Mode Grouping for More Effective Generalized Scheduling of Dynamic Dataflow Applications

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ABSTRACT

For a number of years, dataflow concepts have provided designers of digital signal processing systems with environments capable of expressing high-level software architectures as well as low-level, performance-oriented kernels. To apply these proven techniques to new complex, dynamic applications, we identify repetitive sequences of atomic, repeatable actions ("modes") inside dynamic actors to expose more of the static nature of the application. In this work, we propose a mode grouping strategy that aids in the decomposition of a dynamic dataflow graph into a set of static dataflow graphs that interact dynamically. Mode grouping enables the discovery of larger static subgraphs improving scheduling results. We show that grouping modes results in improved schedules with lower memory requirements for implementations by up to 37% including a common imaging benchmark with dynamic behavior: 3D B-spline interpolation.

Categories and Subject Descriptors

D.4.1 [**Operating Systems**]: Process Management

General Terms

Algorithms, Management

Keywords

dataflow, scheduling, mode grouping

1. INTRODUCTION

Dataflow models have become both an important formal underpinning for tools and a convenient way of reasoning about applications in a precise manner for application areas such as digital signal processing (DSP). Their graph-based formalisms allow natural and yet semantically rigorous application descriptions. Such a semantic foundation enables a variety of analysis tools, including determining buffer bounds and efficient scheduling [6]. As a result, dataflow languages are increasingly popular. Their diversity, portability, and intuitive appeal have extended them to many application areas with a variety of targets. As system complexity increases in digital signal processing platforms, designers are expressing more types of behavior in dataflow languages. While the semantic range of DSP-oriented dataflow models has expanded to cover dynamic interactions, many of the powerful static optimizations algorithms have become less applicable. This is especially problematic in scheduling, which impacts key implementation metrics for embedded software systems, like memory size, performance, and power consumption (e.g., see [9]).

Even though new applications are dynamic, they still exhibit static behavior during execution. This may be in the form of static subsystems or repetitious sequences of actions that occur during otherwise dynamic execution. While current techniques already address the former, the latter is unexploited. Traditional static scheduling techniques are potentially applicable to these application-wide static sequences, but the behavior must be identified and properly modeled based on the original application description.

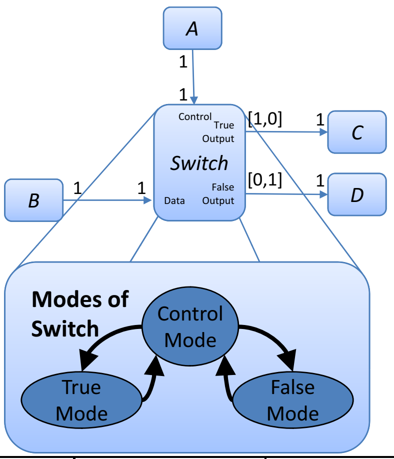
In this paper, we extend a scheduling algorithm [7] that takes a dynamic application described in the functional dataflow interchange format formalism [8] and decomposes it into a set of static dataflow graphs. In particular we introduce a notion of grouping actor modes, which allows certain static sequences of fixed actions to be exposed to a scheduler. This exploits the statically known behavior of an otherwise dynamic actor resulting in a more efficient schedule for the overall application.

2. BACKGROUND

2.1 Dataflow Modeling

Modeling DSP applications through coarse-grain dataflow graphs is widespread in the DSP design community, and a variety of dataflow models have been developed for dataflow-based design. A growing set of DSP design tools support such dataflow semantics. Designers are expected to be able to find a match between their application and one of the well-studied models, including cyclo-static dataflow (CSDF), synchronous dataflow (SDF), single-rate dataflow, homogeneous synchronous dataflow (HSDF), or a more complicated model such as boolean dataflow (BDF).

Common to each of these modeling paradigms is the representation of computational behavior as a dataflow graph. A dataflow graph G is an ordered pair (V, E) , where V is a set of vertices (or nodes), and E is a set of directed edges.



mode	consumes		produces	
	Control	Data	True	False
Control	1	0	0	0
True	0	1	1	0
False	0	1	0	1

Figure 1: Boolean dataflow *Switch* in CFDF.

A directed edge $e = (v_1, v_2) \in E$ is an ordered pair of a source vertex $v_1 \in V$ and a sink vertex $v_2 \in V$. Nodes or *actors* represent computation while edges represents a FIFO communication links between them.

One of the semantic foundations for a structured dynamic dataflow formalism is *core functional dataflow* (CFDF) [8], which is capable of expressing deterministic, dynamic dataflow applications. In this formalism, each actor $a \in V$ has a set of *modes*, M_a, in which it can execute. Each mode, when executed, consumes and produces a fixed number of tokens. For example, consider the *Switch* actor and four SDF actors in Figure 1 with the mode behavior of the *Switch* actor shown below it.

2.2 Dataflow Interchange Format

To describe dataflow applications for the wide range of dataflow modeling techniques that are relevant to DSP system design, application developers can use the dataflow interchange format (DIF) [3], a standard approach founded in dataflow semantics and tailored for DSP system design. It provides an integrated set of syntactic and semantic features that can fully capture essential modeling information of DSP applications without over-specification. DIF is designed to describe mixed-grain graph topologies and hierarchies as well as to specify dataflow-related and actor-specific information. The DIF package transforms DIF descriptions into an internal representation and contains graph utilities, optimization engines, and other utilities. *Functional DIF* also supports CFDF making it an effective environment for modeling dataflow applications, providing interoperability with other design environments, and developing new tools.

2.3 Generalized Scheduling

While there exist techniques for finding static islands in a dynamic application, more static behavior can be found in dataflow graphs described in CFDF. A generalized scheduling approach can utilize the fact that every mode has fixed production and consumption behavior and decompose a dynamic dataflow graph into a set of static subgraphs [7]. To construct a single static subgraph, it finds the combination of modes in which one mode from each actor in the subgraph is producing or consuming on an edge that has a consuming or producing mode respectively at the other end of the edge. For example, consider the decomposition that results from Figure 1 as shown in Figure 2. From these static subgraphs, generalized schedule trees (GSTs) are produced [5]. A GST is a schedule representation based on ordered trees where leaf nodes represent the actors of a dataflow graph and internal nodes represent loop counts.

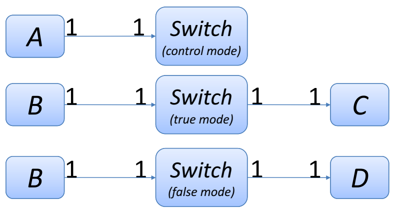


Figure 2: Mode decomposition of switch application

2.4 Related Dynamic Dataflow Work

Besides CFDF, there are a variety of other dataflow models and dataflow based design environments that capture and simulate dynamic applications. In the Stream Based Function (SBF) model of computation [4], actors are represented by a set of functions, a controller, state, and transition function. Ptolemy II encompasses a diversity of dataflow-oriented and other kinds of models of computation [2]. Developers employ a "director" that controls the communication and execution schedule of an application graph.

Beyond modeling, dataflow has been used in the optimization of dynamic systems. For example, systems with data dependent communication can be modeled with variable rate dataflow [10]. When dynamic behavior is modeled as such, buffer capacities can be computed based on throughput constraints in the application. By contrast, our work focuses on identifying more static behavior in a dynamic application so that traditional scheduling techniques can be used. While Functional DIF is used as our demonstration vehicle for extending generalized scheduling, the techniques and results should be applicable across many such tools.

3. MODE GROUPING

While static subgraphs can be successfully found by a generalized scheduling approach to dynamic applications [7], some static behaviors are not considered. For example, in the decomposition of our switch application from Figure 2 the *True* and *False* modes act predictably, always returning to *Control*, which is the mode that transitioned to them in the first place. The repeatable nature of these branches are the kind of static behavior that is exploitable but is not found by existing generalized scheduling approaches.

To this end, we augment our actor description with the concept of *mode grouping*, in which application writers can refine their original application by grouping modes together. For an actor a with modes M_a, we define a mode grouping, $D_a \subseteq M_a$ as a set of modes with a static relationship. The static mode behavior we expose in this work is cyclic mode transitions in which all modes in the grouping return exactly one mode as the next mode, except for one mode, called the

Table 1: The actors in the cubic B-spline application ("control" corresponds to c* edges and "point" corresponds to d* edges)

Actors	Modes	consumed			prod
		control	point	data	out
Grid Lookup	Normal	NA	3	NA	192
Interp Plane	Control	1	0	0	0
	New Cube	0	1	192	48
	Recalc	0	1	0	48
Interp Row	Control	1	0	0	0
	New Plane	0	1	48	12
	Recalc	0	1	0	12
Interp Point	Control	1	0	0	0
	New Row	0	1	12	3
	Recalc	0	1	0	3
Print	Normal	NA	NA	3	NA

entrance mode. The entrance mode may have multiple transitions out, as it marks the single point of dynamic behavior in the grouping, but after it is fired, the modes that follow it do so in a static sequence. The mode grouping can be considered by the scheduler as a single mode that has production and consumption behavior equal to the sum of the individual modes in it. The resulting schedule then includes a repeated firing the size of the mode grouping.

In our switch example, two mode groupings are $D_a = \{\{control, true\}, \{control, false\}\}$, each with *Control* as the entrance mode. This exposes that *Control* always precedes a *True* or a *False*, allowing a larger schedule tree to be formed. For this small example performance benefits are slight, but for more complex applications, the assertion that a set of modes execute in a static sequence can lead to notably smaller buffer requirements.

4. CUBIC B-SPLINE INTERPOLATION

Splines are commonly used in image processing for applying smooth, non-linear transformation to images. Such deformation fields may be modeled by piecewise polynomial interpolation from *basis functions* based on a set of *control points*. They can be computationally efficient by restricting the impact of a control point to a local region, but still be globally smooth. In this work we focus on *cubic B-splines* which use third order polynomials as their basis functions and use contributions from four neighboring control points. A popular way of transforming a 3-dimensional set of control points into deformation field is through B-spline interpolation in three different axes, each time adding the contributions from two control points before and two control points after the voxel in question.

A dataflow implementation of this application (shown in Figure 3) avoids re-computation and additional memory access to the intermediate results of interpolation. Mode behaviors are described in Table 1 and Table 2. Each interpolating actor may accept new inputs for its interpolation step or it may compute another voxel on the shared support of the control points at that step. We exploit grouping in this application by pairing each *Recalc* and *New Cube/Plane/Row* mode with the *Control* mode, creating a total of 6 new modes to the datapath actors.

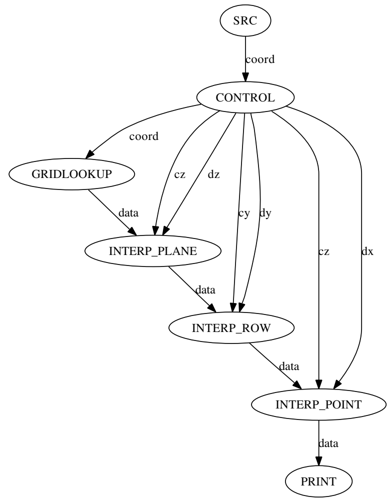


Figure 3: Dataflow graph of 3D cubic B-spline

Table 2: The CONTROL actor modes in B-spline

Modes	cons	produces						
	coord	coord	cz	dz	cy	dy	cx	dx
Control	3	0	0	0	0	0	0	0
New Cube	0	3	1	1	1	1	1	1
New Plane	0	0	1	1	1	1	1	1
New Row	0	0	0	0	1	1	1	1
New Point	0	0	0	0	0	0	1	1

5. RESULTS

To evaluate the benefits of mode grouping, we started with a set of both static and dynamic applications with actors that had mode groupings to exploit: the B-spline application presented in the previous section, a CSDF data distribution of audio streams to be sample-rate-converted, a polyphase decimated DFT filter bank, and an application with multiple polynomial evaluation accelerators (PEAs). For each, we ran the generalized scheduler (using APGAN as the static scheduler [1]) with and without mode groupings that were manually added. The resulting schedule trees were balanced and ordered based on the known input conditions, be it static patterns or probability distributions. In the case of the B-spline application, the steps through the different dimensions were known at run-time, and schedule trees were balanced accordingly. Figure 4 shows these five unique schedule trees (each of which has a root at the second level of the tree) that were replicated and ordered with a modified iteration count to account for the number of voxels to be processed at each step. Also for the B-spline application, a valid schedule could not be found by our generalized scheduler without groups. Instead, we generated the flat schedule balanced with equivalent execution rates as shown in Figure 5.

We pushed hundreds of input data tokens through each of these implementations to monitor the amount of buffering consumed by the application with that schedule as shown in Table 3. The two purely static applications showed no benefit of using mode grouping. While mode groups were identified in CSDF actors, the original generalized scheduler performed equally well with and without groups. Once any

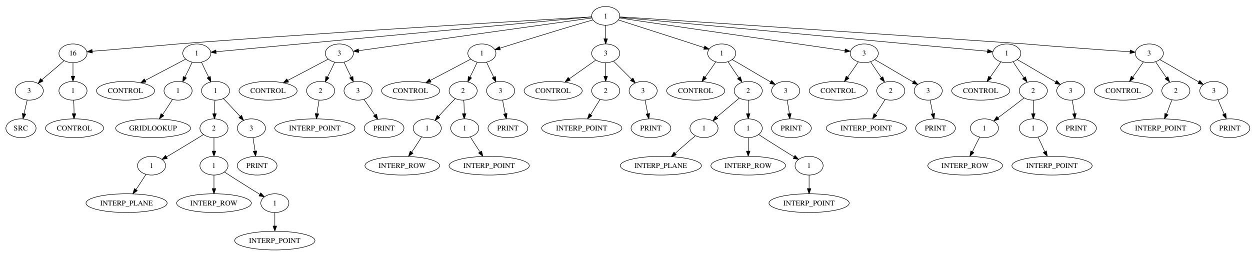


Figure 4: Schedule derived from mode grouping for B-spline application

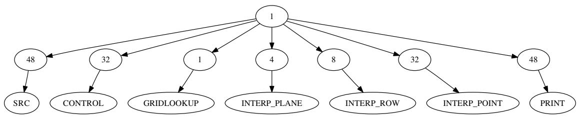


Figure 5: Rate balanced schedule for B-spline

Table 3: Total buffer size requirements with and without mode grouping

Application	Without Groups	With Groups	Percentage Improvement
BSpline Interp	479	304	37%
Sample Rate Conv	2,278	2,278	0%
PolyPhase	24	24	0%
Multi-PEA	3,802	2,976	22%

dynamic behavior was inserted (i.e. the B-spline controller and the PEA dynamic switch and select pair), mode grouping showed a significant improvement finding more (and larger) static schedule trees, which provided a direct savings in buffering by more optimal actor firings. Generalized scheduling with and without groups for each of these examples took less than 5 seconds on a modern CPU.

6. CONCLUSIONS

The rise of complex, dynamic applications has hindered the applicability of traditional static dataflow analysis. In this paper, we have reclaimed some of this ground by presenting a new extension to a generalized scheduling approach that exposes more static behavior of a dynamic application graph. By identifying static groups of "modes" inside actors, we expose more of the static nature of the application, allowing traditional scheduling techniques to improve on memory requirements by up to 37%. We plan to extend this work by developing dynamic schedule tree selector so that a simulator or a final implementation may strategically switch between the known static behaviors at run-time.

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