# N-Body Simulation using CUDA

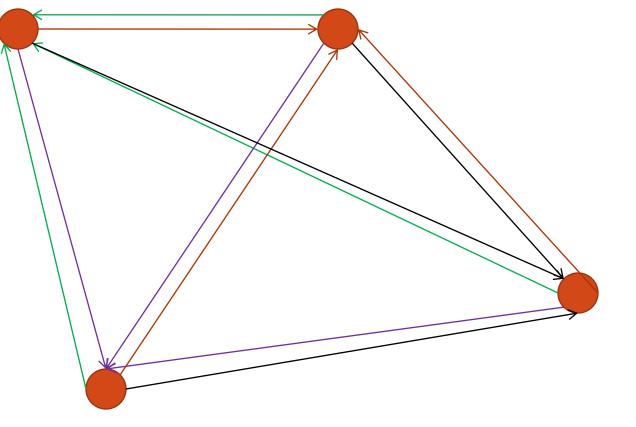
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## Project plan

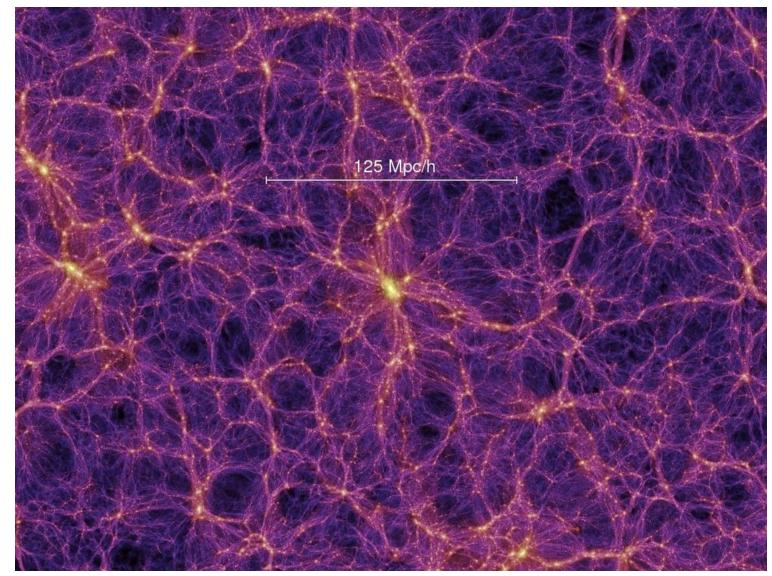
- Develop a program to simulate gravitational forces between *n* bodies in space
- Exploit the massively parallel architecture provided by GPGPUs.
- Compare performance with equivalent openMP and sequential code

#### Simple *n*-body scenario with n=4 bodies



This can get very complicated...

#### A not so simple N body simulation..



 $\sim 10$  billion particles

#### <u>Millennium Run</u>

#### The Equation

$$\vec{F}_i = -\sum_{j \neq i} \frac{Gm_i m_j (\vec{r}_i - \vec{r}_j)}{(|\vec{r}_i - \vec{r}_j|^2 + \epsilon^2)^{3/2}},$$

 $F_i - Force on particle i$   $m_i - Mass of particle i$   $m_j - Mass of particle j$   $r_i - Direction vector for particle i$   $r_j - Direction vector for particle j$ ε - Softening factor

\*Assuming that the other fundamental forces of interaction do not influence the system as much as gravity.

## Parallelism

- The above equation suggests that the cumulative effect of *n*-1 particles on a single particle can be approximated independently for each time step.
- A problem in the parallel computing domain
- nVidia's CUDA allows for massive parallelism.
- Multiple CUDA-enabled devices could also be used for extremely large simulations (<u>E.g.</u>)

#### Advantages of CUDA

- Each GPGPU is effectively a mini-supercomputer
- For cards that support Compute Capability > 1.2:
  - Each Streaming Multiprocessor (SM) allows for 1024 resident threads (employs latency hiding techniques).
  - Each C1060 GPGPU (on Magic cluster) has 30 SMs.
- Shared Memory architecture built into each SM allows for significant performance gain by reducing the global (device) memory access.
- Memory coalescing allows for good data locality improving performance.
- CUDA threads are lightweight compared to CPU threads and easy to schedule.

## Algorithm used:

- All-pairs calculation of all possible combinations (brute force method – O(n<sup>2</sup>))
  - Most accurate values
  - Every particle-particle interaction is calculated
  - Computationally intensive
  - Not necessary in most cases
  - Variable Time-Step schemes can save some of the computations involved.
- Improvement: Barnes Hut Algorithm

## **CUDA Implementation**

- In all-pairs algorithm, force on each body is the sum of acceleration caused by every other particle multiplied by the mass of that body.
- Forces on a single body is independently calculated by a single thread.
  - (Concurrent memory access allows for information of every other body to accessed by every thread)
- The sum of all accelerations are calculated, and further used to calculate the velocity and new position of each particle.

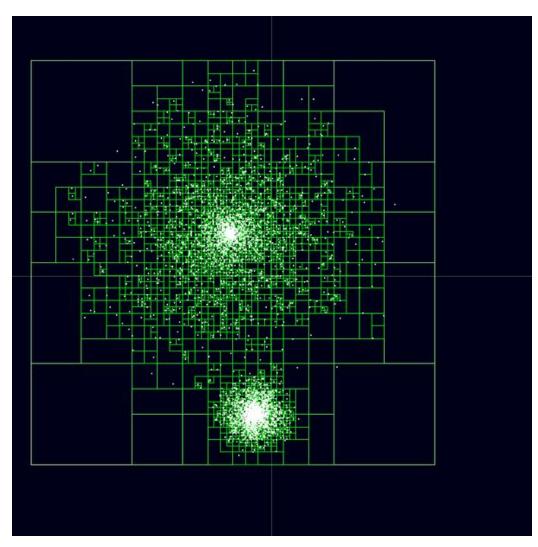
## **CUDA** implementation

- Position and velocity of each particle is updated per time-step.
- Coalesced memory used to store location, mass & velocity of body.
- Shared memory structure used to optimize calculations by having each thread in a block copy one value from the device memory into the shared memory, reducing the total number of device memory accesses.

## Barnes Hut Tree code algorithm

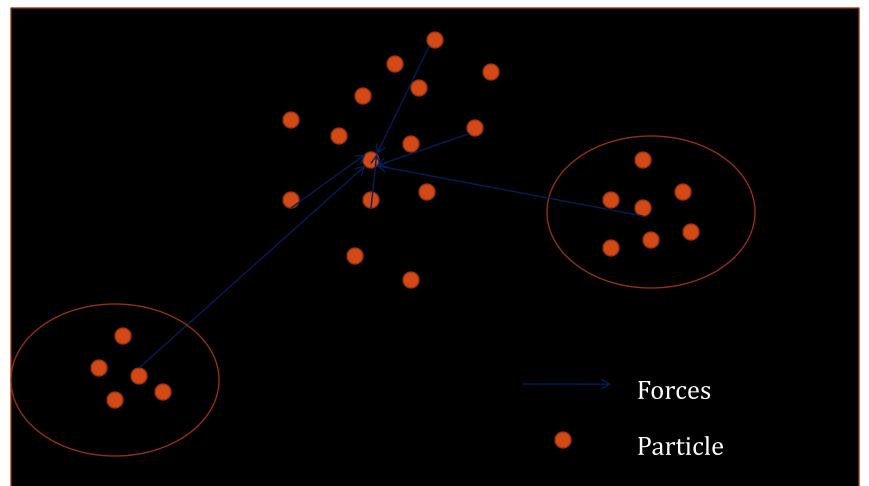
- To be implemented as the next phase of this project.
- Runtime O(*nlogn*)
- Maps the data on to a quad- or oct- tree structure which divides computational region into smaller and smaller regions
- Calculation of forces on a particle is carried out by traversing tree elements close, in detail. The particles farther away are explored only in coarse detail.
- Space devoid of particles is not simulated, which is an additional saving.

## How the algorithm partitions data



Courtesy: <u>Wiki/Barnes-Hut\_Simulation</u>

## Simple Scenario – End effect



Objects, relatively, far away are considered as a single entity to reduce calculations.

#### **Current Status**

- Developed an all-pairs program to simulate gravitational forces between *n* bodies in space
- Compared performance of algorithm on:
  - CUDA flavors:
    - Geforce 240M 48 cores, compute 1.2, 1GB device memory
    - Tesla C1060 240 cores, compute 1.3, 3GB device memory
  - Sequential code (CPU, Intel Core2Duo P8700 ~2.53Ghz, 4GB RAM)
  - Open MP code Edge Cluster 1 node, 8 processors

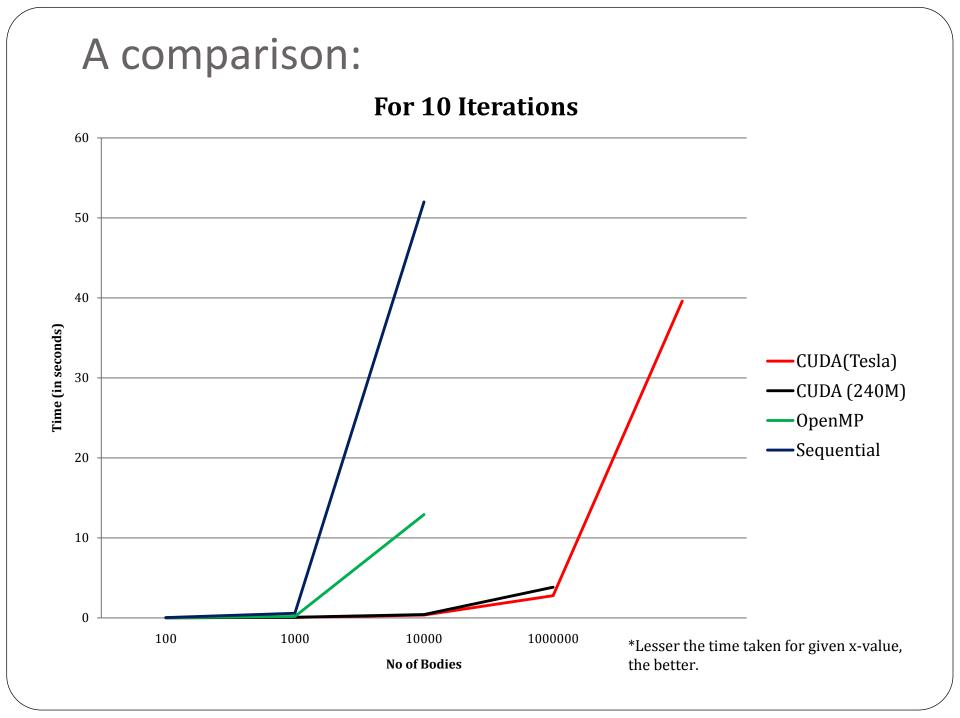
# Problems faced

- CUDA / Visual Studio integration was tricky
- Data structure manipulation (Arrays) on device (global) memory is not as easily accomplished as on Host RAM.
- Cannot be absolutely sure of the accuracy output as debugging toolkit has not been installed yet.
  - Magic compute cluster runs linux, and nVidia's new tool nSight is not available for the platform.
  - Visualization not added yet.

# Verifying the output:

- Manually calculated values for 3 bodies on paper
  - Matches GPU output
  - Extending the result to all cases!

• For all the work done, the output is indeed impressive...



## The rest of the data...

		Iterations			
Platform	Body Count	5	10	20	50
CUDA (Tesla)	480		0.015	0.028	0.067
CUDA (Tesla)	1920		0.06	0.15	0.39
CUDA (Tesla)	7680		0.35	0.73	1.86
CUDA (Tesla)	30720		2.779	6.43	16.119
CUDA (Tesla)	122880	19.85	39.6		
CUDA (240M)	384		0.016	0.03	0.81
CUDA (240M)	1536		0.063	0.123	0.303
CUDA (240M)	6144		0.42	0.81	2.057
CUDA (240M)	24576		3.84	7.67	19.07
OpenMP (Edge)8 cores	100		0.022	0.025	0.036
OpenMP (Edge)8 cores	1000		0.176	0.337	0.784
OpenMP (Edge)8 cores	10000		12.91	25.87	64.688
OpenMP (Edge)8 cores	100000	643.53			
Sequential	100		0.025	0.029	0.085
Sequential	1000		0.578	1.143	4.85
Sequential	10000		52.01	104.23	616.93

## Future Work: Next Semester

- Implement solutions for the computationally efficient Barnes Hut Tree code algorithm
  - Implementing tree structure is complicated.
    - Load Balancing the tree across processors
- Create visualization using a graphics engine
- If possible, implement on the new M2050 GPGPU cluster being installed at CCR .
- Also, the cloud-compute option available with Amazon.
- Scaling issues have to get hardware information at runtime to ensure proper scaling from my 240M graphics card to Tesla C1060 card.
  - Currently using a header file to manually tweak block and grid size for each GPU

## Conclusions:

- CUDA provides an impressive hardware layer to execute extremely parallel applications.
  - CUDA enabled GPUs really perform when pushed to the limits (upwards of 10000 threads per GPU). It also depends on leveraging the compute-specifications
    - Correct Block size
    - Shared memory tiles
    - Grid design
- CUDA is still a developing technology, but given the cost to power ratio, it is already ahead of the previous parallel architectures in use.
- Can be difficult to use at first as it gives programmers all the flexibility in scheduling the threads, handling memory.
  - This can be a boon and a bane.

# References

- <u>http://http.developer.nvidia.com/GPUGems3/gpugems</u>
  <u>3 ch31.html</u>
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- <u>http://www.amara.com/papers/nbody.html</u>
- <u>http://en.wikipedia.org/wiki/Barnes%E2%80%93Hut</u> <u>simulation</u>

## Questions?

