Performance Issues for Sensor–Based HPF Programs

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Abstract

Sensor–based computations are an important and often overlooked application domain for HPF. These applications typically perform regular operations on dense arrays, and often have latency and throughput requirements that can only be achieved with parallel machines. We have written a number of sensor–based applications using a dialect of subset HPF that was developed at Carnegie Mellon. The applications include FFT, synthetic aperture radar, narrowband tracking radar, multibaseline stereo, and magnetic resonance imaging. We have found that good performance is possible for these applications on commercial machines such as the Intel Paragon. In the paper we identify three core operations that are key to achieving good performance for sensor–based computations: parallel loops, index permutations, and reductions and we discuss the implications for HPF compilers. We also introduce some simple tests that HPF programmers and implementors can use to measure the efficiency of the loops, reductions, and permutations produced by an HPF compiler.

1. Introduction

There is an increasingly important class of computer applications that manipulate inputs from the physical environment. The inputs are continuously collected by one or more sensors and then passed on to the computer, where they are manipulated and interpreted. The sensors are devices like cameras, antennas, and microphones. The manipulation of the sensor inputs is variously referred to as signal processing or image processing, depending on the dimensionality of the inputs. We refer to the entire class of applications as *sensor–based computations* to emphasize this common quality of processing inputs from the natural world.

Sensor–based computations have traditionally been found in military applications like radar and sonar, and there are an increasing number of interesting commercial applications such as medical imaging, surveillance, and real–world modeling. For example, a real–world modeling application could use a stereo algorithm to acquire depth information from multiple cameras and then use the information to build realistic 3D models of the environment. The models could then be used for things like virtual 3D conferencing, building walkthroughs, or experiencing a sporting event from the point of view of one of the players.

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Sensor–based computations are an interesting and often overlooked application domain for High Performance Fortran (HPF). The computations, which typically consist of regular operations on dense arrays, are naturally expressed in HPF. Furthermore, there are often stringent latency and bandwidth requirements that demand parallel processing. For example, a stereo program that extracts depth information from multiple cameras can process only a few frames per second on a powerful RISC workstation, which is well below the standard video rate of 30 frames per second. If the results of a sensor–based computation are used to control some process, then there will also be some minimal latency that can be tolerated. For example, an online medical imaging application that gathers and processes multiple images might automatically adjust the scanner to compensate for movement by the patient. The importance of minimizing latency, rather than just maximizing throughput, is one of the key properties that distinguishes sensor–based computations from batch–oriented scientific computations [18].

This paper describes the results of an empirical study of the performance of HPF sensor–based applications on a commercial parallel computer. The results were obtained using a prototype compiler, developed at Carnegie Mellon, for a dialect of HPF running on an Intel Paragon. There are several main points: First, contrary to the fears of many in the HPF community, performance for the HPF applications we studied is good. Second, a few core computational patterns (parallel DO loops, reductions, and index permutations) dominate sensor–based applications. HPF implementors can realize great benefits by focusing on these patterns. Third, there are some simple tests that HPF programmers and developers can use to evaluate the efficiency of the parallel DO loops, reductions, and index permutations that are so crucial to the effective execution of sensor–based computations. Fourth, since the data sets in sensor–based computations are often fixed by properties of the sensors, scalability can be an issue. Finally, the same patterns that appear in sensor–based computations also appear in scientific applications. In particular, we examine a Fx regional air quality modeling code and an Fx earthquake ground motion modeling based on the method of boundary elements.

In Section 2 we give a brief overview of the prototype HPF compiler (the Fx compiler) that was used in the study. Section 3 describes the applications that we implemented in Fx and their performance on the Intel Paragon. Sections 4, 5, and 6 describe some key issues in generating efficient code for HPF DO loops, reductions, and permutations, and introduce some simple tests for measuring the efficiency of these operations. Section 7 discusses the issue of scalability in sensor–based computations. Finally, Section 8 shows how the same DO loops, reductions, and permutations that are crucial to sensor–based also appear in scientific computations.

2. Fx overview

The Fx project was started in Fall 1991 with the goal of learning how to generate efficient code for programs written in the emerging HPF standard[1] The input language is a dialect of subset HPF and consists of F77 with HPF data layout statements, array assignment statements with support for general CYCLIC(k) distributions in an arbitrary number of array dimensions [13, 14], an index permutation intrinsic, and a parallel DO loop that is integrated with arbitrary user–defined associative reduction operators [19]. Fx also provides a mechanism for mixing task and data parallelism in the same program [5, 17, 16]. The initial target was the Intel iWarp. Fx was later ported to the IBM SP/2, the Intel Paragon, and workstation clusters.

Much of the early work on Fx was driven by the 2D fast Fourier transform (FFT) and algorithms for

[1]Although the first meeting of the HPF Forum was not until January 1992, preproposals from Rice, Vienna, and ICASE were already circulating during Summer 1991, so the general form of the HPF programming model was already clear by Fall 1991.

global image processing. The system was generating inefficient versions of the FFT by Spring 1992 and efficient versions of the FFT by Fall 1992. By Spring 1993 task and data parallelism were integrated into the compiler, and by Fall 1993 arbitrary user–defined reductions were integrated into the parallel DO loop. The first significant Fx applications were written in Summer 1994: a multibaseline stereo program (from scratch) and a spotlight synthetic aperture radar program (from F77 code supplied by Sandia Labs). By Spring 1995 there were a number of additional Fx applications, including a stereo front-end for a real–world modeling application developed by the second author (from scratch), a magnetic resonance image reconstruction program (from scratch), an earthquake ground motion modeling program (from F77 code developed at Southern California Earthquake Center), and a regional air quality modeling program (from F77 code derived from the CIT airshed model).

3. Sensor–based computations

Sensor–based applications typically have the high–level two–stage pipelined structure shown in Figure 1. The front–end accepts a stream of inputs from one or more sensors and manipulates these inputs into some

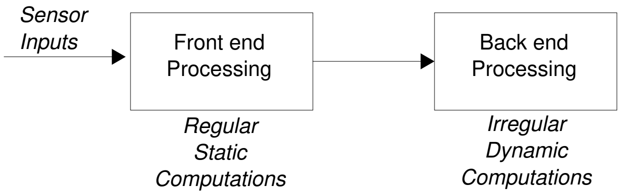


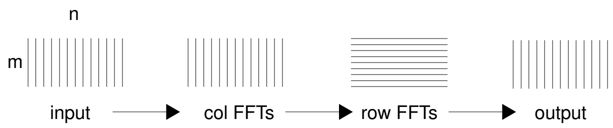
Figure 1: The structure of sensor–based computations.

desired form. The back–end interprets the results of the front–end and either display them or initiates some action. For example, in a radar tracking application, the front–end might transform input phase histories from an antenna array into an image in the spatial domain, and the back–end would manipulate this image to name, identify and track objects of interest.

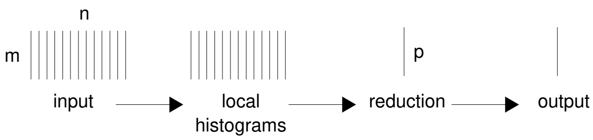
The front–end processing typically consists of numerous, regular, data parallel operations on dense arrays, requires high MFLOPS rates, and the operations performed are usually data–independent. Computations such as the fast Fourier transform (FFT), convolution, scaling, thresholding, data reduction, and histogramming are common operations. The back–end processing is typically more dynamic, irregular, and data–dependent, with real–time scheduling of processes. In this paper, we are concerned with the front–end processing, where HPF on a parallel system is most appropriate. For the remainder of the paper, when we refer to sensor–based computations we are referring to the front–end.

One of the nice qualities of sensor–based computing is that many applications have similar computational patterns. The similarities allow us to focus on a few small application kernels, with the assurance that anything that we learn about compiling these small programs will be accrue benefits in larger, more realistic programs. Two examples that capture most of the key computational patterns, and were of tremendous help in the development of the Fx compiler, are the 2D FFT (FFT2) and the image histogram (HIST). The high–level parallel structure of these computations are shown in Figure 2.

Figure 2 depicts the course–grained parallelism that is available in FFT2 and HIST. The vertical lines depict independent operations on array columns and the horizontal lines depict independent operations on rows. The FFT2 program is collection of independent local 1D FFTs on the columns of an array, followed by a collection of independent local 1D FFTs on the rows. If these columns or rows are distributed across



(a) FFT2 – 2D fast Fourier transform



(b) HIST – Image histogram

Figure 2: Sensor–based computation exemplars

the processors, then each column or row operation can run independently. In HPF, the FFT2 example can be written as:

```
COMPLEX a(N,N),b(N,N)
!HPF$ DISTRIBUTE (*,BLOCK):: a,b

!HPF$ INDEPENDENT
DO k=1,N
 call fft(a(:,k))
ENDDO
b = TRANSPOSE(a)
!HPF$ INDEPENDENT
DO k=1,N
 call fft(b(:,k))
ENDDO
a = TRANSPOSE(b)
```

Notice the use of the TRANSPOSE intrinsic to exploit locality. The HIST example consists of a collection of independent local histograms on the columns of an array, followed by a plus–reduction operation that adds the local histogram vectors to form the final result. This might be written in HPF as:

```
REAL a(N,N),h(M,N),r(M)
!HPF$ DISTRIBUTE (*,BLOCK):: a

h = 0.0
!HPF$ INDEPENDENT
DO j=1,N
 DO i=1,N
  h(i,j) = h(a(i,j),j) + 1
 ENDDO
ENDDO
r = SUM(h,2)
```

The FFT2 and HIST capture the the core computational patterns in sensor–based computations: parallel DO loops, reductions, and index permutations. FFT2 is a pair of parallel DO loops followed by an index permutation (the TRANSPOSE intrinsic). HIST is a parallel DO loop followed by a reduction. These patterns occur again and again in the sensor–based computations we have studied.

Figure 3 shows a collection of sensor–based applications. All but ABI (Figure 3(b)) have been implemented in Fx, and could be ported to HPF with small changes. The STEREO program, developed by the Carnegie Mellon Vision Group, extracts depth information using the images from multiple video cameras [8]. The RADAR program was adapted from a C program developed by MIT Lincoln Labs to measure the effectiveness of various multicomputers for their radar applications [12]. The SAR program was adapted from a Fortran 77 program developed by Sandia National Laboratories[11]. The MR program was developed from an algorithm by Doug Noll at Pitt Medical Center [10].

A striking aspect of Figure 3 is the number of parallel DO loops that operate independently along one dimension or another of the array. Each application contains at least one of these loops. The pointwise scaling operation in RADAR is also another form of parallel DO loop, which is usually expressed as an array assignment. Another common pattern from the FFT2 example is: (1) operate along one dimension, then (2) operate along another dimension. This pattern, which occurs in FFT2, ABI, RADAR, SAR, and MR, is typically implemented with a TRANSPOSE between (1) and (2). Reductions are found in HIST, STEREO, ABI, and RADAR. The point is that FFT2 and HIST capture the basic computational structure of a wide range of sensor–based computations.

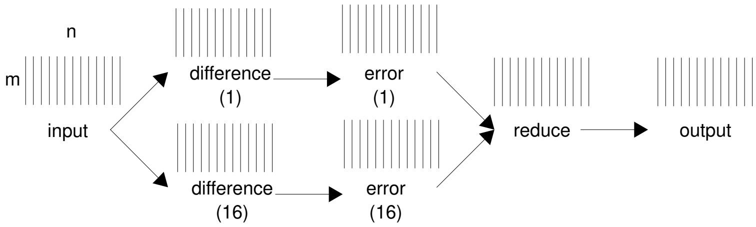
There has been some concern about the performance that can be expected from HPF programs. However, in our experience, the performance of HPF programs using the Fx compiler on Paragon is good, even for moderately sized problems. Figure 4 shows the absolute performance of representatively sized FFT, HIST, and SAR programs. FFT1 is a parallel 1D FFT program, FFT2 is the FFT exemplar, and FFT3 is a parallel 3D FFT program; each is computed in a way similar to FFT. The programs in Figure 4 scale reasonably well (although not linearly) and running time is not dominated by communication overhead. In the case of the SAR program, communication accounts for less 10% of the running time.

While certainly not exhaustive, Figure 4 offers some hope that good performance can be expected from HPF sensor–based computations. In the remaining sections, we will discuss the issues involved in ensuring good performance.

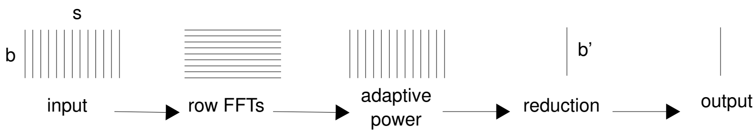
4. Parallel loops

The DO loop is the workhorse of sensor–based applications and the main source of potential parallelism. Generating efficient parallel DO loops is key to achieving good performance in these codes.

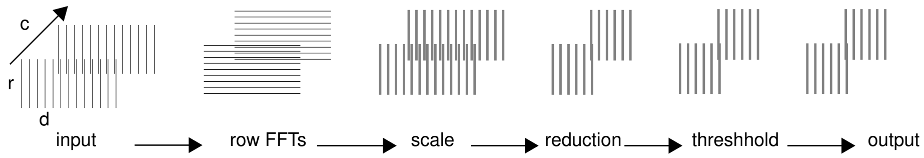
DO loops in the sensor–based computations that we have studied can be efficiently parallelized using a variation on the simple FORTRAN D copy–in copy–out model [7]. The computation in the main body of the program is modeled as a single thread operating on a global data space. Each iteration in a loop is modeled as a separate thread operating on its own local data space. When control reaches the loop, the contents of the global data space are (conceptually) copied in to each of the local data spaces. Each loop iteration then works independently on its local copy of the global data space. When all of the loop iterations have terminated, the contents of the local data spaces are (conceptually) copied out of the local data spaces back into the global data space. If multiple iterations write to the same address in the local address space, then the values are merged with a user–defined binary associative reduction operator before copying back



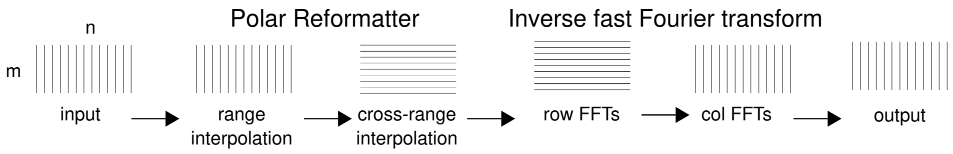
(a) STEREO – Multibaseline stereo.



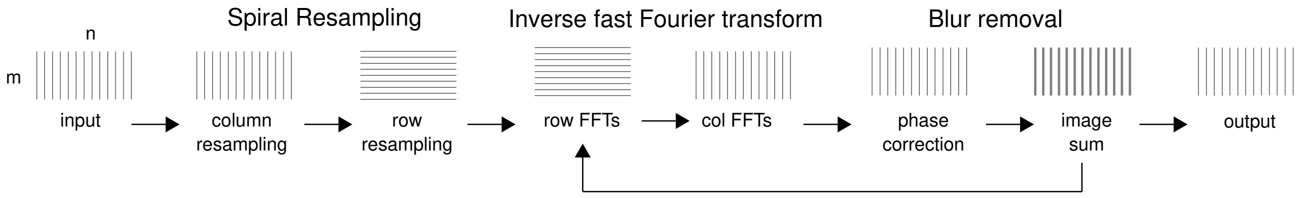
(b) ABI – Sonar adaptive beam interpolation.



(c) RADAR – Narrowband tracking radar.

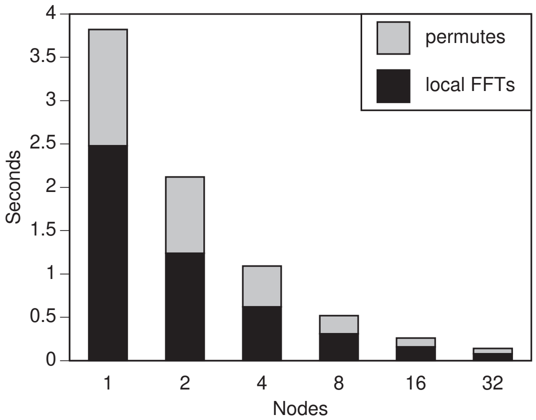


(d) SAR – Synthetic aperture radar image reconstruction.

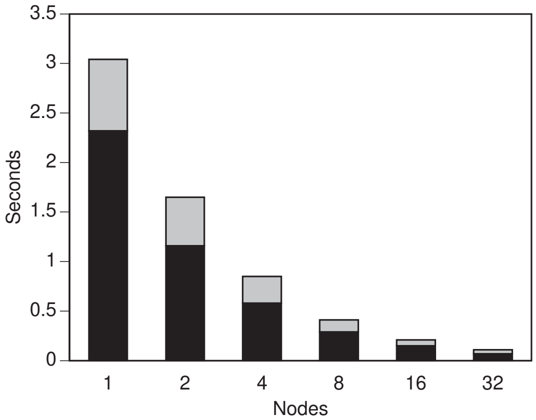


(e) MR – Magnetic resonance image reconstruction.

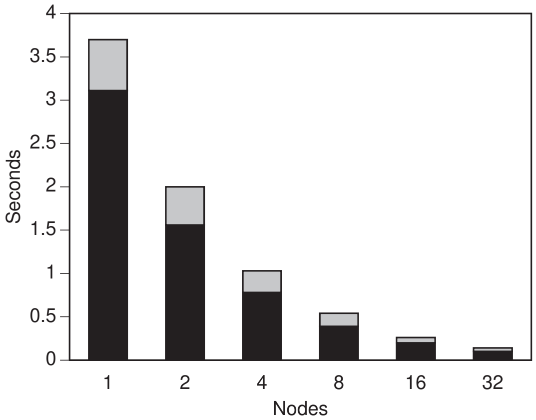
Figure 3: Other Fx/Paragon sensor–based applications



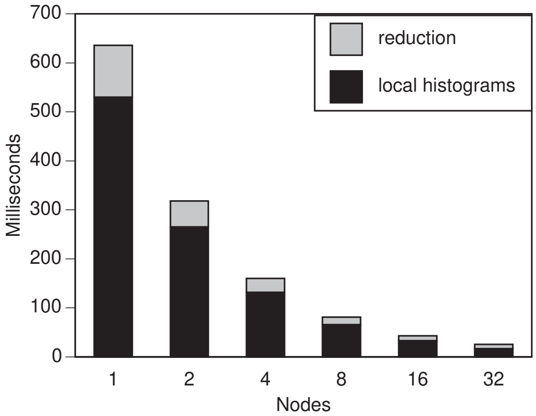
(a) $256K \times 1$ 1D FFT.



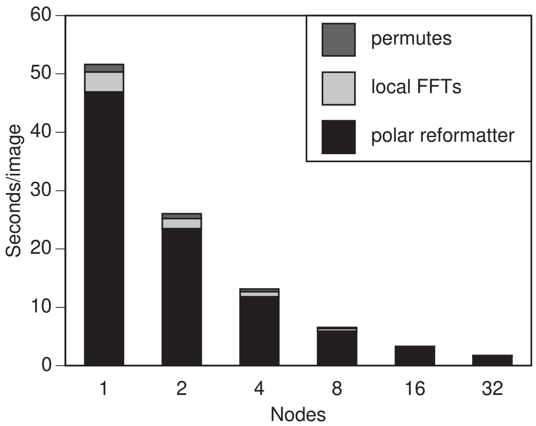
(b) 512×512 2D FFT.



(c) $64 \times 64 \times 64$ 3D FFT.



(d) $1K \times 1K$ image histogram.



(e) 512×512 synthetic aperture radar

Figure 4: Fx/Paragon performance.

to the glocal address space. This loop model, called the *PDO model*, is described in more detail in [19].

A parallel DO loop based on the PDO model can be characterized in terms of the addresses that it references, with R_k denoting the set of addresses read by iteration k and W_k denoting the set of addresses written by iteration k. If each R_k is disjoint, then the loop has *disjoint reads*, otherwise the loop has *overlapped reads*. Similarly, if each W_k is disjoint, then the loop has *disjoint writes*, otherwise the loop has *overlapped writes*.

The most common form of loop in sensor–based computations has disjoint reads and writes. Every application in Figures 2 and 3 has at least one loop with disjoint reads and writes, and FFT2 (Figure 2(a)), SAR (Figure 3(d)), and MR (Figure 3(e)) consist exclusively of these kinds of loops. For example, the FFT2 exemplar consists of HPF DO loops of the form:

```
!HPF$ INDEPENDENT
DO k=1,N
 CALL fft(a(:,k))
ENDDO
```

Each invocation of the `fft()` subroutine performs an inplace 1D FFT on the *kth* column of an array, reading and writing only elements in the *kth* column. Although `fft()` is a complicated subroutine routine with a complex pattern of array references, and might even be an assembly language library routine, the pattern of array references between loop iteration is extremely simple: the *kth* iteration references the *kth* column. This dichotomy of complicated intra–iteration reference patterns and simple inter–iteration reference patterns is a recurring theme in sensor–based computation, with important implications for HPF implementations.

Another important form of DO loop has overlapped reads and disjoint writes. Loops of this form are typically used to perform convolution operations such as the error computation in STEREO (Figure 3(a)). A similar pattern occurs in relaxation algorithms from scientific computing. For example, a simple 1D convolution is of the form:

```
REAL a(N),b(N),h(3)
!HPF$ INDEPENDENT
DO k=2,N-1
  b(k) = a(k-1)*h(1) + a(k)*h(2) + a(k+1)*h(3)
ENDDO
```

Finally, loops with overlapped writes are typically used by sensor–based computations to implement reductions. We discuss this important class of loops in Section 5. The remainder of this section discusses only loops with disjoint writes.

4.1. Implications for HPF implementations

Generating efficient code inside parallel loops is key to achieving good performance with sensor–based HPF programs. And since parallel loops with disjoint writes are so common, occurring in every application we have studied, generating efficient code for these loops is especially important.

Although loops with disjoint writes are often dismissed as “embarrassingly parallel”, it is nontrivial to generate efficient parallel code for them. There are a number of reasons, all complicated by the fact that loop bodies of real applications typically contain a lot of code, with complex intra–iteration reference patterns, calls to external library routines, and even inlined assembly language inserts.

First, the compiler must somehow determine that the write sets are disjoint and that addresses that are written by one iteration are not read by another iteration. The HPF INDEPENDENT directive is a big help here. This informs the compiler that no address is written by one iteration of a DO loop and read or written by another iteration. However, the loop can have either disjoint or overlapped reads. In Fx, we rely on a new PDO keyword for this information. The HPF INDEPENDENT directive conveys the same information and is more compatible with standard F90 compilers, so is a better approach.

Second, the HPF compiler must ensure that the read and write sets are aligned with the loop iterations before the iterations are executed. If the read and write sets are aligned before the loop iterations execute, then all reads and writes are to local data. Aligning the data sets before executing the loops is key to achieving good performance because it allows the programmer to use arbitrary sequential code in the loop body, including calls to efficient sequential math libraries written in assembly language. For example, in a Paragon HPF implementation, the `fft()` routine called by the FFT2 loop might be an assembly language routine hand–crafted for the i860 microprocessor.

Finally, the HPF compiler must compute local loop bounds and translate global array indices in the loop body to local indices. If not handled properly, these computations can be a significant source of runtime overhead.

4.2. Loop efficiency

There is a simple test that implementers and users alike can use to measure the overhead introduced by HPF compilers in the loop bodies of parallel loops. Consider the following canonical parallel DO loop:

```
REAL a(N,N)
!HPF$ DISTRIBUTE (*,BLOCK):: a

!HPF$ INDEPENDENT
DO k=1,N
  a(:,k) = k
ENDDO
```

This loop requires no communication at runtime, but is somewhat subtle to translate because the *lhs* instance of k must be converted from a global index to a local index, but the *rhs* instance must remain a global index. If we compile and run the loop on P nodes, where P divides N evenly, then the total running time is bounded from below by the running time of the following sequential DO loop:

```
COMPLEX sa(N,N/P)

DO k=1,N/P
  sa(:,k) = k
ENDDO
```

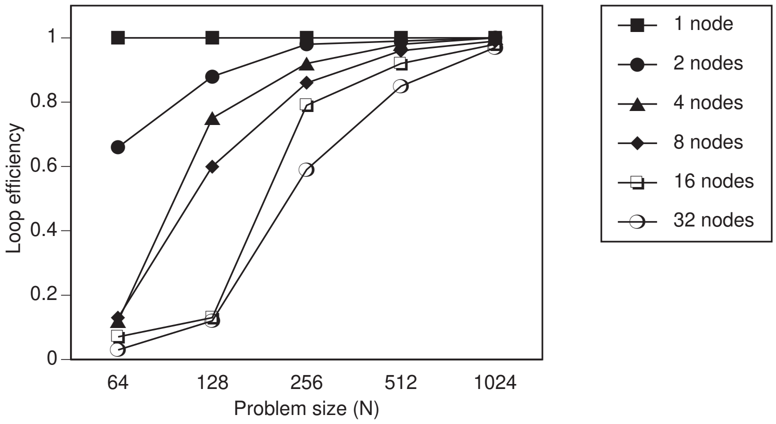


Figure 5: Fx/Paragon loop efficiency ($N \times N$ canonical loop).

If $L_p(N,P)$ is the running time of the canonical parallel DO loop with N iterations and P nodes, and $L_s(N,P)$ the running time of the corresponding sequential DO loop with N/P iterations, then $E_{loop}(N,P) = L_s(N,P)/L_p(N,P)$ is the *loop efficiency* of the parallel DO loop generated by the HPF compiler. Loop efficiency is a useful measure because it provides a way to isolate the runtime loop overheads that are introduced by the compiler, without having to instrument the generated code. It is important to realize that loop efficiency is not the same as the speedup over the single–node version of the parallel code. Instead, we are comparing to the performance of the tightest *sequential* version of the loop.

If we record loop efficiency for different values of N and P, we get an interesting family of curves. Figure 5 shows the results for the Fx version of the canonical loop on the Intel Paragon.

The family of curves in Figure 5 provides some intestesting insight into the quality of the parallel loops generated by the compiler. Loop efficiency is bounded from above by the curve for 1 node and bounded from below by the curve for 32 nodes, so in general it is only necessary to plot two curves. In Figure 5 the loop efficiency for 1 node is almost unity. For a single node the compiler introduces almost no overhead, which tells us that the loop is nearly as tight as the corresponding sequential loop. The curve for 32 nodes converges to near unity, which tells us that the overheads are being amortized across loop iterations. Further, the 32–node curve converges quite rapidly, with $E_{loop} > 0.5$ at $N = 256$ and $E_{loop} > 0.8$ at $N = 512$. Thus the Fx compiler is introducing minimal overheads that are quickly amortized. This conclusion is confirmed by inspecting the F77 code generated by Fx for $N = 1024$ and $P = 8$:

```
IF (fxcellid.LT.8) THEN
 fxloopstart0 = (MAX(((fxcellid * 128) + 1),1))
 fxlmidx0 = IFXLM(fxadesc,1,fxloopstart0)
 DO k = fxloopstart0, MIN(((fxcellid * 128) + 128),1024), 1
  DO fxindex1 = 1, 1024, 1
   a(fxindex1,fxlmidx0) = (k)
  ENDDO
  fxlmidx0 = (fxlmidx0 + 1)
 ENDDO
ENDIF
```

The parallel loop overhead consists of a few statements before the loop that compute the local loop bounds, a function call that computes the initial local index value. The only overhead in the loop body of is a statement that increments the local index value. A similar approach to index conversion is first described in [3]. It is hard to imagine a tighter loop.

In summary, a primary goal of an HPF implementation should be to generate parallel loop bodies that are as efficient as their sequential counterparts. In particular, implementors should focus on minimizing the overhead parallel loops with disjoint reads and writes. The loop efficiency test provides a simple way to characterize these overheads.

5. Reductions

In sensor–based computations, loops with overlapped writes are used primarily to implement reductions. For example,

```
DO k=1,N
 v = v + a(:,k)
ENDDO
```

A common pattern in sensor–based computations is to operate independently on the columns of an array, and then reduce the columns into a single column by adding them together. The HIST, STEREO, ABI, and RADAR program all perform this type of simple reduction. However there are important sensor–based computations, from global image processing, that require a mechanism for the programmer to define generalized reduction operations. For example, a connected components algorithm can be written as a parallel loop over the rows of the image, where each iteration computes a segment table for its row. This is followed by a reduction step that merges the segment tables.

5.1. Implications for HPF implementations

For most sensor–based computations the HPF SUM intrinsic is sufficient. However, HPF provides no support for operations like connected components that require generalized reductions. Achieving good performance in these cases will require sophisticated compiler analysis that recognizes the reductions [4]. In Fx, we avoid this analysis by incorporating a mechanism for defining arbitrary binary associative reductions into the parallel loop construct [19].

5.2. Reduction efficiency

A user or implementer can measure the quality of the parallel reduction loops generated by an HPF compiler using a test similar to the loop efficiency test in Section 4.2. Consider the following loop that adds the columns of an $N \times N$ array.

```
REAL a(N,N),v(N)
!HPF$ DISTRIBUTE (*,BLOCK):: a

v = 0.0
DO k=1,N
```

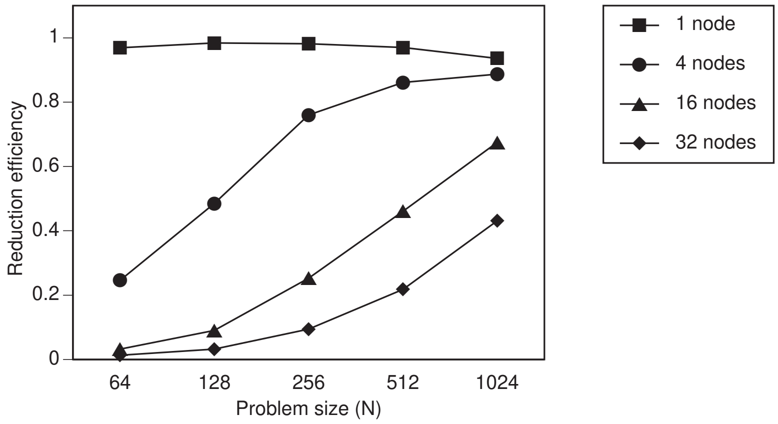


Figure 6: Fx/Paragon reduction efficiency ($N \times N \rightarrow N$ plus-reduction).

```
  v = v + a(:,k)
ENDDO
```

The performance of this loop on P nodes is bounded from below by the performance of the following sequential HPF DO loop:

```
REAL sa(N,N/P),v(N)

v = 0.0
DO k=1,N/P
  v = v + sa(:,k)
ENDDO
```

If $R_p(N, P)$ is running time of the parallel reduction of an $N \times N$ array on P nodes and $R_s(N, P)$ the running time of the corresponding sequential reduction of an $N \times N/P$ array, then $E_{reduce}(N, P) = R_s(N, P)/R_p(N, P)$ is the *reduction efficiency* of the parallel reduction generated by the compiler.[2] Reduction efficiency exposes the runtime overheads that are incurred by performing the reduction in parallel. Unlike loop efficiency, which is completely determined by the compiler, reduction efficiency is a function of overheads due to the compiler, as well as overheads due to the underlying communication system.

Figure 6 shows the results for a simple plus–reduction using the Fx compiler on Paragon. As with the loop efficiency graph, reduction efficiency is bounded from above by the curve for 1 node and from below by the curve for 32 nodes. Surprisingly, the reduction efficiency for a single node actually decreases as the problem size increases. This suggests a problem in the Fx implementation of the reduction. Ideally, the efficiency on a single node should be close to unity. Another point of concern is the slow convergence of the curves for 16 and 32 nodes. Since the local computation step of each parallel reduction grows as roughly N^2/P and the communication step grows as roughly $N \log N$, we might expect these curves to converge faster than they do. Yet even for a relatively large N, the reduction efficiency is below 50%. While the reduction efficiency does not pinpoint the source of the overhead, it does point out an opportunity for improvement in the Fx Paragon implementation.

[2] An alternative formulation of the reduction efficiency test is to use the HPF SUM intrinsic for the parallel reduction. In this case, the sequential reduction must use the same local computational kernel as the SUM intrinsic.

6. Index permutations

As we saw in Section 3 the following computational pattern occurs in many sensor–based computations: (1) operate independently along one dimension of an array, then (2) operate independently along another dimension. The FFT2, ABI, RADAR, SAR, and MR programs all exhibit this pattern. For example, FFT2 performs a local FFT on each column of an array, then performs a local FFT on each row. In order to exploit locality, this pattern is usually implemented with an index permutation (also referred to as a transpose or corner turn) between steps (1) and (2):

```
DO k=1,N
 call fft(a(:,k))
ENDDO
b = TRANSPOSE(a)
DO k=1,N
 call fft(b(:,k))
ENDDO
a = TRANSPOSE(b)
```

Although most of the sensor–based applications that we have studied permute 2D arrays, there are important cases where permutes of higher–dimensional matrices are necessary. In particular, 2D arrays of complex variables are often implemented as 3D arrays of real variables, and for $d > 1$, a d–dimensional FFT must permute two indices of a d–dimensional complex array between each local FFT step.

6.1. Implications for HPF implementations

Efficient index permutation is crucial to achieving good performance in sensor–based computations. In general, an index permutation induces a complete exchange, where each node sends data to every other node. The standard Fortran 90 TRANSPOSE intrinsic adopted by HPF provides an opportunity to optimize this important operation, but unfortunately it is only defined for 2D arrays. So for the general case, HPF implementations will either need to provide an index permutation extrinsic function, or be able to generate efficient code for index permutations that are implemented with a combination of array assignments and DO loops:

```
REAL a(N,N),b(N,N)
!HPF$ DISTRIBUTE (*,BLOCK):: a
!HPF$ DISTRIBUTE (BLOCK,*):: b

b = a
!HPF$ INDEPENDENT
DO k=1,N
 a(:,k) = b(k,:)
ENDDO
```

The Fx compiler provides an index permutation intrinsic. The advantage of this approach is that an intrinsic can leverage off of the existing code for generating array assignment statements. Writing an extrinsic with

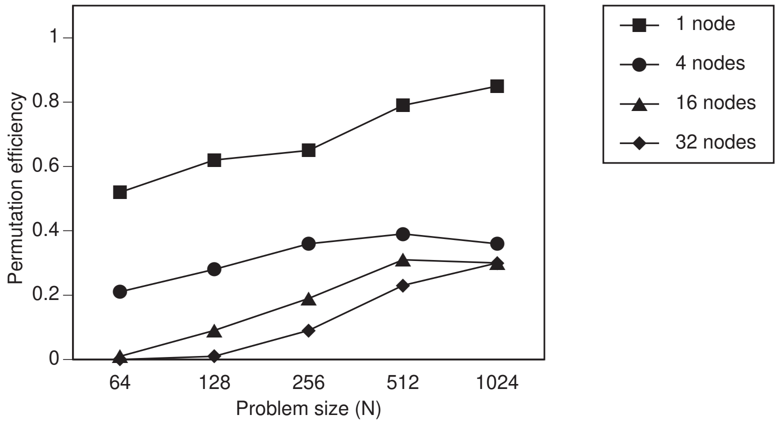


Figure 7: Fx/Paragon permutation efficiency ($N \times N$ 2D transpose).

the same functionality requires duplicating the compiler's array assignment code in the run–time library. Furthermore, capturing the index permutation in an intrinsic allows the compiler to exploit significant optimizations on systems with toroidal interconnects [6]. The disadvantages of our approach are that an index permutation intrinsic is not defined in HPF, which makes it harder to port Fx codes to HPF, and the inherent complexity of describing a complex operation like permutation through an intrinsic..

6.2. Permutation efficiency

Just as with loops and reductions, there is a simple test for measuring the efficiency of HPF index permutations. The execution time of a parallel index permutation of an $N \times N$ array (using either the TRANSPOSE intrinsic, a permutation extrinsic, or an assignment statement and a DO loop) is bounded from below by the time to sequentially permute an $N \times N/P$ array on a single node:

```
REAL sa(N/P,N),sb(N,N/P)

DO k=1,N/P
 sa(k,:) = sb(:,k)
ENDDO
```

If $T_p(N,P)$ is the running time of the parallel index permutation of an $N \times N$ array and $T_s(N,P)$ is the running time of the corresponding sequential permutation of an $N \times N/P$ array, then $E_{permute}(N,P) = T_s(N,P)/T_p(N,P)$ is the *permutation efficiency* of the parallel index permutation generated by the HPF compiler.[3] Permutation efficiency is a rough measure of the percentage of effective local memory bandwidth that is realized by the parallel permutation. Like reduction efficiency, permutation efficiency is influenced by overheads due to the compiler, as well as overheads due to the underlying communication system.

Figure 7 shows the results for a 2D transpose of an $N \times N$ array using the Fx compiler on Paragon. The graph provides a couple of interesting insights. There is substantial overhead even for the single–node version of the parallel transpose, which achieves only 85% of the effective local memory bandwidth

[3]As with the reduction efficiency test, if an intrinsic or extrinsic is used for the parallel permutation, then care must be taken to use the same local copy mechanism in the sequential version.

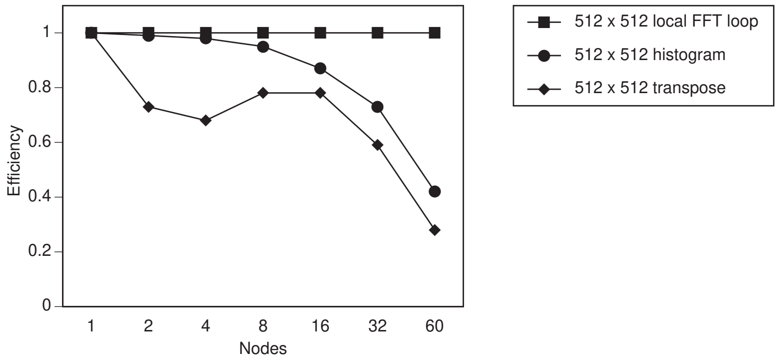


Figure 8: Scalability of various Fx/Paragon functions

for large problems. The multiple–node versions of the parallel permutation converge at about 30% of the effective local memory bandwidth. This suggests that the parallel permutation on the Paragon is communication–bound, and that further improvements will require a new message passing library.

The performance loss is largely due to overhead from the underlying communication system and it is tempting for us to wash our hands of responsibility for its performance. However, in our experience, significant performance benefits can be realized in compiler–generated code by tailoring the runtime communication libraries [14, 15]. Developers need to be aware of the communication overheads for a particular target machine, and measuring reduction and permutation efficiency is a useful way to expose the performance impact of these overheads.

7. Scalability

Sensor–based computations are composed of collections of functions that process continuous streams of data sets. The sizes of the data sets are determined by external factors such as the type of sensor, the number of sensors, and the frequencies of interest. For example, the image size of the STEREO application is fixed at 240×256 by the camera system and cannot be modified by the programmer, the magnetic resonance scanner used by the MR application processes 512×512 images (oversampled from 256×256 input), and the radar subsystem used by the RADAR application produces 512×10 data sets.

The fixed size of the data sets is an important property of sensor–based computations that distinguishes them from scientific computations. Since the data set sizes are fixed, the degree of parallel slackness decreases as the number of nodes increases, and if a data parallel function performs a nontrivial amount of internal communication, then the efficiency of the function will tend to decrease as the number of nodes increases. This behavior is shown in Figure 7 for a 512×512 local FFT loop, a 512×512 image histogram, and a 512×512 transpose. The local FFT function contains no communication, and thus scales perfectly with the number of nodes. However, the histogram and transpose functions contain internal communication and their efficiency decreases significantly as the number of nodes increases.

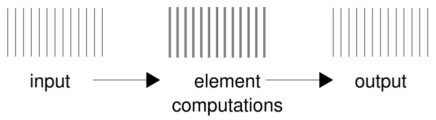
If efficient use of processing nodes is a goal (as it is in embedded systems where additional nodes increase the cost, size power, and weight of the system) then we want to use a smaller number of nodes for functions like the histogram and transpose. But if we have a large parallel system with many nodes, how then do we effectively use the remaining nodes? One approach that has been proposed is to use a mix of task and data parallelism [17, 1, 2, 5].

Task parallelism can significantly improve the performance of applications with functions that do not scale well. For example, using a mix of task and data parallelism doubled the throughput (compared to the most efficient data parallel code) of the 240×256 Fx STEREO program so that it was able to run in real–time [16]. Since HPF does not currently support task parallelism, there is the risk that HPF sensor–based codes with smaller data sets will not run efficiently. This puts additional pressure on HPF developers to maximize the loop, reduction, and permutation efficiencies identified earlier.

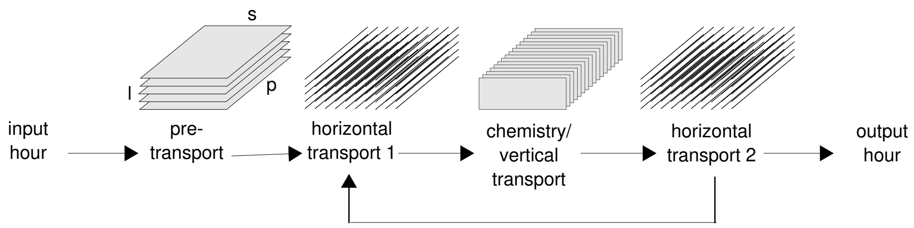
8. Relation to scientific codes

Although this paper does not specifically address scientific HPF codes, outside groups have used Fx to implement two nontrivial physical simulations: QUAKE, a 3D earthquake ground motion simulation (based on the method of boundary elements) and AIR, a regional air quality modeling program [9]. Both codes are legacy F77 codes of about $10,000$ lines that were ported to the Paragon version of Fx. QUAKE is especially interesting because it was ported in a few weeks by a seismologist from the Southern California Earthquake Center who had never written a parallel program.

Figure 9 shows the computational structure of the QUAKE and AIR programs. QUAKE is a single perfectly parallel DO loop. AIR is a sequence of DO loops that operate on different dimensions of an array, with 3D transposes interspersed between the loops. The interesting thing is that at a high level, the structure of these two moderately large scientific codes is almost identical to the FFT! So again, we see that parallel loops and index permutations are important operations for HPF developers to optimize.



(a) QUAKE – Boundary element earthquake ground motion modeling.



(b) AIR – Finite element air quality modeling.

Figure 9: Complex scientific codes with simple data parallel structure

The QUAKE and AIR programs reinforce an important point that we touched on in Section 4: complicated programs with complicated inner loops can nonetheless have a simple data parallel structure that is straightforward to parallelize. The AIR program takes this to extremes: each iteration of the parallel DO loop in each of the qhorizontal transport steps solves an independent *sparse and irregular finite element problem*. We normally assume that HPF is not a good target for sparse codes, but AIR is an example of a sparse code that is quite well suited for HPF.

9. Summary and conclusions

We identified sensor–based computations as an important application domain that is generally well suited for HPF. The performance of these codes is generally determined by the efficiency of three key operations: parallel DO loops, reductions, and index permutations, and these operations can also be important for scientific codes. HPF developers who focus on these three operations will reap large rewards.

We also pointed out that scalability can be an issue in sensor–based computations because of the fixed sizes of the data sets. Using a mix of task and data parallelism can help, but HPF does not yet address this.

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