Compiling Fortran D for MIMD Distributed-Memory Machines

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Abstract

Fortran D, a version of Fortran extended with data decomposition specifications, is designed to provide a machine-independent data-parallel programming model. This paper describes analysis, optimization, and code generation algorithms employed in the Fortran D compiler. The compiler first partitions programs using the *owner computes* rule. It then performs communication analysis, followed by communication and parallelism optimizations based on data dependence. Finally, the Fortran D compiler generates message-passing programs that can execute efficiently on MIMD distributed-memory machines.

1 Introduction

Parallel computing represents the only plausible way to continue to increase the computational power available to scientists and engineers. However, parallel computers are not likely to be widely successful until they are easy to program. A major component in the success of vector supercomputers is the ability of scientists to write Fortran programs in a "vectorizable" style and expect vectorizing compilers to automatically produce efficient code [8, 35]. The resulting programs are easily maintained, debugged, and ported across different vector machines.

Compare this with the current situation for programming parallel machines. Scientists wishing to use such machines must rewrite their programs in an extension of Fortran that explicitly reflects the architecture of the underlying machine. *Multiple-instruction, multiple-data* (MIMD) shared-memory machines such as the Cray Research C90 are programmed with explicit synchronization and parallel loops found in Parallel Computer Forum (PCF) Fortran [24]. *Single-instruction, multiple-data* (SIMD) machines such as the Thinking Machines CM-2 are programmed using parallel array constructs found in Fortran 90 [3].

MIMD distributed-memory machines such as the Intel Paragon provide the most difficult programming model. Users must write message-passing Fortran 77 programs that deal with separate address spaces, synchronizing processors, and communicating data using messages. The process is time-consuming, tedious, and error-prone. Significant blowups in source code size are not only common but expected.

Because parallel programs are extremely machine-specific, scientists are discouraged from utilizing parallel machines because they risk losing their investment whenever the program changes or a new architecture arrives. We propose to solve this problem by developing the compiler technology needed to establish a machine-independent programming model. It must be easy to use yet perform with acceptable efficiency on different parallel architectures, at least for data-parallel scientific codes.

The question is whether any existing Fortran dialect suffices. PCF Fortran is undesirable because it is easy to inadvertently write programs with data races that produce indeterminate results. Message passing Fortran 77 is portable but difficult to use. Fortran 90 is promising but may not be sufficiently flexible. What all these languages lack is a way to specify the decomposition and placement of data in the program.

We find that selecting a data decomposition is one of the most important intellectual steps in developing data-parallel scientific codes. Though many techniques have been developed for automatic data decomposition, we feel that the compiler will not be able to choose an efficient data decomposition for all programs. To be successful, the compiler needs additional information not present in vanilla Fortran. However, most parallel programming languages provide no support for data decomposition [27].

For these reasons, we have developed an enhanced version of Fortran that introduces data decomposition specifications. We call the extended language Fortran D, where "D" suggests data, decomposition, or distribution. As shown in Figure 1, we believe that if a Fortran D program is written in a data-parallel programming style with reasonable data decompositions, it can be implemented efficiently on a variety of parallel architectures. We should note that our goal in designing Fortran D is not to support the most general data decompositions possible. Instead, our intent is to provide data decompositions that are both powerful enough to express data parallelism in scientific programs, and simple enough to permit the compiler to produce efficient programs.

An essential part of the research program is demonstration of a compiler technology capable of achieving both expressive power and efficiency in the generated

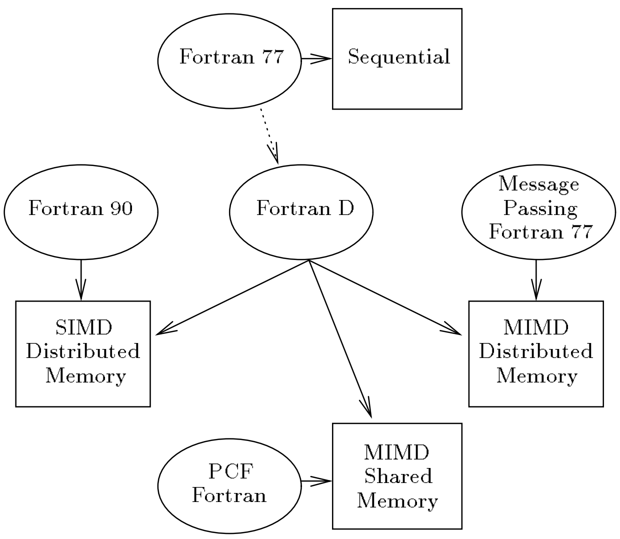


Figure 1: Fortran Dialects and Machine Architectures

code. To that end, we have embarked on a program to implement Fortran D for several different architectures. The most mature implementation, which we have been pursuing for over two years, is for MIMD distributed-memory machines. In this paper we describe the design of that compiler. Its goal is to automate the task of deriving node programs based on the data decomposition. For these machines, it is particularly important to reduce both communication and load imbalance. We present a code generation strategy based on the concept of *data dependence* [23] that unifies and extends previous techniques.

The rest of this paper presents the data decomposition specifications in Fortran D, basic compiler analysis and code generation algorithms, and compiler optimizations to reduce communication cost and exploit pipeline parallelism. We conclude with a comparison with related work and description of the current status of the compiler.

2 Fortran D Language

The data decomposition problem can be approached by considering the two levels of parallelism in data-parallel applications. First, there is the question of how arrays should be *aligned* with respect to one another, both within and across array dimensions. We call this the *problem mapping* induced by the structure of the underlying computation. It represents the minimal requirements for reducing data movement for the program given an unlimited number of processors, and is largely independent of any machine considerations. The alignment of arrays in the program depends on the natural fine-grain parallelism defined by individual members of data arrays.

Second, there is the question of how arrays should be *distributed* onto the actual parallel machine. We call this the *machine mapping* caused by translating the problem onto the finite resources of the machine. It is affected by the topology, communication mechanisms, size of local memory, and number of processors in the underlying machine. The distribution of arrays in the program depends on the coarse-grain parallelism defined by the physical parallel machine.

Fortran D provides data decomposition specifications for these two levels of parallelism using DECOMPOSITION, ALIGN, and DISTRIBUTE statements. A decomposition is an abstract problem or index domain; it does not require any storage. Each element of a decomposition represents a unit of computation. The DECOMPOSITION statement declares the name, dimensionality, and size of a decomposition for later use.

The ALIGN statement is used to map arrays onto decompositions. Arrays mapped to the same decomposition are automatically aligned with each other. Alignment can take place either within or across dimensions. The alignment of arrays to decompositions is specified by placeholders in the subscript expressions of both the array and decomposition. Perfect alignment results if no subscripts are used. In the example below,

```
REAL A(N,N)
DECOMPOSITION D(N,N)
ALIGN A(I,J) with D(J-2,I+3)
```

D is declared to be a two dimensional decomposition of size $N \times N$. Array A is then aligned with respect to D with the dimensions permuted and offsets within each dimension.

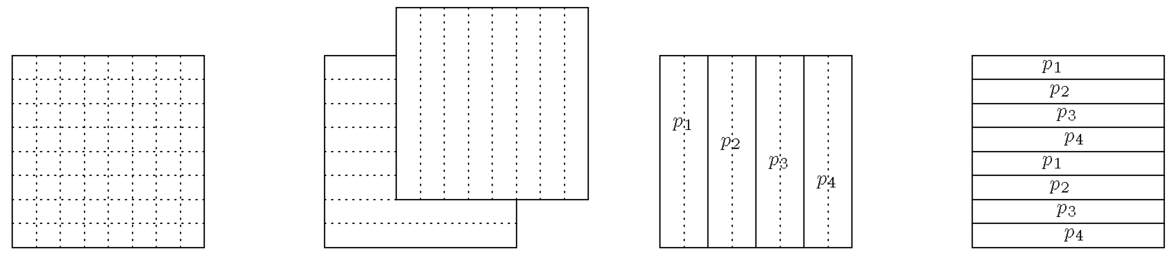
After arrays have been aligned with a decomposition, the DISTRIBUTE statement maps the decomposition to the finite resources of the physical machine. Distributions are specified by assigning an independent *attribute* to each dimension of a decomposition. Predefined attributes are BLOCK, CYCLIC, and BLOCK_CYCLIC. The symbol ":" marks dimensions that are not distributed. Choosing the distribution for a decomposition maps all arrays aligned with the decomposition to the machine. Scalars and unaligned arrays are replicated, *i.e.,* owned by all processors.

In the following example, distributing decomposition D by (:,BLOCK) results in a column partition of arrays aligned with D. Distributing D by (CYCLIC,:) partitions the rows of D in a round-robin fashion among processors. These sample data alignment and distributions are shown in Figure 2.

```
DECOMPOSITION D(N,N)
DISTRIBUTE D(:,BLOCK)
DISTRIBUTE D(CYCLIC,:)
```

Note that data distribution does not subsume alignment. For instance, the DISTRIBUTE statement alone cannot specify that one 2D array be mapped with the transpose of another.

Many previous researchers have supplied data decomposition extensions [7, 22, 28, 30, 32, 37]. Because




```
DECOMPOSITION D(N,N)        REAL A(N,N)                      DISTRIBUTE D(:,BLOCK)     DISTRIBUTE D(CYCLIC,:)
                            ALIGN A(I,J) with D(J-2,I+3)
```

Figure 2: Fortran D Data Decomposition Specifications

its goal is to support both SIMD and MIMD architectures, Fortran D is the first language to implement both alignment and distribution specifications. Fortran D also provides a FORALL loop, irregular data distribution, and dynamic data decomposition, *i.e.,* changing the alignment or distribution of a decomposition at any point in the program. The complete language is described in detail elsewhere [10].

3 Fortran D Compiler

The two major steps in writing a data-parallel program are selecting a data decomposition and using it to derive node programs with explicit data movement. We leave the task of selecting a data decomposition to the user or automatic tools. The Fortran D compiler automates the second step by generating node programs with explicit communication for a given data decomposition.

The main goal of the compiler is to exploit parallelism and reduce communication cost. It translates Fortran D programs into *single-program, multiple-data* (SPMD) form with explicit message-passing that execute directly on the nodes of the distributed-memory machine. The compiler partitions the program using the *owner computes* rule, by which each processor computes values of data it owns [7, 28, 37]. The compiler is subdivided into three major phases—program analysis, program optimization, and code generation. The structure of the compiler is shown in Figure 3.

3.1 Program Analysis

3.1.1 Dependence Analysis

Dependence analysis is the compile-time analysis of control flow and memory accesses to determine a statement execution order that preserves the meaning of the original program. A *data dependence* between two references R_1 and R_2 indicates that they read or write a common memory location in a way that requires their execution order to be maintained [23]. We call R_1 the *source* and R_2 the *sink* of the dependence if R_1 must be executed before R_2. If R_1 is a write and R_2 is a read, we call the result a *true* (or *flow*) dependence.

Dependences may be either loop-independent or loop-carried. *Loop-independent* dependences occur on the same loop iteration; *loop-carried* dependences occur on different iterations of a particular loop. The *level* of a loop-carried dependence is the depth of the loop carrying the dependence [1]. Loop-independent dependences have infinite depth. The number of loop iterations separating the source and sink of the loop-carried dependence may be characterized by a dependence *distance* or *direction* [34].

Dependence analysis is vital to shared-memory vectorizing and parallelizing compilers. We show that it is also highly useful for guiding compiler optimizations for distributed-memory machines. The prototype Fortran D compiler is being developed in the context of the ParaScope programming environment and incorporates the following analysis capabilities [6, 21].

Scalar dataflow analysis Control flow, control dependence, and live range information are computed during the scalar dataflow analysis phase. In addition, scalar and array variables are labeled *private* with respect to a loop if their values are used only within the current loop iteration; this is useful for eliminating unnecessary computation and communication.

Symbolic analysis Constant propagation, auxiliary induction variable elimination, expression folding, and loop invariant expression recognition are performed during the symbolic analysis phase of the Fortran D compiler. The goal of symbolic analysis is to provide a simplified program representation for the Fortran D compiler that improves program analysis and optimization. Consider the example below:

```
do ij = 1,len
 F(ij,n) = (F(ij,n)-TOT(ij)) / B(n)
enddo
```

If constant propagation is able to produce a constant value for n, or if n is identified as a loop-invariant expression, the Fortran D compiler can communicate $B(n)$ with an efficient *broadcast* preceding the loop.

Symbolic analysis also recognizes *reductions*, operations such as SUM, MIN, or MAX that are both commutative and associative. Once identified, reductions

1. Program analysis
    (a) Dependence analysis
    (b) Data decomposition analysis
    (c) Partitioning analysis
    (d) Communication analysis
2. Program optimization
    (a) Message vectorization
    (b) Collective communications
    (c) Runtime processing
    (d) Pipelined computations
3. Code generation
    (a) Program partitioning
    (b) Message generation
    (c) Storage management

Figure 3: Fortran D Compiler Structure

may be executed locally in parallel and the results combined efficiently using collective communication routines. Reduction operations are tagged during symbolic analysis for later use.

Dependence testing Dependence testing determines the existence of data dependences between array references by examining their subscript expressions. Dependences found are characterized by their dependence level, as well as by distance and direction vectors. This information is used to guide subsequent compiler analysis and optimization.

3.1.2 Data Decomposition Analysis

The Fortran D compiler requires a new type of program analysis to generate the proper program—it must determine the data decomposition for each reference to a distributed array.

Reaching decompositions Because data access patterns may change between program phases, Fortran D provides dynamic data decomposition by permitting executable ALIGN and DISTRIBUTE statements to be inserted at any point in a program. This complicates the job of the Fortran D compiler, since it must know the decomposition of each array.

We define *reaching decompositions* to be the set of decomposition specifications that may reach an array reference aligned with the decomposition; it may be calculated in a manner similar to *reaching definitions*. The Fortran D compiler will apply both intra- and interprocedural analysis to calculate reaching decompositions for each reference to a distributed array. If multiple decompositions reach a procedure, runtime or node splitting techniques such as *cloning* may be required to generate the proper code for the program.

3.1.3 Partitioning Analysis

After data decomposition analysis is performed, the program partitioning analysis phase of the Fortran D compiler divides the overall data and computation among processors. This is accomplished by first partitioning all arrays onto processors, then using the *owner computes* rule to derive the functional decomposition of the program. We begin with some useful definitions.

Iteration & index sets, RSDs An *iteration set* is simply a set of loop iterations—it describes a section of the work space. An *index set* is a set of locations in an array—it describes a section of the data space. In many cases, the Fortran D compiler can construct iteration or index sets using *regular section descriptors* (RSDs), a compact representation of rectangular sections (with some constant step) and their higher dimension analogs [14]. The union and intersection of RSDs can be calculated inexpensively, making them highly useful for the Fortran D compiler.

In this paper we will write RSDs as $[\,l_i\!:\!u_i\!:\!s_i,\ldots]$, where l_i, u_i, and s_i indicate the lower bound, upper bound, and step of the ith dimension of the RSD, respectively. A default unit step is assumed if not explicitly stated. In loop nests or multidimensional arrays, the leftmost dimension of the RSD corresponds to the outermost loop or the leftmost array dimension. The other dimensions are listed in order.

Global vs. local indices Because the Fortran D compiler creates SPMD node programs, all processors must possess the same array declarations. This forces all processors to adapt *local indices*. For instance, consider the following program and the node program produced when array A is block-distributed across four processors.

```
{* Original program *}   {* SPMD node program *}
REAL A(100)               REAL A(25)
do i = 1, 100             do i = 1, 25
  A(i) = 0.0                A(i) = 0.0
enddo                     enddo
```

The local indices for A on each processor are all [1:25], even though the equivalent global indices for A are [1:25], [26:50], [51:75], and [76:100] on processors 1 through 4, respectively. A similar conversion of loop indices may also occur, with the global loop indices [1:100] translated to the local loop indices [1:25].

Local index sets As the first step in partitioning analysis, the Fortran D compiler uses the Fortran D statements associated with the reaching decomposition to calculate the *local index set* of each array—the local array section owned by every processor. This creates the data partition used in the program.

We illustrate the analysis required to partition the Jacobi code in Figure 4. For this and all future examples we will be compiling for a four processor machine. In the example, both arrays A and B are aligned identically with decomposition D, so they have the same distribution as D. Because the first dimension of D is local and the second dimension is block-distributed, the local index set for both A and B on each processor (in local indices) is [1:100,1:25].

Local iteration sets Once the local index set for each array has been calculated, the Fortran D compiler uses it to derive the functional decomposition of the program. We define the *local iteration set* of a reference R on a processor to be the set of loop iterations that cause R to access data owned by the processor. It can be calculated by applying the inverse of the array subscript functions to the local index set of R, then intersecting the result with the iteration set of the enclosing loops.

The calculation of local index and iteration sets is vital to the partitioning analysis of the Fortran D compiler. When applying the *owner computes* rule, the set of loop iterations on which a processor must execute an assignment statement is exactly the local iteration set of the left-hand side (*lhs*). The Fortran D compiler can thus partition the computation by assigning iteration sets to each statement based on its *lhs*.

To demonstrate the algorithm, we will calculate the local iteration set for the assignment statement S_1 in the Jacobi example. Remember that the local index set of A is [1:100,1:25]. First we apply to it the inverse of the subscript functions of the *lhs*, $A(i, j)$. This yields the unbounded local iteration set [:,1:25,1:100]. The first entry is ":" since all iterations of the k loop access local elements of A. The inverse subscript functions cause the j and i loops to be mapped to [1:25] and [1:100], respectively.

Next we intersect the unbounded iteration set with the actual bounds of the enclosing loops, since these are the only iterations that actually exist. The iteration set of the loop nest (in global indices) is [1:*time*,2:99,2:99]. Converting it into local indices for each processor and performing the intersection yields the following local iteration sets for each processor (in local indices):

$$\begin{array}{rcl} Proc(1) & = & [\,1 : time,\ 2 : 25,\ 2 : 99\,] \\ Proc(2:3) & = & [\,1 : time,\ 1 : 25,\ 2 : 99\,] \\ Proc(4) & = & [\,1 : time,\ 1 : 24,\ 2 : 99\,] \end{array}$$

Similar analysis produces the same local iteration sets for statement S_2. Note how the local indices calculated for the local index set of each array have been used to derive the local indices for the local iteration set. The calculation of local index and iteration sets is described in greater detail elsewhere [17].

Handling boundary conditions Because alignment and distribution specifications in Fortran D are fairly simple, local index sets and their derived iteration sets may usually be calculated at compile time. In fact, in most regular computations local index and iteration sets are identical for every processor except for boundary conditions. When boundary conditions for each array dimension or loop are independent, as in the Jacobi example, the Fortran D compiler can store each boundary condition separately. This avoids the need to calculate and store a different result for each processor.

```
     REAL A(100,100), B(100,100)
     DECOMPOSITION D(100,100)
     ALIGN A, B with D
     DISTRIBUTE D(:,BLOCK)
     do k = 1,time
       do j = 2,99
         do i = 2,99
S1         A(i,j) = (B(i,j-1)+B(i-1,j)+
                     B(i+1,j)+B(i,j+1))/4
         enddo
       enddo
       do j = 2,99
         do i = 2,99
S2         B(i,j) = A(i,j)
         enddo
       enddo
     enddo
```

Figure 4: Jacobi

We may summarize independent boundary conditions for iteration or index sets as *pre, mid*, and *post* sets for each loop or array dimension. The mid set describes the interior uniform case. The pre and post iteration sets describe the boundary conditions encountered and their positions. These sets are represented in the Fortran D compiler by *augmented* iteration sets. Instead of a single section, each dimension of the augmented iteration set contains three component sections for the pre, mid, and post sets as well as their positions.

Because boundary conditions for iteration and index sets can be handled in the same manner, we will just discuss an example case for iteration sets. When partitioning the Jacobi example, the following *pre, mid*, and *post* iteration sets are calculated by the Fortran D compiler:

$$\left[\ 1 : time,\ \left\{ \begin{array}{l} pre = [2:25]\ @p_1 \\ mid = [1:25] \\ post = [1:24]\ @p_4 \end{array} \right\},\ 2 : 99\ \right]$$

In the *augmented* RSD representing the pre, mid, and post iteration sets, "@" indicates the position for each pre or post set. If an interior processor is causing a boundary condition, processors between it and the edge will not be assigned loop iterations. A pre or post iteration set may also be empty if that boundary condition does not exist.

The iteration set for each processor is calculated by taking the Cartesian product of the pre, mid, and post iteration sets for each dimension of the augmented iteration set. Unfortunately not all boundary conditions may be succinctly represented by augmented iteration sets. In the worst case the Fortran D compiler is forced to derive and store an individual index or iteration set for each processor.

Private variables & reductions Statements performing assignments to scalar and replicated array variables present a special challenge for the Fortran D compiler. Naive application of the *owner computes* rule

```
do l = 1,time
  do j = 2,6
    do k = 2,n
S1      QA = ZA(k,j+1)*ZR(k,j) + ...
S2      ZA(k,j) = ZA(k,j)+.175*(QA-ZA(k,j))
    enddo
  enddo
enddo
```

Figure 5: Livermore Kernel 23

would cause every processor to execute the assignment on all iterations. However, often the assignment can be partitioned because its value is used only in the current loop iteration. These cases are readily recognized, since the variable being assigned will have been labeled *private* during dependence analysis.

To partition statement S, the Fortran D compiler calculates the union of the iteration sets of all statements that use S. These statements can be identified by tracking all true dependence edges with S as its source. This union becomes the iteration set for S. The process is simplified if the iteration sets are calculated in reverse order for statements in each loop nest.

For instance, consider the loop in Figure 5. Because QA is a replicated scalar, the *owner computes* rule would assign all loop iterations as the iteration set for statement S_1. However, since the only use of QA occurs in the same loop iteration, it is classified as a private variable. The Fortran D compiler can thus assign S_1 the same iteration set as S_2, the only statement containing a true dependence with S_1 as its source.

In other cases, a statement or group of statements will be marked during dependence analysis as performing a *reduction*. To parallelize the reduction, an iteration set that partitions the computation across processors should be selected. To reduce data movement, the Fortran D compiler may partition the computation using the local iteration set of a variable on the right-hand side (*rhs*). Communication will be later inserted to accumulate the partial results.

3.1.4 Communication Analysis

Once partitioning analysis determines how data and work are partitioned across processors, communication analysis determines which variable references cause nonlocal data accesses.

Computing nonlocal index sets In this phase, all *rhs* references to distributed arrays are examined. For each *rhs*, the Fortran D compiler constructs the index set accessed by each processor. The index set is computed by applying the inverse subscript functions of the *rhs* to the local iteration set assigned to the statement. The local index set is subtracted from the resulting RSD to check whether the reference accesses nonlocal array locations. If only local accesses occur, the *rhs* reference may be discarded. Otherwise the RSD representing the *nonlocal index set* accessed by the *rhs* is retained.

If boundary conditions exist for the local iteration set of the statement, the Fortran D compiler must compute the index set for each group of processors assigned different iteration sets. In the worst case the index set for each processor must be calculated separately.

We show how index sets are computed for the Jacobi example. We first consider the four *rhs* references to B in statement S_1. The iteration set boundary conditions cause processors to be separated into three groups. The group of interior processors, $Proc(2{:}3)$, have the local iteration set [1:*time*,1:25,2:99]. This derives the following index sets:

$$\begin{aligned}
B(i,j-1) &= [\,2:99,\ 0:24\,]\\
B(i-1,j) &= [\,1:98,\ 1:25\,]\\
B(i+1,j) &= [\,3:100,\ 1:25\,]\\
B(i,j+1) &= [\,2:99,\ 2:26\,]
\end{aligned}$$

Since the local index set for B is [1:100,1:25], $B(i-1,j)$ and $B(i+1,j)$ cause only local accesses and may be ignored. However, $B(i,j-1)$ and $B(i,j+1)$ access nonlocal locations [2:99,0] and [2:99,26], respectively. Both references are marked and their nonlocal index sets stored.

Computing the index sets using the local iteration sets for the other two groups, $Proc(1)$ and $Proc(4)$, does not yield additional nonlocal references. Examination of the index sets for the *rhs* reference to $A(i,j)$ in statement S_2 show that only local accesses occur.

3.2 Program Optimization

The program optimization phase of the Fortran D compiler utilizes the results of program analysis to improve program performance. Its two primary goals are to exploit parallelism and reduce communication overhead. Most computations are fully data-parallel; parallelism is discovered and utilized during partitioning analysis. More advanced optimizations are required to exploit parallelism for *pipeline computations*. We defer their discussion to Section 3.4.

In this section, we concentrate on optimizations to reduce communication overhead. It is particularly useful to consider *cross-processor* dependences—dependences whose endpoints are executed by different processors.

3.2.1 Message Vectorization

A naive but workable algorithm known as *runtime resolution* inserts guarded *send* and/or *recv* operations directly preceding each nonlocal reference [7, 28, 37]. Unfortunately, this simple approach generates many small messages that prove extremely inefficient due to communication overhead [18, 28].

The most basic communication optimization performed by the Fortran D compiler is *message vectorization*. It uses the level of loop-carried data dependences to calculate whether communication may be legally performed at outer loops. This replaces many small messages with one large message, reducing both message startup cost and latency.

Algorithm We use the following algorithm from Balasundaram *et al.* and Gerndt to calculate the appropriate loop level to insert messages for nonlocal references [4, 12]. We define the *commlevel* for loop-carried dependences to be the level of the dependence. For loop-independent dependences we define it to be the level of the deepest loop common to both the source and sink of the dependence.

To vectorize messages for a *rhs* reference R with a nonlocal index set, we examine all cross-processor true dependences with R as the sink. The deepest commlevel of all such dependences determines the loop level at which the message may be vectorized. If the deepest commlevel is for a dependence carried by loop L, we insert a message tag for R marked *carried* at the header for loop L. This tag indicates that nonlocal data accessed by R must be communicated between iterations of loop L.

Otherwise the deepest commlevel is for a loop-independent dependence with loop L as the deepest loop enclosing both the source and sink. We insert a tag for R marked *independent* at the header of the next deeper loop enclosing R at level $L+1$, or at R itself if no such loop exists. This tag indicates that nonlocal data accessed by R must be communicated at this point on each iteration of loop L. Additionally, the Fortran D compiler may move this tag to any statement in loop L between the source and the sink of the dependence in order to combine messages arising from different references.

Example 1: Jacobi We illustrate the message vectorization algorithm with three examples. First we examine the Jacobi code in Figure 4. In the communication analysis phase, we have already determined that for the given data decomposition only the *rhs* references $B(i, j-1)$ and $B(i, j+1)$ from S_1 access nonlocal locations. The only cross-processor true dependences incident on these references are from the definition to B in S_2. These dependences are carried on the k loop, so we insert their tags (labeled carried) at the header of the k loop. The code generation phase will later insert messages for those references inside the k loop.

Example 2: Successive over-relaxation (SOR) In the code for SOR in Figure 6, communication analysis discovers that the *rhs* references $A(i+1, j)$ and $A(i-1, j)$ have nonlocal index sets. Dependence analysis shows that the reference $A(i+1, j)$ has a cross-processor true dependence carried on the k loop, so we insert its tag (labeled carried) at the k loop header. The deepest loop-carried true dependence for reference $A(i-1, j)$ is carried on the i loop, so we insert its tag (also labeled carried) at the i loop header.

Example 3: Red-black SOR In the code in Figure 7, communication analysis discovers that all *rhs* references except $V(i, j)$ possess nonlocal index sets.

```
REAL A(100,100)
DECOMPOSITION D(100,100)
ALIGN A, B with D
DISTRIBUTE D(BLOCK,:)
do k = 1,time
  do j = 2,99
   do i = 2,99
    A(i,j) = (ω/4)*(A(i,j-1)+A(i-1,j)+
         A(i+1,j)+A(i,j+1))+(1-ω)*A(i,j)
   enddo
  enddo
enddo
```

Figure 6: Successive Over-Relaxation (SOR)

```
REAL V(N,N)
DECOMPOSITION D(N,N)
ALIGN V with D
DISTRIBUTE D(BLOCK,BLOCK)
do k = 1,time
  {* compute red points *}
  do j = 3,N-1,2
   do i = 3,N-1,2
S1    V(i,j) = (ω/4)*(V(i,j-1)+V(i-1,j)+
          V(i,j+1)+V(i+1,j))+(1-ω)*V(i,j)
   enddo
  enddo
  do j = 2,N-1,2
   do i = 2,N-1,2
S2    V(i,j) = (ω/4)*(V(i,j-1)+V(i-1,j)+
          V(i,j+1)+V(i+1,j))+(1-ω)*V(i,j)
   enddo
  enddo
  {* compute black points *}
  do j = 3,N-1,2
   do i = 2,N-1,2
S3    V(i,j) = (ω/4)*(V(i,j-1)+V(i-1,j)+
          V(i,j+1)+V(i+1,j))+(1-ω)*V(i,j)
   enddo
  enddo
  do j = 2,N-1,2
   do i = 3,N-1,2
S4    V(i,j) = (ω/4)*(V(i,j-1)+V(i-1,j)+
          V(i,j+1)+V(i+1,j))+(1-ω)*V(i,j)
   enddo
  enddo
enddo
```

Figure 7: Red-black SOR

However, dependence analysis shows that the only cross-processor true dependences incident on the *rhs* references for statements S_1 and S_2 are carried on the k loop from S_3 and S_4. The tags for these references (labeled as carried) are inserted at the header of the k loop. During code generation phase they will generate messages in the k loop.

For statements S_3 and S_4, dependence analysis shows that the only cross-processor true dependences incident on their *rhs* references are loop-independent dependences from S_1 and S_2. Their commlevel is set to the k loop because it is the deepest loop enclosing both the source and sink of these dependences. We insert tags (labeled independent) for all *rhs* references in S_3 at its enclosing j loop, since it is the next loop deeper than k enclosing S_3.

Similar analysis causes us to insert tags (labeled independent) for all *rhs* references in S_4 at its enclosing j loop. As an additional optimization, we can move these tags to the j loop enclosing S_3 to combine these messages. This is legal since we are moving tags to a statement that is at the same loop level and between the source and sink of the dependence. In the code generation phase these tags will cause vectorized messages to be generated before the j loop, to be executed on each iteration of the k loop.

3.2.2 Communication Selection

Message vectorization determines where communication should be inserted, but the Fortran D compiler also needs to select an efficient communication mechanism. We do this by comparing the subscript expression of each distributed dimension in the *rhs* with its aligned dimension in the *lhs* reference.

Consider the following example. Message vectorization determines that communication can be extracted from both the i and j loops. The arrays A and B are aligned identically and both dimensions are distributed, so we need to compare the first dimensions with each other, then the second.

```
DECOMPOSITION D(N,N)
ALIGN A, B with D
DISTRIBUTE D(BLOCK,BLOCK)
do j = 2,N
  do i = 2,N
S1    A(i,j) = B(i,j-1)+B(i-1,j)
S2    A(i,j) = B(c,j)+B(j,i)
S3    A(i,j) = B(f(i),j)
  enddo
enddo
```

In S_1, the aligned dimensions of both the *lhs* and *rhs* references contain constant offsets to the same loop index variable. For these *stencil computations*, individual calls to *send* and *recv* primitives are very efficient. This is the case for the Jacobi, SOR, and Red-black SOR examples previously discussed.

Collective Communication More complicated subscript expressions indicate the need for *collective communication* [25]. For example, the loop-invariant subscript for $B(c,j)$ in S_2 can be efficiently communicated using *broadcast*. Collective communication is also useful in performing transposes for differing alignments between *lhs* and *rhs* references, or accumulating partial results for reductions. Collective communication is selected because these communication patterns are not well-described by individual messages, and can be performed significantly faster using special purpose routines. The Fortran D compiler applies techniques pioneered by Li and Chen [25].

Runtime Processing A third type of communication is needed to communicate the values needed by by $B(f(i),j)$ in S_3. Because f is an irregular function (*e.g.,* an index array), the Fortran D compiler cannot precisely determine at compile-time what communication is required. However, *inspectors* and *executors* may be created during code generation to combine messages at runtime [22, 26].

3.2.3 Additional Optimizations

The Fortran D compiler performs other communication optimizations. Message coalescing combines messages for different references to the same array. Message aggregation combines messages from different arrays to the same processor, at the expense of copying them to a single contiguous buffer.

A number of optimizations seek to hide communication overhead by overlapping messages with computation. Message pipelining attempts to hide message transit time by separating *send* and *recv* primitives for element messages; vector message pipelining does the same for vectorized messages. Iteration reordering extracts local loop iterations to increase the amount of computation that can be overlapped. Nonblocking messages rely on architectural support to hide message copy times. These optimizations are discussed in detail elsewhere [18, 22, 28].

Communication may also be optimized by considering interactions between all the loop nests in the program. Intra- and interprocedural dataflow analysis of array sections can show that an assignment to a variable is *live* at a point in the program if there are no intervening assignments to that variable. This array kill information may be used to eliminate redundant messages. Relaxing the *owner computes* rule may also improve communication.

3.3 Code Generation

Once program analysis and optimization is complete, the code generation phase of the Fortran D compiler utilizes information concerning local index and iteration sets, RSDs, and collective communication to create the actual SPMD node program.

3.3.1 Program Partitioning

During partitioning analysis, the Fortran D compiler applied the *owner computes* rule to calculate the local iteration set for each statement. One of the goals for code generation is to modify the program to ensure that each processor only executes a statement on loop iterations in its local iteration set.

Loop bounds reduction and *guard introduction* are the two program transformations used to instantiate the computation partition. The Fortran D compiler first reduces the loop bounds so that each processor only executes iterations in the unioned local iteration sets of all statements in the loop. It then inserts code to calculate boundary conditions, as shown the bounds generated for the j loop in Figure 8.

With multiple statements in the loop, the local iter-

```
REAL A(100,25), B(100,0:26)
if (P_local = 1) lb1 = 2 else lb1 = 1
if (P_local = 4) ub1 = 24 else ub1 = 25
do k = 1,time
   if (P_local > 1) send(B(2:99,1), P_left)
   if (P_local < 4) recv(B(2:99,26), P_right)
   if (P_local < 4) send(B(2:99,25), P_right)
   if (P_local > 1) recv(B(2:99,0), P_left)
   do j = lb1,ub1
    do i = 2,99
     A(i,j) = (B(i,j-1)+B(i-1,j)+
               B(i+1,j)+B(i,j+1))/4
    enddo
   enddo
   do j = lb1,ub1
    do i = 2,99
     B(i,j) = A(i,j)
    enddo
   enddo
enddo
```

Figure 8: Generated Jacobi

ation set of a statement may be a subset of the reduced loop bounds. For these statements the compiler needs to add explicit guards based on membership tests for the local iteration set of the statement [7, 17, 28, 37].

3.3.2 Message Generation

The Fortran D compiler uses information calculated in the communication analysis and optimization phases to guide message generation. Non-blocking *sends* and blocking *receives* are inserted for the following types of messages:

Loop-independent messages For messages tagged at loop headers for loop-independent cross-processor dependences, the Fortran D compiler inserts calls to *send* and *recv* primitives preceding the loop header. For messages tagged at individual references, the Fortran D compiler inserts *send* and *recv* in the body of the loop preceding the reference. All messages are guarded so that the owners execute *send* and recipients execute *recv*. To calculate the data that must be sent, the Fortran D compiler builds the RSD for the reference at the loop level that the message is generated. This represents data sent on each loop iteration. This strategy is used to generate messages preceding the loop nests enclosing S_3 and S_4 for Red-black SOR in Figure 7.

Loop-carried messages The situation is more complex for messages representing loop-carried dependences. To calculate the data that must be communicated, we build the RSD for each *rhs* reference at the level of the loop L carrying the dependence. If iterations of L are executed by all processors, the Fortran D compiler inserts calls to *send* and *recv* primitives inside the loop header for L, at the beginning of the loop body. If the iterations of L are be partitioned across processors, loop-carried messages represent data synchronization. The compiler inserts calls to *recv* preceding loop L, since they occur before the local iterations of L. Similarly, calls to *send* are inserted after L, since they are executed after the local iterations of L.

```
REAL A(0:26,100)
if (P_local = 1) lb2 = 2 else lb2 = 1
if (P_local = 4) ub2 = 24 else ub2 = 25
do k = 1,time
   if (P_local > 1) send(A(1,2:99), P_left)
   if (P_local < 4) recv(A(26,2:99), P_right)
   do j = 2,99
    if (P_local > 1) recv(A(0,j), P_left)
    do i = lb2, ub2
     A(i,j) = (ω/4)*(A(i,j-1)+A(i-1,j)+
          A(i+1,j)+A(i,j+1))+(1-ω)*A(i,j)
    enddo
    if (P_local < 4) send(A(25,j), P_right)
   enddo
enddo
```

Figure 9: Generated SOR

We illustrate message generation for two examples. For the Jacobi code in Figure 4, recall that k loop carries true dependences for the *rhs* references in S_1. These messages were tagged at the k loop header as carried. We first compute RSDs for the data that need to be communicated. Boundary conditions cause three RSDs to be generated for each *rhs* reference. Below are the RSDs for the reference $B(i, j+1)$ at the k loop level.

$$
\begin{aligned}
Proc(1) &= [\,2:99,\ 3:26\,] \\
Proc(2:3) &= [\,2:99,\ 2:26\,] \\
Proc(4) &= [\,2:99,\ 2:25\,]
\end{aligned}
$$

We subtract the local index set from these RSDs to determine the RSDs for the nonlocal index set. The nonlocal RSDs for $Proc(1)$ and $Proc(2{:}3)$ are both [2:99, 26] and are therefore combined. The RSD for $Proc(4)$ consists of only local data and is discarded.

The sending processor is determined by computing the owners of the section [2:99,26] @ $Proc(1{:}3)$, resulting in $Proc(2{:}4)$ sending data to their left processors. To compute the data that must be sent, we translate the local indices of the receiving processors to that of the sending processors, obtaining the section [2:99,26−25] = [2:99,1]. Since loop k is executed by all processors, the messages are inserted at the beginning of the loop body. Messages for $B(i, j-1)$ are calculated in a similar manner. The communication generated is shown in Figure 8.

Now consider the SOR code depicted in Figure 6. Dependences for $A(i+1, j)$ are carried on the k loop, causing vectorized messages to be inserted at the beginning of the k loop body as in Jacobi. The compilation of $A(i-1, j)$ is more complicated. Boundary conditions and dependences carried by the i loop cause the following three RSDs to be generated at the level of the i loop.

$$
\begin{aligned}
Proc(1) &= [\,1:24,\ j\,] \\
Proc(2:3) &= [\,0:24,\ j\,] \\
Proc(4) &= [\,0:23,\ j\,]
\end{aligned}
$$

The local index set is subtracted from these RSDs to determine the RSDs for the nonlocal index set, producing the empty set for $Proc(1)$. The nonlocal RSDs for both $Proc(2{:}3)$ and $Proc(4)$ are $[0,j]$ and are combined. This shows that processors 2 through 4 require data from their left neighbor. Iterations of the i loop are partitioned, alerting the Fortran D compiler to the fact that the *send* for $A(i-1,j)$ occurs after the last local i loop iteration, and the *recv* occurs before the first local i loop iteration. It thus inserts the *recv* before the i loop and the *send* after the i loop, resulting in the code shown in Figure 9.

Collective Communication During communication optimization, opportunities for reductions and collective communication have been marked separately. Instead of individual calls to *send* and *recv*, the Fortran D compiler inserts calls to the appropriate collective communication routines. Additional communication is also appended following loops containing reductions to accumulate the results of each reduction.

Runtime Processing Runtime processing is applied to computations whose nonlocal data requirements are not known at compile time. An *inspector* [26] is constructed to preprocess the loop body at runtime to determine what nonlocal data will be accessed. This in effect calculates the *receive* index set for each processor. A global transpose operation between processors is then used to calculate the *send* index sets. Finally, an *executor* is built to actually communicate the data and perform the computation.

An inspector is the most general way to generate *send* and *receive* sets for references without loop-carried true dependences. Despite the expense of additional communication, experimental evidence from several systems show that it can improve performance by grouping communication to access nonlocal data outside of the loop nest, especially if the information generated may be reused on later iterations [22, 26].

The inspector strategy is not applicable for unanalyzable references causing loop-carried true dependences. In this case the Fortran D compiler inserts guards to resolve the needed communication and program execution at runtime [7, 28, 37].

3.3.3 Storage Management

One of the major responsibilities of the Fortran D compiler is to select and manage storage for all nonlocal array references. There are three different storage schemes.

Overlaps Overlaps are expansions of local array sections to accommodate neighboring nonlocal elements [12]. For programs with high locality of reference, overlaps are useful for generating clean code. However, they are permanent and specific to each array, and thus may require more storage.

Buffers Buffers avoid the contiguous and permanent nature of overlaps. They are useful when storage for nonlocal data must be reused, or when the nonlocal area is bounded in size but not near the local array section.

Hash tables Hash tables may be used when the set of nonlocal elements accessed is sparse, as for many irregular computations. They also provide a quick lookup mechanism for arbitrary sets of nonlocal values [19].

The extent of all RSDs representing nonlocal accesses produced during message generation are examined to select the appropriate storage type for each array. If overlaps have been selected, array declarations are modified to take into account storage for nonlocal data. For instance, array declarations in the generated code in Figures 8 and 9 have been extended for overlap regions. If buffers are used, additional buffer array declarations are inserted. Finally, all nonlocal array references in the program are modified to reflect the actual data location selected.

3.4 Parallelism Optimizations

This section describes how the Fortran D compiler exploits parallelism found in *pipelined computations.* We begin by describing some program transformations.

3.4.1 Program Transformations

Shared-memory parallelizing compilers apply program transformations to expose or enhance parallelism in scientific codes, using dependence information to determine their legality and profitability [1, 21, 23, 34]. Program transformations are also useful for distributed-memory compilers. The legality of each transformation is determined in exactly the same manner, since the same execution order must be preserved in order to retain the meaning of the original program. However, their profitability criteria are now totally different.

Loop Distribution *Loop distribution* separates independent statements inside a single loop into multiple loops with identical headers. Loop distribution may be applied only if the statements are not involved in a recurrence and the direction of existing loop-carried dependences are not reversed in the resulting loops [21, 23]. It can separate statements in loop nests with different local iteration sets, avoiding the need to evaluate guards at runtime. Loop distribution may also separate the source and sink of loop-carried or loop-independent cross-processor dependences, allowing individual messages to be combined into a single vector message.

Loop Fusion *Loop fusion* combines multiple loops with identical headers into a single loop. It is legal if the direction of existing dependences are not reversed after fusion [23, 34]. Loop fusion can improve data locality, but its main use is to enable loop interchange and strip-mine.

Loop Interchange *Loop interchange* swaps adjacent loop headers to alter the traversal order of the iteration space. It may be applied only if the source and sink of each dependence are not reversed in the resulting program. This may be determined by examining the distance or direction vector associated with each dependence [1, 34].

Strip Mining *Strip mining* increases the step size of an existing loop and adds an additional inner loop. The legality of applying strip-mine followed by loop interchange is determined in the same manner as for *unroll-and-jam* [21]. The Fortran D compiler may apply strip mining in order to reduce storage requirements for computations. It may also be used with loop interchange to help exploit pipeline parallelism, as discussed in the next section.

3.4.2 Pipelined Computations

In *loosely synchronous* computations all processors execute SPMD programs in a loose lockstep, alternating between phases of local computation and synchronous global communication [11]. These problems achieve good load balance because all processors are utilized during the computation phase. For instance, Jacobi and Red-black SOR are loosely synchronous. The Fortran D compilation strategy presented so far is well-suited to compiling such programs, since it identifies and inserts efficient vector or collective communication at appropriate points in the program.

However, a different class of computations contain loop-carried cross-processor data dependences that sequentialize computations over distributed array dimensions. Synchronization is required and processors are forced to remain idle at various points in the computation, resulting in poor load balance. We call these computations, such as SOR, *pipelined.* They present opportunities for optimization to exploit partial parallelism through pipelining, enabling processors to overlap computation with one another (hence the name).

Cross-Processor Loops The Fortran D compiler identifies pipelined computations using *cross-processor* loops. We classify loops in numeric computations as either time-bound or space-bound. *Time-bound* loops correspond to time steps in the computation, with each iteration accessing much or all of the data space. They are usually outermost loops that need to be executed sequentially. In comparison, *space-bound* loops iterate over the data space, with each iteration accessing part of each array. These loops are usually parallel in data-parallel computations, but may be sequential if they cause a computation *wavefront* to sweep across the data space.

The Fortran D compiler labels loops as *cross-processor* if they are sequential space-bound loops causing computation wavefronts that cross processor boundaries (*i.e.,* sweep over the distributed dimensions of the data space). Cross-processor loops may be calculated by considering all pairs of array references that cause loop-carried true dependences. If non-identical subscript expressions occur in a distributed dimension of the array, index variables appearing in the subscript expressions belong to cross-processor loops. The algorithm is shown in Figure 10. In most cases, cross-processor loops are loops carrying true dependences whose iterations have been partitioned across processors.

INPUT:
  Loop nest $\{L_1, \ldots, L_n\}$ with index variables $\{I_1, \ldots, I_n\}$
  List of all loop-carried true dependences
  Data decomposition of all distributed arrays in loop nest

OUTPUT:
  Loops = Set of cross-processor loops

ALGORITHM:
  Loops $\leftarrow \emptyset$
  for each loop-carried true dependence between
      references $A(f_1, \ldots, f_m)$ and $A(g_1, \ldots, g_m)$ **do**
    for each distributed dimension k of A **do**
      {* f_k and g_k are subscripts in dimension k *}
      if $f_k \neq g_k$ **or** f_k is not of form $\alpha I_j + \beta$ **then**
        for each index variable I_j in either f_k or g_k **do**
          if L_j encloses both references to A **then**
            Loops $\leftarrow$ *Loops* $\cup \{L_j\}$
          endif
        endfor
      endif
    endfor
  endfor

Figure 10: Finding Cross-Processor Loops

Figure 11 illustrates cross-processor dependences and loops. We denote cross-processor loops as `do*`. All loops in the example are space-bound loops that sweep the data space. In Loop 1, the i loop is cross-processor because the computation wavefront sweeps the i dimension across processors. There are no cross-processor loops in Loop 2 because the computation wavefront is internalized and does not cross processor boundaries. In Loop 3 both the i and j loops are cross-processor because the computation wavefront sweeps across processors in both dimensions.

These examples make it clear how cross-processor loops may be used to classify computations. Computations such as Loop 2 that do not possess cross-processor loops are loosely synchronous, since all processors may execute in parallel. Computations such as Loops 1 & 3 that do possess cross-processor loops are pipelined, since processors must wait in turn for computation to be completed.

Exploiting Pipeline Parallelism Parallelism may be exploited in pipelined computations through *message pipelining*—sending a message when its value is first computed, rather than waiting until its value is needed [28]. Rogers and Pingali applied this optimization to a Gauss-Seidel computation (a special case of SOR) that is distributed cyclically. However, more sophisticated approaches are usually required.

Loop 1

Data Decomposition

```
DECOMPOSITION A(N,N)
REAL X(N,N)
ALIGN X(I,J) with A(I,J)
DISTRIBUTE A(BLOCK,:)
```

Loop Nest & Cross-Processor Loops

```
do* i = 2,N
  do j = 1,N
    X(i,j) = X(i-1,j)
  enddo
enddo
```

Loop 2

```
DECOMPOSITION A(N,N)
REAL X(N,N)
ALIGN X(I,J) with A(I,J)
DISTRIBUTE A(:,BLOCK)
```

```
do i = 2,N
  do j = 1,N
    X(i,j) = X(i-1,j)
  enddo
enddo
```

Loop 3

```
DECOMPOSITION A(N,N)
REAL X(N,N)
ALIGN X(I,J) with A(I,J)
DISTRIBUTE A(BLOCK,BLOCK)
```

```
do* i = 2,N
 do* j = 2,N
  X(i,j) = X(i-1,j)+X(i,j-1)
 enddo
enddo
```

Data Space & Cross-Processor Dependences

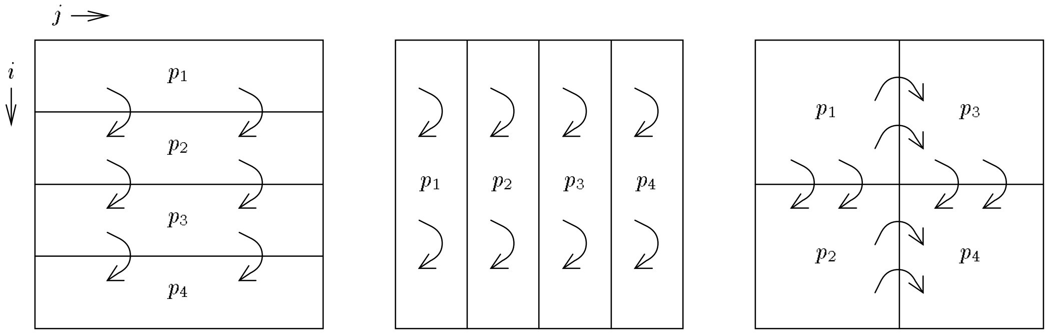


Figure 11: Examples of Cross-Processor Dependences and Loops

Figure 12 illustrates the tradeoffs between communication and parallelism that must be considered when compiling pipelined computations. It presents the program text, data space traversal order, and a processor trace for three versions of the computation. In the processor trace, elapsed time proceeds from left to right. The computation for each processor is represented as a solid line, and messages are shown as dashed lines between processors.

In the original program execution order, message vectorization minimizes communication overhead but sequentializes the computation. Applying message pipelining alone is insufficient, since only the computation for the last row will be pipelined. The key observation is that for some pipelined computations, the program execution order must also be changed. We present two optimizations to exploit pipeline parallelism. *Fine-grain pipelining* interchanges cross-processor loops as deeply as possible to maximize parallelism. This is a major improvement over sequentialized computation, but incurs the most communication overhead since a message is sent for every nonlocal array element.

Coarse-grain pipelining strip-mines all loops enclosed by cross-processor loops, then interchanges the strip-mined loops outside. A message is sent for each block of nonlocal data, decreasing communication overhead at the expense of some parallelism. Selecting an efficient block size depends on the data decomposition, processor topology, and ratio of communication to computation cost for the underlying machine. A detailed algorithm is presented elsewhere [18]. Empirical results show that exploiting pipeline parallelism is important for common scientific computations such as tridiagonal solvers.

4 Related Work

We view the Fortran D compiler as a second-generation distributed-memory compiler that integrates and extends analysis and optimization techniques from many other research projects. It is related to other distributed-memory compilation systems such as AL [33], CM FORTRAN [32], C* [29], DATAPARALLEL C [13], DINO [30], MIMDIZER [15], PANDORE [2], PARAGON [9], and SPOT [31], but mostly builds on the following research projects.

SUPERB is a semi-automatic parallelization tool that supports arbitrary user-specified contiguous BLOCK distributions [12, 37]. It originated *overlaps* as a means to both specify and store nonlocal data accesses. *Exsr* statements are inserted in the program to communicate overlap regions. Data dependence information is then used to apply *loop distribution* and vectorize these statements, resulting in vectorized messages. SUPERB also performs interprocedural analysis and code generation.

CALLAHAN & KENNEDY propose distributed-memory compilation techniques based on data dependence [7]. User-defined distribution functions are used to specify the data decomposition for Fortran programs. The compiler inserts *load* and *store* statements to handle data movement, then applies numerous program transformations to optimize guards and messages.

Data Decomposition

```
DECOMPOSITION A(N,N)
ALIGN X(I,J) with A(I,J)
DISTRIBUTE A(BLOCK,:)
```

Cross-Processor Loops & Communication

Original Order

```
{recv row from P_left}
do* i = 1,N/P
  do j = 1,N
    X(i,j) = X(i-1,j)
  enddo
enddo
{send row to P_right}
```

Fine-grain Pipelining

```
do j = 1,N
  {recv element from P_left}
  do* i = 1,N/P
    X(i,j) = X(i-1,j)
  enddo
  {send element to P_right}
enddo
```

Coarse-grain Pipelining

```
do jj = 1,N,Bk
  {recv block from P_left}
  do* i = 1,N/P
    do j = jj,jj+Bk-1
      X(i,j) = X(i-1,j)
    enddo
  enddo
  {send block to P_right}
enddo
```

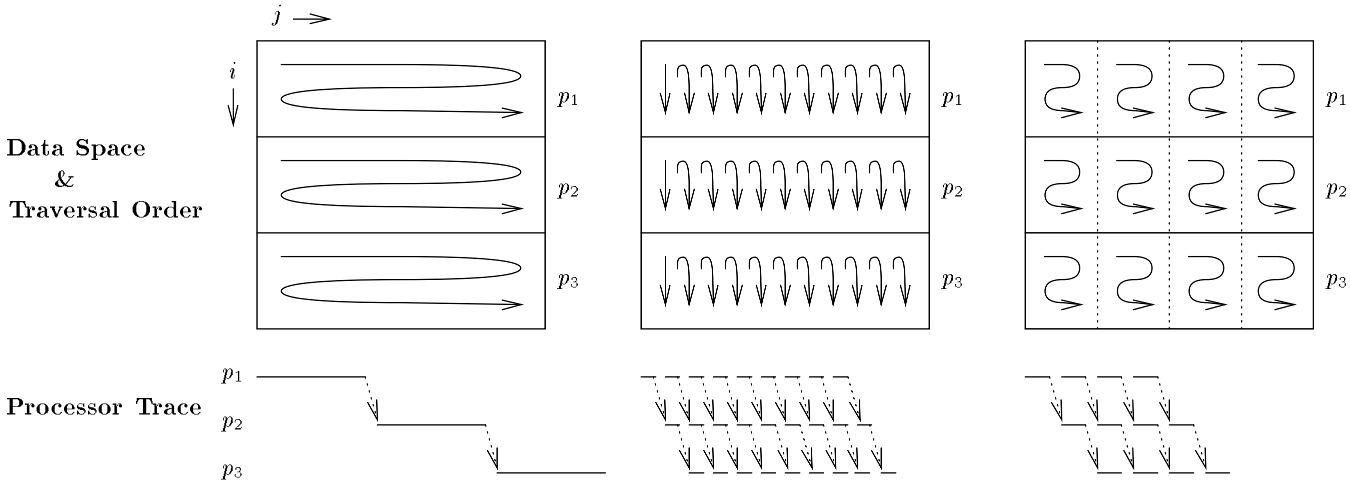


Figure 12: Examples of Pipelined Computations

ID NOUVEAU is a functional language enhanced with BLOCK and CYCLIC distributions [28]. Initially, *send* and *receive* statements are inserted to communicate each nonlocal array access. *Message vectorization* is applied to combine messages for previously written array elements. *Loop jamming (fusion)* and *strip mining* are used when writing array elements. Analysis is considerably simplified through the use of write-once arrays called *I-structures*. Global *accumulate* (reduction) operations are supported. Unlike other systems, program partitioning produces distinct programs for each node processor.

CRYSTAL is a high-level functional language compiled to distributed-memory machines using both automatic data decomposition and communication generation [25]. Program analysis and optimization are different because it targets a purely functional language. CRYSTAL pioneered the strategy of identifying collective communication opportunities used in the Fortran D compiler.

ASPAR is a Fortran compiler that performs simple dependence analysis of using *A-lists* to detect parallel loops [20]. Loop iterations are then partitioned and used to automatically derive data decompositions. A *micro-stencil* based on the computation is used to generate a *macro-stencil*, identifying communication requirements. Collective communications are also generated.

KALI is the first compiler that supports both regular and irregular computations on MIMD distributed-memory machines [22]. Since dependence analysis is not provided, programmers must declare all parallel loops. Instead of deriving a parallel program from the data decomposition, KALI requires that the programmer explicitly partition loop iterations onto processors using an *on clause*.

ARF is a compiler that automatically generates *inspector* and *executor* loops for runtime preprocessing of programs with BLOCK, CYCLIC, and user-defined irregular distributions [36]. It was motivated by PARTI, a set of runtime library routines that support irregular computations on MIMD distributed-memory machines. PARTI is the first to propose and implement user-defined irregular distributions [26] and a hashed cache for nonlocal values [19].

4.1 Comparison with Fortran D

The Fortran D compiler integrates more compiler optimizations than the first generation research systems described, and in addition possesses two main advantages. First, dependence analysis enables the compiler to exploit parallelism without relying on single-assignment semantics (*e.g.,* CRYSTAL, ID NOUVEAU) or explicitly parallel programs (*e.g.,* KALI, ARF). Precise analysis also allows the compiler to perform more optimizations. Most systems vectorize messages by extracting communication out of parallel regions, but systems such as SUPERB or Fortran D can also vectorize messages in sequential regions such as those found in SOR.

Second, the Fortran D compiler performs its analysis up front and uses the results to drive code generation, unlike transformation-based systems (*e.g.,* CALLAHAN & KENNEDY, ID NOUVEAU, SUPERB) that begin by inserting guards and element-wise messages, then apply program transformations and partial evaluation in order to produce more efficient code. This approach is simpler and provides greater flexibility. For instance, the Fortran D compiler may apply program transformations without the possibility of introducing deadlock due to message reordering.

5 Conclusions

A usable yet efficient machine-independent parallel programming model is needed to make large-scale parallel machines useful for scientific programmers. We believe that Fortran D, a version of Fortran enhanced with data decompositions, provides such a portable data-parallel programming model. Its success will depend on the effectiveness of the compiler, as well as environmental support for automatic data decomposition and static performance estimation [4, 5, 16].

The current prototype of the Fortran D compiler performs message vectorization, collective communication, fine-grain pipelining, and several other optimizations for block-distributed arrays. Though significant work remains to implement other optimizations presented in this paper, preliminary results lead us to believe that the Fortran D compiler will generate efficient code for a large class of data-parallel programs with only minimal user effort.

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