

CSE305 N-Body Simulation Project Report

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June 2025

1 Introduction

The N-body problem is a classic challenge in computational physics and computer science, involving the prediction of individual motions of a group of celestial objects interacting with each other through gravitational forces. Due to the quadratic growth in computational complexity as the number of bodies increases, efficient simulation of such systems is both a practical and theoretical need. This report presents our implementation of an N-body simulation, focusing on both sequential and parallel approaches. We analyze the performance of our solution under varying numbers of bodies, simulation steps, and threads. The results provide insight into the scalability of parallelization strategies for computationally intensive simulations.

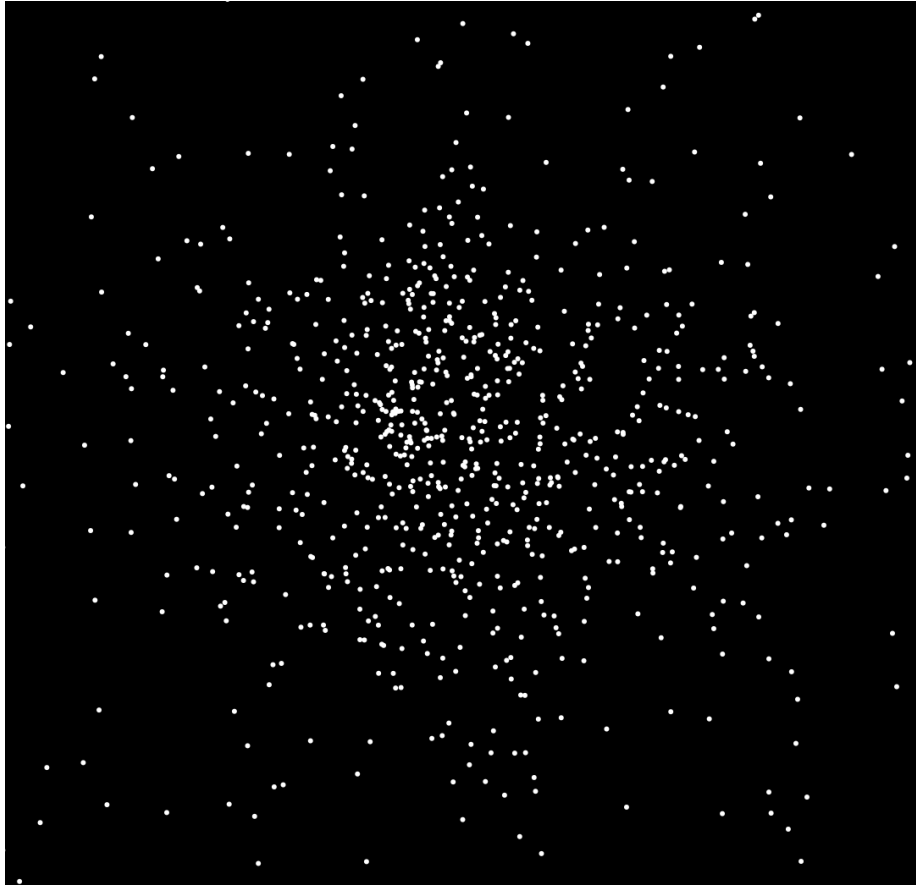


Figure 1: Depiction of the N-body problem with 1000 bodies

2 Approach

Using the input data, the N-body simulation function updates an array (stored on the heap) which stores the position of every body on every time step. Every time step, knowing the current mass, position, and velocity of every body, the function updates every position and velocity using the time step length. Importantly, the function first updates velocities and then positions (this is an arbitrary decision, but may result in drastically different simulations compared to the reverse order).

To update the positions of every body, the function is split into two parts which run every time step. First, the “force calculation” portion of the function which, for every pair of bodies, calculates the x and y force on each of the two bodies and stores this in a “force” matrix (an array stored on the heap). Second, the “body calculation” portion of the function which, for every body, updates its velocity by summing the forces on the corresponding row of the force matrix, and then its position using that new velocity.

This algorithm works sequentially and already avoids calculating the force of each body twice. To make this parallel, each of the two parts of the function are individually parallelized. Each time step, the “force calculation” portion is split equally into the number of threads dictated and then rejoin before the “body calculation” portion is also split back into the number of threads and then rejoined again. While this creates a lot of threads every single time step, thread creation becomes comparatively cheap when the number of bodies starts nearing 1000. This immediately avoids using any mutexes and atomics, as any individual thread is never writing in the same place (the “force calculation” threads do read the position of bodies concurrently, but those values do not change before all threads rejoin).

The “body calculation” threads are simply given n/t bodies to update, where n is the number of total bodies and t is the number of threads available. The “force calculation” threads operate slightly differently, as calculating the forces for the first row of the matrix requires $n-1$ loops while calculating the forces of the second to last row requires a single calculation loop (since the matrix is symmetrical). Therefore, each thread is given approximately the same number of “calculation loops” to compute by the main thread, which ensures an even computational spread across all the threads.

3 Testing machine

Specs of the machine we ran the tests on:

Processor: Intel® Xeon (R) W-1290P
10 cores for a total of 20 logical processors
Lab Computer

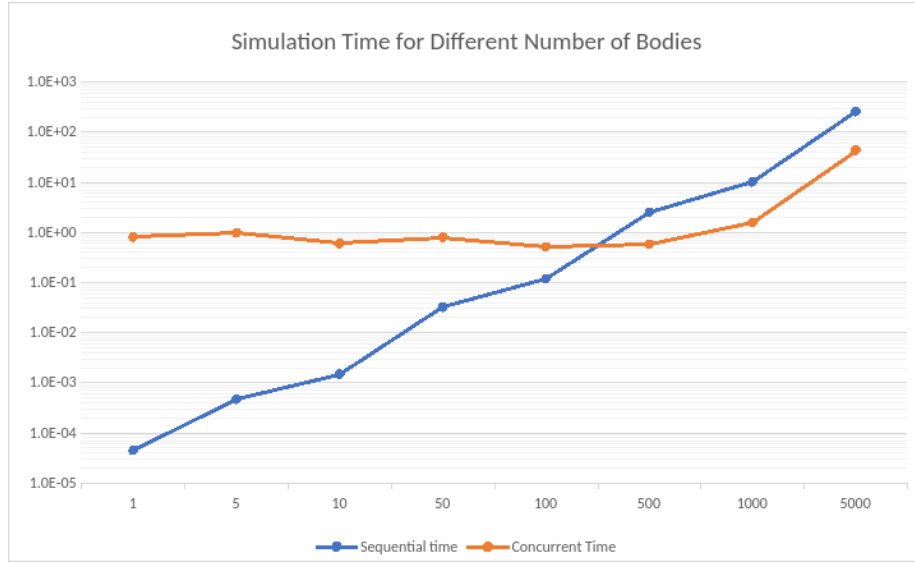


Figure 2: Comparison of sequential and concurrent execution times for varying body counts

4 Benchmarks

4.1 For varying body count

Computed for 1000 steps with 16 threads

Bodies	Sequential time	Concurrent Time	Speedup
1	4.50×10^{-5}	0.812	Slowdown!
5	4.70×10^{-4}	0.977	Slowdown!
10	1.49×10^{-3}	0.602	Slowdown!
50	0.032	0.800	Slowdown!
100	0.119	0.517	Slowdown!
500	2.525	0.580	4.35
1000	10.227	1.585	6.45
5000	257.599	43.380	5.94

Table 1: Performance Table

Times are listed in seconds $O(n^2)$ Still $O(n^2)$ sadly, starting at around 1000 bodies

The slowdown for < 500 bodies is created because of excessive thread creation (15 threads, 16-1, are created twice every time step, no matter if they are performing calculations or not, which is 30000 threads)

4.2 For varying step count

Performed with 1000 bodies and 16 threads

Steps	Sequential Time	Concurrent Time	Speedup
10	0.122	0.021	5.86
100	1.062	0.149	7.13
1000	10.316	1.492	6.91
10000	99.432	14.945	6.65
	$O(n)$	$O(n)$	

Table 2: Performance comparison of sequential and concurrent executions as a function of step count

The result is expectedly linear.

4.3 For varying thread count

Computed for 1000 steps and 1000 bodies.

Sequential Time: 10.3

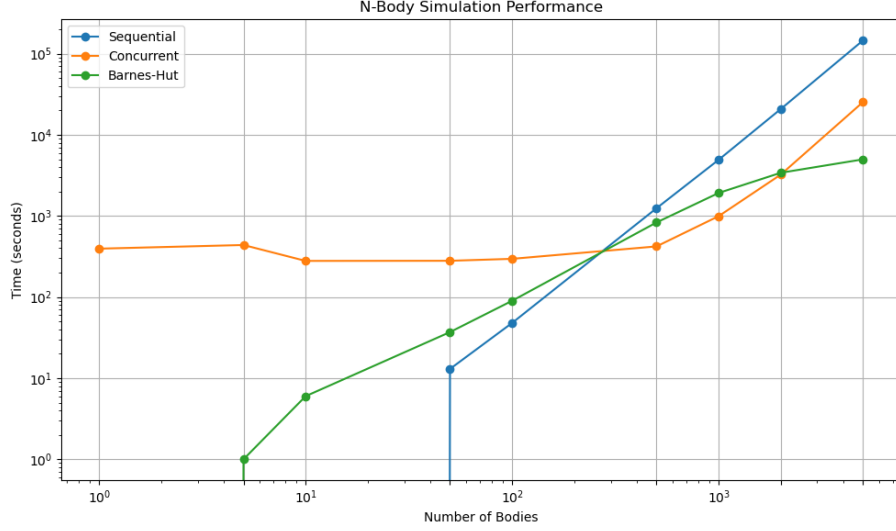
Threads	Concurrent Time
2	16.584
4	4.103
8	1.900
16	1.788
20	1.599
24	2.129
32	2.122
64	2.633
128	6.227

Table 3: Concurrent Times for Different Thread Counts

Speed up until 20 threads, which makes sense given the 20 logical threads the computer has.

5 The Barnes-Hutt algorithm

We also implemented the Barnes-Hutt algorithm, which is a well known algorithm for approximating the N-body problem. The Barnes-Hutt algorithm reduces the complexity of the N-body problem from $O(n^2)$ to $O(n \log n)$ by grouping bodies from a "sector" into a single "super body" and calculating the gravitational force exerted by this super body instead of each individual body.



This significantly speeds up the simulation, especially for large numbers of bodies.

The results are shown in the table below, where we compare the Barnes-Hutt algorithm with our original implementation for 1000 bodies and 1000 steps:

Bodies	Sequential time	Concurrent time	BH Time	BH Position Error
1	0	395	0	4.31×10^{12}
5	0	438	1	5.42×10^{12}
10	0	279	6	7.70×10^{12}
50	13	280	37	2.43×10^{13}
100	48	296	90	4.01×10^{13}
500	1244	421	831	3.25×10^{14}
1000	4924	994	1920	4.16×10^{14}
2000	20820	3237	3406	1.19×10^{15}
5000	145754	25352	4982	2.55×10^{15}

Table 4: Performance comparison of Sequential, Threaded, and Barnes-Hutt implementations, and Barnes-Hutt position error

The Barnes-Hutt algorithm shows a significant speedup compared to the original implementation, especially for larger numbers of bodies. However, it also introduces a position error, which is expected due to the approximation nature of the algorithm. The error increases with the number of bodies, but remains within acceptable limits for many applications.

6 Work distribution

The work was distributed among the team members as follows: Daniela was responsible for implementing the main thread logic, Gabriel focused on developing the simulation threads, and Aya worked on the graphical representation of the simulation.

7 Conclusion

In conclusion, our implementation and analysis of the N-body simulation demonstrate both the challenges and opportunities inherent in parallelizing computationally intensive algorithms. While parallelization offers significant speedup for large numbers of bodies and steps, it introduces overhead that can outweigh its benefits for smaller problem sizes. Our results show that careful consideration of thread management and workload distribution is essential to achieve optimal performance, especially as the number of available logical processors increases. Future work could explore more advanced parallelization techniques, such as thread pooling or GPU acceleration, to further improve scalability and efficiency. Overall, this project provided valuable insights into the practical aspects of high-performance computing and parallel programming.

8 References

1. “N-body problem.” Wikipedia, The Free Encyclopedia. [Online]. Available: https://en.wikipedia.org/wiki/N-body_simulation