ICCS School

Advanced GPU Programming for Science

Lecture 5: Input Binning for Regular Data Sets

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Objective

- To understand how data scalability problems in gather parallel execution motivate input binning
- To learn basic input binning techniques
- To understand common tradeoffs in input binning



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However

- Input tends to be much less regular than output
 - It may be difficult for each thread to efficiently locate all inputs relevant to its output
 - Or, to efficiently exclude all inputs irrelevant to its output
- In a naïve arrangement, all threads may have to process all inputs to decide if each input is relevant to its output
 - This makes execution time scale poorly with data set size – data scalability problem
 - Especially a problem for many-cores designed to process large data sets

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DCS Algorithm for Electrostatic Potentials Revisited



- At each grid point, sum the electrostatic potential from all atoms
 - All threads read all inputs
- Highly data-parallel
 - But has quadratic complexity
 - Number of grid points × number of atoms
 - Both proportional to volume
 - Poor data scalability in terms of volume

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Algorithm for Electrostatic Potentials With a Cutoff



- Ignore atoms beyond a cutoff distance, r_c
 - Typically 8Å-12Å
 - Long-range potential may be computed separately
 - Number of atoms within cutoff distance is roughly constant (uniform atom density)
 - 200 to 700 atoms within
 8Å–12Å cutoff sphere for
 typical biomolecular
 structures

Cut-off Summation

With fixed partial charge q_i, electrostatic potential
 V at position r over all N atoms:

$$V(\vec{r}; \vec{r}_1, \vec{r}_2, \dots, \vec{r}_N) = \sum_{i=1}^N \frac{q_i}{4\pi\epsilon_0 |\vec{r} - \vec{r}_i|} s(|\vec{r} - \vec{r}_i|)$$

$$s(r) = \begin{cases} (1 - r^2 / r_c^2)^2, & \text{if } r < r_c, \\ 0, & \text{otherwise} \end{cases}$$

Direct Summation is accurate but has poor data scalability 1000 CPU-SSE3 LargeBin 100 SmallBin Execution time (seconds) SmallBin-Overlap DirectSum 10 0.1 Same scalability among all cutoff implementations 0.01 0.00164000 1000 8000 1e+06 8e+06 Volume of potential map (Angstrom³)

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Implementation Challenge

- For each tile of grid points, we need to identify the set of atoms that need to be examined
 - One could naively examine all atoms and only use the ones whose distance is within the given range
 - But this examination still takes time, and brings the time complexity right back to
 - number of atoms * number of grid points
 - Each thread needs to avoid examining the atoms outside the range of its grid point(s)

Binning

- A process that groups data to form a chunk called *bin*
- Each bin collectively represents a property for data in the bin
- Helps problem solving due to data coarsening
- Uniform bin arrays, Variable bins, KD Trees, ...





Binning for Cut-Off Potential

- Divide the simulation volume with nonoverlapping uniform cubes
- Every atom in the simulation volume falls into a cube based on its spatial location
 - Bins represent location property of atoms
- After binning, each cube has a unique index in the simulation space for easy parallel access



(a) Simulation volume

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(b) Simulation volume with eight bins

Spatial Sorting Using Binning



- Presort atoms into bins by location in space
- Each bin holds several atoms
- Cutoff potential only uses bins within r_c
 - Yields a linear complexity cutoff potential algorithm
 - Some atoms will be examined by a thread but not used

Terminology

- Bin Size
 - The size of the bin cubes that partition the simulation volume
 - The bigger the bin size, the more the atoms that will fall into each bin
- Bin Capacity
 - The number of atoms that can be accommodated by each bin in the array implementation

Bin Design

- Uniform sized/capacity bins allow array implementation
 And the relative offset list approach
- Bin capacity should be big enough to contain most of the atoms that fall into a bin (> 95%)
 - Cut-off will screen away atoms that weren't processed
 - Performance penalty if too many are screened away



Bin Capacity Considerations

- Capacity of atom bins needs to be balanced
 - Too large many dummy atoms in bins
 - Too small some atoms will not fit into bins
 - Target bin capacity to cover more than 95% or atoms
- Place all atoms that do not fit into bins into an overflow bin
 - Use a CPU sequential algorithm to calculate their contributions to the energy grid lattice points.
 - CPU and GPU can do potential calculations in parallel

Small-bin Kernels – Work Efficiency

- Thread block examines atom bins up to the cutoff distance
 - Use a sphere of bins
 - All threads in a block scan the same bins and atoms
 - No hardware penalty for multiple simultaneous reads of the same address
 - Simplifies fetching of data
 - The sphere has to be big enough to cover all grid points at corners
 - There will be a small level of divergence
 - Not all grid points processed by a thread block relate to all atoms in a bin the same way
 - (A within cut-off distance of N but outside cut-off of M)

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The Neighborhood is a volume

- Calculating and specifying all bin indexes of the sphere can be quite complex
 - Rough approximations reduce efficiency



Neighborhood Offset List (Pre-calculated)

- A list of relative offsets enumerating the bins that are located within the cutoff distance for a given location in the simulation volume
- Detection of surrounding atoms becomes realistic for output grid points
 - By visiting bins in the neighborhood offset list and iterating atoms they contain



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Pseudo Code of an Implementation

// 1. binning
for each atom in the simulation volume,
 index_of_bin := atom.addr / BIN_SIZE
 bin[index_of_bin] += atom

// 2. generate the neighborhood offset list
for each c from -cutoff to cutoff,
 if distance(0, c) < cutoff,
 nlist += c</pre>

```
CPU
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// 3. do the computation
for each point in the output grid, GPU
index_of_bin := point.addr / BIN_SIZE
for each offset in nlist,
for each atom in bin[index_of_bin + offset],
point.potential += atom.charge / (distance from point to atom)

Performance

- O(MN') where M and N' are the number of output grid points and atoms in the neighborhood offset list, respectively
 - In general, N' is small compared to the number of all atoms
- Works well if the distribution of atoms is uniform

Details on Small Bin Design

- For 0.5Å lattice spacing, a (4Å)³ cube of the potential map is computed by each thread block
 - 8×8×8 potential map points
 - 128 threads per block (4 points/thread)
 - Using the same cube bin size 34% of examined atoms are within cutoff distance



Tiling Atom Data

- Shared memory used to reduce Global Memory bandwidth consumption
 - Threads in a thread block collectively load one bin at a time into shared memory
 - Once loaded, threads scan atoms in shared memory
 - Reuse: Loaded bins used 128 times



Coalesced Global Memory Access to Atom Data

- Full global memory bandwidth only with 64byte, 64-byte-aligned memory accesses
 - Each bin is exactly 128 bytes
 - Bins stored in a 3D array
 - 32 threads in each block load one bin into shared memory, then processed by all threads in the block
- 128 bytes = 8 atoms (x,y,z,q)
 - Nearly uniform density of atoms in typical systems
 - 1 atom per 10 Å³
 - Bins hold atoms from $(4\text{\AA})^3$ of space (example)
 - Number of atoms in a bin varies
 - For water test systems, 5.35 atoms in a bin on average
 - Some bins overfull

Handling Overfull Bins

- In typical use, 2.6% of atoms exceed bin capacity
- Spatial sorting puts these into a list of extra atoms
- Extra atoms processed by the CPU
 - Computed with CPU-optimized algorithm
 - Takes about 66% as long as GPU computation
 - Overlapping GPU and CPU computation yields in additional speedup
 - CPU performs final integration of grid data

Cutoff Summation Runtime



QUESTIONS?

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