Ray Tracing on a Sphere:

Performance Analysis of CUDA Performance

Sonia Sharapova

Introduction:

This report outlines various speedup strategies for rendering a three-dimensional reflective sphere illuminated by a single light source using a ray tracing algorithm. In the sphere simulation implemented, light rays started at the observer and went backwards to the light source. The execution time was compared across a serial implementation, a parallel implementation and across different GPUs using CUDA.

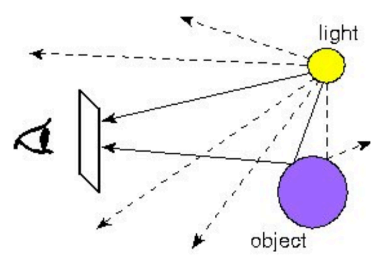


Figure 1: Illustration of Ray-Tracing.

For each implementation, the calculations were run on a 1000 x 1000 pixel grid, for 1 billion light rays. The pixel grid was initialized with zeros and was iteratively updated at every calculation.

Methodology

The ray-tracing algorithm was implemented in C and the results were visualized in Python using Matplotlib across all strategies.

Serial Implementation

The serial version of the ray tracing algorithm was used as a baseline benchmark to measure the performance of the parallelization strategies. In serial, each pixel was processed one at a time. For each pixel, the algorithm calculates the light's path, including reflections, refractions, and shadows, to determine the final color of that pixel. The algorithm iterates over all pixels in the image, rendering each scene sequentially. This approach, while straightforward, does not leverage modern multi-core processors' capabilities, leading to long rendering times for complex scenes or high-resolution images.

Without any parallelization, this approach took 5.5 minutes to render 1 billion rays.

Serial Code Usage:

Compile:

```
$ gcc -fopenmp -O3 -g -o serial ray_tracing_serial.c -lm
```

Run:

```
$ ./serial
```

Parallel Implementation

To improve the performance of the serial implementation, OpenMP was implemented to parallelize the code and distribute work for the ray tracing function for a multi-core CPU. To ensure thread safety, the vector computations were performed locally, without the use of helper functions. This modification also increased the runtime further as the functions did not have to be called at every step. The rand_r() function was used to ensure thread safety across computations and updates.

On 3 threads, the program had an execution time of 2.26 minutes and a speedup of 2.56 when compared to the serial implementation, and on 16 threads the time was 26.5 seconds with a speedup of 13.16 compared to the serial implementation.

Parallel Code Usage:

Compile:

```
$ gcc -fopenmp -O3 -g -o parallel ray_tracing_parallel.c -lm
```

Run: One command-line argument: n = number of threads

```
$ ./parallel n

Ex:
$ ./parallel 16
```

CUDA Implementation

To further optimize the computation time, CUDA was invoked and compared across a variety of available GPUs. The CUDA implementation mapped the ray-object intersection calculations to GPU threads, which allowed for further parallel processing of the multiple rays, drastically reducing the total rendering time.

The scene was decomposed into elements processed in parallel by the GPU. This device specific code included computationally intensive tasks in the ray tracing function such as ray generation, vector computations, and shading/lighting calculations. The host-side code is responsible for initialization of the final grid, setup tasks, and memory allocation on the GPU. It also ensures that data is safely transferred between the host and the device. The results are then gathered back on the host for final image composition and output on the grid.

For the computation of the randomized vector, CUDA's cuRAND function was used to ensure thread-safety. With cuRAND, each thread can independently sample the directions for the vector which will not lead to conflicts during parallelization. For consistency, all computations were performed on 1000 blocks. The number of threads per block varied according to GPU availability and optimal performance. This approach takes full advantage of the GPU's architecture, designed for high-throughput parallel computations.

The CUDA solution was incredibly efficient with a completion time of 0.459s and a speedup of 758.32 times compared to the serial implementation.

CUDA Code Usage:

Compile:

```
$ nvcc -O3 -use_fast_math -o ray_tracings ray_tracing_cuda.cu -arch=sm_75
```

Run:

```
$ ./ray_tracings
```

Data Visualization

The computed results of the n x n grid were stored in a file and visualized with python code. They simulated the visualization of the sphere when all the rays have been computed. The states were plotted using matplotlib.

Performance Comparison

To compare the performance of the serial and CUDA implementations, we measure the rendering time of a sphere with varying GPUs, grid dimensions, thread number (per block), and single vs. double precision. The performance metrics are measured in the total time the program took to execute the ray tracing function and the total program computation time. These standardizations ensured a fair comparison between the CPU and GPU processing capabilities.

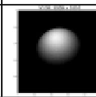
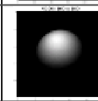
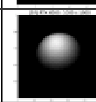
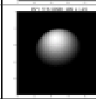
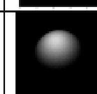
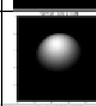
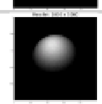
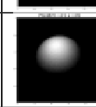
Proc	Grid	Time (SP)	K Time (SP)	Time (DP)	K Time (DP)	Blk/TPB	Cores	Samples	Image
A100	1000^2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
A100	100^2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
V100	1000^2	0.299	0.179603	0.839	0.720831	256 Threads	1	14, 926,918,271	
V100	100^2	0.302	0.177101	0.858	0.730012	512 Threads	1	14, 926,417,231	
RTX6000	1000^2	0.301	0.204290	9.950	9.758760	512 Threads	1	14, 926,918,283	
RTX6000	100^2	0.287	0.188481	12.624	12.553495	512 Threads	1	14, 926,734,271	
CPU Serial	1000^2	348.807	N/A	409.827	N/A	N/A	N/A	Timed-out	
CPU Serial	100^2	336.183	N/A	396.787	N/A	N/A	N/A	Timed-out	
CPU OMP	1000^2	16.385	N/A	15.436	N/A	On 32 threads	32	14, 927,936,827	
CPU OMP	100^2	16.685	N/A	16.730	N/A	On 32 threads	32	14, 927,842,972	
> 1 GPU*	1000^2								
> 1 GPU*	100^2								

Figure 2: Performance comparisons across all strategies and architectures.

Optimization Strategies

Helper/Built-in Functions

Throughout this project, I observed a variety of techniques that reduced the computation time. One of the best optimizations I observed was bringing the helper functions I had into the driver function. This included removing built-in math functions, such as pow(), and calculating everything manually. Having these computations done locally reduced the running time by 0.4s. Surprisingly, I found that the fabs() function performed 0.2s better than the manual computation in single precision, but this had a worse performance in double precision.

Writing to File

Writing data to a binary file rather than a CSV file often had a shorter runtime compared to writing to a text file. This was most likely because binary files are a more efficient data representation and result in a reduced file size. Because we were generating and storing large amounts of data, this reflected in the total runtime and performance of the program.

Double vs. Single Precision

The precision of computation, single or double, significantly affected both performance and memory usage. Single precision using 32-bit floating-point numbers had better execution speeds compared to double precision using 64-bit floating-point numbers. This makes sense because single-precision uses less memory in the program.

Different Flags

Flags such as -use_fast_math increased the speed by 0.1s, which was not too big but still something interesting.

Possible Further Optimizations:

Integrating MPI with CUDA for distributed parallelism would further optimize this program. This would scale CUDA beyond the GPU resources of a single node, facilitating distributed parallelism across multiple GPUs and nodes.

Results

The CUDA implementation demonstrated a significant improvement in rendering times compared to the serial version. For simple scenes, the speedup can be substantial, often in the order of tens to hundreds of times faster, depending on the scene complexity and resolution. As the scene's complexity increases, the advantage of CUDA becomes even more pronounced, showcasing the scalability of parallel processing for graphics rendering.

Conclusion

By using the GPU's parallel processing capabilities, the CUDA implementation offers dramatically reduced rendering times, making real-time ray tracing and the rendering of complex scenes more feasible. Furthermore, optimization strategies for both serial and CUDA implementations can yield additional performance gains, emphasizing the importance of both algorithmic efficiency and hardware utilization in high-performance computing applications.

This report underscores the transformative potential of GPU computing in graphics rendering and other computationally intensive tasks, highlighting the shift towards parallel processing in modern computing environments.

Sample Larger Image:

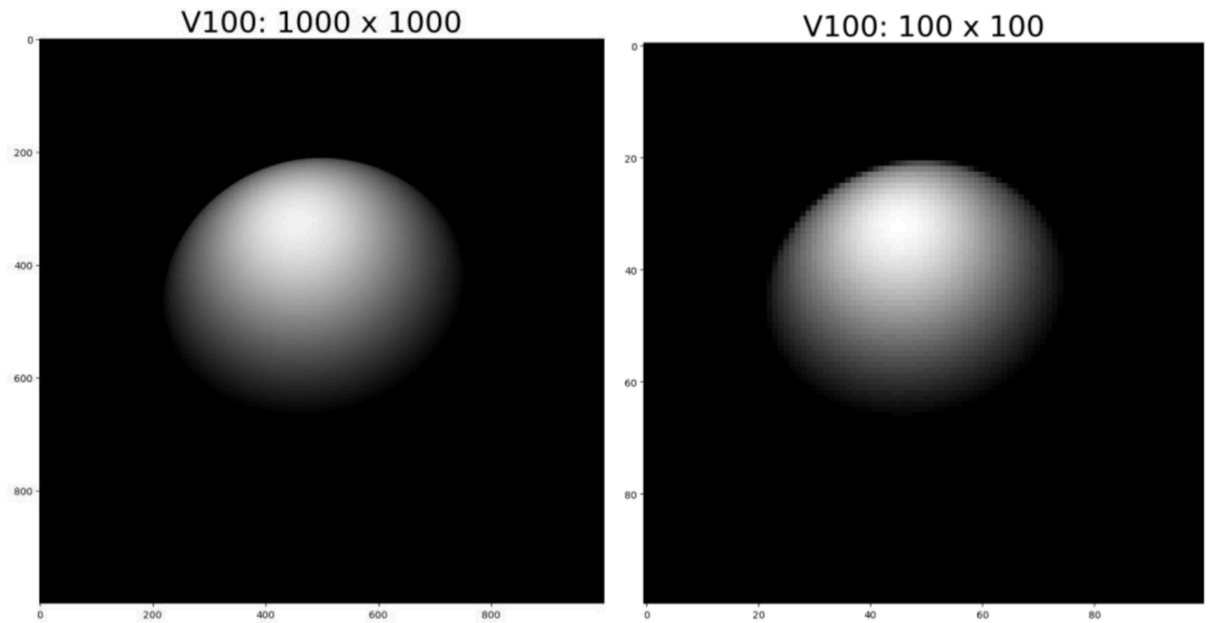


Figure 3: Sphere rendering on NVIDIA's V100 GPU on a 1000x1000 pixel grid vs. 100x100 pixel grid.