A Practical Approach to Exploiting Coarse-Grained Pipeline Parallelism in C Programs

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Abstract

The emergence of multicore processors has heightened the need for effective parallel programming practices. In addition to writing new parallel programs, the next generation of programmers will be faced with the overwhelming task of migrating decades' worth of legacy C code into a parallel representation. Addressing this problem requires a toolset of parallel programming primitives that can broadly apply to both new and existing programs. While tools such as threads and OpenMP allow programmers to express task and data parallelism, support for pipeline parallelism is distinctly lacking.

In this paper, we offer a new and pragmatic approach to leveraging coarse-grained pipeline parallelism in C programs. We target the domain of streaming applications, such as audio, video, and digital signal processing, which exhibit regular flows of data. To exploit pipeline parallelism, we equip the programmer with a simple set of annotations (indicating pipeline boundaries) and a dynamic analysis that tracks all communication across those boundaries. Our analysis outputs a stream graph of the application as well as a set of macros for parallelizing the program and communicating the data needed. We apply our methodology to six case studies, including MPEG-2 decoding, MP3 decoding, GMTI radar processing, and three SPEC benchmarks. Our analysis extracts a useful block diagram for each application, and the parallelized versions offer a 2.78x mean speedup on a 4-core machine.

1. Introduction

As multicore processors are becoming ubiquitous, it is increasingly important to provide programmers with the right abstractions and tools to express new and existing programs in a parallel style. The problem of legacy code is especially daunting, as decades' worth of (often-undocumented) C programs need to be reverse-engineered and gradually migrated to a parallel representation. Given the broad array of programming tasks, there is unlikely to be a "silver bullet" solution to these problems; rather, it will be beneficial to develop a number of orthogonal techniques, each of which caters to a style of parallelism that is present in a certain class of algorithms. Already, several kinds of parallelism have good language-level support. For example, task parallelism – in which separate routines execute independently – is naturally supported by threads. Also, data parallelism – in which one routine is parallelized across many data elements – is naturally expressed using dialects such as OpenMP. However, one style of parallelism that has been largely neglected is pipeline parallelism, in which a loop is split into multiple stages that communicate in a pipelined fashion.

Pipeline parallelism is an important abstraction, suitable to both new and existing programs, that all parallel programmers should have at their disposal. Firstly, pipeline parallelism is often lurking in otherwise sequential codes. Loops with carried dependences can admit a pipeline-parallel mapping (the dependence being carried by a single pipeline stage) even though a data-parallel mapping is impossible. Secondly, pipeline parallelism can be more efficient than data parallelism due to improved instruction and data locality within each pipeline stage, as well as point-to-point communication between cores (there is no global scatter/gather). Pipeline parallelism also offers appeals over task parallelism, as all shared data can be communicated in a deterministic producer/consumer style, eliminating the possibility of data races.

Previous efforts to exploit pipeline parallelism in C programs have been very fine-grained, partitioning individual instructions across processing cores [19]. Such fine-grained communication is inefficient on commodity machines and demands new hardware support [19, 22]. While a coarse-grained partitioning is more desirable, it is difficult to achieve at compile time due to the obscured data dependences in C; constructs such as pointer arithmetic, function pointers, and circular buffers (with modulo operations)

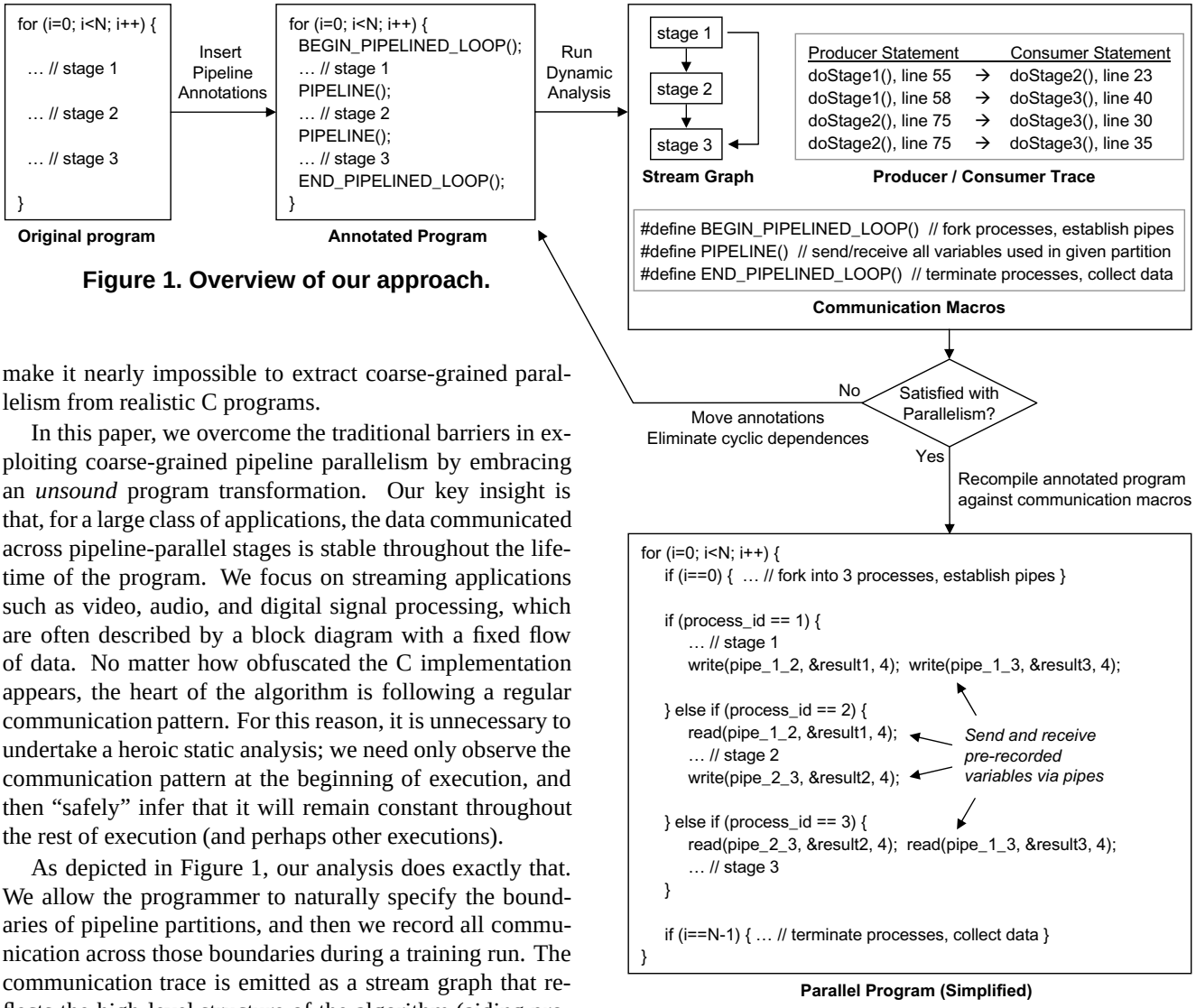


Figure 1. Overview of our approach.

make it nearly impossible to extract coarse-grained parallelism from realistic C programs.

In this paper, we overcome the traditional barriers in exploiting coarse-grained pipeline parallelism by embracing an *unsound* program transformation. Our key insight is that, for a large class of applications, the data communicated across pipeline-parallel stages is stable throughout the lifetime of the program. We focus on streaming applications such as video, audio, and digital signal processing, which are often described by a block diagram with a fixed flow of data. No matter how obfuscated the C implementation appears, the heart of the algorithm is following a regular communication pattern. For this reason, it is unnecessary to undertake a heroic static analysis; we need only observe the communication pattern at the beginning of execution, and then "safely" infer that it will remain constant throughout the rest of execution (and perhaps other executions).

As depicted in Figure 1, our analysis does exactly that. We allow the programmer to naturally specify the boundaries of pipeline partitions, and then we record all communication across those boundaries during a training run. The communication trace is emitted as a stream graph that reflects the high-level structure of the algorithm (aiding program understanding), as well as a list of producer/consumer statements that can be used to trace down problematic dependences. The programmer never needs to worry about providing a "correct" partitioning; if there is no parallelism between the suggested partitions, it will result in cycles in the stream graph. If the programmer is satisfied with the parallelism in the graph, he recompiles the annotated program against a set of macros that are emitted by our analysis tool. These macros serve to fork each partition into its own process and to communicate the recorded locations using pipes between processes.

Though our transformation is grossly unsound, we argue that it is quite practical within the domain of streaming applications. Because pipeline parallelism is deterministic, any incorrect transformations incurred by our technique can be identified via traditional testing methods, and failed tests can be fixed by adding the corresponding input to our training set. Further, the communication trace provided by our analysis is useful in aiding manual parallelization of the code – a process which, after all, is only sound insofar as the programmer's understanding of the system. By improving the programmer's understanding, we are also improving the soundness of the current best-practice for parallelizing legacy C applications.

We have applied our methodology to six case studies: MPEG-2 decoding, MP3 decoding, GMTI radar processing, and three SPEC benchmarks. Our tool was effective at parallelizing the programs, providing a mean speedup of 2.78x on a four-core architecture. Despite the potential unsoundness of the tool, our transformations correctly decoded ten popular videos from YouTube, ten audio tracks from MP3.com, and the complete test inputs for GMTI and SPEC benchmarks. At the same time, we did identify specific combinations of training and testing data (for MP3) that lead to erroneous results. Thus, it is important to maxi-

mize the coverage of the training set and to apply the technique in concert with a rigorous testing framework.

To summarize, this paper makes the following contributions:

- We show that for the class of streaming applications, pipeline parallelism is very stable. Communication observed at the start of execution is often preserved throughout the program lifetime, as well as other executions (Section 2).
- We define a simple API for indicating potential pipeline parallelism in the program. Comparable to threads for task parallelism or OpenMP for data parallelism, this API serves as a fundamental abstraction for pipeline parallelism (Section 3).
- We present a dynamic analysis tool, built on top of Valgrind, for tracking producer/consumer relationships between coarse-grained program partitions. The tool outputs a stream graph of the application, which validates or refutes the parallelism suggested by the programmer. It also provides a detailed statement-level trace and a set of macros for automatic parallelization (Sections 3-4).
- We apply our methodology to six case studies, encompassing MPEG-2 decoding, MP3 decoding, GMTI radar processing, and three SPEC benchmarks. We extract meaningful stream graphs of each application, and achieve a 2.78x mean speedup on a 4-core architecture (Section 5).

2. Stability of Stream Programs

A dynamic analysis is most useful when the observed behavior is likely to continue, both throughout the remainder of the current execution as well as other executions (with other inputs). Our hypothesis is that streaming applications – such as audio, video, and digital signal processing codes – exhibit very stable flows of data, enhancing the reliability of dynamic analyses toward the point where they can be trusted to validate otherwise-unsafe program transformations. For the purpose of our analysis, we consider a program to be *stable* if there is a predictable set of memory dependences between pipeline stages. The boundaries between stages are specified by the programmer using a simple set of annotations; the boundaries used for the experiments in this section are illustrated by the stream graphs that appear later (Figure 7).

2.1. Stability Within a Single Execution

Our first experiment explores the stability of memory dependences within a single program execution. We profiled MPEG-2 and MP3 decoding using the most popular content from YouTube[1] and MP3.com; results appear in Figures 2 and 3. These graphs plot the cumulative number of unique addresses that are passed between program partitions as execution proceeds. The figures show that after a few frames, the program has already performed a communication for most of the addresses it will ever send between pipeline stages.

In the case of MPEG-2, all of the address traces remain constant after 50 frames, and 8 out of 10 traces remain constant after 20 frames. The videos converge at different rates in the beginning due to varying parameters and frame types; for example, video 10 contains an intra-coded frame where all other videos have a predictive-coded frame, thereby delaying the use of predictive buffers in video 10. Video 1 communicates more addresses than the others because it has a larger frame size.

MP3 exhibits a similar stability property, though convergence is slower for some audio tracks. While half of the tracks exhibit their complete communication pattern in the first 35 frames, the remaining tracks exhibit a variable delay (up to 420 frames) in making the final jump to the common communication envelope. These jumps correspond to elements of two parameter structures which are toggled only upon encountering certain frame types. Track 10 is an outlier because it starts with a few layer-1 frames, thus delaying the primary (layer-3) communication and resulting in a higher overall communication footprint. The only other file to contain layer-1 frames is track 9, resulting in a small address jump at iteration 17,900 (not illustrated).

It is important to note that there does exist a dynamic component to these applications; however, the dynamism is contained within a single pipeline stage. For example, in MP3, there is a Huffman decoding step that relies on a dynamically-allocated lookup tree. Throughout the program, the shape of the tree grows and shrinks and is manipulated on the heap. Using a static analysis, it is difficult to contain the effects of such dynamic data structures; a conservative pointer or shape analysis may conclude that the dynamism extends throughout the entire program. However, using a dynamic analysis, we are able to observe the actual flow of data, ignoring the intra-node communication and extracting the regular patterns that exist between partitions.

2.2. Stability Across Different Executions

The communication patterns observed while decoding one input file can often extend to other inputs as well. Tables 1 and 2 illustrate the minimum number iterations (i.e., frames) that need to be profiled from one file in order to

[1] YouTube videos were converted from Flash to MPEG-2 using ffmpeg and vixy.net.

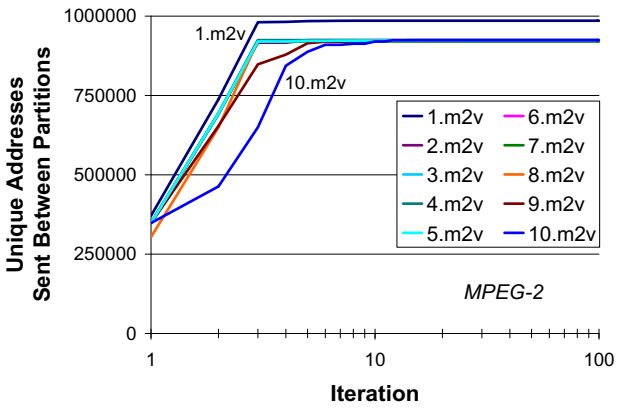


Figure 2. Stability of streaming communication patterns for MPEG-2 decoding. The decoder was monitored while processing the top 10 short videos from YouTube. See Figure 7a for a stream graph of the application.

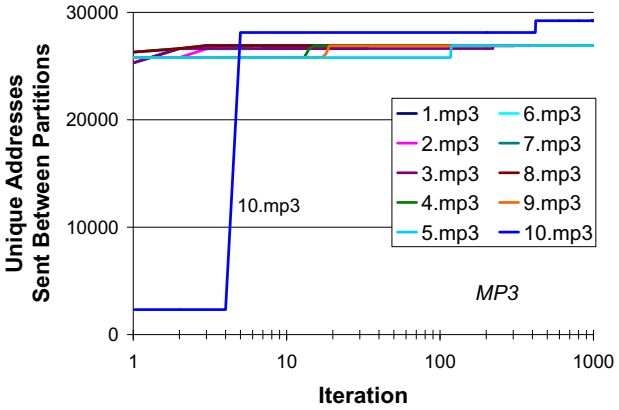


Figure 3. Stability of streaming communication patterns for MP3 decoding. The decoder was monitored while processing the top 10 tracks from MP3.com. See Figure 7b for a stream graph of the application.

MPEG-2		Testing File									
		1.m2v	2.m2v	3.m2v	4.m2v	5.m2v	6.m2v	7.m2v	8.m2v	9.m2v	10.m2v
Training File	1.m2v	3	3	3	3	3	3	3	3	3	3
	2.m2v	3	3	3	3	3	3	3	3	3	3
	3.m2v	5	5	5	5	5	5	5	5	5	5
	4.m2v	3	3	3	3	3	3	3	3	3	3
	5.m2v	3	3	3	3	3	3	3	3	3	3
	6.m2v	3	3	3	3	3	3	3	3	3	3
	7.m2v	3	3	3	3	3	3	3	3	3	3
	8.m2v	3	3	3	3	3	3	3	3	3	3
	9.m2v	3	3	3	3	3	3	3	3	3	3
	10.m2v	4	4	4	4	4	4	4	4	4	4

Table 1. Minimum number of training iterations (frames) needed on each video in order to correctly decode the other videos.

MP3		Testing File									
		1.mp3	2.mp3	3.mp3	4.mp3	5.mp3	6.mp3	7.mp3	8.mp3	9.mp3	10.mp3
Training File	1.mp3	1	1	1	1	1	1	1	1	—	—
	2.mp3	1	1	1	1	1	1	1	1	—	—
	3.mp3	1	1	1	1	1	1	1	1	—	—
	4.mp3	1	1	1	1	1	1	1	1	—	—
	5.mp3	1	1	1	1	1	1	1	1	—	—
	6.mp3	1	1	1	1	1	1	1	1	—	—
	7.mp3	1	1	1	1	1	1	1	1	—	—
	8.mp3	1	1	1	1	1	1	1	1	—	—
	9.mp3	1	1	1	1	1	1	1	1	17900	—
	10.mp3	5	5	5	5	5	5	5	5	5	5

Table 2. Minimum number of training iterations (frames) needed on each track in order to correctly decode the other tracks.

enable correct parallel decoding of the other files. In most cases, a training set of five loop iterations is sufficient to infer an address trace that correctly decodes the other inputs in their entirety. The exceptions are tracks 9 and 10 of MP3 decoding, which are the only two files containing layer-1 frames; because they execute code that is never reached by the other files, training on the other files is insufficient to expose the full communication trace. In addition, track 9 is insufficient training for track 10, as the latter contains an early CRC error that triggers a unique recovery procedure. As each of these hazards is caused by executing code that is untouched by the training set, the runtime system could easily detect such cases (using guards around untrained code) and revert to a sequential execution for the iterations in question. Rigorous testing practices that incorporate code coverage metrics would also help to reduce the risk of encountering unfamiliar code at runtime.

The ability to generalize short training runs across multiple executions relies on two aspects of our methodology. First, as described later, we require the user to supply a symbolic size for each dynamically-allocated variable; this allows MPEG-2 address traces to apply across different frame sizes. Second, we coarsen the granularity of the trace to treat structure types and dynamically-allocated segments as atomic units. That is, whenever a single element of such a structure is communicated between partitions, the rest of the structure is communicated as well (so long as it does not conflict with a local change in the target partition). Such coarsening increases the tolerance to small element-wise changes as observed in later iterations of MPEG-2 and MP3. However, it does not trivialize the overall result, as coarsening is only needed for a small fraction of communicated addresses (15% for MP3 and dependent on frame size for MPEG-2).

While we have focused on MPEG-2 and MP3 in this section, we observe similar stability across our other bench-

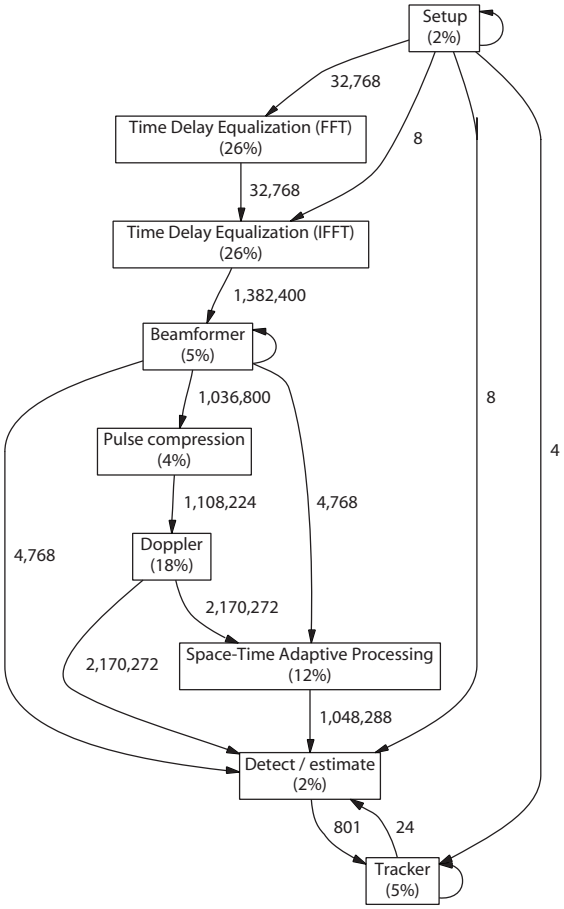


Figure 4. Stream graph for GMTI, as extracted using our tool. Nodes are annotated with their computation requirements, and edges are labeled with the number of bytes transferred per steady-state iteration.

marks (GMTI, bzip2, parser, and hmmer). As described in Section 5, we profile five iterations of a training file and (with minimal programmer intervention) apply the trace to correctly execute a test file.

3. Programmer Workflow

Typically, the process of parallelizing a legacy C application is an arduous and time-consuming process. The most important resources that could help with parallelization – such as the original author of the code, or the high-level design documents that guided its implementation – are often unavailable. Thus, a fresh programmer is left with the daunting task of obtaining an in-depth understanding of all the program modules, the dependences between them, and the possibilities for safely extracting parallelism.

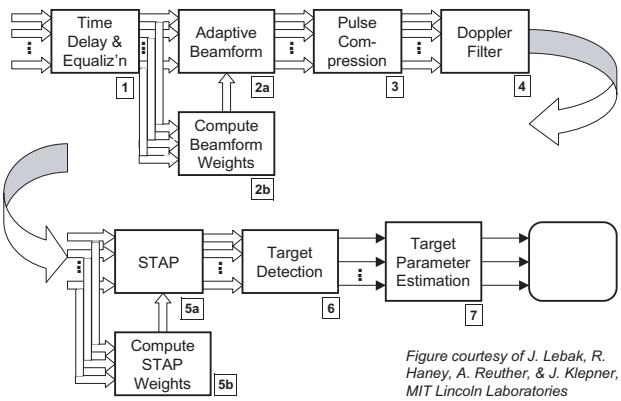


Figure 5. Stream graph for GMTI, as it appears in the GMTI specification [24].

We introduce a dynamic analysis tool that empowers the programmer in migrating legacy C applications to a parallel representation. Using this tool, the programmer follows the workflow illustrated in Figure 1. The first step is to identify the main loop in the application, which is typically iterating over frames, packets, or another long-running data source. The programmer annotates the start and end of this loop, as well as the boundaries between the desired pipeline-parallel partitions. The tool reports the percentage of execution time spent in each pipeline stage in order to help guide the placement of pipeline boundaries.

In our current implementation, there are some restrictions on the placement of the partition boundaries. All boundaries must appear within the loop body itself, rather than within a nested loop, within nested control flow, or as part of another function (this is an artifact of using macros to implement the parallelism). The programmer may work around these restrictions by performing loop distribution or function inlining. Also, though both `for` loops and `while` loops are supported, there cannot be any `break` or `continue` statements within the loop; such statements implicitly alter the control flow in all of the partitions, an effect that is difficult to trace in our dynamic analysis. If such statements appear in the original code, the programmer needs to convert them to a series of `if` statements, which our tool will properly handle.

Once a loop has been annotated with partition boundaries, the programmer selects a set of training inputs and runs our dynamic analysis to trace the communication pattern. The tool outputs a stream graph, a list of producer/consumer statements, and a set of communication macros for automatically running the code in parallel.

An example stream graph for GMTI radar processing appears in Figure 4. The graph extracted by our tool is very similar to the block diagram from the GMTI specification, which appears in Figure 5. Our graph contains some

additional edges that are not depicted in the specification; these represent communication of minor flags rather than the steady-state dataflow. Edges flowing from a node back unto itself (e.g., in Setup, Beamformer, and Tracker) indicate mutable state that is retained across iterations of the main loop. Nodes without such dependences are stateless with respect to the main loop, and the programmer may choose to execute them in a data-parallel manner (see below). Overall, the tight correspondence between our extracted stream graph and the original specification demonstrates that the tool can effectively capture the underlying communication patterns, assisting the programmer in understanding the opportunities and constraints for parallelization.

Many nodes in a streaming application are suitable to data parallelism, in which multiple loop iterations are processed in parallel by separate instances of the node. Such nodes are immediately visible in the stream graph, as they lack a carried dependence[2] (i.e., a self-directed edge). Our tool offers natural support for exploiting data parallelism: the user simply provides an extra argument to the `PIPELINE` annotation, specifying the number of ways that the following stage should be replicated (see Figure 6). While this annotation does not affect the profiler output, it is incorporated by the runtime system to implement the intended parallelism.

Depending on the parallelism evident in the stream graph, it may be desirable to iterate the parallelization process by adjusting the pipeline partitions as well as the program itself. The partitions can execute in a pipeline-parallel manner so long as there are no cyclic dependences between them. If there are any strongly connected components in the stream graph, they will execute sequentially; the programmer can reduce the overhead by collapsing such partitions into one. Alternately, the programmer may be able to verify that certain dependences can safely be ignored, in which case our analysis tool will filter them out of future reports. For example, successive calls to malloc result in a data dependence that was originally reported by our tool; however, this dependence (which stems from an update of a memory allocation map) does not prohibit parallelism because the calls can safely execute in any order. Additional examples of non-binding dependences include legacy debugging information such as timers, counters, etc. that are not observable in the program output. Sometimes, dependences can also be removed by eliminating the reuse of certain storage locations (see Section 5 for details).

Once the programmer is satisfied with the parallelism in the stream graph, the code can automatically be executed in a pipeline-parallel fashion using the communication macros

[2]In some cases, nodes with carried dependences on an outer loop can still be data-parallelized on an inner loop. We perform such a transformation in MP3, though it is not fully automatic.

```
for (i=0; i<N; i++) {
  BEGIN_PIPELINED_LOOP();
  … // stage 1
  PIPELINE(W);
  … // stage 2
  PIPELINE();
  … // stage 3
  END_PIPELINED_LOOP();
}
```

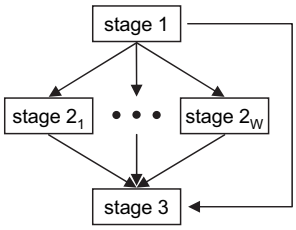


Figure 6. Programmers can specify data parallelism by passing an extra argument to the pipeline annotation. In this case, the runtime system executes W parallel copies of stage 2.

emitted by the tool. In most cases, the macros communicate items from one partition to another using the corresponding variable name (and potential offset, in the case of arrays) from the program. However, a current limitation is in the case of dynamically-allocated data, where we have yet to automate the discovery of variable name given the absolute addresses that are communicated dynamically. Thus, if the tool detects any communication of dynamically-allocated data, it alerts the user and indicates the line of the program that is performing the communication. The user needs to supply a symbolic expression for the name and size of the allocated region. Only two of our six benchmarks (MPEG-2 and bzip2) communicate dynamically-allocated data across partition boundaries.

4. Implementation

4.1. Dynamic Analysis Tool

Our tool is built on top of Valgrind, a robust framework for dynamic binary instrumentation [18]. Our analysis interprets every instruction of the program and (by tracing the line number in the annotated loop) recognizes which partition it belongs to. The analysis maintains a table that indicates, for each memory location, the identity of the partition (if any) that last wrote to that location. On encountering a store instruction, the analysis records which partition is writing to the location. Likewise, on every load instruction, the analysis does a table lookup to determine the partition that produced the value being consumed by the load. Every unique producer-consumer relationship is recorded in a list that is output at the end of the program, along with the stream graph and communication macros.

There are some interesting consequences of tracking dependence information in terms of load and store instructions. In order to track the flow of data through local variables, we disable register allocation and other optimizations when preparing the application for profiling. However, as

we do not model the dataflow through the registers, the tool is unable to detect cases in which loaded values are never used (and thus no dependence exists). This pattern often occurs for short or unaligned datatypes; even writes to such variables can involve loads of neighboring bytes, as the entire word is loaded for modification in the registers. Our tool filters out such dependences when they occur in parallel stack frames, i.e., a spurious dependence between local variables of two neighboring function calls. Future work could further improve the precision of our reported dependences by also tracking dependences through registers (in the style of Redux [17]).

As the dynamic analysis traces communication in terms of absolute memory locations, some engineering was required to translate these addresses to variable names in the generated macros. (While absolute addresses could also be used in the macros, they would not be robust to changes in stack layout or in the face of re-compilation.) We accomplish this mapping using a set of gdb scripts[3], which provide the absolute location of every global variable as well as the relative location of every local variable (we insert a known local variable and print its location as a reference point). In generating the communication code, we express every address as an offset from the first variable allocated at or below the given location. In the case of dynamically-allocated data, the mapping from memory location to variable name is not yet automated and requires programmer assistance (as described in the previous section).

4.2. Parallel Runtime System

The primary challenge in implementing pipeline parallelism is the need to buffer data between execution stages. In the sequential version of the program, a given producer and consumer takes turns in accessing the shared variables used for communication. However, in the parallel version, the producer is writing a given output while the producer is still reading the previous one. This demands that the producer and consumer each have a private copy of the communicated data, so that they can progress independently on different iterations of the original loop. Such a transformation is commonly referred to as "double-buffering", though we may wish to buffer more than two copies to reduce the synchronization between pipeline stages.

There are two broad approaches for establishing a buffer between pipeline stages: either explicitly modify the code to do the buffering, or implicitly wrap the existing code in a virtual environment that performs the buffering automatically. The first approach utilizes a shared address space and modifies the code for the producer or consumer so that they access different locations; values are copied from one location to the other at synchronization points. Unfortunately, this approach requires a deep program analysis in order to infer all of the variables and pointer references that need to be remapped to shift the produced or consumed data to a new location. Such an analysis seems largely intractable for a language such as C.

The second approach, and the one that we adopt, avoids the complexities of modifying the code by simply forking the original program into multiple processes. The memory spaces of the processes are isolated from one another, yet the processes share the exact same data layout so no pointers or instructions need to be adjusted. A standard inter-process communication mechanism (such as pipes) is used to send and buffer data from one process to another; a producer sends its latest value for a given location, and the consumer reads that value into the same location in its private address space. At the end of the loop's execution, all of the processes copy their modified data (as recorded by our tool during the profiling stage) into a single process that continues after the loop. Our analysis also verifies that there is no overlap in the addresses that are sent to a given pipeline stage; such an overlap would render the program non-deterministic and would likely lead to incorrect outputs.

5. Case Studies

To evaluate our approach, we applied our tool and methodology to six realistic programs. Three of these are traditional stream programs (MPEG-2 decoding, MP3 decoding, GMTI radar processing) while three are SPEC benchmarks (parser, bzip2, hmmer) that also exhibit regular flows of data. As illustrated in Table 3, the size of these benchmarks ranges from 5 KLOC to 37 KLOC. Each program processes a conceptually-unbounded stream of input data; our technique adds pipeline parallelism to the toplevel loop of each application, which is responsible for 100% of the steady-state runtime. (For bzip2, there are two toplevel loops, one for compression and one for decompression.)

In the rest of this section, we first describe our experience in parallelizing the benchmarks before presenting performance results.

5.1. Parallelization Experience

During the parallelization process, the programmer relied heavily on the stream graphs extracted by our tool. The final graphs for each benchmark appear in Figures 7 and 8. In the graphs, node labels are gleaned from function names and comments in the code, rather than from any domain-specific knowledge of the algorithm. Nodes are also annotated with the amount of work they perform, while edges are labeled with the number of bytes communicated per steady-state iteration. Nodes that were data-parallelized are anno-

[3]Our scripts rely on having compiled with debug information.

Benchmark	Description	Source	Lines of Code
MPEG-2	MPEG-2 video decoder	MediaBench [14]	10,000
MP3	MP3 audio decoder	Fraunhofer IIS [9]	5,000
GMTI	Ground Moving Target Indicator	MIT Lincoln Laboratory [24]	37,000
197.parser	Grammatical parser of English language	SPECINT 2000	11,000
256.bzip2	bzip2 compression and decompression	SPECINT 2000	5,000
456.hmmer	Calibrating HMMs for biosequence analysis	SPECCPU 2006	36,000

Table 3. Benchmark characteristics.

tated with their multiplicity; for example, the Dequantize stage in MP3 (Figure 7b) is replicated twice.

As described in Section 3, our tool relies on some programmer assistance to parallelize the code. The manual steps required for each benchmark are summarized in Figure 9 and detailed in the following sections.

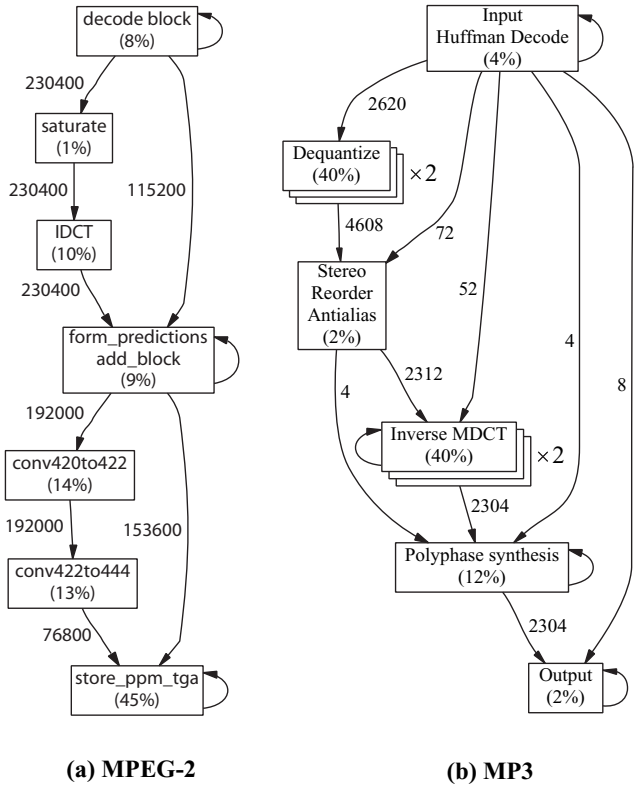
MPEG-2 Decoding

To obtain the stream graph for MPEG-2 (Figure 7a), the programmer iteratively refined the program with the help of the dynamic analysis tool. Because the desired partition boundaries fell in distinct functions, those functions were inlined into the main loop. Early return statements in these functions led to unstructured control flow after inlining; the programmer converted the control flow to if/else blocks as required by our analysis. The tool exposed an unintended data dependence that was inhibiting parallelism: a global variable (progressive_frame) was being re-used as a temporary variable in one module. The programmer introduced a unique temporary variable for this module, thereby restoring the parallelism. In addition, the updates to some counters in the main loop were reordered so as to place them in the same pipeline stage that the counters were utilized.

In generating the parallel version, our tool required two interventions from the programmer. First, as the pipeline boundaries spanned multiple loop nests, the communication code (auto-generated for a single loop nest) was patched to ensure that matching send and receive instructions executed the same number of times. Second, as described in Section 3, the programmer supplied the name and size of dynamically-allocated variables (in this case, frame buffers) that were sent between partitions.

MP3 Decoding

The extracted stream graph for MP3 decoding appears in Figure 7b. In the process of placing the pipeline boundaries, the programmer inlined functions, unrolled two loops, and distributed a loop. Four dynamically-allocated arrays (of fixed size) were changed to use static allocation, so that our tool could manage the communication automatically.



(a) MPEG-2 **(b) MP3**

Figure 7. Extracted stream graphs for MPEG-2 and MP3 decoding.

As profiling indicated that the dequantization and inverse MDCT stages were consuming most of the runtime, they were each data-parallelized two ways.

In analyzing the parallelism of MP3, the programmer made three deductions. First, the initial iteration of the loop was found to exhibit many excess dependences due to one-time initialization of coefficient arrays; thus, the profiling and parallelization was postponed to the second iteration. Second, though the tool reports a carried dependence in the inverse MDCT stage, the programmer found that this dependence is on an outer loop and that it is safe to data-parallelize the stage on an inner loop. Finally, the programmer judged the execution to be insensitive to the ordering of

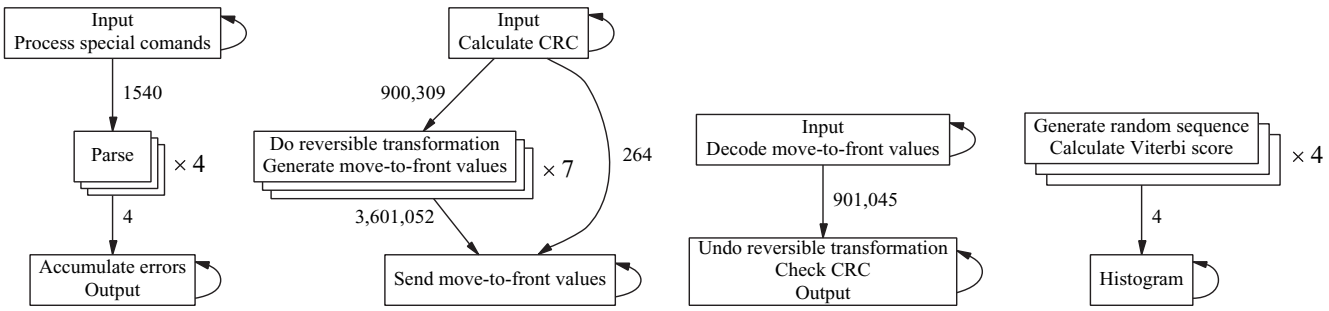


Figure 8. Extracted stream graphs for parser, bzip2 (compression and decompression) and hmmer.

diagnostic print statements, allowing the dependences between statements to be ignored for the sake of parallelization. (With some additional effort, the original ordering of print statements can always be preserved by extracting the print function into its own pipeline stage.)

As in the case of MPEG-2, the programmer also patched the generated communication code to handle nested loops.

GMTI Radar Processing

The Ground Moving Target Indicator (GMTI) is a radar processing application that extracts targets from raw radar data [24]. The stream graph extracted by our tool (Figure 4) is very similar to the one that appears in the GMTI specification (Figure 5).

In analyzing GMTI, the programmer made minor changes to the original application. The programmer inlined two functions, removed the application's self-timers, and scaled down an FFT window from 4096 to 512 during the profiling phase (the resulting communication code was patched to transfer all 4096 elements during parallel execution).

As print statements were judged to be independent of ordering, the tool was instructed to ignore the corresponding dependences. Dependences between calls to memory allocation functions (malloc/free) were also disregarded so as to allow pipeline stages to manage their local memories in parallel. The programmer verified that regions allocated within a stage remained private to that stage, thus ensuring that the parallelism introduced could not cause any memory hazards.

Our tool reported an address trace that was gradually increasing over time; closer inspection revealed that an array was being read in a sparse pattern that was gradually encompassing the entire data space. The programmer directed the tool to patch the parallel version so that the entire array was communicated at once.

Parser

The stream graph for 197.parser appears in Figure 8a. Each steady-state iteration of the graph parses a single sentence; the benchmark runs in batch mode, repeatedly parsing all of the sentences in a file. As indicated in the graph, the cyclic dependences in the benchmark are limited to the input stage (which performs file reading and adjusts the configuration of the parser) and the output stage (which accumulates an error count). The parsing stage itself (which represents most of the computation) retains no mutable state from one sentence to the next, and can thus be replicated to operate on many sentences in parallel. In our optimized version, the parsing stage is replicated four times.

During the iterative parallelization process, the programmer made three adjustments to the program. Our tool reported a number of loop-carried dependences due to the program's implicit use of uninitialized memory locations; the program allocates space for a struct and later copies the struct (by value) before all of the elements have been initialized. This causes our tool to report a dependence on the previous write to the uninitialized locations, even though such writes were modifying a different data structure that has since been de-allocated. The programmer eliminated these dependence reports by initializing all elements to a dummy value at the time of allocation.

The programmer also made two adjustments to the communication trace emitted by our tool. One block of addresses was expanding gradually over the first few iterations of the program. Closer inspection revealed that that sentences of increasing length were being passed between partitions. The programmer patched the trace to always communicate the complete sentence buffer. Also, the programmer observed that in the case of errors, the parser's error count needs to be communicated to the output stage and accumulated there. As none of our training or testing samples elicited errors, our trace did not detect this dependence.

	I. Modifications to sequential version	II. Annotations to tool during parallelization	III. Patches to parallel version
MPEG-2	- inlined functions - reordered statements - expanded temporary variable into two - regularized control flow		- patched communication across nested loops - patched communication of malloc'd data
MP3	- inlined functions - unrolled loops - distributed a loop - converted dynamically-allocated arrays to statically-allocated arrays	- postponed parallelization to second loop iteration - identified IMDCT as data-parallel on outer loop - ignored dependences between print statements *	- patched communication across nested loops
GMTI	- inlined functions - removed self-profiling functionality - scaled down FFT size (for training only)	- ignored dependences between print statements * - ignored dependences between mem. allocations*	- expanded address trace to cover full array
197.parser		- ignored dependences on uninitalized memory - ignored dependences between print statements *	- expanded address trace to cover full array - manually accumulated reduction variable
256.bzip2	- reordered statements		- patched communication of malloc'd data
456.hmmer		- ignored order of incremental buffer expansion - ignored dependences between calls to rand * - ignored dependences between mem. allocations*	- reset random seed in each parallel partition

Figure 9. Steps taken by the programmer to assist in parallelizing each benchmark. Assistance may be needed to expose parallelism in the original code, to verify parallelism using the tool, or to handle special cases in the parallelized code. Steps annotated with an asterisk (*) may change the observable behavior of the program[1].

Our data-parallel version of the program may reorder the program's print statements. If desired, the print statements can be serialized by moving them to the output stage.

Bzip2

The stream graphs for 256.bzip2 appear in Figures 8b and 8c. The benchmark includes both a compression and decompression stage, which were parallelized separately.

Because bzip2 compresses blocks of fixed size, the main compression routine is completely data-parallel. The only cyclic dependences in the compressor are at the input stage (file reading, CRC calculation) and output stage (file writing). The programmer replicated the compression stage seven ways to match the four-core machine; this allows three cores to handle two compression stages each, while one core handles a single compression stage as well as the input and output stages. The decompression step lacks data-parallelism because the boundaries of the compressed blocks are unknown; however, it can be split into a pipeline of two stages.

In parallelizing bzip2, the programmer reordered some statements to improve the pipeline partitioning (the call to `generateMTFValues` moved from the output stage to the compute stage). The programmer also supplied the name and size of two dynamically-allocated arrays.

[1]Reordering calls to malloc (or reordering calls to free) will only change the program's behavior if one of the calls fails.

Hmmer

In 456.hmmer, a Hidden Markov Model is loaded at initialization time, and then a series of random sequences are used to calibrate the model. Figure 8d shows the extracted stream graph for this benchmark. The calibration is completely data-parallel except for a histogram at the end of the loop, which must be handled with pipeline parallelism. In our experiments, the programmer replicated the data-parallel stage four ways to utilize the four-core machine.

Our tool reports three parallelism-limiting dependences for hmmer. The first is due to random number generation: each iteration generates a new random sample and modifies the random seed. The programmer chose to ignore this dependence, causing the output of our parallel version to differ from the original version by 0.01%. Also, the programmer made an important patch to the parallel code: after forking from the original process, each parallel partition needs to set its random seed to a different value. Otherwise each partition would follow an identical sequence of random values, and the parallel program would sample only a fraction of the input space as the original program.

The second problematic dependence is due to an incremental resizing of an array to fit the length of the input sequence. Since each parallel partition can expand its own private array, this dependence is safely ignored. Finally, as in the case of GMTI, dependences between memory allocation functions were relaxed for the sake of the parallelization.

5.2. Performance Results

Following parallelization with our tool, all of the benchmarks obtain the correct results on their training and testing sets. For MPEG-2 and MP3, we train using five iterations of input files 1 and 10, respectively (see Section 2). For GMTI, we only have access to a single input trace, so we use five iterations for training and the rest (300 iterations) for testing. For the SPEC benchmarks, we train on five iterations of the provided training set and test on the provided testing set.

Our evaluation platform contains two AMD Opteron 270 dual-core processors (for a total of 4 cores) with 1 MB L2 cache per processor and 8 GB of RAM. We measure the speedup of the parallel version, which uses up to 4 cores, versus the original sequential version, which uses 1 core. We generate one process per stage of the stream graph, and rely on the operating system to distribute the processes across cores (we do not provide an explicit mapping from threads to cores). All speedups reflect total (wall clock) execution time.

Our performance results appear in Table 4. Speedups range from 2.03x (MPEG-2) to 3.89x (hmmer), with a geometric mean of 2.78x. While these results are good, there is some room for improvement. Some benchmarks (MPEG-2, decompression stage of bzip2) suffer from load imbalance that is difficult to amend without rewriting parts of the program. The imperfect speedups in other benchmarks may reflect synchronization overheads between threads, as the operating system would need to interleave executions in a specific ratio to avoid excessive blocking in any one process. The volume of communication does not appear to be a significant bottleneck; for example, duplicating all communication instructions in MP3 results in only a 1.07x slowdown. Ongoing work will focus on improving the runtime scheduling of the processes, as well as exploring other inter-process communication mechanisms (e.g., using shared memory).

Benchmark	Pipeline Depths	Data-Parallel Widths	Speedup
GMTI	9	—	3.03x
MPEG-2	7	—	2.03x
MP3	6	2,2	2.48x
197.parser	3	4	2.95x
256.bzip2	3,2	7	2.66x
456.hmmer	2	4	3.89x
GeoMean			**2.78x**

Table 4. Characteristics of the parallel stream graphs and performance results on a 4-core machine. Data-parallel width refers to the number of ways any data-parallel stage was replicated.

6. Related Work

6.1. Static Analysis

The work most closely related to ours is that of Bridges et al. [2], which was developed concurrently. They exploit pipeline parallelism using the techniques of Decoupled Software Pipelining [19, 22]. In addition, they employ thread-level speculation to speculatively execute multiple loop iterations in parallel. Both of our systems require some assistance from the programmer in parallelizing legacy applications. Whereas we annotate spurious dependences within our tool, they annotate the original source code with a new function modifier (called "commutative") to indicate that successive calls to the function can be freely reordered. Such source-level annotations are attractive (e.g., for malloc/free) and could be integrated with our approach. However, our transformations rely on a different property of these functions, as we call them in parallel from isolated address spaces rather than reordering the calls in a single address space.

Once parallelism has been exposed, their compiler automatically places the pipeline boundaries and generates a parallel runtime, whereas we rely on the programmer to place pipeline boundaries and to provide some assistance in generating the parallel version (see Section 3). Our approaches arrive at equivalent decompositions of 197.parser and 256.bzip2. However, our runtime systems differ. Rather than forking multiple processes that communicate via pipes, they rely on a proposed "versioned memory" system [28] that maintains multiple versions of each memory location. This allows threads to communicate via shared memory, with the version history serving as buffers between threads. Their evaluation platform also includes a specialized hardware construct termed the synchronization array [22]. In comparison, our technique runs on commodity hardware.

Dai et al. presents an algorithm for automatically partitioning sequential packet-processing applications for pipeline-parallel execution on network processors [5]. Their static analysis targets fine-grained instruction sequences within a single procedure, while our dynamic analysis is coarse-grained and inter-procedural. Du et al. describes a system for pipeline-parallel execution of Java programs [8]. The programmer declares parallel regions, while the compiler automatically places pipeline boundaries and infers the communicated variables using an inter-procedural static analysis. Unlike our system, the compiler does not check if the declared regions are actually parallel.

6.2. Dynamic Analysis

The dynamic analysis most similar to ours is that of Rul et al. [25], which also tracks producer/consumer relationships between functions and uses the information gleaned to assist the programmer in parallelizing the program. They use bzip2 as a case study and report speedups comparable to ours. However, it appears that their system requires the programmer to determine which variables should be communicated between threads and to modify the original program to insert new buffers and coordinate thread synchronization.

Karkowski and Corporaal also utilize dynamic information to uncover precise dependences for parallelization of C programs [13]. Their runtime system utilizes a data-parallel mapping rather than a pipeline-parallel mapping, and they place less emphasis on the programmer interface and visualization tools.

Redux is a tool that traces instruction-level producer/consumer relationships for program comprehension and debugging [17]. Unlike our tool, Redux tracks dataflow through registers in addition to memory locations. Because it generates a distinct graph node for every value produced, the authors note that the visualization becomes unwieldy and does not scale to realistic programs. We address this issue by coarsening the program partitions.

A style of parallelism that is closely related to pipeline parallelism is DOACROSS parallelism [4, 20]. Rather than devoting a processor to a single pipeline stage, DOACROSS parallelism assigns a processor to execute complete loop iterations, spanning all of the stages. In order to support dependences between iterations, communication is inserted at pipeline boundaries to pass the loop-carried state between processors. While DOACROSS parallelism has been exploited dynamically using inspector/executor models (see Rauchwerger [23] for a survey), they lack the generality needed for arbitrary C programs. The parallelism and communication patterns inferred by our tool could be used to generate a DOACROSS-style mapping; such a mapping could offer improved load balancing, at the possible expense of degrading instruction locality and adding communication latency to the critical path.

Giacomoni et al. describe a toolchain for pipeline-parallel programming [10], including BDD-based compression of dependence traces [21]. Such techniques could extend our stream graph visualization to a much finer granularity. There are additional dynamic analyses that offer visualizations to aid program understanding [1, 16], though they do not focus on extracting streams of data flow.

Program slicing is a technique that aims to identify the set of program statements that may influence a given statement in the program. Slicing is a rich research area with many static and dynamic approaches developed to date; see Tip [27] for a review. The problem that we consider is more coarse-grained than slicing; we divide the program into partitions and ask which partitions affect a given partition. Also, we identify a list of memory locations that are sufficient to convey all the information needed between partitions. Finally, we are interested only in direct dependences between partitions, rather than the transitive dependences reported by slicing tools.

6.3. Stream Programming

An alternate approach to extracting a streaming representation from legacy C programs is to re-write the application in a programming language that has built-in support for streams. For example, the StreamC/KernelC language has been compiled [7] to stream processors such as Imagine [12] and Merrimac [6]; Brook [3] has been mapped to graphics processors [3] and multicores [15]; and StreamIt [26] has targeted the Raw architecture [11]. We anticipate that many of the techniques developed in these efforts will be directly applicable to the streaming representation extracted by our analysis.

7. Conclusions

This work represents one of the first systematic techniques to exploit coarse-grained pipeline parallelism in C programs. Rather than pipelining small instruction sequences or inner loops, we pipeline the outermost toplevel loop of a streaming application, which encapsulates 100% of the steady-state runtime. Our approach is applicable both to legacy codes, in which the user has little or no knowledge about the structure of the program, as well as new applications, in which programmers can utilize our annotations to easily express the desired pipelining.

The key observation underlying our technique is that for the domain of streaming applications, the steady-state communication pattern is regular and stable, even if the program is written in a language such as C that resists static analysis. To exploit this pattern, we employ a dynamic analysis to trace the memory locations communicated between program partitions at runtime. Partition boundaries are defined by the programmer using a simple set of annotations; the partitions can be iteratively refined to improve the parallelism and load balance. Our tool uses the communication trace to construct a stream graph for the application as well as a detailed list of producer-consumer instruction pairs, both of which aid program understanding and help to track down any problematic dependences.

Our dynamic analysis tool also outputs a set of macros to automatically parallelize the program and communicate the needed data between partitions. While this transformation is unsound, it is deterministic and suitable to rigorous testing. Applying the transformation to six realistic case

studies, the parallel programs produced the correct output and offered a mean speedup of 2.78x on a 4-core machine.

There are rich opportunities for future work in enhancing the soundness and automation of our tool. If the runtime system encounters code that was not visited during training, it could execute the corresponding loop iteration in a sequential manner (such a policy would have fixed the only unsoundness we observed). A static analysis could also lessen the programmer's involvement, e.g., by automatically handling nested loops or automatically placing the pipeline partitions. However, fully-automatic solutions for such large-scale program transformations are not only unnecessary but often distrusted in an industrial setting. By leveraging a pragmatic combination of programmer annotations, dynamic analysis, visualization tools, and parallelization macros, our approach immediately eases the burden of migrating C applications to multicores.

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