

Compiler-Based I/O Prefetching for Out-of-Core Applications

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Current operating systems offer poor performance when a numeric application's working set does not fit in main memory. As a result, programmers who wish to solve "out-of-core" problems efficiently are typically faced with the onerous task of rewriting an application to use explicit I/O operations (e.g., read/write). In this paper, we propose and evaluate a fully automatic technique which liberates the programmer from this task, provides high performance, and requires only minimal changes to current operating systems. In our scheme the compiler provides the crucial information on future access patterns without burdening the programmer; the operating system supports nonbinding *prefetch* and *release* hints for managing I/O; and the operating system cooperates with a run-time layer to accelerate performance by adapting to dynamic behavior and minimizing prefetch overhead. This approach maintains the abstraction of unlimited virtual memory for the programmer, gives the compiler the flexibility to aggressively insert prefetches ahead of references, and gives the operating system the flexibility to arbitrate between the competing resource demands of multiple applications. We implemented our compiler analysis within the SUIF compiler, and used it to target implementations of our run-time and OS support on both research and commercial systems (Hurricane and IRIX 6.5, respectively). Our experimental results show large performance gains for out-of-core scientific applications on both systems: more than 50% of the I/O stall time has been eliminated in most cases, thus translating into overall speedups of roughly twofold in many cases.

Categories and Subject Descriptors: D.4.2 [**Operating Systems**]: Storage Management—*Virtual memory*; D.4.8 [**Operating Systems**]: Performance; D.3.4 [**Programming Languages**]: Processors—*Compilers; Optimization*

General Terms: Performance, Design, Experimentation

Additional Key Words and Phrases: Virtual memory, compiler optimization, prefetching

This research is supported by a grant from NASA. Todd C. Mowry is partially supported by an Alfred P. Sloan Research Fellowship.

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1. INTRODUCTION

Many of the important computational challenges facing scientists and engineers today involve solving problems with very large data sets. For example, global climate modeling, computational physics and chemistry, and many engineering problems (e.g., aircraft simulation) can easily involve data sets that are too large to fit in main memory [Crandall et al. 1995; del Rosario and Choudhary 1994; Poole 1994]. For such applications (which are commonly referred to as “out-of-core” applications), main memory simply constitutes an intermediate stage in the memory hierarchy, and the bulk of the data must reside on disk or other secondary storage. Ideally one could efficiently solve an out-of-core problem by simply taking the original in-core program and increasing the problem size. In theory, a paged virtual memory system could provide this functionality by transparently migrating data between main memory and disk in response to page faults and memory pressure. While this approach does yield a logically correct answer, the resulting performance is typically so poor that it is not considered a viable technique for solving out-of-core problems [Womble et al. 1993].

In practice, scientific programmers who wish to solve out-of-core problems typically write a separate version of the program with explicit I/O calls for the sake of achieving reasonable performance. Writing an out-of-core version of a program is a formidable task—it is not simply a matter of inserting a few I/O read or write statements, but often involves significant restructuring of the code, and in some cases can have a negative impact on the numerical stability of the algorithm [Womble et al. 1993]. Thus the burden of writing a second version of the program (and ensuring that it behaves correctly) presents a significant barrier to solving large scientific problems.

The goal of our research is to preserve the abstraction of unlimited virtual memory for the programmer, while providing performance competitive with that which can be achieved by explicitly managing I/O. To motivate the approach we have taken, we first discuss the limitations of existing methods. Section 1.1 explains why existing virtual memory systems perform poorly for these types of applications. Section 1.2 explains why existing explicit I/O approaches are undesirable. Given the limitations of current methods, Section 1.3 gives a high-level description of our scheme and presents the key contributions of this work.

1.1 The Problem with Paged Virtual Memory

The promise of virtual memory is to free programmers from concerns of the underlying system such as the size of memory and the available I/O devices. This approach works well, as long as the application exhibits good temporal and spatial locality, i.e., as long as the application’s working set fits in physical memory most of the time. Unfortunately, it does not work well for applications with poor locality, even if disks are available to deliver the data fast enough. Womble et al. note that the general-purpose nature of

VM systems makes them inefficient for many scientific applications [Womble et al. 1993]. The performance of out-of-core applications that rely simply on paged virtual memory to perform their I/O is typically quite poor, as we will demonstrate later in Section 5.

For persistent data (e.g., input and output data sets), mapped file I/O shares many of the advantages and disadvantages of virtual memory. It presents the same familiar interface to the application programmer, and the same page fault mechanism is used to bring data into memory. The difference is that the data are backed by an ordinary file, rather than the system swap file. Compared with explicit I/O requests, mapped file I/O has reduced copying overhead, reduced memory overhead (since there are no redundant copies of the same data and since only the data actually touched will be brought into memory), and allows concurrency of reads, as multiple threads can have outstanding faults to the same mapped region. Unlike explicit I/O which provides a uniform interface to all I/O devices, however, mapped file I/O can only be used for devices that support block-oriented random accesses such as disks [Krieger et al. 1991]. For our purposes, we will not distinguish further between virtual memory and mapped files, since they share many important characteristics.

There are three primary reasons why virtual memory systems are unable to provide the best I/O performance for out-of-core applications: the timing of requests, the size of requests, and replacement decisions.

First, in a virtual memory system data are brought into memory in response to a *page fault*, which occurs when the process attempts to read a virtual memory location that is not in physical memory. Since the request is triggered when the data are needed, the process must stall for the full latency of a disk read. Typically, the operating system will give the CPU to another process when a page fault occurs because the latency is so large. If other runnable processes exist, this technique keeps the CPU busy and improves system throughput, but it does not help the performance of the faulting process in any way.

Second, page faults typically result in only a single outstanding page-sized read request at a time for a given process. High-bandwidth disk arrays cannot generally be exploited for such small requests (unless a single page is striped across multiple disks), since only a single disk is busy at any time. Although most operating systems attempt some form of page fault prefetching both to hide latency and to have multiple outstanding disk requests, it is difficult to do this efficiently for reasons we will discuss later in Section 2.2. In our experiments, the performance loss is *not* due to limited I/O bandwidth (in fact, the disk utilization is fairly low), but rather to *I/O latency*, since each page fault causes the application to suffer the full delay of a disk read.

Finally, when the amount of data accessed is greater than the size of physical memory, the operating system must decide what to evict to make room for new requests. Without knowledge of the application's future accesses the memory manager may reallocate pages that are about to be used again, increasing the need to perform I/O and further degrading

performance. Park, Scott, and Sechrest have shown that customizing the replacement policy on a per-application basis can significantly improve the performance of out-of-core applications [Park et al. 1996]. An additional concern from a resource management perspective is that the memory manager may allocate more memory to a process than it actually needs in order to delay making these replacement decisions. This may have a negative impact on competing processes.

Having shown why virtual memory delivers poor performance for out-of-core applications, we now discuss how explicitly managing I/O can overcome some of these difficulties and the new complications that explicit I/O introduces.

1.2 The Problem with Explicit I/O

One can potentially achieve better performance by rewriting out-of-core applications to use explicit I/O calls (e.g., the read/write interface in UNIX) for the following three reasons: (i) nonblocking I/O calls allow file accesses to be overlapped with computation; (ii) large requests make better use of available bandwidth; and (iii) replacement decisions are made by the application and can therefore take into account the application's access patterns.

First, asynchronous I/O interfaces are available that allow applications to issue I/O requests without blocking. By properly scheduling these requests, the application can overlap file I/O with computation, in the best case allowing all the disk latency to be hidden.

Second, read and write requests can affect a large number of blocks in a single request. This is important in a system with high disk bandwidth (i.e., a large number of disks), since issuing large requests is one way to exploit the parallelism in the underlying disk system.

Finally, with a read/write interface the application specifies the buffers that are the source or target of the file data. Hence, the application can ensure that data that will soon be accessed are buffered in memory. Also, the application can minimize the amount of memory used by ensuring that buffers that it will not access for a long time are freed, and if modified, written to disk.

While explicit I/O offers the potential for improved performance over paging, it unfortunately suffers from several disadvantages. The primary drawback is the large burden placed on the programmer of rewriting an application to insert the I/O calls—our goal is to avoid this burden altogether. Another disadvantage is the performance overhead of these I/O system calls, which typically involve copying overhead to transfer data between the system's I/O buffers and the buffers managed by the application.

A third, less obvious disadvantage is that with explicit I/O the application is implicitly making low-level policy decisions with its I/O requests (e.g., the size of the requests, and the amount of memory to be used for I/O buffering). However, the best policy decisions depend not only on application

access patterns, but also on the physical resources available. Hence an application written assuming a particular amount of physical memory and disk bandwidth may perform poorly on a machine with a different set of resources, or in a multiprogrammed environment where some of the resources are being used by other applications. To illustrate how the available physical resources affect an application's performance, consider the amount of memory available for buffering I/O. If sufficient physical memory is available such that the entire data set can fit in memory, then an application with explicit I/O will pay the system call overhead with no benefit. On the other hand, if the application uses more buffer space for I/O than the available physical memory, then the buffers will suffer page faults, possibly resulting in worse performance than if the application had simply relied on paged virtual memory from the start.

1.3 Our Solution

It seems clear that if a paged virtual memory system had full knowledge about an application's future access pattern, all the performance advantages of explicit I/O could be achieved without the disadvantages. In particular, the memory manager could make large requests to allow disk bandwidth to be efficiently exploited, manage the memory efficiently to minimize memory used and to avoid paging out data that will soon be accessed, and prefetch data that will soon be accessed to hide from applications the latency of I/O. Moreover, the memory manager could perform these optimizations while taking into account the total resources available, and while avoiding the system call and copying overhead of explicit I/O interfaces.

The application access patterns are best known at the application level, either as the result of programmer intervention or analysis performed by a compiler. Knowledge regarding resource usage is naturally available to the operating system. To unify the required information, there is thus a choice between communicating access patterns down to the operating system where resource usage is known or communicating resource usage up to the application level. Most (if not all) current research in improving I/O performance has focused on informing the operating system about application access patterns. The problem with this approach is that applications may have very complicated (but regular) access patterns which are difficult to convey to the OS. Even if full disclosure is possible, the complexity required by the memory manager to make the best use of the given information may hurt performance for in-core applications that do not require such functionality. In contrast, the relevant information about memory usage can be transferred to the application level quite concisely, which is the approach we use.

In our scheme, the compiler provides the crucial information on future access patterns without burdening the programmer; the operating system provides a simple interface for managing I/O which is optimized to the needs of the compiler; and a run-time layer uses information provided by

the operating system to accelerate performance by adapting to dynamic behavior and minimizing prefetch overhead. In this paper, we propose and evaluate a fully automatic scheme for prefetching I/O whereby the operating system and the compiler cooperate to combine the advantages of both explicit I/O and paged virtual memory without suffering from the disadvantages. Our experimental results demonstrate that our scheme effectively hides the I/O latency in out-of-core versions of the entire NAS Parallel benchmark suite [Bailey et al. 1991], thus resulting in speedups of roughly twofold for the majority of these applications, and over threefold in one case.

This paper is organized as follows. We begin in Section 2 by discussing how the compiler and the operating system can cooperate to automatically prefetch disk accesses for out-of-core applications. Section 3 provides a more detailed description of the analysis performed by the compiler and the changes from the original compiler algorithm for cache prefetching that were needed to support I/O prefetching. Next, Section 4 describes the framework used to evaluate our ideas, and Section 5 presents our experimental results. Finally, Sections 6 and 7 discuss related work and our conclusions.

2. AUTOMATICALLY TOLERATING I/O LATENCY

This section describes our system for automatically tolerating I/O latency. We begin by discussing the fundamental challenges that we have overcome. We then present an overview of our system, and finally we discuss the three major components of the system (i.e., the compiler, operating system, and run-time layer support) in more detail.

2.1 Fundamental Performance Issues

Our goal is to fully hide I/O latency, thus eliminating its impact on overall execution time. Conceptually, one can view our approach as enhancing the performance of virtual memory, since that is the abstraction we present to the programmer. Under paged virtual memory, an out-of-core application invokes two types of disk accesses: (i) faulting pages are read from disk into memory, and (ii) dirty pages are written out to disk to free up memory. Hiding write latency is reasonably straightforward, since writes can be buffered and pipelined. Hiding *read* latency, on the other hand, is difficult because the application stalls waiting for the read (i.e., the page fault) to complete. The key to tolerating read latency is to split apart the *request* for data and the *use* of that data, while finding enough useful work to keep the application busy in between. We can accomplish this by *prefetching* pages sufficiently far in advance in the execution stream such that they reside in memory by the time they are needed.

Since prefetching does not reduce the number of disk accesses, but simply attempts to perform them over a shorter period of time, it cannot reduce the execution time of an application whose I/O bandwidth demands already outstrip the bandwidth provided by the hardware. Fortunately, we can

construct cost-effective, high-bandwidth I/O systems by harnessing the aggregate bandwidth of multiple disks [Chen et al. 1994; Krieger and Stumm 1997; Sweeney et al. 1996]. Roughly speaking, one can always increase the I/O bandwidth by purchasing additional disks. Since prefetching naturally results in many small, independent requests, it is possible to harness the available bandwidth in a multiple-disk system.

In addition to hiding I/O latency and providing sufficient I/O bandwidth, a third challenge in achieving high performance is effectively managing main memory, which can be viewed as a large, fully associative cache of data that actually resides on disk. There are two issues here. First, to minimize page faults, we would like to choose the optimal page to evict from memory when we need to make room for a new page that is being faulted in. Toward this goal, most commercial operating systems use an approximation of LRU replacement to select victim pages. While LRU replacement may be a good choice for a default policy, there are cases where it performs quite poorly, and in such cases we would like to exploit application-specific knowledge to choose victim pages more effectively. The second issue is that we would like to minimize memory consumption, particularly when doing so does not degrade performance. For example, rather than filling up all of main memory with data that we are streaming through, we may be able to achieve the same performance by using only a small amount of memory as buffer space. By minimizing memory consumption, more physical memory will be available to the rest of the system, which is particularly important in a multiprogrammed environment. To accomplish both of these goals, we introduce an explicit *release* operation whereby the application provides a hint to the operating system that a given page is not likely to be referenced again soon, and hence is a good candidate for replacement.

In summary, our approach overcomes the fundamental challenges of accelerating paged virtual memory as follows: (i) *prefetches* are used to tolerate disk read latency, (ii) *multiple disks* are used to provide high-bandwidth I/O, and (iii) *release* operations are used to effectively manage memory. We now discuss the overall structure of our software system.

2.2 Software Architecture Overview

To prefetch and release data effectively, we need detailed knowledge of an application's future access patterns. Although one might attempt to deduce this information from inside the operating system by looking for repeated patterns in the access history, such an approach would be limited only to simple access patterns (e.g., even the simple indirect references that commonly occur in sparse-matrix applications would be extremely difficult for the operating system to predict), and would require adding additional complexity to the operating system, which is something we wish to avoid. (This additional complexity may not be acceptable in a general-purpose operating system, since it would likely increase the critical page fault path, thus hurting the performance of the majority of applications that do not

require it.) Instead, we turn to the compiler to provide information on future access patterns, since it has the luxury of being able to examine the entire program all at once. Also, by using the compiler to extract this information automatically, we avoid placing any burden on the programmer, who continues to enjoy the abstraction of unlimited virtual memory.

2.2.1 The Compiler/Operating System Interface. Given that the compiler will be extracting and passing access pattern information to the operating system, an important question is what form this interface should take. Note that this interface will *only* be used by the compiler, and *not* by the programmer—the programmer’s interface will be unlimited virtual memory, and the compiler and operating system cooperate to preserve this illusion. Ideally, we would like an interface that requires minimal complexity within the operating system (so that it can be readily incorporated into existing commercial operating systems), and which maximizes the compiler’s ability to improve performance, given the strengths and weaknesses of realistic compilation technology.

One possibility would be for the compiler to pass a summary of future access patterns to the operating system through a single call at the start of execution. However, from the compiler’s perspective this approach is undesirable, since the access patterns in real applications often depend on dynamic control and data dependencies that can only be resolved at run-time. For example, in the bucket sort application (BUK) discussed later in this paper, the important data accesses are indirect references based on the contents of a large array. The values in this array are unknown at startup time; but even if they were known, passing this very large array along with a description of how to use it to compute addresses would greatly complicate not only the interface and the compiler, but also the operating system, which would ultimately be responsible for generating the addresses. Another disadvantage of this approach is that it pushes the complexity of matching up the access patterns with *when* those accesses actually take place into the operating system. For example, if the compiler indicates that the program will be streaming through a large array, it is not helpful if the operating system brings the data into memory too fast (or too slow) relative to the rate at which it is being consumed. Since tracking an application’s access patterns means that the operating system must see either page faults or explicit I/O on a regular basis, it is unclear that this interface offers any less overhead than an interface requiring regular system calls. Hence we will focus instead on an interface where prefetch addresses are passed in at roughly the time when the prefetch should be sent to disk, and where release addresses are passed in when the data are no longer needed.

The next logical question is whether we can simply compile to an existing asynchronous read/write I/O interface, or whether a new interface is actually needed. There are two reasons why existing read/write I/O interfaces are unacceptable for our purposes. First, for the compiler to successfully move prefetches back far enough to hide the large latency of I/O, it is


```

(a) Original Code
    foo(double *a, double *b) {
        /* Assume that a & b reside */
        /* on disk at this point. */
        ...
        for (i = 0; i < 100; i++) {
            a[i+1] = a[i] + b[i];
        }
    }

(b) Read/Write Interface
    foo(double *a, double *b) {
        double a_buf[101], b_buf[100];
        /* Read a & b from disk into buffers. */
        read(a, &a_buf[0], 101*sizeof(double));
        read(b, &b_buf[0], 100*sizeof(double));
        ...
        for (i = 0; i < 100; i++) {
            a_buf[i+1] = a_buf[i] + b_buf[i];
        }
        /* Write a_buf back out to disk. */
        write(a, &a_buf[0], 101*sizeof(double));
    }

(c) Prefetch/Release Interface
    foo(double *a, double *b) {
        /* Prefetch a & b into memory. */
        prefetch(a, 101*sizeof(double));
        prefetch(b, 100*sizeof(double));
        ...
        for (i = 0; i < 100; i++) {
            a[i+1] = a[i] + b[i];
        }
        /* Finished with a & b. */
        release(a, 101*sizeof(double));
        release(b, 100*sizeof(double));
    }
    
```

Fig. 1. Example illustrating the importance of nonbinding prefetches.

essential that prefetches be *nonbinding* [Mowry 1994]. The nonbinding property means that when a given reference is prefetched the data value seen by that reference is bound at *reference* time; in contrast, with a binding prefetch, the value is bound at *prefetch* time. The problem with a binding prefetch is that if another store to the same location occurs during the interval between a prefetch and a corresponding load, the value seen by the load will be stale. Hence, we cannot move a binding prefetch back beyond a store unless we are certain that they are to different addresses—unfortunately, this is one of the most difficult problems for the compiler to resolve in practice (i.e., the problem of “alias analysis,” also known as “memory disambiguation” or “dependence analysis”). Since an asynchronous I/O read call implicitly renames data by copying it into a buffer, it is a binding prefetch. To illustrate this problem, consider the code in Figure 1(a). If we use the read/write interface, we might generate code similar to Figure 1(b). Unfortunately, this code produces an incorrect result if the parameters *a* and *b* are aliased (e.g., `foo(&X[0], &X[0])`) or even partially overlap (e.g., `foo(&X[10], &X[0])`). To implement nonbinding prefetching, the data should have the same name (or address) both in memory and on disk, which corresponds to the abstraction of paged virtual memory. Figure 1(c) shows the preferred code which uses nonbinding prefetch and release operations, and always produces a correct result.

The second problem with an asynchronous read/write interface is that it compels the operating system to perform an I/O access. Instead, we would

prefer to give the operating system the flexibility to drop requests if doing so might achieve better performance, given the dynamic demands for and availability of physical resources. For example, if there is not enough physical memory to buffer prefetched data, or if the disk subsystem is overloaded, we may want to drop prefetches. Hence, the preferred interface is a natural extension of paged virtual memory which includes *prefetch* and *release* as nonbinding performance hints. This interface provides flexibility on two fronts: the compiler can aggressively insert prefetches ahead of references, and the operating system can still arbitrate between the competing resource demands of multiple applications. (Note that the “MADV_WILLNEED” and “MADV_DONTNEED” hints to the `madvise()` interface can potentially be used to implement prefetch and release in UNIX.) In this paper, we use the term “I/O prefetching” to refer to prefetching data from disks into main memory. Given our preferred virtual memory interface, this takes the form of prefetching pages, either from mapped files or from the swap file.

2.2.2 Minimizing Prefetch Overhead. Earlier studies on compiler-based prefetching to hide cache-to-memory latency have demonstrated the importance of avoiding the overhead of unnecessarily prefetching data that already reside in the cache [Mowry 1994; Mowry et al. 1992]. To address this problem, compiler algorithms have been developed for inserting prefetches only for those references that are likely to suffer misses. An analogous situation exists with I/O prefetching, since we do not want to prefetch data that already reside in main memory—hence, we perform similar analysis in our compiler (as we discuss later in Section 3). Unfortunately, it is considerably more difficult to avoid unnecessary prefetches with I/O prefetching, since main memory is so much larger than a cache that our loop-level compiler analysis tends to underestimate its ability to retain data. As a result, unnecessary prefetches do occur, and we must be careful to minimize their overhead.

Compared with cache-to-memory prefetching, where the overhead of an unnecessary prefetch is simply a wasted instruction or two (since unnecessary prefetches are dropped as soon as the cache tag check indicates that the data are already in the cache), the overhead of an unnecessary I/O prefetch is considerably larger, since it involves making a system call and checking the page table before discovering that the prefetch can be dropped. To reduce this overhead, we introduce a run-time layer in our system which keeps track at the *user level* of whether pages are believed to be in memory or not. Therefore we can typically drop unnecessary prefetches without performing a system call, and we have found this to be essential in achieving high performance, as we will show in Section 5.3.2.

Having introduced the three layers of our system—the compiler, the operating system, and the run-time layer—we now discuss each layer in more detail.

2.3 Compiler Support

The bulk of our compiler algorithm is a straightforward extension of an algorithm that was developed earlier for prefetching cache-to-memory misses in dense-matrix and sparse-matrix codes [Mowry 1994; Mowry et al. 1992]. Conceptually, prefetching from disks into main memory entails moving down one level in the memory hierarchy. To accommodate this transition, we changed the input parameters that describe the cache size, line size, and miss latency to correspond to main memory size, the page size, and the page fault latency, respectively. Based on this memory model, the compiler uses *locality analysis* to predict when misses (i.e., page faults) are likely to occur; it isolates these faulting instances through *loop splitting* techniques, and schedules prefetches early enough using *software pipelining*. More details on each of these steps and the changes needed to properly support I/O prefetching are described in Section 3.

The static prefetching decisions made by the compiler may be inappropriate if the amount of available memory or the time to service a page fault are vastly different from the parameters used at compile-time (i.e., prefetches may not occur often enough if there is less memory, or they may not occur early enough if the I/O latency is greater than expected). In general, we try to underestimate the amount of available memory and rely on the run-time layer to remove unnecessary prefetches; however, generating code that is fully adaptable to the range of conditions that could occur during execution is beyond the scope of this paper. In our experiments (see Section 5), we run each out-of-core benchmark on a dedicated machine, eliminating variations in available memory and page fault service time due to other applications.

2.4 Operating System/Run-Time Layer Interaction

The next two subsections describe the run-time layer that we introduce to reduce the overhead of unnecessary prefetches, and the support provided by the operating system.

2.4.1 The Run-Time Layer. The run-time layer tracks pages that are expected to be in memory by using a bit vector to construct a map of the application's virtual memory space. Each bit in the vector represents one or more contiguous virtual memory pages, with a set bit indicating that the corresponding page is in physical memory. The run-time layer uses the bit vector to *filter* the prefetches inserted by the compiler by checking to see if the requested page is already in memory. In many cases this simple test can avoid the cost of a system call to the operating system, thus substantially reducing overhead. If a block of contiguous pages are specified in the prefetch request, we check each page until one is found that is not in memory or until the end of the block is reached. When a page is found that needs to be prefetched, the run-time layer issues a request to the operating system for the missing page and all subsequent pages in the block. In this way, at most one system call is required for a block prefetch.

Although it would be possible for the run-time layer to approximate the state of main memory entirely at the user level by setting bits for prefetched pages and clearing bits for released pages, the run-time layer would be unaware of pages brought into memory by page faults, or reclaimed by the operating system. To give the run-time layer a more accurate view, we instead make the bit vector shared with the operating system which is responsible for setting or clearing bits as pages are transferred in or out of memory.

2.4.2 Operating System Support. To support compiler-directed prefetching, the operating system needs to be able to respond to the prefetch and release requests issued by the application. For a prefetch request, the operating system allocates a memory page from the list of free pages to hold the requested data and issues an asynchronous read request to the file system before returning control to the application. When the data become available the page is mapped into the application's page table, but no entry is made in the TLB, thus preventing prefetched pages that are not yet in use from evicting useful entries. In the event that there is no free memory available the operating system is permitted to drop the prefetch request, rather than forcing pages to be evicted to make room for the prefetched data. This choice is reasonable because prefetching applications are expected to attempt to limit their memory consumption by releasing pages that are not currently needed. If all pages are in use at some time, choosing to evict one to satisfy a prefetch request could hurt performance. For a release request the operating system unmaps the specified page and places it on the free list, scheduling a write if necessary. Functionality for these operations is easy to add, since most operating systems already support asynchronous requests to the file system and need to be able to unmap pages of memory for existing memory management activities.

A more interesting issue is having the operating system actively share a data structure (i.e., the bit vector) with the user level. The operating system agrees to provide a user-level process with a range of memory that can be used as a map of the process' virtual memory usage. The operating system is responsible for allocating memory for the shared data, making it readable by the application, and mapping it into a specified location in the application's virtual address space. A new system call is thus needed to allow the application to request the shared bit vector and provide the address that the application will use to access it. The operating system must, of course, record the address that it will use to access each prefetching application's shared bit vector as well.

The memory overhead created by allocating the bit vector is minimal. For small to medium sized systems, a single page of physical memory is sufficient. In IRIX, for instance, the base page size is 16KB, which allows us to map an entire 32-bit user-level virtual address space ($2^{14} \times 8$ pages can be mapped using one bit per page, and each page is 2^{14} bytes, allowing 2^{31} bytes of virtual memory to be mapped). Bits in the page can be indexed directly by virtual page number, making it simple and efficient to check

and set or clear them. Smaller page sizes make it impossible to map the entire virtual address space with a single page using one bit per page. Two possible solutions are to use more than one page of memory for the shared bit vector, or to increase the *granularity* of the bit vector, such that each bit represents more than one contiguous page of the virtual address space. The approach we have taken in our Hurricane implementation (in which the base page size is only 4KB) is to increase the granularity of the bit vector when necessary. Details on this implementation decision will be given in Section 4.1. For applications that require 64-bit address spaces, however, neither simply increasing the granularity or the number of pages used by the bit vector will provide an acceptable solution if we wish to continue indexing the bit vector directly by virtual page number. If the granularity is increased, each bit will represent an unacceptably large number of virtual pages; if enough pages are supplied to index the entire virtual address space directly, the memory overhead will be unacceptably large. Since such large address spaces are likely to be sparsely populated, switching to a multilevel bit vector implementation (similar in spirit to multilevel page table schemes) would allow fast indexing of the bit vector with a reasonable amount of memory overhead.

3. THE COMPILER ALGORITHM

In this section we provide a more detailed description of our compiler algorithm for generating prefetch and release requests. The bulk of this algorithm is a straightforward extension of one that was developed earlier for prefetching cache-to-memory misses in dense-matrix and sparse-matrix codes [Mowry 1994; Mowry et al. 1992]. Essentially, we simply move down one level in the memory hierarchy to prefetch data from disks into main memory. Thus, the basic input parameters that describe the cache size, line size, and miss latency in the original algorithm are changed to reflect memory capacity, page size, and page fault latency, respectively.

Additional modifications to the original algorithm are needed for the following reasons:

- (1) We need to generate *release* requests to identify pages that are no longer needed by the application.
- (2) The cost of issuing a prefetch request is much greater for I/O prefetching, since operating system interaction is required. We seek to amortize the system call overhead by requesting multiple pages with a single *block prefetch* request whenever possible.
- (3) A memory page contains many more data items than a cache line. While this may seem obvious, the implications for how the compiler schedules prefetches need to be carefully considered. In particular, different techniques for splitting loops and pipelining prefetches must be applied.

We consider a *reference* to be an instruction that reads or writes a memory location. Specifically, since the compiler analysis is only applied to array accesses (i.e., $A[i]$), we will use the term *reference* to mean memory accesses through arrays.

Most of the required changes to the algorithm relate to how prefetches are scheduled; however, it is difficult to understand why certain references need to be handled in a particular manner without first seeing how the compiler determines what needs to be prefetched. Hence, we begin in Section 3.1 with a description of how the compiler uses *locality analysis* to predict when misses (i.e., page faults) are likely to occur. Most of the work in this section has been presented previously in Mowry's thesis on cache prefetching [Mowry 1994] and is reproduced here for completeness and ease of reference. Next, Section 3.2 discusses how the compiler first isolates these faulting instances through *loop splitting* techniques, and then schedules prefetches early enough using *software pipelining*.

3.1 Locality Analysis

The goal of the *locality analysis* step of the prefetching algorithm is to identify which references are likely to incur page faults. To accomplish this, it is necessary to determine both when data are reused and whether those data are expected to remain in memory between uses. The locality analysis step is fundamentally unchanged from that developed for cache prefetching; however, it is important to understand how the compiler decides what to prefetch to understand why some references are “missed.”

It should be noted that locality analysis is only applied to “direct” array references (i.e., $A[i]$) and not to “indirect” references (i.e., $A[B[i]]$), because it is impossible to determine the index values, $B[i]$, at compile-time. In the best case, all of the values may be the same, and the reference would only need to be prefetched on the first access. At the other end of the spectrum, each index may point to a different page, and the reference would need to be prefetched all the time. In general, we choose to always prefetch indirect references (since the benefit of potentially eliminating I/O stalls is so great) and rely on run-time techniques to reduce the overhead when they are unnecessary.

The key ideas needed for locality analysis are introduced in Section 3.1.1, and Section 3.1.2 uses an illustrative example to show how these ideas can be expressed in terms of loop iterations. With this framework, the remaining three subsections describe each step of the locality analysis algorithm in detail.

3.1.1 Fundamental Concepts. A data item has *reuse* if it is referenced multiple times. Reuse is thus an intrinsic property of a given data access pattern. In contrast, *locality* only results when subsequent references find the data item still in memory. Hence, it is a function of the size of memory, the volume of data accessed between reuses, and the page replacement policy used by the operating system. Since the operating system's replacement policy is beyond the compiler's ability to analyze, we simply assume

that a page is likely to be replaced if the amount of data accessed between reuses is greater than the size of physical memory. This assumption would be true for a strict LRU replacement policy. If memory were unlimited, then reuse and locality would be identical; in reality, the references with data locality are a subset of those with data reuse.

To properly identify what needs to be prefetched, we must distinguish three types of data reuse (and three corresponding types of locality), each of which needs to be handled in a different manner. *Temporal reuse* occurs when a particular reference accesses exactly the same data location in different iterations. *Spatial reuse* occurs when a particular reference accesses different data locations found on the same page. *Group reuse* occurs when different references access data locations found on the same page.

Given the relationship between reuse and locality, the locality analysis algorithm is comprised of three steps:

- (1) Discover the intrinsic data reuses within a loop nest through *reuse analysis*. This would be equivalent to solving the locality analysis problem if memory were unlimited.
- (2) Given that we have a *finite* memory, determine the set of reuses that actually result in locality. This is accomplished by computing the *localized iteration space*, which is the set of nested loops that access less data than the specified memory capacity. Data locality is then computed by intersecting the intrinsic data reuses with the localized iteration space. i.e.,

$$\text{Data Reuse} \cap \text{Localized Iteration Space} \Rightarrow \text{Data Locality}$$

- (3) Express the data locality for each reference in terms of a *prefetch predicate*, which is a logical predicate that is true during each dynamic iteration when the reference is expected to incur a page fault. These predicates are used during scheduling to split loops, statically isolating the faulting references.

The first two steps produce a mathematical description of locality in a *vector space* representation. The third step translates this description into a representation which is more directly applicable to the problem of scheduling the required prefetches. To gain an intuition for the concepts captured by the vector space notation and the reuse analysis step, we present an example in Section 3.1.2. We then show how the localized iteration space is computed in Section 3.1.3 and converted into prefetch predicates in Section 3.1.4. The details of computing the reuse vector space are presented in Appendix A.

3.1.2 An Example of the Reuse Vector Space. The types of reuse that can be identified using *reuse analysis* are shown in Figure 2(a). For this example, assume the data are stored in row-major order and that each memory page holds two array elements. These parameters are chosen for illustrative purposes only, and are unrealistically small. The iterations that

(a) Example Code

```

for (i = 0; i < 3; i++)
  for (j = 0; j < 8; j++)
    A[i][j] = B[j][0] + B[j+1][0];

```

(b) Data Reuse

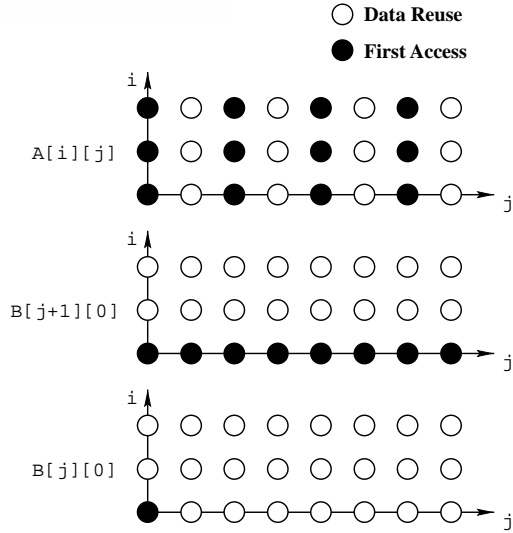


Fig. 2. Data reuse example.

first touch a new page and those that reuse the same page are shown graphically in Figure 2(b) using *iteration space* plots. In these plots, the horizontal axis represents the j loop, while the vertical axis represents the i loop. In other words, each row of the plots corresponds to a single iteration of the i loop, while each node within a row corresponds to a single iteration of the j loop. Hence, each node represents the result of the data access in a particular iteration. During the execution of the corresponding code, the nodes within a row would be visited from left to right, and the rows would be visited from bottom to top.

The $A[i][j]$ reference in Figure 2 accesses each data element exactly once, traversing the rows of the matrix along the inner loop. Since each page contains two array elements, a new page is touched on every other iteration of the inner loop as page boundaries are crossed. The iterations that first touch new pages are illustrated in the first plot of Figure 2(b). This reference exhibits *spatial reuse*.

The $B[j+1][0]$ reference traverses the columns of the matrix along the inner loop, causing each reference to touch a different page during the first iteration of the j loop. However, exactly the same locations are used again on subsequent iterations of the i loop, resulting in *temporal reuse* for this reference. This effect is illustrated in the second plot of Figure 2(b).

The $B[j][0]$ and $B[j+1][0]$ references provide an example of *group reuse*. In this case, the $B[j][0]$ reference uses the same data locations first

accessed by the $B[j+1][0]$ reference during the previous iteration of the j loop. Thus, the $B[j][0]$ reference only touches a new page during the first j loop iteration. The third plot of Figure 2 shows this effect. For references with group locality, we need to identify the *leading reference*, which is the reference that accesses new data first and thus will incur most of the page faults. We also need to identify the *trailing reference*, which is the last reference to touch the data. Only the leading reference is considered when scheduling prefetches, while the trailing reference is used for releases. In this example, $B[j+1][0]$ is the leading reference, and $B[j][0]$ is the trailing reference.

For loops as small as the ones shown in this example, it is probable that the reuse would also result in locality. Section 3.1.3 shows how the compiler determines when reuse leads to locality, using the concept of the *localized iteration space*. Details of how the reuse vector space is computed are given in Appendix A.

3.1.3 Localized Iteration Space. The *localized iteration space* is defined as the set of innermost loops that access less data in a single iteration than the available memory capacity. This definition implies that the localized iteration space includes only those loops for which reuse can result in locality, since if the volume of data accessed in a single iteration is greater than the size of memory, then reuse that occurs in subsequent iterations is unlikely to find the data in memory. The total aggregate data traffic across a particular loop nest is computed by taking the amount of data accessed by each reference and multiplying it by the number of times that reference is seen (i.e., the number of loop iterations), subject to the type of reuse that the reference may have.

The localized iteration space is represented as a vector space so that it can be directly compared with the vector space representation of data reuse, facilitating the computation of data locality.

To illustrate these concepts, we consider the example shown in Figure 3. For this example, we will assume that we have 500 memory pages, that each page contains two array elements, and that the data are laid out in row-major order. The code for Figure 3(a) is identical to that in Figure 2; however, in Figure 3(b) the number of j loop iterations has been increased from eight to 10,000. Iteration space plots are shown only for the $B[j+1][0]$ reference, which has temporal reuse along the outer loop. The localized iteration space for this example is computed by comparing the number of pages accessed by all references against the number of pages in memory.

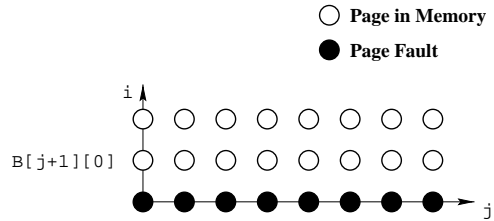
Consider first the $A[i][j]$ reference, which has spatial reuse along the inner loop (since each page contains two array elements) and no reuse along the outer loop (since different columns are being accessed). A single iteration of the j loop will bring one page into memory. To find the number of pages accessed in a single iteration of the outer loop, we simply multiply the number of pages accessed in an inner loop iteration and divide by the spatial reuse factor. Thus, for a single iteration of the outer loop in Figure

(a) Few Iterations in Inner Loop

```

for (i = 0; i < 3; i++)
  for (j = 0; j < 8; j++)
    A[i][j] = B[j][0] + B[j+1][0];

```

**(b) Many Iterations in Inner Loop**

```

for (i = 0; i < 3; i++)
  for (j = 0; j < 10000; j++)
    A[i][j] = B[j][0] + B[j+1][0];

```

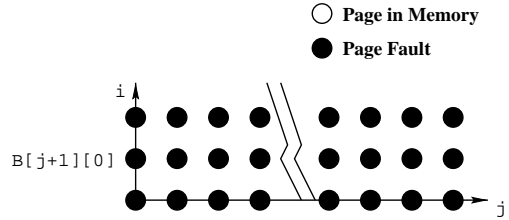


Fig. 3. Example of how loop iteration counts affect locality.

3(a) the $A[i][j]$ reference brings $(8 \times 1)/2 = 4$ pages into memory, whereas in Figure 3(b) $(10,000 \times 1)/2 = 5,000$ pages are brought into memory. To find the number of pages accessed in the entire loop nest by this reference, we simply multiply the pages accessed in a single iteration by the number of iterations (since $A[i][j]$ has no reuse along the outer loop).

For the $B[j][0]$ reference, which has group reuse with the $B[j+1][0]$ reference, only the first iteration of the inner loop (when $j = 0$) causes a new page to be brought into memory. Hence, for both examples in Figure 3, this reference contributes a single page to the total data traffic across the entire loop nest. In practice, because this reference has group reuse its contribution to the total data traffic is expected to be small, and thus the reference is ignored.

Finally, the $B[j+1][0]$ reference, which has temporal reuse along the outer loop, touches a distinct page during each iteration of the inner loop with no savings due to spatial reuse. The number of pages accessed in a single iteration of the outer loop is thus the same as the number of times the inner loop is executed (i.e., 8 for the code in Figure 3(a) and 10,000 for the code in Figure 3(b)). Since this reference has temporal reuse along the outer loop, the total number of pages accessed in the entire loop nest does not increase any further.

By summing each reference's contribution to the total data traffic, we can now determine whether each loop lies within the localized iteration space or not. For the code in Figure 3(a), a single iteration of the j loop brings at most three pages into memory (one for the $A[i][j]$ reference, one for the $B[j][0]$ reference, and one for the $B[j+1][0]$ reference). Since this is much less than our memory capacity of 500 pages, we can conclude that the j loop is within the localized iteration space. Similarly, a single iteration of

the i loop brings only 13 pages into memory (four for $A[i][j]$, eight for $B[j+1][0]$, and one for $B[j][0]$). For this example, both loops are within the localized iteration space. In contrast, for the code in Figure 3(b), a single iteration of the inner loop brings only three pages into memory (as before), while a single iteration of the outer loop brings 15,001 pages into memory (5,000 for $A[i][j]$, 10,000 for $B[j+1][0]$, and one for $B[j][0]$). In this case, only the inner loop is within the localized iteration space.

Once the localized iteration space has been computed and expressed using vector space notation, computing locality is simply a matter of intersecting the reuse vector space with the localized iteration space, i.e.,

$$\begin{aligned} &\text{Reuse Vector Space} \cap \text{Localized Iteration Space} \\ &\Rightarrow \text{Locality Vector Space.} \end{aligned}$$

In practice, a number of considerations complicate the computation of data locality. First, symbolic loop bounds make it difficult to determine the exact amount of data accessed in a loop nest. Aggressive constant propagation can resolve some of these cases, but in other instances the compiler must simply assume unknown loop bounds to be either small (always localized) or large (never localized). Second, the actual amount of memory available at run-time may be quite different from that specified at compile-time, due to the resource demands of other applications. This problem can be handled by underestimating the amount of available memory at compile-time and relying on the run-time layer to reduce the overhead of unnecessary prefetches generated by this approach.

We turn now to the final step in the locality analysis algorithm—converting the vector space representations of data locality into prefetch predicates that can be used for scheduling the prefetches.

3.1.4 The Prefetch Predicate. The purpose of constructing prefetch predicates is to associate a logical predicate which evaluates to “True” whenever a reference is expected to incur a page fault. These predicates can then be used to split loops such that iterations where the predicate has the same value are grouped together, and faulting iterations are isolated. Different predicates are constructed corresponding to each type of locality that a reference may have. For instance, if a reference has no locality, it is expected to page fault on every iteration, and the associated prefetch predicate is simply “True.” A reference with temporal locality with respect to a particular loop will only page fault during the first iteration of that loop; thus the associated predicate is “`loop_index = initial_value`.” A reference that has spatial locality with respect to a given loop will only page fault when page boundaries are crossed. If the number of data elements in a page is l , this will occur whenever “`loop_index mod l = 0`,” which is the prefetch predicate for spatial locality. Finally, references with group locality that are not the leading reference are rarely expected to incur page faults; thus the prefetch predicate is set to “False,” indicating that these references should never be prefetched.

(a)

```

for (i = 0; i < 3; i++)
  for (j = 0; j < 100; j++)
    A[i][j] = B[j][0] + B[j+1][0];

```

(b)

Reference	Locality	Prefetch Predicate
A[i][j]	$\begin{bmatrix} i \\ j \end{bmatrix} = \begin{bmatrix} \text{none} \\ \text{spatial} \end{bmatrix}$	$(j \bmod 2) = 0$
B[j+1][0]	$\begin{bmatrix} i \\ j \end{bmatrix} = \begin{bmatrix} \text{temporal} \\ \text{none} \end{bmatrix}$	$i = 0$
B[j][0]	$\left(\begin{array}{c} \text{Group with} \\ \text{B[j+1][0]} \end{array} \right)$	<i>False</i>

Fig. 4. Example of how prefetch predicates are constructed.

To calculate the overall prefetch predicate for a reference within a multilevel loop, we first construct the predicate with respect to each surrounding loop and then take the conjunction of all these predicates. Figure 4(b) shows an example of how prefetch predicates are constructed for the given code. For instance, the $A[i][j]$ reference has spatial locality with respect to the j loop, and each page contains two array elements, yielding a predicate of “ $j \bmod 2 = 0$.” This reference has no locality with respect to the i loop, giving a predicate of “True.” Taking the conjunction of these two predicates, the overall prefetch predicate for $A[i][j]$ is simply “ $j \bmod 2 = 0$.” The other two references are handled in a similar fashion, and the results are shown in Figure 4.

The reasoning applied to the locality vector space representation to construct prefetch predicates can also be applied to determine when data are no longer needed and can thus be released. In general, the instances when we want to release pages are closely related to when we need to prefetch them. For example, a reference with no locality needs to be prefetched *before* every use, and can be released *after* each use (since it will not be used again). A reference with temporal locality needs to be prefetched before the *first* loop iteration, and can only be released after the *last* iteration. For spatial locality, we prefetch before the first reference to a new page, and release after the last reference to that page. For references with group locality, we need to prefetch ahead of the leading reference and release after the trailing reference.

After constructing the prefetch predicates, the compiler needs to schedule prefetches for the references that are expected to incur page faults (i.e., those for which the predicate evaluates to true), and releases for data that are no longer being used. The next section describes how loop splitting techniques are applied to transform loops and isolate faulting references, and how software pipelining is used to schedule prefetches the right amount of time before the expected reference.

(a) Code Before Peeling <pre> for (i = 0; i < n; i++) { if (i == 0) f(i); g(i); if (i == n-1) h(i); } </pre>	(b) Code After Peeling <pre> f(0); g(0); for (i = 1; i < n-1; i++) { g(i); } g(n-1); h(n-1); </pre>
--	---

Fig. 5. Example of peeling the first and last iterations of a loop.

3.2 Scheduling Prefetches

Most of the changes made to the original compiler algorithm for prefetching [Mowry 1994] are related to how loops are split and how prefetch and release operations are scheduled. The objectives of the scheduling phase are twofold: first, we want to issue prefetches early enough that the requested data are found in memory when they are needed; second, we want to minimize the overhead associated with issuing prefetch and release requests. To minimize overhead, we apply two techniques. First, we isolate faulting references by splitting loops to avoid introducing conditional statements in inner loops. This technique was developed for cache prefetching and remains an important optimization. Second, we attempt to minimize the number of times the application/system boundary is crossed, since the cost of making a system call contributes greatly to the software overhead of issuing prefetches.

In the following subsections, we discuss how prefetch and release operations are scheduled, and emphasize the changes required for I/O prefetching.

3.2.1 Loop Splitting Techniques. The purpose of loop splitting is to isolate statically all iterations in which the prefetch predicate for a particular reference has the same value. Once this has been done, there is no need to evaluate the predicate to decide when to prefetch—we either always prefetch at a given static point in the code, or never prefetch. Just as a different predicate was constructed for each type of locality, a different splitting technique is applied for each type of predicate.

The simplest case is if the prefetch predicate is either “True” or “False”; no transformation is required, since the loop is already in a form where we either always prefetch or never prefetch.

For temporal locality, the predicate is “loop_index = 0”; we need to prefetch during the first iteration and release during the last iteration. In this case, we would isolate the instances where we need to prefetch and the instances where we need to release by *peeling* the first and last iterations respectively. An example of the effect of this transformation on a generic loop is shown in Figure 5.

For spatial locality, the predicate is “loop_index mod l = 0”; we need to prefetch and release once every l iterations. With cache prefetching, the preferred technique was to replicate the body of the loop l times, using *loop*

```

(a) Original Code
    for (i = 0; i < n; i++) {
        if ((i mod 64) == 0)
            f(i);
        g(i);
        if ((i mod 64) == 0)
            h(i);
    }

(b) Code After Unrolling
    for (i = 0; i < n; i+=64) {
        f(i);
        g(i);
        g(i+1);
        g(i+2);
        ...
        g(i+63);
        h(i);
    }

(c) Code After Strip-Mining
    for (j = 0; j < n; j+=64) {
        f(j);
        for (i = j; i < j+64; i++)
            g(i);
        h(j);
    }

```

Fig. 6. Example of unrolling and strip-mining a loop by a factor of 64.

unrolling. However, for I/O prefetching l may be large (typically several hundred or thousand elements will fit on a page), and the preferred technique is to *strip-mine* the loop by a factor of l , since replicating the loop body several hundred times is unreasonable. Examples of both unrolling and strip-mining are shown in Figure 6. These large strip-mining factors lead to one additional complication: if a given loop nest accesses less than a full page of data, it will be impossible to strip-mine the loop. Since many items fit on a page, it is quite likely that the innermost loop, and even several surrounding loops, will not access enough data to make strip-mining feasible. In contrast, with cache prefetching it was extremely unlikely that a loop would access less data than a cache line; thus it was reasonable to focus on the innermost loop. We also need to be more careful about scheduling for these types of references, as will be discussed in more detail in the following section.

These loop splitting techniques can be applied recursively to nested loops to handle multiple prefetch predicates. One possible area of concern is the amount of code expansion that results from repeatedly replicating loops. Increasing the code size may have a negative impact on the instruction cache as well as on the ability of compilers to optimize the code. To manage these concerns, the original compiler algorithm records how large a loop is growing and suppresses transformations that replicate the loop body (e.g., peeling) when it becomes too large. In our experiments, however, we have found that the benefits of successfully prefetching needed pages from disk far outweigh the harmful effects of code expansion.

3.2.2 Software Pipelining. For prefetches to be effective, they should be issued early enough that the data arrive in memory before they are needed, but not so early that they risk being replaced before they are used. To hide

(a) Original Loop

```
for (i = 0; i < 100000; i++)
    A[i] = 0;
```

(b) Software Pipelined Loop

```
prefetch_block(&A[0], 24);           /* Prolog */

for (i1 = 0; i1 < 88064; i1 += 2048) { /* Steady State */
    prefetch_block(&A[i1+12288], 4);
    for (i = i1; i < i1 + 2048; i++) { /* Strip-mined loop */
        A[i] = 0;
    }
    release_block(&A[i1], 4);
}

for (i = 88064; i < 100000; i++)     /* Epilog */
    A[i] = 0;
release_block(&A[88064], 24);
```

Fig. 7. Example of how software pipelining is used to schedule prefetches the proper amount of time in advance. For this example, 12,288 iterations are required to hide I/O latency.

the latency of disk accesses, we overlap prefetches for a future iteration with the computation of the current iteration using a technique called *software pipelining* [Lam 1988]. A simple example of this technique is shown in Figure 7. The important part of the software pipeline is the *steady state*, where we have both prefetches issued and computation performed. The *prolog* section is used to initialize the pipeline, while the *epilog* performs the last few iterations where prefetching is no longer needed.

Given that loop iterations are used as the unit of scheduling in the pipelining algorithm, two key issues need to be resolved to schedule prefetches effectively. The first issue is unique to I/O prefetching: how to choose the proper loop across which to pipeline in the presence of multiple loop nests. As discussed in Section 3.2.1 with regard to strip-mining, it is possible that several levels of loop nests access less than a page of data. Not only is it impossible to strip-mine these loops, attempting to software pipeline across them is also ineffective, since the pipeline never gets into the steady state. The second issue, common to both cache and I/O prefetching, is determining the *prefetch distance* (i.e., the number of iterations in advance that prefetches should be issued).

To illustrate how the proper choice of pipeline loop is affected by the presence of small loop bounds, it is useful to first look at an example of how software pipelining is used to transform code and schedule prefetches. We will thus tackle the problem of finding the prefetch distance first, and examine a simple example of how prefetches are scheduled. We will then consider a slightly more complicated example, where the correct choice of pipeline loop is essential to scheduling the prefetches effectively.

3.2.2.1 Finding the Prefetch Distance. Given the amount of latency that needs to be hidden, the problem of finding the prefetch distance (in terms of

the number of iterations of the pipeline loop) is simply a matter of determining how much computation is needed. If the latency is expressed as a number of cycles, and we assume that each instruction takes a single cycle, then the number of iterations required, d is given by

$$d = \left\lceil \frac{l_m}{s + l_p} \right\rceil \quad (1)$$

where d is the prefetch distance, l_m is the expected I/O latency, s is the number of instructions in the shortest path through the loop body, and l_p is the software overhead introduced by adding a prefetch instruction to the loop body. In general, it is impossible to determine exactly how many instructions will be executed; however, we choose the shortest path to ensure that prefetches are issued early enough. The prefetch overhead latency parameter, l_p , is used to more closely approximate the time spent executing a loop iteration *after* a prefetch request is inserted in the loop. This consideration is especially important for short loop bodies, since the time spent issuing the prefetch can be a significant fraction of the time to execute an iteration. The ceiling of the ratio is used to ensure that all of the latency is hidden.

Figure 7 shows a simple example of how prefetches and releases are scheduled using software pipelining. For this example, we have chosen parameters that correspond to our experimental architecture: the page size is 4,096 bytes; the I/O latency is 100,000 cycles; and the prefetch latency is 10,000 cycles. Since the `A[i]` reference has spatial locality, the `i` loop is first strip-mined into loops `i1` and `i` using a block size of four pages. Using Eq. (1), the compiler then determines that six iterations of the outer `i1` loop (with a prefetch call added) are needed to fully hide the I/O latency. To initialize the pipeline, a *prolog* is constructed to prefetch the first 24 pages in a single block prefetch call, thus minimizing system call overhead. This is in contrast to cache prefetching where a *prolog loop* would have been constructed to request each page independently. Next, the *steady state* loop is executed. In this loop, blocks of four pages are prefetched in every iteration of the `i1` loop, and used in the inner `i` loop. After each block of pages has been used, block release calls are issued to free the pages. Finally, the *epilog* loop performs the final iterations of computation, after which a block release call frees the last block of pages. This example presents a somewhat idealized version of how release requests are scheduled. In practice, we are also concerned about reducing the number of system calls; hence release operations are bundled with prefetches in a single call whenever possible. When there is no prefetch with which to bundle the release, we simply suppress issuing it.

Now that we have seen how software pipelining schedules prefetches using *prolog*, *steady state*, and *epilog* sections, we return to the question of how to select the right loop across which to pipeline.

3.2.2.2 Choosing the Pipelining Loop. Ordinarily, prefetches are software pipelined around the innermost loop nest that changes the value of the array-indexing function (i.e., the first loop that changes the address referenced). For example, in Figure 8(a) the m loop would be chosen as the pipeline loop. Also, since the m loop has spatial locality, we would like to request blocks of four pages with each prefetch. Since each iteration of the m loop accesses only 20 bytes of data, it would take 820 m loop iterations to cover a four-page block, which means that strip-mining is not performed, since only five iterations are available. Using Eq. (1), the compiler determines that prefetches need to be issued roughly 12,000 m loop iterations ahead, causing a block prefetch for 12 pages to be inserted for the prolog section of the pipeline, as shown in Figure 8(b). Now, since the spatial locality of the $A[i][j][k][l][m]$ reference suggests that we only need to prefetch every 820 m loop iterations, and since there are only five iterations in the code, the steady state and epilog sections of the pipeline are not created. The effect is that when new pages are prefetched at all the request is issued just before entering the m loop as part of the prolog, but are never early enough to be useful. The fundamental problem is that the pipeline never gets into the steady state.

To cope with this problem, we modified the scheduling part of the algorithm to consider the amount of data actually used in what would ordinarily be chosen as the pipeline loop. If the pipeline loop has spatial locality, and the total data traffic across *all* iterations of that loop is less than a block (i.e., four pages in our experiments), then we choose the next surrounding loop nest as the pipeline loop instead. We apply this heuristic recursively until a loop that accesses more than a block of data or the outermost loop is found. The result of this modification is shown in Figure 8(c), where prefetches are software pipelined across the j loop, rather than the m loop. It is now possible to schedule prefetches early enough to hide all the latency.

3.2.2.3 Scheduling Indirect Prefetches. Indirect references such as $A[\text{index}[i]]$ are assumed to have no locality; hence it is not necessary to perform any loop splitting transformations (i.e., the prefetch predicate is always “True”). Indirect prefetches are scheduled using software pipelining in the same manner as direct prefetches, with one minor modification. In addition to fetching the indirect reference itself ($A[\text{index}[i]]$), it may also be necessary to schedule a prefetch for the indexing reference, $\text{index}[i]$. The indexing reference is treated like any other reference for the purposes of determining locality; however, for scheduling, it needs to be prefetched early enough to be used in the *prefetch* of the indirect reference, rather than in the indirect reference itself. More details on prefetching indirect references are given in Mowry’s thesis on cache prefetching [Mowry 1994].

3.2.2.4 A More Detailed Example. Figure 9 shows an example of the output of our compiler for a simple loop body (notice that it is able to prefetch the indirect $a[b[i]]$ reference as well as the dense $b[i]$ and $c[i][j]$ references). Notice that loop i has been strip-mined twice (into

(a) Sample Code Without Prefetching

```

for (i = 0; i < 64; i++) {
  for (j = 0; j < 64; j++)
    for (k = 0; k < 64; k++)
      for (l = 0; l < 5; l++)
        for (m = 0; m < 5; m++)
          A[i][j][k][l][m] = 0;
}

```

(b) Code After Software Pipelining (original)

```

for (i = 0; i < 64; i++) {
  for (j = 0; j < 64; j++)
    for (k = 0; k < 32; k++)
      for (l = 0; l < 5; l++) {
        prefetch_block(&A[i][j][k][l][0], 12);    /* Prolog */
        for (m = 0; m < 5; m++)
          A[i][j][k][l][m] = 0;
      }
}

```

(c) Code After Software Pipelining (new)

```

for (i = 0; i < 64; i++) {

  prefetch_block(&A[i][0][0][0][0], 12);          /* Prolog */

  for (j0 = 0; j0 < 45; j0 += 5) {                /* Steady State */
    prefetch_block(&A[i][j+19][0][0][0], 4);
    for (j = j0; j < j0 + 5; j++)
      for (k = 0; k < 32; k++)
        for (l = 0; l < 5; l++)
          for (m = 0; m < 5; m++)
            A[i][j][k][l][m] = 0;
  }

  for (j = 45; j < 64; j++)                        /* Epilog */
    for (k = 0; k < 32; k++)
      for (l = 0; l < 5; l++)
        for (m = 0; m < 5; m++)
          A[i][j][k][l][m] = 0;
}

```

Fig. 8. Example of software pipelining with small loop bounds.

loops i_0 and i_1) to account for the spatial locality of $b[i]$ and $c[i][j]$. (The i loop has been strip-mined twice, since $c[i][j]$ accesses data more quickly than $b[i]$, and therefore needs to be prefetched at a faster rate.) Second, to fully exploit the available bandwidth in our I/O subsystem, we prefetch several pages at a time for references with spatial locality (e.g., four pages are fetched at a time for $b[i]$ and $c[i][j]$). Similarly, we convert the prolog loops from the original algorithm into block prefetches

(a) Original Code

```

int a[1000000];
int b[1000000];
int c[1000000][8];

for (i = 0; i < 1000000; i++)
    for (j = 0; j < 8; j++)
        a[b[i]] = a[b[i]] + c[i][j];
    
```

(b) Code with Prefetching

```

prefetch_block(&b[0], 8);
prefetch_block(&c[0][0], 4);
for (i = 0; i < 128; i++)
    prefetch(&a[b[i]]);
/* Note: 995328 = ( $\lfloor \frac{1000000}{4096} \rfloor - 1$ ) * 4096 */
for (i1 = 0; i1 < 995328; i1 += 4096) {
    prefetch_release_block(&b[i1+8192], &b[i1-1], 4);
    for (i0 = i1; i0 < i1 + 4096; i0 += 512) {
        prefetch_release_block(&c[i0+512][0], &c[i0-1][0], 4);
        for (i = i0; i < i0 + 512; i++) {
            prefetch(&a[b[128+i]]);
            for (j = 0; j < 8; j++)
                a[b[i]] = a[b[i]] + c[i][j];
        }
    }
}
for (i = 995328; i < 1000000; i++)
    for (j = 0; j < 8; j++)
        a[b[i]] = a[b[i]] + c[i][j];
    
```

Fig. 9. Example of the output of the prefetching compiler. The first argument to all prefetch calls is the prefetch address; the second argument to `prefetch_release_block` is the release address; the final argument to “block” versions is the number of 4KB pages to be fetched and/or released.

whenever possible, as shown in the first two lines of Figure 9(b). For references without spatial locality—e.g., `a[b[i]]`—we prefetch only a single page at a time. Also notice how the `b[i]` reference is prefetched well in advance of the prefetch for `a[b[i]]` so that the data will be available to compute the prefetch address. Finally, this example also shows how we bundle prefetch and release requests together whenever appropriate, to minimize the number of system calls.

4. EXPERIMENTAL FRAMEWORK

We now describe our experimental platform including the hardware platforms and the operating system and run-time support in each system, the compiler framework used, and the applications which we study in our experiments. Both of our hardware platforms are NUMA (nonuniform memory access) shared-memory multiprocessors; however, the specific memory model is unimportant to these experiments (all we require is support for virtual memory). Our choice of systems was motivated primarily

Table I. Hector/Hurricane Characteristics

Hardware Characteristics Processor		Software Characteristics Kernel Operation Overhead	
Processor type:	Motorola 88100	IPC request:	70 μ sec
Clock rate:	16.67MHz	In-core fault:	200 μ sec
Data cache size:	16KB	Out-of-core fault:	800 μ sec
Instruction cache size:	16KB	Base prefetch:	60 μ sec
Physical Memory		+ per out-of-core page:	200 μ sec
Total size:	64MB	+ per in-core page:	30 μ sec
Available to application:	48MB	+ per in-page table page:	10 μ sec
Disks		File System Operation Overhead	
Number of disks:	7	Prefetch (per-page):	70 μ sec
Maximum transfer rate:	640 KB/sec	Read/Write (per-page):	70 μ sec
Average rotational latency:	8.61 msec		
Track-to-track seek time:	5 msec		

by the availability of operating system source code and support from the authors of the operating systems. A secondary consideration was support for high-bandwidth I/O subsystems. In both of our experimental setups, each out-of-core benchmark is executed alone on the system, thus eliminating variations in the amount of available memory and contention at the disks due to other applications.

4.1 Research System Infrastructure

The first experimental platform used to evaluate our scheme is the Hurricane File System (HFS) [Krieger and Stumm 1997] and Hurricane operating system [Unrau et al. 1995] running on the Hector NUMA (nonuniform memory access) shared-memory multiprocessor [Vranesic et al. 1991]. Hurricane is a hierarchically clustered, microkernel-based operating system that is mostly POSIX compliant. The Hurricane microkernel provides basic interprocess communication and memory management facilities, including support for mapped file I/O. Most of HFS is implemented outside of the microkernel as a user-level server. HFS implements files using *building blocks* to specify the structure of the file and the file system policies applied to a file [Krieger and Stumm 1997]. Applications are allowed to specify the structure of the file (for instance, the layout of data across the disks) at creation time, and to dynamically change the policies applied when using a file (for example, for replicated files, the application can specify which replica should be used). The basic characteristics of our experimental platform (with the instrumentation disabled) are shown in Table I, and more detailed descriptions of the platform can be found in earlier publications [Krieger and Stumm 1997; Unrau et al. 1995; Vranesic et al. 1991].

Our experiments are performed on a 16-processor Hector prototype with seven Conner CP3200 disks attached to it. Each disk is directly attached to

a different processor, and the local processor is responsible for initiating all requests to its disk and servicing all interrupts from its disk. For all experiments shown in subsequent sections, the pages of the applications are striped by the file system round-robin across all seven disks. An extent-based policy is used to store the file on each of the disks, where contiguous file blocks are stored to contiguous blocks on the disk to avoid seek operations for sequential file accesses. We chose to evaluate our ideas under this system primarily because we had access to the source code for Hurricane and were able to modify it to support the required operations and to provide detailed information on system-level activities. The fact that the hardware platform is a multiprocessor is largely irrelevant: the key feature is the disk array that provides our applications with the bandwidth that they require.

Hurricane supports our approach in the following three ways. First, when a prefetch request is received by the operating system, the kernel checks to see if the specified page is already in memory (or if another read request for that page has already been scheduled). If the page is not in memory, then (1) the memory manager allocates a physical page from the free list to hold the file data, (2) an asynchronous read request is sent to the Hurricane file system, and (3) control is returned to the application. The disk scheduler treats prefetches the same as normal disk read requests (both read and prefetch requests are serviced ahead of write requests). In the event that there are no pages on the free list, the memory manager drops the prefetch request and clears the corresponding bit in the shared bit vector to indicate that the requested page has not been fetched. We believe this to be a reasonable strategy, since prefetch requests are non-binding performance hints that do not need to be satisfied for program correctness. Also, we want to encourage prefetching applications to balance their memory requirements by explicitly releasing pages that they no longer need—thus, when all memory is in active use it is better to drop the prefetch than risk replacing data that will be needed before the prefetched data. Second, when a release request is received, the kernel removes the mapping for that page from the process' page table (and from the TLB if necessary) and places the page at the end of the free list. We choose to place explicitly released pages at the end of the free list rather than at the head so that they can be reclaimed easily if imperfect compiler analysis causes the page to be released too early. Third, the operating system supports the shared bit vector as follows.

The operating system agrees to provide a user-level process with a single 4KB page of physical memory that can be used as a map of the process' virtual address space. Since only a single page will be provided, the *granularity* of the bit vector must be established. For instance, with a 4KB page size and each bit representing a single page, the bit vector is capable of tracking only 2^{15} pages of virtual memory or 134MB of data. If the application accesses more data than can be represented with a single bit per page, then each bit must represent multiple pages, and both the

operating system and the run-time layer must agree on the granularity to use. In general, either the operating system or the run-time layer could decide on the appropriate granularity and inform the other layer of the choice; in our implementation the decision is made by the run-time layer. The granularity of the bit vector needs to be considered by both the run-time layer and the operating system, not only to ensure that the right bits are set, but also to ensure that the bit vector remains useful for the purposes of the run-time layer. For example, if the compiler schedules a prefetch request for a single page the corresponding bit is set, then it will appear as if all pages in the same *group* (i.e., all pages represented by the same bit) are already in memory. The result is that a prefetch request for another page in that group will be filtered out by the run-time layer. The same problem can occur when the operating system sets bits for pages brought into memory through page faults. In our implementation we handle granularities greater than a single page as follows. The run-time layer asks the operating system to prefetch *all* the pages in a group whenever a prefetch is needed for *any* page in that group, thus preserving the notion that the pages are in memory if the corresponding bit is set. In turn, when a single page is brought into memory due to a page fault the operating system does not set the bit, allowing the run-time layer to still issue prefetch requests for the other pages in the group.

When a prefetching application is executed, the run-time layer binds a page-sized region of memory to a fixed virtual address to use as the bit vector. Information about the size of mapped files is used to set the granularity of the bit vector. Next, a system call passes the starting virtual address and the granularity of the bit vector to the operating system, which records the physical page corresponding to the specified virtual address and the granularity in the process' address space descriptor. At this point, the operating system and the run-time layer have agreed on which page will be shared and how it will be used to map the process's virtual address space. The operating system can now set bits in the vector whenever the process page faults or prefetches, and clear them whenever pages belonging to the process are unmapped.

In addition to adding prefetch and release operations to Hurricane and supporting the shared page, we also added extensive instrumentation to enable us to observe the effect of each static prefetch request. Each static prefetch instruction in the code is given a unique identifier by the compiler. This identifier is passed to the kernel together with the prefetch address and the number of pages to fetch. When a prefetch request is received by the kernel, we record the requested address, the time the request was received, and the identifier of the static prefetch instruction in a *prefetch record*. When a page fault occurs, the kernel checks if the faulting page was prefetched, and updates a set of counters based on the result. This technique allows us to observe the success rate of each static prefetch instruction added to the code by the compiler, and was essential for us to be able to identify the parts of the compiler algorithm that needed to be modified to handle I/O prefetching efficiently. This instrumentation is also

Table II. SGI Origin 200 Characteristics

Processor	
Processor type:	MIPS R10000
Number of Processors:	4
Clock rate:	180MHz
Physical Memory	
Total size:	128MB
Available to application:	75MB
Page size:	16KB
Disks	
Manufacturer:	Seagate
Model:	Cheetah 4LP
Number of disks used for swap:	10
Maximum external (I/O) transfer rate:	40MB/sec/disk
Average rotational latency:	2.99 msec
Track-to-track seek, read:	18 msec (typical)
Track-to-track seek, write:	19 msec (typical)
Number of SCSI controllers:	5
Disks per controller:	2

used to produce the detailed statistics shown in the Hurricane results sections (Sections 5.1–5.5).

4.2 Commercial System Infrastructure

To further validate our scheme for tolerating page fault latency in out-of-core applications, we also implemented our operating system support and run-time layer on a current commercial system. We used a four-processor SGI Origin 200 [Laudon and Lenoski 1997], running our modified version of the IRIX 6.5 operating system to obtain our commercial system results. The system was configured so that approximately 75MB of physical memory was available to user programs, and the system swap space was striped across 10 Seagate Cheetah 4LP disks using raw swap partitions. Five SCSI adapters each control two of these 10 disks; the SCSI adapters are in turn connected to the PCI busses on the Origin. The basic hardware characteristics of our system are summarized in Table II.

We have implemented support for user-level paging directives (i.e., prefetch and release) within the SGI IRIX 6.5 operating system. IRIX 6.5 supports a Memory Management Control Interface, which consists of policy modules that allow users to select various policies for page size, allocation, migration, and replication. A policy module may be connected to any range of an application’s virtual address space, down to the level of a single page. We have defined a new policy module—called “PagingDirected”—that allows a user-level process to invoke prefetch and release operations on pages of its address space associated with this policy. In addition, the PagingDirected policy module shares information about memory usage with the application through a single 16KB page. This page is allocated by

the operating system and mapped read-only into the application's address space when the PagingDirected policy module is created. The page is used primarily as a bitmap, indexed by virtual page number, in which bits are set to indicate that the corresponding page is in memory, and cleared otherwise.

When the PagingDirected policy module receives a request to prefetch a page, it performs actions similar to those that occur for a page fault, with two notable exceptions. First, if there is no free memory available to allocate for the prefetched data, the prefetch request is discarded immediately. Second, when the request completes, the prefetched page is not fully validated, and no entry is made in the TLB. The second feature prevents mappings for prefetched (and not yet referenced) pages from displacing TLB entries which are still in use.

Requests to release pages are handled by passing the released addresses to a new system-releasing daemon—called the releaser—which is similar in function to the paging daemon, but is specialized to reclaim only the pages specified by the application. When a release request is made, the PagingDirected policy module clears the bits for the pages and enters the request in the releaser's work queue. The releaser handles requests from each prefetching/releasing application as they are received, first checking the bit vector to make sure that the pages have not been referenced again (either by a prefetch or a real reference) between the time that the application made the request and the time that the request is handled. The releaser then performs all actions needed to free the pages, including the allocation of swap space and writing back dirty pages if necessary. Released pages are placed at the end of the free list, so that they will not be reallocated for another purpose immediately. This strategy gives pages that were released too early a chance to be rescued from the free list.

All updates to the shared page are handled by the operating system. When the PagingDirected policy module is created, all bits in the shared page are initially set. When the application attaches the policy module to a region of its virtual address space, the bits corresponding to those addresses are all cleared. Thereafter, bits are set whenever a physical page is allocated for a virtual page associated with this policy module, either due to prefetch requests or ordinary page faults. Bits are cleared when pages are reclaimed, either by an explicit release request or due to default page replacement activity. Note, that since the base page size in IRIX 6.5 is 16KB, we are able to represent 2GB of memory using a granularity of one page per bit, which is sufficient for a 32-bit address space. For 64-bit address spaces that are expected to be sparsely populated, a multilevel bit vector scheme may be more appropriate than requiring a single bit to represent multiple pages.

To achieve the full benefit of prefetching, we need to be able to both fetch data asynchronously (so the application can continue after issuing the prefetch) and take advantage of any available parallelism in the underlying disk subsystem. The run-time layer accomplishes these requirements by creating a number of *Pthreads* [IEEE 1992] that make the actual calls to

Table III. Description of Applications

Name	Description
BUK	integer bucket sort algorithm
CGM	solves an unstructured sparse linear system using the conjugate gradient method
EMBAR	Monte Carlo simulation
FFT	3D FFT PDE, performs forward and inverse FFTs
MGRID	computes 3D scalar potential field on a uniform cubical grid using a multigrid solver
APPLU	solves four coupled parabolic elliptic PDEs using SSOR method to invert jacobian matrix
APPSP	solves five coupled parabolic elliptic PDEs using diagonalized approximate factorization method
APPBT	solves three coupled parabolic elliptic PDEs using block approximate factorization method

the PagingDirected policy module and wait for the prefetches to complete. When a prefetch request inserted by the compiler is intercepted by the run-time layer, the bit vector is first checked to see if a prefetch is really needed. Then, if necessary, the request is placed on a work queue, and then one of the prefetching threads is signaled to handle the request. The prefetching threads simply remove requests from the queue and issue them to the PagingDirected policy. This Pthreads-based approach to achieving asynchronous prefetching is very similar to the implementation of the asynchronous I/O library in IRIX.

4.3 Compiler Framework and Benchmark Applications

We implemented our prefetching algorithm as a pass in the SUIF (Stanford University Intermediate Format) compiler [Tjiang and Hennessy 1992]. The output from the SUIF compiler is C code containing prefetch and release calls (as illustrated earlier in Figure 2(b)). We also use the SUIF compiler to convert the original Fortran source code of each application into C code for the original, nonprefetching versions that we use in our experiments. We then compile the resulting C code into an executable for our target system using gcc version 2.5.8 (with the -O2 optimization flag set) for the Hurricane system and SGI's MIPSpro compilers version 7.2.1 (with the -O3 optimization flag set) for the IRIX system. During the second compilation step, the prefetching versions are linked to a set of library routines that implement the run-time layer support. Routines to check and set the bit vector to filter prefetch requests are inlined for performance.

To evaluate the effectiveness of our approach, we measured its impact on the performance of the entire NAS Parallel benchmark suite [Bailey et al. 1991]. We chose these applications because (1) they represent a variety of different scientific workloads, (2) their data sets can easily be scaled up to out-of-core sizes, and (3) they have not been written to manage I/O explicitly. Our goal is to show that these scientific benchmarks can achieve high performance with out-of-core data sets without requiring any extra effort to rewrite the program.

A brief description of each of the benchmarks is given in Table III. BUK sorts a large array of integers using the *bucket sort* algorithm and contains both direct and indirect references. This program illustrates a number of features of I/O prefetching, yet is easy to understand and is thus the subject of the case study in Section 5.5. CGM is an example of a sparse-matrix computation; it also contains both direct and indirect references. EMBAR has an extremely simple data access pattern—it repeatedly references a single large array to perform a Monte Carlo simulation. MGRID, in contrast, has a very interesting access pattern, despite all the references being direct. In this application, a wavefront moves through a uniform three-dimensional grid representing a potential field. At each point, a computation is performed using the center of the wavefront and the 27 nearest neighboring points (i.e., 6 points that differ by one in only one index, 12 points that differ by one in exactly two of the indices, and 8 points that differ by one in all three indices) [Bailey et al. 1991]. Although the references are all regular, and the pattern is detectable by the compiler, it would be extremely difficult to identify the pattern dynamically in the operating system. FFT solves three-dimensional partial differential equations using both forward and inverse fast-Fourier transforms. The data set is accessed in a different order as this application switches between forward and inverse FFT phases. Finally, APPLU, APPSP, and APPBT all solve systems of coupled partial differential equations, using different methods. The structure of these three applications is similar, although they manage their data in slightly different fashions. The common characteristic that is important in our experiments is that they all use multidimensional loops in which the innermost dimensions are very small.

Because Hurricane is a research operating system, it does not contain all the functionality that is required of a commercial system. In particular, it does not have support for writing and reading virtual memory pages to and from swap space. Instead, we needed to modify these benchmark programs to use mapped files to provide the backing storage space for their data in the Hurricane experiments. For the IRIX experiments, no changes were made to the benchmarks, other than increasing the size of their data sets. Characteristics of the benchmarks as used in each experimental setup are given in Sections 5.1 and 5.6.

5. EXPERIMENTAL RESULTS

We now present the results of our experiments, first looking in-depth at the results on our research platform, then presenting our results on the commercial system. We begin by focusing on the impact of our scheme on overall execution time. We then look at the performance from a system-level perspective, including the effects on disk and memory utilization. Section 5.3 examines the effectiveness of the compiler and the run-time layer at scheduling prefetches and reducing overhead. In Section 5.4 we look at the effect of varying problem sizes on our results. Section 5.5

Table IV. Application Characteristics on Hurricane

Name	Input Data Set	Memory Required		Original Execution Time (mins)
		Absolute	% of Available	
BUK	2^{23} 19-bit integers	103MB	215%	21.0
CGM	sparse matrix with 7,607,024 nonzeros	103MB	215%	57.2
EMBAR	2^{24} random numbers	134MB	279%	53.9
FFT	128 x 128 x 128 matrix of complex numbers	117MB	244%	87.9
MGRID	128 x 128 x 128 matrix	58MB	121%	31.9
APPLU	5 x 5 x 64 x 64 x 32 matrices	120MB	250%	48.9
APPSP	90 x 90 x 90 matrices	117MB	244%	224.3
APPBT	5 x 5 x 64 x 64 x 32 matrices	94MB	196%	85.2

presents a detailed case study of one of the applications (BUK). Finally, we present our IRIX results in Section 5.6.

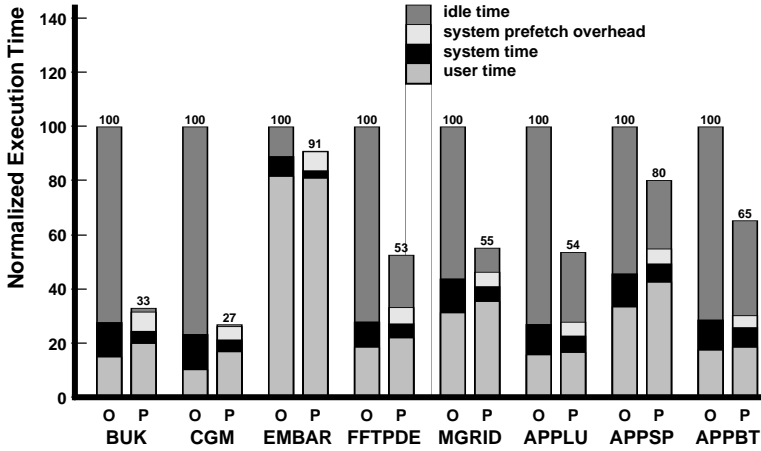
5.1 Overall Performance on the Research System

Table IV gives basic characteristics of the NAS Parallel benchmarks as executed on the Hurricane platform, including a description of the data set, the total amount of memory required (both in megabytes and as a percentage of the physical memory available), and the absolute time required to execute the original nonprefetching versions.

Figure 10(a) shows the overall performance improvement achieved through our automatic prefetching scheme. For each application, we show two bars representing normalized execution time: the original program relying simply on paged virtual memory to perform its I/O (**O**), and the program once it is compiled to prefetch and release data explicitly (**P**). In each bar, the top section is the amount of time when the processor was idle, which corresponds roughly to the I/O stall time, since we run only a single application during these experiments. The bottom section of each bar is the time spent executing in user mode—for the prefetching experiments, this includes the instruction overhead of issuing prefetches, including any overhead in the run-time layer of checking the bit vector to filter out unnecessary prefetches. The middle sections of each bar are the time spent executing in system mode. For the original programs, this is the time required for the operating system to handle page faults; for the prefetching programs, we also distinguish the time spent in the operating system performing prefetch operations.

As we see in Figure 10(a), the speedup in overall performance ranges from 9% to 270%, with the majority of applications speeding up by more than 80%. Figure 10(b) presents additional information on page faults¹ and stall time. As we see in Figure 10(b), more than half of the I/O stall time

¹Throughout this discussion, we will refer to page faults that cause the application to stall waiting for I/O simply as faults, and ignore page faults for in-core data.



(a)

Benchmark	Original		With Prefetch		
	Total Faults (x1000)	Avg. Stall Time (msec)	Total Faults (x1000)	Avg. Stall Time (msec)	I/O Stall Reduction (%)
BUK	41.529	24.5	0.810	16.1	98.7%
CGM	135.066	22.0	0.207	26.5	99.8%
EMBAR	65.535	7.7	0.005	13.5	100.0%
FFT	135.646	31.1	28.432	39.3	73.6%
MGRID	62.231	19.9	7.642	24.2	85.1%
APPLU	91.220	26.3	31.663	26.4	65.2%
APPSP	412.234	20.5	143.996	26.2	55.4%
APPBT	156.172	26.2	77.035	25.6	51.9%

(b)

Fig. 10. Overall performance improvement from prefetching on Hurricane. (a) Execution time breakdown (O = original, P = with prefetch), (b) I/O stall statistics.

has been eliminated in seven of the eight applications, with three applications eliminating over 98% of their I/O stall time.

Having established the benefits of our scheme, we now focus on the costs. Figure 10(a) shows that the instruction overhead of generating prefetch addresses and checking whether they are necessary in the run-time layer causes less than a 20% increase in user time in five of the eight applications—in the worst case (CGM), the user time increases by 70%. However, in all cases this increase is quite small relative to the reduction in I/O stall time. If we focus on the system-level overhead of performing prefetch operations, we see in Figure 10(a) that in most cases this overhead is directly offset by a reduction in system-level overhead for processing page faults. Hence the overheads of our scheme are low enough to translate into significant overall performance improvements in all of these applications.

We wish to emphasize that all of these results are fully automatic—we have not rewritten any of the applications or modified the code generated by the compiler. Having discussed the performance from a high-level perspective, we now look at the impact of explicitly prefetching and releasing data on system resources.

5.2 Disk and Memory Utilization

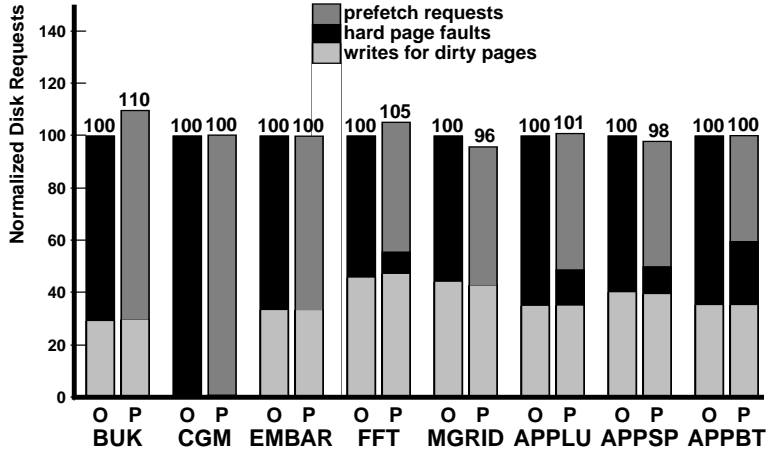
In Figures 11(a) and (b) we break down the types of requests seen by the disks and show average disk utilization during execution for both the original and prefetching versions of the applications. In almost all cases, the total disk requests do not increase as a result of prefetching, and for two of the applications they actually decrease, as prefetches prevent the system from writing out dirty pages that will be referenced again soon. Hence, the increased disk utilization shown in Figure 11(b) is simply due to the fact that we are performing roughly the same number of disk accesses over a shorter period of time. Although we have increased disk utilization by a considerable amount, the disks are still idle more than half of the time.

Memory usage during each application's execution is summarized in Figure 11(c). Since our current compiler implementation is not aggressive about inserting release operations, most applications do not contain a significant number of them. However, when release operations are used (e.g., BUK and EMBAR), we see that a large percentage of memory is kept free at all times. This result occurs because these applications return any pages that are not actively being used to the system and because the working set is significantly smaller than the total data set. We expect that being able to increase the amount of free memory in the system would greatly reduce the impact of an out-of-core program on other applications in a multiprogrammed environment, and we intend to explore this issue further in future work.

5.3 Effectiveness of the Compiler and Run-Time Layer

Figure 12 presents information which is useful for evaluating how effective our compiler is at inserting prefetches appropriately, and how effective the run-time layer is at minimizing prefetching overhead. We begin by examining the success of the static analysis performed at compile-time and then look at how well the run-time layer adapts to the dynamic conditions during execution.

5.3.1 The Compiler. To assess the compiler analysis, we consider what happens to the original page faults when prefetching is added. There are three possibilities: (i) a previously faulting page is successfully prefetched (we call this a *prefetched hit*), (ii) a faulting page is prefetched but still faults when the reference occurs (we call this a *prefetched fault*), and (iii) no prefetch is issued for a faulting page (this is a *nonprefetched fault*). We refer to the combination of the first two cases as the *coverage factor* (i.e., the fraction of original page faults that were prefetched). Figure 12(a) shows a breakdown of the impact of prefetching on the original page faults



(a)

Benchmark	Original	With Prefetch
BUK	11.8%	40.1%
CGM	11.6%	46.0%
EMBAR	5.9%	9.0%
FFT	18.9%	35.1%
MGRID	15.8%	29.0%
APPLU	18.6%	31.8%
APPSP	16.3%	20.7%
APPBT	15.8%	20.1%

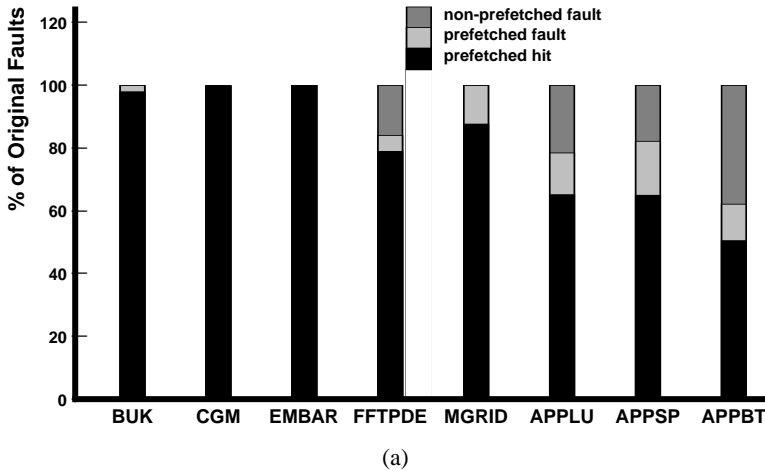
(b)

Bench	Original			With Prefetch and Release			
	Pages Freed by System (pages)	Minimum Free Memory (%)	Average Free Memory (%)	Pages Freed by System (pages)	Pages Freed by Release (pages)	Minimum Free Memory (%)	Average Free Memory (%)
BUK	68916	5.8%	26.9%	3461	41729	29.2%	73.7%
CGM	125817	14.8%	21.1%	125710	834	7.3%	23.4%
EMBAR	55647	15.0%	22.0%	0	65504	98.4%	98.5%
FFT	146699	14.9%	20.9%	156463	7164	9.9%	26.0%
MGRID	59181	14.3%	23.4%	60349	0	12.3%	25.9%
APPLU	82978	11.9%	25.0%	84395	0	7.9%	28.9%
APPSP	450507	10.5%	18.6%	448732	17196	9.0%	35.4%
APPBT	148174	11.3%	22.8%	148580	516	11.7%	25.5%

(c)

Fig. 11. Impact of prefetch and release on system resources on Hurricane. (a) Breakdown of requests sent to disk (O = original program, P = with prefetch), (b) average disk utilization, (c) memory subsystem activity and amount of free memory.

in each application that we study. In all cases except APPBT, the coverage factor is greater than 75% (in four cases it is greater than 99%), indicating



Benchmark	Unnecessary Prefetches Issued to OS	Inserted Prefetches Filtered at Run-Time	Total Prefetches Considered at Run-Time
BUK	0.07%	99.79%	25,216,058
CGM	0.08%	99.74%	53,285,582
EMBAR	0.00%	0.02%	65,537
FFT	7.99%	99.59%	39,874,709
MGRID	8.03%	99.17%	9,004,863
APPLU	3.75%	96.99%	2,529,757
APPSP	7.55%	99.51%	89,813,618
APPBT	2.54%	98.31%	4,008,500

(b)

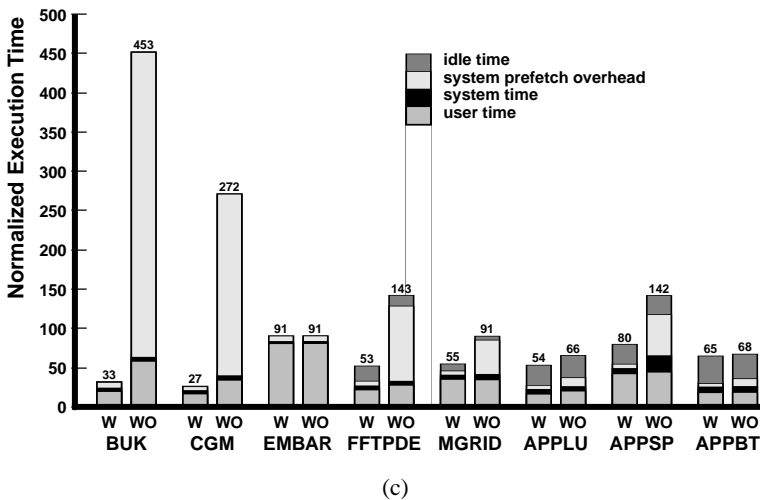


Fig. 12. Effectiveness of the compiler analysis and run-time filtering. (a) Impact of prefetching on the original page faults, (b) unnecessary prefetches, (c) performance of prefetching with (W) and without (WO) filtering (normalized to the original, nonprefetched case).

that the compiler is quite successful at identifying references that need to be prefetched. In the half the cases, however, we see that there are still a nontrivial number of page faults that are not prefetched.

Although in most cases the coverage is extremely good, we are interested in discovering why the compiler sometimes fails to prefetch needed data. There are three basic causes that can contribute to poor coverage for the types of applications that we are interested in.² Briefly stated, they are:

- (1) Loop bounds and array dimensions may be unknown at compile-time.
- (2) Data may not be aligned well with respect to page boundaries.
- (3) Some references that should be prefetched do not look like array accesses when the prefetching pass of the compiler is executed.

Each of these causes are a contributing factor in the relatively poor coverage for APPLU, APPSP, and APPBT.

First, when both the loop bounds and the array dimensions are unknown, the compiler must make an assumption about the amount of data accessed in the loop. If the compiler incorrectly assumes unknown loops to be small, it can fail to schedule needed prefetches. The fundamental problem is that such loops appear to be localized, implying that reuse can be exploited and prefetching is needed only for the first reference. Unfortunately, simply assuming unknown bounds to be large is not a reasonable solution, since it can cause another scheduling problem if the loops are actually small (as discussed in Section 3.2.2). A better solution would be to have the compiler generate multiple versions of the loop. At run-time the correct version to execute could be chosen based on the actual values of the loop bounds. The question of how to handle quantities that are unknown at compile-time is a subject for further investigation.

The second instance in which some pages are not prefetched arises when the data are not well aligned with respect to the page boundaries. When calculating group reuse, the compiler assumes that two references will probably touch the same page if the data locations that they access are separated by less than half a page (see Section A.3 of the Appendix for details on the calculation of group reuse). If the two data locations are actually on *adjacent* virtual pages, then only the first page will be prefetched, and the second will still suffer a page fault. In general we expected this problem to be rare; however, it arises relatively frequently in APPLU, APPSP, and APPBT.

The final problem is best explained with the use of an illustrative example. Consider the code shown in Figure 13. In this loop, procedure `f00` is called with *the address* of `A[i]`, while procedure `bar` is called with *the value* of `B[i]`. Ideally, we would like to prefetch both of these references, but the current prefetching pass of the compiler only recognizes the `B[i]`

²A fourth potential cause involves data that are not accessed via affine array references (e.g., pointer dereferences); however, such accesses are insignificant in the Fortran applications we consider, and are beyond the scope of this study.

```

for (i = 0; i < 100; i++) {
    foo(&A[i]);      /* not recognized as an array reference */
    bar(B[i]);
}

```

Fig. 13. Example of a reference not recognized as an array reference (inside `foo`) by the compiler.

reference. The reason is that earlier passes of the SUIF compiler have converted the high-level source code shown in Figure 13 to an internal representation where `&A[i]` is not identified as an array reference.³ This situation arises during the initialization phase in APPLU, APPSP, and APPBT. While this problem does not contribute greatly to the non-prefetched page faults in these applications, it could be an important case to recognize in general.

Having shown why the compiler is unable to prefetch all of the original faults, we now turn our attention to the *prefetched fault* category in Figure 12(a). A page fault can occur for prefetched pages for two reasons: either the prefetch has not had time to complete and the page has not yet arrived in memory, or the prefetch was issued far too early and the page has been replaced from memory. This category reflects the effectiveness of our compiler in scheduling prefetches the right amount of time in advance. In the cases where prefetched faults are noticeable in Figure 12(a), the problem is almost always that the prefetches were not issued early enough.

Two observations help to explain why prefetches may not have time to complete before the data are needed. First, the compiler schedules prefetches so that they will be issued early enough during the *steady state* of the software pipeline. Prefetches issued in the prolog sections are intended to initialize the pipeline, but are not scheduled to complete before the data are needed. Second, when loop bounds in multidimensional loops are unknown at compile-time, the compiler may pipeline around the wrong loop nest. As shown in Section 3.2.2, the result is that prefetches are only issued in the prolog and that the steady state is never reached. Again, we expect that to correct this problem we will need to generate multiple versions of such loops and choose the right one dynamically when the program is executed.

Finally, the middle column of Figure 12(b) shows that most of the prefetch requests scheduled by the compiler are actually *unnecessary* (i.e., the page was already mapped into memory) and are filtered out by the run-time library. For BUK and CGM, most of these unnecessary prefetches result from always prefetching indirect references. Locality analysis is not applied to these types of references; instead, the compiler assumes that each such reference could touch a different page of data. For these applications

³In fact, handling this case properly may require interprocedural analysis, since whether or not the data at `&A[i]` need to be brought into memory depends on what the procedure `foo` does with the argument that is passed to it. Also, scheduling a prefetch properly for these data depends on *when* they are used by `foo`.

```

for (i = 0; i < 100; i++)
  A[i] = i;

for (i = 0; i < 100; i++)
  A[i] = A[i] * i;

```

Fig. 14. Example of reuse not identified by the compiler.

this “worst-case” behavior rarely occurs, and thus most of the prefetches are unnecessary. We will examine the utility of prefetching indirect references more closely during our case study of BUK in Section 5.5. In all cases, unnecessary prefetches occur whenever the compiler underestimates memory’s ability to retain data. One cause of this effect is that locality analysis is applied to each set of nested loops independently—if two independent loops access the same data, both will be treated as the first reference to that data, regardless of the amount of data accessed. Thus, the type of reuse shown in Figure 14 cannot be discovered by the current compiler algorithm. In general, this problem is extremely difficult to solve, since it may require interprocedural analysis to evaluate all the loops in a program. A notable exception to the problem of unnecessary prefetches is EMBAR; the data access pattern in this program is simple enough to be analyzed perfectly by the compiler. All array references are sequential and within one-dimensional loops; thus the problems of strip-mining the loop correctly and choosing a pipelining loop (discussed in Sections 3.2.1 and 3.2.2 respectively) do not occur. Furthermore, since the single array used in EMBAR is large enough to flush all of memory, there are no unnecessary prefetches that result from only considering a single loop at a time.

5.3.2 The Run-Time Layer. The primary purpose of the run-time layer is to efficiently filter out prefetches for pages that are already in memory, thus reducing the overhead of the unnecessary prefetches scheduled by the compiler. To evaluate the effectiveness of the run-time layer at this task, Figure 12(b) presents statistics on how many prefetches were *unnecessary*. Note that a prefetch for a page that is in memory but is on the free list is not considered to be unnecessary, since it performs useful work by reclaiming the page. The left-hand column of Figure 12(b) shows that almost all of the prefetches issued to the system by the run-time layer are useful. All unnecessary prefetches that are issued to the system occur as part of a block prefetch request in which prefetching is required for at least one page. The middle column of Figure 12(b) shows the fraction of dynamic prefetches that were inserted by the compiler and filtered out by the run-time layer. As discussed in the previous section, it would be extremely difficult to remove many of these unnecessary prefetches statically, making run-time filtering the best option for reducing overhead. Finally in the third column of Figure 12(b) we show how many prefetches are checked by the run-time layer. The large numbers in this column provide a strong argument for making the filtering as efficient as possible, and help to explain why the user time component in Figure 10(a) increases significantly for some applications.

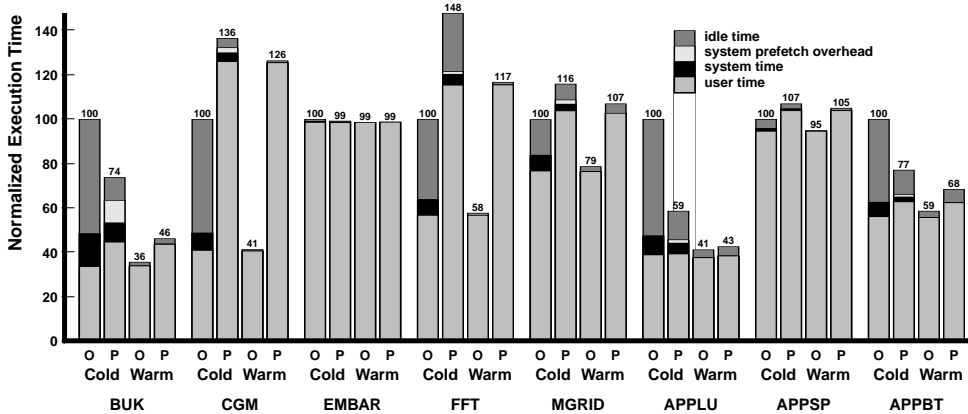


Fig. 15. Performance with in-core data sets (O = original, P = with prefetch; Cold = cold-started, Warm = warm-started). Performance is normalized to the original, cold-started cases.

Figure 12(c) quantifies the performance advantage of the run-time layer. As we see in this figure, half of the applications (BUK, CGM, FFT, and APPSP) run *slower* than the original nonprefetching versions when the run-time layer is removed. This is not surprising, since the overhead of dropping an unnecessary prefetch in the run-time layer is roughly 1% as expensive as issuing it to the operating system. From these results, we conclude that the run-time layer is clearly an essential component for achieving good performance in our system.

5.4 Problem Size Variations

Having demonstrated the benefits of I/O prefetching where the problem size is roughly twice as large as the available memory, we now look at the performance when the problem size is varied.

5.4.1 In-Core Problem Sizes. We begin with cases where the data sets fit within main memory. In these cases, we would expect prefetching to degrade performance, since the prefetches incur overhead but provide little or no benefit. Figure 15 shows two sets of experiments—the cold-started and warm-started cases—on data sets that are roughly 10–35% as large as the available memory. Starting with the cold-started cases, we see that prefetching degrades performance in four cases, but actually *improves* performance in three cases (BUK, APPLU, and APPBT) by hiding the latency of cold page faults. To further isolate the prefetching overhead, we also warm-started the applications by preloading all of their data from the input files into memory before timing the runs. As expected, prefetching typically degrades performance in the warm-started cases, since it offers no potential advantage. However, we believe that the cold-started cases are more realistic for most applications, since real programs must read their input data from disk.

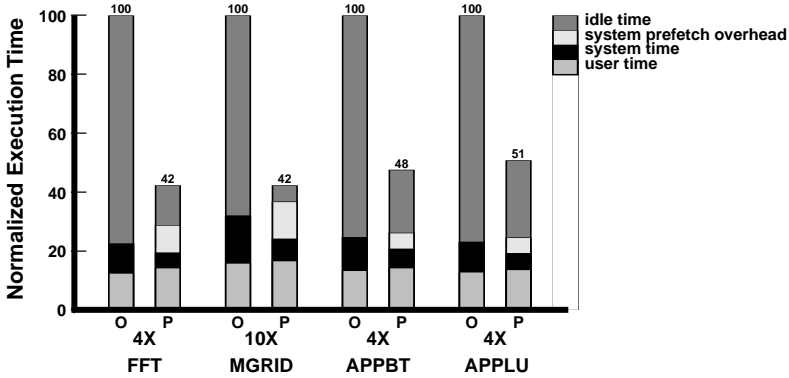


Fig. 16. Performance with larger out-of-core problem sizes. Numbers above application names indicate how much larger the problem sizes are than available memory.

In these experiments, we made no attempt to minimize prefetching overhead for in-core data sets, but this is a problem that we are planning to address in future work. In particular, we can generate code that dynamically adapts its behavior by comparing its problem size with the available memory at run-time, and suppressing prefetches (after the cold faults have been prefetched in) if the data fit within memory. The fact that I/O prefetching can still potentially improve performance even on relatively small data sets by hiding cold page faults is an encouraging result.

5.4.2 Larger Out-of-Core Problem Sizes. In addition to looking at smaller problem sizes, we also experimented with much larger data sets than our earlier out-of-core problem sizes. Figure 16 shows the performance of four applications where the problem size is 4–10 times larger than the available memory.

For FFT, APPLU, and APPBT the problem size used in this experiment is approximately 200MB, which requires that each bit in the bit vector represent two contiguous virtual memory pages (recall from Section 2.4 that we restrict the size of the bit vector to a single page). A larger size is used for MGRID because the structure of the program requires that the data set be cubical. The problem size used in our earlier experiments was only 20% larger than the available memory—the next larger problem size (shown in Figure 16) requires 464MB of memory, which is approximately 10 times more than what is available; hence each bit in the bit vector represents four pages.

The granularity of the bit vector can potentially have an impact on performance because the run-time layer is given a less detailed view of the state of main memory. However, the results in Figure 16 show, that for these applications, the performance improvements remain large. In fact, prefetching offers slightly larger speedup in all these cases, since there is more I/O latency to hide. In addition, APPLU and APPBT benefit from the coarser granularity, since fetching both pages in the set corresponding to a given bit automatically solves the alignment problem discussed in Section 5.3.

5.5 Case Study: BUK

In this section we take a closer look at how explicitly prefetching and releasing pages affects application performance by focusing on a single application. We have chosen to examine BUK for this case study for three reasons: (i) the program is short and easy to understand; (ii) the problem size can be scaled linearly; and (iii) the program contains both direct and indirect references, allowing us to evaluate the costs and benefits of indirect prefetches. Before looking at the indirect prefetches, we begin by describing the computation and data accesses performed in BUK. Finally, we examine what happens to execution time as we move from in-core problem sizes to out-of-core problem sizes, both with and without prefetching.

5.5.1 Description of Application. Figure 17 shows the main computations performed by BUK as C source code. (The actual program that we use in our experiments is written in Fortran; in our C representation of this code, we only show the computations that are relevant to this discussion.) BUK takes an array of unsorted integers that are held in `key`, computes the position that each integer should have when sorted and stores the position in `rank`, and finally copies the integers from `key` into `key2` using the values stored in `rank`.

The computations performed in BUK are organized in two phases. During the `bucksort` procedure, the input array `key` and the temporary storage array `rank` are both accessed using direct references. The temporary array `keyden` is used to record the number of times each distinct value in the input array `key` occurs, and then to calculate the position each integer should have when sorted. The `keyden` array is accessed by direct references in some loops, and by indirect references in others. We refer to this phase as the *ranking phase* in our discussion. The second phase occurs after `bucksort` in the main procedure when the integers are sorted by copying each one from `key` to its proper position in `key2` using the values stored in `rank`. In this phase, which we will refer to as the *copying phase*, `rank` and `key` are accessed by direct references while `key2` is accessed indirectly.

All of the array references in BUK are identified and prefetching by our compiler (the bar for BUK in Figure 12(a) shows that the coverage factor is 100%).

5.5.2 Benefits of Indirect Prefetches. Since the compiler has no information about the locality of indirect references a decision must be made at compile-time to either always or never prefetch them. To evaluate the costs and benefits of prefetching indirect references we examine the performance of BUK when only direct references are prefetched, and when both direct and indirect references are prefetched. In addition to considering the overall effects, we also consider the impact of prefetching indirect references in each phase of the program separately. The results of these experiments are shown in Figure 18. In this figure, all bars have been normalized to the original, nonprefetching execution time. The first set of

```

extern int main() {
    int i, j;
    int key[8388777], key2[8388777], rank[8388777], keyden[524288];

    /* Get the rank for each key */
    bucksort(key, rank, keyden, 8388608, 524288);

    /* Copy keys in sorted order into key2 */
    for (i = 0; i <= 8388607; i++)
        key2[rank[i]] = key[i];

    /* Test if any keys are out of order */
    j = 0;
    for (i = 0; i <= 8388606; i++) {
        if (key2[i + 1] < key2[i])
            j = j + 1;
    }
    if (j == 0) printf("PASSED: 0 out of place.");
    else printf("FAILED: %d out of place", j);

    return 0;
}

extern int bucksort(int *key, int *rank, int *keyden, int n, int maxkey) {
    int i;

    /* Zero the keyden array */
    for (i = 0; i < maxkey; i++)
        keyden[i] = 0;

    /* Count occurrences of each key (the 'key density') */
    for (i = 0; i < n; i++)
        keyden[key[i]] = keyden[key[i]] + 1;

    /* Create running sum (i.e. starting index) of keyden array */
    for (i = 1; i < maxkey; i++)
        keyden[i] = keyden[i] + keyden[i - 1];

    /* Compute rank for each key */
    for (i = 0; i < n; i++) {
        keyden[key[i]] = keyden[key[i]] - 1;
        rank[i] = keyden[key[i]];
    }
    return 0;
}

```

Fig. 17. Source code (C representation) for BUK.

three bars (labeled **Overall**) show the execution time breakdown for the entire program for the original (**O**), direct-only prefetching (**D**), and both direct and indirect prefetching (**B**) versions. From these bars, it can be seen that prefetching indirect references reduces execution time by an additional 9% over direct prefetching alone. The second set of three bars shows what happens during the ranking phase, while the final set of three bars

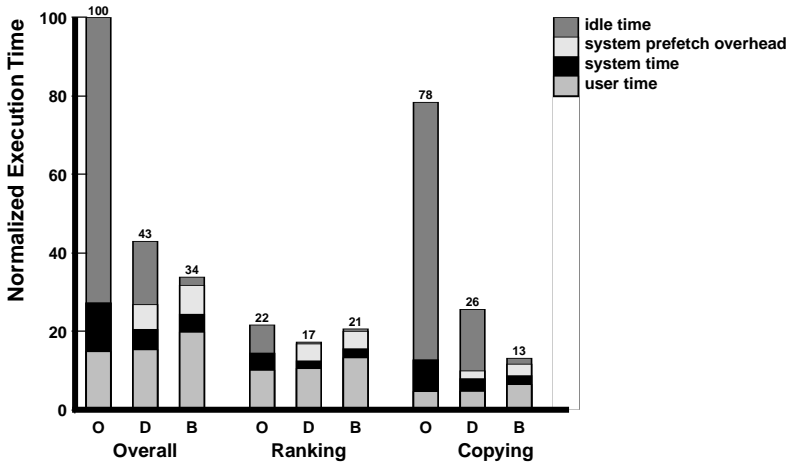


Fig. 18. Performance for different phases of BUK, normalized to the original, nonprefetching case (**O** = original, **D** = with direct-only prefetching, **B** = with direct and indirect prefetching).

shows what happens during the copying phase of the program. During ranking, the indirect prefetches are for the `keyden` array, which is small compared to the size of memory (only 2MB) and is always found in core. In this phase, direct prefetching alone is able to capture all the important references, and the indirect prefetches merely introduce overhead with no benefit. In the copying phase however, the indirect prefetches are for the `key2` array, which is much larger (33MB). During this phase, a large number of important references are missed by only prefetching the direct references. The additional overhead of filtering the indirect prefetches is amply offset by the reduction in I/O stall time for the copying phase.

Ideally, we would like to be able to achieve the best of both worlds—avoid scheduling indirect prefetches when the locality of the indirect references is good (as in the ranking phase) and issue indirect prefetches aggressively when the locality is poor (as in the copying phase). Once again, this could potentially be accomplished by creating multiple versions of the loops (one in which indirections are prefetched and one in which they are ignored) and choosing the best one to execute based on the dynamic conditions at run-time.

5.5.3 Crossing the In-Core/Out-of-Core Boundary. In BUK, the amount of work to be done grows linearly with the problem size. Ignoring page faults, we would normally expect the execution time to also increase linearly with the problem size. To show how performance is affected when an application runs out of physical memory, we executed BUK with problem sizes ranging from roughly one quarter to twice the size of main memory both with and without prefetching. The execution times for each problem size are plotted in Figure 19.

The original version of BUK (without prefetching) suffers a large discontinuity in execution time once the problem no longer fits in memory (recall

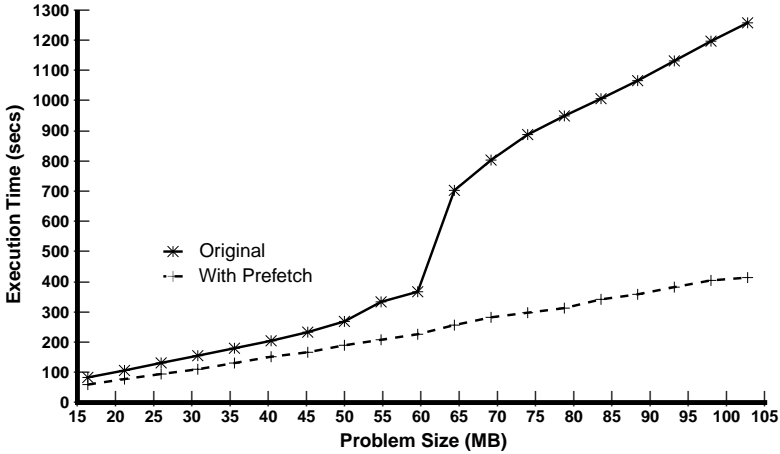


Fig. 19. Performance of BUK (cold-started) across a range of problem sizes.

that our prototype has 64MB of physical memory, with about 48MB available to the application). In contrast, the prefetching version of the code suffers no such discontinuity—execution time continues to increase linearly. For this particular application, the prefetching version of the code consistently outperforms the original code, since even small problem sizes benefit from prefetching cold misses. (For BUK, it is more realistic to cold-start the application, since it must always read its input data set from disk.) Hence this application exemplifies what we are attempting to accomplish with automatic I/O prefetching: programmers can write their code in a natural manner and still achieve good performance, even for out-of-core data sets.

5.6 Overall Performance on the Commercial System

Having demonstrated the effectiveness of compiler-inserted I/O prefetching on a research platform, we now focus on whether these significant performance gains can also be achieved on a modern commercial system—in this case, an SGI Origin 200 machine [Laudon and Lenoski 1997] running our modified version of IRIX 6.5. Since this modern system has more available physical memory than the research platform we considered earlier (75MB versus 48MB, as discussed earlier in Section 4), we have increased the problem sizes of the NAS Parallel benchmarks accordingly, as shown in Table V.

Figure 20 shows the results of our experiments, where execution time is once again broken down into four categories. Just as before, the top section is I/O stall time; the bottom section is user mode time; and the middle two sections are system mode time. In contrast with our Hurricane experiments, however, these latter two components are now broken down into time spent executing system code (*system*), which in this case is primarily time spent in the fault-handling code, and time spent waiting for resources

Table V. Application Characteristics on IRIX

Name	Input Data Set	Memory Required		Original Execution Time (mins)
		Absolute	% of Available	
BUK	2^{24} 20-bit integers	206MB	275%	10.7
CGM	sparse matrix with 15,167,342 nonzeros	206MB	275%	40.7
EMBAR	2^{24} random numbers	134MB	179%	10.6
FFT	$256 \times 128 \times 128$ matrix of complex numbers	235MB	313%	28.7
MGRID	$256 \times 256 \times 256$ matrix	452MB	600%	16.5
APPLU	$5 \times 5 \times 62 \times 62 \times 62$ matrices	219MB	292%	13.4
APPSP	$110 \times 110 \times 110$ matrices	213MB	284%	76.5
APPBT	$5 \times 5 \times 64 \times 64 \times 64$ matrices	189MB	252%	36.6

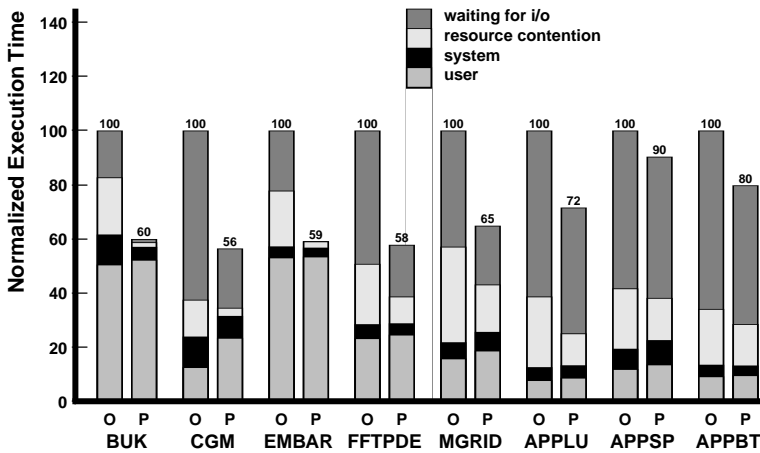


Fig. 20. Overall performance improvement from prefetching and releasing on IRIX (O = original, P = with prefetching and releasing).

held by other processes (*resource contention*) such as locks, the CPU, memory, etc.

As we see in Figure 20, most of the applications are enjoying large performance gains as a result of compiler-inserted I/O prefetching on this commercial system. In five of the eight cases (BUK, CGM, EMBAR, FFT, and MGRID), the I/O stall times have been reduced by 50% to 99%, thus resulting in overall program speedups ranging from 35% to nearly twofold. In the other three cases (APPLU, APPSP, and APPBT), I/O stall times are reduced by only 10% to 22%, resulting in more modest overall program speedups. While a direct comparison with the earlier Hurricane experiments would be meaningless because so many parameters have changed (e.g., the hardware, the system software, the application inputs, etc.), we nevertheless observe the same general trends.

In all cases, we observe in Figure 20 that system overheads (i.e., *system time* and *resource contention* combined) actually *decrease* once we add prefetching and releasing. There are two reasons for this. First, prefetch

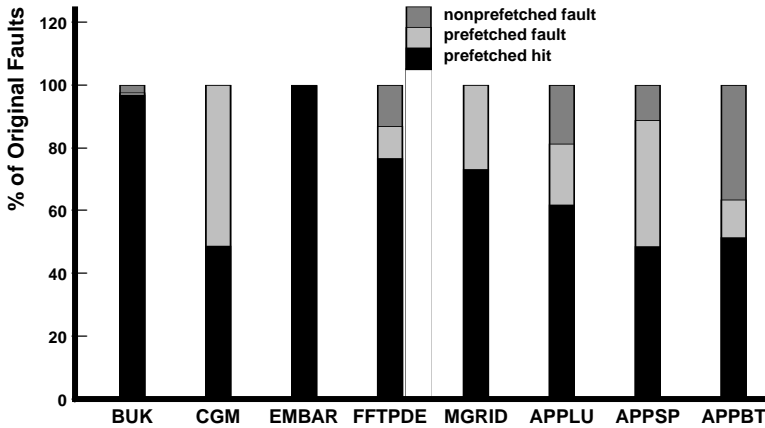


Fig. 21. Impact of prefetching on the original page faults under IRIX.

requests are serviced by separate threads (implemented using *Pthreads* [IEEE 1992], as discussed earlier in Section 4.2) that can potentially run on other processors, since the Origin 200 is a multiprocessor. Hence some of the system software overhead associated with servicing page faults can potentially be overlapped with useful computation. Second, by using release operations to keep a sufficient amount of physical memory free, we can avoid resource contention with the system-paging daemon as it tries to determine which pages it should reclaim. (A detailed analysis of this latter effect was published recently [Brown and Mowry 2000].) While the reduction in I/O stall time is the dominant effect in improving performance, many applications also benefit significantly from these overhead reductions.

To help gain further insight into the performance of these applications on IRIX, Figure 21 shows a breakdown of how prefetching affected the original page faults. It is interesting to compare this graph with Figure 12(a), which showed the same breakdown for the Hurricane experiments. As expected, the fraction of original page faults that the compiler failed to prefetch (i.e., the *nonprefetched fault* category) is quite similar across the two systems, since it largely reflects limitations in the compiler analysis that are common across both platforms. The most noticeable change between the Hurricane and IRIX experiments is the relative fraction of prefetches that were early enough (i.e., *prefetched hit*) versus too late (i.e., *prefetched fault*). Comparing Figure 21 with Figure 12(a), we see that more of the prefetches on the IRIX platform were not launched early enough, and thus failed to hide all of the page fault latency. The reason is that we have a significantly larger relative disk latency on the Origin 200, due to its much faster processors, which is harder to hide fully. Problems with late prefetches in the Hurricane experiments that were already apparent in Figure 12(a)—as discussed in Section 5.3—tend to be amplified, and are exposed in new places. The most dramatic example of this effect is CGM: just over half of the prefetches are issued too late under IRIX, while they

were nearly perfect under Hurricane. To overcome this limitation, the compiler must do a better job of using software pipelining to schedule prefetches early enough in the presence of small or statically unknown loop bounds; we are planning to investigate such techniques in our future work. Despite these late prefetches, however, we are still achieving impressive performance gains for the majority of the applications, confirming that compiler-inserted I/O prefetching is an effective technique for accelerating out-of-core applications, even on state-of-the-art commercial systems.

6. RELATED WORK

The problem that we address in this paper has been considered by many other researchers in a range of different areas. We can classify related research into six broad areas: (i) using prefetching to improve the performance of paged virtual memory systems; (ii) using knowledge of application-specific access information to improve the operating system's replacement policies; (iii) determining the best strategy for combined prefetching and caching given complete and accurate information about all future accesses; (iv) prefetching in file systems by automatically detecting access patterns; (v) prefetching in file systems based on information supplied by the application; and (vi) compilation techniques for out-of-core programs. We now look at each of these areas in turn. The idea of using a compiler to extract access patterns from an application and passing this information to the operating system to improve virtual memory performance is not a new one. The first study in this area was conducted nearly 20 years ago by Trivedi [1977], who looked at the use of application access patterns extracted by a compiler to implement "prepaging." Although the interface between the compiler and the operating system is nearly identical to that which we propose, there are some significant differences. First, Trivedi's compiler analysis was restricted to programs in which blocking could be performed whereas previous studies on prefetching for caches have shown that many programs which can be prefetched cannot be blocked [Mowry et al. 1992]. Thus, our approach is much more widely applicable. Second, we introduce the idea of a run-time layer to filter the prefetches inserted by the compiler, thus allowing the compiler to be much more aggressive about adding prefetches when the analysis cannot be performed perfectly. This component of our system is essential to achieving good performance. Without a way to filter prefetches efficiently, the compiler must be much more careful and may fail to fetch many important references. Earlier work did not try to prefetch indirect references or references in loops where the bounds were unknown.

Other work has also been done in the area of prefetching for paged virtual memory systems; however, this research generally depends on the operating system being able to detect patterns to initiate prefetching. Curewitz, Krishnan, and Vitter investigate using techniques developed for data compression to predict what to prefetch [Curewitz et al. 1993]. Their target environments are object-oriented databases and hypertext systems,

and they assume that the CPU will be mostly idle, allowing the operating system to perform complicated calculations without affecting a user's perceived response time. Song and Cho use the fault history to detect patterns and initiate prefetching [Song and Cho 1993]. These techniques all suffer from the fact that some number of faults are required to establish patterns before prefetching can begin, and when the patterns change unnecessary prefetches will occur. For instance, in FFT these schemes would incur page faults whenever the application moves between forward and inverse FFT phases.

Using application-specific knowledge to assist memory management replacement policies was studied by Malkawi and Patel [1985] and by Park et al. [1996]; however, these schemes only consider retaining needed pages in memory and do not attempt to prefetch. Although the amount of I/O needed can be reduced by intelligent memory management, the latency of the remaining I/O operations is still a serious concern.

Finding the best combined prefetching and caching strategy (i.e., the one that gives the shortest execution time) for a fully known sequence of accesses has been studied by Cao et al. [1995] for the case of a single disk and by Kimbrel et al. [1996] for varying numbers of disks. Kimbrel et al. show that the best behavior depends on the amount of contention of the disks, but that for reasonable data layouts on more than four disks contention is rarely a problem.

Prefetching in file systems by automatically detecting file access patterns has been well studied [Arunachalam et al. 1995; Griffioen and Appleton 1994; Grimshaw and Loyot 1991; Huber et al. 1995; Kotz and Ellis 1990; 1993; Kroeger and Long 1996]. Kroeger and Long look at using the compression technique known as *prediction by partial match* to detect access patterns and to decide what to prefetch [Kroeger and Long 1996]. Griffioen and Appleton construct a *probability graph* based on prior file system accesses. Both approaches attempt to improve the performance of the overall file system by predicting which *files* are likely to be referenced next when a particular file is opened. In contrast, our focus is on improving performance for out-of-core applications that typically access a small number of very large files. Once again, techniques that depend on being able to detect an access pattern cannot prefetch until the pattern has been established, may do the wrong thing when the pattern changes, and may have difficulty detecting the types of complicated access patterns that can occur in scientific codes. Another technique implemented in file systems is to support prefetching based on information supplied explicitly by the application [Patterson et al. 1995; Singh and Choudhary 1994; Thakur et al. 1994b]. Of these approaches, the TIP system developed by Patterson et al. [1995] is most relevant to our work in that hints provided by the application level are used by the operating system to optimize file prefetching and replacement. In fact, the cost model employed by TIP might be very useful for our memory manager. However, TIP targets applications which are written to use explicit I/O, and they depend on the programmer (rather than the compiler) instrumenting the code with hints. Also, they expect

applications to fully disclose their access patterns at start-up, relying on the operating system to decide what to do with this information. Thus, no concept of time is embedded in the hints, and the operating system must be able to determine when the prefetch should be initiated. The resulting operating system support is more complex than ours, and would be even more difficult to provide in a mapped file or virtual memory system where the operating system does not see regular read requests. Recently, another approach for automatically modifying applications to provide hints about their future accesses to the TIP system has been presented by Chang and Gibson [1999]. Applications are modified automatically (using a binary modification tool on the program executable) to speculatively execute the code for the purpose of generating read request hints to be passed to the TIP system. Because it is much more costly to track all virtual memory references (versus explicit file requests only) we believe it would be difficult to apply this technique to applications that did not contain explicit I/O.

Compiling for out-of-core codes tends to focus on three areas. The first area is reordering computation to improve data reuse and reduce the total I/O required [Bordawekar et al. 1996]. The second area is inserting explicit I/O calls into array codes [Colvin and Cormen 1998; Kennedy et al. 1993; Paleczny et al. 1995; Thakur et al. 1994a]. In general, the compilers are aided by extensions to the source code that indicate particular structures are out-of-core. In addition, some of the work specifically targets I/O performance for parallel applications [Bordawekar et al. 1996], while we have achieved impressive speedups for even single-threaded applications. The third compilation approach is to take programs that already contain explicit I/O calls, move them to an earlier program point, and change them to asynchronous I/O calls instead. We feel that compiler analysis that targets an I/O interface is limited by the alias analysis problem described earlier in Section 2.2.1, and in general cannot be as aggressive as an algorithm that supports nonbinding prefetching.

7. CONCLUSIONS

This paper has demonstrated that with only minor modifications to current operating systems, we can enhance paged virtual memory to deliver high performance to out-of-core applications without placing any additional burden on the programmer. We have proposed and evaluated a fully automatic scheme whereby the operating system and the compiler cooperate as follows: the compiler analyzes future access patterns to predict when page faults are likely to occur and when data are no longer needed; the operating system uses this information to manage I/O through nonbinding *prefetch* and *release* hints; and a run-time layer interacts with the operating system to accelerate performance by adapting to dynamic behavior and minimizing prefetch overhead. We implemented our scheme in the context of a modern research compiler and both research and commercial operating systems.

Our experimental results demonstrate that our scheme yields substantial performance improvements when we take unmodified, “in-core” versions of scientific applications and run them with out-of-core problem sizes. For our initial implementation, we successfully hid more than half of the I/O latency in all of the NAS Parallel benchmarks—in three cases, we eliminated over 98% of the latency. For five of the eight applications, this reduction in I/O stalls translates into speedups of roughly twofold, with two cases speeding up by threefold or more. Using our implementation on a commercial system, we were able to eliminate over 65% of the I/O latency in six of the eight applications. Since I/O stall time generally contributes less to the original execution time on the IRIX system, the speedups achieved by reducing I/O stall time are correspondingly smaller. Overall performance is still improved by a factor of 1.3 to 1.5 for five of the eight benchmarks. The results obtained on a fully featured commercial operating system demonstrate that automatic I/O prefetching can still yield significant performance improvements for out-of-core applications over page fault prefetching performed by the operating system alone.

We have also shown that good performance can only be achieved by adapting to dynamic conditions, since the compiler analysis may be hampered by quantities that are unknown at compile-time. Toward this end, we have implemented a run-time layer that adapts by filtering out unnecessary prefetches at the user-level without performing an expensive system call. In addition, we have shown that generating even more adaptive code would be useful for scheduling prefetches the right amount of time in advance.

APPENDIX

A. REUSE ANALYSIS

Since locality can only occur if there is reuse, the first step in locality analysis is determining the intrinsic data reuse through *reuse analysis*. Reuse analysis attempts to discover those instances of array accesses that refer to the same page of memory. The difference is that while reuse is an inherent property of code, locality also depends on the ability of memory to retain data. Therefore, if we had an infinitely large memory, which would retain data perfectly, reuse would be equivalent to locality.

A key simplification of reuse analysis is that rather than trying to precisely compute the sets of iterations (i.e., actual loop index values) that use the same data, which is prohibitively expensive, we instead express the intuitive notion that reuse is carried by a specific loop with the following mathematical formulation. We represent an n -dimensional loop nest as a polytope in an n -dimensional iteration space (i.e., a finite convex polyhedron bounded by the loop bounds), with the outermost loop represented by the first dimension in the space. We represent the shape of the set of iterations that use the same data by a *reuse vector space* [Wolf and Lam 1991]. The remainder of this subsection describes how this mathematical representation is used to compute temporal, spatial, and group reuse.

A.1 Temporal Reuse

Since temporal reuse occurs whenever a given reference accesses the same location in multiple iterations, we can isolate these cases by solving for whenever the array-indexing functions yield identical results given different loop indices. To facilitate this task, we represent an array-indexing function $\tilde{f}(\tilde{i})$ which maps n loop indices into d array indices, where n is the depth of the loop nest and d is the dimensionality of the array, as

$$\tilde{f}(\tilde{i}) = H\tilde{i} + \tilde{c}$$

where H is a $d \times n$ linear transformation matrix, \tilde{i} is an n -element iteration space vector, and \tilde{c} is a d -element constant vector. For example, the three array references in Figure 2 would be written as

$$A[i][j] = A\left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} i \\ j \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}\right),$$

$$B[j][0] = B\left(\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} i \\ j \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}\right),$$

and

$$B[j + 1][0] = B\left(\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} i \\ j \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}\right).$$

Given this representation, temporal reuse occurs between iterations \tilde{i}_1 and \tilde{i}_2 whenever $H\tilde{i}_1 + \tilde{c} = H\tilde{i}_2 + \tilde{c}$, i.e., when $H(\tilde{i}_1 - \tilde{i}_2) = \tilde{0}$. Rather than worrying about individual values of \tilde{i}_1 and \tilde{i}_2 , we say that reuse occurs along the direction vector \tilde{r} when $H(\tilde{r}) = \tilde{0}$. The solution to this equation is $\ker H$ (also known as the *nullspace* of H), which is a vector space in \mathcal{R}^n (i.e., each vector has n components).

To make this analysis more concrete, consider the $B[j+1][0]$ reference from our example in Figure 2. This reference accesses the same location in iterations (i_1, j_1) and (i_2, j_2) whenever

$$\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} i_1 \\ j_1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} i_2 \\ j_2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

or

$$\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} i_1 - i_2 \\ j_1 - j_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}.$$

This equation is true whenever $j_1 = j_2$, and regardless of the difference between i_1 and i_2 . In our vector space representation, we would say that

temporal reuse occurs whenever the difference between the two iterations lies in the nullspace of $\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$, i.e., $\text{span}\{(1, 0)\}$. We refer to this vector space as the temporal reuse vector space. This mathematical approach succinctly captures the intuitive concept that the direction of reuse of $B[j][0]$ lies along the outer loop. More complicated access patterns can also be expressed using the same analysis.

A.2 Spatial Reuse

Computing spatial reuse requires a slight variation on how we compute temporal reuse. Assuming the data are stored in row major order (an assumption we make without loss of generality), accesses to the same page will only occur when the same row is accessed.⁴ In addition, the row index expressions must be different, but still fall within the size of a cache line. We can test for all of these conditions as follows.

Two different iterations access the same row whenever all but the row index are equivalent. This is in contrast with temporal reuse, where *all* indices, including the row, must be equivalent. To extract this *spatial reuse vector space*, we simply replace the last row in H with zeros to create H_S , and solve for the nullspace of H_S . For example, consider the $A[i][j]$ reference in Figure 2, where $H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, and therefore $H_S = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$.

The resulting nullspace of $\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$ is $\text{span}\{(0, 1)\}$, which indicates that the same row of $A[i][j]$ is accessed along the inner loop.

To check whether *different* elements are being accessed within the same row, we compare whether the temporal and spatial reuse vector spaces are identical. This can occur, since reusing the same data item is a degenerate case of reusing the same page (i.e., $\ker H \subset \ker H_S$). If the temporal and spatial reuse vector spaces *are* identical, then there is strictly temporal reuse—if they differ, then there is spatial reuse along the vectors that are unique to the spatial reuse vector space. For example, the $A[i][j]$ reference in Figure 2 has a temporal reuse vector space of $\text{span}\{(0, 1)\}$ (i.e., there is no temporal reuse), and a spatial reuse vector space of $\text{span}\{(0, 1)\}$; therefore, unique elements within the row are accessed along $\text{span}\{(0, 1)\}$ (i.e., the inner loop). For the $B[j][0]$ reference, however, the temporal and spatial reuse vector spaces are both $\text{span}\{(1, 0)\}$, and therefore there is only temporal reuse.

Once we identify accesses to different elements within the same row, the final step is to check whether the stride is less than the page size. If so, then the reference has spatial reuse.

⁴If the data are laid out in *column* major order, then accesses to the same page can only occur when the same *column* is accessed.


```

for (i = 0; i < n; i++)
    for (j = 0; j < n; j++)
        foo(C[i], C[j]);
        bar(D[2i][j], D[2i+1][j]);
    
```

Fig. 22. Example of references without exploitable group reuse.

A.3 Group Reuse

For reuse among different array references, Gannon et al. observe that data reuse is exploitable only if the references are *uniformly generated*, i.e., references whose array index expressions differ in at most the constant term [Gannon et al. 1988]. For example, references $B[j][0]$ and $B[j+1][0]$ in Figure 2 are uniformly generated, while references $C[i]$ and $C[j]$ in Figure 22 are not. In the former case, $B[j][0]$ is accessing data brought into the cache by $B[j+1][0]$ during the previous j iteration, making it very likely that this reuse will result in locality. In the latter case, only iterations near the diagonal (i.e., when $i = j$) are likely to have exploitable reuse. Thus we will only consider group reuse among sets of uniformly generated references.

Although uniformly generated references are the likely candidates for group reuse, it is still possible that they never access the same data. For example, the $D[2i][j]$ and $D[2i+1][j]$ references in Figure 22 are uniformly generated, but never touch the same data, since $D[2i][j]$ only accesses even rows while $D[2i+1][j]$ only accesses odd rows of matrix D . To exclude such cases, we check whether a *particular solution* to the common transformation matrix H exists that yields the constant difference between the two array index functions. We express this mathematically by saying that two distinct references $A[H\vec{i} + \vec{c}_1]$ and $A[H\vec{i} + \vec{c}_2]$ access the same data if and only if

$$\exists \vec{r} : H\vec{r} = \vec{c}_1 - \vec{c}_2. \quad (2)$$

For example, the two references to the D matrix in Figure 22 would be represented as

$$D[2i][j] = D\left(\begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} i \\ j \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}\right)$$

and

$$D[2i + 1][j] = D\left(\begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} i \\ j \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}\right).$$

These two references access the same data if an integer solution (i_r, j_r) exists to

$$\begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} i_r \\ j_r \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

However, there is no integer solution in this case, since there is no integer i_r such that $2i_r = 1$. In contrast, the $B[j][0]$ and $B[j+1][0]$ references in Figure 2 access the same data, since $(i_r, j_r) = (0, 1)$ is one particular solution to

$$\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} i_r \\ j_r \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

While Eq. (2) specifies cases where distinct references access the same *data item*, we are also interested in cases where distinct references access the same *page*.

To detect all of these group reuse cases, we modify Eq. (2) slightly by replacing the last rows in H , \bar{c}_1 , and \bar{c}_2 with zeros to form H_S , $\bar{c}_{S,1}$, and $\bar{c}_{S,2}$, respectively. We therefore say that two distinct references $A[H\vec{i} + \bar{c}_1]$ and $A[H\vec{i} + \bar{c}_2]$ have group reuse if and only if

$$\exists \vec{r} : H_S \vec{r} = \bar{c}_{S,1} - \bar{c}_{S,2}, \quad (3)$$

and provided that the constant difference between the last rows of \bar{c}_1 and \bar{c}_2 is less than the page size divided by the element size. In reality, the alignment of the two references with respect to the page boundaries may also be a concern. In the worst case, adjacent references may always straddle page boundaries, potentially never reusing the same pages. In our implementation, we account for this probabilistically by assuming that two references within half a page of each other probably fall within the same page.

ACKNOWLEDGMENTS

This research is supported by a grant from NASA. Todd C. Mowry is partially supported by an Alfred P. Sloan Research Fellowship.

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Received: January 2000; revised: November 2000; accepted: November 2000