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Exploiting Fine Grained Parallelism in SPE

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Introduction

Fundamental Problem

- RAM does not capture memory access complexity
- Computational complexity is not enough on actual machines

Strategy

- Machine models (memory and processor)
- Algorithmic techniques

Questions

- What can be imported from other settings/contexts?
- Is it possible/convenient to exploit parallelism in a scalar setting?

Models Previous Work Our Work

Models and Algorithms

Two major strategies to cope with latency:

• Temporal/Spatial Locality

Concurrency

Models Previous Work Our Work

Models and Algorithms

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- Temporal/Spatial Locality
 - \Rightarrow Hierarchical Memories, Block Transfer

- Concurrency
 - \Rightarrow Pipelined Memories

Models Previous Work Our Work

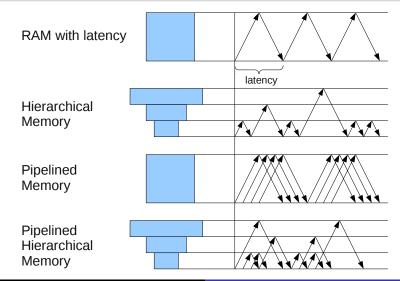
Models and Algorithms

Two major strategies to cope with latency:

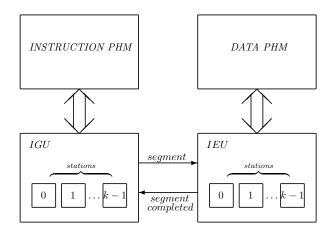
- Temporal/Spatial Locality
 - \Rightarrow Hierarchical Memories, Block Transfer
 - \Rightarrow Memory access function a(x)
- Concurrency
 - \Rightarrow Pipelined Memories
 - \Rightarrow Constant access request rate

Models Previous Work Our Work

Memory Models



Models Previous Work Our Work



Models Previous Work Our Work

Speculative Prefetcher and Evaluator

 Instructions are executed in segments of variable size (segmentsize())

Models Previous Work Our Work

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- No slow down because of data dependencies. . .

Models Previous Work Our Work

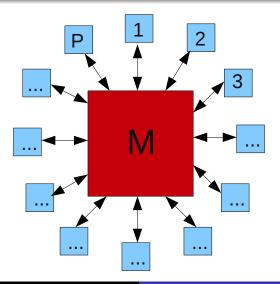
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- ... or even O(1) address dependence depth

Models Previous Work Our Work

- Instructions are executed in segments of variable size (segmentsize())
- No slow down because of data dependencies. . .
- ... or even O(1) address dependence depth
- Enhancements such as dynamic loop unrolling and branch prediction are allowed

Models Previous Work Our Work

Parallel Random Access Machine



Models Previous Work Our Work

Parallel Random Access Machine

Many equivalent flavours: SIMD, MIMD...

The actual difference is in how shared memory is managed:

- EREW: exclusive read, exclusive write
- CREW: concurrent read, exclusive write
- CRCW: concurrent read, concurrent write (contention policy)

Models Previous Work Our Work

Work-Time Framework

• Parallel Programming Model which targets PRAMs

Models Previous Work Our Work

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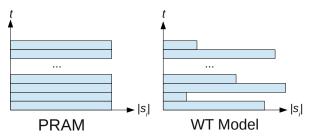
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• Time T; Work
$$W = \sum_{i=1}^{T} p_i$$

Models Previous Work Our Work

- Parallel Programming Model which targets PRAMs
- pardo statement defines parallel steps
- sets s_1, \ldots, s_T of instructions on M cells of memory
- in general, each s_i has a different size p_i
- Time T; Work $W = \sum_{i=1}^{T} p_i$
- Easily schedulable on PRAM: O(W/P + T)



Models Previous Work Our Work

Exploiting Parallelism

PRAM to Disk Model

Chiang, Y., Goodrich, M. T., Grove, E. F., Tamassia, R., Vengroff, D. E.,

Vitter, J. S.: External-Memory Graph Algorithms. SODA '95

 D-BSP to Hierarchical Memory Fantozzi, C., Pietracaprina, A. A., Pucci, G.: Translating Submachine Locality into Locality of Reference. *Journal of Parallel and Distributed Computing 66*

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- PRAM to Pipelined Memory Luccio, F., and Pagli, L.: A model of sequential computation with pipelined access to memory. *Math. Syst. Theory 26*

Models Previous Work Our Work

Our Work

Our Work

- Parallel model: Work-Time Framework
- Sequential model: SPE
- A general technique for implementing WT Algorithms on SPE
- Large classes of optimal SPE programs

Novelty

- Explicitly refer to a feature of problems: available parallelism
- Target physically implementable machines, not bound to a particular memory access function

Single Step Whole Algorithm Applications

WT Simulation - Single Step

Simulation of parallel step *i* (exclusive write)

WT

 $\begin{array}{c} \text{for } j, 1 \leq j \leq p \text{ pardo} \\ \text{operation}_j \end{array}$

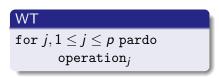
SPE

 $\begin{array}{ll} \text{segmentsize}\,(\min(k,\ p))\\ \text{for}\,j,1\leq j\leq p\;\text{do}\\ & \text{instructions}_j \end{array}$

Single Step Whole Algorithm Applications

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SPE

 $\begin{array}{ll} \text{segmentsize}(\min(k, p)) \\ \text{for } j, 1 \leq j \leq p \text{ do} \\ & \text{instructions}_j \end{array}$

- Program size: O(1)
- Δ Space: $O(p_i)$
- Time: $O(p + a(M_{SPE}^i))$

Single Step Whole Algorithm Applications

WT Simulation - Single Step

• Program size does not depend on input size

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 \Rightarrow negligible instruction load latency

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- Memory accesses fully overlap

 \Rightarrow proportional to p_i and $a(M_{SPE}^i)$

Single Step Whole Algorithm Applications

WT Simulation - Concurrent Write

Different solutions, depending on the concurrent write policy:

- priority policy \rightarrow predicated instructions
- associative op. policy \rightarrow accumulation

```
\begin{array}{ll} \text{segmentsize}(\min(k, p)) \\ \text{for } j, 1 \leq j \leq p \text{ do} \\ & \text{instructions}_j \\ & acc \leftarrow \max\{acc; output_j\} \end{array}
```

• Also an if(test) statement can be used... ...when the test is simple enough!

Single Step Whole Algorithm Applications

WT Simulation - Whole Algorithm

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Single Step Whole Algorithm Applications

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• Total space complexity: $M_{PH} = O(n + W)$

Single Step Whole Algorithm Applications

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Single Step Whole Algorithm Applications

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Optimal SPE programs if

- Work–optimal WT algorithms
- The average parallelism is larger than worst case latency

Single Step Whole Algorithm Applications

Merge

Problem: merging 2 sorted lists of *n* elements.

• Kruskal algorithm: $T = O(\log n)$, W = O(n)

Single Step Whole Algorithm Applications

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Single Step Whole Algorithm Applications

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•
$$\Rightarrow$$
 $T_{SPE} = O(W + T \cdot a(M)) = O(n + \log n \cdot a(n))$

• linear for $a(x) = x^{\alpha}, 0 < \alpha < 1$, $a(x) = \log x$.

On other hierarchical models:

- $O(n \log n)$ if $a(x) = x^{\alpha}, 0 < \alpha < 1$
- $O(n \log^* n)$ if $a(x) = \log x$

Single Step Whole Algorithm Applications

MergeSort

Problem: sorting a list of *n* **elements.**

Warning

Merge is linear only if the input is in the fastest O(n) locations.

Solution

When merge istances are too small wrt latency, execute them in an interleaved fashion.

Single Step Whole Algorithm Applications

Non–local Matrix Multiplication

Problem: multiplying 2 $n \times n$ matrices.

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Space complexity

 $O(n^3)$ memory is required!

Conclusions and Future Work

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- Large memory footprint, if too much parallelism

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Future Work

- Integration with locality exploitation
- Exploitation of *coarse grained* parallelism (D-BSP)

Thank you!

Conclusions and Future Work

Thank you for your attention!

... questions?