optimization.  

Abstract—MPI is the de facto standard for portable parallel programming on high-end systems. However, while the MPI standard provides functional portability, it does not provide sufficient performance portability across platforms. We present a framework that enables users to provide hints about communication patterns used within MPI applications. These annotations are then used by an automated program transformation system to leverage different MPI operations that better match each system's capabilities. Our framework currently supports three automated transformations: coalescing of operations in MPI one-sided communications; transformation of blocking communications to nonblocking, which enables communication-computation overlap; and selection of the appropriate communication operators based on the cache-coherence support of the underlying platform. We use our annotation-based approach to optimize several benchmark kernels, and we demonstrate that the framework is effective at automatically improving performance portability for MPI applications.

Keywords—high performance computing, parallel programming, automatic programming

I. INTRODUCTION

MPI [9] is a de facto standard for parallel programming in scientific domains. Performance portability for MPI programs, however, is challenging because of the hard-to-predict relative cost of MPI operations across systems, due to unknown variations in hardware parameters, system capabilities, and features provided by MPI implementations.

To elaborate, the rich communication semantics of MPI provide users with multiple algorithmic choices so that the same application functionality can be implemented using a variety of different operations in MPI. For instance, Fourier transform can either be implemented in a bulk synchronous model where different processes compute and collectively exchange data at regular synchronization points (using MPI collective communication operations) or through a more asynchronous model using MPI one-sided communication where data is moved when it is ready. While the two models are functionally equivalent, the performance they achieve varies on different systems. For example, InfiniBand based clusters can utilize hardware-supported asynchronous progress capabilities, making them ideal platforms for using MPI one-sided communications. On the other hand, platforms such as IBM Blue Gene provide hardware support for collective acceleration, making them ideal for using group communication operations. Which MPI communication routines perform better is highly platform specific, making it hard for the application developers to determine the right algorithmic choice a priori in a portable manner. Unfortunately, state-of-the-art MPI implementations, in spite of their many aggressive dynamic optimizations, only see each MPI operation individually and focus on optimizing it. As a result, they cannot always handle such performance differences internally due to the lack of a holistic view of the application algorithms.

This paper presents an annotation-based program transformation framework to help MPI applications enhance their performance portability across different platforms. The central idea is to build automated program transformations that utilize user-supplied hints about their underlying algorithmic models as well as system-specific information to automatically transform user applications to utilize the best MPI operations for each platform. By modulating the behaviors of both the application and MPI implementations, our approach enables applications to automatically leverage system-specific capabilities that enhance the efficiency of some MPI operations over others. Consequently, it provides a portable means for accessing system-specific features beyond the MPI standard.

The workflow of our framework is shown in Figure 1. Specifically, we allow developers to annotate their applications with concise information about the MPI communication mechanisms used in varying blocks of statements in their applications. Based on these user annotations combined with additional information of the underlying runtime platform, the optimization analysis component of our framework determines possible program transformations to enhance the efficiency of MPI operations in the user application. The transformation decisions are then fed into a program transformation component, which automatically specializes the annotated communication blocks for the underlying platform before sending the user application to the vendor compiler to generate executables.

Our framework currently supports a number of user annotations that provide simple hints on the opportunities of applying three program transformations: coalescing of MPI one-sided communications, overlapping communications with computations, and automatic selection of the appropriate communication operators based on the cache-coherence support of the underlying platform. We present experiment results using the Graph500 benchmark [3], a
The structure of each annotated block. Line 2 of Figure 2 specifies that each annotated block must start with \#pragma mpi followed by a specific annotation and a block of statements. Our framework currently supports five annotations, defined at Lines 3–7.

The data coalescing annotation (cco at Line 3), which starts with the keyword “cco” followed by a list of the windows and buffers of one-sided communications \((\text{win\_buf\_list})\) whose data could be coalesced. An optional specification, no_\_overlap, can be used to indicate that the data of different MPI operations are never sent to the same addresses (by default, overlapping is assumed when MPI\_Accumulate is involved).

The cco annotation (cco at Line 4), which starts with the keyword “cco” followed by a list of the MPI communications, each specified as an MPI operator (e.g., MPI\_Send) followed by an optional list of parameters or as an MPI window (MPI\_Win) followed by a window name, that could be moved to better overlap with independent computations.

The remote-memory access annotation (rma at Line 5), which includes a keyword “rma” followed by a list of the windows and buffers of one-sided communications \((\text{win\_buf\_list})\) that may be converted to local loads and stores when appropriate.

The local load/store annotation (ldst at Line 6), which includes a keyword “ldst” followed by a list of the windows and buffers \((\text{win\_buf\_list})\) being operated by the annotated block through local load/store operations. An optional specification, no_\_overlap, can be used to specify that there is no aliasing or overlapping among these buffers.

The independent annotation (indep at Line 7), which includes the keyword “indep” followed by a list of the MPI communications that are independent of the statement block being annotated; that is, the annotated statements do not interfere with or use any data received from the listed MPI communications.

Our Optimization Analyzer in Figure 1 uses the above annotations to ensure both the safety and the profitability of the relevant program transformations, through the analysis algorithm shown in Figure 3. The algorithm takes as input the underlying platform configuration \((\text{config})\) and the input MPI code to optimize. It traverses the input program, searches for occurrences of user-annotated code segments, and then invokes the corresponding optimizing transformations to modify the input code accordingly based on current platform configurations. Each of the annotations at Lines 3–6 of Figure 2 is used to enable an automated transformation currently supported within our framework, and the independent annotation at Line 7 is combined with the other annotations to ensure the correctness of the program transformations.

In essence, our framework requires developers to manually insert annotations to automate the necessary transformations of porting their applications to varying execution platforms. The annotations themselves are minimally...
intrusive to the original source code. While developers need to deliberately consider alternative implementations to insert annotations correctly, the annotations allow their applications to automatically attain performance portability without having to be manually specialized for each MPI platform. In particular, our framework allows developers to specify a single, possibly simplest, algorithm implementation and provides developers with the ability to automatically synthesize alternative implementations from the original one based on different platform configurations, thereby significantly improving the productivity of porting MPI applications to varying platforms.

III. ANNOTATION-BASED FRAMEWORK

As shown in Figure 1, the workflow of our overall framework includes the following three key components.

• Platform analysis, which collects information about the underlying platform, e.g., the number of available nodes and processing cores, the cache coherence protocol, and the MPI library installed, by querying the operating system or by empirically evaluating varying MPI operations using different system configurations.

• Optimization analysis, which identifies opportunities for modifying an MPI application to use more efficient communications based on configurations generated by the platform analyzer and annotations inserted by software developers in their applications.

• Program transformations, which include a collection of program transformation routines invoked by the optimization analyzer to modify the input application for better performance. The modified MPI application is then fed into a vendor compiler (e.g., icc or gcc) to generate a machine executable.

Currently we have implemented the platform analyzer using simple shell scripts that automatically detect the relevant system configurations. Both the optimization analysis and transformations are implemented using POET [14], an interpreted program transformation language designed to support the programmable control and parameterization of source-to-source compiler optimizations. Our POET scripts are extensively parameterized, and variations of alternative implementations can be flexibly generated via non-intrusive to the original source code. While developers need to deliberately consider alternative implementations to insert annotations correctly, the annotations allow their applications to automatically attain performance portability without having to be manually specialized for each MPI platform. In particular, our framework allows developers to specify a single, possibly simplest, algorithm implementation and provides developers with the ability to automatically synthesize alternative implementations from the original one based on different platform configurations, thereby significantly improving the productivity of porting MPI applications to varying platforms.

A. Coalescing of One-sided Communication Operations

MPI remote memory access (RMA) or one-sided communication follows an epoch-based model for memory consistency. Specifically, a group of processes can expose a part of their memory as public memory, which is referred to as a “window”. Then, a process can open an epoch within which it can access such public memory using RMA operations such as MPI_Get, MPI_Put, and MPI_Accumulate. Figure 4 shows an example of such an RMA epoch, which operates inside window win using both MPI_Put and MPI_Accumulate enclosed by a pair of MPI_Win_fence operations.

Applications often issue multiple RMA operations per epoch. When compatible, these operations can be combined. For example, the first and third MPI_Put operations in Figure 4 can be combined into a single MPI_put. The end result is fewer messages being sent, thus reducing communication overheads.

Note that the coalescing optimization could be rather complex to apply manually for non-trivial codes, and the degree to which it is beneficial depends on the system and software architectures (e.g., network latency or eager message protocol threshold). It is difficult for the MPI library to apply this optimization due to the lack of application context and the knowledge of when to prioritize latency, bandwidth, or communication/computation overlap. It is also not advisable for developers to hardwire this optimization inside their applications as the transformation could seriously detriment the readability of their applications, and implementations specialized for one platform may perform poorly on a different platform.

Our framework supports the coalescing of all MPI operators (get, put, and accumulate) within a single epoch, driven by the “coalesce” annotation. The transformation algorithm is summarized in Figure 6. Figure 5 illustrates the result of applying the algorithm to BFS, a benchmark from Graph500 [3]. The annotation at Line 1 of Figure 5(a) specifies that the MPI one-sided communications in windows p[2]_win and q[2]_win can be coalesced when appropriate. These communications start with the two invocations of MPI_Win_fence at Lines 3–4, contain two MPI_Accumulate calls at Lines 9–10, and end with two MPI_Win_fence calls at Lines 11–12. The transformed code is shown in Figure 5(b), which contains the following modifications to the original code for each of the annotated windows (p[2]_win and q[2]_win).

• Declare and allocate arrays to save the information for coalescing each communication operator, at Lines 1–2 of Figure 5(b). In particular, four arrays (_data_cntr, _tgt_disp, and _ctree) are used to track the various source and destination windows. Further, MPI_Win_fence operations are inserted at Lines 3 and 4 to delimit the window and at Lines 11 and 12 to end the window.
The above transformations are applied at Steps 5, 8, 9, and 6 of the algorithm in Figure 6, respectively. Finally, the address, size, destination process, and overlapping of destination addresses, respectively, of the coalescing buffer allocated for each MPI operator.

- Postpone communications until a coalescing buffer is full, at Lines 9–10 of Figure 5(b). The code at Line 9.1 first identifies `p2_win_MIN_data[rank]`, where `rank` identifies the destination process, as the address of the coalescing buffer and allocates space if the address is NULL. Lines 9.2 and 9.3 send the buffered data if no space is available or if the buffered data size exceeds a preset limit (CL_FACTOR); otherwise, Line 9.4 packs the data into the buffer while using an AVL tree [1] (`p2_win_MIN_cTREE[rank]`) to track conflicting addresses.

- Modify each final synchronization of the communication epoch to send any data that have been buffered but not yet sent, at Lines 11–12 of Figure 5(b).

- Free the coalescing buffers so that their spaces can be used for other purposes, at Line 13 of Figure 5(b).

Step 10 of the algorithm searches the annotated block for any statement (e.g., unknown function calls) that may interfere with the communication windows being coalesced. If found, it inserts statements to send off the coalesced data to make sure that any new MPI communications that may be triggered by the unsafe statement do not interrupt the original flow of MPI communications. Developers can use the independent annotation at Line 7 of Figure 2 to declare statements as independent of the MPI windows being optimized. These independent statements will be treated as safe statements regarding the windows, so no extra communications will be inserted before them.

The algorithm in Figure 6 adopts the following strategies to guarantee the correctness of the transformation.

- **Grouping of MPI communications.** The algorithm allocates a dedicated buffer for each group of MPI communications that belong to the same window, have the same destination process, and communicate by using the same MPI Put/MPI Get or the same reduction operator in MPI Accumulate. This strategy ensures that all the coalesced data will arrive at their original destinations. Since MPI standard maintains that an epoch does not enforce any sequential ordering of communications, the coalesced communications have the same semantics as the original ones.

- **Overlapping of destination addresses.** When using MPI Put and MPI Get, the addresses to place the communicated data on the destination process are not allowed to overlap by MPI standard. When invoking MPI Accumulate, however, the displacement of the data can indeed overlap, and values sent to the same location need to be accumulated by using the reduction operator of MPI Accumulate. When the developer does not rule out such overlapping using a “no_overlap” clause, our transformation uses an AVL tree [1] to keep track of the displacements of all the data being communicated via MPI Accumulate. And whenever an overlapping is detected, local reduction of the data within the coalescing buffer is invoked.

- **Handling unknown function calls.** When an MPI epoch invokes unknown function calls, the functions could include MPI synchronizations that end the epoch being optimized. Our transformation algorithm considers each unknown function call as an unsafe
MPI provides several nonblocking operations, e.g., `MPI_Isend` and `MPI_Irecv`, to overlap computation and communication. However, the right amount of computation to be perfectly overlapped with communication is specific to a given platform, the destination process of the communication (e.g., whether the process can be reached over shared memory or the network), and the kind of data being communicated (e.g., contiguous data vs. noncontiguous data). Such constraints make it hard to portably decide on the right amount of computation that needs to be interleaved with communication operations.

Our framework allows developers to implement their algorithms using simple blocking MPI send/recv operations and then simply insert a few annotations to enable the transformations to be automatically applied when desired.

Within our framework, the computation-communication overlapping transformation is driven by the `cco` annotation, illustrated at Line 1 of Figure 7(a), which specifies that the `MPI_Send` and `MPI_Recv` operations with either `MPI_Isend` or `MPI_Irecv` need to be interleaved as early as possible. In Figure 7(a), the `wait` operations that appear before `ncomm` and after `wait` respectively, where `in1` and `in2` contain the `ncomm` and the `wait` operations respectively, so that `in1` and `in2` can be easily interchanged with statements immediately before or after them later.

Insert new variable declarations. In Figure 7(b), these declarations are inserted at Line 2, the beginning of the innermost body of the annotated block.

Safely move up `in1`, which contains the asynchronous operation `ncomm`, so that it can be evaluated as early as possible. In Figure 7(b), the `wait` operations for `ncomm` and `ncomm` are placed at Lines 5–9, since they cannot be moved further up in the original code.

Safely move down `in2`, which contains the MPI wait operation for `ncomm`, so that it can be evaluated as late as possible. In Figure 7(b), the wait operations for `ncomm` and `ncomm` are moved to Lines 11 and Line 13, respectively.

The correctness of the transformation algorithm in Figure 8 hinges on careful implementations of Steps 5, 7, and 8. Note that in the optimization analysis algorithm in Figure 3, the innermost body of the annotated block is used as the input parameter when invoking the `cco` transformation algorithm. Therefore, the transformation rearranges only the relative execution order of the statements within the

(a) Original code with annotation

```c
1: for( i=0; i<niter; i++ ) {
2: ...declarations for new variables...
3: fill_send_buf( data, send_buf, send_buf, nx, ny, nz );
4: fill_recv_buf( data, recv_buf, send_buf, nx, ny, nz );
5: if (ns_id < ns_comm_size-1)
6: MPI_Send(send_buf,ny*nz,MPI_DOUBLE,ns_id,0,n_comm);
7: if (ns_id < ns_comm_size-1)
8: MPI_Recv(recv_buf,ny*nz,MPI_DOUBLE,ns_id+1,0,n_comm,&s1);
9: if (ns_id > 0 )
10: MPI_Send(nsnd_buf,ny*nz,MPI_DOUBLE,ns_id-1,0,n_comm);
11: if (ns_id < ns_comm_size-1)
12: MPI_SendRecv(nsnd_buf,nsnd_buf,nsnd_buf,nsnd_buf,nsnd_buf,90,0,100);
13: if (ns_id < ns_comm_size-1)
14: update_east_west( data_next, data, nx, ny, nz, ew_buf);
15: if (ns_id > 0 )
16: update_north_south(data_next, data, nx, ny, nz, ew_buf);
17: for( i=0; i<niter; i++ ) {
18: compute_inter_stencil(data_next, data, nx, ny, nz);
19: update_front_rear(data_next, data, nx, ny, nz);
20: update_corners(data_next, data, nx, ny, nz, ew_buf);
21: temp = data_next; data_next = data; data = temp;
22: }
```

(b) Outline of transformed code

Figure 7: Example: comp/comm overlapping.

Statement and automatically inserts communications to send the coalesced data before the invocation, unless these calls have been annotated by developers as independent of the MPI window being optimized.

B. Overlapping of Computation and Communications

... Nonblocking operations for `ew_comm` and `ns_comm`...
REMOTE MEMORY Access WITH ANNOTATIONS

C. Transformations for Cache-coherent Architectures

D. Generality of the Framework

Among the three groups of optimizations supported by our framework, data-coalescing and computation-communication overlapping have been well-acknowledged as important optimizations for MPI applications, while the conversion between RMA and local load/store operations targets at specializing MPI applications for varying platforms in order to improve their performance portability. Manually applying these optimizations is cumbersome.
and compromises both the readability and the portability of applications. By allowing developers to single out important regions of code that implement epochs of MPI communications, a lightweight MPI transformation system has been used to automatically specialize MPI applications and thus significantly enhance their performance portability across different systems. With the help of developer supplied algorithmic hints, the overhead of applying the necessary program transformations becomes negligible (linear to the size of code regions being transformed). The scalability of the overall approach can be enhanced by utilizing optimizing compilers to automatically determine the dependence constraints within the application and by utilizing performance modeling techniques to automatically identify hot regions of code to specialize, both of which are topics of our future work.

IV. EXPERIMENTAL RESULTS

Attaining performance portability is the ultimate goal of high performance computing. While the small collection of program transformations currently supported within our framework is far from addressing the full range of performance portability issues in MPI programming, our proposed lightweight annotation-based approach serves to demonstrate a migration path that may eventually lead to fully portable MPI applications. We have studied four benchmarks, shown in Table I, to validate the potential of this annotation-based approach and to demonstrate the sensitivity of our application-level optimizations to varying runtime configurations. Three of these benchmarks, bfs, stencil, and NAS FT, represent well-acknowledged important scientific computations, while rma-ldst is a synthetic kernel we developed to study the sensitivity of MPI RMA vs local load/store operations. We have optimized bfs, rma-ldst, and stencil by manually inserting annotations into selected functions and then applying our framework to automatically optimize their MPI communications for varying platforms. The NAS FT benchmark, however, was transformed manually without using our framework, as its MPI communications are scattered across several procedures and thus beyond the capacity of our existing framework. Since supporting automated inter-procedural optimization of MPI communications is a topic of our future work, we present our performance study of FT.

We evaluated our benchmarks on two supercomputers at Argonne National Laboratory: Fusion, a cluster with 320 compute nodes, each with two Intel Nehalem Quad-Core 2.6 GHz processors and 36 GB of memory, interconnected via InfiniBand QDR at 4 GB/s per link; and Surveyor, a Blue Gene/P system with 1024 compute nodes, each with a quad-core 850 MHz PowerPC 450 processor and 2 GB memory. On both machines, we compiled the benchmarks using the default mpicc compilers, which use mvapich2 1.4.1 and gcc 4.1.2 on the Fusion machine and use gcc 4.4.6 on Surveyor. We compiled all benchmarks using the -O2 optimization flag, which enables all the relevant advanced optimizations within gcc but avoids some overly aggressive optimizations in -O3 which might actually slow down the applications. For Graph500 and FT, we present the default performance metrics reported by the benchmarks, specifically the average time of running the Graph500 bfs kernel 64 times and the total elapsed time of running 6 iterations of the FT computation. For both the stencil and the rma-ldst benchmarks, we report their average performance across 10 different runs.

A. Optimizing the Graph500 Benchmark

The Graph500 benchmark suite [3] currently includes one reference graph algorithm, a breadth-first search (bfs) of undirected graphs. We inserted an osc_coalesce annotation inside an implementation of the search kernel that uses MPI one-sided communications, an outline of which is shown in Figure 5(a). The original implementation of bfs in Figure 5(a) has two MPI_Accumulate invocations, each sending a single data item, at the innermost loop. Although these communications are overlapped with other computations (omitted as ...... in Figure 5), the communication overhead may be too high. Our framework automatically coalesced the many small messages so that an actual communication is triggered only when the size of the coalesced message exceeds a predetermined threshold (CL_FACTOR at Line 9.3 of Figure 5(b)).

An overhead of applying data-coalescing is the extra memory required. Our framework allows the user to specify a limit on the overall size of memory used for the coalescing buffers. For example, if this limit is 64 MB when using 64 processes, each process is allowed to use at most 1 MB for message coalescing. If the process runs out of memory, it stops coalescing.

Figure 11 shows the overall execution time of Graph500 when running both the original and the coalesced implementations of bfs, using a variety of different coalescing factors and memory limit, on the Fusion machine using 64, 128, and 256 processes, respectively, with 8 processes allocated to each node of the cluster. The input is an undirected graph of \(16 \times 16 \times 12\) edges. Because Graph500 uses some Assembly intrinsics that work only on Intel architectures and because the Surveyor machine uses PowerPC processors, we were not able to collect results for bfs on the Surveyor machine.

From Figure 11, the best optimization speedup from data coalescing is around 190x when using 64 processes. Because the graph size is constant in all the evaluations, as the number of processes increase, each process has a smaller amount of work, resulting in fewer remote memory accesses and thus less optimization benefit.

<table>
<thead>
<tr>
<th>Name</th>
<th>Benchmark</th>
<th>Description</th>
<th>Transformation</th>
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<tbody>
<tr>
<td>bfs</td>
<td>graph500</td>
<td>breadth-first search</td>
<td>OSC data coa-</td>
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<td></td>
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<tr>
<td>rma-ldst</td>
<td>synthetic</td>
<td>random communica-</td>
<td>RMA vs. local</td>
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<td>ld/st translation</td>
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<td>stencil</td>
<td>synthetic</td>
<td>3D stencil using MPI</td>
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<td>send/recv</td>
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<td>FT</td>
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<td>3D PDE using MPI</td>
<td>collective vs.</td>
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From all three graphs in Figure 11, having a larger amount of memory available for coalescing does increase the effectiveness of the optimization, especially when using a large number of processes. In order to obtain the best speedup, the coalescing factor needs to be adjusted based on the amount of memory available. In particular, when the memory demand is high, it is better to make coalescing buffers smaller (i.e., using smaller coalescing factors) so that the coalesced data can be sent sooner and thus free up more available memory for other needs.

In summary, the performance benefit of data coalescing depends on the number of small messages that are sent to the same destinations and thus could be coalesced; the speedup could be orders of magnitude. It is difficult to automatically determine the best memory limit and coalescing factors a priori because their best configurations are sensitive to the internal memory demands of the application, although a reasonable default configuration can be used. Note that while data coalescing appears to be beneficial for Graph500, it can be rather platform-sensitive when considered together with overlapping computation with communication, discussed in Section IV-D.

B. Optimizing Stencil Computations

Stencil computations are among the most important kernels of scientific computing and are good candidates for exploring overlapping of computation with communications since each process needs to communicate only with its neighbors about their boundary values. An outline of the original 3-D stencil and the transformed code, which uses MPI blocking primitives for better readability, is written using MPI Isend/Irecv operations. Figure 12 shows the performance of both the original 3-D stencil and the transformed code, which uses asynchronous MPI operations to better overlap the communications with the inner stencil computation of each process. The stencil size is $2048 \times 2048 \times 4096$ on Fusion and $2048 \times 2048 \times 1024$ on Surveyor, since each node on Surveyor has smaller memory than the nodes on Fusion.

The transformed code has consistently performed better, with 15% to 2.4x speedup, on both machines. However, one anomaly exists when using 256 processes on Surveyor, where the original blocking communications result in less stress on the high memory demand of each process. This demonstrates that while overlapping computation with communication typically results in better performance of MPI applications, using blocking communications can sometimes perform better.

Since the stencil size stays constant on each machine, as more processes participate in the computation, the ratio between the amount of computation and communication per process decreases, and it becomes increasingly important to hide the latency of the communications in order to reduce their overhead, therefore resulting in more significant performance benefit from the overlapping transformation.

In summary, while it is profitable to overlap communications with computations in most situations, blocking synchronizations can sometimes outperform asynchronous operations. It is advantageous for developers to use annotations to facilitate the optimization instead of directly modifying their applications since MPI blocking communications are easier to debug and maintain and allows the logistics of local computations to be better grouped together. Further, this optimization could become highly platform-sensitive when considered together with the data coalescing transformation, discussed in Section IV-D.

C. Cache-Coherence-Aware Transformations

To compare the efficiencies of different MPI operations on varying platforms, we developed a synthetic benchmark, illustrated in Figure 9(a), which randomly sends data to other processes using the MPI_Put operation. The code is then annotated with our rma annotation so that it can be automatically translated to equivalent local load/store operations on platforms that support cache coherence.

Figure 13 shows the performance of running our synthetic benchmark to perform 1 million RMA accesses (99% are local memory accesses), with and without our cache-coherence-aware transformation using 8–1024 processes. Since both machines support cache coherence, in all cases the local-load/store version automatically generated by our framework performed significantly better than the RMA version.

Among the three groups of optimizations currently supported in our framework, the cache-coherence-aware optimizations are the most platform sensitive and therefore need to be automated via application-level transformations. Our annotation-based framework is lightweight and can be supported as a preprocessor of MPI applications within a mpicc compiler before the vendor compiler (e.g., gcc) is invoked.

D. Optimizing The NAS FT Benchmark

While both the data-coalescing and computation-communication overlapping optimizations are profitable in most situations, combining them often results in a tradeoff in performance. In particular, while frequently
Alltoall. In contrast, the transformed operation, while the transformed transformers for the performance study.

implementations customized for each platform by autogenerates topology-specific routines and then implementations of MPI collectives targeting microbenchmarks.

implementations of MPI libraries. Gropp et al. [8] studied options and the associated cost of implementing the synchronization mechanisms of MPI one-sided communications. Almási et al. [2] optimized implementations of MPI collectives targeting microbenchmarks on Blue Gene/L. Sur et al. [12] exploited RDMA read and selective interrupt-based asynchronous progress in order to provide better computation/communication overlap on InfiniBand clusters. Faraj [7] presented a system that produces efficient MPI collective communication implementations customized for each platform by automatically generating topology-specific routines and then

careful optimization decisions need to be made based on the underlying node structures and network connections of each parallel platform, as the efficiencies of different MPI operations vary significantly across platforms.

V. RELATED WORK

Existing work on optimizing MPI codes mostly focused on producing efficient implementations of MPI libraries. Gropp et al. [8] studied options and the associated cost of implementing the synchronization mechanisms of MPI one-sided communications. Almási et al. [2] optimized implementations of MPI collectives targeting microbenchmarks on Blue Gene/L. Sur et al. [12] exploited RDMA read and selective interrupt-based asynchronous progress in order to provide better computation/communication overlap on InfiniBand clusters. Faraj [7] presented a system that produces efficient MPI collective communication implementations customized for each platform by automatically generating topology-specific routines and then

Figure 12: Result of applying computation-communication overlapping to stencil on (left) Fusion and (right) Surveyor.

Figure 13: Result of translating RMA to local load/store operations on (left) Fusion and (right) Surveyor.

Figure 14: Result of optimizing the NAS FT benchmark on (left) Fusion and (right) Surveyor.

```c
for(...)
  for(each i=...) {
    for(each j=...) {
      computation using array[i,j];
      exchange array using blocking communications
    }
  }

(a) Original code using all-to-all communications.

for(...){
  for(each i=...) {
    for(each j=...) {
      computation using array[i,j];
      exchange array[i] using MPI one-sided communications
    }
  }
}

(b) Optimized code using one-sided communications.

Figure 15: Optimizing MPI communications in NAS FT.

sending small messages does not fully utilize the network bandwidth, it is easy to hide the latency of frequent small communications by overlapping them with independent computations. On the other hand, while coalescing small messages may reduce the overhead of communication, the coalesced messages may not overlap well with local computations due to the delays in sending the messages. We demonstrate the issues in making optimization decisions using FT from the NAS parallel benchmarks [4]. Because MPI communications within FT are scattered across a number of subroutines, we have manually applied the transformations for the performance study.

Figure 15(a) illustrates the original communication pattern of NAS FT, which solves a 3-D partial differential equation (PDE) using forward and inverse FFTs. It first computes an entire 3D array and then scatters the data across all processes using MPI_Alltoall. In contrast, the manually transformed code in (b) scatters a single row of the 3D array immediately after each row of the array has been computed, using MPI one-sided communications. In essence, the original code coalesces all the communications and wait until the end before sending all the data using a single MPI_Alltoall operation, while the transformed code breaks up the communications into smaller messages to enable better overlapping with local computations.

Figure 14 shows the performance of the original and manually transformed code on both the Fusion and Surveyor machines, where the transformed code was able to attain 5%-25% speedup on Surveyor but resulted in almost 2x slowdown on Fusion. The results clearly indicate that careful optimization decisions need to be made based on the underlying node structures and network connections of each parallel platform, as the efficiencies of different MPI operations vary significantly across platforms.

```
empirically selecting the best implementations. Xu and Kuang [13] developed a systematic method to estimate the communication overhead of three message-passing operations (point-to-point communication, collective communication, and collective computation). Our work focuses on utilizing developer annotations and automated program transformations to improve the use of MPI operations within user applications instead of MPI libraries.

Similar to our work, Danalis et al. investigated program transformations directed toward improving communication-computation overlap in MPI applications that use collective operations [5] and proposed the development of MPI-aware compilers that exploit the knowledge of MPI call effects [6]. Preissl et al. [10] explored automated identification of communication patterns from dynamically generated MPI traces to support debugging of communications and enable performance optimizations [11]. Our work also focuses on optimizing MPI applications but emphasizes automatically supporting their performance portability through a light-weight annotation-based program transformation framework.

VI. CONCLUSIONS

This paper presents an annotation-based program transformation framework where users can annotate MPI applications with concise information about the communication mechanisms used inside varying blocks of statements, so that these blocks can be modified to use alternative communication mechanisms in MPI in order to achieve portable high performance on different platforms. Our framework currently supports three optimizations: data coalescing for MPI one-sided communications, overlapping communications with independent computations, and automatic selection of communication operators based on the cache-coherence support of the underlying platform.

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