Constrained Agglomerative Hierarchical Software Clustering with Hard and Soft Constraints

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Abstract: Although agglomerative hierarchical software clustering technique has been widely used in reverse engineering to recover a high-level abstraction of the software in the case of limited resources, there is a lack of work in this research context to integrate the concept of pair-wise constraints, such as must-link and cannot-link constraints, to further improve the quality of clustering. Pair-wise constraints that are derived from experts or software developers, provide a means to indicate whether a pair of software components belongs to the same functional group. In this paper, a constrained agglomerative hierarchical clustering algorithm is proposed to maximize the fulfilment of must-link and cannot-link constraints in a unique manner. Two experiments using real-world software systems are performed to evaluate the effectiveness of the proposed algorithm. The result of evaluation shows that the proposed algorithm is capable of handling constraints to improve the quality of clustering, and ultimately provide a better understanding of the analyzed software system.

1 INTRODUCTION

Software requires continuous change and enhancement to satisfy new business rules and technologies. This is a human intensive task that requires deep understanding and comprehension of a software before any decision to modify it. Therefore, software maintainers must first gain a complete understanding of the structure and behavior of the software to be maintained before making any major changes. However, most software that had undergone instant changes does not have up-to-date documentation. Thus, software maintainers may need to reverse engineer the source code to gain a high-level abstraction view of the software. Software clustering is one of the techniques used to recover a semantic representation of the software design and documentation. It has received a substantial attention in recent years because of its capability to help in improving the modularity of poorly designed software systems.

However, in certain scenarios, software maintainers may have access to additional information or domain knowledge about the software to be maintained. For instance, the core business rules and functionalities of a software remain unchanged after undergoing several major updates, or stakeholders have additional knowledge about the software because they were involved in the early stage of software development. Thus, even if the software documentation is not up-to-date, maintainers are able to salvage some useful information about the structure of the software. However, such information are worthless unless there is a proper way to synthesis them.

An improvement to conventional clustering techniques was proposed in (Basu et al., 2004) by incorporating side information to further improve the accuracy of clustering results. The side information is commonly referred as "*constraints*" which reveal the similarity between pairs of clustering entities, or user preferences about how those entities should be grouped during clustering.

It has been proven in several fields of research that constrained clustering can significantly improve the reliability and accuracy of clustering results (Davidson and Ravi, 2009). However, there is still a lack of studies on integrating constrained clustering to effectively improve the modularity of poorly designed software. In cases where end-users or developers have side information regarding the software to be maintained, the relevant knowledge

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can help improve the results of clustering by the means of constraints.

In this study, we focus on fulfilling different types of constraints using agglomerative hierarchical clustering. Agglomerative hierarchical clustering is a bottom-up approach that iteratively merge pair of clusters until all clusters are merged into a big cluster. Unlike the work by (Davidson and Ravi, 2009) which solely imposed absolute constraints (must be fulfilled regardless of any situation), the constrained clustering technique to be presented in this paper involves several types of constraints which differ according to their importance, i.e. must be fulfilled, or good to have. As such, a constrained clustering algorithm is introduced in this study to help ease the software maintenance problem when the system documentation is non-existent or inconsistent with real implementation.

2 RELATED WORK

Software maintenance and verification is crucial to discover and validate the relationship between technology and business models. How well a certain software fulfills stakeholders' requirements often depicts the effectiveness of the software.

A major fraction of software life cycle's expenditure is contributed by software maintenance and support. The authors estimated that over 50% of software development budget is spent on maintaining and supporting the software itself. This shows that maintenance indeed plays a very important role in the software life cycle. Before performing any relevant maintenance work, the person in charge must first gain a complete understanding of the particular software. This is to ensure that when there are requests to update a particular functionality, maintainers can recognise in advance, the interrelated components. Eventually, the threats of introducing faults and bugs during maintenance can be minimized. Therefore, maintainers often need to spend a significant amount of time in comprehending the structure and design of the software. Accomplishment of maintenance is highly dependent on how much information can be extracted by maintainers.

However, maintainers are typically not involved in early stages of software design and development. Furthermore, the documentation of the software is usually not up-to-date, especially for projects that follow agile software development where software requirements and solutions evolve rapidly. Thus, maintainers require additional options. One way to alleviate these problems is through remodularization of software, which is one of the reverse engineering techniques used to help recover a semantic representation of the design and documentation.

Software clustering is one of the techniques used to perform remodularization of software. The goal of clustering is to form multiple groups of clusters, such that components within the same group are similar to each other, and dissimilar from components in other groups. The measurement of similarities between components is based on inter-relationships between components or common features shared by them (Maqbool and Babri, 2007). Mutual exclusive groups of components can be identified to provide more insight toward the analyzed software. The results of clustering can also help maintainers to understand the behavior and dependencies of programs, identify orphaned source code, and allow adding of new software modules without interfering with the general workflow of the software system (Antonellis et al., 2009).

2.1 Software Clustering

Clustering can be based on either a supervised or unsupervised approach to pick from a collection of entities, then form multiple groups of entities such that entities within the same group are similar to each other, while dissimilar from entities in other groups. In the context of software clustering, entities are normally source code or classes. Similarity measures are normally common global variables used by an entity or function calls made by an entity. The identification of similarity is often depending on what kind of reliable information is available.

Generally, clustering can be categorized into partitional and hierarchical clustering. Given a collection of data, partitional clustering works by directly decomposing it into a set of disjoint clusters. On the other hand, hierarchical clustering iteratively merge smaller clusters into larger ones or divide large clusters into smaller ones, depending on either it is a bottom-up or top-down approach. Merging or dividing operations are usually depend on the clustering algorithm used in the existing studies. The result of partitional clustering are usually presented in several disjoint set of clusters, with each cluster contains at least one entity and each entity belongs to only one cluster. Meanwhile, the final result of hierarchical clustering is a tree diagram, called dendrogram. A dendrogram shows taxonomic relationships of clusters produced by hierarchical clustering. Cutting the dendrogram at a certain height produces a set of disjoint clusters.

In the domain of software clustering, partitional clustering is less viable because it is almost impossible to know the initial number of clusters before performing software clustering (Chong et al., 2013). According to the work by (Wiggerts, 1997), the working principle of agglomerative clustering (bottom-up hierarchical clustering) is actually similar to reverse engineering where the abstractions of software designs are recovered in a bottom-up manner. Thus, in this research, agglomerative clustering will be used to recover high-level abstraction of a poorly documented or poorly designed software system.

Agglomerative hierarchical clustering starts by forming all entities as initial clusters. At each step, a pair of entities is merged and the algorithm ends with one big cluster. The following steps show a standard agglomerative hierarchical clustering algorithm.

Input: Set $T = \{x_1, x_2, \cdots, x_n\}$ of entities.

Output: Dendrogram

1. Each entity x_i forms an initial cluster G_i. The total number of clusters $K = n$. For each pair of clusters G_i and G_j, $i \neq j$, the distance between G_i and G_j is denoted by $d(G_i, G_j)$.
2. Find a pair of clusters with minimum distance, $d(G_i, G_j)$:

   Let $(G_a, G_b) = min\, d(G_i, G_j)$

   Merge $G_c = G_a \cup G_b$ and reduce the number of clusters K= K-1
3. If K = 1, stop the iteration; else update distance $d(G_c, G_j)$, for all other clusters G_j. (Follow step 2)

Although some clustering algorithms produce a single clustering result for any given dataset, a dataset may have more than one natural and optimum clustering. For instance, source code can only tell very limited information about the architectural design of a software system since it is a very low-level software artifact. The work by Deursen and Kuipers (1999) adopted a greedy search method by using mathematical concept analysis to analyze the structure of cluster entities and identify the features that are shared by them. The proposed approach finds all of the possible combination of clusters and evaluates the quality of each combination. Agglomerative clustering is used in this work. The authors discovered that it is hard to analyze all possible combination and useful information might be missing if no attention is given to analyze the results of different dendrogram cutting points.

In contrast to the greedy search method proposed by Deursen and Kuipers, the work by (Fokaefs et al., 2009; Fokaefs et al., 2012) proposed an approach that results in multiple solutions from which software designers can select their best solution. Their goal is to decompose large classes by identifying Extract Class refactoring opportunities. The authors used agglomerative clustering to generate the dendrogram that demonstrated how the clusters are formed.

On other hand, our previous work (Chong et al., 2013) proposed a technique to enhance existing agglomerative clustering algorithms by minimizing redundant effort and penalizing for the formation of singleton clusters during software clustering. By utilizing a least-squares polynomial regression analysis, the algorithm finds the optimum result that produces sets of clusters with high cohesion and low coupling. The proposed technique is based on a bottom-up approach, which starts by transforming source code into a flat sequence of class diagrams, and finally restructures them into a package diagram to provide a high-level semantic view of the whole system design. Figure 1 shows the overall workflow of the work presented in (Chong et al., 2013). The clustering process are summarized as follow.

1. Identification of entities and features - UML classes are represented as cluster entities, while relationships between classes are used to calculate the distance between a pair of entities.
2. Calculation of similarity measure - Sorensen-Dice coefficient (Sørensen, 1948) is used to calculate the similarity between pairs of cluster entities because it is more suitable to be applied to asymmetric binary features, which is similar to the behavior of functional dependencies and method calling.
3. Application of clustering algorithm - Un-weighted Pair-Group Method using Arithmetic Average (UPGMA) is used to merge pairs of entities and form the dendrogram.

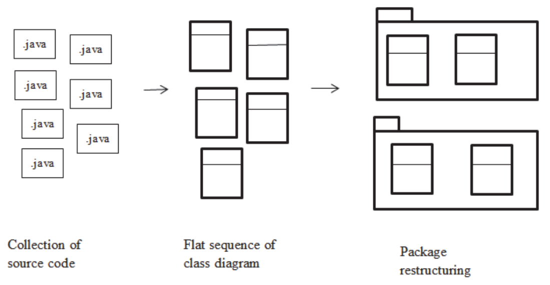

Figure 1: Architecture recovery process proposed in (Chong et al., 2013).

Our previous work does not differentiate between aggregation, association, cardinality and generalization through different weightage. The presence of any type of correlation will be represented as a direct relationship between two entities. The technique does not have the ability to integrate domain knowledge or other sources of information which can further improve the quality of clustering result. Such way of incorporating domain knowledge is also known as semi-supervised software clustering.

If one has the ability to exploit high-level information to guide and improve clustering, this will further improve the quality of the results. Constrained clustering, for instance, is one of the semi-supervised clustering techniques that combine external information in order to improve clustering results.

2.2 Constrained Software Clustering

Recent works (Basu et al., 2004; Davidson and Ravi, 2009; Wagstaff and Cardie, 2000) have attempted to discover the benefits of instance-level constraints in both hierarchical and non-hierarchical clustering. The must-link (ML) and cannot-link (CL) constraints specify that two entities must both be part of or not part of the same cluster respectively. These constraints are useful when the information of cluster entities is vague, allowing domain experts to guide the clustering process. The information is normally given as a set of pairwise constraints which involve two entities and impose restriction such as determining whether the involved entities should be clustered into the same group or not. Constrained clustering method is contrary to traditional unsupervised clustering method where users have no influence toward the clustering results.

Work by (Wagstaff and Cardie, 2000) has found that side information such as constraints can improve the quality of clustering when compared against those without constraints. Meanwhile, the work by (Davidson and Ravi, 2009) examined the complexity of traditional clustering algorithms and investigated methods to improve the efficiency of constrained agglomerative hierarchical clustering. The authors introduced new constraints apart from the traditional ML and CL constraints to further improve the run-time of agglomerative hierarchical clustering. They discovered that small amounts of constraints not only improve the accuracy of agglomerative hierarchical clustering but also the overall run-time. However, clustering under all types of constraints is NP-complete, which means that creating a feasible cluster hierarchy under all types of constraints is intractable.

We found that there is a lack of research that focuses on applying constrained clustering in the field of software reverse engineering to remodularize poorly designed software systems. The NP-complete problem stated in the work by (Davidson and Ravi, 2009) can be minimized if each constraint is assigned with a certain degree of importance, i.e. constraints that must be fulfilled, or optional constraints that are good to have. Therefore, different from the work by (Davidson and Ravi, 2009), this study aims to maximize the fulfillment of software constraints according to the degree of importance derived from stakeholders.

Generally, current works involving constrained clustering methods can be divided into three categories, namely distance based, constrained based, or hybrid of both. In distance based constrained clustering, a distance metric is trained to satisfy the constraints before the clustering process. The distance metric represents the dissimilarity strength between pairs of entities. Merging or splitting of clusters is based on the distance metric. Thus, training the distance metric allows one to manipulate the process of clustering to allow certain pairs of entities to be clustered into the same group, or separated if otherwise. Examples of methods to train distance metrics include shortest path (Klein et al., 2002), expectation maximization (Bilenko and Mooney, 2003), and convex optimization (Shental and Weinshall, 2003).

On the other hand, constrained based methods work by modifying the cluster assignments, i.e. manually assign entities to designated clusters. For instance, must-link constraints can be used to initialize the baseline of cluster hierarchy so that the must-link constraints can be satisfied indefinitely(Kestler et al., 2006). Constrained based approaches ensure that all the constraints are fulfilled because the clustering assignments are manipulated by users based on the given constraints. However, experiments performed by (Davidson and Ravi, 2009) discovered that manipulating with the clustering assignments might lead to "dead-end" situation where no pair of clusters can be merged to obtain a feasible clustering result. Thus, a proper way to ensure the fulfillment of constraints must be formulated before enforcing any kind of clustering constraints.

Fulfillment of constraints can be classified as either hard or soft constraints associated with some cost of violation if those constraints cannot be fulfilled (Basu et al., 2004). Hard constraints are constraints that cannot be violated during the clustering process regardless of any condition. These sets of constraints are usually highly reliable knowledge or information given by domain experts. In general, the cost of violating hard constraints supersedes the objective function of constrained clustering. Constrained based clustering method is one of the most reliable approaches to make sure that all hard constraints are fulfilled as much as possible.

Meanwhile, soft constraints are usually associated with uncertainties and ambiguous information (Basu etal., 2004). The cost of violating soft constraints varies depending on the level of confidence provided by the stakeholders. Clustering results will still be acceptable if some of the soft constraints are not fulfilled, with a condition that it falls within an acceptable threshold (Ares et al., 2012). Soft constraints are more robust against "noisy" or incorrect. As a general rule, most of the objective functions attempt to maximize the fulfillment of hard and soft constraints. However, it is to be noted that constrained clustering can fall into a NP-Complete problem if the must-link and cannot-link constraints are contradicting with each other, for instance, $(\text{Must-Link} \cup \text{Cannot-Link}) > 0$. Thus, potential conflicts among hard constraints must be identified in advance.

All in all, we found that it is feasible to incorporate the notion of constrained clustering with remodularization of software system. For instance, experienced software developers can provide opinions with a certain degree of confidence to suggest if two entities should be clustered into the same group. Furthermore, relationships among software entities such as inheritance and dependency suggest that two entities have strong affiliation and they must be grouped together. There are plenty of methods to derive constraints from the software itself or side information from stakeholders. However, there are certain cases where the stakeholder is not assertive enough to judge whether the given constraints are absolute, especially in the domain of software engineering. For instance, as mentioned in Section 1, the stakeholder who was involved in the early stage of software design might provide some constraints about the software to be maintained. However, such constraints might not be valid anymore after several phases of software updates and changes. Thus, the constraints given by the aforementioned stakeholder might be ambiguous or contains erroneous information. A proper method is needed to distinguish between absolute constraints and optional constraints, and subsequently fulfill those constraints according to their level of importance. Therefore, in this study, a constrained software clustering algorithm is proposed to alleviate the problem mentioned above for aiding in reverse engineering.

3 PROPOSED APPROACH

Constraints can be derived easily from stakeholders, who are not necessary experts in a particular domain, by asking them to make judgment whether two items are similar or not (Hong and Yiu-ming, 2012). The stakeholders can evaluate their judgments based on their level of confidence or based on background knowledge to support their decisions. In this proposed approach, if the stakeholder is highly confident that the provided constraints are reliable, they will be categorized as hard constraints. These sets of constraints must be fulfilled under any kind of conditions. On the other hand, if the stakeholder is doubtful about the given constraints, it will be categorized as soft constraints.

3.1 Constraints with High Level of Confidence

If a stakeholder has a high degree of confidence that a pair of entities must be grouped together or separated, these sets of constraints will be categorized as the Must-Link Hard (MLH) or Cannot-Link Hard (CLH) constraints. MLH and CLH constraints are relatively easier to fulfill using k-mean clustering because clustering assignment can be manipulated during the process of clustering. However, it is more difficult to achieve the same results for agglomerative hierarchical clustering because all entities in the dataset are linked together at some level of the cluster hierarchy (Bair, 2013). MLH and CLH constraints must always be fulfilled at all levels of the hierarchy. The work by (Miyamoto, 2012) introduced a distance based approach to impose MLH constraints by requiring entities linked by MLH constraints to be clustered together at the lowest level of cluster hierarchy. This is done by reducing the dissimilarities between pairs of MLH constraints to zero.

Given a $T = \{x_1, x_2, \cdots, x_n\}$ with entities $x_1, x_2, \cdots, x_n$. For $(x_i, x_j) \in MLH$, the distance between x_i and x_j is modified to $d(x_i, x_j) = 0$.

This will eventually form a baseline model for the clustering hierarchy. Since the MLH constraints are unconditionally fulfilled at the lowest level of the hierarchy, one can ensure that the same can be achieved all the way through the top of hierarchy. Thus in this study, we will adopt the same technique proposed by (Miyamoto, 2012) to ensure the fulfillment of MLH constraints.

For CLH constraints, there are typically two ways to enforce using either constrained based or distance based method. Constrained based methods modify the cluster assignments by inspecting the merger of two entities. If the chosen entities belong to the CLH pairs, one will need to look for the next pair of entities with the second highest similarity score. However, the work by (Davidson and Ravi, 2009) found that the formation of dendrogram may stop prematurely in a certain scenario. The authors called this scenario as the "dead-end" situation where unless CLH constraints are violated, there will be no more merging possible to form the final dendrogram. Thus, constrained based approach to fulfill CLH constraints is a less viable option in our case.

Distance based approaches, on the other hand, modify the dissimilarities between pairs of CLH constraints to be a value high enough to prevent them from merging.

Given a set $T = \{x_1, x_2, \cdots, x_n\}$ with entities $x_1, x_2, \cdots, x_n$. For $(x_i, x_j) \in CLH$, $d(x_i, x_j) = d(x_i, x_j) + Const$ where $Const$ is a constant large enough to prevent linkage in between entities x_i, x_j.

By enforcing this rule, the pairs of CLH constraints will not be chosen to merge unless there is no more entities pair with distance more than $d(x_i, x_j) + Const$. Entities which belong to CLH constraints will then be merged at the top of the hierarchy to form the complete dendrogram. By looking into another perspective, the CLH constraints are violated at the top of the hierarchy since without violating them, "dead-end" situation will occur. However, we argue that violating CLH constraints at the top of the hierarchy is negligible because it is almost impossible to cut the dendrogram at that location. In a typical scenario, cutting the dendrogram at the top of hierarchy will yield very small number of clusters because this decision is at the trade-off of relaxing the constraint of cohesion in the cluster membership. Clusters formed under this cutting point are usually made up of entities with very fragile cohesion strength.

However, changing the distance measure of MLH and CLH pairs will most likely result in violating the triangle inequality of resemblance matrix (Klein et al., 2002). This means that for some entities $(x_s, x_t) \notin MLH, (x_s, x_t) \notin CLH$ which were distance $d(x_s, x_t)$ apart before imposing MLH or CLH constraints may now be $d'(x_s, x_t) < d(x_s, x_t)$ along some path which skip through the MLH or CLH pairs. As pointed out by (Klein et al., 2002), this problem can be solved by finding a new distance value with respect to the modified constraints pairs using all-pairs-shortest-path algorithm.

For instance, Figure 2a shows a simple example of 6 entities, Classes A,B,C,D,E, and F. The number on the edges indicate the distance between two entities. In Figure 2a, the shortest distance between Class A and Class C is 0.9 with the following order: A-D-E-F-C.

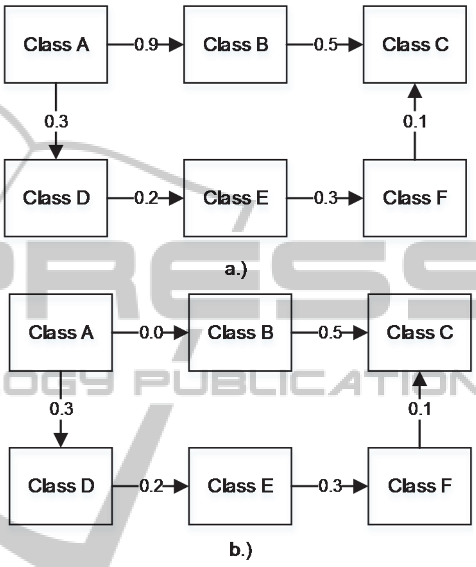

Figure 2: Example of problem when imposing MLH and CLH constraints.

After several discussions, the original developers discovered that Class A and Class B in fact are very closely related and impose a MLH constraint onto the cluster. Thus, the distance between A and B is now 0.0 to reflect the MLH constraint, as illustrated in Figure 2b. Therefore, the shortest path between Class A and Class C after the imposition of MLH constraint is now 0.5, with the following order: A-B-C. If we do not update the distance matrix accordingly, the final clustering results might contain erroneous outcome. The overall algorithm to fulfill both MLH and CLH constraints is shown below.

Input: A set of entities S = $\{x_1, x_2, \cdots, x_n\}$, a set of MLH (must-link hard constraints) and a set of CLH (cannot-link hard constraints)

Output: A modified distance matrix

1. Calculate the distance between each pair of entities and store it in a distance matrix *D* where $D_{i,j} = D_{j,i}$
2. Initialize: Let *D'* = *D* (create a clone distance matrix to modify the original one)

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3. while ¬ [(∀(x_p, x_q) ∈ MLH) ∩ (∀(x_r, x_s) ∈ CLH) > 0]
   i. for $(x_i, x_j) \in MLH,\ D'(x_i, x_j) = 0$
      run all-pair-shortest-path algorithm to prevent violation of triangular inequality
   ii. for $(x_i, x_j) \in CLH,\ D'(x_i, x_j) = D'(x_i, x_j) + Const$ where $Const$ is a constant large enough to prevent linkage in between entities $x_i, x_j$
      run all-pair-shortest-path algorithm to prevent violation of triangular inequality
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3.2 Constraints with Low Level of Confidence

In cases where users are not confident enough to judge whether the given constraints are absolute, these sets of constraints will be categorized as soft constraints. Since soft constraints are not definite, clustering results with partial fulfillment of soft constraints are still acceptable in most cases. However, soft constraints might be derived with a different level of importance and ranking, subject to the information provided by users. Fulfilling a handful of higher importance soft constraints might overshadow the fulfillment of several less important ones. Soft constraints are typically assigned with a penalty score. The penalty score is used to evaluate the quality of clustering results where minimization of the penalty score is preferred. Thus, a prioritization and ranking mechanism of soft constraints is introduced in this study.

The nature of prioritizing a given set of constraints is a multi-criteria decision-making (MCDM) problem. MCDM is a research of methods and procedures by which it concerns about evaluating multiple conflicting criteria and derive a way to come to a compromise. This set of criteria often differs in the degree of importance. Examples of methods to handle MCDM problems are analytic hierarchical process (AHP), fuzzy AHP, goal programming, scoring methods, and multi-attribute value functions.

In this study, ranking and prioritizing the importance of soft constraints are achieved using the fuzzy AHP technique. Fuzzy AHP is capable of handling the fuzziness of users' opinions with respect to the importance of soft constraints (Chong et al., 2014). The results gathered from fuzzy AHP will be represented in a table which shows a list of candidate criteria (soft constraints) associated with weightage (importance toward the analyzed software), where a higher weightage value represents higher priority. The result will act as a baseline to evaluate the penalty score of each soft constraint. MLS and CLS will be evaluated separately because the notion of ML and CL is opposing to each other. The objective function of MLS and CLS constraints is shown below:

Given a set S = $\{x_1, x_2, \cdots, x_n\}$ with entities $x_1, x_2, \cdots, x_n$, a set of MLS (must-link soft constraints) and a set of CLS (cannot-link soft constraints). The objective function is to maximize the number of satisfied MLS and CLS constraints:

$$max\ f(Z) = \frac{1}{n_c}\sum_{i=1}^{m}\gamma(x_i) - \frac{1}{2}\sum_{i=1}^{m}\delta(x_i)$$

Subject to $\gamma(x_i) \geq 0, i = 1, \cdots m$

$$0 \leq \delta(x_i) \leq 1, i = 1, \cdots m$$

Where n_c is the total number of available soft constraints (including MLS and CLS) and $\gamma(x_i)$ is the number of satisfied soft constraints involving pairs of entities with x_i as one of the entities. The left side of the equation is the ratio of fulfilled soft constraints over the total number of soft constraints. Meanwhile, $\delta(x_i)$ is the penalty score for violated constraints involving pairs of entities with x_i as one of the entities. The penalty score is based on its importance toward the overall software system using fuzzy AHP technique. The cumulative weightage (penalty score) of either MLS or CLS constraints is equal to 1. Thus, a scaling constant of 1/2 is used to normalize the second part of the equation when adding both the MLS and CLS constraints. Maximization of function $f(Z)$ is the goal of this objective function. The evaluation of soft constraints fulfillment is performed after the formation of dendrogram. The dendrogram needs to be cut at a certain height to produce a set of disjoint clusters. Evaluation of soft constraints can then be done by inspecting the set of disjoint clusters, to check whether or not the soft constraints are violated. A few cutting points can be executed to compare and contrast the quality of each cut with respect to the minimization of soft constraints penalty.

3.3 Constrained Agglomerative Hierarchical Clustering Algorithm

All in all, the complete algorithm of the proposed constrained agglomerative hierarchical software clustering is shown below.

Given a set of entities S, the distance for each pair of entities x and y in S is $1 \geq d(x, y) \geq 0$ and a set of constraints $\alpha = MLH, MLS, CLH, CLS$.

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1. Construct the baseline clusters from MLH
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   constraints resulting in $n$ number of initial
   clusters $M_1, M_2, \cdots M_n$.
2. If there is a pair of entities $(x, y)$ in
   $M_1, M_2, \cdots M_n$ and $\text{CLH}(x, y) \in \alpha$, then this is a
   NP-Complete problem with no solution.
3. Construct an initial clustering with $t_{max}$ clusters
   consisting of the $n$ clusters $M_1, M_2, \cdots M_n$ and a
   singleton cluster for each entity. $t_{max}$ is the
   maximum number of clusters for the set of
   entities $S$.
4. while $t \neq 1$
   a. Find the pair of entities $(S_p, S_q)$ with
      minimum distance.
   b. Merge $S_r = S_p \cup S_q$ at the level of
      dissimilarity.
   c. Remove $S_p, S_q$.
   d. $t = t - 1$.
   e. repeat step 4.
5. Generate a dendrogram tree based on the
   clustering results.
6. Cut dendrogram at several points.
7. Evaluate the fulfillment of MLS and CLS with
   respect to the penalty score.
```

The overall workflow of the proposed technique work in the following manner:

Software maintainers provide the UML class diagrams of the software to be analyzed. If class diagrams are not available, source codes are converted into class diagrams using an off-the-shelf round-trip engineering tool. The formation of clustering entities, identification of features, construction of dissimilarity matrix, and formation of dendrogram are executed based on our previous work (Chong et al., 2013) as discussed in Section 2.1. After the dendrogram is formed, software maintainers and/or the original developers can then provide domain knowledge to aid in the software clustering process. Based on the confidence level of the maintainers and/or developers, each input is categorized into hard or soft constraints. Dendrograms are cut based on the available constraints. Each cutting point is evaluated using the objective function proposed in Section 3.2. Cutting points that can fulfill the most constraints are prioritized.

4 EVALUATION

The work by Anquetil and Lethbridge (Anquetil and Lethbridge, 1999) discussed that instead of recovering a software system's architecture, clustering techniques actually create a new one based on the parameters and settings used by the clustering algorithm. Thus, a way to evaluate the effectiveness of the produced result is needed. MoJoFM is a well-established technique used to compare the similarity between clustering result and gold standard. High similarity between two partitions is more desirable as it indicates that the produced result resemble the gold standard.

However, Mitchell and Mancoridis (2001) discussed that often time, gold standard does not

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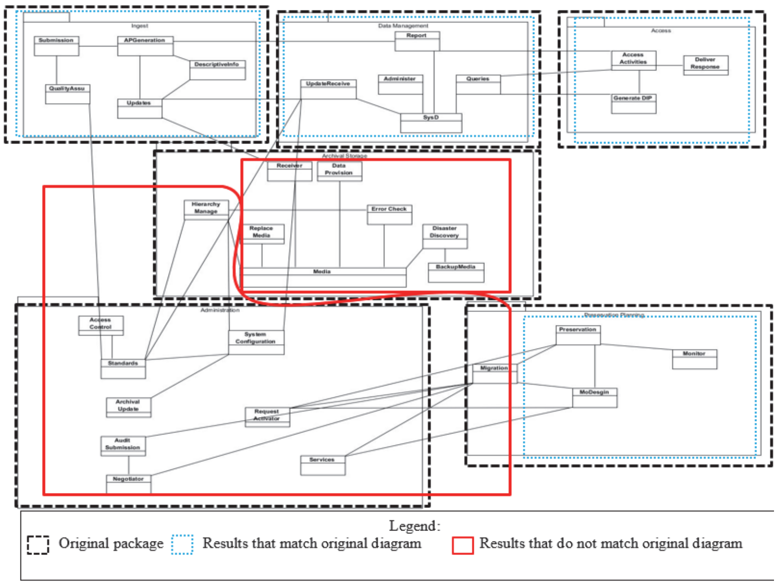

Figure 3: Overview of the original package diagram and the constrained software clustering results.

exist. The author suggested another approach by clustering the analyzed software using different clustering algorithms. Then, the similarity between the results of different algorithms are compared with each other. This will allow one to identify not only the quality of the clustering results, but also the stability of the clustering algorithm.

Thus, in this paper, we perform the evaluation of the proposed technique in the following manner.

1. Perform normal software clustering (without any constraints) based on our previous work (Chong et al., 2013).
2. Perform constrained software clustering using our proposed technique by incorporating hard and soft constraints.
3. Retrieve the original package diagram of the analyzed software. The original package diagram is by no means the gold standard since we could not verify the quality of the decomposition. However, it can be treated as a guideline to evaluate and compare between the results produced by the proposed technique and the documented artifact.
4. Use MoJoFM to calculate the similarity between all three results (normal clustering, constrained clustering, and package diagram).

Two evaluations were carried to assess the feasibility of the proposed method. First, we choose a university research project, MathArc ("MathArc - Ensuring Access to Mathematics Over Time," August 2009), as the input for our experiment. This project is aimed at creating a system that is capable of the long-term preservation and dissemination of digital journals in mathematics and statistics. This system is a joint project by Cornell University Library and Göttingen State University Library, which took two years to develop. The system contains 33 classes with an average of 8 attributes and 4 methods per class.

The system's functional modules are presented in Figure 3. Dotted black boxes represent the original UML packages. There are a total of six subsystems in this software. Since the software design of the MathArc system is documented properly, we can test the feasibility of our proposed algorithm in the following manner:

1. Prior to the experiment, we assume that all the entities are scattered around and not grouped in their respective packages.
2. Based on the original UML package diagram, we extract a few MLH, CLH, MLS, and CLS constraints. For instance, based on Figure 3, we understand that class "Monitor" and "Preservation" must be grouped into the same cluster because they are from the same subsystem. Thus, a MLH constraint "Monitor-Preservation" is generated in Table 1.
3. For MLS and CLS constraints, penalty score for violating the soft constraints are generated randomly. Besides that, we intentionally generate an erroneous constraint, but assign a very low penalty score to see how the proposed algorithm handles the constraint. For instance, although the original package diagram indicates that "Media" and "Standards" classes belong to different packages, we create a MLS constraint with penalty score of 0.1. This MLS constraint simulates the situation where stakeholders are not very confident about the given constraint.
4. Apply the proposed constrained clustering algorithm to restructure the class diagram, so that similar classes are grouped into the same package, while dissimilar ones are separated from each other.
5. Use MoJoFM to compare the result of the proposed constrained clustering technique with the original packages to identify its effectiveness.

Table 1 shows some of the constraints generated for this experiment. Note that the bracketed value in MLS and CLS represents the cost of violating a constraint. Davies-Bouldin index (Davies & Bouldin, 1979) is used in this experiment to evaluate the quality of cluster cohesion and separation.

Table 1: Generated constraints for MathArc system.

Constraints			
MLH	***CLH***	***MLS(penalty)***	***CLS (penalty)***
Submission-QualityAssu	AccessControl-Submission	Report-SysD(0.3)	Monitor-Negotiator (0.5)
Monitor-Preservation	Report-Services	Standards-AccessControl(0.3)	Submission-Services(0.5)
ErrorCheck-Media		Updates-APGeneration(0.3)	
ReplaceMedia-Media		Media-Standards(0.1)	

Figure 3 shows the clustering results using the proposed algorithm. The blue and red boxes represent the experimental results, with each box representing one subsystem. The blue boxes indicate the clustering results that match the original package diagram, while the red boxes indicate the mixture of results that match and do not match the original package diagram. The diagram was redrawn to normalize all of the association, aggregation, and generalization into the form of normal association notation.

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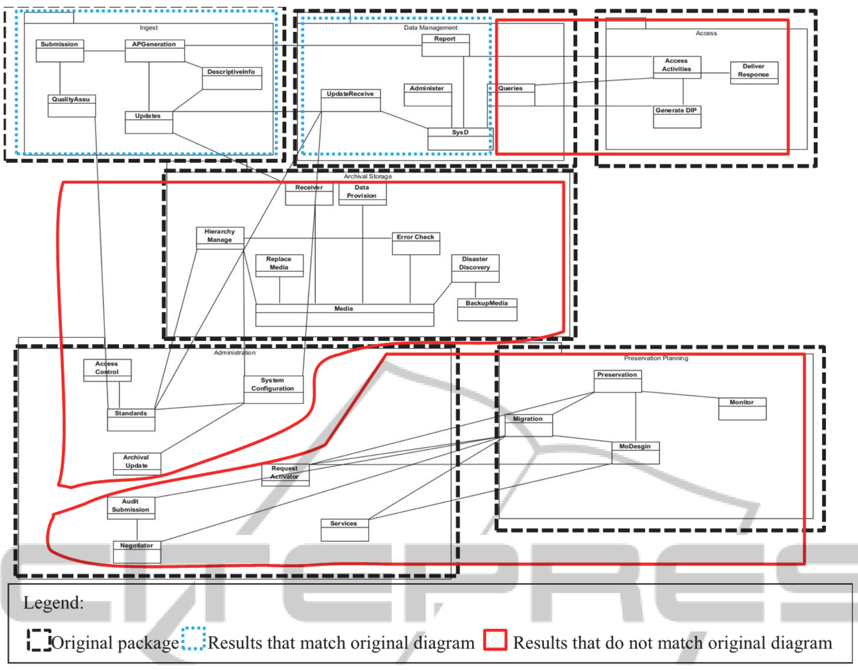

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Figure 4: Overview of the original package diagram and the clustering results without pairwise constraints.

Table 2: Generated Constraints for JSPWiki system.

Constraints			
MLH	***CLH***	***MLS(penalty)***	***CLS(penalty)***
GroupCommand-AbstractCommand	Workflow-TemplateDirTag	Tast-Outcome (0.3)	Command-WikiEventUtil(0.2)
AbstractCommand-WikiCommand	MailUtil-Entry	WatchDog-RSSThread(0.3)	WikiPrinciple-WikiPage(0.3)
UserCheckTag-WikiServletFilter	Workflow-CommandResolver	PageManager-EditorManager(0.2)	Step-ParseException(0.3)
AdminBeanManager-WikiEngineEvent	PageRenamer-Entry	Feed-RSS20Feed(0.1)	UserBean-Editor(0.1)
UserDatabase-WikiSession	Workflow-WikiRPCHandler	Editor-RSSGenerator(0.1)	BlogUtil-FileUtil(0.1)
Entry-AclImpl	MessageTag-Denounce		
WikiSession-UserProfile	MessageTag-Entry		
FormClose-FormSelect	FileUtil-RPCCallable		
FormElement-FormSet	Heading-MarkupParser		
FormOutput-FormOpen	Heading-ProviderException		
FormInput-FormTestArea	SecurityVerifier-WikiException		
InsertPage-TableofContents	FileUtil-ClassUtil		
Entry-FileSystemProvider	BasicPageFilter-CoreBean		
InitializablePlugin-Plugin	Util.PageSorter-Outcome		
TemplateDirTag-WikiRPCHandler	Outcome-Feed		

Note that all the MLH and CLH constraints are fulfilled in the result. However, the MLS constraint of "Media-Standards was violated. This is because based on Davies-Bouldin index, fulfilling the MLS constraint of “Media-Standards” will result in low cohesion strength among the associated clusters. Since the cost of violation is relatively smaller, selecting another cutting point that violates this MLS constraint is a better option. The objective function of soft constraints in this experiment is $f(Z) = [(5/6) - (0.05)] = 0.7833$. The left side of the equation signifies that 5 out of 6 soft constraints are fulfilled. The value of 0.05 is calculated based on the penalty score of violating the constraint "Media-Standards" and multiplying it with scaling constant of 1/2.

By using the MoJoFM tool provided by (Zhihua and Tzerpos, 2004), we manage to achieve MoJoFM metric of 92.59%. This shows a very high resemblance between the result of our proposed constraint clustering technique and the original package diagram. However, as mentioned earlier, the original package diagram is by no mean the 'gold standard' because we are unable to verify if it is the best abstraction to represent the software design of MathArc system. Thus, we perform another evaluation by comparing the results without imposing the pairwise constraints. The result is shown in Figure 4.

In Figure 4, we can observe that the 'Administrator' package (lower left hand side) contains classes from two other packages. The reason is that these classes behave similarly to utility classes, for which the association strengths within the same package are relatively weak compared to the other packages. When compared with the original package diagram, the MoJoFM achieves value of 88.89%. Although there are slight improvement when using the proposed constrained clustering technique, it is not significant enough. Thus, we decided to perform another experiment using a larger software.

We chose another open-source project, the JSPWiki which is a Wiki engine written in J2EE component. Wiki engines are used to host and manage Wiki web pages. JSPWiki contains 42560 lines of code and 425 classes with an average of 5.5 methods per class.

We extracted 15 MLH and CLH constrains, and 5 MLS and CLS constraints from the original package diagram of JSPWiki. The constraints are listed in Table 2. However, due to the number of classes exist in the project, the size of the class diagram is too large to be displayed. We decided to report the MoJoFM metric instead.

MoJoFM Metric: Constrained clustering compared to original package = 76.25%

MoJoFM Metric: Normal clustering (without constraints) compared to original package = 62.45%

The improvement by imposing pairwise constraints, observing from the perspective of MoJoFM metric, is more significant in larger software systems. The same observation was also found in the work by (Davidson and Ravi, 2009), where the author claimed that when performing on large datasets, a small number of constraints can significantly improve the results of agglomerative hierarchical clustering.

5 CONCLUSION AND FUTURE WORK

This paper presents a technique to integrate the concept of constrained clustering with agglomerative hierarchical software clustering to remodularize poorly designed and documented software systems. The proposed algorithm is capable of handling four types of constraints, namely MLH, CLH, MLS, and CLS constraints. Hard constraints are fulfilled throughout the whole clustering process while soft constraints are optional constraints associated with some validation of penalty if they are violated.

The proposed algorithm has been successfully implemented on two projects, the MathArc and JSPWiki system. Several MLH, MLS, CLH, and CLS constraints were generated to test the proposed technique. We managed to restructure the software and present it in the form of package diagram. When compared against clustering without any constraints, our proposed approach managed to achieve better results measured using MoJoFM metric.

Finally, we believe that there is potential research that can further improve the effectiveness of the proposed technique. For example, one can attempt to adapt the technique to be applied on partitional clustering algorithms such as k-mean clustering.

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