Fast Binding Site Mapping using GPUs and CUDA

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Why Bother?

Problem: Combat the bird flu virus

Method: Inhibit its function by "gumming up" Neuraminidase, a surface protein, with an inhibitor

- Neuraminidase helps release progeny viruses from the cell.

Procedure*:

- Search protein surface for likely sites
- Find a molecule that binds there (and only there)

Binding site mapping:

- Very compute intensive: Usually run on clusters
- GPU based desktop alternative

*Landon, et al. Chem. Biol. Drug Des 2008 #From *New Scientist* <u>www.newscientist.com/channel/health/bird-flu</u>





Outline

- Overview of Binding Site Mapping
 - Rigid Docking
 - Energy Minimization
- Overview of NVIDIA GPUs / CUDA

- Rigid Docking on GPU
- Energy Minimization on GPU
- Results

Binding Site Mapping

Purpose: Identification of hot spots

Significance: Very effective for drug-discovery

Rationale:

- Hot spots are major contributors to the binding energy
- They bind a large variety of small molecules

Process: Docking small probes

- Rigid Docking
- Energy Minimization



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H₁C-CH

H₂N.

Mapping: Two Step Process

Rigid Docking of Probes into Protein

- Grid-based computation
- Exhaustive 6D search
- Find an approximate conformation



Collision

Good fit

Poor fit

- Local refinement Energy Minimization
 - Model the flexibility in the side-chains



FTMap*

- 16 small molecule probes
- Dock each probes into the protein
 - 500 rotations 10⁶ translations per rotation
 - 30 minutes on a single CPU
- Energy minimize 2000 conformations per protein-probe complex
 - Up to 30 seconds per conformation
 - 16 hours per probe!

* Brenke R, Kozakov D, Chuang G-Y, Beglov D, Mattos C, and Vajda S. Fragment-based identification of druggable "hot spots" of proteins using Fourier domain correlation, Bioinformatics.



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NVIDIA GPU Architecture



Memory Hierarchy



CUDA Programming Model



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Rigid Docking: Procedure





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* Janin, J., Henrick, K., Moult, J., Eyck, L., Sternberg, M., Vajda, S., Vakser, I., and Wodak, S. CAPRI: A critical assessment of predicted interactions. Proteins, 52 (2003), 2-9

Rigid Docking on GPUs - Correlation

- Direct Correlation (better than FFT!)
 - For small grid sizes
 - Replaces FFT, voxel-voxel summation, IFFT
- Each multiprocessor accesses both the grids
 - Protein grid on the global memory
 - Probe grid duplicated on shared memories
- Multiple correlations together
 - Voxel represents multiple energy functions







Direct Correlation on GPUs

Shared memory limits the probe size

- With 8 correlations 8 cubed
- Probe grids are typically 4 cubed

Multiple rotations together

- 8 rotations
- Effectively loop-unrolling
- Multiple computations per global memory fetch
- 2.7x additional performance improvement



Direct Correlation on GPUs

Distribution of work among threads / blocks

- Scheme 1: Entire 2D-plane to a thread block
- Scheme 2: Part of the 2D-plane to a thread block
- Both yield similar results



Scoring and Filtering on GPUs

Score Computation

- Divide work among different threads
- Sync and Serialize to find the best-ofthe-best
- Only one multiprocessor utilized
- Flagging for exclusion



- Serial code Exclusion bit-vector
- GPU Solution 1 Exclusion index array
- GPU Solution 2 Exclusion bit-vector on GPU global memory



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Energy Minimization

Minimizing energy between two molecules

- Iterative process
- Optimization moves
- Used to model flexible side chains



N-body problem with a cut-off



Looks like MD, but it's not

- Performed on a local region
 - Many fewer atoms, typically few thousand
- Much smaller atom neighborhoods
 - Very small cut-off radius
- Move to the next position
 - Coordinate adjustments No motion / velocity updates
- No cell-lists / efficient filtering
 - Refinement step; close to dest. small motions
- Neighbor lists are very sparse, with nonuniform distribution

Different geometry

Different computations

Energy Minimization step of FTMap



FTMap Electrostatics Model

 $E^{total} = E^{vdw} + E^{elec} + E^{bond} + E^{angle} + E^{torsion}$

Analytic Continuum Electrostatics (ACE)

Atom Self Energy: Electrostatic energy due to the charge itself

$$E_{i}^{self} = \frac{q_{i}^{2}}{2\varepsilon_{s}R_{i}} + \sum_{k \neq i} E_{ik}^{self}$$

$$E_{ik}^{self} = \frac{\tau q_{i}^{2}}{\omega_{ik}} e^{-\left(\frac{r_{ik}^{2}}{\sigma_{k}^{2}}\right)} + \frac{\tau q_{i}^{2} \tilde{V}_{k}}{8\pi} \left(\frac{r_{ik}^{3}}{r_{ik}^{4} + \mu_{ik}^{4}}\right)^{4}$$
Pairwise interaction – Generalized Born eqn.: Electrostatic energy due to the presence of other charges
$$E_{ij}^{int} = 332 \sum_{j \neq i} \frac{q_{i}q_{j}}{r_{ij}} - 166 \tau \sum_{j \neq i} \frac{q_{i}q_{j}}{\sqrt{r_{ij}^{2} + \alpha_{i}\alpha_{j}e^{-\left(\frac{r_{ij}^{2}}{\sigma_{k}^{2}}\right)}}$$
Born Radii – depends on E^{self}

FTMap Data Structure - Neighbor Lists



- Random updates for second atoms
 - Can't distribute the atoms list across multiprocessors
- Write conflicts

- Second atom might appear in multiple lists
- Not suitable for parallel implementations
- Memory conflicts during
 updates
 - Serialization during accumulation

Energy Minimization on GPU – Challenges

- Little to no data reuse (within and across iterations)
- Small computation per iteration
- Inherent to the algorithm

 $q_i q$

 Multiple accumulations – self energy of each atom must

 be computed

 Born Radii – depends on Eself

 $E_{ij}^{\text{int}} = 332 \sum_{i \neq i} \frac{q_i q_j}{r_{ij}} - 166 \tau \sum_{i \neq i} \frac{1}{r_{ij}}$



Large data transfer time Architecture related Random updates – write conflicts

Accumulation requires serialization



 r_{ij}^{2} 4 $\alpha_{i}\alpha_{j}$

Self Energy

Neighbor Lists on GPUs

- Separate energy arrays for first and second atoms
 - Allows parallel updates by multiple threads
- Multiple copies of arrays for second atom
 - One in each thread block
 - Parallel updates no conflicts
- First arrays reduced to single values
 - Within the shared memory
- Second atoms arrays merged by moving to global memory
 - Large copy and accumulation time
 - Slow





Modified Data Structure - Pairs List

- 2D neighbor 📄 1D pair list
 - Each pair contains atom indices and types





- Distribute pairs across multiple threads
 - More uniform work distribution
- Compute partial energies in parallel
- Perform accumulations serially

	Atom	index	Atom Type	
Pair #	Atom 1	Atom 2	Atom 1	Atom 2
0	0	2	T5	T1
1	0	1	T5	Т3
2	0	11	T5	T2
3	0	14	T5	T4
4	1	2	T3	T1
5	1	5	T3	T3
6	2	4	T1	Т8
7	2	15	T1	T7
8	2	12	T1	T4
9	3	4	T5	Т8

Pairs List on GPUs – Initial Attempts

Pairs distributed on different threads

- Energy of an atom computed in different multiprocessors
- Serialization during accumulation

Accumulation on GPU

From global memory: Slow

Accumulation on host

- Fast, but requires energy arrays to be transferred every iteration
- 2x-3x speedup

	Atom index		Self er	nergy
Pair id	Atom 1	Atom 2	Atom 1	Atom 2
0	0	2		
1	0	1		
2	0	11		
3	0	14		
4	1	2		
5	1	5		
6	2	4		
7	2	15		
8	2	12		
9	3	4		

Pairs List on GPUs – Improved Scheme

Pairs list with two changes

- Conflicts due to random occurrence of second atoms
 - Split forward and reverse pair list
 - Process only the first atom of each list
 - Indeterminate distribution requires serialization during accumulation
 - Statically map the pairs onto GPU threads
 - New data structure: Assignment tables

	Atom	index	Self e	nergy
Pair id	Atom 1	Atom 2	Atom 1	Atom 2
0		2		
1	0	1		
2	0	11		
3		14		
4	Ť	2		
5	1	5		
6	2	4		
7	2	15		
8	2	12		
9	3	4		

Split Pairs List

- Forward list: Same as before
- Reverse list: Treat every second atom as a first atom
- Process only the first atoms of each list
- Adds determinism => Better distribution

Forward List

	Atom	n index	Self er	nergy
Pair id	Atom 1	Atom 2	Atom 1	Atom 2
0	0	(2)		1 1
1	0			
2	0	11		
3	0	14		
4	1	(2)		Y
5	1			Λ
6	2	4		
7	2	15		
8	2	/ 12		
9	3	4		

Reverse List



Static Mapping - Assignment Table

Pairs can be grouped by first atom

- Groups mapped to different thread blocks
 - Look for next block with enough threads
- One pair per thread (multiple if N_{pair} > N_{threads})
 - Reverse Assignment table for the second atoms



Computing and Accumulating Energies

Threads store partial energies in shared memory

Address = Local Thread Id



- Master thread performs accumulation
 W locations starting from its thread id
 - ' 'N' locations starting from its thread id
- Multiple parallel accumulations per thread block (from shared memory)



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Results - Speedups

Speedups for Rigid Docking Step

Computation	Serial Runtime (ms)	GPU Runtime	Speedup	
(Per Rotation)		(ms)	vs. 1 core	vs. 4 cores*
Rotation + Grid Assignment	80	80	1x	
Correlations	3600	13.5	267x	70x
Accum. Of Desolvation Terms	180	1	180x	
Scoring and Filtering	200	30	6.67x	
Total time per rotation	4060	125.5	32.6x	11x

Results - Speedups

Speedups for Energy Minimization Step

	Computation	Serial Runtime (ms)	GPU Runtime* (ms)	Speedup
2260 atoms 9780 atom-pairs	Self Energy	6.15	0.23	26.7x
	Pairwise Interaction	2.75	0.10	17x
	van der Waals	0.5	0.19	
	Force Updates	0.95	0.14	6.7x
	Optimization move	0.005	0.005	1x

* Overall Speedup on EM computations :

18.5x

* Overall FTMap speedup (including overhead): 15x

* GPU runtimes include data transfer time

Results – Precision Analysis

- Single vs Double Precision
 - RMSD error on force values for first iteration: 10⁻⁶
 - Convergence in 50 iterations (as opposed to 600)
 - Error on final energy and force values
 - Energy : 10⁻³
 - Forces : 10⁻⁵
 - Error on atom coordinates after minimization
 - 0.5 Å

Exact match for double precision

- Atom coordinates within 10⁻⁵ Å
- More complex mapping on GPU Similar speedup numbers

Conclusion

GPUs can deliver high performance

- Even for double precision computations
- To obtain good performance:
 - Alternate algorithms are often needed
 - Restructuring of data-structures is crucial
 - Efficient use of memory hierarchy is essential
- Getting it right on the GPU is easy ...
 - ... getting good performance is not so much!

