

A GPU Sparse Symmetric Indefinite Solver with Pivoting

Jonathan Hogg,

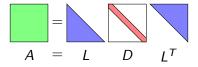
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* Thanks also to Jeremy Appleyard of NVIDIA

Factorization



- Sparse
- Symmetric: $A = A^T$
- Non-singular (for purposes of talk)
- Do it on a GPU
- Aim to be bit-compatible



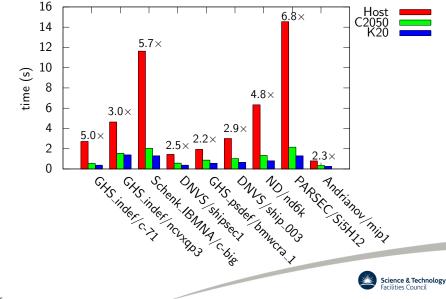
Why GPU

Chip	Cores	GB/	TFLOP/	GFLOPS/
		sec	sec	Watt
NVIDIA K40	15 imes 64	288	1.43	6.1
NVIDIA Titan Z	2 imes15 imes64	672	2.66	7.1
AMD R9 295X2	$2 \times 44 \times 8^*$	640	1.43	2.9
Intel Xeon Phi	60 imes 8	320	1.00	4.5
Intel Desktop E5-2687W	16 imes 4	50	0.40	1.3
NVIDIA Titan Z AMD R9 295X2 Intel Xeon Phi	2 imes 15 imes 64 $2 imes 44 imes 8^{*}$ 60 imes 8	288 672 640 320	1.43 2.66 1.43 1.00	6.1 7.1 2.9 4.5

 * double precision cores. single precision is 8×.



Results preview



Sparse Direct Solver for GPUs

Modern direct solver design

Four phases

Ordering Find fill-reducing permutation

Analyse Find dense submatrix structure. Setup data representation.

Factor Perform factorization with pivoting.

Solve Use factorization to solve Ax = b.



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GPU Challenges

- Thousands of *small* dense subproblems (e.g. 8×1)
- ▶ Pivoting on *large* dense subproblems (e.g. 4000 × 2000)
- Substantial sparse scatter/gather
- Complicated kernels (register pressure)



Previous work

Pre-existing work

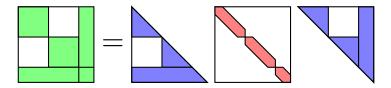
- Just offloading large BLAS 3/LAPACK operations. Very modest speedups on whole problem.
- A few codes go beyond this.
 None publicly available?
 No pivoting: potentially unstable
 Fairly modest speedups: CPU↔GPU bottleneck

Our implementation

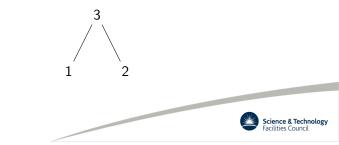
- Puts entire factorization and solve phases on GPU
- Open source, including all auxiliary codes
- ▶ Delivers over 5× speedup vs 2 CPU sockets on large problems

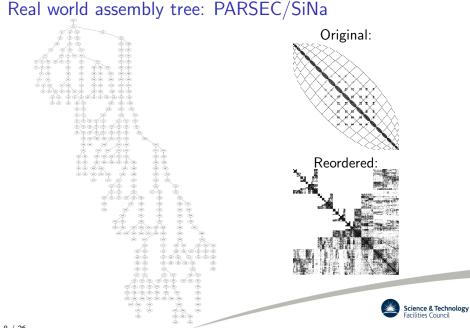


Tree parallelism



Operations in first two block columns are independent. Data flow graph called Assembly Tree





Node parallelism

For an individual block, in order:

Assemble contributions from children (sparse gather) Factor $m \times k$ matrix with threshold pivoting (partial dense LDL^T) Contribution given by Schur complement (dgemm)

Each task itself can be parallelized (some better than others!)



First challenge: Exploit both tree and node parallelism

Note: CUBLAS only supports multiple BLAS on same dimensions. \Rightarrow Have to write our own routines.

- ► For lots of small nodes, dominant cost is kernel setup!
- CPU populates a data structure of tasks
- Assigns an appropriate number of blocks to each task
- Launches a kernel on \sum blocks

Limited registers:

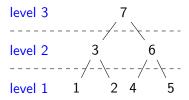
Costs several registers to do this (can't use constant cache)



Enforcing task ordering

Need to enforce assembly tree ordering

- Ideally would do so via global memory with single kernel
- Want to support Fermi, insufficient registers
- Use level based approach instead

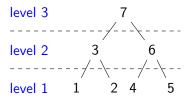




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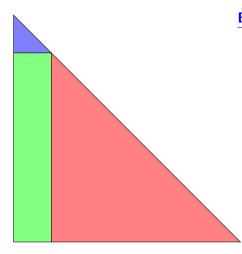
Outstanding Issues

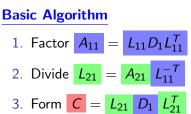
Load balance:

- Disparate node sizes
- Freedom of assignment



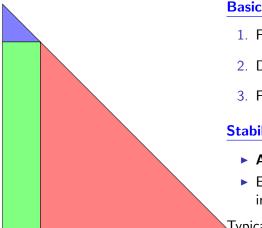
Factorization: basics







Factorization: basics



Basic Algorithm 1. Factor $A_{11} = L_{11}D_1L_{11}^T$

- 2. Divide $L_{21} = A_{21} L_{11}^{-T}$
- 3. Form $C = L_{21} D_1 L_{21}^T$

Stability

- ▶ All entries in $L_{21} < u^{-1}$
- Entries of D₁ calculated in stable fashion

Typically u = 0.01.



Factorization: parallel pivoting I

Traditional algorithm

- Work column by column
- Bring column up-to-date
- Find maximum element α in column of A_{21}
- ▶ Pivot test $\alpha/a_{11} < u^{-1}$. Accept/reject pivot



Factorization: parallel pivoting I

Traditional algorithm

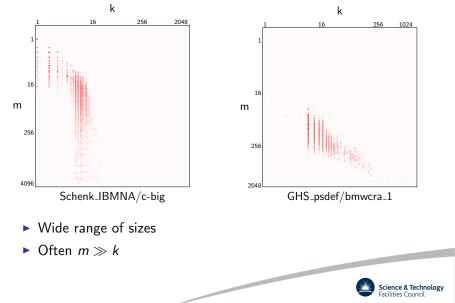
- Work column by column
- Bring column up-to-date
- Find maximum element α in column of A_{21}
- ▶ Pivot test $\alpha/a_{11} < u^{-1}$. Accept/reject pivot

Problems

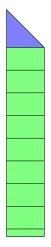
- Very stop-start (one column at a time)
- All-to-all communication for every column



Size distributions



Factorization: parallel pivoting II



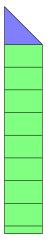
Solution

- Try-it-and-see pivoting (a posteriori pivoting)
 New algorithm
 - ► Work by blocks of *L*₂₁
 - Every block factorizes copy of A_{11}
 - Every block checks max $|l_{21}| < u^{-1}$
 - All-to-all communication when all blocks are done

Discard columns that have failed on *any* block
 We use a block size of 32 × 8.



Factorization: parallel pivoting III

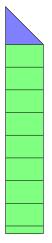


Implementation Issues

- Inefficient if lots of rejected pivots
- Still quite stop-start
- High register pressure (especially on Fermi)



Factorization: parallel pivoting III



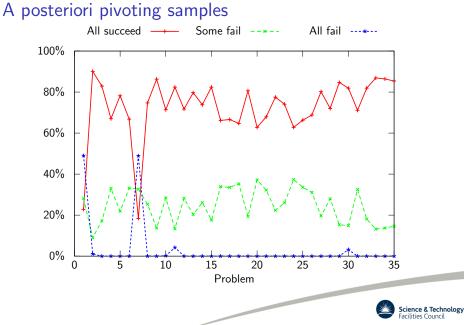
Implementation Issues

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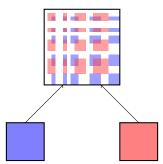
Future work

- Implement Subset pivoting or other CA technique as fall back
- Move to DAG-based implementation (Kepler only) (Significant performance improvement expected)





Assembly: Sparse gather/scatter



Can be framed as either sparse gather or sparse scatter.

- Need to enforce ordering: prefer sparse gather
- Launch one kernel per child (i.e. all first children, then all second, ...)



Auxiliary codes

Many auxiliary routines are required that are still CPU-based:

- Ordering (Nested Dissection)
- Analyse (Assorted Graph Algorithms)
- Scaling (MC64 or SpMv)
- ... but only run once for a sequence of problems

Auction-based scaling: alternative to MC64

For some problems, serial MC64 scaling takes > 75% of time

- ▶ 95% of the quality
- 10% of the time
- Parallelizable



Results

Test Problems

- ► 3× Optimization (IPM)
- ▶ 3× Finite Element
- ► 3× Other assorted



Times(s) and Speedup: Factor+Solve

Problem	CPU	GPU	Speedup
GHS_indef/c-71	2.76	0.64	4.3
GHS_indef/ncvxqp3	4.75	1.61	2.9
$Schenk_IBMNA/c-big$	11.81	2.35	5.0
DNVS/shipsec1	1.51	0.61	2.5
$GHS_psdef/bmwcra_1$	2.09	0.93	2.3
$DNVS/ship_003$	3.12	1.08	2.9
ND/nd6k	6.42	1.36	4.7
PARSEC/Si5H12	14.65	2.20	6.7
Andrianov/mip1	0.82	0.38	2.2

<u>CPU:</u> Westmere-EP

> 2× E5620
> 8 cores
> [76.8GFlops, 160W TDP]

GPU: Fermi

 C2050 GPU [515GFlops, 238 TDP]

Flops ratio about $7\times$



Times(s) and Speedup: Factor+Solve

Problem	CPU	GPU	Speedup
GHS_indef/c-71	1.67	0.43	3.9
GHS_indef/ncvxqp3	2.31	1.42	1.6
Schenk_IBMNA/c-big	6.63	1.49	4.4
DNVS/shipsec1	0.63	0.40	1.6
GHS_psdef/bmwcra_1	0.77	0.60	1.3
$DNVS/ship_003$	1.24	0.68	1.8
ND/nd6k	2.84	0.82	3.5
PARSEC/Si5H12	7.20	1.32	5.4
Andrianov/mip1	0.40	0.28	1.5

CPU: Sandybridge-EP

2×E5-2687W
 = 16 cores
 [397GFlops,
 300W TDP]

<u>GPU</u>: Kepler

 K20 GPU [1170Flops, 225 TDP]

Flops ratio about $3\times$

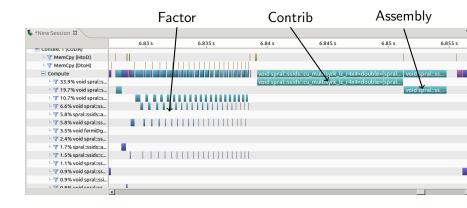


Factorization phase hot-spots

	c-72	c-big	shipsec1	Lin
Speedup	1.4	6.2	1.9	4.4
Contrib	19	780	1607	1568
Assembly	27	446	38	302
Factor	82	481	850	666
Waiting	143	525	405	352

Times are in ms. Waiting = time not in kernels.

Dense factor is poor





Conclusions and Future Work

Story so far

- New open source sparse direct solver in CUDA
 - http://www.numerical.rl.ac.uk/spral/
 - Report forthcoming
- Speedups over host of around 5 on large problems
- Needed to both:
 - Handle peculiarities of device
 - Use new algorithms for massive parallelism

Long-term

- DAG-based factor
- GPU-based scaling
- Auto-generation from stencil?





Thanks for listening! Questions?

A Supplementary slide

Some supplementary text.

(Note numbering of supplementary slides is outside that of normal slides.)

