

Motivation

Distributed-memory architectures

- Physically distributed memory, disjoint addresses
- Advantages → high price/performance, scalability
- Disadvantages → local address spaces, communication
- Communicate via explicit send/recv messages
- Large messages amortize communication overhead

Data-Parallel Languages

- Uniform fine-grain operations on arrays
- Shared data in large, global arrays
- Implicit synchronization between operations
- Implicit communication derived from mapping hints
- Examples: APL, Fortran 90

At one point, data-parallel languages were viewed as the most feasible programming model for large distributed-memory multiprocessors.

High Performance Fortran (HPF)

TEMPLATE

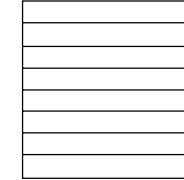
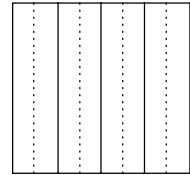
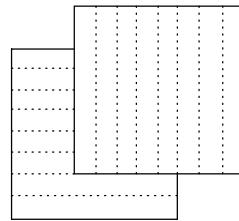
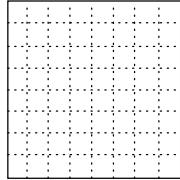
→ abstract problem domain

ALIGN

→ map from array to decomposition

DISTRIBUTE

→ map from decomposition to machine



Example

```
REAL X(8,8)
TEMPLATE A(8,8)
ALIGN X(i,j) WITH A(j+3,i-2)
DISTRIBUTE A(*,BLOCK)
DISTRIBUTE A(CYCLIC,*)
```

FORALL → parallel loop with copy-in/copy-out semantics

INDEP → parallel loop

Intrinsics → parallel functions from Fortran 90

Using HPF

Help analysis with assertions

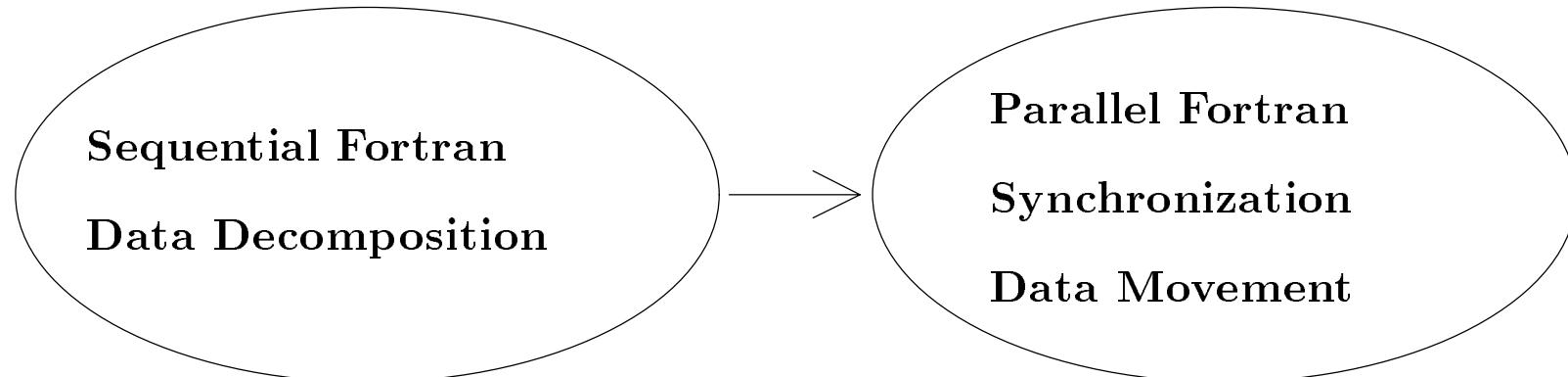
- Align, distribute
- Forall, independent
- Intrinsics

Distribute array dimensions for parallelism

- data updated in parallel should be on different processors
- data used together should be on the same processors

Don't try to hide from compiler what you're doing!

HPF Compiler



Requirements

- Partition data & computation
- Generate communication

Single-program, multiple-data (SPMD) node programs

“Owner Computes” Rule

- Owner of datum computes its value
- Dynamic data decomposition

Compiling for Distributed-Memory Machines

Data decomposition

- User-specified (HPF) or automatic
- Derive computation distribution
- Simple decompositions appear sufficient

Compilation process

- 1) Analyze program → apply dependence analysis
- 2) Partition data → template, align, distribute
- 3) Partition computation → owner computes rule
- 4) Analyze communication → find nonlocal references
- 5) Optimize communication → select communication
- 6) Manage storage → select overlaps and buffers
- 7) Generate code → instantiate partition & messages

Compilation approaches

- Calculates nonlocal data, generates send/recv
- Selects communication type, calls run-time library

HPF Compilation Example

{ HPF Program }	{ Compiler Output }
REAL A(100), B(100)	REAL A(1:25), B(0:25)
N\$PROC = 4	P = myproc() { 0 ... 3 }
TEMPLATE D(100)	lb\$1 = max(P*25+1,2)-(P*25)
ALIGN A, B WITH D	IF (P < 3) <u>send</u> B(25) to P _{right}
DISTRIBUTE D(BLOCK)	IF (P > 0) <u>recv</u> B(0) from P _{left}
DO i = 2,100	DO i = lb\$1,25
A(i) = B(i-1)	A(i) = B(i-1)
ENDDO	ENDDO

- Local data → A(1:25), B(1:25)
- Local computation → [DO i = 1:25]
- Nonlocal accesses → B(0:24) – B(1:25) = B(0)
- Communication → send B(25) to P_{right}
- Overlap storage → Extend B to hold B(0)

Communication Optimization Example

```
post B,C,D  
send B,C,D  
{ computation, communication } }  
recv B,C,D  
DO i = 1,100  
    A(i) = B(i+10) + B(i+11) + C(i+10) + D(100)  
ENDDO
```

message coalescing collective communication

message aggregation

unbuffered messages
vector message pipelining
iteration reordering
message vectorization

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```

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Message Vectorization

Key optimization & code generation technique

Place communication at level of deepest loop that carries a true dependence OR contains endpoints of a loop-independent true dependence

Classify references as independent, carried-all, or carried-part

DO k = 1,M	<u>send</u> & <u>recv</u> B
DO i = 1,N	DO k = 1,M
δ_∞ A(i) = B(i+2)	<u>send</u> & <u>recv</u> C
δ_k C(i) = C(i+2)	<u>recv</u> D
δ_i D(i) = D(i-2)	DO i = 1,N/P
ENDDO	A(i) = B(i+2)
ENDDO	C(i) = C(i+2)
	D(i) = D(i-2)
	ENDDO
	<u>send</u> D
	ENDDO

Communication Selection

Utilize Collective Communication Primitives

- Simplifies communication, utilizes efficient primitives
- Syntactic pattern matching

Example

TEMPLATE D(N,N)

ALIGN A, B with D

DISTRIBUTE D(BLOCK,BLOCK)

do j = 2,N

 do i = 2,N

$A(i,j) = B(i,j-1) + B(i-1,j)$

[shift]

$A(i,j) = B(c,j)$

[broadcast]

$A(c,j) = B(i,j)$

[gather]

$A(i,j) = B(j,i)$

[all-to-all,transpose]

$A(f(i),j) = A(f(i),j) + B(g(i),j)$

[inspector/executor]

 enddo

enddo

Handling Irregular Accesses

Irregular codes

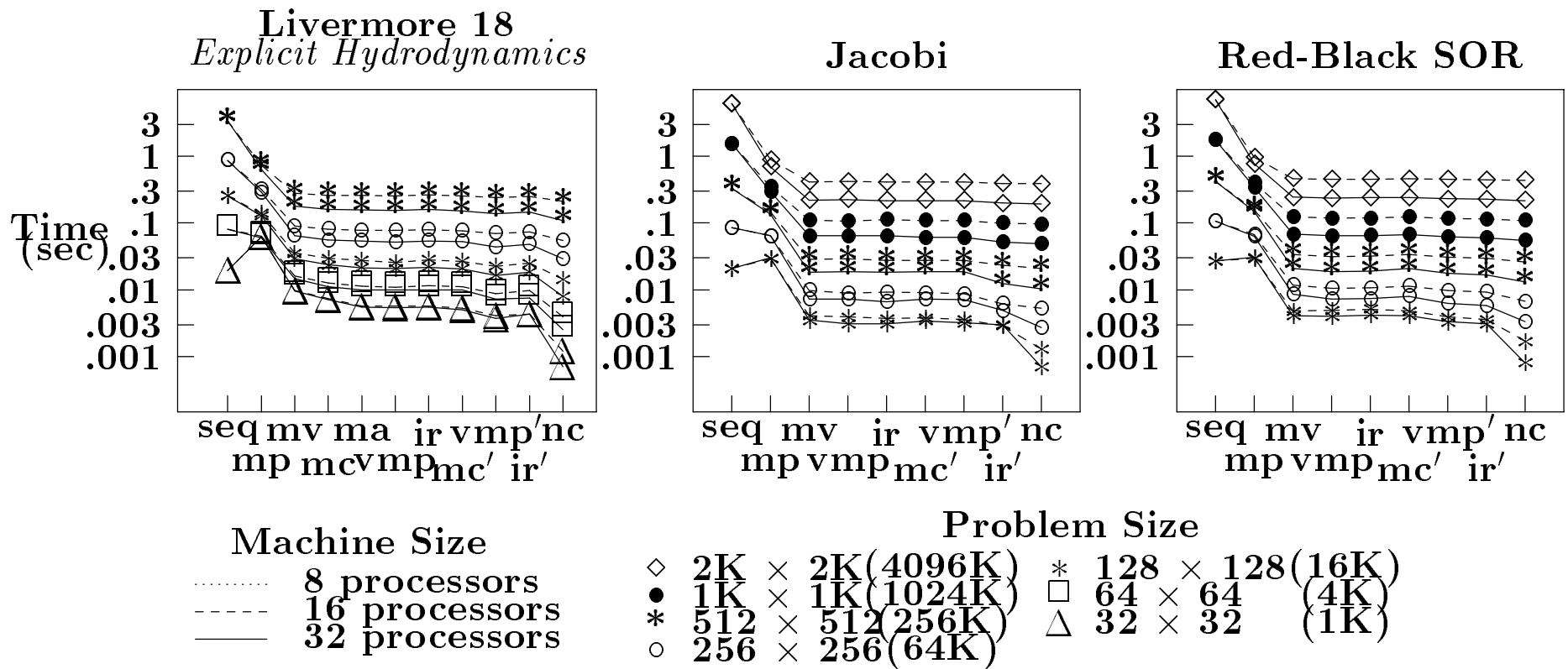
- Memory access pattern determined by index array
- Value of index array unknown at compile time

Inspector-executor approach

- Compiler inserts call to *inspector* (possible reuse)
...which examines index array, calculates communication
- Compiler transforms loop into *executor*
...which performs communication & computation based on inspector

// irregular code	// compiler output
do j = 1,100	inspect IDX, calculate MYIDX
B(...) =	do j = 1,100
do i = 1,100	B(...) =
A(i) = B(IDX(i))	execute communication
	do i = 1,100
	A(i) = B(MYIDX(i))

Comparing Communication Optimizations



Experimental evaluation

- Applied communication optimizations by hand
- iPSC/860 timings for different data sizes, # of processors
- Message vectorization (mv) main optimization

HPF Experience

Successes

- Standardized data-parallel languages
- Language quickly adopted (< 2 year)
- Multiple commercial compilers implemented
- Extensions proposed for HPF-2

Failures

- Initial compilers poor
- Performance unstable
- Support for complex applications limited
- Bleeding-edge users preferred message-passing standard (MPI)
- Casual users avoided distributed-memory multiprocessors