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Visualizing and exploring profiles with calling context ring charts

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SUMMARY

Calling context profiling is an important technique for analyzing the performance of object-oriented software with complex inter-procedural control flow. The Calling Context Tree (CCT) is a common data structure that stores dynamic metrics, such as CPU time, separately for each calling context. As CCTs may comprise millions of nodes, there is a need for a condensed visualization that eases the localization of performance bottlenecks. In this article, we discuss *Calling Context Ring Charts* (*CCRCs*), a compact visualization for CCTs, where callee methods are represented in ring segments surrounding the caller's ring segment. In order to reveal hot methods, their callers, and callees, the ring segments can be sized according to a chosen dynamic metric. We describe two case studies where CCRCs help us to detect and fix performance problems in applications. A performance evaluation also confirms that our implementation can efficiently handle large CCTs. Copyright © 2010 John Wiley & Sons, Ltd.

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1. INTRODUCTION

Currently, software systems have become more and more complex as they may comprise many different components from various sources. Consequently, understanding the whole software system has become more challenging for application developers, and pure static program analyzes have become less effective [1]. As a result, program profiling techniques are widely used by application developers to collect information about the behaviors of programs at runtime [2]. This information can be used for instance to identify algorithmic bottlenecks or inefficient code [3]. A large body of work exists that benefits from profiling techniques in program comprehension tasks such as debugging [4–6], testing [7, 8], reverse engineering [9, 10], and optimizing software systems [11].

Calling context profiling is a common profiling technique that yields dynamic metrics separately for each calling context, such as the number of method invocations or the CPU time spent in a calling context. A calling context is a sequence of methods that were invoked but not yet completed; that is, a calling context corresponds to the methods represented on the call stack at some moment during program execution. Calling context profiling is powerful since it helps us to analyze the dynamic inter-procedural control flow of applications. This technique is particularly important for

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understanding and optimizing modern object-oriented software, where polymorphism, dynamic binding, and reflection often hinder static analysis approaches.

The *Calling Context Tree* (*CCT*), which was first introduced by Ammons *et al.* [3], is the prevailing data structure for representing calling context profiles. Each node in the CCT corresponds to a calling context and stores the measured dynamic metrics for that calling context; it also refers to a unique identifier of the method in which the metrics were collected. The parent of a CCT node represents the caller's context, whereas the children nodes correspond to the callee methods. If the same method is invoked in distinct calling contexts, the different invocations are represented by distinct nodes in the CCT. In contrast, if the same method is invoked multiple times in the same calling context, the dynamic metrics collected during the executions of that method are stored in the same CCT node. Hence, by distinguishing dynamic metrics for each distinct calling context, the CCT provides detailed information about the dynamic program behavior which is required in many software engineering areas including profiling [3], debugging [4], testing [8] or reverse engineering [9]. There is a large body of work dealing with various techniques to generate CCTs [2, 3, 12–16], highlighting the importance of the CCTs for calling context profiling.

The prevailing techniques for generating CCTs typically illustrate them in the form of expandable rooted trees [17]. However, CCTs can become quite large, sometimes comprising millions of nodes. Moreover, the depth of CCTs can be high such that CCTs with 50–400 layers are common in practice. In this situation, navigating and exploring CCTs for a particular dynamic metric of interest (e.g. locating invocations of a particular method in various calling contexts) can be quite cumbersome when a simple expandable tree representation is used, and hence, better visualization techniques are required.

Visualizing hierarchical structures is an important area in the information visualization community that aim to provide better representations of hierarchical structures with enhanced navigation capabilities [18, 19]. One main category of these techniques are *radial* approaches [18] that illustrate hierarchical structures in circular patterns. Previous research has shown that these techniques are quite effective in aiding the users in exploring hierarchical structures [20, 21]. With respect to this discussion, this article introduces *Calling Context Ring Charts (CCRCs)* [22] as a way of visualizing and exploring CCTs. In a CCRC, the CCT root is represented as a circle in the center. Callee methods are represented by ring segments surrounding the caller's ring segment. With CCRCs, it is possible to display all calling contexts of a CCT in a single chart, preserving the caller/callee relationships conveyed in the CCT. For a detailed analysis of certain calling contexts, CCT subtrees can be selected to be visualized separately and the tree depth can be limited.

Currently, CCRCs support three different kinds of visualizations [22]. First, for each caller, the ring segments of the callees have the same size and completely surround the caller's ring segment. While this representation eases the analysis of caller/callee relationships, it does not convey any information about dynamic metrics collected within different calling contexts. In the second visualization, the angle covered by each ring segment is proportional to the contribution of the corresponding calling context to a chosen dynamic metric, relative to the respective caller's contribution. For example, if CPU time is chosen as metric, this representation reveals the invoked hot methods, for each calling context. While in the first and second visualizations the width of each layer in the ring chart is the same, the third representation continuously reduces the width of outer layers such that the area occupied by each ring segment is proportional to the overall metric contribution of the corresponding calling context.

This article complements the above three visualizations with four tree manipulation operations on the CCT: *subtree selection* and *depth limitation* for handling large CCTs; *recursion elimination* to remove CCT nodes representing recursive calls; and, *dynamic metric aggregation* to determine the overall metric contribution of each method. We provide three implementations of the above CCRC visualizations and these tree manipulations based on JavaScript, Java Swing, and Eclipse SWT. We also report on two case studies where CCRCs have been successfully applied to locate performance problems in two different applications (a lexical analyzer generator and a cryptography library),

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which were optimized afterwards. These case studies are complemented with a performance evaluation on visualizing the CCTs resulting from the execution of the DaCapo benchmarks [23] for Java, confirming that our implementation can efficiently handle large CCTs.

In summary, this article presents (1) an introduction to CCRCs and the use of radial visualization techniques to represent the hierarchical structures of calling context trees, (2) an introduction to four tree manipulation operations on CCTs, (3) three implementations of the CCRC visualizations and tree manipulation operations, (4) two case studies where CCRCs were successfully applied to find performance issues in two different applications, which were optimized afterwards, and (5) an evaluation that confirms that our implementation can efficiently handle large CCTs. With respect to the earlier versions of the work that were presented in [22] and [24], the novel contributions of the article are in the items (2), (4), and (5).

The remainder of this article is organized as follows: Section 2 presents some background information about the CCT. Section 3 shows the three types of CCT visualizations supported by CCRC, while Section 4 discusses our various tree manipulation operations. Section 5 describes our implementations and Section 6 presents the two case studies. Section 7 discusses the results of our performance evaluation. Section 8 compares CCRCs with related work, and finally, Section 9 concludes.

2. BACKGROUND: THE CALLING CONTEXT TREE (CCT)

The Calling Context Tree (CCT) [3] is a popular data structure for representing calling context profiles at runtime. Each node in the CCT corresponds to a calling context and stores the measured dynamic metrics for that particular calling context. The CCT does not restrict which and how many dynamic metrics are stored in the tree nodes. The common metrics include the number of method invocations, the CPU time, the number of cache misses, the number of object allocations or the amount of allocated memory.

For some metrics M, it is useful to consider also the aggregated metrics $ag(M)$ for subtrees of the CCT, in order to explore the overall costs of method executions, including the costs incurred by all direct and indirect callees. In other words, for each CCT node n, $ag(M_n)$ is computed as the sum of the metric values M_x of all nodes x in the CCT subtree rooted at node n. Aggregated metrics are usually not stored in the CCT nodes, but are computed on demand. For instance, for a given CCT node n, the metric CPU_n shows the CPU time spent executing the instructions within the body of the method m_n represented by the node n, excluding the CPU time spent in callees of m_n. In contrast, the metric $ag(CPU_n)$ gives the overall CPU time spent in the calling context corresponding to node n and in all callees. Common metrics where aggregation for subtrees helps locate performance problems include the CPU time spent in a calling context or the amount of memory allocated in a calling context. Some other metrics, such as the number of method invocations, are rarely aggregated.

The example in Figure 1(b) shows a conceptual representation of the CCT resulting from executing the Java code sample in Figure 1(a); the colors used differentiate the distinct methods. The illustrated CCT represents one invocation of method `main(String[])`. For instance, such a CCT may be created with the profiler described in [15, 16]. In this example, we assume that two dynamic metrics are collected for each calling context, the number of method invocations and the number of executed bytecodes (in a Java Virtual Machine). Regarding the latter metric, which is a rather platform-independent alternative to the common CPU time metric, we are also computing the aggregated number of executed bytecodes ag(bytecodes) for subtrees of the CCT.

There are several variations of the CCT. For instance, calls to the same method from different call sites in a calling method may be represented by the same node or by different nodes in the CCT, depending on whether or not the user wants to distinguish between these call sites [3]. Furthermore, in the presence of recursions, the depth of the CCT may be unbounded, representing each recursive call to a method by a separate CCT node. As an alternative, dynamic metrics for recursive calls may be stored in the same node, effectively limiting the theoretical depth of the

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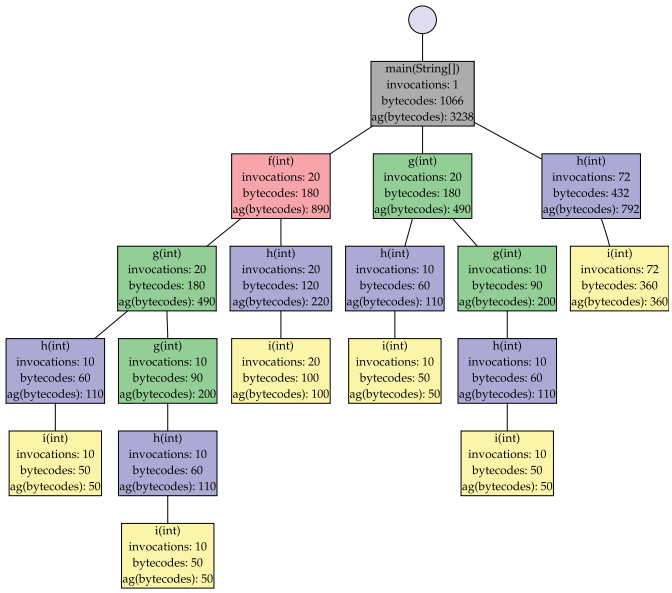
```
void main (String[] args) {
   for (int j=0; j<20; j++) {
      f(j);
      g(j);
      for (int k=1; k<j/2; k++)
         h(k);
   }
}
void f(int n) {
   int k = g(n);
   k=h(k)*k;
}
int g(int n) {
   if (n%2==0)
      return h(n/2);
   else
      return g(n+1);
}
void i(int n) {
   n=n*n;
}
int h(int n) {
   i(n);
   return n-1;
}
```

(a)



(b)

Figure 1. Sample Java code and the CCT generated for one execution of method `main(String[])`. As dynamic metrics, each CCT node stores the number of method invocations and the number of executed bytecodes in the corresponding calling context. For each CCT node n, the aggregated metric ag(bytecodes) sums up the executed bytecodes in the whole subtree rooted at node n: (a) example code and (b) generated CCT (conceptual representation).

CCT (to the number of methods in the profiled program) and introducing back-edges in the CCT [3] (actually, the resulting CCT has not a tree structure).

3. CCT VISUALIZATION AS CALLING CONTEXT RING CHARTS

This section presents three ways of visualizing CCTs as Calling Context Ring Charts. All three visualizations use an *onion-like* structure with circular layers in which each layer corresponds to a layer in the CCT. Beginning with the root node as the central ring, nodes are illustrated as ring segments, and children nodes (callees) are represented on the outer ring of their parent (caller).

3.1. Ring segments of equal length

Figure 2 illustrates a ring segment s and its n children nodes $c_1, \ldots, c_n$. In this first visualization, given α as the angle covered by s, the angle θ_i covered by its ith child c_i is computed as follows:

$$\theta_i = \alpha \frac{1}{n} \tag{1}$$

Figure 3 shows this first visualization for our example code from Figure 1. As a consequence of Equation (1), the children completely surround their parent. For instance, in the second layer the ring segments representing the callees of `main(String[])` (i.e. `f(int)`, `g(int)`, and `h(int)`) have the same length and completely surround the ring segment of `main(String[])`. The root node of the CCT is represented by the central circle.

This visualization gives a condensed view of the overall CCT and eases the analysis of caller/callee relationships. However, the visualization does not convey any dynamic metric stored in the CCT.

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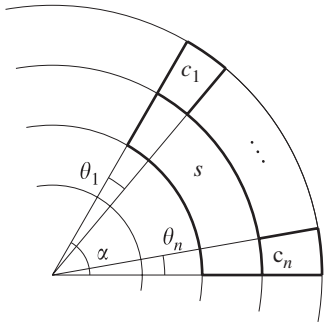

Figure 2. Representation of a CCT node as a ring segment s.

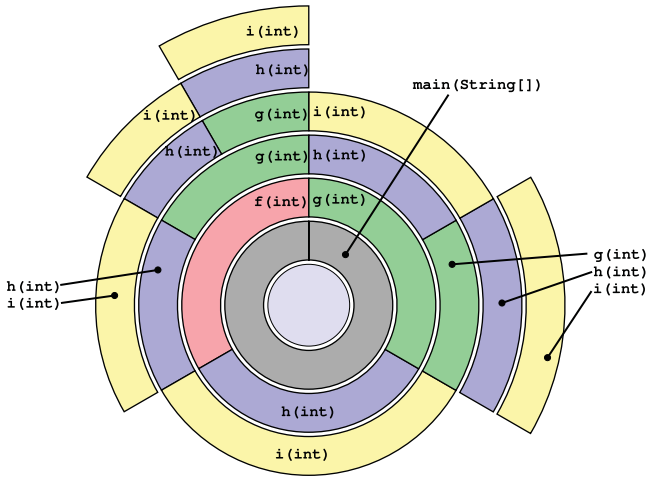

Figure 3. First CCT visualization: Callees are represented by ring segments of equal length.

3.2. *Ring segment length proportional to a selected aggregated metric*

To ease locating performance problems, we support a second visualization in which each ring segment is sized proportionally to an aggregated metric $ag(M)$ chosen by the user. In this visualization, θ_i is computed according to the following equation:

$$\theta_i = \alpha \frac{ag(M_{c_i})}{ag(M_s)} \tag{2}$$

Using Equation (2), the sum of all θ_i can be less than α; that is, the children ring segments do not entirely surround the parent ring segment. The remaining portion of the parent ring segment represents the metrics contribution of the parent excluding its callees.

Figure 4 presents a ring chart where ring segments are sized according to the aggregated metric *ag*(bytecodes). In this example, only about 67% of the ring segment of `main(String[])` is surrounded by the callees' ring segments, and the remaining 33% illustrates the contribution of method `main(String[])` to the overall bytecode execution.

This visualization helps locate hot calling contexts, since the length of ring segments is proportional to an aggregated metric. However, ring segments representing calling contexts with a low metric contribution can be very small such that the user may not be able to see all the callees of a method. Hence, our different visualizations are complementary, and the user can switch between the different views.

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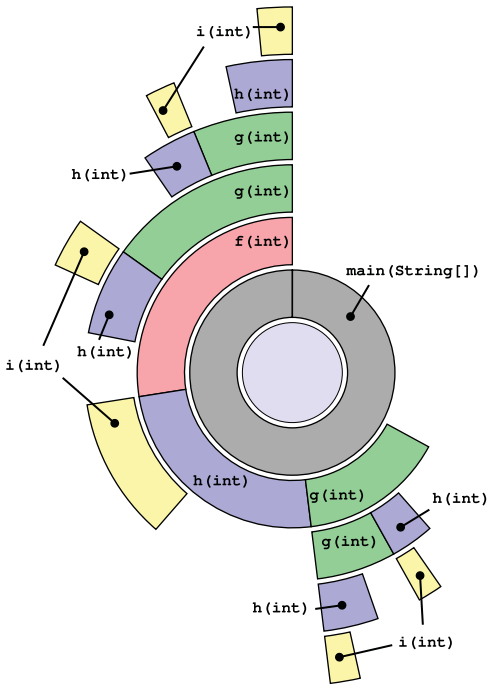

Figure 4. Second CCT visualization: Ring segment *length* is proportional to the aggregated bytecode metric.

3.3. Ring segment area proportional to a selected aggregated metric

In the previous visualization, we considered sizing ring segments with respect to the angle, which can be misleading: A node close to the center (i.e. with a low depth in the CCT) will appear smaller in terms of area than a node with the same aggregated metric contribution but in a deeper CCT layer. The third visualization presented below compensates for this bias by reducing the width of outer layers such that any two nodes with the same aggregated metric contribution will be represented by ring segments of the same area.

We call r_i the radius of the ith concentric circle, r_0 being the radius of the central circle. In the two previous visualizations, we implicitly defined $r_i = r_{i-1} + c$, where c is the constant width of ring segments. Since the area of a circle sector is $\frac{\alpha}{2}r^2$ (where r is the radius and α is measured in radians), the area A_s of the ring segment s in layer i is given by:

$$A_s = \frac{\alpha}{2}(r_i^2 - r_{i-1}^2) \tag{3}$$

For an area-proportional visualization of a calling context according to its aggregated metric contribution, but independently of its depth in the CCT, the term $(r_i^2 - r_{i-1}^2)$ in Equation (3) must be constant. This is achieved by redefining r_i according to (4) in which K is a constant corresponding to the desired overall area of a ring (layer) in the chart:

$$r_i = \sqrt{r_{i-1}^2 + \frac{K}{\pi}} \tag{4}$$

We illustrate this visualization in Figure 5. Whereas this visualization better supports locating hotspots, in a deep tree outer rings may become too thin to be easily visible. Thus, it is important to let the user toggle between the different views.

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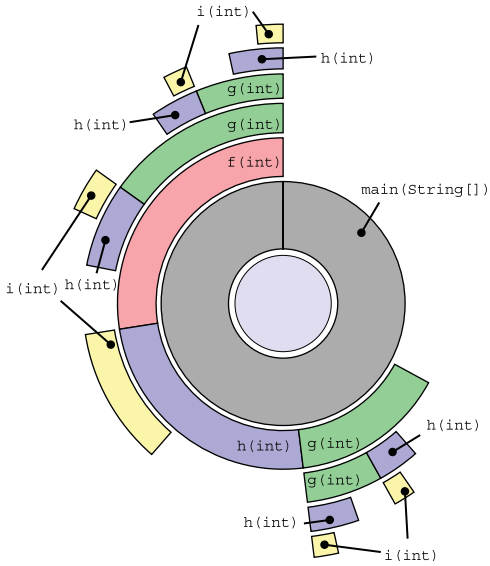

Figure 5. Third CCT visualization: Ring segment *area* is proportional to the aggregated bytecode metric.

4. CCT MANIPULATION OPERATIONS

In this section, we discuss four tree manipulation operations on the CCT which complement our visualizations and help in exploring calling context profiles. The first two CCT manipulations [22], *subtree selection* and *depth limitation*, are essential for handling large CCTs. The third manipulation, *recursion elimination*, removes CCT nodes representing recursive calls. This operation can significantly reduce the CCT size in the presence of recursions. Finally, the fourth operation, *dynamic metric aggregation*, aggregates metrics for each method, completely discarding calling context information.

4.1. Subtree selection

This manipulation allows the selection of any CCT node as the root, hence resulting in the visualization of a subtree as a CCRC. In this way, the user can focus on a particular calling context of interest, together with the direct and indirect callees.

Our implementation supports interactive subtree selection by clicking on the ring segment to become the new root. The history of selected subtrees is preserved, allowing the user to revert to previous views of the CCT. Clicking on the central circle representing the root node of the currently visualized CCT subtree, the previously displayed subtree is restored. Clicking on the root of the overall CCT has no effect.

Figure 6(a) shows an example of the subtree selection operation, where the ring segment corresponding to `f(int)` is selected as the new root (cp. the original CCT in Figure 1). In this example, we use our second visualization where the length of ring segments is proportional to the metric *ag*(bytecodes).

4.2. Depth limitation

The second CCT manipulation, limiting the depth of the visualized CCT, also helps to analyze large CCTs with deep calling contexts. By reducing the CCT depth, the remaining layers in the CCT can be visualized with wider rings.

As in the case of subtree selection, also depth limitation can be applied interactively, either by entering a new maximum depth value or by using the scroll wheel on the mouse. In particular, the latter possibility gives the user an easy way of (un)zooming the center of the displayed CCT. By successively applying subtree selection and adapting the depth limit, the user can navigate faster

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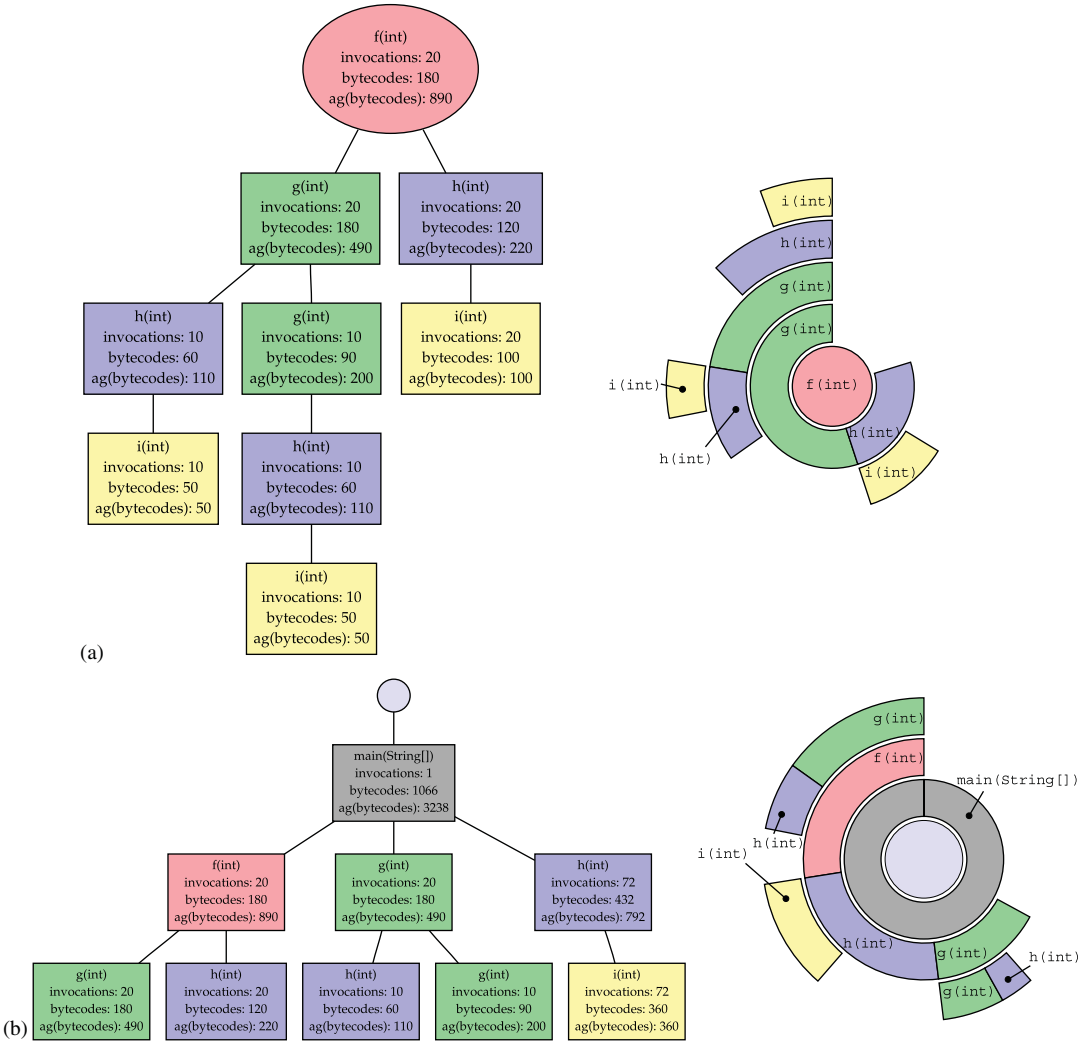

Figure 6. Subtree selection and depth limitation operations (the original CCT is depicted in Figure 1): (a) subtree selection: the ring segment of method `f(int)` has been selected as root and (b) depth limitation: the CCT depth has been limited to 3 layers.

in the CCT. With the aid of subtree selection, the interesting part of program execution can be chosen, and depth limitation allows the user to adjust the details of the CCT to be visualized. Figure 6(b) illustrates the effect of limiting the CCT depth to 3, i.e. displaying only 3 layers of the CCT. Note that the aggregated metrics $ag(M)$ (for any metric M) are not recomputed. Aggregated metrics are initially computed on the complete CCT.

4.3. Recursion elimination

In Section 2 we discussed different variations of the CCT in which recursive calls may be represented either by the same CCT node or by different CCT nodes. In the former case, back-edges are introduced in the CCTs [3]. Nevertheless, the CCTs can become very deep in the latter case when representing executions of recursive programs. To address this issue, this section provides a CCT transformation that takes a (potentially very deep) CCT where recursive calls are represented by separate nodes and produces a corresponding (more compact) CCT where the metrics collected in recursive method executions are stored within the same node. Figure 7(a) illustrates this transformation with an example.

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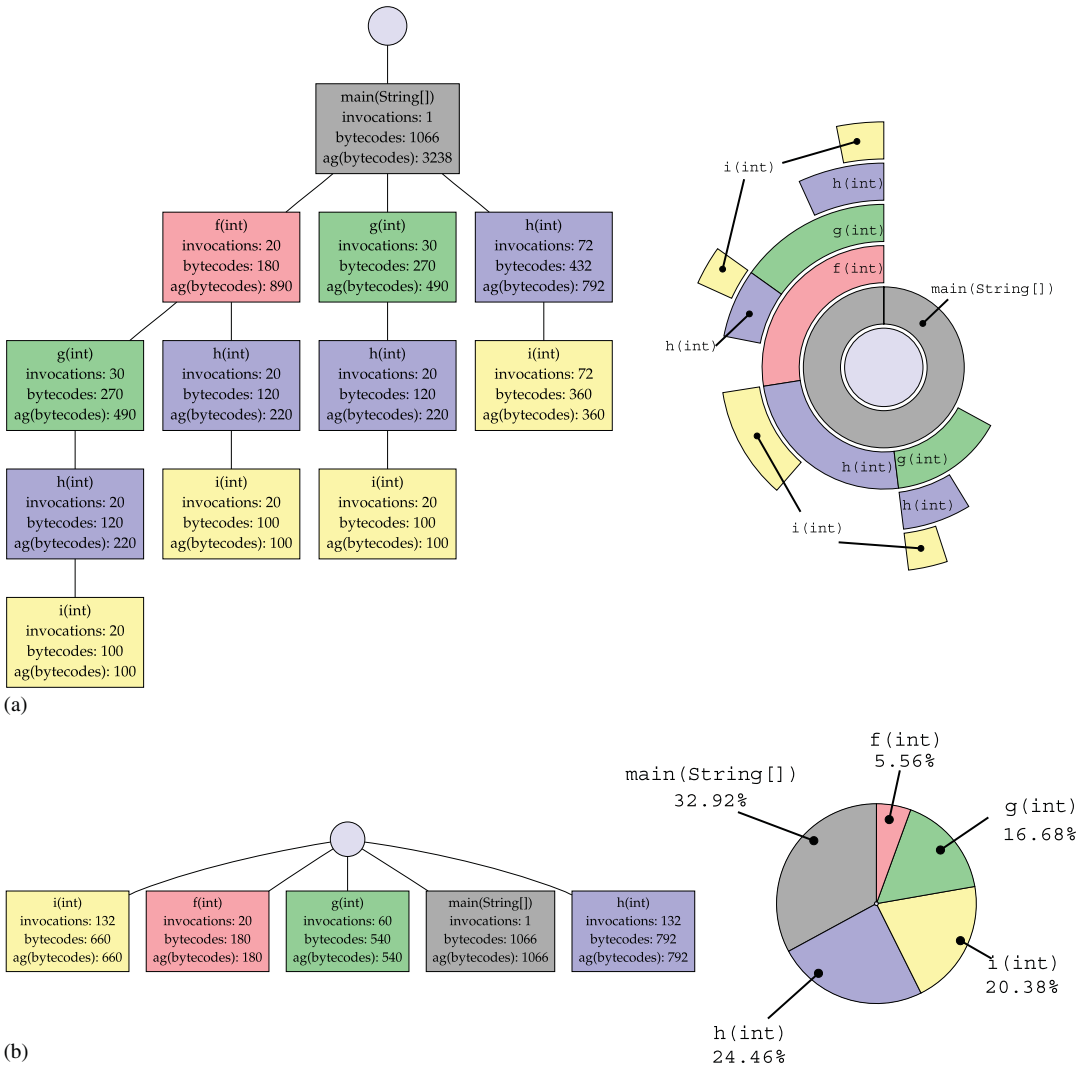

Figure 7. Recursion elimination and metrics aggregation operations (the original CCT is depicted in Figure 1): (a) recursion elimination: CCT nodes representing recursive calls have been removed (back-edges are not shown) and (b) metrics aggregation by method: calling context information has been discarded.

The transformation is specified using Java-style pseudocode in Figure 8. The `eliminateRecursions(...)` method takes the root node of a CCT and returns the root of a new CCT (not sharing any nodes with the input CCT) without any recursive structures. To this end, `eliminateRec(...)` traverses the input CCT in pre-order (depth-first) and builds the corresponding output CCT. Before creating a new node in the output CCT, `eliminateRec(...)` checks whether a matching node is on the current path to the root (`findMatchingAncestor(...)`). In that case, no new node is created in the output CCT. As back-edges cannot be visualized, they are not created in the output CCT.

The pseudocode assumes that CCT nodes are represented by the type `Node`, which supports the operations `methodID()` (returning a string uniquely identifying the method for which the node stores dynamic metrics), `parent()` (returning the parent node in the CCT or `null` for the root node), `children()` (returning the set of children nodes), and `metrics()` (returning the dynamic metrics for the node). The `getOrCreateChild(String calleeName)` method returns the `Node` instance representing the callee with the given method name. If a child node for the given callee name does not yet exist, a new node is created. The dynamic metrics collected

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```
Node eliminateRecursions(Node rootIn) {
  Node rootOut = new Node();
  eliminateRec(rootIn, rootOut);
  computeAggregatedMetrics(rootOut);
  return rootOut;
}

void eliminateRec(Node in, Node out) {
  for (Node nIn: in.children()) {
    Node nOut = findMatchingAncestor(out, nIn.methodID());
    if (nOut == null)
      nOut = out.getOrCreateChild(nIn.methodID());
    nOut.metrics().add(nIn.metrics());
    eliminateRec(nIn, nOut);
  }
}

Node findMatchingAncestor(Node n, String id) {
  if (n == null) return null;
  else if (n.methodID().equals(id)) return n;
  else return findMatchingAncestor(n.parent(), id);
}
```

Figure 8. Pseudocode for eliminating recursive structures in a CCT.

for a node are represented by the type `Metrics`, which supports, among others, the operation `add(Metrics from)`, incrementing the metric values by the values from the argument `Metrics` instance. Finally, `computeAggregatedMetrics(Node root)` computes all desired aggregated metrics in a CCT.

4.4. Dynamic metrics aggregation for each method

While the CCT gives detailed information about each calling context, it is difficult to estimate the overall metric contribution of a method if it is used in many different calling contexts. In our example (see Figure 1), `i(int)` appears in six CCT nodes, which makes it difficult to evaluate the total metric contribution of that method in comparison to other methods. Hence, we provide a transformation that discards all calling context information. Each method occurring in the original CCT is represented by a single node that stores the summed up metrics for that method (disregarding any callees).

Figure 7(b) illustrates an example of this operation. Since all calling context information is discarded, the resulting tree has a depth of one and can be represented as a conventional pie chart. Whereas such pie charts are not unique to our approach (many prevailing profilers provide similar views), they provide a useful, complementary means for the performance analysis. The transformation is also applicable for CCT subtrees (in conjunction with subtree selection).

5. IMPLEMENTATION

We implemented three versions of our CCRC visualization tool. The first version is based on JavaScript and on the standard XML-based Scalable Vector Graphics (SVG[‡]) format, whereas the second version is a Java application using the Swing toolkit. The third version is also implemented in Java by using the Eclipse's Standard Widget Toolkit (SWT)[§].

Our first implementation uses JavaScript to create and dynamically transform the CCT, which is represented as an XML structure. This implementation allows us to visualize CCRCs directly

[‡]`http://www.w3.org/Graphics/SVG/`.
[§]`http://www.eclipse.org/swt/`.

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in standard web browsers. The rendered page consists of two parts, one part is showing the ring chart, whereas the other part presents the detailed calling context information of the currently selected CCT node (a node is automatically selected when it is pointed to by the mouse), such as the complete call stack and collected dynamic metrics. The navigation in the CCT representation is implemented using events which are handled by the browser and trigger calls to JavaScript routines that update the displayed information. On one hand, this implementation is well suited for integration into web-based collaboration tools. On the other hand, JavaScript execution engines embedded in currently available browsers are often unable to handle very large structures as those required for representing CCTs. Moreover, the limited performance of Javascript for complex tree manipulations can result in poor user experience.

In our second Java-based implementation, the GUI has the same structure and similar behavior as in the first implementation. However, in contrast to the first implementation, it has been designed to handle very large CCTs. Additional features were added, such as an advanced search tool to find and highlight CCT nodes with certain properties. For instance, the user can search for calling contexts representing execution in a particular package, class, or method. It is also possible to quickly locate CCT nodes where the collected metrics meet given constraints (e.g. exceeding some thresholds).

Our third implementation, which is based on Eclipse SWT, has the same advanced features as the Swing-based version. In addition, it can be used in the Eclipse IDE. We integrated our CCRC visualization in the Senseo Eclipse plugin [25], which enriches Eclipse's static source view with dynamic metrics from a running application. Senseo provides the developer with various dynamic metrics, such as runtime receiver, argument, and return types of invoked methods, the number of allocated objects, and an estimation of total memory consumption. The integration of CCRC enhances Senseo with complete calling context information. It also supports interactions between the CCRC and the corresponding methods in the source code, such as highlighting the calling contexts in the CCRC corresponding to a chosen method, or showing the method source code of a selected calling context in the CCRC.

6. CASE STUDIES

This section presents two case studies where CCRCs have been successfully applied to locate performance problems in applications, which were optimized afterwards. In both case studies, the calling context profiles are collected with the profiler described in [15, 16], which collects the number of executed bytecodes in each calling context (in addition to other dynamic metrics); this metric is largely platform-independent. This profiler has the advantage of profiling overall application execution, including the execution of methods in the Java class library. Recursions are fully represented in the generated profiles, that is, the CCTs do not have any back-edges.

For CCRC visualization, we use our Java Swing-based implementation. We do not remove any recursions in the presented CCRCs. For the CCRCs in this case study, we use our second kind of visualizations, where the ring segment length is proportional to the aggregated bytecode metric (see Section 3.2). The CCRCs show the `main(String[])` method as root in the center, that is, we use subtree selection in order to concentrate on application execution, disregarding the execution of system threads, which is also conveyed in the profiles generated by our profiler. For all shown CCRCs, we limit the depth to 10 layers.

The primary contribution of these case studies is to show that CCRCs help to quickly locate hotspots in calling context profiles. As secondary contribution, the case studies also demonstrate that profiling using a platform-independent metric (i.e. the number of executed bytecodes)—instead of the common CPU time metric—is a useful technique for detecting hotspots and for optimizing applications. The resulting optimized applications not only execute less bytecodes, but they also perform significantly better in terms of execution time.

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6.1. Case study 1: *JLex*

Our first case study is inspired by a paper describing the profiler generator ProfBuilder [26]. The authors of ProfBuilder analyzed and detected a hotspot in the lexical analyzer generator JLex [27]. In this case study, we show that CCRCs ease locating such a hotspot. We generated the CCT for the execution of a sample grammar included in the JLex distribution.

Figure 9 (top) shows a CCRC representing the execution of the original, unmodified JLex. Looking at the aggregated bytecodes, we were able to locate a hot calling context, an invocation of the `sortStates(...)` method. This method is executed in two different calling contexts; in one of them, it executes a high number of bytecodes, contributing 23.6% of the overall executed bytecodes. The large ring segment corresponding to this calling context is highlighted (both in color and in bold) in Figure 9 (top). The corresponding call stack (together with the aggregated bytecode metric) is also shown in Figure 9. The other calling context, where `sortStates(...)` is executed, is marked in color (but not in bold); its contribution to the overall executed bytecodes is relatively insignificant.

The `sortStates(...)` method uses a primitive selection sort algorithm of complexity $O(n^2)$. In order to optimize the code, we replace it with the merge sort algorithm of complexity $O(n\ log\ n)$. Figure 9 (bottom) shows the resulting CCRC after the optimization. The number of executed bytecodes in the previously hot calling context representing the `sortStates(...)` method is reduced to 10.86% of the overall executed bytecodes.

In order to confirm that our optimization based on the bytecode metric also results in a speedup in the execution time, we run both versions of JLex (original and optimized) on an Intel Core 2 Duo 2.33 GHz computer with 2GB RAM (Linux Fedora 10), using Sun JDK 1.6.0_12. Regarding the execution time, we present the median of 15 runs. The original JLex executes 20 393 685 bytecodes in 37.04 ms (including the profiled bytecodes executed by system threads, which are not shown in Figure 9), whereas the optimized JLex executes 16 955 185 bytecodes in 27.7 ms. In the number of executed bytecodes metric, the optimized version is 20.3% 'faster', whereas in the CPU time metric, the optimized version is 33.7% faster[¶].

6.2. Case study 2: *Shamir's secret sharing* (*SSS*)

Our second case study analyzes an implementation of the Shamir's Secret Sharing (SSS) cryptography algorithm [28] done by Ricardo Padilha at the University of Lugano. We asked the developer to analyze his implementation with CCRCs in order to validate his design choices and to optimize his code.

Figure 10 illustrates a CCRC corresponding to one hundred thousand *put* and *get* operations. It also represents the bytecode distribution of different computations. In this implementation of the SSS algorithm, a secret is divided into parts (by using the *split* operation) and the parts are distributed among the participants (by using the *hash(put)* operation). Then, all the parts or some of them are fetched (by using the *hash(get)* operation) in order to reconstruct the secret (by using the *join(get)* operation). The *join(put)* operation is also needed because of the API which was used in programming the putting of shares. According to this API, when replacing a stored value, the old value must be returned, forcing the join to be calculated also upon putting the shares. In this figure, a symmetry between the calculations of putting the shares and getting them back can be seen as well.

After analyzing the CCRC in Figure 10, the developer first observed that the execution of the split operation was dominated by the use of the `java.security.SecureRandom` class. As an optimization, he decided to use the non-secure class `java.util.Random` instead since the security of his implementation was not dependent on the randomly generated coefficients [29, 30]. Figure 11 represents the CCRCs before and after the change. The highlighted segments in Figure 11 (top and bottom) correspond to the `BigInteger.randomBits()` method, which

[¶]Whereas the number of executed bytecodes is exactly reproducible in each run, the measured execution time varies considerably, but the optimized version is consistently faster.

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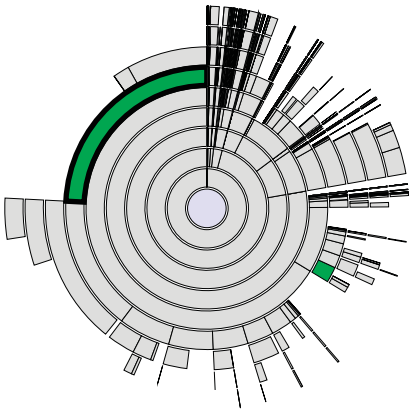
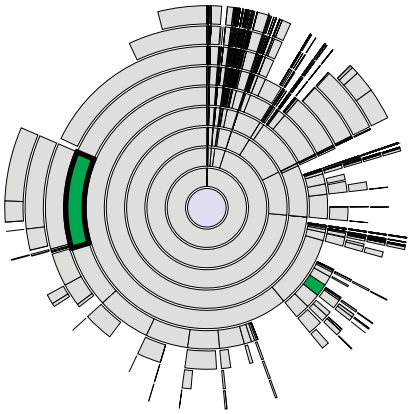


JLex.Main.main	19,898,560	97.57%
JLex.CLexGen.generate	19,898,200	97.53%
JLex.CLexGen.userRules	19,084,734	93.58%
JLex.CNfa2Dfa.make_dfa	15,475,299	75.88%
JLex.CNfa2Dfa.make_dtrans	15,457,240	75.88%
JLex.CNfa2Dfa.e_closure	13,197,769	64.71%
JLex.CNfa2Dfa.sortStates	**4,813,648**	**23.60%**



JLex.Main.main	16,572,245	97.74%
JLex.CLexGen.generate	16,562,941	97.69%
JLex.CLexGen.userRules	15,758,116	92.94%
JLex.CNfa2Dfa.make_dfa	12,188,083	71.88%
JLex.CNfa2Dfa.make_dtrans	12,188,024	71.88%
JLex.CNfa2Dfa.e_closure	10,106,654	59.61%
JLex.CNfa2Dfa.sortStates	**1,841,091**	**10.86 %**

Figure 9. CCRCs for JLex with the original (top) and optimized (bottom) sort algorithms.

is the common code executed when using the `SecureRandom` and `Random` classes. Thanks to this optimization, the calculation of the random coefficients in the SSS formula [28] was reduced from 5.96 to 0.43% of the overall executed bytecodes.

Second, the developer noticed that a high percentage of executed bytecodes was used to calculate the hash function (see Figure 10). He decided to revise his implementation of the SSS algorithm and remove the use of hash function. Figure 12 shows the CCRC for the final SSS implementation. Compared to the original implementation (see Figure 10), the total number of executed bytecodes has been reduced from 29 568 435 996 to 15 129 000 509.

In order to confirm that the optimizations based on profiles with bytecode metrics also result in a speedup, we measured the execution times of the three different versions (initial version, version without secure random, and final version with neither secure random nor hash), using the same settings as in the previous case study. The original implementation took 9150 ms

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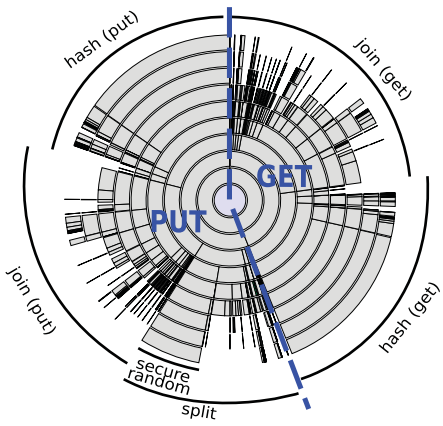
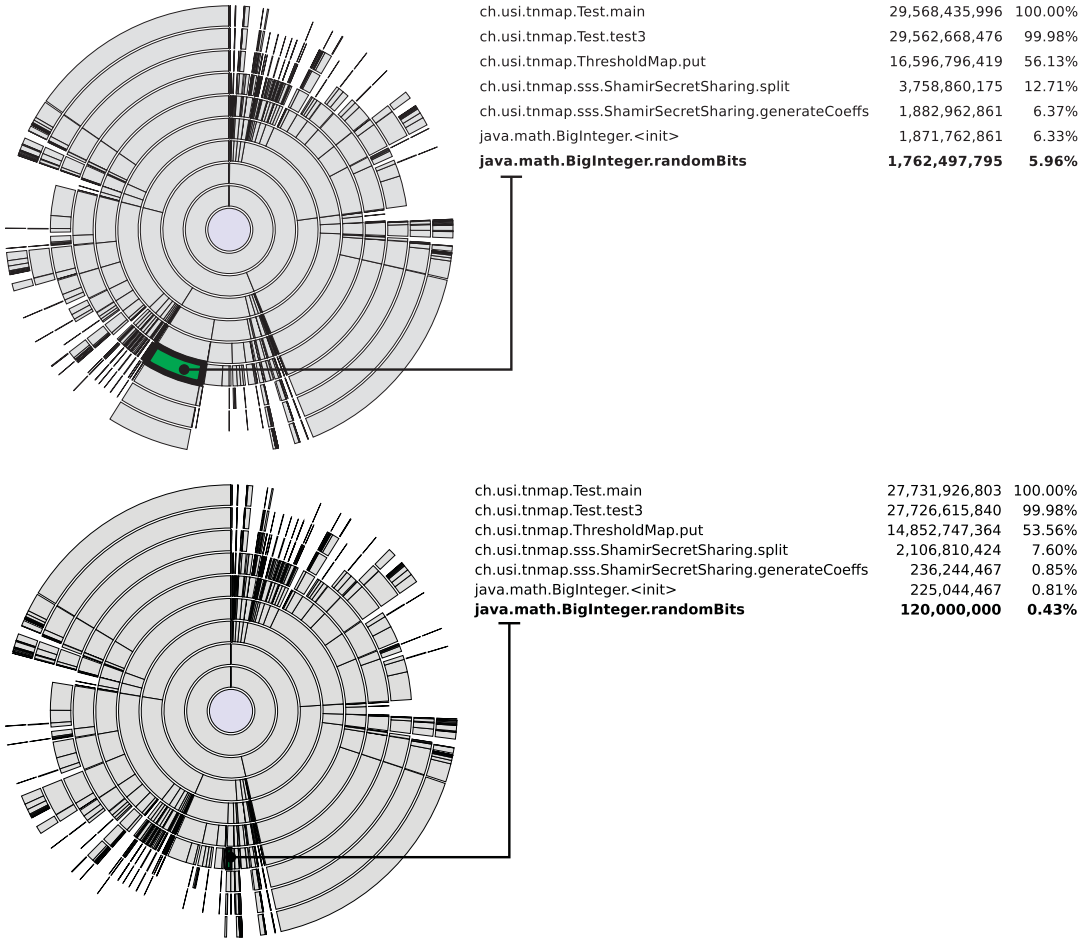


Total number of executed bytecodes: 29,568,435.996

Figure 10. CCRC for the initial implementation of SSS algorithm.



ch.usi.tnmap.Test.main	29,568,435,996	100.00%
ch.usi.tnmap.Test.test3	29,562,668,476	99.98%
ch.usi.tnmap.ThresholdMap.put	16,596,796,419	56.13%
ch.usi.tnmap.sss.ShamirSecretSharing.split	3,758,860,175	12.71%
ch.usi.tnmap.sss.ShamirSecretSharing.generateCoeffs	1,882,962,861	6.37%
java.math.BigInteger.<init>	1,871,762,861	6.33%
java.math.BigInteger.randomBits	**1,762,497,795**	**5.96%**

ch.usi.tnmap.Test.main	27,731,926,803	100.00%
ch.usi.tnmap.Test.test3	27,726,615,840	99.98%
ch.usi.tnmap.ThresholdMap.put	14,852,747,364	53.56%
ch.usi.tnmap.sss.ShamirSecretSharing.split	2,106,810,424	7.60%
ch.usi.tnmap.sss.ShamirSecretSharing.generateCoeffs	236,244,467	0.85%
java.math.BigInteger.<init>	225,044,467	0.81%
java.math.BigInteger.randomBits	**120,000,000**	**0.43%**

Figure 11. SSS implementation using `java.security.SecureRandom` (top) versus SSS implementation using `java.util.Random` (bottom).

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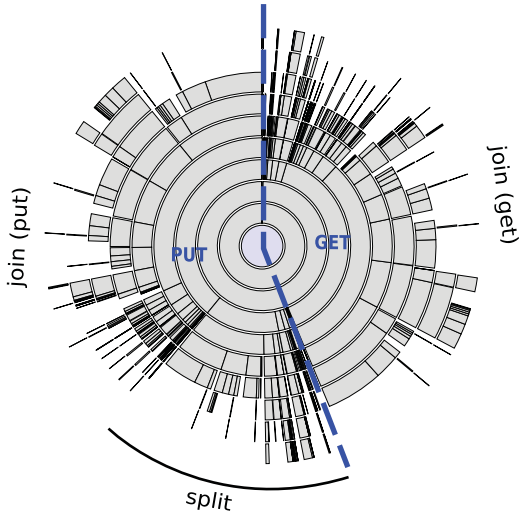

Figure 12. CCRC of the final implementation of SSS (without hashing and without secure random).

The implementation without secure random took 7579 ms (speedup of 20.7%). Finally, the implementation with neither secure random nor hash took 5557 ms (speedup of 64.7%).

In summary, our case studies demonstrate that CCRCs are useful in optimizing real-world applications.

7. EVALUATION

To validate our implementation of CCRC visualizations with very large profiles, we generated and visualized the CCTs for the standard DaCapo benchmark suite [23]. In the following, Section 7.1 presents some statistics on the generated CCTs that correspond to the execution of one run of each benchmark with its default settings. Then, these CCTs were rendered and visualized using our Java Swing-based implementation, with different tree depth settings. Section 7.2 discusses the results of measuring these renderings and shows the relationship between the number of visualized tree layers with the rendering time and the number of rendered segments. All measurements were collected with Sun JDK 1.6_18 running on a laptop with an Intel Core 2 Duo 2.33 GHz processor, 3 GB of memory, and the Linux Fedora 12 operating system.

7.1. Statistics of generated CCTs

This section presents some statistics of the CCTs generated for the standard DaCapo benchmark suite. To generate these CCTs, we benefitted from the same calling context profiler [15, 16] as was used in our two case studies in Section 6. We also transformed the CCTs by removing recursive structures to explore how much recursion is used in the benchmarks and to see to which extent the algorithm presented in Figure 8 is able to reduce the size of the CCTs.

Table I indicates the statistics computed for the original CCTs and the transformed CCTs. In this table, column '#Method Calls' indicates the total number of method invocations (in all CCT nodes), which can be very high (e.g. over 1 billion for the 'bloat' benchmark). Column '#Unique Methods' illustrates the number of unique methods that were invoked at least once. These two statistics are not affected by the transformation that removes recursions.

The columns 'Original CCTs' and 'Transformed CCTs' respectively illustrate the number of nodes (column '#Nodes') and the maximum depth of trees (column 'Max Depth') for the originally generated CCTs and for the transformed ones after removing all recursions. The two statistics in the column 'Original CCTs', i.e. '#Nodes" and 'Max Depth', give an idea of the sizes of the CCTs

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Table I. Statistics of original CCTs and the transformed ones after removing all recursions.

			Original CCTs		Transformed CCTs	
DaCapo Benchmark	#Method Calls	#Unique Methods	#Nodes	Max Depth	#Nodes	Max Depth
Antlr	165 465 913	2498	627 577	164	254 289	39
Bloat	1 055 927 864	3033	645 316	128	212 927	48
Chart	404 140 995	4554	92 272	65	75 266	55
Eclipse	941 528 217	11 555	2 166 169	131	977 531	56
Fop	43 143 714	4013	149 492	76	100 590	55
Hsqldb	214 764 027	2507	66 391	62	60 533	60
Jython	945 580 102	4574	1 941 246	223	553 124	76
Luindex	443 252 127	1969	58 834	52	46 155	38
Lusearch	502 521 414	1768	33 189	63	28 414	35
Pmd	462 558 862	3663	800 071	416	106 841	79
Xalan	636 834 930	3679	211 213	79	97 547	56

to be visualized. For instance, for the 'eclipse' benchmark, the original CCT consists of more than 2 million nodes, and for the 'pmd' benchmark, the CCT depth exceeds 400 layers.

Considering the statistics for the transformed CCTs indicates a significant reduction in the sizes of the CCTs compared to the original ones. In particular, the transformed CCTs have less than 1 million nodes and the maximum depth of the trees do not exceed 80 layers. These data show that recursive algorithms play an important role in typical Java workloads. It is worth mentioning that recursive algorithms are not only found in the DaCapo benchmark suite, but also in the standard Java class library. Prominent examples include classloading (classloaders use a delegation model by default) and balanced tree algorithms in the `java.util` package.

7.2. CCT visualization performance

We visualized the original CCTs generated in the previous subsection using our Java Swing-based implementation and our second type of visualization (see Section 3.2) on a screen resolution of 1440×900 pixels. Then, we varied the number of displayed tree layers from 2 to 150 using the tree depth limitation operation, and measured the relationship between the number of visualized tree layers in the CCRC with rendering time and the number of visualized ring segments. For each setting, we took the median of 15 runs, so as to avoid perturbations such as garbage collection that may be triggered during the renderings.

Figures 13–16 illustrate the results of our measurements. In these diagrams, the number of displayed segments in the CCRCs ranges from 2 to 4206, and the rendering time is between 14 and 204 ms for varying number of displayed tree layers. As experimented in [31], users will not notice delays in their mouse interactions when the response time is up to 195 ms. So, these diagrams support our claim that rapid navigation of CCRCs is easily possible, allowing us to explore large calling context profiles smoothly.

The above interesting results are achieved by some optimizations in the rendering engine in which the segments that get too small to be visualized (e.g. their sizes would be less than a pixel) are replaced by a line. If the user is interested in this subtree, he can select a parent node as the new root and specify a desired tree depth accordingly for further visualization. These optimizations are also the reason for the diagrams are not continuous lines, and the number of displayed segments decrease after a while as the number of layers increase (i.e. the subtrees that would not be visible anyway are not rendered). In the case of 'jython' and 'pmd', a different pattern is seen in their corresponding diagrams: the number of rendered segments increases as the number of displayed tree layers increases (we go deeper into their CCTs). The reason for this situation in these two particular diagrams is that some branches appear only when more tree layers are visualized.

In summary, our performance evaluation confirms that CCRC rendering is perceived almost instantaneously by the users, even for very large CCTs.

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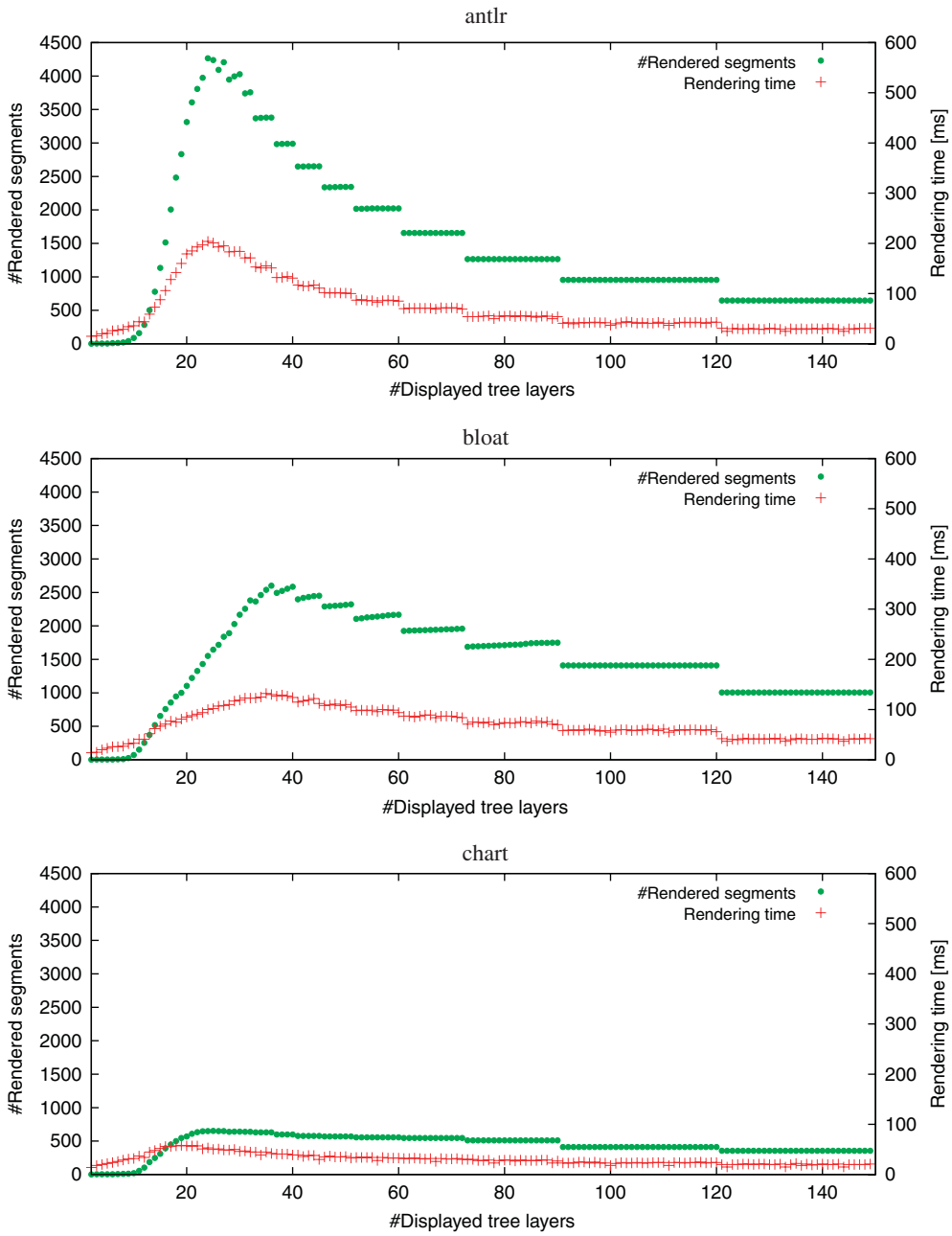

Figure 13. Relationship between the number of visualized tree layers in the CCRC and the rendering time and the number of visualized ring segments for the benchmarks 'antlr', 'bloat', and 'chart'.

8. RELATED WORK

This section considers the related work in the areas of visualizing hierarchical structures and visualizing profiling data as follows.

8.1. Visualizing hierarchical structures

As CCTs have hierarchical structures, different techniques for visualizing hierarchical structures are of interest in this article. A large body of work exists for visualizing hierarchical structures, most

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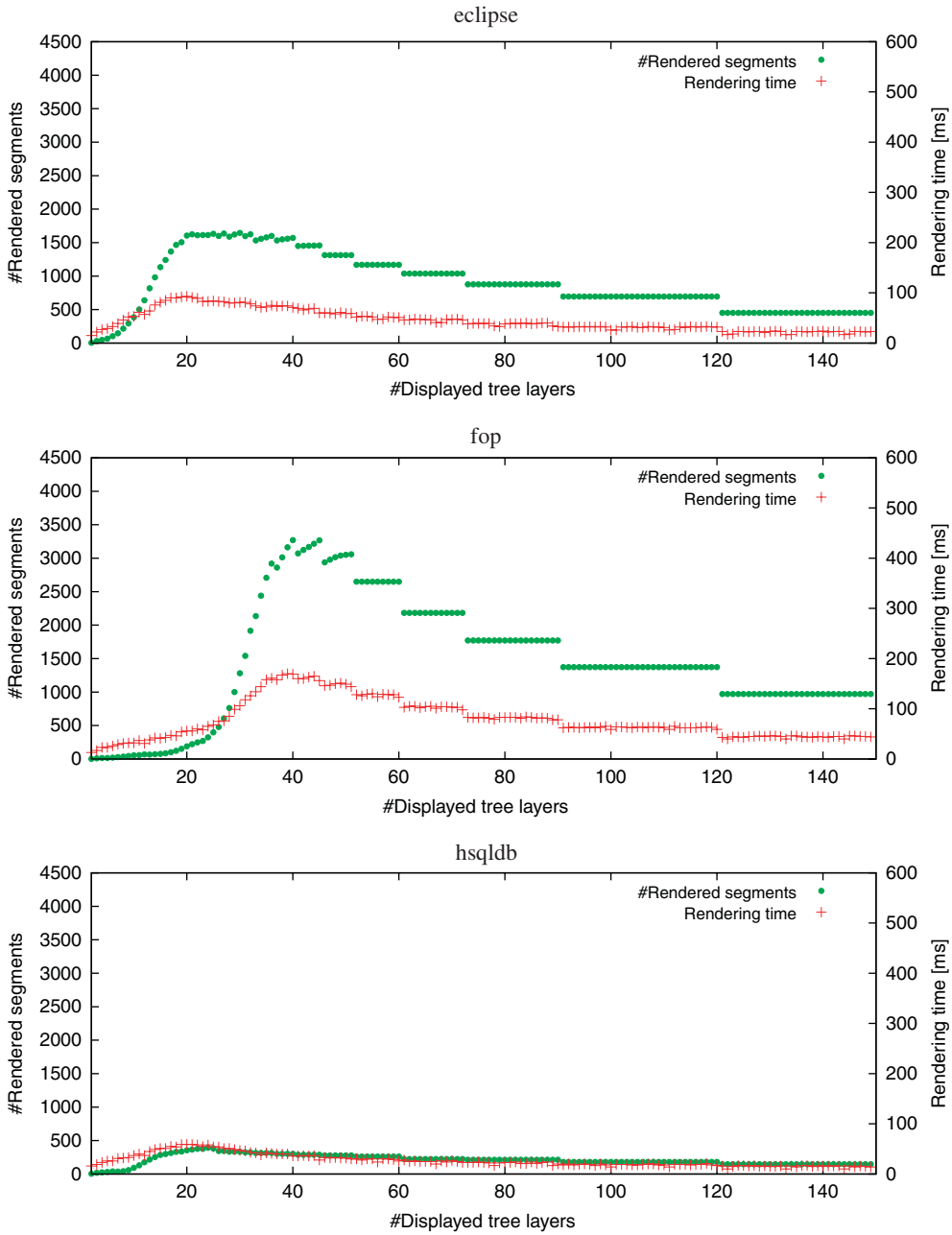

Figure 14. Relationship between the number of visualized tree layers in the CCRC and the rendering time and the number of visualized ring segments for the benchmarks 'eclipse', 'fop', and 'hsqldb'.

of which focus on the challenge to display large hierarchies in a comprehensible form [32]. One can refer to [19] for a detailed survey of the different techniques. Examples include *SunBurst views* [21, 33], *tree-maps* [34], *rooted trees* [17], *cone trees* [35], *radial trees* [19, 17], *reconfigurable disk trees* [36], *botanical trees* [37], *collapsible cylindrical trees* [32], *hyperbolic layouts* [38, 39], and *SHriMP views* [40]. One main category of these approaches is space-filling techniques that aim to utilize the display space very efficiently.

One of the most well-known space-filling techniques is the tree-map approach [34] and its variations [41–43]. In tree-maps, nodes are represented as rectangular areas sized proportionally to a metric. Although tree-maps cover 100% of the display space, only leaf nodes are clearly

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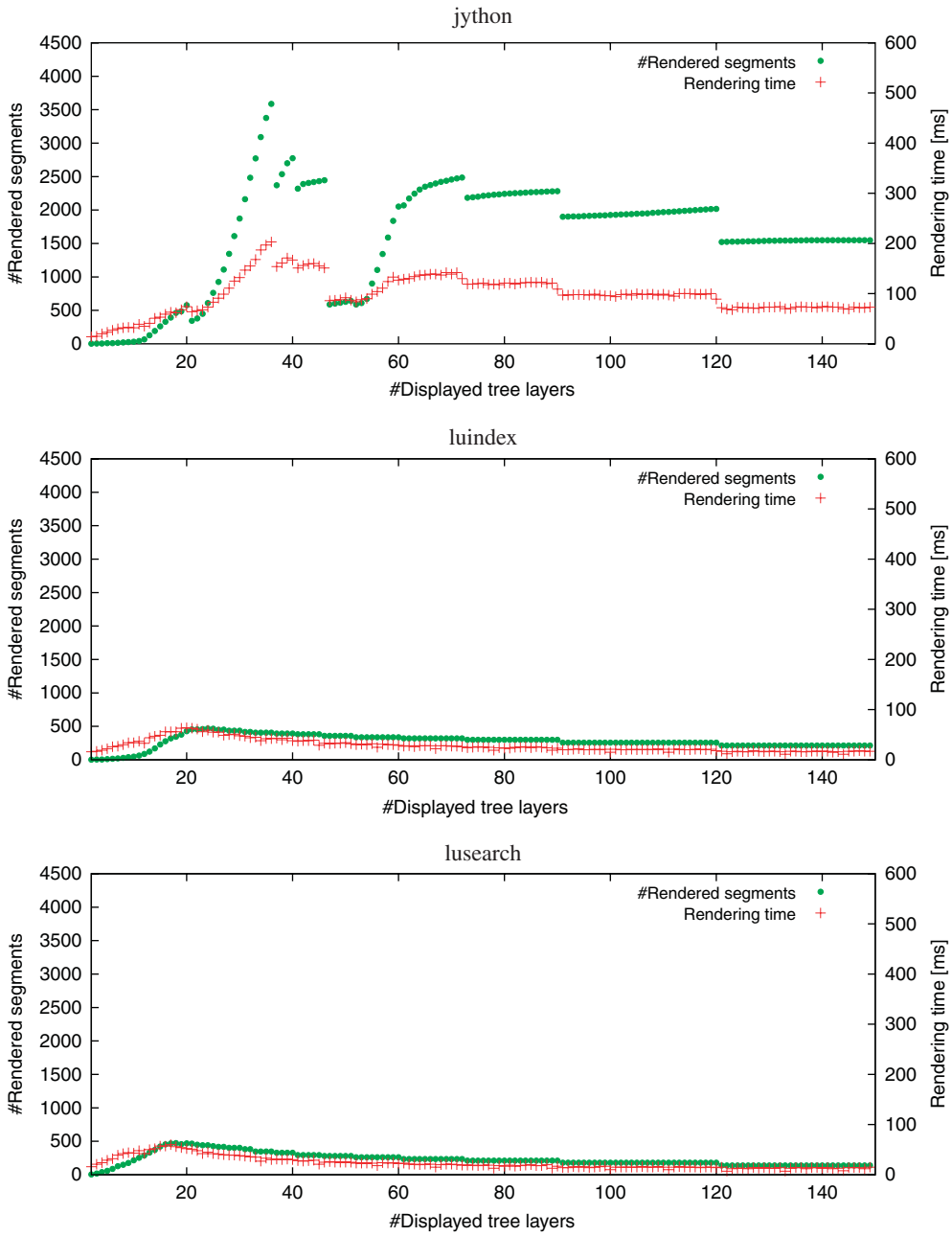

Figure 15. Relationship between the number of visualized tree layers in the CCRC and the rendering time and the number of visualized ring segments for the benchmarks 'jython', 'luindex', and 'lusearch'.

identifiable, which complicates understanding of the hierarchical structure. Moreover, the original layout, called the slice and dice, tends to create outstretched rectangles which are difficult to see, as pointed out in [41, 42]. Several improvements to the original tree-maps have been proposed, such as changing the layout policy [42] to obtain better proportioned rectangle nodes while keeping ordering information, such that a slight change in the tree does not cause a major change in the tree-map. In [41] polygons are used instead of rectangles so as to provide a way to distinguish different branches. Whereas CCRCs do not cover the entire display space due to their circular shape, they offer a convenient way to view the hierarchical structure of a CCT, to navigate in the tree, and to identify calling contexts with a significant contribution to a selected dynamic metric.

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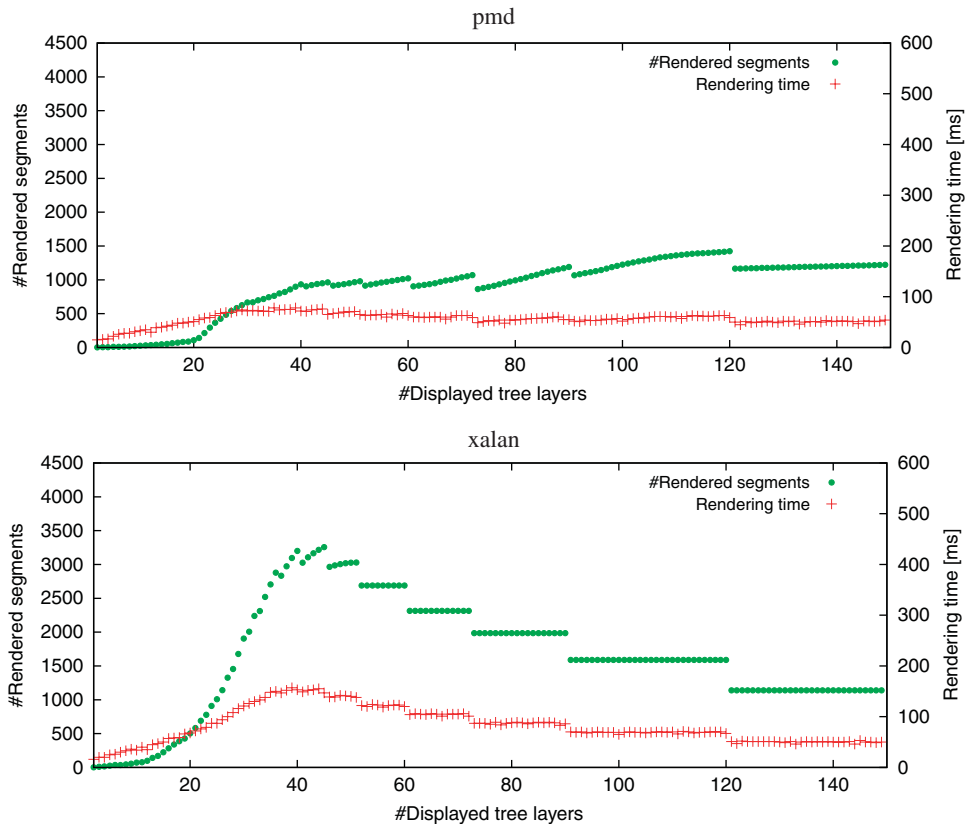

Figure 16. Relationship between the number of visualized tree layers in the CCRC and the rendering time and the number of visualized ring segments for the benchmarks 'pmd' and 'xalan'.

Another category of space-filling techniques are radial methods [18]. An example of radial methods are SunBurst views [21, 33] which highly resemble CCRCs. In SunBurst views, the items in a hierarchy are laid out radially, with the top of the hierarchy at the center and the deeper layers further away from the center. The sweep angle of an item is proportional to a desired metric and its color may correspond to some desired attributes. Previous empirical studies, such as [20, 21], have illustrated that radial visualization techniques work better for navigating and exploring hierarchical structures compared to rectangular space filling techniques such as tree-maps. However, they suffer from the inherent difficulty that slices may become too small to distinguish. This issue is addressed by context+focus techniques, such as the ones in [33] or *information slices* [44] in which two semi-circular areas are used as a form of two-level overview and detail. While CCRCs deal with hierarchies that may include millions of elements, the paper on SunBurst views [33] considers a hierarchy that comprises only 500 elements. The large size of CCTs requires specific navigation techniques. To address this requirement, CCRCs support zooming by depth limitation as well as subtree selection for exploring different parts of a CCT, whereas SunBurst navigation offers different zooming features that show the whole hierarchy and a zoomed part within the same view.

8.2. Visualizing profiling data

Tree-maps have been used to visualize profiling data. For instance, in [45] the authors present KCacheGrind, a front end to a simulator-based cache profiling tool, using a combination of tree-maps and call graphs to visualize the data. In contrast, CCRCs use a specialized representation that is suited both for understanding caller/callee relationships and for locating hotspots by sizing ring segments proportionally to a chosen metric.

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Execution traces may be used for analyzing the dynamic program behavior. Execution traces are logged events, such as method entry and exit, or object allocation. However, the resulting amount of data can be excessive. In [46] execution traces are visualized with nodes representing classes and edges representing method calls. Node size and edge thickness are mapped to properties (e.g. number of method invocations). A time range can be selected to limit the data to be visualized. Another approach to visualizing execution traces has been introduced in [47]. It uses the concept of hierarchical edge bundles [48], where similar edges are put together to improve the visualization of larger traces. Execution traces allow us to keep calls in sequences and to select a precise time interval to be visualized, which helps us to understand a particular phase in the execution of a program. In our approach, the profiling data is stored in a CCT, a more compact structure that does not keep calls in sequences, but gives a view of the overall program execution, which is more suitable for locating hotspots.

Several profilers, such as JProfiler [49] or NetBeans Profiler [50], generate calling context profiles, but are usually visualized as expandable trees. In such a representation, calling contexts are sorted by their contribution to an aggregated metric (usually execution time) and can be expanded or collapsed to show or hide callees. Although such a view is simple and straightforward to use, CCRCs convey more profiling information in a single view and give a better understanding of caller/callee relationships. Thanks to subtree selection and depth limitation, CCRCs efficiently support navigation in any interesting part of the CCT.

9. CONCLUSION

Calling context profiling is an important technique for exploring the dynamic behavior of programs. However, the resulting profiles, usually represented as CCTs, can be huge, comprising up to millions of calling contexts and typically reaching tree depths of 50–400 layers. Such large profiles can hardly be analyzed in a textual representation, and prevailing visualizations, such as expandable trees used in several profiling tools, are too verbose and do not make good use of space.

To ease handling large calling context profiles, this article presented Calling Context Ring Charts (CCRCs). A CCRC visualizes a CCT in a compact way while representing all caller/callee relationships. Each calling context is displayed as a ring segment, surrounded by the ring segments representing the callees. Ring segments can be sized according to a chosen dynamic metric to ease the localization of hotspots. Several CCT tree manipulation operations, such as selecting subtrees or limiting the tree depth, complement CCRC visualizations. We presented two case studies where CCRCs were successfully applied to locate and fix performance problems in applications. A performance evaluation confirms that our CCRC implementation easily handles very large calling context profiles, and that the rendering time is quite fast.

Regarding ongoing research, we are working on representing two different metrics within the same CCRC using a coloring scheme. We are also conducting a study on the productivity increase thanks to CCRC visualizations when profiling complex applications. To this end, collaboration partners have started using our tools. Furthermore, we are working on an advanced set of tree manipulation and metrics aggregation operations that are exposed to the user through a domain-specific, declarative language.

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