

Porting LAMMPS to GPUs

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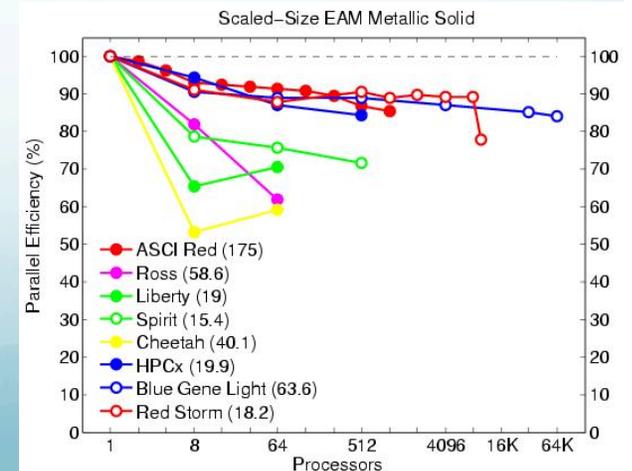
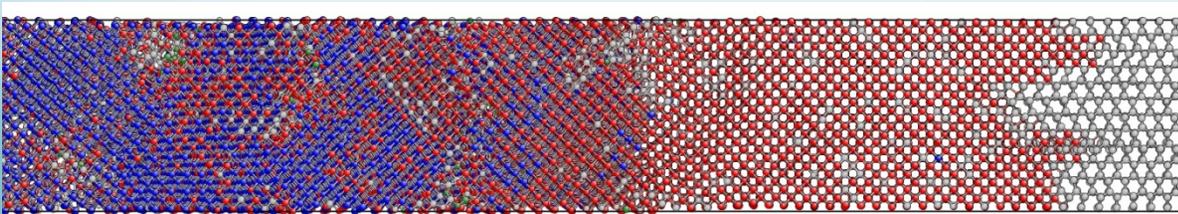
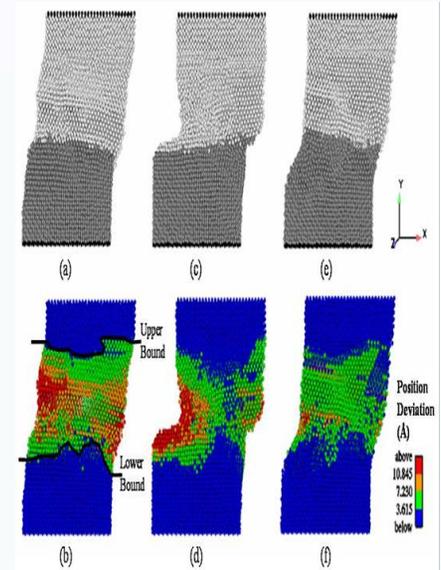
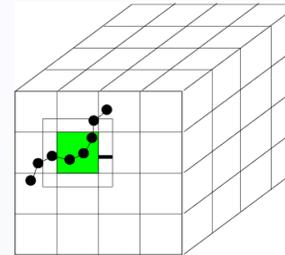


LAMMPS

(Large-scale Atomic/Molecular Massively Parallel Simulator)

<http://lammps.sandia.gov>

- **Classical MD code.**
 - Particles interact with neighbors within some cutoff
 - Gradient of the potential energy surface gives forces
 - Simulate by integrating equations of motion at timestep
- Open source, highly portable C++.
- Freely available for download under GPL.
- Easy to download, install, and run.
- Well documented.
- Easy to modify or extend with new features and functionality.
- Active user's e-mail list with over 650 subscribers.
- Since Sept. 2004: over 50k downloads, grown from 53 to 175 kloc.
- **Spatial-decomposition of simulation domain for parallelism.**
- Energy minimization via conjugate-gradient relaxation.
- Radiation damage and two temperature model (TTM) simulations.
- Atomistic, mesoscale, and coarse-grain simulations.
- **Variety of potentials (including many-body and coarse-grain).**
- Variety of boundary conditions, constraints, etc.

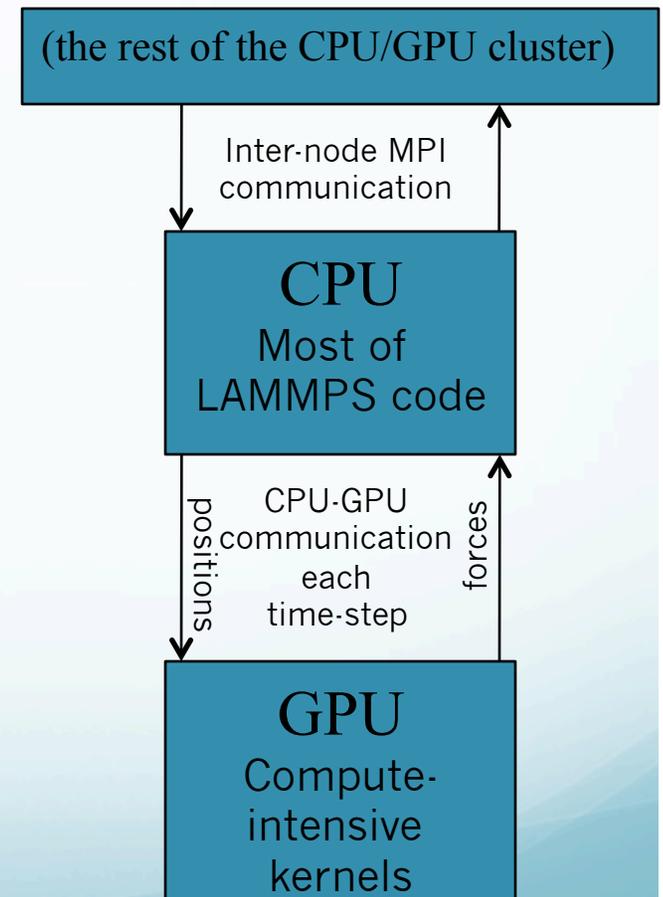


Extending LAMMPS via Styles

- In hindsight, this is best feature of LAMMPS
 - 80% of code is “extensions” via styles
 - only 35K of 175K lines is core of LAMMPS
- Easy for us and others to add new features via 14 “styles”
 - new particle types = atom style
 - new force fields = pair style, bond style, angle style, dihedral style, improper style
 - new long range = kspace style
 - new minimizer = min style
 - new geometric region = region style
 - new output = dump style
 - new integrator = integrate style
 - new computations = compute style (global, per-atom, local)
 - new fix = fix style = BC, constraint, time integration, ...
 - new input command = command style = read_data, velocity, run, ...
- Enabled by C++
 - virtual parent class for all styles, e.g. pair potentials
 - defines interface the feature must provide
 - compute(), init(), coeff(), restart(), etc

GPU-LAMMPS strategy

- Enable LAMMPS to run efficiently on future CPU-based clusters that have GPU accelerators.
- Not aiming for running on a single GPU.
- Not aiming to rewrite all of LAMMPS in CUDA.
- Rewrite the most compute-intensive LAMMPS kernels in CUDA.
- At each time-step, ship particle positions from CPU to GPU, compute forces on the GPU, and then ship forces back to the CPU.
- Domain decomposition across processes; force decomposition on GPU

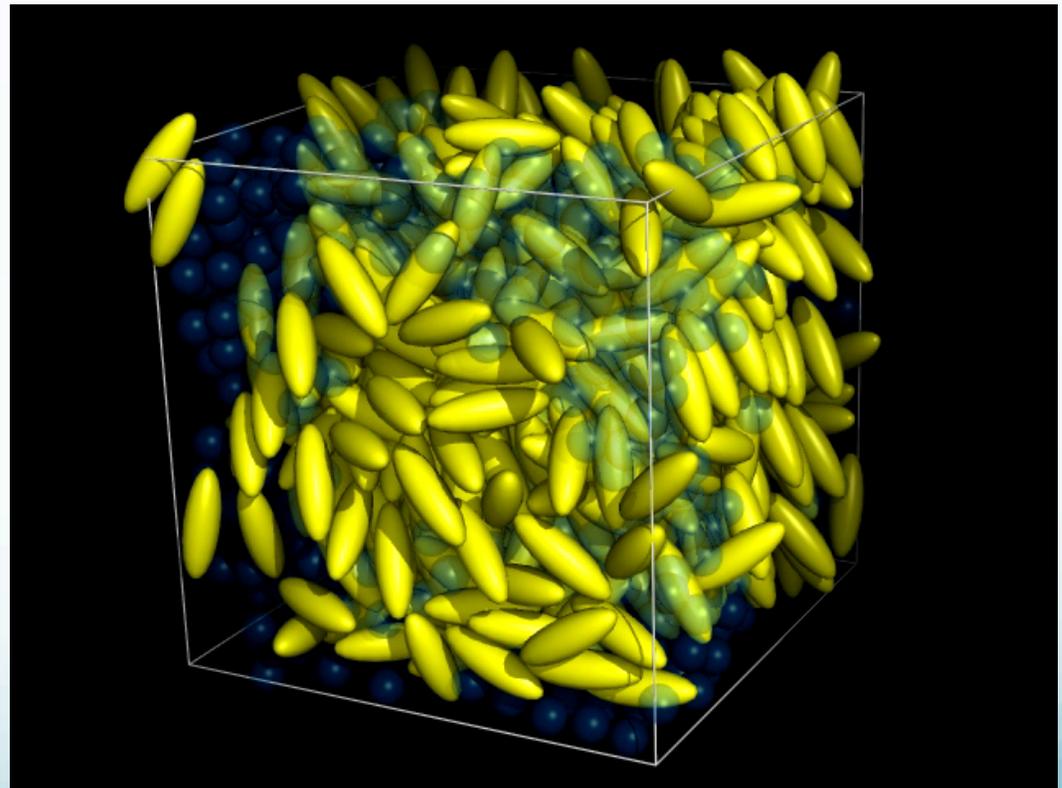


Example

Aspherical Particle Simulation

Why Aspherical Particles?

- Particles in nature and manufacturing often have highly irregular shapes
- Liquid crystal simulations
- Coarse Graining
- Majority of computational particle mechanics (CPM) simulators treat only spherical particles
- Need a parallel and scalable implementation to attack realistic problems (LAMMPS)



Gay-Berne Potential

- Single-site potential for biaxial ellipsoids
- h is the distance of closest approach
- \mathbf{S} is the shape matrix
- The \mathbf{E} matrix characterizes the relative well depths of side-to-side, face-to-face, and end-to-end interactions
- ~30 times the cost of an LJ interaction

$$U = U_r(\mathbf{A}_1, \mathbf{A}_2, \mathbf{r}_{12}) \eta_{12}(\mathbf{A}_1, \mathbf{A}_2) \chi_{12}(\mathbf{A}_1, \mathbf{A}_2, \hat{\mathbf{r}}_{12})$$

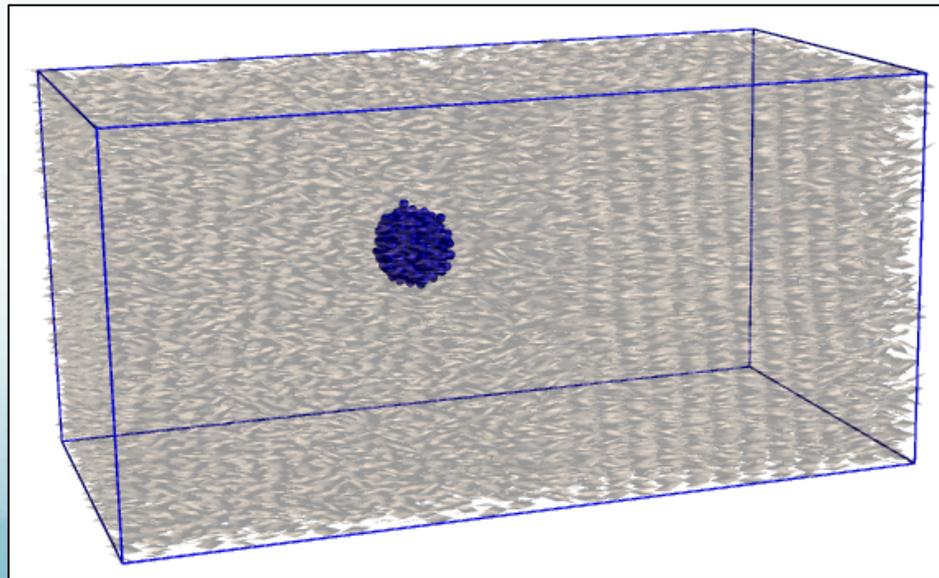
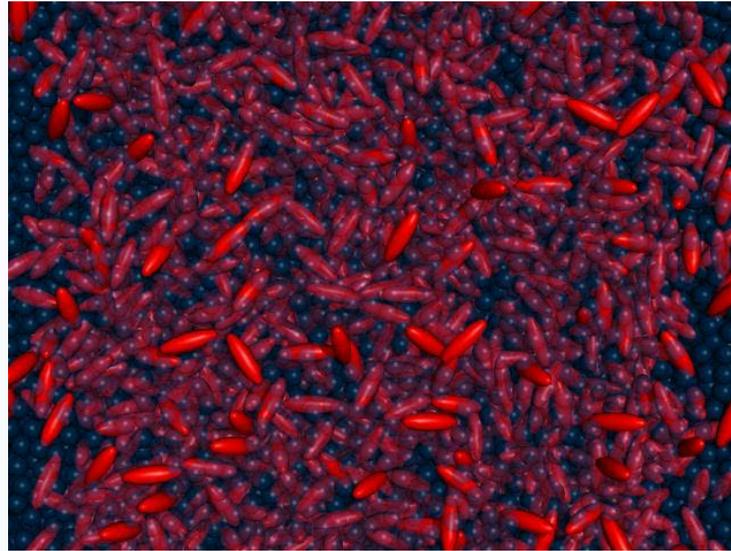
$$U_r = 4\epsilon \left[\left(\frac{\sigma}{h_{12} + \gamma\sigma} \right)^{12} - \left(\frac{\sigma}{h_{12} + \gamma\sigma} \right)^6 \right]$$

$$\eta_{12} = \left[\frac{2s_1 s_2}{\det[\mathbf{A}_1^T \mathbf{S}_1^2 \mathbf{A}_1 + \mathbf{A}_2^T \mathbf{S}_2^2 \mathbf{A}_2]} \right]^{v/2}$$

$$s = [a_i b_i + c_i c_i] [a_i b_i]^{1/2}$$

$$\chi_{12} = \left[2\hat{\mathbf{r}}_{12}^T (\mathbf{A}_1^T \mathbf{E}_1 \mathbf{A}_1 + \mathbf{A}_2^T \mathbf{E}_2 \mathbf{A}_2)^{-1} \hat{\mathbf{r}}_{12} \right]^\mu$$

Liquid Crystal Simulations



Accelerated Gay-Berne in LAMMPS

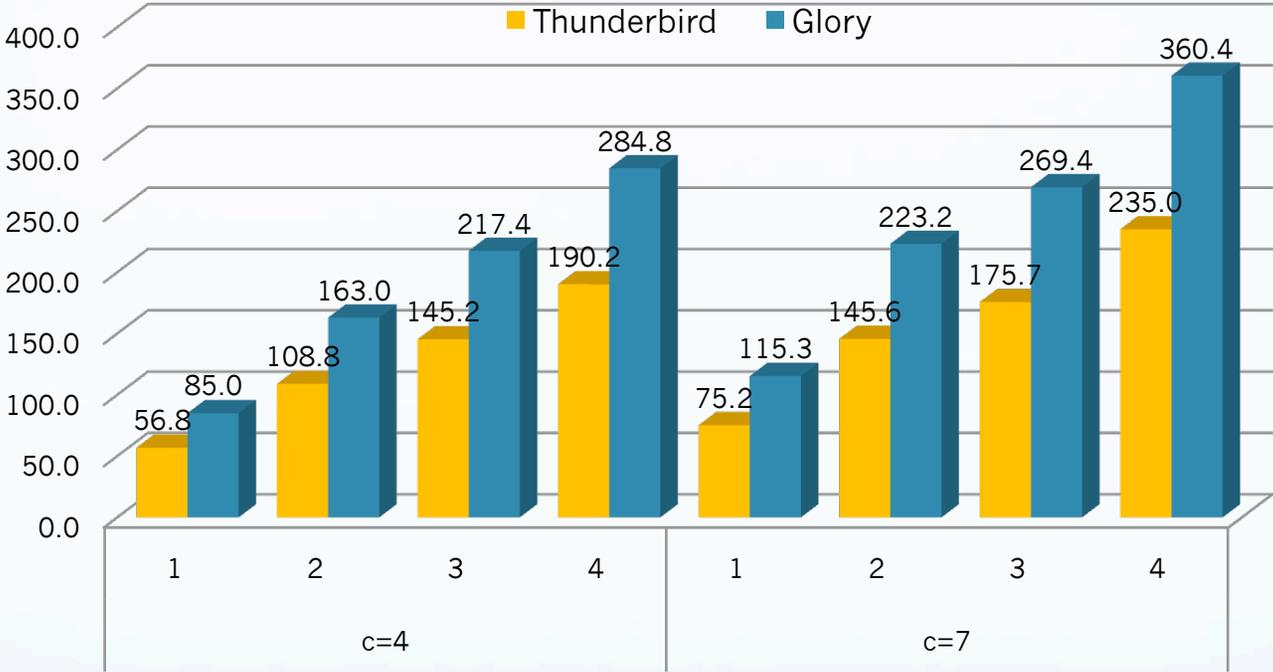
- Good candidate for GPU acceleration
 - *Very* expensive force calculation
- Available in the GPU package (make yes-asphe
yes-gpu)
 - Can run on multiple GPUs on a single node or in a cluster
 - Multiple precision options: Single, Single/Double, and Double
 - Can simulate millions of particles per GPU

Algorithm

- 1. Copy atom positions and quaternions to device
- 2. Did reneighbor occur ? copy neighbor list to device
- 3. Call neighbor_pack kernel
 - 1 Atom per GPU Core
 - Perform cutoff check for all neighbors and store for coalesced access
 - *This limits thread divergence for the relatively expensive force computation*
- 4. Call force computation kernel
 - 1 Atom per GPU Core
 - Use full neighbor lists (double the amount of computations versus the CPU)
 - *No collisions with this approach*
 - Compute force, torque, energies, and virial terms
- 5. Copy forces, torques, energies, and virial terms to host

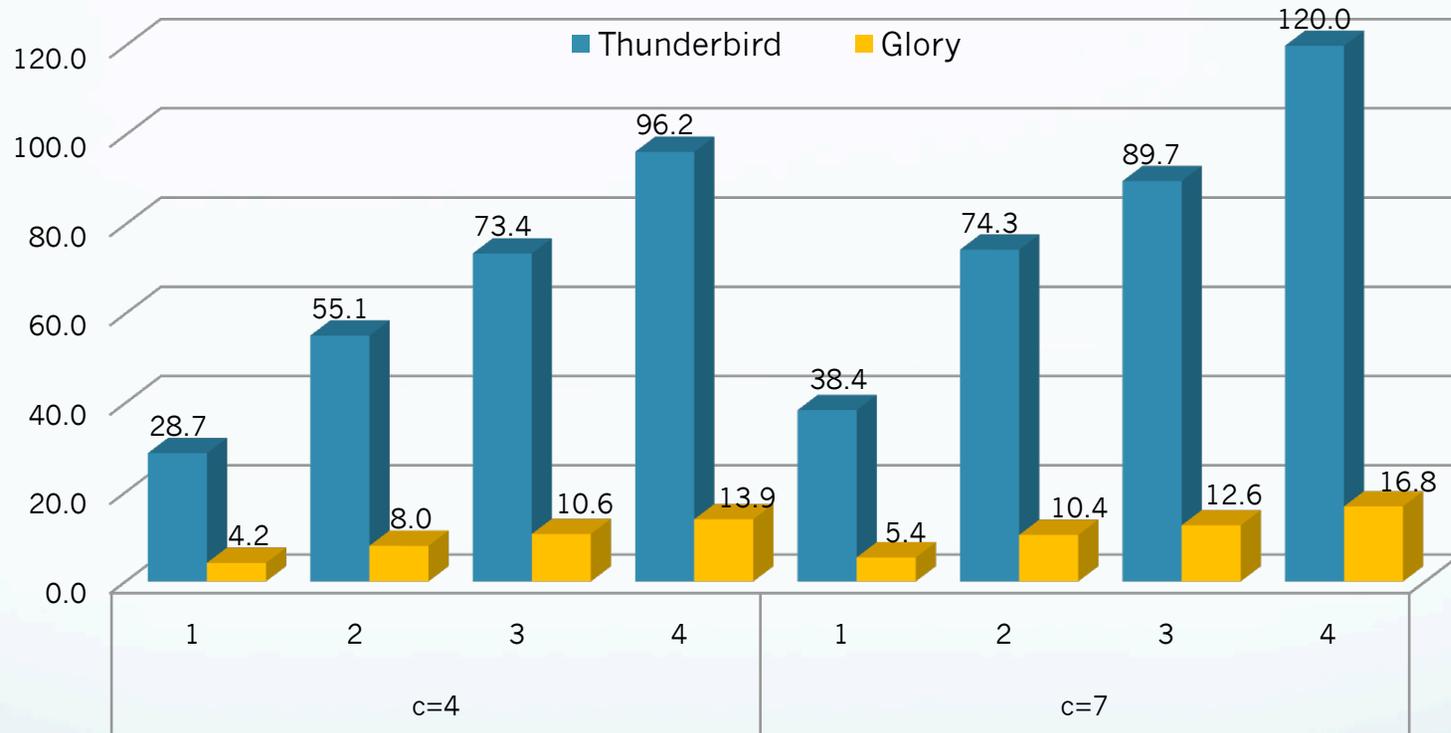
GPGPU Times Speedup vs 1 Core

(c=cutoff, 32768 particles)



GPGPU: 1, 2, 3, or 4 NVIDIA, 240 core, 1.3 GHz Tesla C1060 GPU(s)
Thunderbird: 1 core of Dual 3.6 GHz Intel EM64T processors
Glory: 1 core of Quad Socket/Quad Core 2.2 GHz AMD

GPGPU Times Speedup vs 1 Node (c=cutoff, 32768 particles)



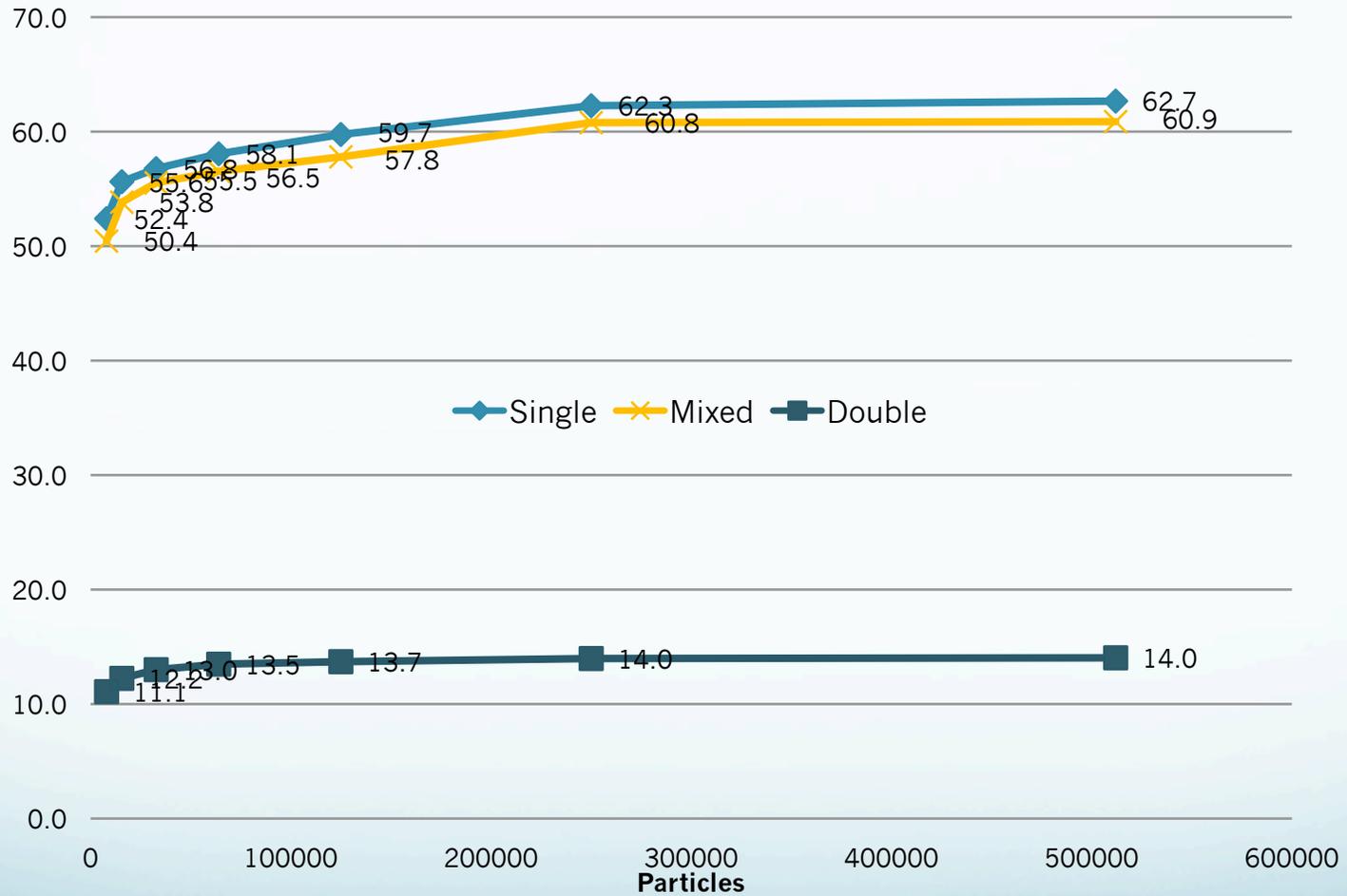
GPGPU: 1, 2, 3, or NVIDIA, 240 core, 1.3 GHz Tesla C1060 GPU(s)

Thunderbird: 2 procs, Dual 3.6 GHz Intel EM64T processors

Glory: 16 procs, Quad Socket/Quad Core 2.2 GHz AMD

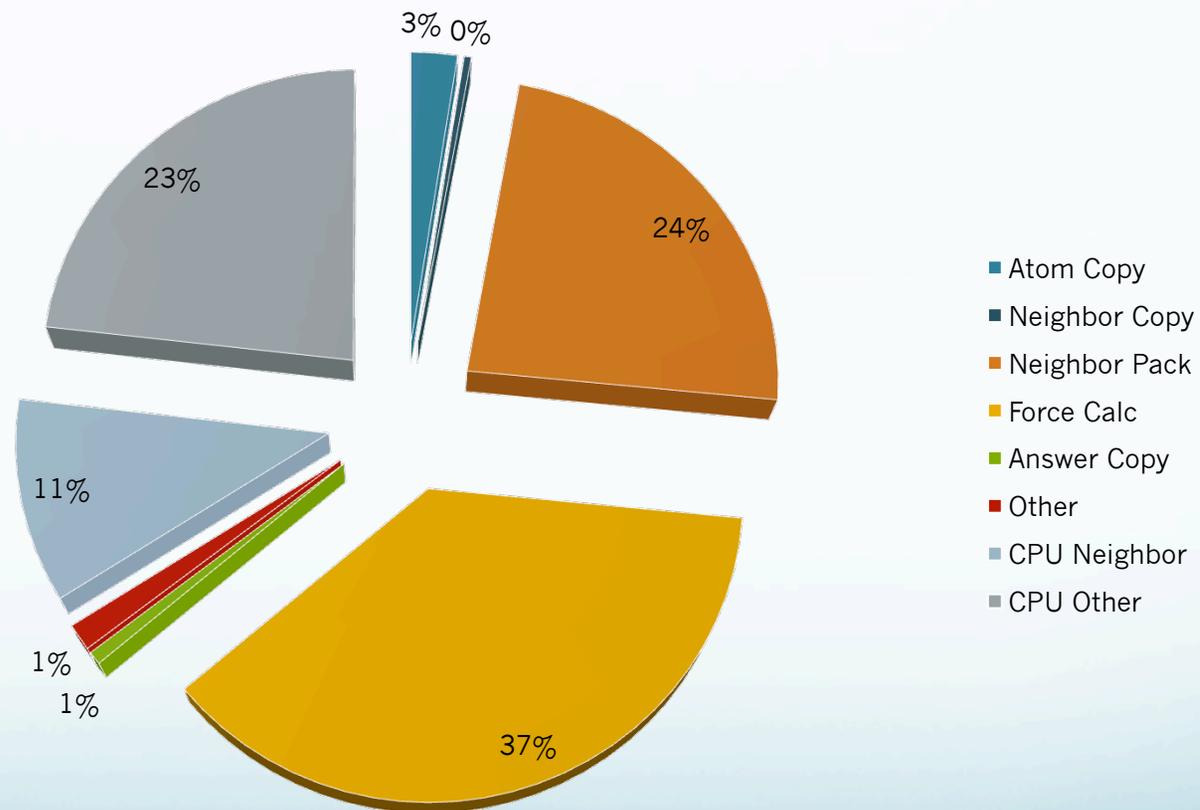
Times Speedup vs 1 Core

(c=4, 1 Tesla C1060, 3.6 GHz Intel EM64T processor)

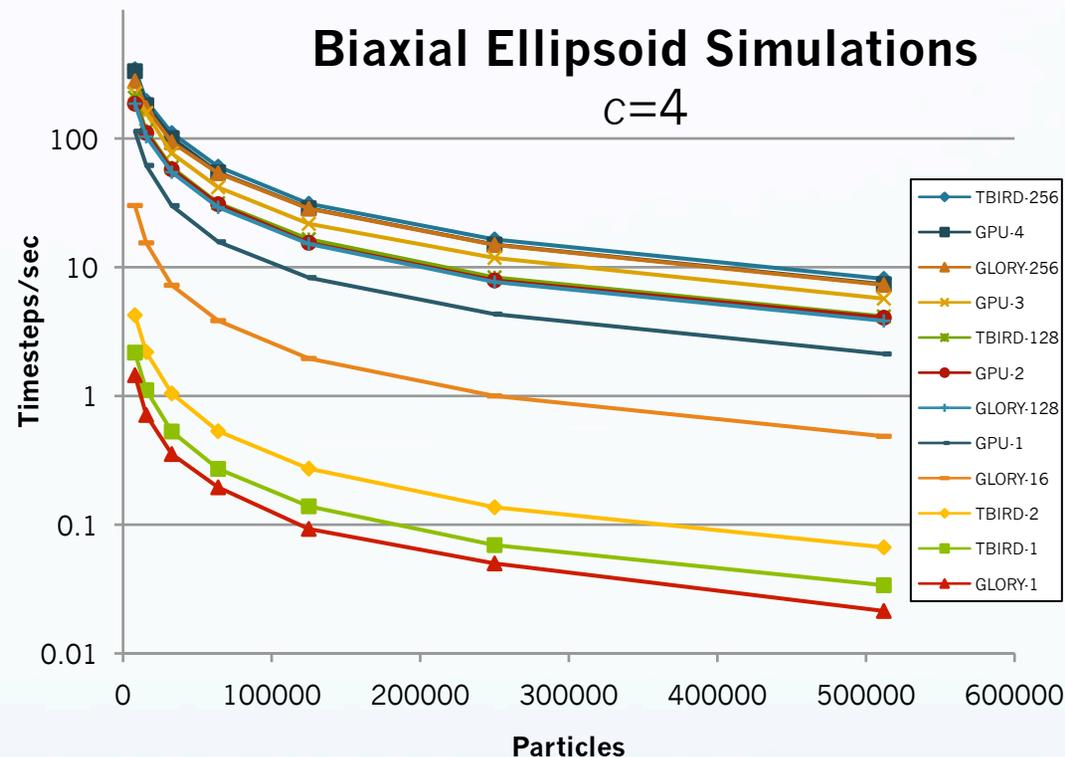


Simulation Time Breakdown

32K Particles, Cutoff=4, 1 Tesla C1060



HPC Comparison



- A single 4-GPU accelerated node can run a simulation in the same amount of time as a 256-core simulation on Thunderbird or Glory.
- The power requirements for the GPU accelerated run were <1.2 kW versus 11.2 kW on Glory or 44.8 kW on Thunderbird

Coding Issues

- Difficult to keep force computation in registers
 - Had to manually scope variables to fit single precision in registers
 - Double precision goes to global memory
- Had to manually unroll Gaussian elimination loop
 - Compiler could not figure out array pointer arithmetic
- Complicated memory management can lead to separate implementations
 - e.g. what if a given simulation has atom type constants that do not fit in shared memory?
 - Many GPU implementations are “benchmark codes” meant for publication, not real use

Alternative Algorithms

- Forces divided evenly among GPU cores (as opposed to per atom)
 - Need atomic operations to avoid collisions
 - No floating point atomic operations on current hardware
 - Slower for large simulations
 - *>20x speedup for a 128 particle simulation with Gay-Berne (<1 particle per core)*
- Neighbor list computation on the GPU
 - For Lennard-Jones, the simulation time is halved using a GPU cell list implementation
- Concurrent CPU execution
 - Multithreaded force decomposition (OpenMP)
 - Domain decomposition (separate MPI process for GPU and CPU computations)
 - Multiple threads/processes utilizing same GPU
 - For Gay-Berne, the upper-bound for concurrent execution performance gains is small
 - Overhead (full neighbor lists, thread creation, domain sizes)
 - For some potentials, concurrent execution may be needed in order to achieve good speedups

Future Work

- Currently available in the main LAMMPS distribution
 - Lennard-Jones and Gay-Berne
- Adding more potentials
 - 3-body, MEAM, etc.
- Long range electrostatics

Porting LAMMPS to GPUs

- Contact Paul Crozier (pscrozi@sandia.gov)
- Still largely a research effort

Marc Adams (Nvidia)
Pratul Agarwal (ORNL)
Sarah Anderson (Cray)
Mike Brown (Sandia)
Paul Crozier (Sandia)
Massimiliano Fatica (Nvidia)
Scott Hampton (ORNL)
Ricky Kendall (ORNL)
Hyesoon Kim (Ga Tech)
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Doug Kothe (ORNL)
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Arnold Tharrington (ORNL)
John Turner (ORNL)
Peng Wang (Nvidia)
Lars Winterfeld (UTI Germany)
Andrew Zonenberg (RPI)

OpenCL, CUDA-Driver, CUDA-Runtime?

- OpenCL offers a general API that is supported by many vendors and allows the potential to run kernels efficiently on the CPU in addition to coprocessor devices.
- CUDA Driver is a more mature GPGPU programming API with stable compilers, freedom in the choice of host compilers, and can potentially generate the most efficient code for Nvidia devices.
- CUDA Runtime offers a more succinct API and support for GPU code integrated with host code.
- **Geryon – Software library that allows a single code to compile using any of the 3 APIs. Change namespace to change API.**

<http://www.cs.sandia.gov/~wmbrown/geryon>

Questions