



#### Exploiting Coarse-Grained Task, Data, and Pipeline Parallelism in Stream Programs

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#### **Multicores Are Here!**







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## **Common Machine Languages**



Uniprocessors:	Multicores:	
<b>Common Properties</b>	Common Properties	
Single flow of control	Multiple flows of control	
Single memory image	Multiple local memories	
Differences:	Differences:	
Differences: Register File Register Alloca	Differences:	
Differences: Register File Register Alloca ISA Instruction Selection	Differences: tion mber and capabilities of cores Communication Model	

von-Neumann languages represent the common properties and abstract away the differences

Need common machine language(s) for multicores



#### Streaming as a Common Machine Language

- Regular and repeating computation
- Independent filters with explicit communication
  - Segregated address spaces and multiple program counters
- Natural expression of Parallelism:
  - Producer / Consumer dependencies
  - Enables powerful, whole-program transformations



## Types of Parallelism





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Task Parallelism

- Parallelism explicit in algorithm
- Between filters *without* producer/consumer relationship

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### **Types of Parallelism**



Task Parallelism

- Parallelism explicit in algorithm
- Between filters *without* producer/consumer relationship

#### Data Parallelism

- Between iterations of a stateless filter
- Place within scatter/gather pair (fission)
- Can't parallelize filters with state

#### **Pipeline Parallelism**

- Between producers and consumers
- Stateful filters can be parallelized





### **Types of Parallelism**



#### Traditionally:

Task Parallelism

- Thread (fork/join) parallelism

Data Parallelism

- Data parallel loop (forall)

**Pipeline Parallelism** 

- Usually exploited in hardware





### **Problem Statement**

#### Given:

- Stream graph with compute and communication estimate for each filter
- Computation and communication resources of the target machine

#### Find:

 Schedule of execution for the filters that best utilizes the available parallelism to fit the machine resources





#### **Our 3-Phase Solution**



- 1. Coarsen: Fuse stateless sections of the graph
- 2. Data Parallelize: parallelize stateless filters
- 3. Software Pipeline: parallelize stateful filters

Compile to a 16 core architecture

11.2x mean throughput speedup over single core



### Outline



- StreamIt language overview
- Mapping to multicores
  - Baseline techniques
  - Our 3-phase solution

### The StreamIt Project



#### **Applications StreamIt Program** DES and Serpent [PLDI 05] - MPEG-2 [IPDPS 06] - SAR, DSP benchmarks, JPEG, ... Front-end Programmability - StreamIt Language (CC 02) - Teleport Messaging (PPOPP 05) Annotated Java Programming Environment in Eclipse (P-PHEC 05) **Domain Specific Optimizations** - Linear Analysis and Optimization (PLDI 03) Simulator Stream-Aware **Optimizations** Optimizations for bit streaming (PLDI 05) (Java Library) Linear State Space Analysis (CASES 05) Architecture Specific Optimizations Compiling for Communication-Exposed Uniprocessor Cluster Raw **IBM X10** Architectures (ASPLOS 02) backend backend backend backend Phased Scheduling (LCTES 03) Cache Aware Optimization (LCTES 05)

C/C++

**MPI-like** 

C/C++

C per tile +

msg code

Streaming

X10 runtime

 Load-Balanced Rendering (Graphics Hardware 05)



## Model of Computation

- Synchronous Dataflow [Lee '92]
  - Graph of autonomous filters
  - Communicate via FIFO channels
- Static I/O rates
  - Compiler decides on an order of execution (schedule)
  - Static estimation of computation







### **Example StreamIt Filter**







### **Example StreamIt Filter**





## StreamIt Language Overview

- StreamIt is a novel language for streaming
  - Exposes parallelism and communication
  - Architecture independent
  - Modular and composable
    - Simple structures composed to creates complex graphs
  - Malleable
    - Change program behavior with small modifications





### Outline



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- Inherent task parallelism between two processing pipelines
- Task Parallel Model:
  - Only parallelize explicit task parallelism
  - Fork/join parallelism
- Execute this on a 2 core machine
  ~2x speedup over single core
- What about 4, 16, 1024, ... cores?



### **Evaluation: Task Parallelism**





#### Baseline 2: Fine-Grained Data Parallelism





- Each of the filters in the example are stateless
- Fine-grained Data Parallel Model:
  - Fiss each stateless filter N
    ways (N is number of cores)
  - Remove scatter/gather if possible
- We can introduce data parallelism
  - Example: 4 cores
- Each fission group occupies entire machine

#### Evaluation: Fine-Grained Data Parallelism



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### Outline



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## Phase 1: Coarsen the Stream Graph



- Before data-parallelism is exploited
- *Fuse* stateless pipelines as much as possible without introducing state
  - Don't fuse stateless with stateful
  - Don't fuse a peeking filter with anything upstream

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## Phase 1: Coarsen the Stream Graph



- Before data-parallelism is exploited
- *Fuse* stateless pipelines as much as possible without introducing state
  - Don't fuse stateless with stateful
  - Don't fuse a peeking filter with anything upstream
- Benefits:
  - Reduces global communication and synchronization
  - Exposes inter-node optimization opportunities





### Phase 2: Data Parallelize



#### Data Parallelize for 4 cores





### Phase 2: Data Parallelize







### Phase 2: Data Parallelize



#### Data Parallelize for 4 cores

- Task-conscious data parallelization
  - Preserve task parallelism
- Benefits:
  - Reduces global communication and synchronization

Task parallelism, each filter does equal work Fiss each filter 2 times to occupy entire chip

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#### **Evaluation:**



#### **Coarse-Grained Data Parallelism**







#### **Simplified Vocoder**



Target a 4 core machine





#### **Data Parallelize**



Target a 4 core machine

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### Data + Task Parallel Execution



Target 4 core machine



#### We Can Do Better!



Target 4 core machine







#### **Greedy Partitioning**





#### Target 4 core machine

#### Evaluation: Coarse-Grained Task + Data + Software Pipelining



# Generalizing to Other Multicores

CSAIL

- Architectural requirements:
  - Compiler controlled local memories with DMA
  - Efficient implementation of scatter/gather
- To port to other architectures, consider:
  - Local memory capacities
  - Communication to computation tradeoff
- Did not use processor-to-processor communication on Raw



#### **Related Work**



- Streaming languages:
  - Brook [Buck et al. '04]
  - StreamC/KernelC [Kapasi '03, Das et al. '06]
  - Cg [Mark et al. '03]
  - SPUR [Zhang et al. '05]
- Streaming for Multicores:
  - Brook [Liao et al., '06]
- Ptolemy [Lee '95]
- Explicit parallelism:
   OpenMP, MPI, & HPF





#### Conclusions

- Streaming model naturally exposes task, data, and pipeline parallelism
- This parallelism must be exploited at the correct granularity and combined correctly

	Task	Fine-Grained Data	Coarse-Grained Task + Data	Coarse-Grained Task + Data + Software Pipeline
Parallelism	Not matched	Good	Good	Best
Synchronization	Not matched	High	Low	Lowest

- Good speedups across varied benchmark suite
- Algorithms should be applicable across multicores