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Advances in Parallel-Stage Decoupled Software Pipelining

Leveraging Loop Distribution, Stream-Computing and the SSA Form

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Abstract

Decoupled Software Pipelining (DSWP) is a program partitioning method enabling compilers to extract pipeline parallelism from sequential programs. Parallel Stage DSWP (PS-DSWP) is an extension that also exploits the data parallelism within pipeline filters.

This paper presents the preliminary design of a new PS-DSWP method capable of handling arbitrary structured control flow, a slightly better algorithmic complexity, the natural exploitation of nested parallelism with communications across arbitrary levels, with a seamless integration with data-flow parallel programming environments. It is inspired by loop-distribution and supports nested/structured partitioning along with the hierarchy of control dependences. The method relies on a data-flow streaming extension of OpenMP.

These advances are made possible thanks to progresses in compiler intermediate representation. We describe our usage of the Static Single Assignment (SSA) form, how we extend it to the context of concurrent streaming tasks, and we discuss the benefits and challenges for PS-DSWP.

Categories and Subject Descriptors D.3.4 [Programming Languages]: Processors-Compilers, Optimization

General Terms optimization

Keywords automatic parallelization, stream-computing, loop distribution

1. Introduction

In recent years, the CPU manufacturers have embraced chip multiprocessors because of technology, power consumption and thermal dissipation constraints, and because of diminishing returns in instruction-level parallelism. The amount of performance gained by the use of multicore processor depends highly on the software fraction that can be parallelized to run on multiple cores simultaneously. Multiprocessor programming leaves the burden to programmer who faces the extra complexity, heisenbugs, deadlocks and other problems associated with parallel programming. The situation is worse when dealing with the migration of legacy code.

Decoupled Software Pipelining (DSWP) is an automatic thread partitioning method which could partition a sequential program to run on multiple cores, and Parallel-Stage DSWP (PS-DSWP) exposes data parallelism into task pipelines extracted by DSWP. These automatic thread partitioning methods free the programmer from manual parallelization. They also promise much wider flexibility than data-parallelism-centric methods for processors, aiming for the effective parallelization of general-purpose applications.

In this paper, we provide another method to decouple control-flow regions of serial programs into concurrent tasks, exposing pipeline and data parallelism. The power and simplicity of the method rely on the restriction that all streams should retain a synchronous semantics [8]. It amounts to checking the sufficient condition that the source and target of any decoupled dependence are control-dependent on the same node in the control dependence tree (this assumes structured control flow). This restriction may appear as a severe one for experienced parallel programmers; but at the potential expense of adding extra levels of nested parallelism, it does not restrict the degree of pipeline parallelism. In fact, any pair of computational statements can be decoupled and assigned to different concurrent tasks. The partitioning algorithms also handle DOALL parallelization within task pipelines, and arbitrarily nested data-parallel pipelines following the control dependence tree of a structured control flow graph. Unlike existing DSWP algorithms, our method does not explicitly copy conditional expressions and can handle arbitrary backward data and control dependences.

We are using two intermediate representations.

- A conventional SSA-based representation, annotated with natural loop and control dependence trees (for structured control flow).
- And a streaming data-flow extension of the latter representation as a backend for our partitioning algorithm, still in SSA form but with explicit task boundaries (for single-entry single-exit regions) and multi-producer multi-consumer streams to communicate across tasks.

The backend representation streamlines the decoupling of multi-producer multi-consumer data flow through explicit, compiler-controlled sampling and merging stages. Multi-producer multi-consumer semantics is absolutely essential to handle general decoupling patterns where data-parallel stages feature an unbalance in the number of worker threads. Sampling is handled transparently by nesting tasks into enclosing control flow. Merging is captured by \( \Phi \) functions at task boundaries, introducing a minor variant of the SSA form satisfying the so-called task-closed property that multiple incoming flows targeting the same use in a given task should be explicitly merged by a dedicated \( \Phi \) function at the task entry point. Relying on SSA avoids building the complete program dependence graph; with the exception of the array dependence graph, our method only processes linear-size data structures, as opposed to the worst-case quadratic program dependence graph in DSWP.

2. Related Work

The most closely related work to this paper is decoupled software pipelining and loop distribution. We recall the state-of-the-art in both and present the original finding at the source of this work: by extending loop distribution with pipelining and asserting a synchronous concurrency hypothesis, arbitrary data and control dependences can be decoupled very naturally with only minor changes to existing algorithms that have been proposed for loop distribution [10].

2.1 Decoupled software pipelining

Decoupled Software Pipelining (DSWP) [13] is one approach to automatically extract threads from loops. It partitions loops into long-running threads that communicate via inter-core queues. DSWP builds a Program Dependence Graph (PDG) [7], combining control and data dependences (scalar and memory). Then DSWP
introduces a load-balancing heuristic to partition the graph according
to the number of cores, making sure no recurrence spans across
multiple partitions. In contrast to DOALL and DOACROSS [4]
methods which partition the iteration space into threads, DSWP
partitions the loop body into several stages connected with pipelin-
ing to achieve parallelism. It exposes parallelism in cases where
DOACROSS is limited by loop-carried dependences on the critical
path. And generally speaking, DSWP partitioning algorithms han-
dles uncounted loops, complex control flow and irregular pointer-
based memory accesses.

Parallel-Stage Decoupled Software Pipelining [16] (PS-DSWP)
is an extension to combine pipeline parallelism with some stages
executed in a DOALL, data-parallel fashion. For example, when
there are no dependences between loop iterations of a DSWP stage,
the incoming data can be distributed over multiple data-parallel
worker threads dedicated to this stage, while the outgoing data can
be merged to proceed with downstream pipeline stages.

These techniques have a few caveats however. They offer lim-
lited support for decoupling along backward control and data
dependences. They provide a complex code generation method to de-
couple dependences among source and target statements governed
by different control flow, but despite its complexity, this method
remains somewhat conservative.

By building the PDG, DSWP also incurs a higher algorithm-
ic complexity than typical SSA-based optimizations. Indeed, al-
though traditional loop pipelining for ILP focuses on innermost
loops of limited size, DSWP is aimed at processing large control
flow graphs after aggressive inter-procedural analysis optimization.
In addition, the loops in DSWP are handled by the standard algo-
rithm as ordinary control flow, missing potential benefits of treat-
ing them as a special case. To address these caveats, we turned our
analysis to the state of the art in loop distribution.

2.2 Loop distribution
Loop distribution is a fundamental transformation in program re-
structuring systems designed to extract data parallelism for vector
or SIMD architectures [10].

In its simplest form, loop distribution consists of breaking up
a single loop into two or more consecutive loops. When aligning
loop distribution to the strongly connected components of the data-
dependence graph, one or more of the resulting loops expose iter-
tations that can be run in parallel, exposing data parallelism. Barri-
ers are inserted after the parallel loops to enforce precedence con-
straints with the rest of the program. An example is presented in
Figure 1.

```
for (i = 1; i < N; i++) {
    S1 A[i] = B[i] + 1;
    S2 C[i] = A[i-1] + 1;
    <barriers inserted here>
}
```

Figure 1. Barriers inserted after loop distribution.

3. OpenMP Extension for Stream-Computing as
a Code Generation Target
A recently proposed stream-computing extension to OpenMP [14]
allows the expression of pipeline parallelism by making explicit
the flow dependences, or producer-consumer patterns, between
OpenMP tasks. It provides a simple way for explicitly building
dynamic task graphs, where tasks are connected through streams
that transparently privatize the data.

The extension consists of two additional clauses, input and
output to the task construct, that define the producer-consumer
relationships between tasks. The OpenMP language, with this ex-
tension, is a natural fit as a target for our code generation. It pro-
vides for dynamic task creation and connection in the task graph, it
handles arbitrary nesting of pipelined tasks in control-flow, and it
allows the hierarchical nesting of tasks.

The task construct is extended with input and output clauses as
presented on Figure 2. Both clauses take a list of items, each of
which describes a stream and its behavior w.r.t. the task to
which the clause applies. In the abbreviated item form, stream,
the stream can only be accessed one element a time through the
same variable s. In the second form, stream >> window, the
programmer uses the C++ flavoured >> stream operators to
connect a sliding window to a stream, gaining access, within the
body of the task, to horizon elements in the stream.

One of the main issues that needs to be addressed in order to
distribute a PDG to the OpenMP stream-computing extension is
that, in the latter, the data flow bypasses the control flow. In other
words, when a task produces values on an output stream, these
values will all reach the consumers of the stream, even if, in the
serial semantics, the values would have been overwritten before
reaching the consumers. This means that the only case where a
direct annotation scheme will work is if all tasks are in the same
control flow. There are multiple ways this issue can be handled,
the most systematic one being to always ensure that every producer-
consumer pair share the same control dependence. This is achieved
by sinking all control flow surrounding the tasks, and not shared
by both producer and consumer, in the tasks. To avoid the loss
of parallelization opportunities, each task’s body can be further
partitioned into nested pipelines.

The GCC implementation of the OpenMP extension for stream-
computing has been shown to be efficient to exploit mixed pipeline-
and data-parallelism, even in dynamic task graphs [14]. It relies
on compiler and runtime optimizations to improve cache locality
and relies on a highly efficient lock-free and atomic operation-free
synchronization algorithm for streams.

4. Observations
It is quite intuitive that the typical synchronization barriers in be-
tween distributed data-parallel loops can be weakened, resulting
into data-parallel pipelines. We aim to provide a comprehensive
treatment of this transformation, generalizing PS-DSWP in the pro-
cess.

4.1 Replacing loops and barriers with a task pipeline
In the previous example, we could remove the barriers between two
distributed loops with pipelining so that the two loops could run in
parallel.

```
/* Initialize the stream, inserting a delay. */
void INIT_STREAM() {
    produce(stream, A[0]);
}
```

```
/* Decoupled producer and consumer. */
void PRODUCER() {
    for (i = 1; i < N; i++) {
        S1 A[i] = B[i] + 1;
        produce(stream, A[i]);
    }
}
```

Figure 3. Pipelining inserted between distributed loops. Initialize
the stream (left), producer and consumer thread (right).

Figure 3 shows that pipelined execution is possible: the INIT_STREAM
function inserts one delay into a communication stream; the
produce/consume primitives implement a FIFO, enforcing the precedence constraint of the data dependence on array A and communicating the value in case the hardware needs this information.

When distributing loops, scalar and array expansion (privatization) is generally required to eliminate memory-based dependences. The conversion to a task pipeline avoids this complication through the usage of communication streams. This transformation can be seen as an optimized version of scalar/array expansion in bounded memory and with improved locality [15].

4.2 Extending loop distribution to PS-DSWP

The similarity between DSWP and distributed loops with data-parallel pipelines is striking. First, both of them partition the loop into multiple threads. Second, both of them avoid partitioning the loop iteration space: they partition the instructions of the loop body instead. But four arguments push in favor of refining DSWP in terms of loop distribution.

1. Loop distribution leverages the natural loop structure, where the granularity of thread partitioning can be easily controlled. Moreover, it is useful to have a loop control node to which to attach information about the iteration of the loop, including closed forms of induction variables; this node can also be used to represent the loop in additional transformations.

2. Using a combination of loop distribution and fusion, replacing barriers with pipelining leads to an incremental path in compiler construction. This path leverages existing intermediate representations and loop nest optimizers, while DSWP relies on new algorithms and a program dependence graph.

3. Considering the handling of control dependences, a robust and general algorithm already exists for loop distribution. McKinley and Kennedy’s technique handles arbitrary control flow [10] and provides a comprehensive solution. The same methods could be applied for DSWP, transforming control dependences into data dependences, and storing boolean predicates into stream. After restructuring the code, updating the control dependence graph and data dependence graph, the code generation algorithm for PDGs [2, 5, 6] can be used to generate parallel code. This solution would handle all cases where the current DSWP algorithm fails to clone a control condition.

4. Since loop distribution does not partition the iteration space, it can also be applied to uncounted loops. Unfortunately, the termination condition needs to be propagated to downstream loops. This problem disappears through the usage of a conventional communication stream when building task pipelines. From this high-level analysis, it appears possible to extend loop distribution with pipelining to implement PS-DSWP and handle arbitrary control dependences. Yet the method still seems rather complex, especially the if-conversion of control dependences and the code generation step from the PDG. We go one step further and propose a new algorithm adapted from loop distribution but avoiding these complexities.

4.3 Motivating example

Our method makes one more assumption to reduce complexity and limit risks of overhead. It amounts to enforcing the synchronous hypothesis on all communicating tasks in the partition [8]. A sufficient condition is to check if the source and target of any decoupled dependence is dependent on the same control node.

Consider the example in Figure 4. S1 and S7 implement the loop control condition and induction variable, respectively. S2, S3 and S6 are control dependent on S1. S3 is a conditional node, S4, S5 and L1 are control dependent on it. In the inner loop, L2 and L3 are control dependent on L1. When we apply DSWP to the outer loop, the control dependences originating from S1 must be if-converted by creating several streams (the number of streams depends on the number of partitions). When decoupling along the control dependence originating from S3, a copy of the conditional node must be created as well as another stream.

![Figure 4. Uncounted nested loop before partitioning.](image)

```c
S1 while (p != NULL) {
    S2 x = p->value;
    S3 if(c1) {
        S4 x2 = p->value/2;
        S5 ip1 = p->inner_loop;
        L1 while (ip2 = S3) {
            L2 do_something(ip2);
            L3 ip3 = ip2->next;
        }
        S6 ... = x3;
        S7 p = p->next;
    }
}
```

![Figure 5. Uncounted nested loop in SSA form.](image)

```c
S1 while (p1 = S1(x1, x2)) {
    S2 x1 = p1->value;
    S3 if(c1) {
        S4 x2 = p1->value/2;
        S5 ip1 = p1->inner_loop;
        L1 while (ip2 = S3(x1, x2)) {
            L2 do_something(ip2);
            L3 ip3 = ip2->next;
        }
        S6 ... = x3;
        S7 p2 = p1->next;
    }
}
```

![Figure 6. Loops after partitioning and annotated with OpenMP stream extension.](image)

Figure 5 shows the conversion to SSA form. Just like GCC, we use a loop-closed SSA form distinguishing between loop-Φ and cond-Φ nodes. The latter take an additional condition argument, appearing as a subscript, to explicit the selection condition. The
Among these, the same variable \( x \) task1_1 could be decoupled, to be used in task1_2, and task1_3, to be used in task1_3. This output dependence must be eliminated prior to partitioning into tasks, so that task1_1 and task1_2 could be decoupled, while task1_3 may decide which value to use internally.

Nested tasks are introduced to provide fine grained parallelism. It is of course possible to adapt the partition and the number of nesting levels according to the load balancing and synchronization overhead. The generated code will be well structured, and simple top-down heuristics can be used.

In the execution model of OpenMP 3.0, a task instance is created whenever the execution flow of a thread encounters a task construct; no ordering of tasks can be assumed. Such an execution model is well suited for unbalanced loads, but the overhead of creating tasks is significantly more expensive than synchronizing persistent tasks. To improve performance, we use the persistent task model for pipelining, in which a single instance will handle persistent tasks. To improve performance, we use the persistent model to reduce the overhead of the full iteration space, consuming data on the input stream and the control dependence graph, in which a single instance will handle persistent tasks. To improve performance, we use the persistent model to reduce the overhead of the full iteration space, consuming data on the input stream and the control dependence graph, in which a single instance will handle persistent tasks.

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The systematic elimination of output dependencies is also facilitated by the SSA form, with a \( \Phi \) node in task3_1. Notice that the conditional expression from which this \( \Phi \) node selects one or another input also needs to be communicated through a data stream.

When modifying loop distribution to rely on tasks and pipelining rather than barriers, it is not necessary to distribute the loop control node and one may run it all in the master task, which in turn will activate tasks for the inner partitions. The statements inside each partition form a treegion whose root is the statement that is dependent on the loop control node. With pipelining inserted, distributed loops could be connected with pipelining when there are data dependences.

One concern here is that loop distribution with task pipelines may not provide expressiveness to extract pipeline parallelism. This is not a problem however, since we may apply the same method to every conditional statement root treegion, with some special care to the nested tasks, we could get fine grained parallelism without explicitly decoupling the control dependences. Considering again the example in Figure 4, its control dependence tree is given in Figure 9. The root treegion includes all the nodes in the control dependence graph, treegion1_2 represents the treegion at conditional level 1 and its root is node 2. treegion1_3 is at conditional level 1 and includes nodes (S3,S4,S5,L1,L2,L3). treegion2_1 is in conditional level 2 and its root is node (L1), which is the loop control node of the inner loop.

So following our approach, we may start from the treegion at conditional level 0, which is the whole loop, an implicit task will be created as the master task. For the treegions at level 1, we could create them as sub-tasks running at the context of the main task. If there are data dependences between the treegions at the same level and without recurrence, we will connect them with communication streams. If there is a dependence from the master task to one inner task, the value from the enclosing context can be forwarded to the inner task like in a firstprivate clause of OpenMP. Dependences from an inner task to the master task are also supported, although lastprivate is not natively supported for OpenMP 3.0 tasks, it is a necessary component of our streaming task representation. lastprivate (\( x \)) is associated with a synchronization point at the end of the task and makes the value of \( x \) available to the enclosing context. The same algorithms could be recursively applied to the treegion at the next inner level. e.g. For treegion1_3 at level 1, the sub treegion at level 2 is...
5. Partitioning Algorithm

In this section, we present our partitioning algorithm, based on the SSA and treegion representations. We define our model and the important constructs that will be used by our algorithm, then we present and describe our algorithm.

5.1 Definitions

In this work, we are only targeting natural structured loops [3]. Such loops are single-entry single-exit CFG sub-graphs with one entry block and possibly several back edges leading to the header from inside of the loop. break and continue statements can be preprocessed to comply with this restriction, but we plan to lift it altogether in the future.

Treegion The canonical definition of a treegion is a non-linear, single-entry multiple-exit region of code containing basic blocks that constitute a sub-graph of the CFG. We alter this definition to bear on the Control-Dependence Graph (CDG) instead, so we will be looking at single-entry multiple-exit sub-graphs of the CDG.

Loop Control Node In the representation we employ later, we will use the loop control node to represent the loop. The loop control node include statements which will evaluate the loop control expression and determines the next iteration.

Although control dependences in loops can be handled by the standard algorithm by converting them to a control flow graph, there are advantages in treating them as a special case with coalescing them in a single node (loop control node): not only the backward dependence is removed by building the loop control node so that the control dependence graph will form a tree, but also, this node can be used to represent the loop in all sort of transformations.

Conditional Level The control dependence graph of the structured code is a tree after building the loop control node. The root of the tree is the loop control node at the loop’s outermost level. We define the conditional level for every node in the control dependence graph as the depth of the node in the tree. The root of the tree with depth 0 has conditional level 0.

We define the conditional level for the treegion is the conditional level of the root node of the treegion (subtree). We define treegion(M, N) to identify a treegion where M is the conditional level of the treegion and N is the root node number of the treegion.

5.2 The algorithm

The algorithm takes an SSA representation of a single function, and returns a concurrent representation annotated with tasks and communication streams.

Step 1: Transform Conditional Statements to Conditional Variables To achieve fine-grained pipelining, conditional statements are split to conditional variables. As showed in Figure 10. Full conversion to three-address SSA form is also possible (as it is performed in GCC or LLVM, for example).

```c
if (condition(i))
  //is transformed to
c1 = condition(i)
if (c1)
```

Step 2: Build the Program Dependence Graph under SSA By building the program dependence graph, the control dependence graph, data dependence graph (through memory) and scalar dependence graph (through registers) are built together.

The control dependence graph for the structured code is a tree, the root of the tree is the loop control node. The leaves of the tree are non-conditional statements and the other nodes inside the tree are the conditional statements or the loop control node of the inner loops. We start from building the control dependence graph, and evaluate the conditional level for each node in the graph. Every node inside the control dependence graph is an statement from the compiler’s intermediate representation of the loop except for the loop control node. The loop control node will be built by searching the strongly connect component started from the loop header node (at each loop nest level) in the program dependence graph.

The data dependence graph could be built by the array dependence analysis [9] for the loop. We should analyze every pair of data dependences to mark the irriducible edges in a later step if there are recurrence.

Step 3: Marking the Irreducible Edges A partition can preserve all dependences if and only if there exists no dependence cycle spanning more than one output loop [1, 12]. In our case, for the treegion at the same conditional level, if there are dependences that form a cycle, we mark the edges in between as irreducible. If we have statements in different conditional level, we promote the inner one to its ancestor until both of them are in the same treegion, mark the promoted root node and the other root node as irreducible. The algorithms is presented in Figure 11.

Step 4: Structured Typed Fusion Before partitioning, to reveal data parallelism, we type every node in the dependences graph as parallel or !parallel. If there are loop-carried dependences inside this node, then it should be typed as !parallel, otherwise, typed as parallel.

The parallel type nodes are candidates for data parallelization. The goal is to merge this type of nodes to create the largest parallel loop, reducing synchronization overhead and (generally) improving data locality. Further partitioning can happen in the following step, staring from this maximally type-fused configuration. Given a DAG with edges representing dependences and the vertices representing statements in the loop body, we want to produce an equivalent program with minimal number of parallel loops. We want it to be as large as possible to balance the synchronization...
each pair of node (Vx, Vy) in SCC:

TypedFusion(G, T, B, t0)

for SCC in SCCs:
    for each pair of node (Vx, Vy) in SCC:
        if they are in the same treegion, merge into one node.
        if Vx.CL == Vy.CL,
            merge_to_one_nodes(Vx, Vy)
            continue
        if not in the same treegion, go up for n=|Vx.CL-Vy.CL|
            levels. And mark the edge between the nodes as irreducible.

max_CL = Vx.CL>Vy.CL?Vx.CL:Vy.CL
Vy = up_n_level(CDG, max_CL - Vy.CL)
//mark edge (Vx, Vy) irreducible
Irreducible_edge_set.insert(edge(Vx, Vy))

Figure 11. Algorithm for marking the irreducible edges.

overhead. Even when we don’t want that coarse grained parallel loops, we could also partition between iterations if possible.

In our case, we need a structured typed loop fusion algorithm. We revisit McKinley and Kennedy’s fast typed fusion [11] into a recursive algorithm traversing the control dependence tree. Starting from the treegion at conditional level 0, which is the whole loop, we will check if there are loop carried dependences between iterations. If there are no loop carried dependences, we will stop here by annotating the whole loop as parallel. If there are, we are going into each inner treegion, identifying those that have no loop carried dependences. If some of them carried no loop carried dependence, mark the nodes as parallel and try to merge them. There are some constraints when we fuse the nodes: (1) parallelization-inhibiting constraints; (2) ordering constraints. The parallelization-inhibiting fusion is that there are no loop-carried dependences before fusion, but will have the loop carried dependences after. So we should skip this kind of fusion which will degrades data parallelism. The ordering constraints describe that two loops cannot be validly fused if there exists a path of loop-independent dependences between them that contains a loop or statement that is not being fused with them.

The time complexity of the typed fusion algorithm is O(E+V) [11], and our structured extension has the same complexity.

void StructuredTypedFusion()
    Queue queue = new Queue()
    G = build_pdg_by_treegion(treegions)
    for each treegion in treegions:
        if loop_carried_no_dependence (treegion) {
            parallel_treegion.insert(treegion)
            update_typed_dependence_graph(G, treegion.num)
        }else{
            treegions_at_inner_level.insert(treegion)
        }
    queue.push(treegions_at_inner_level)
    B = Get_parallelization_inhabiting_edges
    (parallel_treegion)
    t0 = "Parallel"
    TypedFusion(G, T, B, t0)
}

procedure TypedFusion(G, T, B, t0)
    //G=(V,E) is the TYPED dependences graph,
    //including control data, scalar dependences.
    //type(n) will return the type of a node.
    //B is the set of parallelization-inhabiting edges.
    //t0 is a specific type for which we will find a minimal fusion
    end TypedFusion

Figure 12. Structured typed fusion algorithm.

Step 5: Structured Partitioning Algorithms Updating the CDG after typed fusion, start from the treegion which has conditional level 0 for our partitioning algorithms, and for all of its child treegions at conditional level 1, we should decide where to partition. The partition point could be any point between each of these treegions at the same level except the irreducible edges that we have created in step 3. The algorithm may decide at every step if it is desirable to further partition any given task into several sub-tasks.

Look at the example Figure 13:

```plaintext
for(1...)
    x = work(i)
    if (c1)
        y = x + i;
    END
for (1...)
    x = work(i)
    if (c1)
        BEGIN task1
        z = x + i;
        END
```
6.2 SSA representation

We are using the Static Single Assignment (SSA) form as an intermediate representation for the source code. A program in SSA form if every variable used in the program appears a single time in the left hand side of an assignment. We are using the SSA form to eliminate the output dependences in the code, and to disambiguate the flow of data across tasks over multiple producer configurations.

When enforcing this property, we first need to migrate the existing OpenMP expansion pass of GCC to work under SSA form, which has been a long-running extension of OpenMP, with a persistent task semantics to eliminate the overhead of scheduling task instances each time a pair of tasks need to communicate. Our method is inspired by the synchronous hypothesis: communicating concurrent tasks share the same control flow. This hypothesis simplifies the coordination of communicating tasks over nested levels of parallelism. Synchrony also facilitates the definition of generalized, structured typed fusion and partition algorithms preserving the loop structure information. These algorithms have been proven to be essential to the adaptation of the grain of parallelism to the target and to the effectiveness of compile-time load balancing. These partitioning algorithms also handle DOALL parallelization inside a task pipeline. We are using a combination of SSA, control dependence tree and (non-)dependence graph as an IR. With the support of SSA, our method leverages the nested multiple producer and multiple consumer problems of PS-DSWP. SSA also provides additional applicability, elegance and complexity benefits. This work is currently under development in a development branch of GCC, the partitioning algorithms is partially developed. For the code generation part, we first need to migrate the existing OpenMP expansion pass of GCC to work under SSA form, which has been a long-running challenge. When this work is complete, our method will leverage the array data-flow analysis of the Graphite polyhedral compilation pass of GCC to provide more precise data dependence information in loop nests with regular control flow.

\[ r_{1} = ... \]
\[ S1: \text{if (condition)} \]
\[ S2: \text{if (condition)} \]
\[ S3: r_{1} = ... \]
\[ S4: ... = r_{1} \]
\[ S5: ... = r_{1} \]

Figure 15. Normal form of code (left) and SSA form of the code (right).

Considering the example in Figure 15, if we partition the statements into (S1), (S2,S3), (S4), we need to implement precedence constraints for the output dependence between partition (S1) and (S2,S3), which decreases the degree of parallelism and induces synchronization overhead.

Eliminating the output dependences with the SSA form leads to the introduction of multiple streams in the partitioned code. In order to merge the information coming from different control flow branches, a \( \Phi \) node is introduced in the SSA form. The \( \Phi \) function is not normally implemented directly, after the optimizations are completed the SSA representation will be transformed back to ordinary one with additional copies inserted at incoming edges of (some) \( \Phi \) functions. We need to handle the case where multiple producers in a given partition reach a single consumer in a different partition. When decoupling a dependence whose sink is a \( \Phi \) node, the exact conditional control flow leading to the \( \Phi \) node is not accessible for the out-of-SSA algorithm to generate ordinary code.

**Task-closed \( \Phi \) node** In SSA loop optimization, there is a concept called loop-closed \( \Phi \) node, which implements the additional property that no SSA name is used outside of loop where it is defined. When enforcing this property, \( \Phi \) nodes must be inserted at the loop exit node to catch the variables that will be used outside of the loop. Here we give a similar definition for \textit{task-closed} \( \Phi \) node: if multiple SSA variables are defined in one partition and used in another, a \( \Phi \) node will be created at the end of the partition for this variable. This is the place where we join/split the stream. We need to make sure that different definitions of the variable will be merged in this partition before it continues to a downstream one. This node will be removed when converting back from SSA.

**Task-closed stream** Our partitioning algorithms generate nested pipelining code to guarantee that all communications follow the synchronous hypothesis. For each boundary, if there are one or more definitions of a variable coming through from different partitions, we insert a consumer at this boundary to merge the incoming data, and immediately insert a producer to forward the merged data at the rate of the downstream control flow.

1. **When partitioning from a boundary, if inside the treegion, there are multiple definitions of a scalar and it will be used in other treegions which has the same conditional level, we create a \( \Phi \) node at the end of this partition to merge all the definitions, and also update the SSA variable in later partitions.**
2. **If there is a \( \Phi \) node at the end of a partition, insert a stream named with the left-hand side variable of the \( \Phi \) node.**
3. **At the place where this variable is used, which is also a \( \Phi \) node, add a special stream-\( \Phi \) node to consume.**
4. **To generate code for the stream-\( \Phi \), use the boolean condition associated with the conditional phi node it originates from.**

Let us consider the SSA-form example in Figure 15 where we partition the code into (S1,S2,S3) and (S4,S5). A \( \Phi \) node will be inserted at the end of the first partition, \( r_{1} = \text{phi}(r_{1}, r_{1}) \).

The \( \Phi \) node in a later partition should be updated from \( r_{1} = \text{phi}(r_{1}, r_{2}) \) to \( r_{1} = \text{phi}(r_{1}, r_{4}) \). In the second step, we find out that in partition (S1,S2,S3), there is a \( \Phi \) node at the end, so we insert a stream to produce there. And in partition (S4,S5), after the \( \Phi \) node there is a use of the variable, so we insert a stream consume. The generated code will look like Figure 16.

\[
S1: r_{1} = ... \\
S2: \text{if (condition)} \\
S3: r_{1} = ... \\
S4: ... = r_{1} \\
S5: ... = r_{1} \\
\]

Figure 16. Apply our algorithm to generate the parallel code. Producer thread (left) and consumer thread (right).

This example illustrates the generality of our method and shows how fine-grain pipelines can be built in presence of complex, multi-level control flow.

If we decide to partition the statements into (S1), (S2,S3), (S4,S5), which is the case for multiple producers, the generated code will look like in Figure 17.

\[
S1: r_{1} = ... \\
S2: \text{if (condition)} \\
S3: r_{1} = \text{phi}(r_{1}, r_{2}) \\
S4: r_{1} = \text{phi}(r_{1}, r_{4}) \\
S5: ... = r_{1} \\
\]

Figure 17. Multiple producers with applied our algorithm, the generated code.

For multiple consumers, the stream extension of OpenMP will broadcast to its consumers, which is appropriate for our case.

7. Conclusion

In this paper, we propose a method to decouple independent tasks in serial programs, to extract scalable pipelining and data-parallelism. Our method leverages a recent proposition of a stream-processing extension of OpenMP, with a persistent task semantics to eliminate the overhead of scheduling task instances each time a pair of tasks need to communicate. Our method is inspired by the synchronous hypothesis: communicating concurrent tasks share the same control flow. This hypothesis simplifies the coordination of communicating tasks over nested levels of parallelism. Synchrony also facilitates the definition of generalized, structured typed fusion and partition algorithms preserving the loop structure information. These algorithms have been proven to be essential to the adaptation of the grain of parallelism to the target and to the effectiveness of compile-time load balancing. These partitioning algorithms also handle DOALL parallelization inside a task pipeline. We are using a combination of SSA, control dependence tree and (non-)dependence graph as an IR. With the support of SSA, our method leverages the nested multiple producer and multiple consumer problems of PS-DSWP. SSA also provides additional applicability, elegance and complexity benefits. This work is currently under development in a development branch of GCC, the partitioning algorithms is partially developed. For the code generation part, we first need to migrate the existing OpenMP expansion pass of GCC to work under SSA form, which has been a long-running challenge. When this work is complete, our method will leverage the array data-flow analysis of the Graphite polyhedral compilation pass of GCC to provide more precise data dependence information in loop nests with regular control flow.

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References


