Bachelor of Science in Computer Science February 2018

Performance Evaluation of Boids on the GPU and CPU

Sebastian Lindqvist

Faculty of Computing Blekinge Institute of Technology SE–371 79 Karlskrona, Sweden

This thesis is submitted to the Faculty of Computing at Blekinge Institute of Technology in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science. The thesis is equivalent to 10 weeks of full time studies.

Contact Information: Author(s): Sebastian Lindqvist E-mail: seli13@student.bth.se

University advisor: M.Sc Diego Navarro Department of Creative Technologies

Faculty of Computing Internet : www.bth.se Blekinge Institute of Technology Phone : $+46455385000$ SE–371 79 Karlskrona, Sweden Fax : +46 455 38 50 57

Abstract

Context. Agent based models are used to simulate complex systems by using multiple agents that follow a set of rules. One such model is the boid model which is used to simulate movements of synchronized groups of animals. Executing agent based models partially or fully on the GPU has previously shown to increase performance, opening up the possibility for larger simulations. However, few articles have previously compared a full GPU implementation of the boid model with a multi-threaded CPU implementation.

Objectives. The objectives of this thesis are to find how parallel execution of boid model performs when executed on the CPU and GPU respectively, based on the variables frames per second and average boid computation time per frame.

Methods. A performance benchmark experiment will be set up where three implementations of the boid model are implemented and tested.

Results. The collected data is summarized in both tables and graphs, showing the result of the experiment for frames per second and average boid computation time per frame. Additionally, the average results are summarized in two tables.

Conclusions. For the largest flock size the GPGPU implementation performs the best with an average FPS of 42 times over the single-core implementation while the multi-core implementation performs with an average FPS 6 times better than the single-core implementation. For the smallest flock size the single-core implementation is most efficient while the GPGPU implementation has 1.6 times slower average update time and the multi-core implementation has an average update time of 11 times slower compared to the single-core implementation.

Keywords: boid, ABM, agent based model, GPGPU

Contents

List of Figures

List of Tables

Chapter 1

Introduction

As entertainment industry move towards more advanced graphical content, new graphical techniques are utilized to create different visual effects. One technique is the simulation of synchronized groups. These simulations are based on a large amount of individuals, or agents, coordinating with each other by individually following a set of rules. This computational model is called agent-based model (ABM) [4].

One of the first ABMs for simulating movement in a group of animals was proposed by Reynolds in 1987 and is based on three rules that each agent follows; collision avoidance, velocity matching, and flock centering. Reynolds called the agents in the model boids, an abbreviation to birdoids, which have been commonly used ever since [7].

In a naive implementation of the boid model where every agent calculates each rule against all other agents in the flock, the algorithm would get a computational complexity of $O(n^2)$ where n is the flock size [7][5]. This means that as the size of the flock grows, the computation needed for the simulation grows quadratically. Multiple implementations have been proposed to achieve simulations with larger flock sizes. Solutions include discarding one of the rules, increasing efficiency of finding neighbors, or by moving parts or the full implementation to the graphical processing unit (GPU) $[5][3][2][8]$.

Utilizing General-Purpose Computing on Graphics Processing Units (GPGPU) with ABMs can reduce the computation time for iterations due to the GPU being optimized for executing parallel tasks. Previous research has shown that ABM implementations on the GPU can outperform CPU implementations with a speedup of up to 40 times [6]. However, there are few similar measurements for the boid model to this date.

This thesis will evaluate and compare the performance of parallel computing of the boid model on the GPU and the CPU. The experiment will be a benchmark experiment based on three variations of a traditional boid implementation; singlethreaded CPU, multi-threaded CPU and GPGPU. The single-threaded CPU implementation will be used as a reference system. A series of tests will be performed where frames per second (FPS) and average computation time for all agents per frame will be compared based on varying flock sizes. Lastly, the implementations will be evaluated and discussed based on their performance in the tests.

1.1 Hypothesis and Research Questions

This thesis aims to answer the following questions:

RQ1: How does a GPGPU implementation of the boid model compare to a multi-threaded CPU implementation looking at most agents simulated in realtime?

RQ2: At what flock size does a GPGPU implementation of the boid model outperform a multi-threaded CPU implementation?

The hypothesis is that the GPGPU implementation may have a better performance compared to the multi-threaded CPU implementation when dealing with large flock sizes. The reason is due to the parallel abilities of the GPU as well as the fact that this has been previously observed on similar ABMs. However, it is suspected that for small flock sizes the multi-threaded CPU implementation will calculate agent logic faster due to less thread overhead.

1.2 Outline

Chapter 2 summarizes previous research related to performance in ABMs and additionally describes the theoretical background of this area. The tools, hardware, implementations and experiment are described in chapter 3. Chapter 4 summarizes the results from the experiment. In chapter 5 the results are discussed and analyzed. Lastly, conclusions and possible future work is discussed in chapter 6.

Chapter 2

Related Work

In this section research related to performance in ABMs is summarized and the theoretical background of this thesis is discussed.

2.1 Previous Research

Reynolds proposed the original boid model which was based on a group of agents interacting through a set of three rules:

- Avoid collision
- Match velocity
- Stay close to the flock

Agents were independently simulated through their observation of the environment which led to a computational complexity of $O(n^2)$. The author stated that "This does not say the algorithm is slow or fast, merely that as the size of the problem (total population of the flock) increases, the complexity increases even faster." To handle bigger flocks it was suggested to use spacial hashing, incremental collision detection or distributed systems [7].

Lee, Cho and Calvo proposed an algorithm for increasing the performance of boid algorithms that use spacial hashing. The method is based on the fact that the k-nearest neighbors (kNN) of boids seldom change. The algorithm can efficiently calculate whether the kNN has changed and only then re-calculate the new kNN. This improvement achieved a performance increase of 57.7% with regards to FPS [5].

Joselli et al. introduced a proximity based data structure which was called "neighborhood grid". Each cell in the grid only contain one agent and can approximate its neighboring cells. The implementation had low parallel complexity which resulted in high performance and scalability while maintaining believability. The technique was implemented in a 3D environment and tested on the GPU with a minimum speedup of 2.94 over two traditional spacial hashing methods [3].

Perumalla and Aaby did a comparison of three ABMs; Mood Diffusion, Schelling Segregation and Game of Life, comparing GPU implementations of the models to optimized traditional CPU implementations as well as equivalent implementations using ABM toolkits. Conclusions drawn were that the GPU implementations executed 100 to 1000 times faster than leading ABM toolkits "at the cost of decrease in modularity, ease of programmability and reusability." GPU implementations also gained a performance increase of up to 40 times over the CPU implementations. Lastly they discussed the challenges faced with parallel ABM execution on the CPU and the GPU [6].

More recently, Hermellin and Michel did an experimental study based on the conclusions by Perumalla and Aaby [6]. They implemented and tested four different computational models using the GPU environmental delegation principle. This principle separates the computation by moving agent behavior to the CPU and environmental dynamics to the GPU, creating a hybrid approach. Additionally the authors stated that "Especially, one major idea underlying this principle is to identify some computations (such as agent-level perceptions) which can be transformed into environmental dynamics." They concluded that while an all-in GPU approach would yield bigger performance gains, their hybrid approach improved reusability, modularity, and since the GPU didn't run the entire simulation "[...] the knowledge required is less important." [1]

In another paper Hermellin and Michel applied the above principle to the boid model which led to a speed up of 25% while also improving reusability [2].

Da Silva, Lages and Chaimowicz proposed a methodology for the boid model where boids, through visibility estimation, only considered other boids which was visible in its field of view and also not blocked by another boid. The methodology was tested in three different GPU implementations: one with GPGPU techniques using the Cg (Central Graphics) shader language, one optimized using Nvidia's CUDA (Compute Unified Device Architecture), and one naive CUDA implementation. The authors concluded that visibility culling could achieve up to three times faster update speed, with the CUDA implementations constructing the grid system quicker and the GPGPU implementation being significantly faster executing the simulation, and thus, also overall [8].

2.2 Background

2.2.1 The Boid Model

The boid model is based on agents, or boids, that act based on their individual perception of the environment to simulate a group of moving animals. The model achieves this by using three rules that continuously regulate the direction of all boids. The first rule is that the boid should avoid collision with other boids within a certain radius. The second rule is that boid should match its velocity to other

boids. Lastly, the third rule is that the boid should move towards the average position of other boids [7].

Rules can be calculated in any order and return vectors which are added together using vector addition to get the new direction. Each rule vector is multiplied by pre-defined constants that determine the total impact each rule has on the new direction. Altering these constants will affect the behavior of the flock. The number of boids each boid perceive differs between implementations and also affects the behavior of the flock. In this thesis boids perceives all other boids. The boid model can be used to simulate different groups of animals but for the purpose of this thesis, a gathering of agents are referred to as "flock".

2.2.2 GPGPU

General-Purpose Computing on Graphics Processing Units, or GPGPU for short, is the act of utilizing the GPU for non-graphical computation. Modern GPUs are created with thousands of cores and certain parallelizable tasks can benefit from running on a GPU. Multiple smaller cores are especially effective when repeatedly executing the same operation on a data set compared to the fewer bigger cores seen in CPU's which are more suited for general computing.

Compute shaders were made to execute arrays of data in parallel on the GPU. There are several compute shader APIs, the one used for this thesis is DirectCompute.

Chapter 3

Method

In order to answer the research questions in this thesis three different implementations of the boid algorithm were implemented and tested in a performance benchmark experiment. This chapter describes the tools, hardware, implementations as well as the test cases for the experiment.

3.1 Development Tools

Implementations in this thesis are mainly written in $C++$ using Visual Studio Community 2017 with the exception of parts the GPGPU implementation which is written in HLSL Compute Shader. DirectX 11 is used for the graphical output.

 C_{++} and DirectX 11 were used because the author had previous knowledge and experience with both. DirectX also gave the benefit of GPU programming and rendering support.

3.2 Implementations

The implementations simulate a flock of multiple boids in a 3D environment. Each boid is represented by a model consisting of six triangles in the shape of a pyramid. The flock is contained within a fixed area visualized with the help of a grid. In order to keep the boids interacting with each other, the boids who leave the area are relocated to the opposite side of the grid from the point that they exited. Speed and acceleration is limited in order to get a smooth movement and visible interactions between agents. All boids perceives all other boids when following the three rules described in section 2.2.1. The base loop of the three implementations can be described with the following pseudo-code:

```
WHILE isRunning
  IF shouldUpdateLogic
    SingleCoreUpdate (scene, deltaTime)
    //MultiCoreUpdate ( scene , deltaTime )
    //GPGPUUpdate( scene , deltaTime )
  UpdateCamera
  Render (scene)
```
Based on the implementation the dedicated update function is called.

Rendering is identical for all implementations and also separated from the agent logic. Additionally, the new up vector for the models are calculated each frame in order to keep boid direction visible as seen in figure 3.1. The model faces are calculated each frame based on the position and direction vector of the boids. The code for the three update implementations can be found in appendix B.

Figure 3.1: Example initial positions and directions of flock size 64

3.2.1 Single-core CPU Implementation

The single-core CPU implementation is used as the control point for the benchmark experiment. Agent logic is executed sequentially on the CPU. The boids are stored in two data sets where one set is used for reading the boid data from the previous frame and the other set is used for writing data for the next frame.

The single-core CPU implementation update can be described using the following pseudo code:

SingleCoreUpdate (scene, deltaTime) scene. SwitchCurrentAndPreviousBoids FOR each boid in scene calculate and add all rule vectors limit new direction vector size set new direction vector and model up vector calculate new position move position if out of bounds set boid position send boids data to GPU for rendering

3.2.2 Multi-core CPU Implementation

This implementation executes boid logic in parallel on the CPU. As in the singlecore CPU implementation, boids are stored in two datasets. The multi-core CPU implementation uses the $C++$ std thread library to create eight threads; one for each hyper-thread in the CPU described in section 3.3.1. Eight threads were chosen to utilize all of the CPU cores fully while also minimizing the number of created threads. Threads compute one eighth of the boids' logic each and the program waits for all of them to finish before continuing.

The multi-core CPU implementation update can be described using the following pseudo code:

```
MiltiCoreUpdate (scene, deltaTime)
  scene. SwitchCurrentAndPreviousBoids
 initThreads(nroffhreads)FOR each thread
    run boid thread function
 FOR each thread
    wait for thread to finish
 send boids data to GPU for rendering
```
The boid thread function is identical to the boid update loop in Section 3.2.1 with the addition of the range of which boid indices to update.

3.2.3 GPGPU Implementation

This implementation executes all agent logic-related functionality on the GPU. Boid positions and velocities are initiated on the CPU and then sent to the GPU memory. The data is then handled solely in the GPU memory for the remainder of the simulation. Data is stored in two buffers; one buffer for writing the boid data being used for the next frame and one buffer for reading the boid data from the previous frame. All helper functions from the CPU implementations which are needed for the boid logic are replicated in the compute shader and are designed to be as similar as possible to achieve a fairer comparison.

The GPGPU implementation update can be described with the following pseudo code.

```
GPGPUUpdate( scene , deltaTime )
  set compute shader
  set deltaTime in buffer
  send deltaTime, constants and boid buffers to GPU memory
  dispatch compute shader
  null resources
  unset compute shader
  switch Current And Previous Buffers
```
The compute shader runs 64 threads per core and uses the same logic pattern as seen in the loop of the single-core pseudo code.

3.3 Experimentation

The experiment in this thesis test three different implementations of the boid algorithm; single-threaded CPU, multi-threaded CPU and GPGPU. The singlethreaded CPU implementation is be used as a reference system.

3.3.1 Experimental Setup

The tests were run on Windows 10 Home x64 with an Intel Core i7-6700HQ @ 2.6GHz processor, 8.0 GB RAM and a GeForce GTX 950M. The CPU main properties are listed in Table 3.1 and the GPU main properties are listed in Table 3.2. Each test run with a resolution of 1024x800 in Visual Studio 64-bit release mode.

The tests measures the number of frames per second and average computation time for all agents per frame. FPS is an occurring unit of measurement in boid model simulations [5][3]. FPS can show us the efficiency of the implementation work flow. Average computation time for all agents per frame can show us efficiency of the agent calculations separate from the rest of the implementation.

Chapter 3. Method 10

This can strengthen that any FPS increases observed are due to a more efficient calculation of the agents new positions.

To get FPS, a frame counter is incremented once for each frame. Each second the total frames for that second is saved to a data set. Computation time for all agents is extracted by starting a timer before the execution of agent logic is initiated and stopping the timer when logic execution for all agents is completed for that frame. That value is then added to a total execution time. Each second the average computation time for that second is calculated and the total execution time is reset. The resulting value is then saved to a data set.

Property	Value	Property	Value
Nr of cores		CUDA cores	640
Nr of threads		Processor clock	914 MHz
Base frequency	2.60 GHz	Memory size	2 GB
Cache size	6 MB	Memory bandwidth	32 GB/s
Bus speed	8 GT/s DMI3	Memory type	128-bit GDDR3

Table 3.1: Properties of the Intel Core i7-6700HQ

Table 3.2: Properties of the NVIDIA GeForce GTX 950M

3.3.2 Test Cases

Each implementation will be run through three different test cases in order to test their individual performance. The implementations will be run through the test cases three times each and will all have identical initial conditions. To observe the performance pattern when flock size grows, test cases will be run with the flock sizes 64, 512 and 4094. These flock sizes are chosen with two things in mind. The first is that all are evenly dividable by 8 as that is the number of logical threads for the CPU used for the tests as seen in Table 3.1. The second reason is that all three sizes are evenly dividable by 64, which is the number of threads used for each GPU core as described in section 3.2.3. This experimental scenario delivered 27 test runs.

All boids will start with a randomly assigned direction and speed within a set range. The camera will be fixed in its initial position. The simulation is then started by the push of a button, also initiating the selected test. The simulation will then run without interference while data is being collected. Each second the measurements are saved as data points in the memory. After 60 seconds the test ends and the collected data is saved to a file.

3.3.3 Validity Threats

The validity of the experiment is reliant on the fact that the implementations are implemented in an equivalent manner to achieve a fair comparison. To achieve this the rendering is separated from the agent logic and identical for all implementations. Additionally, optimizations are only applied when they can improve all implementations in an equal manner. Furthermore, tests will be run with the same background conditions to ensure equal processing power is offered. For each data point to have a fair value the tests are executed three times and then the average is calculated.

The results of the experiment are heavily dependent on the hardware used for the tests. To achieve a fair comparison, the CPU and GPU used for the experiment were released the same year and are both in the mid-tier price class.

Chapter 4

Results

In this chapter the Results from the experiment are summarized and discussed. Results are shown for each individual implementation and a summary is offered in section 4.4. Each data point is the average from three test runs for each flock size as described in section 3.3.2. The graphs show the FPS as well as the average computation time of all agents per frame in milliseconds. For each implementation there are two graphs containing all data points from all tested flock sizes. The compiled data points are available in appendix A.

4.1 Single-core CPU

The single-core implementation has a more predictable decrease in FPS as flock size becomes bigger compared to the other implementations. The average update time for flock size 4096 is higher than the other two flock sizes. For all flock sizes the FPS and update time remains stable throughout the simulation.

Figure 4.1: Average FPS of all data points for the single-core implementation.

Figure 4.2: Average update time per frame on all data points for the single-core implementation.

4.2 Multi-core CPU

FPS in the multi-core implementation is similar for flock size 64 and 512. The same can be seen in the update time. The FPS and update time stays stable throughout the simulation for all flock sizes, though the flock sizes 64 and 512 present a somewhat irregular pattern.

Figure 4.3: Average FPS of all data points for the multi-core implementation.

Figure 4.4: Average FPS of all data points for the multi-core implementation.

4.3 GPGPU

The FPS and update time for the GPGPU implementation are both similar with 64 and 512 boids if compared to the single-core measurements. In the early stages of the simulation the update time is increased at the same time as the FPS is decreased. The most unstable FPS is for for flock size 64 which can be seen in the early stages of the simulation where the update time is increased at the same time as the FPS is decreased. The other flock sizes are more stable throughout the simulation.

Figure 4.5: Average update time per frame on all data points for the GPGPU implementation.

Figure 4.6: Average update time per frame on all data points for the GPGPU implementation.

4.4 Summary

The graph below summarizes the average FPS for the full simulation run for each implementation and flock size. Average update time per frame is not summarized in a graph since the difference of the highest and lowest value makes it difficult to illustrate. Average FPS and update time values for each flock size are compiled in appendix A. The tables below assumes the single-core CPU implementation as a benchmark measurement.

In table 4.1 and 4.2 the multi-core implementation outperforms the single-core implementation for flock size 4096. Additionally, the GPGPU implementation outperforms the single-core implementation for flock sizes 512 and 4096. However, for flock size 64 the single-core implementation has the best FPS and average update time.

	Flock size Single-core Multi-core GPGPU			
64	10	0.151	0.787	
512	1 ∩	0.431	2.164	
4096	1.0	ჩ Ი	42.40	

Table 4.1: Average FPS of the multi-core and GPGPU implementations compared to the single-core implementation.

	Flock size Single-core Multi-core GPGPU			
64	10	11.161	1.580	
512	1.0	2.398	0.368	
4096	1.0	0.140	0.032	

Table 4.2: Average logic update time per frame of the multi-core and GPGPU implementations compared to the single-core implementation.

Figure 4.7: Average FPS of the implementations for each flock size.

Chapter 5

Analysis and Discussion

In this section the multi-core and GPGPU implementations are discussed and analyzed based on their performance in the tests.

5.1 Multi-core

As mentioned in the hypothesis in section 1.1, the multi-core implementation was expected to have longer boid update time for the lower computation flock sizes due to thread overhead, this has been illustrated in figure 4.7. Additionally, FPS and update time does not vary as much as the single-core implementation when flock size is increased from 64 to 512. The thread overhead is most likely the cause of the bottleneck in contrast to the computation of the boid logic for the single-core implementation. For flock size 4096 figure 4.7 illustrates the multi-core implementation outperforming the single-core implementation.

Tables 4.1 and 4.2 illustrates the rate of which the multi-core implementation increases in performance compared to the single-core implementation as flock size increases. Even though the rate is lower than the GPGPU implementation, the multi-core implementation inherits a speed up of six times over the single-core implementation in terms of FPS at flock size 4096.

5.2 GPGPU

All three implementations yielded a stable performance throughout the tests with the GPGPU being the most volatile for flock size 64 as illustrated in figure 4.5. However, the fluctuations were not by a degree that affects the test in any major aspect.

As initially discussed in the hypothesis, the GPGPU implementation was expected to have the highest total thread overhead and thus would perform worst for the lowest flock size, as illustrated in figure 4.7, this was not the case. The GPGPU implementation outperformed the multi-core implementation at all flock sizes looking at both FPS and update time. At flock size 4096 it performed exceptionally well with a speed up of 42 times in terms of FPS. However, the single-core implementation did achieve the highest FPS and lowest update time per frame for flock size 64 as expected in the hypothesis.

Tables 4.1 and 4.2 illustrates the rate of which the GPGPU implementation excel in performance compared to the single-core implementation as flock size increases. The GPGPU implementation shows a higher rate over the multi-core implementation.

Chapter 6

Conclusions and Future Work

In this chapter the conclusions from the experiment are stated and the future work is discussed.

6.1 Conclusions

It is observed that the GPGPU implementation outperformed the multi-core implementation for all flock sizes in terms of FPS and average boid logic update time per frame. Looking at the performance trend from the flock sizes there is nothing to indicate that the GPGPU implementation's performance advantage would change for lower nor higher flock sizes.

From the results in this thesis it can be concluded that when implementing a parallel basic boid algorithm to simulate large flock sizes it should be implemented on the GPU rather than the CPU when considering performance.

6.2 Future Work

This paper focuses on a basic boid implementation with few additions. There are many different variations and optimizations of the boid algorithm and it would be interesting to see if the same conclusions can be drawn for alternative implementations. Additionally, rendering for the implementations in this thesis does not put much load on the GPU. A possible future work would be to to investigate how the GPGPU implementation performs when the GPU is under heavier graphical computation load.

References

- [1] Emmanuel Hermellin and Fabien Michel. GPU delegation: Toward a generic approach for developping MABS using GPU programming. In Proceedings of the 2016 International Conference on Autonomous Agents \mathcal{B} Multiagent Systems, AAMAS '16, pages 1249–1258. International Foundation for Autonomous Agents and Multiagent Systems.
- [2] Emmanuel Hermellin and Fabien Michel. GPU environmental delegation of agent perceptions: Application to reynolds's boids. In Benoit Gaudou and Jaime Simão Sichman, editors, Multi-Agent Based Simulation XVI, volume 9568, pages 71–86. Springer International Publishing. DOI: 10.1007/978-3- 319-31447-1_5.
- [3] M. Joselli, E. B. Passos, M. Zamith, E. Clua, A. Montenegro, and B. Feijó. A neighborhood grid data structure for massive 3d crowd simulation on GPU. In 2009 VIII Brazilian Symposium on Games and Digital Entertainment, pages 121–131.
- [4] Yushim Kim and Callie McGraw. Use of agent-based modeling for egovernance research. In Proceedings of the 6th International Conference on Theory and Practice of Electronic Governance, ICEGOV '12, pages 531–534. ACM.
- [5] Jae Moon Lee, Se Hong Cho, and Rafael A. Calvo. A fast algorithm for simulation of flocking behavior. pages 186–190. IEEE, August 2009.
- [6] Kalyan S. Perumalla and Brandon G. Aaby. Data parallel execution challenges and runtime performance of agent simulations on GPUs. In Proceedings of the 2008 Spring Simulation Multiconference, SpringSim '08, pages 116–123. Society for Computer Simulation International.
- [7] Craig W. Reynolds. Flocks, Herds and Schools: A Distributed Behavioral Model. In Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH '87, pages 25–34, New York, NY, USA, 1987. ACM.

References 21

[8] Alessandro Ribeiro Da Silva, Wallace Santos Lages, and Luiz Chaimowicz. Boids that see: Using self-occlusion for simulating large groups on GPUs. 7(4):51:1–51:20.

Appendix A

Metrics

Time is listed in milliseconds.

	Flock size Single-core Multi-core GPGPU		
64		(1)4	
512	25		
4096			ാ1

Table A.1: Average FPS of the single-core, multi-core and GPGPU implementations.

Flock size	Single-core	Multi-core GPGPU	
64	0.84141	9.39100	1.32975
512	4.21427	10.10588	1.5501
4096	241.83176	33.93527	7.7305

Table A.2: Average logic update time per frame of the single-core, multi-core and GPGPU implementations.

684	0.855442667	225	4.204943333	5	242.75333
687	0.841007	224	4.2196	5	241.64300
685	0.83641	226	4.199343333	5	241.18367
689	0.847558667	225	4.208233333	5	241.32767
680	0.842190333	226	4.201566667	5	241.97300
685	0.840686	226	4.187566667	5	241.99900
691	0.839681	224	4.220563333	5	242.38367
688	0.854046667	224	4.21329	5	240.80067
681	0.854764	225	4.210953333	5	240.94067
689	0.841733667	225	4.218793333	5	240.65367
683	0.835376333	224	4.218733333	5	241.93900
686	0.826323	224	4.213076667	5	241.88033
692	0.828525667	226	4.179153333	5	241.40600
693	0.838429333	224	4.215866667	5	241.32567
691	0.842371333	227	4.175306667	5	241.15433
685	0.848685667	224	4.206806667	5	243.00933
682	0.833780333	225	4.205713333	5	246.35800
687	0.830802667	226	4.19085	5	242.99767
694	0.830349	226	4.194993333	5	241.04200
695	0.838469	226	4.1929	5	241.00067
691	0.835347667 m 1 1	224 1111	4.228993333	5	242.02567

Table A.3: All data point averages for the single-core $\emph{implementation}$

Appendix A. Metrics 25

Table A.5: All data point averages for the GPGPU implementation

Appendix B

Code

Below are the main update functions for the three implementations along with the relevant logic functions.

B.1 CPU helper functions

```
glm::vec3 BoidLogicHandler::CenterRule(Boid* allBoids, int
\overline{1}currentBoidIndex) {
      g \text{Im}::\text{vec}3 \text{ center} = g \text{Im}::\text{vec}3(0.0, 0.0, 0.0);\overline{2}\overline{3}for (int i = 0; i < NR OF BOIDS; i++) {
           center + allBoids [i]. GetPosition();
\overline{5}ł
\overline{6}center = allBoids[currentBoidIndex]. GetPosition();
\overline{7}center = center / (float)(NR_OF_BOIDS 1);
8
\overline{9}10 return center * CENTER FACTOR;
  \mathcal{F}11
12
_{13} glm::vec3 BoidLogicHandler::AvoidRule(Boid allBoids, int
      currentBoidIndex) {
_{14} glm::vec3 avoid = glm::vec3(0.0, 0.0, 0.0);
_{15} glm::vec3 currentBoidPos = allBoids[currentBoidIndex].
      GetPosition();
_{16} glm::vec3 vecToBoid = glm::vec3(0.0, 0.0, 0.0);
17
18 for (int i = 0; i < NR_OF_BOIDS; i++) {
_{19} if (i != currentBoidIndex) {
20 vecToBoid = allBoids[i]. GetPosition() currentBoidPos;
21 if (glm::length(vecToBoid) < MIN SEPERATION DISTANCE) {
22 avoid = vecToBoid;
23
                }
           \mathcal{E}24
25
       ł
26
27
28 return avoid * AVOID FACTOR;
29}
```

```
30
31 \text{ glm}: vec3 BoidLogicHandler: VelocityRule(Boid * allBoids, int
      currentBoidIndex) {
_{32} glm::vec3 velocity = glm::vec3(0.0, 0.0, 0.0);
33
_{34} for (int i = 0; i < NR OF BOIDS; i++) {
\begin{array}{c|c|c|c} \text{35} & \text{velocity} & \text{+} & \text{allBoids} & \text{i}. \text{GetVelocity}(); \end{array}ł
36
37 velocity = allBoids[currentBoidIndex]. GetVelocity();
38 velocity = velocity / (float)(NR OF BOIDS 1);
39
40 return velocity * MATCH FACTOR;
  \mathcal{E}41
42
43 glm::vec3 BoidLogicHandler::LimitSpeed(glm::vec3 oldVelocity, glm::
      vec3 newVelocity, float deltaTime) {
_{44} glm::vec3 limitedVelocity = newVelocity;
_{45} float newSpeed = glm::length(newVelocity);
_{46} float oldSpeed = glm::length(oldVelocity);
47
\begin{bmatrix} 48 \\ 48 \end{bmatrix} if (newSpeed > MAX SPEED || newSpeed < MIN SPEED) {
49 limitedVelocity = oldVelocity;
\begin{array}{c} 50 \\ 51 \end{array} else {
50
52 if (newSpeed > oldSpeed) {
53 limitedVelocity = glm::normalize(limitedVelocity) * (
      oldSpeed + (MAX ACCELERATION * deltaTime));
           ł
54
55 else
\begin{array}{c} 56 \end{array} limitedVelocity = glm::normalize(limitedVelocity) * (
      oldSpeed (MAX ACCELERATION * deltaTime));
            ł
57
       \mathcal{F}58
59
60 return limitedVelocity;
  ₹
61
62
63 glm::vec3 BoidLogicHandler::CalculateNewPos(glm::vec3 oldPosition,
      glm::vec3 newVelocity, float deltaTime) {
\epsilon_{4} glm::vec3 newPos = oldPosition + (newVelocity * deltaTime *
      BOID SPEED);
65
66 return newPos;
  \mathcal{F}67
68
69 glm::vec3 BoidLogicHandler:: MoveIfOutOfBounds(glm::vec3 position) {
70 glm:: vec3 newPosition = position;
71
72 float sideLength = GRID SIDE LENGTH;
73
\begin{array}{ll} \text{float xMax} = 0.0 \text{ f} + (\text{sideLength} / (\text{float})2); \end{array}
```

```
75 float xMin = 0.0f (sideLength /(float)2);
76 float yMax = 0.0f + (sideLength / (float)2);
77 float yMin = 0.0f (sideLength /(float)2);
78 float zMax = 0.0f + (sideLength / (float)2);
\begin{array}{c|c}\n\hline\n\text{r}}\n\text{float zMin} = 0.0 \text{f} & \text{(sideLength)} \text{ (float)}\n\text{2}\n\end{array}80
81 / X82 if (position.x > xMax) {
|83| new Position. x = xMin;
84
85 if (position.x < xMin) {
86 newPosition.x = xMax;\begin{array}{c} 87 \\ 88 \end{array} //Y
87
89 if (position.y > yMax) {
90 newPosition.y = yMin;ļ
91
92 if (position.y < yMin) {
93 newPosition.y = yMax;ł
Q_495 //Z
96 if (position.z > zMax) {
97 \quad \text{newPosition} \cdot z = zMin;98
99 if (position.z < zMin) {
100 newPosition.z = zMax;₹
101
102
103 return newPosition;
104
  7
105
106 void BoidLogicHandler::BoidThread(Scene* scene, int startIndex, int
      endIndex, float deltaTime) {
107 Boid* allBoidsPrevious = scene >GetAllBoidsPrevious();
_{108} Boid* allBoids = scene >GetAllBoids();
_{109} glm::vec3 newVelocity = glm::vec3(0.0, 0.0, 0.0);
_{110} glm::vec3 previousVelocity = glm::vec3(0.0, 0.0, 0.0);
111
_{112} for (int i = startIndex; i < endIndex; i++) {
113 previousVelocity = allBoidsPrevious[i]. GetVelocity(i);
114 newVelocity = previousVelocity;
115
116 //1. Fly towards center
117 glm::vec3 centerRuleVec = CenterRule(allBoidsPrevious, i);
118
119 //2. Avoid boids
120 glm::vec3 avoidRuleVec = AvoidRule(allBoidsPrevious, i);
121
122 //3. Match velocity/direction with all boids
123 glm::vec3 velocityRuleVec = VelocityRule(allBoidsPrevious, i
      );
```

```
124
125 //Add all rules
_{126} newVelocity += centerRuleVec + avoidRuleVec +
     velocityRuleVec;
127
128 //Limit speed
_{129} newVelocity = LimitSpeed(previousVelocity, newVelocity,
     deltaTime);
130
131 //Set new boid velocity and up direction
132 allBoids[i].SetVelocityAndUp(newVelocity);
133
134 //Calculate new boid position
_{135} glm::vec3 oldPosition = allBoidsPrevious[i]. GetPosition();
_{136} glm::vec3 newPosition = CalculateNewPos(oldPosition,
     newVelocity, deltaTime);
137
138 //Move if out of bounds
_{139} newPosition = MoveIfOutOfBounds (newPosition);
140
141 //Set boid new position
142 allBoids[i]. SetPosition(newPosition);
      }
143
  \mathcal{E}144
```
B.2 Single-core CPU update function

```
void BoidLogicHandler:: SingleThreadUpdate(Scene* scene, float
\mathbf{1}deltaTime) {
       scene >SwitchCurrentAndPreviousBoids();
\overline{2}Boid * allBoidsPrevious = scene >GetAllBoidsPrevious();
\overline{\mathbf{3}}Boid* allBoids = scene >GetAllBoids();
      g \text{Im}::\text{vec}3 new Velocity = g \text{Im}::\text{vec}3(0.0, 0.0, 0.0);\overline{5}g \text{Im}::vec3 previousVelocity = g \text{Im}::vec3(0.0, 0.0, 0.0);
\mathcal{L}for (int i = 0; i < NR OF BOIDS; i++) {
\overline{8}previousVelocity = allBoidsPrevious[i]. GetVelocity();
\overline{9}10 newVelocity = previousVelocity;11
12 //1. Fly towards center
13 glm::vec3 centerRuleVec = CenterRule(allBoidsPrevious, i);
14
15 //2. Avoid boids
_{16} glm::vec3 avoidRuleVec = AvoidRule(allBoidsPrevious, i);
17
18 //3. Match velocity/direction with all boids
```

```
19 glm::vec3 velocityRuleVec = VelocityRule(allBoidsPrevious, i
     );
20
\frac{21}{10} //Add all rules
22 newVelocity += centerRuleVec + avoidRuleVec +
     velocityRuleVec;
23
24 //Limit speed
25 newVelocity = LimitSpeed(previousVelocity, newVelocity,
     deltaTime);
26
27 //Set new boid velocity and up direction
28 allBoids[i].SetVelocityAndUp(newVelocity);
29
30 //Calculate new boid position
\text{glm}::\text{vec}3 \text{ old}Position = allBoidsPrevious [i]. GetPosition ();
\text{sum} glm::vec3 newPosition = CalculateNewPos(oldPosition,
     newVelocity, deltaTime);
33
34 //Moveif out of bounds
\substack{35 \\ 35}} newPosition = MoveIfOutOfBounds (newPosition);
36
37 //Set boid new position
38 allBoids[i].SetPosition(newPosition);
      \mathcal{F}39
40\text{41} scene >GetBoidBuffer(0) >SetData(scene >GetAllBoids(), sizeof(
     Boid * NR OF BOIDS);
42
 <sup>}</sup>
```
B.3 Multi-core CPU update function

```
void BoidLogicHandler:: MultiThreadUpdate (Scene* scene, float
\overline{1}deltaTime) {
       scene >SwitchCurrentAndPreviousBoids();
\overline{2}const int THREADS = 8;
\overline{3}std::thread threadPool[THREADS];
\overline{A}\mathbf{K}int startIndex = 0;
\overline{6}int endIndex =0;
\overline{7}s
       for (int i = 0; i < THREADS; i++) {
\Omega10 startIndex = i * (NR _{OF~BOLDS}/ THENERADS);11 endIndex = (i * (NR_OF_BOIDS / THREADS)) + (NR_OF_BOIDS /
      THREADS);
12 threadPool[i] = std::thread(BoidThread, scene, startIndex,
      endIndex, deltaTime);
```

```
\mathcal{F}13
14
15 for (autok th: threadPool) {
16 th.join ();
17
      Y
18
19
20 scene >GetBoidBuffer(0) >SetData(scene >GetAllBoids(), sizeof(
      Boid) * NR OF BOIDS);
21
  \mathcal{F}
```
B.4 Multi-core CPU thread function

```
void BoidLogicHandler:: BoidThread(Scene* scene, int startIndex, int
\overline{1}endIndex, float deltaTime) {
      Boid * allBoidsPrevious = scene >GetAllBoidsPrevious();
\overline{2}Boid* allBoids = scene >GetAllBoids();
\overline{3}g \ln:: vec3 newVelocity = g \ln:: vec3(0.0, 0.0, 0.0);
      g \text{Im}::vec3 previousVelocity = g \text{Im}::vec3(0.0, 0.0, 0.0);
\mathbf{K}\overline{6}for (int i = startIndex; i < endIndex; i++) {
\overline{7}previousVelocity = allBoidsPrevious[i]. GetVelocity();
8
          newVelocity = previousVelocity;\alpha10
11 //1. Fly towards center
12 glm::vec3 centerRuleVec = CenterRule(allBoidsPrevious, i);
13
14 //2. Avoid boids
_{15} glm::vec3 avoidRuleVec = AvoidRule(allBoidsPrevious, i);
16
17 //3. Match velocity/direction with all boids
18 glm::vec3 velocityRuleVec = VelocityRule(allBoidsPrevious, i
     );
19
20 //Add all rules
21 newVelocity += centerRuleVec + avoidRuleVec +
     velocityRuleVec;
22
23 //Limit speed
24 newVelocity = LimitSpeed(previousVelocity, newVelocity,
     deltaTime);
25
26 //Set new boid velocity and up direction
27 allBoids[i].SetVelocityAndUp(newVelocity);
28
29 //Calculate new boid position
30 glm::vec3 oldPosition = allBoidsPrevious [i]. GetPosition ();
```

```
31 glm::vec3 newPosition = CalculateNewPos(oldPosition,
     newVelocity, deltaTime);
32
33 //Moveif out of bounds
_{34} newPosition = MoveIfOutOfBounds(newPosition);
35
36 //Set boid new position
37 allBoids[i]. SetPosition(newPosition);
      ∤
38
39
  \mathcal{F}
```
B.5 GPGPU update function

```
void BoidLogicHandler::GPUUpdate(Scene* scene, float deltaTime) {
\overline{1}\overline{2}ID3D11DeviceContext* dxContext = this >rendererPtr >GetDxDeviceContext();
\overline{3}//Set computeshader
      dxContext >CSSetShader(this>computeShader,
\mathbf{K}6
          nullptr,
          0);
\overline{7}8
      //Set delta time
\alpha10 this >deltaTimeBuffer >SetData(&deltaTime, sizeof (float));
11
12 //Dispatch shader
13 ID3D11ShaderResourceView * srvArray |\cdot| = \{ scene >GetBoidBuffer(
      boidBufferSwitchIndex)>GetShaderResourceView(),
\frac{1}{4} this >deltaTimeBuffer >GetShaderResourceView() ,
\frac{15}{15} this >constantsBuffer >
     GetShaderResourceView() };
16 ID3D11UnorderedAccessView * uavArray | \cdot | = \{ scene >GetBoidBuffer((
      boidBufferSwitchIndex + 1) % 2) >GetUnorderedAccessView() };
17 dxContext >CSSetShaderResources(0, 3, srvArray);
18 dxContext >CSSetUnorderedAccessViews(0, 1, uavArray, 0);
19 dxContext >Dispatch(NR_OF_BOIDS/64, 1, 1);
20
21 //Null resources
22 ID3D11ShaderResourceView srvNullArray \begin{bmatrix} \end{bmatrix} = \begin{bmatrix} \end{bmatrix} nullptr \begin{bmatrix} \end{bmatrix};
23 ID3D11UnorderedAccessView * uavNullArray [ = { nullptr };
_{24} dxContext >CSSetShaderResources(0, 1, srvNullArray);
25 dxContext >CSSetUnorderedAccessViews(0, 1, uavNullArray, 0);
26
27 //Unset computeshader
28 dxContext >CSSetShader(nullptr,
29 nullptr,
```
 $30 \t 0);$ 31 32 //Switch buffers for next frame 33 boidBufferSwitchIndex = 1 boidBufferSwitchIndex; 34 [}]

B.6 Compute shader

```
struct Boid {
\mathbf{1}float3 position: POSITION;
\overline{2}float3 velocity: VELOCITY;
\overline{3}float3 up: UP;
\overline{4}};
\overline{5}\overline{6}struct Constants
\overline{7}8
  \{float MIN SEPERATION DISTANCE;
\overline{9}10 uint COHESION THRESHHOLD;
11 float BOID SPEED;
12 float MAX SPEED;
_{13} float MIN SPEED;
_{14} float MAX ACCELERATION:
15
16 float CENTER FACTOR;
<sup>17</sup> float AVOID FACTOR;
18 float MATCH FACTOR;
19
20 uint NR OF BOIDS;
21 float BOID SEPERATION;
22
_{23} float GRID SIDE LENGTH;
24 };
25
26 StructuredBuffer<Boid>readBufferBoids: register(t0);
27 RWStructuredBuffer<Boid> writeBufferBoids : register(u0);
28
29 StructuredBuffer<float>readBufferDeltaTime: register(t1);
30
_{31} StructuredBuffer<Constants> readBufferConstants: register(t2);
32
33
34 float3 CenterRule(int currentBoidIndex) {
35 float3 center = 0.0f;
36
37 for (int i = 0; i < readBufferConstants[0].NR OF BOIDS; i++){
38 center +=\text{readBufferBoids} [i]. position;
       \mathcal{E}39
```

```
40 center = readBufferBoids[currentBoidIndex].position;
41 center = center / (float) (readBufferConstants[0].NR_OF_BOIDS
      1);
42
43 return center * readBufferConstants[0].CENTER FACTOR;
  ₹
\overline{A}A45
_{46} float3 AvoidRule(int currentBoidIndex) {
47 float3 avoid = 0.0f;
48 float3 currentBoidPos = readBufferBoids[currentBoidIndex].
      position;
49 float3 vecToBoid = 0.0f;
50
51 for (int i = 0; i < readBufferConstants[0].NR_OF_BOIDS; i++) {
52 if (i != currentBoidIndex) {
[53] vecToBoid = readBufferBoids[i].position
      readBufferBoids[currentBoidIndex].position;
_{54} if (length(vecToBoid) < readBufferConstants[0].
      MIN_SEPERATION_DISTANCE)
\begin{array}{c}\n\text{55} \\
\text{56}\n\end{array} avoid = vecToBoid;
55
5'}
           \}58∤
59
60
61 return avoid * readBufferConstants[0].AVOID FACTOR;
62
  \mathcal{F}63
_{64} float3 VelocityRule(int currentBoidIndex) {
65 float3 velocity = 0.0f;
66
67 for (int i = 0; i < readBufferConstants[0].NR OF BOIDS; i++){
68 velocity +=\text{readBufferBoids}[i]. velocity;
       }
69
\sigma velocity = readBufferBoids[currentBoidIndex].velocity;
\vert v_1 \vert velocity = velocity / (float) (readBufferConstants[0].
      NR OF BOIDS 1);
72
73 return velocity * readBufferConstants[0].MATCH FACTOR;
  <sup>}</sup>
74
75
76 float3 LimitSpeed(float3 oldVelocity, float3 newVelocity, float
      deltaTime) {
77 float3 limitedVelocity = newVelocity;
78 float newSpeed = length(newVelocity);
\begin{array}{c|c|c|c} \hline \text{float} & \text{oldSpeed} & = \text{length}(\text{oldVelocity}); \end{array}80
\text{S1} if (newSpeed > readBufferConstants[0].MAX_SPEED || newSpeed <
      readBufferConstants[0].MIN_SPEED)
82
\begin{array}{c} 82 \ \text{83} \end{array} limitedVelocity = oldVelocity;
```

```
∤
84
85 else
86 if (newSpeed > oldSpeed) {
\begin{array}{c} \text{simitedVelocity} = \text{normalize(limitedVelocity)} * (oldSpeed) \end{array}+ (readBufferConstants[0].MAX_ACCELERATION * deltaTime));
           ł
88
89 else
90 limitedVelocity = normalize(limitedVelocity) * (oldSpeed
          (\text{readBufferConstants}[0].\text{MAX}\text{AOCELERATION } * \text{ deltaTime}));^{+}91
       ł
92
93
94 return limitedVelocity;
  \mathcal{E}95
96
_{97} void SetBoidVelocityAndUp(uint index, float3 newVelocity) {
98 float3 forward = normalize(newVelocity);
99 float3 newRight = normalize (cross (float3 (0.0f, 1.0f, 0.0f),
      forward));
_{100} float3 newUp = cross(forward, newRight);
101 writeBufferBoids[index].up = newUp;
102
103 writeBufferBoids[index].velocity = newVelocity;
104
  - 1
105
106 float3 CalculateNewPos(float3 oldPosition, float3 newVelocity, float
       deltaTime) {
107 float3 newPos = oldPosition + (newVelocity * deltaTime *
      readBufferConstants[0].BOID SPEED);
108
109 return newPos;
110
  \mathcal{F}111
112 float3 MoveIfOutOfBounds(float3 position) {
113 float3 newPosition = position;
114
115 float sideLength = readBufferConstants[0].GRID SIDE LENGTH;
116
117 float xMax = 0.0f + (sideLength / (float) 2);118 float xMin = 0.0f (sideLength / (float) 2);
119 float yMax = 0.0f + (sideLength / (float) 2);120 float yMin = 0.0f (sideLength / (float) 2);
_{121} float zMax = 0.0f + (sideLength / (float) 2);
_{122} float zMin = 0.0f (sideLength /(float) 2);
123
124 //X
125 if (position.x > xMax) {
126 newPosition. x = xMin;
127
128 if (position.x < xMin) {
_{129} newPosition.x = xMax;
```

```
130 }
_{131} //Y
_{132} if (position y > yMax) {
_{133} newPosition . y = yMin;
134 }
_{135} if (position y < yMin) {
_{136} newPosition . y = yMax;
137 }
138 //Z
_{139} if (position z > zMax) {
_{140} newPosition . z = zMin;
141 }
_{142} if (position. z < zMin) {
_{143} newPosition . z = zMax;
144 }
145
_{146} return newPosition;
147 }
148
_{149} [ numthreads (64, 1, 1) ]
_{150} void main ( uint3 DTid : SV DispatchThreadID ) {
\begin{array}{rcl} 151 \end{array} int i = DTid.x;
_{152} float3 previous Velocty = read Buffer Boids [i]. velocity;
_{153} float3 newVelocity = previousVelocty;
154
|155| //1. Fly towards center
_{156} float3 centerRuleVec = CenterRule(i);
157
158 //2. Avoid boids
_{159} float3 avoidRuleVec = AvoidRule(i);
160
|161| //3. Match velocity/direction with all boids
_{162} float3 velocityRuleVec = VelocityRule(i);
163
_{164} //Add all rules
165 newVelocity + centerRuleVec + avoidRuleVec + velocityRuleVec;
166
_{167} //Limit speed
_{168} float deltaTime = readBufferDeltaTime [0];
\begin{array}{c|c} \text{newVelocity} = \text{LimitSpeed} \text{(previousVelocity} , \text{ newVelocity} , \text{deltaTime} \end{array}) ;
170
171 // Set new boid velocity and up direction
172 SetBoidVelocityAndUp(i, newVelocity);
173
174 // Calculate new boid position
_{175} float3 oldPosition = readBufferBoids [i]. position;
176 float 3 new Position = CalculateNew Pos (old Position, new Velocity,
      deltaTime ) ;
177
178 //Move if out of bounds
```
 179 newPosition = MoveIfOutOfBounds (newPosition); 180 $\begin{array}{c|c} 181 & // Set \quad \textbf{boid new} \quad \textbf{position} \end{array}$ $\begin{array}{lll} \text{182} \end{array} \quad \quad \text{writeBut} \text{ferBoids} \, [\, \text{i} \,] \, . \ \text{position} \, = \, \text{newPosition} \, ;$ ¹⁸³ }