs of methods and the relative number of directly or indirectly connected pairs of methods, respectively. TCC considers two methods to be connected if they share the use of at least one attribute. A method uses an attribute if the attribute appears in the method's body or the method invokes another method, directly or indirectly, that has the attribute in its body. LCC considers two methods to be connected if they share the use of at least one attribute directly or transitively. Badri [5] introduces two class cohesion metrics, Degree of Cohesion-Direct (DC_D) and Degree of Cohesion-Indirect (DC_I), that are similar to TCC and LCC, respectively, but differ by considering two methods connected also when both of them directly or transitively invoke the same method. Briand et al. [3] propose a cohesion metric (called Coh) that computes cohesion as the ratio of the number of distinct attributes accessed in methods of a class. Fernandez and Pena [6] propose a class cohesion metric, called Sensitive Class Cohesion Metric (SCOM), that considers the cardinality of the intersection between each pair of methods. In the metric presented by Bonja and Kidanmariam [7], the degree of similarity between methods is used as a basis to measure class cohesion. The similarity between a pair of methods is defined as the ratio of the number of shared attributes to the number of distinct attributes referenced by both methods. Cohesion is defined as the ratio of the summation of the similarities between all pairs of methods to the total number of possible pairs of methods. The metric is called Class Cohesion (CC). Al Dallal and Briand [1] propose a metric based on measuring the degree of similarity between each pair of methods in terms of the number of shared attributes.

Bansiya et al. [8] propose a design-based class cohesion metric called Cohesion among Methods in a Class (CAMC). In this metric, only the method-method interactions are considered. The CAMC metric uses a parameter occurrence matrix that has a row for each method and a column for each data type that appears at least once as the type of a parameter in at least one method in the class. The value in row *i* and column *j* in the matrix equals 1 when the *i*th method has a parameter of *j*th data type. Otherwise, the value equals 0. The CAMC metric is defined as the ratio of the total number of 1s in the matrix to the total size of the matrix.

Counsell et al. [9] propose a design-based class cohesion metric called Normalized Hamming Distance (NHD). In this metric, only the method-method interactions are considered. The metric uses the same parameter occurrence matrix used by the CAMC metric. NHD calculates the average of the parameter agreements between each pair of methods. The parameter agreement between a pair of methods is defined as the number of places in which the parameter occurrence vectors of the two methods are equal. Al Dallal [10] proposes a distance-based HLD cohesion metric and discusses its sensitivity to changes in the class cohesive interactions. The metric is based on information available in the UML class diagram. That work is extended in [13] to consider more types of cohesive relations. Related work in the area of software cohesion can be found in [2, 11, 12,14, 20, 21].

3. Transitive LCOM

LCOM [16] is defined as the difference between the number of method pairs that do and do not "directly" share instance variables. A pair of methods directly shares a common attribute when the common attribute is referenced within the body of each of the two methods. For example, the Java sample class given in Figure 1 has three methods. The number of method pairs is three and the number of method pairs that share a common attribute is one (i.e., *m1* and *m2* reference attribute *a1*), whereas the number of methods pairs that do not share common attributes is 2 (i.e., (m1,m3) and (m2,m3)). As a result, LCOM value is 2 - 1 = 1.

```
class SampleClass {
        int a1,a2;
        void m1(){
                a1=1;
        }
        void m2(){
                a1=a2;
        }
        void m3(){
                m2();
        }
}
```

Figure 1: Java sample class

Transitive LCOM (TLCOM) is defined as the number of method pairs that directly or transitively share a common attribute. A method transitively references an

attribute when the method directly or indirectly calls another method that directly references the attribute. A pair of methods "transitively" shares a common attribute when the common attribute is referenced transitively by both methods or referenced transitively by one of the methods and directly by the other. For example, method *m3* given in Figure 1 transitively references both attributes *a1* and *a2* because it calls method *m2* that directly references these two attributes. In this case, method *m3* transitively shares attribute *a1* and *a2* with method *m2*, and it transitively shares attribute *a1* with method *m1*. Since all method pairs in the sample class directly or transitively share common attributes, the value of TLCOM is zero (i.e., no pairs of methods do not directly or transitively share common attributes).

4. Empirical Study

We chose two Java open source software systems from two different domains: Art of Illusion v.2.5 [22] and JabRef v.2.3 beta 2 [23]. Art of Illusion consists of 481 classes and about 88 thousand lines of code (KLOC), and is a 3D modeling, rendering, and animation studio system. JabRef consists of 569 classes and about 48 KLOC, and is a graphical application for managing bibliographical databases. We chose these two open source systems randomly from http://sourceforge.net.The restrictions taken into account in choosing these systems were that they (1) are implemented using Java, (2) are relatively large in terms of the number of classes, (3) are from different domains, and (4) have available source code and fault repositories.

We excluded all classes that have less than two methods because LCOM value is not defined for such classes. This implies excluding 39 classes from the first system and 133 classes from the second system. We applied the LCOM and TLCOM to the rest of the classes. We developed our own Java tool to automate the cohesion measurement process for Java classes using LCOM and TLCOM. The tool analyzed the Java source code, extracted the information required to build the models that represent the cohesive interactions, and calculated the cohesion values using the two metrics. Tables 1 and 2 show descriptive statistics for each cohesion measure including the minimum, 25% quartile, mean, median, 75% quartile, maximum value, and standard deviation. Note that the following analyses do not take into account class inheritance. The impact of inheritance on the study results is left as a subject for further research.

Expectedly, the descriptive statistics results show that accounting for transitive relations reduces LCOM values. This is because accounting for transitive relations increases the number of pairs of methods that share common attributes. Hence, this decreases the number of method pairs that do not share common attribute and consequently decreases LCOM values.

To study the relationship between the values of the collected metrics and the extent to which a class is prone to faults, we applied logistic regression [24], a standard and mature statistical method based on maximum likelihood estimation. This method is widely applied to predict fault-prone classes (e.g., [3, 25, 26, 27, 29, 30, 31, 32]). In logistic regression, explanatory or independent variables are used to explain and predict dependent variables. A dependent variable can only take discrete values and is binary in the context where we predict fault-prone classes. The logistic regression model is univariate if it features only one explanatory variable and multivariate when including several explanatory variables. In this case study, the dependent variable indicates the presence of one or more faults in a class, and the explanatory variables are the cohesion metrics. Univariate regression is applied to study the fault prediction of each metric separately, whereas multivariate regression is applied to study the fault prediction of different combinations of metrics to determine the best model. In this paper, we focus on comparing the results for the metrics in terms of their individual fault prediction power, and therefore, we consider only univariate regression.

Table 1: Descriptive statistics for the cohesion measures applied on classes of Art of Illusion system

Statistic	LCOM	TLCOM
Min	0	0
Max	91	90
25%	0	0
Med	4	3
Mean	10.6	9.0
75%	14	11
Std. Dev.	15.1	13.5

Table 2: Descriptive statistics for the cohesion measures applied on classes of JabRef system

Statistic	LCOM	TLCOM
Min	0	0
Max	58	52
25%	0	0
Med	1	1
Mean	5.0	3.9
75%	5	4
Std. Dev.	9.4	7.8

We collected fault data for the classes in the considered software systems from publicly available fault repositories. The developers of the considered systems used an on-line Version Control System (VCS) to keep track of the changes performed on the source code of the system. The changes, called revisions, are due to either detected faults or required feature improvements. Each revision is associated with a report including the revision description and a list of classes involved in this change. Two research assistants, one with a B.Sc. in computer science and six

years of experience in software development activities and another with a B.Sc. and Master both in computer science; each alone, manually traced the description of each revision and identified the ones performed due to detected faults. Author of this paper compared the manual results and rechecked the results in which the two assistants differ to choose the correct one. Finally, we used the lists of classes involved in changes due to detected faults to count the number of faults in which each class is involved. We classified each class as being fault-free or as having at least one fault. Ideally, class cohesion should be measured before each fault occurrence and correction, and used to predict this particular fault occurrence. However, not only this would mean measuring cohesion for dozens of versions (between each fault correction) for each system, but we would not be able to study the statistical relationships of a set of faults with a set of consistent cohesion measurements for many classes. Our cohesion measurement is based on the latest version of the source code, after fault corrections, and is therefore an approximation. This is however quite common in similar research endeavors (e.g., [3,25,26,27]) and is necessary to enable statistical analysis.

The results of the univariate regression study are reported in Tables 3 and 4. Estimated regression coefficients are reported. The larger the absolute value of the coefficient is, the stronger the impact (positive or negative, according to the sign of the coefficient) of the metric on the probability of a fault being detected in a class. The considered metrics have different standard deviations as shown in Tables 1 and 2. Therefore, to help compare the coefficients, we standardized the explanatory variables by subtracting the mean and dividing by the standard deviation and, as a result, they all have an equal variance of 1 and the coefficients reported in Tables 3 and 4 are also standardized. These coefficients represent the variation in standard deviations in the dependent variable when there is a change of one standard deviation in their corresponding independent variable. The p-value is the probability of the coefficient being different from zero by chance, and is also an indicator of the accuracy of the coefficient estimate. We use a typical significance threshold (α=0.05) to determine whether a metric is a statistically significant fault predictor.

To evaluate the performance of a prediction model regardless of any particular threshold, we used the receiver operating characteristic (ROC) curve [28]. In a fault prediction context, the ROC curve is a graphical plot of the ratio of classes correctly classified as faulty versus the ratio of classes incorrectly classified as faulty at different thresholds. The area under the ROC curve shows the ability of the model to correctly rank classes as faulty or non-faulty. A 100% ROC area represents a perfect model that correctly classifies all classes. The larger the ROC area, the better the model in terms of classifying classes. The results for all the coefficients and for all considered metrics are reported in Tables 3 and 4.

The results in Tables 3 and 4 lead to the following conclusions:

1. Both the original LCOM and the extended metric are statistically significant at α=0.005 (i.e., their coefficients are significantly different from 0).
2. As expected, the estimated regression coefficients for the inverse cohesion measures LCOM and TLCOM are positive. This indicates an increase in the predicted probability of fault detection as the lack of cohesion of the class increases.
3. In both systems, the results of the standard coefficient and the area under the ROC curve are improved when considering transitive relations as well as the direct ones in the computation of LCOM.

Table 3: Univariate logistic regression results for classes of Art of Illusion system

Metric	LCOM	TLCOM
Std. Coeff.	0.037	0.043
p-value	<0.0001	<0.0001
ROC area	66.6%	67.5%

Table 4: Univariate logistic regression results for classes of JabRef system

Metric	LCOM	TLCOM
Std. Coeff.	0.135	0.235
p-value	0.002	<0.001
ROC area	69.8%	70.3%

As a result, the empirical results above show that the extended LCOM that accounts for transitive relations predicts faulty classes more accurately than the original LCOM that accounts only for direct relations. These results indirectly indicate that the ability of LCOM in indicating class cohesion improves when accounting for both transitive and direct cohesive relations.

5. Conclusions and Future Work

This paper extends LCOM, a widely referenced class cohesion metric. The extension considers the transitive cohesive relations caused by method invocation. The original and extended versions of the metric are empirically compared by applying them on classes of two open source systems. The results show that the extended version of the metric predicts faulty classes, and thus indicates cohesion, better than the original version of the metric. An evidence of this improvement was observed in the reported empirical study for both of the two considered applications. As a result, software engineers and practitioners are recommended to consider both direct and transitive cohesive relations in the LCOM measurement when it is used in predicting fault-prone classes.

In the future, we plan to empirically address the accounting for transitive cohesive relations in the computation of other class cohesion metrics. In addition, we intend to empirically study the impact of considering other factors when applying cohesion metrics such as inheritance and access methods.

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