The Cilk++ Concurrency Platform

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<td>As Published</td>
<td><a href="http://dx.doi.org/10.1145/1629911.1630048">http://dx.doi.org/10.1145/1629911.1630048</a></td>
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<tr>
<td>Publisher</td>
<td>Association for Computing Machinery</td>
</tr>
<tr>
<td>Version</td>
<td>Final published version</td>
</tr>
<tr>
<td>Accessed</td>
<td>Fri Nov 17 08:12:08 EST 2017</td>
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<tr>
<td>Citable Link</td>
<td><a href="http://hdl.handle.net/1721.1/59828">http://hdl.handle.net/1721.1/59828</a></td>
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The Cilk++ Concurrency Platform

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Abstract

The availability of multicore processors across a wide range of computing platforms has created a strong demand for software frameworks that can harness these resources. This paper overviews the Cilk++ programming environment, which incorporates a compiler, a runtime system, and a race-detection tool. The Cilk++ runtime system guarantees to load-balance computations effectively. To cope with legacy codes containing global variables, Cilk++ provides a “hyperobject” library which allows races on nonlocal variables to be mitigated without lock contention or substantial code restructuring.

Categories and Subject Descriptors

D.1.3 [Software]: Programming Techniques—Concurrent Programming

General Terms

Algorithms, Performance, Design, Reliability, Languages.

Keywords

Amdahl’s Law, dag model, hyperobject, multicore programming, multithreading, parallelism, parallel programming, race detection, reducer, span, speedup, work.

1 Introduction

Although the software community has extensive experience in serial programming using the C [18] and C++ [30] programming languages, they have found it hard to adapt C/C++ applications to run in parallel on multicore systems. In earlier work, the MIT Cilk system [14, 32] extended the C programming language with parallel computing constructs. The Cilk++ solution similarly extends C++, offering a gentle and reliable path to enable the estimated three million C++ programmers [31] to write parallel programs for multicore systems. Cilk++ is available for the Windows Visual Studio and the Linux/gcc compilers.

This work was supported in part by the National Science Foundation under Grants 0615215, 0712243, and 0822896 and in part by the Defense Advanced Research Projects Agency under Contract W31P4Q-08-C-0156. Cilk, Cilk++, and Cilkscreen are registered trademarks of Cilk Arts, Inc.

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DAC’09, July 26-31, 2009, San Francisco, California, USA
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1 // Parallel quicksort
2 using namespace std;
3
4 #include <algorithm>
5 #include <iterator>
6 #include <functional>
7
8 template <typename T>
9 void qsort(T begin, T end) {
10   if (begin != end) {
11     T middle = partition(begin, end, bind2nd
12       less<typename iterator_traits<T>::
13       value_type>(), begin);
14     cilk_spawn qsort(begin, middle);
15     qsort(max(begin + 1, middle), end);
16     cilk_sync;
17   }
18 }
19
20 int main() {
21   int n = 100;
22   double a[n];
23   
24   cilk_for (int i=0; i<n; ++i) {
25      a[i] = sin((double) i);
26   }
27   
28   cilk_spawn qsort(a, a + n);
29   copy(a, a + n, ostream_iterator<double>(cout , "\n");
30 
31   return 0;
32 }
33
34

Figure 1: Parallel quicksort implemented in Cilk++.

Like the MIT Cilk system [14, 32], Cilk++ is a faithful linguistic extension of C++, which means that parallel code retains its serial semantics when run on one processor. The Cilk++ extensions to C++ consist of just three keywords, which can be understood from an example. Figure 1 shows a Cilk++ program adapted from http://www.cvgpr.uni-mannheim.de/heiler/qsorot.html, which implements the quicksort algorithm [7, Chapter 7]. Observe that the program would be an ordinary C++ program if the three keywords cilk_spawn, cilk_sync, and cilk_for were elided.

Parallel work is created when the keyword cilk_spawn precedes the invocation of a function. The semantics of spawning differ from a C++ function (or method) call only in that the parent can continue to execute in parallel with the child, instead of waiting for the child to complete as is done in C++. The scheduler in the Cilk++ runtime system takes the responsibility of scheduling the spawned functions on the individual processor cores of the multicore computer.

A function cannot safely use the values returned by its children until it executes a cilk_sync statement. The cilk_sync statement is a local “barrier,” not a global one as, for example, is used in...
message-passing programming [23, 24]. In the quicksort example, a cilk_sync statement occurs on line 14 before the function returns to avoid the anomaly that would occur if the preceding calls to qsort were scheduled to run in parallel and did not complete before the return, thus leaving the vector to be sorted in an intermediate and inconsistent state.

In addition to explicit synchronization provided by the cilk_sync statement, every Cilk function syncs implicitly before it returns, thus ensuring that all of its children terminate before it does. Thus, for this example, the cilk_sync before the return is technically unnecessary.

Cilk++ improves upon the original MIT Cilk in several ways. It provides full support for C++ exceptions. Loops can be parallelized by simply replacing the keyword for with the keyword cilk_for keyword, which allows all iterations of the loop to operate in parallel. Within the main routine, for example, the loop starting on line 26 fills the array in parallel with random numbers. In the MIT Cilk system, such loops had to be rewritten by the programmer as divide-and-conquer recursion, but Cilk++ provides the cilk_for syntax for automatically parallelizing such loops. In addition, Cilk++ includes a library for mutual-exclusion (mutex) locks. Locking tends to be used much less frequently than in other parallel environments, such as Pthreads [17], because all protocols for control synchronization are handled by the Cilk++ runtime system.

The remainder of this paper is organized as follows. Section 2 provides a brief tutorial on the theory of parallelism. Section 3 describes the performance guarantees of Cilk++’s “work-stealing” scheduler and overviews how it operates. Section 4 briefly describes the Cilkscreen race-detection tool which guarantees to find race bugs in ostensibly deterministic code. Section 5 explains Cilk++’s “hyperobject” technology, which allows races on nonlocal variables to be mitigated without lock contention or restructuring of code. Finally, Section 6 provides some concluding remarks.

2 An overview of parallelism

The Cilk++ runtime system contains a provably efficient workstealing scheduler [4, 14], which scales application performance linearly with processor cores, as long as the application exhibits sufficient parallelism (and the processor architecture provides sufficient memory bandwidth). Thus, to obtain good performance, the programmer needs to know what it means for his or her application to exhibit sufficient parallelism. Before describing the Cilk++ runtime system, it is helpful to understand something about the theory of parallelism.

Many discussions of parallelism begin with Amdahl’s Law [1], originally proffered by Gene Amdahl in 1967. Amdahl made what amounts to the following observation. Suppose that 50% of a computation can be parallelized and 50% cannot. Then, even if the 50% that is parallel can be run on an infinite number of processors, the total time is cut at most in half, leaving a speedup of at most 2. In general, if a fraction p of a computation can be run in parallel and the rest must run serially, Amdahl’s Law upper-bounds the speedup by 1/(1−p).

Although Amdahl’s Law provides some insight into parallelism, it does not quantify parallelism, and thus it does not provide a good understanding of what a concurrency platform such as Cilk++ should offer for multicore application performance. Fortunately, there is a simple theoretical model for parallel computing which provides a more general and precise quantification of parallelism that subsumes Amdahl’s Law. The dag (directed acyclic graph) model of multithreading [3] views the execution of a multithreaded program as a set of instructions (the vertices of the dag) with graph edges indicating dependencies between instructions. (See Figure 2.) We say that an instruction x precedes an instruction y, sometimes denoted x < y, if x must complete before y can begin. If neither x < y nor y < x, we say that the instructions are in parallel, denoted x || y. In Figure 2, for example, we have 1 < 2, 6 < 12, and 4 || 9.

The dag model of multithreading can be interpreted in the context of the Cilk++ programming model. A cilk_spawn of a function creates two dependency edges emanating from the instruction immediately before the cilk_spawn: one edge goes to the first instruction of the spawned function, and the other goes to the first instruction after the spawned function. A cilk_sync creates dependency edges from the final instruction of each spawned function to the instruction immediately after the cilk_sync. A cilk_for can be viewed as divide-and-conquer parallel recursion using cilk_spawn and cilk_sync over the iteration space.

The dag model admits two natural measures that allow us to define parallelism precisely, as well as to provide important bounds on performance and speedup.

The Work Law

The first important measure is work, which is the total amount of time spent in all the instructions. Assuming for simplicity that it takes unit time to execute an instruction, the work for the example dag in Figure 2 is 18.

We can adopt a simple notation to be more precise. Let Tp be the fastest possible execution time of the application on P processors. Since the work corresponds to the execution time on 1 processor, we denote it by T1. Among the reasons that work is an important measure is because it provides a lower bound on P-processor execution time:

\[ T_p \geq T_1 / P. \] (1)

This Work Law holds, because in our simple theoretical model, each processor executes at most 1 instruction per unit time, and hence P processors can execute at most P instructions per unit time. Thus, with P processors, to do all the work, it must take at least T1/P time.

We can interpret the Work Law (1) in terms of the speedup on P processors, which using our notation, is just T1/Tp. The speedup tells us how much faster the application runs on P processors than on 1 processor. Rewriting the Work Law, we obtain T1/Tp ≤ P, which is to say that the speedup on P processors can be at most P. If the application obtains speedup proportional to P, we say that the application exhibits linear speedup. If it obtains speedup exactly
$P$ (which is the best we can do in our model), we say that the application exhibits \textit{perfect linear speedup}. If the application obtains speedup greater than $P$ (which cannot happen in our model due to the Work Law, but can happen in models that incorporate caching and other processor effects), we say that the application exhibits \textit{superlinear speedup}.

\textbf{The Span Law}

The second important measure is \textit{span}, which is the longest path of dependencies in the dag. The span of the dag in our example is 9, which corresponds to the path $1 \times 2 < 3 \times 6 < 7 \times 8 < 11 < 12 < 18$. This path is sometimes called the \textit{critical path} of the dag, and span is sometimes referred to in the literature as critical-path length. Since the span is the theoretically fastest time the dag could be executed on a computer with an infinite number of processors (assuming no overheads for communication, scheduling, etc.), we denote it by $T_\infty$. Like work, span also provides a bound on $P$-processor execution time:

$$ T_P \leq T_\infty . $$

This \textit{Span Law} arises for the simple reason that a finite number of processors cannot outperform an infinite number of processors, because the infinite-processor machine could just ignore all but $P$ of its processors and mimic a $P$-processor machine exactly.

\textbf{Parallelism}

We define \textit{parallelism} as the ratio of work to span, or $T_1 / T_\infty$. Parallelism can be viewed as the average amount of work along each step of the critical path. Moreover, perfect linear speedup cannot be obtained for any number of processors greater than the parallelism $T_1 / T_\infty$. To see why, suppose that $P > T_1 / T_\infty$, in which case the Span Law (2) implies that the speedup satisfies $T_1 / T_P \leq T_1 / T_\infty < P$. Since the speedup is strictly less than $P$, it cannot be perfect linear speedup. Another way to see that the parallelism bounds the speedup is to observe that, in the best case, the work is distributed evenly along the critical path, in which case the amount of work at each step is the parallelism. But, if the parallelism is less than $P$, there isn’t enough work to keep $P$ processors busy at every step.

As an example, the parallelism of the dag in Figure 2 is $18/9 = 2$. That means that there’s little point in executing it with more than 2 processors, since additional processors will be surely starved for work.

As a practical matter, many problems admit considerable parallelism. For example, matrix multiplication of $1000 \times 1000$ matrices is highly parallel, with a parallelism in the millions. Many problems on large irregular graphs, such as breadth-first search, generally exhibit parallelism on the order of thousands. Sparse matrix algorithms can often exhibit parallelism in the hundreds.

\section{Runtime system}

Although optimal multiprocessor scheduling is known to be NP-complete [15], Cilk++’s runtime system employs a “work-stealing” scheduler [4, 14] that achieves provably tight bounds. An application with sufficient parallelism can rely on the Cilk++ runtime system to dynamically and automatically exploit an arbitrary number of available processor cores near optimally. Moreover, on a single core, typical programs run with negligible overhead (less than 2%).

\textbf{Performance bounds}

Specifically, for an application with $T_1$ work and $T_\infty$ span running on a computer with $P$ processors, the Cilk++ works-stealing sched-

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig3.png}
\caption{Parallelism profile of quicksort produced by the Cilk++ performance analyzer.}
\end{figure}

uler achieves expected running time

$$ T_P \leq T_1 / P + O(T_\infty) . $$

If the parallelism $T_1 / T_\infty$ exceeds the number $P$ of processors by a sufficient margin, this bound (proved in [4]), guarantees near-perfect linear speedup. To see why, assume that $T_1 / T_\infty \gg P$. Equivalently, we have $T_\infty \ll T_1 / P$. Thus, in Inequality (3), the $T_1 / P$ term dominates the $O(T_\infty)$ term, and thus the running time is $T_P \approx T_1 / P$, leading to a speedup of $T_1 / T_P \approx P$.

The Cilk++ development environment contains a performance-analysis tool that allows a programmer to analyze the work and span of an application. Figure 3 shows the output of this tool running the quicksort program from Figure 1 on 100 million numbers. The upper bound on speedup provided by the Work Law corresponds to the line of slope 1, and the upper bound provided by the Span Law corresponds to the horizontal line at 10.31. The performance analysis tool also provides an estimated lower bound on speedup — the lower curve in the figure — based on \textit{hardened parallelism}, which takes into account the estimated cost of scheduling. Although quicksort seems naturally parallel, one can show that the expected parallelism for sorting $n$ numbers is only $O(\log n)$. Practical sorts with more parallelism exist, however. See [7, Chapter 27] for more details.

In addition to guaranteeing performance bounds, the Cilk++ runtime system also provides bounds on stack space. Specifically, on $P$ processors, a Cilk++ program consumes at most $P$ times the stack space of a single-processor execution. Consider the following simple code fragment:

\begin{verbatim}
for (int i=0; i<1000000000; ++i) {
    cilk_spawn foo(i);
}
    cilk_sync;
\end{verbatim}

This code conceptually creates one billion invocations of \texttt{foo} that operate logically in parallel. Executing on one processor, however, this Cilk++ code uses no more stack space than a serial C++ execution, that is, the call depth is of whichever invocation of \texttt{foo} requires the deepest stack. On two processors, it requires at most twice this space, and so on. This guarantee contrasts with that of more naive schedulers, which may create a work-queue of one billion tasks, one for each iteration of the subroutine \texttt{foo}, before executing even the first iteration, thus blowing out physical memory.
Work stealing

Cilk++’s work-stealing scheduler operates as follows. When the runtime system starts up, it allocates as many operating-system threads, called *workers*, as there are processors (although the programmer can override this default decision). Each worker’s stack operates like a work queue. When a subroutine is spawned, the subroutine’s activation frame containing its local variables is pushed onto the bottom of the stack. When it returns, the frame is popped off the bottom. Thus, in the common case, Cilk++ operates just like C++ and imposes little overhead.

When a worker runs out of work, however, it becomes a *thief* and “steals” the top frame from another *victim* worker’s stack. Thus, the stack is in fact a double-ended queue, with the worker operating on the bottom and thieves stealing from the top. This strategy has the great advantage that all communication and synchronization is incurred only when a worker runs out of work. If an application exhibits sufficient parallelism, one can prove mathematically [4,14] that stealing is infrequent, and thus the cost of communication and synchronization to effect a steal is negligible.

The dynamic load-balancing capability provided by the Cilk++ runtime system adapts well in real-world multiprogrammed computing environments. If a worker becomes descheduled by the operating system (for example, because another application starts to run), the work of that worker can be stolen away by other workers. Thus, Cilk++ programs tend to “play nicely” with other jobs on the system.

Cilk++’s runtime system also makes Cilk++ programs *performance-composable*. Suppose that a programmer develops a parallel library in Cilk++. That library can be called not only from a serial program or the serial portion of a parallel program, it can be invoked multiple times in parallel and continue to exhibit good speedup. In contrast, some concurrency platforms constrain library code to run on a given number of processors, and if multiple instances of the library execute simultaneously, they end up thrashing as they compete for processor resources.

4 Race detection

The Cilk++ development environment includes a *race detector*, called Cilkscreen, a powerful debugging tool that greatly simplifies the task of ensuring that a parallel application is correct. We define a *strand* to be a sequence of serially executed instructions containing no parallel control, that is, a path in the multithreaded dag, where each vertex except the first in the path has at most one incoming edge and every vertex except the last in the path has at most one outgoing edge. A *data race* [26] exists if logically parallel strands access the same shared location, the two strands hold no locks in common, and at least one of the strands writes to the location. A data race is usually a bug, because the program may exhibit unexpected, nondeterministic behavior depending on how the strands are scheduled. Serial code containing nonlocal variables is particularly prone to the introduction of data races when the code is parallelized.

As an example of a race bug, suppose that line 13 in Figure 1 is replaced with the following line:

```cpp
qsort(max(begin + 1, middle-1), end);
```

The resulting serial code is still correct, but the parallel code now contains a race bug, because the two subproblems overlap, which could cause an error during execution.

Race conditions have been studied extensively [6, 8–12, 16, 20–22, 25, 27–29]. They are pernicious and occur nondeterministically. A program with a race bug may execute successfully millions of times during testing, only to raise its head after the application is shipped. Even after detecting a race bug, writing regression tests to ensure its continued absence is difficult.

The Cilkscreen race detector is based on provably good algorithms [2,6,11] developed originally for MIT Cilk. In a single serial execution on a test input for a deterministic program, Cilkscreen guarantees to report a race bug if the race bug is *exposed*: that is, if two different schedulings of the parallel code would produce different results. Cilkscreen uses efficient data structures to track the series-parallel relationships of the executing application during a serial execution of the parallel code. As the application executes, Cilkscreen uses dynamic instrumentation [5, 19] to intercept every load and store executed at user level. Metadata in the Cilk++ binaries allows Cilkscreen to identify the parallel control constructs in the executing application precisely, track the series-parallel relationships of strands, and report races precisely. Additional metadata allows the race to be localized in the application source code.

5 Reducer hyperobjects

Many serial programs use *nonlocal variables*, which are variables that are bound outside of the scope of the function, method, or class in which they are used. If a variable is bound outside of all local scopes, it is a *global variable*. Nonlocal variables have long been considered a problematic programming practice [33], but programmers often find them convenient to use, because they can be accessed at the leaves of a computation without the overhead and complexity of passing them as parameters through all the internal nodes. Thus, nonlocal variables have persisted in serial programming. In the world of parallel computing, nonlocal variables may inhibit otherwise independent parts of a multithreaded program from operating in parallel, because they introduce races. This section describes Cilk++ reducer hyperobjects [13], which can mitigate races on nonlocal variables without creating lock contention or requiring code restructuring.

As an example of how a nonlocal variable can introduce a data race, consider the problem of walking a binary tree to make a list of those nodes that nodes satisfy a given property. A C++ code to solve the problem is abstracted in Figure 4. If the node x being visited is nonnull, the code checks whether x has the desired property in line 8, and if so, it appends x to the list stored in the global variable output_list in line 10. Then, it recursively visits the left and right children of x in lines 12 and 13.

Figure 5 illustrates a straightforward parallelization of this code in Cilk++. In line 12 of the figure, the walk function is spawned recursively on the left child, while the parent continues on to execute an ordinary recursive call of walk in line 13. As the recursion unfolds, the running program generates a tree of parallel execution
that follows the structure of the binary tree. Unfortunately, this
naive parallelization contains a data race. Specifically, two par-
allel instantiations of walk may attempt to update the shared global
variable output_list in parallel at line 10.

The traditional solution to fixing this kind of data race is to as-
associate a mutual-exclusion lock (mutex) L with output_list, as is
shown in Figure 6. Before updating output_list, the mutex L is
acquired in line 11, and after the update, it is released in line 13. Although this code is now correct, the mutex can create a bottle-
neck in the computation. If there are many nodes that have the
desired property, the contention on the mutex can destroy all the
parallelism. For example, on one set of test inputs for a real-world
tree-walking code that performs collision-detection of mechanical
assemblies, lock contention actually degraded performance on 4
processors so that it was worse than running on a single processor.
In addition, the locking solution has the problem that it jumbles up
the order of list elements. That might be okay for some applica-
tions, but other programs may depend on the order produced by the
serial execution.

An alternative to locking is to restructure the code to accumulate
the output lists in each subcomputation and concatenate them when
the computations return. If one is careful, it is also possible to keep
the order of elements in the list the same as in the serial execution.
For the simple tree-walking code, code restructuring may suffice,
but for many larger codes, disrupting the original logic can be time-
consuming and tedious undertaking, and it may require expert skill,
making it impractical for parallelizing large legacy codes.

Cilk++ provides a novel approach [13] to avoiding data races in
code with nonlocal variables. A Cilk++ reducer hyperobject is a
linguistic construct that allows many strands to coordinate in updat-
ing a shared variable or data structure independently by providing
them different but coordinated views of the same object. The state
of a hyperobject as seen by a strand of an execution is called the
strand’s “view” of the object at the time the strand is executing. A
strand can access and change any of its view’s state independently,
without synchronizing with other strands. Throughout the execu-
tion of a strand, the strand’s view of the reducer is private, thereby
providing isolation from other strands. When two or more strands
join, their different views are combined according to a system- or
user-defined reduce() method. Thus, reducers preserve the advan-
tages of parallelism without forcing the programmer to restructure
the logic of his or her program.

As an example, Figure 7 shows how the tree-walking code from
Figure 4 can be parallelized using a reducer. Line 3 declares output_list to be a reducer hyperobject for list appending. The
reducer_list_append class implements a reduce function that
concatenates two lists, but the programmer of the tree-walking code
need not be aware of how this class is implemented. All the pro-
grammer does is identify the global variables as the appropriate
type of reducer when they are declared. No logic needs to be re-
structured, and if the programmer fails to catch all the use instances,
the compiler reports a type error.

This parallelization takes advantage of the fact that list append-
ing is associative. That is, if we append a list L1 to a list L2 and
append the result to L3, it is the same as if we appended list L1 to
the result of appending L2 to L3. As the Cilk++ runtime system
load-balances this computation over the available processors, it en-
sures that each branch of the recursive computation has access to
a private view of the variable output_list, eliminating races on this
global variable without requiring locks. When the branches
synchronize, the private views are reduced (combined) by concate-
nating the lists, and Cilk++ carefully maintains the proper ordering
so that the resulting list contains the identical elements in the same
order as in a serial execution.

6 Conclusion

Multicore microprocessors are now commonplace, and Moore’s
Law is steadily increasing the pressure on software developers to
multicore-enable their codebases. Cilk++ provides a simple but
effective concurrency platform for multicore programming which leverages almost two decades of research on multithreaded programming. The Cilk++ model builds upon the sound theoretical framework of multithreaded dags, allowing parallelism to be quantified in terms of work and span. The Cilkscreen race detector allows race bugs to be detected and localized. Cilk++’s hyperobject library mitigates races on nonlocal variables. Although parallel programming will surely continue to evolve, Cilk++ today provides a full-featured suite of technology for multicore-enabling any compute-intensive application.

Acknowledgments

Many thanks to the great team at Cilk Arts and to our many customers who have helped us refine the Cilk++ system. Thanks to Patrick Madden of SUNY Binghamton for proposing extensive revisions to the original manuscript.

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