Using Heuristic Search Techniques to Extract Design Abstractions from Source Code

Brian S. Mitchell and Spiros Mancoridis
Department of Mathematics & Computer Science
Drexel University, Philadelphia, PA 19104
{bmitchel, smancori}@mcs.drexel.edu

Abstract

As modern software systems are large and complex, appropriate abstractions of their structure are needed to make them more understandable and, thus, easier to maintain. Software clustering tools are useful to support the creation of these abstractions. In this paper we describe our search algorithms for software clustering, and conduct a case study to demonstrate how altering the clustering parameters impacts the behavior and performance of our algorithms.

1 Introduction & Background

Software supports many business, government, and social institutions. As the processes of these institutions change, so must the software that supports them. Changing software systems that support complex processes can be quite difficult, as these systems can be large (*e.g.*, thousands or even millions of lines of code) and dynamic.

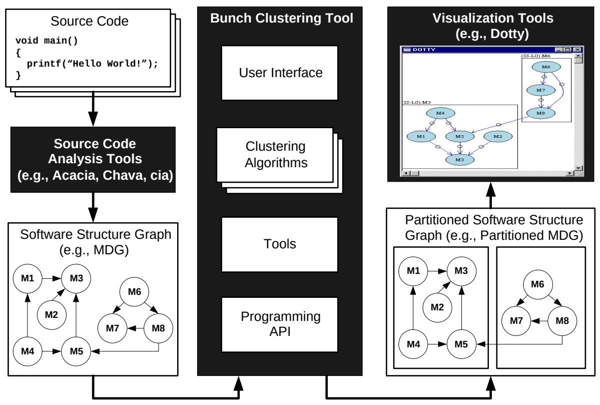
There is a need to develop sound methods and tools to help software engineers understand large and complex systems so that they can modify the functionality or repair the known faults of these systems. Understanding how the software is structured – at various levels of granularity – is one of several kinds of understanding that is important to a software engineer. As the software structure can itself be very complex, the appropriate abstractions of a system's structure must be determined. Techniques and tools can then be designed and implemented to support the creation of these abstractions.

Automatic design extraction methods have been proposed to create abstract views – similar to "road maps" – of a system's structure. Such views help software engineers cope with the complexity of software development and maintenance. Design extraction starts by parsing the source code to determine the components and relations of the software. The parsed code is then analyzed to produce a variety of views of the software structure, at varying levels of abstraction.

Detailed views of software structure are appropriate when the software engineer has isolated the subsystems that are relevant to his or her analysis. However, abstract (architectural) views are more appropriate when the software engineer is trying to understand the global structure of the software. Software clustering is used to produce such abstract views. These views feature module-level components and relations contained within subsystems. The source code level components and relations can be determined using source code analysis tools. The subsystems, however, are not found in the source code. Rather, they are inferred from the source code components and relations either automatically, using a clustering tool, or manually, when tools are not available.

The problem of automatically creating abstract views of software structure is very computationally expensive (NP-hard) (Garey and Johnson, 1979), so a hope for finding a general solution to the software clustering problem is unlikely. Nevertheless, several heuristic approaches to solving this problem have been proposed. These approaches generally differ in the way that they create subsystems. For example, some popular clustering techniques use source code component similarity (Hutchens and Basili, 1985; Schwanke, 1991; Choi and Scacchi, 1999; Müller *et al.*, 1992), concept analysis (Lindig and Snelting, 1997; Deursen and Kuipers, 1999), or implementation information such as module, directory, and/or package names (Anquetil *et al.*, 1999) to derive the subsystems. Our clustering approach differs from the others as it is based on heuristic search techniques (Mancoridis *et al.*, 1998; Doval *et al.*, 1999; Mancoridis *et al.*, 1999; Mitchell *et al.*, 2001).

In this paper we examine the latest features of the software clustering techniques that are implemented in our clustering tool named Bunch. We will focus on the enhancements that we have made to our hill-climbing clustering algo-


Source Code
Bunch Clustering Tool
Visualization Tools (e.g., Dotty)
User Interface
Source Code Analysis Tools (e.g., Acacia, Chava, cia)
Clustering Algorithms
Software Structure Graph (e.g., MDG)
Tools
Partitioned Software Structure Graph (e.g., Partitioned MDG)
Programming API
M1
M2
M3
M4
M5
M6
M7
M8

```
void main()
{
  printf("Hello World!");
}
```

Figure 1: Bunch's Design Extraction Process

rithm since it was first published in the 1998 IWPC proceedings (Mancoridis *et al.*, 1998). We also conduct a case study to demonstrate how the various clustering parameters supported by our latest hill-climbing algorithm impact the clustering results when applied to several systems of varying size. Our goal is to help Bunch users understand the parameters of our clustering algorithms.

2 Design Extraction using Bunch

The first step in our design extraction process (see Figure 1) is to determine the resources and relations in the source code and store the resultant information in a database. Readily available source code analysis tools – supporting a variety of programming languages – can be used for this step (Chen, 1995; Korn *et al.*, 1999). After the resources and relations have been stored in a database, the database is queried and a Module Dependency Graph (MDG) is created. For now, consider the *MDG* to be a directed graph that represents the software modules (e.g., classes, files, packages) as nodes, and the relations (e.g., function invocation, variable usage, class inheritance) between modules as directed edges. Once the *MDG* is created, Bunch's clustering algorithms can be used to create the partitioned *MDG*. The clusters in the partitioned *MDG* represent subsystems that contain one or more modules, relations, and possibly other subsystems. The final result can be visualized and browsed using a graph visualization tool such as dotty (North and Koutsofios, 1994).

An example *MDG* for a small compiler developed at the University of Toronto is illustrated in Figure 2. We show a sample partition of this *MDG*, as created by Bunch, in Figure 3. Notice how Bunch automatically created four subsystems to represent the abstract structure of a compiler. Specifically, there are subsystems for code generation, scope management, type checking, and parsing.

The center of Figure 1 depicts additional services that are supported by the Bunch clustering tool. These services are discussed thoroughly in Bunch's user and pro-

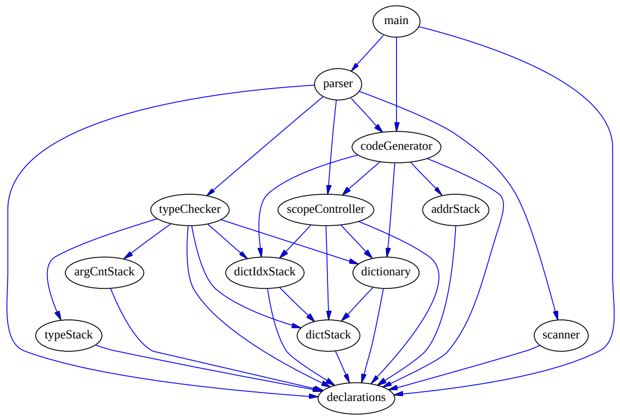


Figure 2: The MDG for a Small Compiler

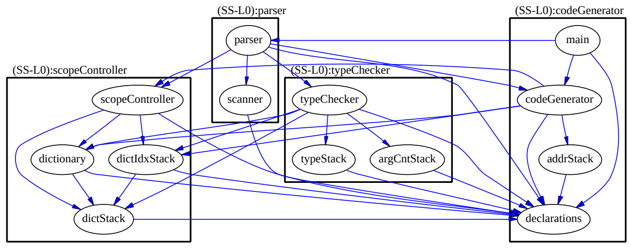


Figure 3: The Partitioned MDG for a Small Compiler

grammer documentation, which can be accessed on the Drexel University Software Engineering Research Group web page (SERG, 2002).

3 Bunch's Updated Clustering Algorithms

The goal of Bunch's clustering algorithms is to partition the Module Dependency Graph (MDG) so that the clusters represent meaningful subsystems. We formally define the *MDG* to be a graph $MDG = (M, R)$, where M is the set of named modules in the software system, and $R \subseteq M \times M$ is a set of ordered pairs of the form $\langle u, v \rangle$ which represents the source-level relationships that exist between module u and module v. Also, the *MDG* can have weighted edges to establish the "strength" of the relation between a pair of modules. An example *MDG* consisting of 8 modules is shown on the left side of Figure 4.

Once the *MDG* of a software system is determined, we search for a "good" partition of the *MDG*. We accomplish this task by using heuristic searches whose goal is to maximize the value of an objective function that is based on a formal characterization of the trade-off between coupling (*i.e.*, connections between the components of two distinct clusters) and cohesion (*i.e.*, connections between the components of the same cluster). We refer to our objective function as the *Modularization Quality* (*MQ*) of a partition of an *MDG*. This measurement represents the "quality" of a system decomposition. *MQ* adheres to our fundamental

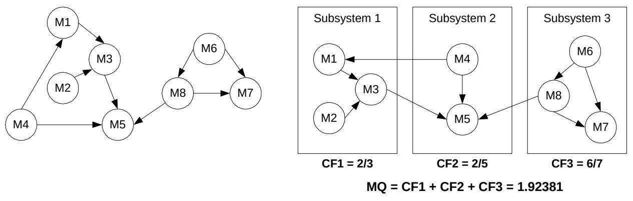


Figure 4: Modularization Quality Example

assumption that well-designed software systems are organized into cohesive clusters that are loosely interconnected. The *MQ* expression is designed to reward the creation of highly cohesive clusters yet penalize excessive inter-cluster coupling.

The *MQ* for an *MDG* partitioned into k clusters is calculated by summing the *Cluster Factor* (*CF*) for each cluster of the partitioned *MDG*. The Cluster Factor, CF_i, for cluster i ($1 \leq i \leq k$) is defined as a normalized ratio between the total weight of the internal edges (edges within the cluster) and half of the total weight of external edges (edges that exit or enter the cluster). We split the weight of the external edges in half in order to apply an equal penalty to both clusters that are are connected by an external edge. We refer to the internal edges of a cluster as intra-edges (μ_i), and the edges between two distinct clusters i and j as inter-edges ($\varepsilon_{i,j}$ and $\varepsilon_{j,i}$ respectively). If edge weights are not provided by the *MDG*, we assume that each edge has a weight of 1. Also, note that $\varepsilon_{i,j} = 0$ and $\varepsilon_{j,i} = 0$ when $i = j$. Below, we define the *MQ* calculation:

$$MQ = \sum_{i=1}^{k} CF_i \qquad CF_i = \begin{cases} 0 & \mu_i = 0 \\ \dfrac{\mu_i}{\mu_i + \frac{1}{2} \sum\limits_{\substack{j=1 \\ j \neq i}}^{k} (\varepsilon_{i,j} + \varepsilon_{j,i})} & otherwise \end{cases}$$

Figure 4 illustrates an example *MQ* calculation for an *MDG* consisting of 8 modules that are partitioned into 3 subsystems. The value of *MQ* is approximately 1.924, which is the result of summing the Cluster Factor for each of the three subsystems. The larger the value of *MQ*, the better the partition. For example, the *CF* for Subsystem 2 is 0.4 because there is 1 intra-edge, and 3 inter-edges. Applying these values to the expression for *CF* results in $CF_2 = 1/(1 + \frac{3}{2}) = 2/5 = 0.4$.

The *MQ* measurement described above is the most recent objective function that we have integrated into the Bunch tool. Our older objective function, which was described in an earlier paper (Mitchell *et al.*, 2001) worked well, but we noticed after significant testing that the clusters produced by Bunch tended to minimize the inter-edges that exited the clusters, and not minimize the number of inter-edges in general. Also, the above described *MQ* measurement supports *MDGs* that contain edge weights, which is a feature that was not supported by our original *MQ* measurement (Mancoridis *et al.*, 1998).

3.1 Clustering Algorithms

One way to find the best partition of an *MDG* is to perform an exhaustive search through all of the valid partitions, and select the one with the largest *MQ* value. However, this is often impossible because the number of ways the *MDG* can be partitioned grows exponentially with respect to the number of its nodes (modules) (Mancoridis *et al.*, 1998).[1] Because discovering the optimal partition of a *MDG* is only feasible for small software systems (*e.g.*, fewer then 15 modules), we directed our attention, instead, to using heuristic search algorithms that are capable of discovering approximation results quickly. The approximation search strategies that we have investigated and implemented in the Bunch (Mancoridis *et al.*, 1999) clustering tool, are based on hill-climbing (Mancoridis *et al.*, 1998) and genetic (Doval *et al.*, 1999) algorithms.

3.1.1 Hill-Climbing Algorithm

Bunch's hill-climbing clustering algorithms start by generating a random partition of the *MDG*. Modules from this partition are then rearranged systematically in an attempt to find an "improved" partition with a higher *MQ*. If a better partition is found, the process iterates, using the improved partition as the basis for finding even better partitions. This hill-climbing approach eventually converges when no additional partitions can be found with a higher *MQ*.

Neighboring Partitions

Our hill-climbing algorithms move modules between the clusters of a partition in an attempt to improve *MQ*. This task is accomplished by generating a set of neighboring partitions (*NP*).

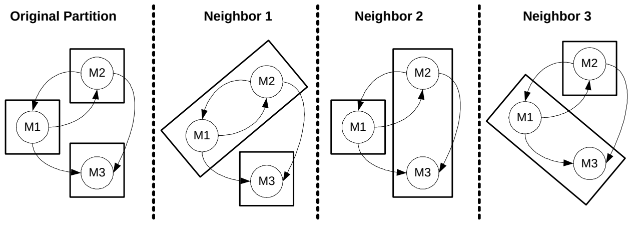


Figure 5: Neighboring Partitions

We define a partition *NP* to be a neighbor of a partition P if and only if *NP* is exactly the same as P except that a single element of a cluster in partition P is in a different cluster

[1]It should also be noted that the general problem of graph partitioning (of which software clustering is a special case) is NP-hard (Garey and Johnson, 1979).

in partition *NP*. If partition P contains m nodes and k clusters, the total number of neighbors is $O(n \cdot k)$. Figure 5 illustrates an example partition, and all of its neighboring partitions.

3.1.2 Genetic Algorithm

Hill-climbing search algorithms suffer from the well-known problem of “getting stuck” at local optimum points, and therefore possibly missing the global optimum (best solution). To address this concern we have investigated other search algorithms such as Genetic Algorithms (GA) (Goldberg, 1989; Mitchell, 1997), and applied these algorithms to the software clustering problem. We have found that the results produced by Bunch’s hill-climbing algorithm are typically better than the Bunch GA (Doval *et al.*, 1999). Upon studying this outcome, we concluded that further work on our encoding and crossover techniques are necessary.

4 Hill-Climbing Algorithm Enhancements

The previous section of this paper describes the clustering algorithms that are supported by Bunch. The emphasis since the Bunch project was started has been on our hill-climbing clustering algorithms. The rest of this section describes various enhancements that we recently made to the hill-climbing algorithm described in Section 3.1.1.

4.1 Adjustable Hill-Climbing Threshold

The hill-climbing algorithm described in Section 3.1.1 starts with a generated random partition of the *MDG*. It then iterates using our neighboring partition strategy[2] to find an “improved” partition using the *MQ* objective function. During each iteration several options are available for controlling the behavior of the hill-climbing algorithm:

1. The neighboring process uses the first partition that it discovers with a larger *MQ* as the basis for the next iteration.
2. The neighboring process examines all neighboring partitions and selects the partition with the largest *MQ* as the basis for the next iteration.
3. The neighboring process ensures that it examines a minimum number of neighboring partitions during each iteration. If multiple partitions with a larger *MQ* are discovered within this set, then the partition with the largest *MQ* is used as the basis for the next iteration. If no partitions are discovered that have a larger *MQ*, then the neighboring process continues and uses the next partition that it discovers with a larger *MQ* as the basis for the next iteration.

[2]The hill-climbing algorithm examines the set of neighboring partitions in random order.

To address the last option from the above list, the latest version of the hill-climbing algorithm uses a threshold η ($0\% \leq \eta \leq 100\%$) to calculate the minimum number of neighbors that must be considered during each iteration of the hill-climbing process. A low value for η generally results in the algorithm taking more “small” steps prior to converging, and a high value for η results in the algorithm taking fewer “large” steps prior to converging.

Our experience has shown that examining many neighbors during each iteration (*i.e.*, using a large threshold such as $\eta \geq 75\%$) increases the time the algorithm needs to converge to a solution. One obvious question is if the increased runtime increases the likelihood of finding a better solution than if the first discovered neighbor with a higher *MQ* ($\eta = 0\%$) is used as the basis for the next iteration of the hill-climbing algorithm. Answering this question is one of the goals of the case study that is described in Section 5.

4.2 Simulated Annealing

A well-known problem of hill-climbing algorithms is that certain initial starting points may converge to poor solutions (*i.e.*, local optima). To address this problem, our hill-climbing algorithm does not rely on a single random starting point, but instead uses a collection of random starting points.

Another way to overcome the above described problem is to use Simulated Annealing (SA) (Kirkpatrick *et al.*, 1983). SA algorithms are based on modeling the cooling processes of metals, and the way liquids freeze and crystalize. When applied to optimization problems, SA enables the search algorithm to accept, with some probability, a worse variation as the new solution of the current iteration. As the computation proceeds, the probability diminishes. The slower the *cooling schedule*, or rate of decrease, the more likely the algorithm is to find an optimal or near-optimal solution. SA techniques typically represent the cooling schedule with a *cooling function* that reduces the probability of accepting a worse variation as the optimization algorithm runs.

We defined a cooling function that establishes the probability of accepting a worse, instead of a better partition during each iteration of the hill-climbing algorithm. The idea is that by accepting a worse neighbor, occasionally the algorithm will “jump” to explore a new area in the search space. Our cooling function is designed to respect the properties of the SA cooling schedule, namely: (a) decrease the probability of accepting a worse move over time, and (b) increase the probability of accepting a worse move if the rate of improvement is small. Below we present our cooling function that is designed with respect to the above requirements.

$$P(A) = \begin{cases} 0 & \triangle MQ \geq 0 \\ e^{\frac{\triangle MQ}{T}} & \triangle MQ < 0 \end{cases} \qquad T(k+1) = \alpha \cdot T(k)$$

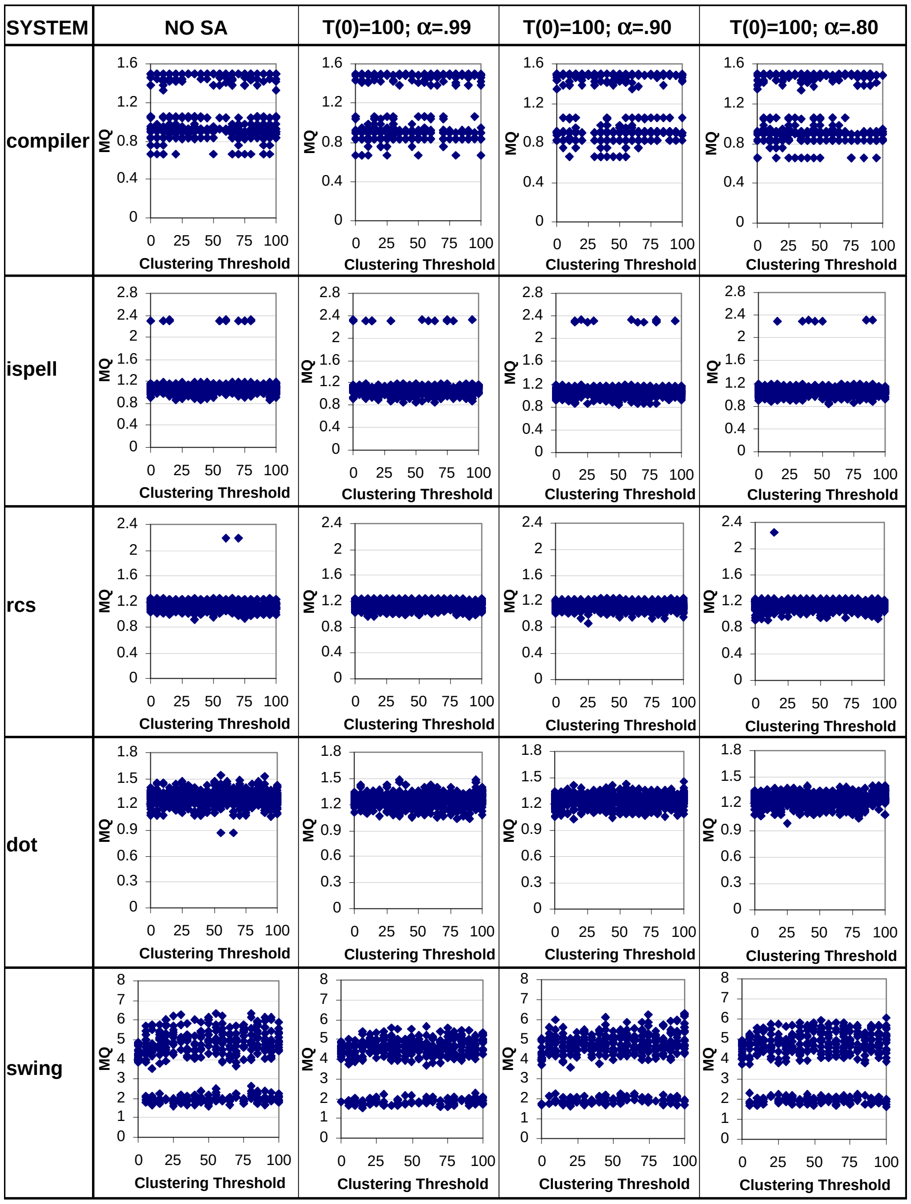


Figure 6: Case Study Results – MQ versus η Scatter Plot

Each time the cooling function is evaluated, $T(k)$ is reduced. The initial value of T (*i.e.*, $T(0)$) and the rate of reduction constant α are established by the user. Furthermore, $\triangle MQ$ must be negative, which means that the *MQ* value has decreased. Once the probability of accepting a partition of the *MDG* with a lower *MQ* is calculated, a uniform random number between 0 and 1 is chosen. If this random number is less than the probability $P(A)$, the partition is accepted.

5 Case Study

In the previous section we described some recent enhancements that were made to Bunch's hill-climbing clustering algorithms. These new features require the user to set configuration parameters to guide the clustering process. In this section we present a case study to investigate the impact of altering these parameters on systems of various size.

Table 1 describes the 5 systems that we used in our case study. We selected these systems because they vary in size and complexity. Our basic test involved clustering each system 1,050 times, consisting of 21 tests, with 50 runs in each test. The first 50 clustering runs were executed with the adjustable clustering threshold η set to 0%. The next set of 20 tests (with 50 runs in each test) involved incrementing η by 5% until η reached 100%.

We then repeated the above test for each of the systems described in Table 1, this time using the simulated annealing

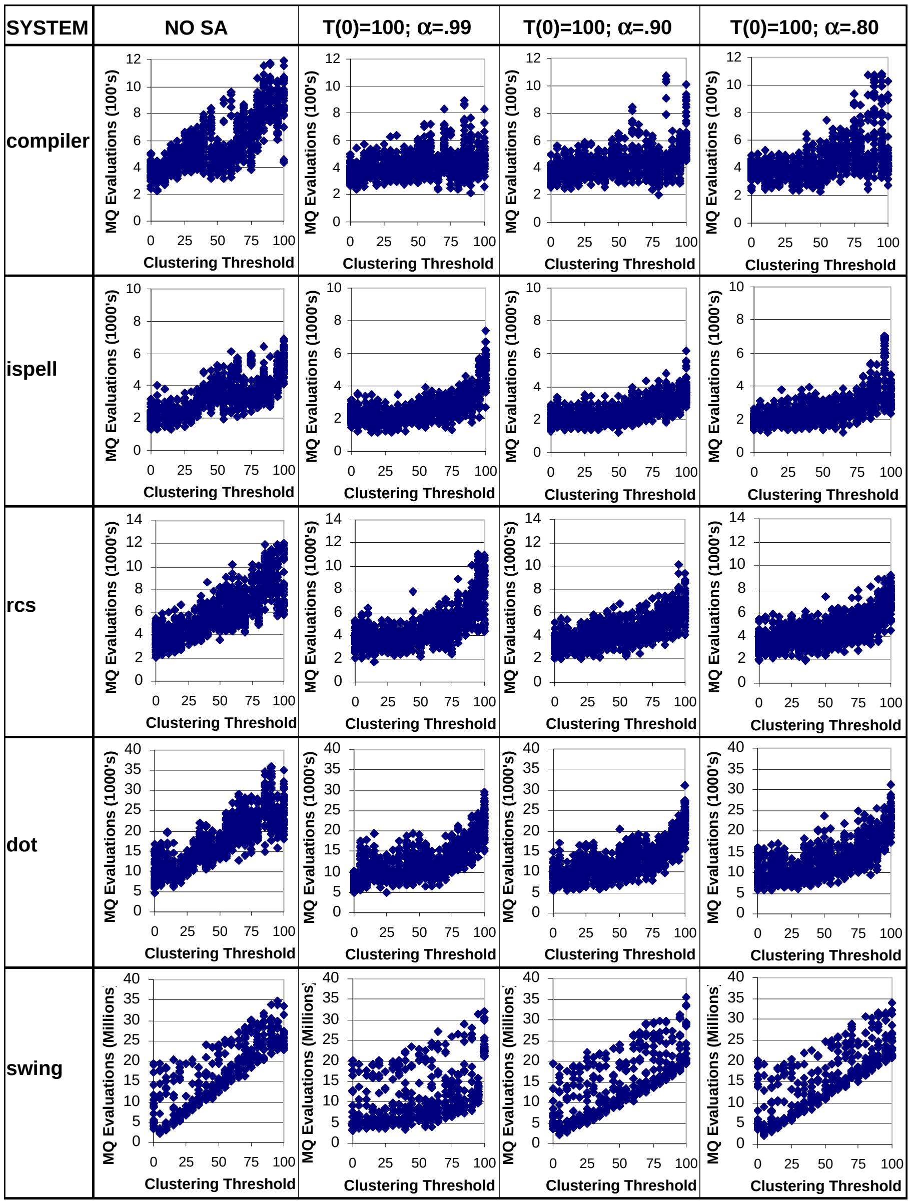


Figure 7: Case Study Results – MQ Evaluations versus η Scatter Plot

feature. Each of these tests altered the parameters used to initialize the *cooling function* that was described in Section 4.2. For these tests we held the initialization value for the starting temperature constant, $T(0) = 100$, and varied the cooling rate as follows: $\alpha = \{0.99, 0.9, 0.8\}$.

The following observations were made based on the data collected in the case study:

- As expected, the clustering threshold η had a direct and consistent impact on the clustering runtime, and the number of *MQ* evaluations. As η increased so did the overall runtime and the number of *MQ* evaluations. This behavior is illustrated consistently in Figure 7.
- Figure 6 shows that although increasing η increased the overall runtime and number of *MQ* evaluations, altering η did not appear to have an observable impact on the overall quality of the clustering results. The data in Figure 6 also shows that our simulated annealing implementation did not improve *MQ*. However, the simulated annealing algorithm did appear to help reduce the total runtime needed to cluster each of the systems in this case study.

Figure 7 shows the number of *MQ* evaluations performed for each of the systems in the case study. Since the overall runtime is directly related to the number of *MQ* evaluations, it appears that the use of our SA cool-

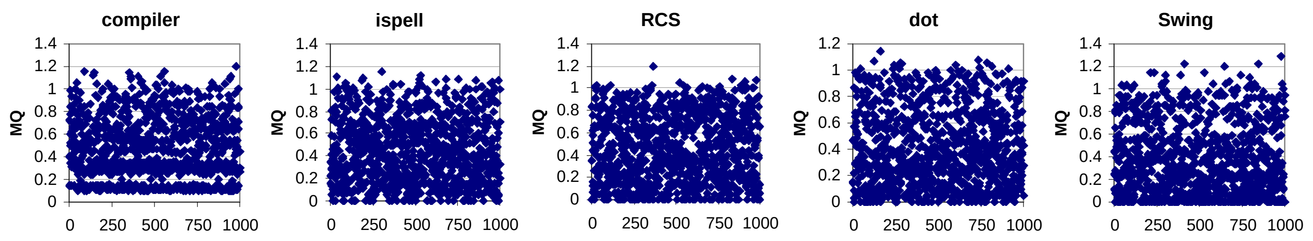


Figure 8: Case Study Results – Random Partition Scatter Plot

Table 1: Systems Examined in the Case Study

System Name	System Description & MDG Size
compiler	The compiler shown in Figure 2. MDG: modules = 13, relations = 32
ispell	An open source spell checker. MDG: modules = 24, relations = 103
rcs	An open source version control system. MDG: modules = 34, relations = 163
dot	A graph drawing tool (Gansner *et al.*, 1993). MDG: modules = 42, relations = 256
swing	The Java user interface class library. MDG: modules = 413, relations = 1513

ing technique is a promising way to reduce the clustering time. Table 2 compares the average number of *MQ* evaluations executed in each SA test to the average number of *MQ* evaluations executed in the non-SA test. For example using $T(0) = 100$ and $\alpha = .99$ reduced the number of *MQ* evaluations needed to cluster the swing class library by an average of 32%.

- Figure 6 indicates that the hill-climbing algorithm converged to a consistent solution for the ispell, dot and `rcs` systems.

- Figure 6 shows that the hill-climbing algorithm converged to one of two families of related solutions for the compiler and swing systems. For the compiler system, 53.7% of the results were found in the range $0.6 \leq MQ \leq 1.0$, and 46.3% of the results were found in the range $1.3 \leq MQ \leq 1.5$. For the swing system, 27.3% of the results were found in the range $1.5 \leq MQ \leq 2.5$, and 72.7% of the results were found in the range $3.75 \leq MQ \leq 6.3$.

- Figure 6 shows two interesting results for the ispell and rcs systems. For the ispell system, 34 out of 4,200 samples (0.8%) were found to have an *MQ* around 2.3, while all of the others samples had an *MQ* value in the range $0.8 \leq MQ \leq 1.2$. For the rcs system, 3 out of 4,200 samples (0.07%) were found to have an *MQ* around 2.2, while all of the other samples had *MQ* values concentrated in the range of $1.0 \leq MQ \leq 1.25$. This outcome highlights that some rare partitions of an *MDG* may be discovered if enough runs of our hill-climbing algorithm are executed.

- Figure 8 illustrates 1,000 random partitions for each system examined in this case study. The random partitions have low *MQ* values when compared to the clustering results shown in Figure 6. This result provides some confidence that our clustering algorithms produce better results than examining many random partitions, and that the probability of finding a good partition by means of random selection is small.

- As α increased, so did the number of simulated annealing (non-improving) partitions that were incorporated into the clustering process. In Figure 9 we show the number of SA partitions integrated into the clustering process for the swing class library. As expected, the number of partitions decreased as α decreased. Although we only show this result for swing, all of the systems examined in this case study exhibited this expected behavior.

Table 2: Reduced Percentage of *MQ* Evaluations Associated with using Simulated Annealing

	Simulated Annealing Parameters		
System	$T(0) = 100$ $\alpha = .99$	$T(0) = 100$ $\alpha = .90$	$T(0) = 100$ $\alpha = .80$
compiler	27%	26%	23%
ispell	22%	25%	21%
rcs	25%	27%	26%
dot	28%	29%	25%
swing	32%	15%	10%

6 Conclusions

This paper describes the latest enhancements that we made to our hill-climbing clustering algorithm, and examined several configuration parameters that impact the overall runtime and quality of the clustering results. A case study was also conducted to evaluate the impact of altering some of our clustering parameters when the Bunch tool was used to cluster several systems of varying sizes.

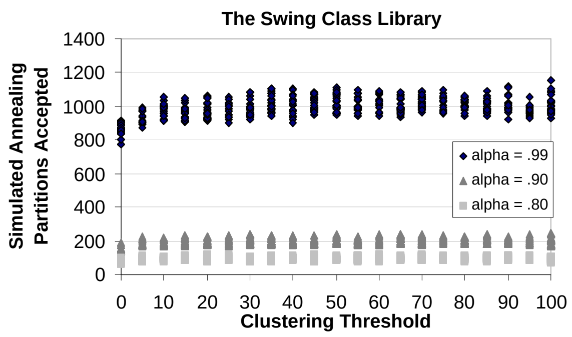


Figure 9: Case Study Results – Simulated Annealing Partitions used for Clustering swing

Our case study produced some interesting results, some of which were surprising. We expected that altering the clustering threshold η would either improve *MQ* or reduce variability in the clustering results, neither was found to be true. Also, although our simulated annealing technique did not impact *MQ* it did reduce the number of *MQ* evaluations, and therefore the overall clustering runtime for the systems that we examined. We also observed that our clustering algorithm tended to converge to a single "neighborhood" of related solutions for the ispell, rcs, and dot systems, and to two "neighborhoods" of related solutions for the compiler and swing systems. Finally, some rare solutions, with a significantly higher *MQ*, were discovered for the ispell and rcs systems.

As future work we intend to reevaluate our genetic algorithm in order to make some of the improvements that were suggested in this paper, and to investigate some alternative SA cooling functions.

7 Acknowledgements

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