Work Assignment - Phase 3

Parallel Computing

José Miguel Ferreira Barbosa PG52689 Braga, Portugal Tiago Adriano Gomes Moreira PG52704 Braga, Portugal

Abstract—This document is the written report of the third and final phase of work assignments of the curricular unit, Parallel Computing. The focus of this phase was how to design and implement an efficient parallel version of the case study.

I. INTRODUCTION

The final phase of this work assignment aims to understand how to design and implement an efficient parallel version of the case study, eventually incorporating accelerators, with the main goal still being of reducing the execution time. In this report, we will explore the adopted strategies, the challenges encountered, and the proposed solutions to optimize the system's performance, emphasizing the crucial importance of parallel approaches in the pursuit of computational efficiency. It's worth noting that because of the issues we had in the two previous phases regarding results, we choose to pick up the original code and work from there again.

II. THE APPLICATION HOT-SPOTS

As we figured out in the previous phases of this work assignment, we have two code blocks that call our hot-spots, those being:

- Potential
- computeAccelarations

It is imperative to acknowledge that both these functions were identified as hot-spots not only in the original code, that we will pick up again when working on this final phase, but also in the sequential version we had made and worked on during phase 2. So our main efforts will once again be directed towards optimizing and enhancing the performance of these components.

III. THE CHOOSEN PATH

In this final work assignment, we had the freedom to choose one of three paths to improve the execution. After a discussing upon ourselves, we decided to look into the approach where we would be challenged with designing and implementing a new version for accelerators (GPU with CUDA). We choose this one because we find more suitable than the other two, as it also was the focus of the last classes of the semester of this curricular unit. We will then, work with CUDA, on the functions **Potential** and **computeAccelarations** specifically.

IV. CHANGES AND SEQUENTIAL CODE

As we mentioned in the introduction, we started from scratch again. Because of that, the code is different from the one we delivered in the versions prior to this one. First of all, to enhance our code's efficiency, we've shifted to Struct of Arrays (SoA). We made this change because it offers advantages like improved memory access patterns and better alignment with GPU parallelism.

We kept all the functions that are not the two hot spots, pretty much the same as they were in the original code (of course we adapted them to fit SoA), since they are not going to be worked on using CUDA. Also, we changed them in the first phase, but since we encountered problems with the simulation results we also felt like making more changes than required gave us a bigger chance of getting wrong results again, so we focused solely on Potential and computeAccelarations and worked carefully to make sure the same thing didn't happen again. We added a function called **power** (fig 11) with the sole purpose of replacing the pow, making the code a bit more efficient in the process. We only did this in natural powers, because non-natural powers are more complex to calculate, and it could lead to incorrect results. The function **Potential**, follows the same logic we applied in phase 1, when we worked on it, where we made slight changes in the operations made when calculating the potential, to improve the execution time, removing some time-consuming operations in the process, for example divisions and the call of the function srqt. When it comes to computeAccelarations we also followed the same logic we did in phase 1, where we removed of for cycles and also made slight changes to the operations made, for example we eliminated some redundant operations, and we introduced some intermediate variables to optimize the calculations and reduce repetition.

V. PHASE II CORRECTIONS

As we talked about, we started from scratch and made changes to the sequential code we had worked on previously. Since we changed the code we are working on and are working with CUDA for this final phase, we didn't pick up OpenMP again. However, we were informed that we had a data race in our last assignment, that went by unnoticed, and we identified it and decided to correct it and that correction can be seen in fig 1. To resolve this issue, we added a barrier like shown in the correction that will also guarantee that all the acceleration

```
| Section (Companion Contention (Companion Contention C
```

Fig. 1. Correction of data race issue in phase 2

arrays are initialized correctly before the calculation starts, and we believe this small addiction solves our problem.

VI. APPROACH WITH CUDA

After finishing and making sure that the simulation results from the sequential version were correct, we went ahead and started our CUDA implementation.

In regards to the CUDA adaptation of the function Potential (fig 2) and to really explain what we did, let's just quickly get into what it does. The potential function calculates the potential energy of each particle in the system and sums them all, thus obtaining the total potential energy of the particle system in question. In the sequential version, the function performs these two steps almost simultaneously, where the accumulated value of the system's potential energy is stored in the variable Pot. So we came to the conclusion, that this function has two distinct parts: a mapping, corresponding to the stage of calculating the potential energy of all particles, and a reduction, corresponding to the sum of all these potential energies to obtain the potential energy of the system. It's important to note that the calculation of potential energies for different particles is embarrassingly parallel, as these calculations have no dependencies among them. The same can be said for the reduction phase, which aims to obtain the total potential energy of the system in a parallel fashion. With this understanding of the function in mind, we decided to divide this function into two different kernels, one for each component of this function: **Potential_Map**, which will fill an array with the potential energy values of each particle in the system, and Potential_Reduce, which will sum all the values calculated by **Potential Map**, cumulatively placing the total sum value in the first position of the array. Additionally, we also launched a device called power_cuda (fig 12), which will solely perform the exponentiation of various values.

The **Potential_Map** Kernel will receive arrays with the positions of each particle (drx, dry, and drz), as well as their size (N) and sigma. It is worth mentioning that we are creating one thread for each particle in the system, that is, each thread will fill in the Pot array with the potential energy of its



Fig. 2. Side by Side comparison of the CUDA and Sequential version of Potential

corresponding particle at the position corresponding to the number of that particle. For example, the potential energy of particle 0 should be located at position 0 in the Pot array. Each thread needs a specific identifier, 'i'. This way, it places the calculated potential energy in the correct location in the Pot array. This identifier should be calculated as follows: the identifier of each thread (ranging from 0 to the number of threads defined for each block), added to the identifier of each block (ranging from 0 to the number of blocks we decided on) times its dimension (which is equal to the total number of threads in the block). This formula allows us to correctly identify each thread independently of its block because we need to add the overhead given by the product between the block it is in and its dimension to its identifier within the block. In other words, we are positioning ourselves in the specific location.

example:

with 256 threads per block, thread 7 in block 8, 'i' = 2055. It is worth noting that the calculation itself has not changed since our changes in phase 1, that we mentioned briefly in the previous section, so we will write the value of the potential energy of the respective particle into the Pot array at the correct position, as mentioned earlier. The other auxiliary variables (r3, r2, r6, pot, sig6), being local to the kernel, will be private to each thread.

Potential_Reduce will receive the array of previously calculated potential energies, as well as the number of elements that should undergo an initial reduction. The first reduction involves reducing the number of elements from 5000 to a number where we can have one thread per particle in a single block, in this case, 256 elements. In other words, this initial reduction involves going from 5000 elements to 256 elements. This necessity arises from how the reduction operation functions. The **Potential_Reduce** will perform accumulated sums of different elements. However, to do this, we

must ensure synchronization at the thread level; otherwise, we would encounter data races. For this purpose, we are using the synchronization primitive __syncthreads(), which ensures that within the same block, threads cannot overtake each other. In other words, thread 1 cannot finish before thread 2. However, given the maximum block size of 1024 threads, to have one thread per element, we proceed with the initial reduction described above. Thus, with 256 threads, we can handle 5000 elements. It is worth noting that this initial **syncthreads()** ensures that all threads write to the shared array before moving on to the next phase, it functions as a barrier in other words. Next, we will enter the loop of the second reduction, which is essentially a sequence of cascade sums, where in each iteration we will successively need half of the threads. For each iteration, a thread will sum two elements. For instance, thread 0 adds values 0 and 1, thread 1 adds values 2 and 3. In other words, with each iteration, we will halve the number of necessary threads until we only have to sum two values. At that point, thread 0 will add them and store the final value in the first position of the result array, Pot_r.

A small additional point to mention is that in this function, we leverage the concept of shared memory. The use of shared memory (__shared__ double partial_sum[256];) is implemented to minimize the number of accesses to global memory, which is slower compared to shared memory. Each thread block maintains a local copy of the partial_sum variable, which is utilized to accumulate the partial sum of the Pot vector elements for each thread.

These two kernels are launched by the **PotentialPrepare** function, which will be responsible for sending the values of the three position arrays (rx, ry, rz) to the GPU. It is worth noting that the array where the potential energies of each particle will be stored has a size of 5120, and not the expected 5000. This increase in size is done so that in the reduction phase, we have the correct calculations regarding the number of values to sum in the initial reduction phase which, in this case is, 20 values at a time. These additional 120 positions will have no impact since this array is initialized with 0, meaning their presence will not affect the calculation of the system's potential energy in any way.

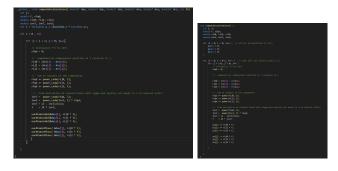


Fig. 3. Side by Side comparison of the CUDA and Sequential version of computeAccelarations

Now let's get in to the other hot spot function **computeAccelerations** (fig 3). In our new version, the **computeAccel-**

erationsPrepare function is responsible for launching the kernel, initializing all accelerations to 0, and copying these values to the GPU. The **computeAccelerations** function in the sequential version calculates the accelerations of each particle from scratch every time it is called. For the CUDA version, the procedure is similar. To perform this task, we create one thread per particle and launch a single kernel that will perform this calculation for each particle. Just like in the potential function, all threads need a universal identifier calculated. The calculation itself is not altered from the sequential version to this CUDA version; what changes is the complexity of the function, decreasing from $O(N^2)$ to O(N). In this function, we use the ourAtomicAdd and ourAtomicMinus (fig 7) functions from the device, which will ensure the absence of data races. This is the solution we came up with, and it works making sure that everything goes well and the one that is in the final code sent. However, we have another possible approach that we thought of, that we didn't implement, but we think is worth mentioning.

In this alternative approach (fig 8), instead of using the **ourAtomicAdd** and **ourAtomicMinus** devices, we employ the synchronization primitive **__syncthreads()**. As mentioned earlier, it serves as a barrier, preventing threads from the same block from overlapping. Each thread will have a different 'i', so we wouldn't have problems with data races. The value of 'j' depends on 'i', where 'j = i+1', and within the same block, thanks to **__syncthreads()**, no thread would surpass another. Therefore, for a single block, we wouldn't encounter any issues. However, as we are using more than one block, to achieve this, we would need to use an interblock synchronization mechanism, ensuring that all threads from all blocks cannot surpass each other (it would be a kind of general barrier). We attempted to use **cooperative_groups**, but it didn't work.

Nevertheless, we believe that this approach would be very efficient, but since we couldn't guarantee the absence of "data races" we went with the strategy mentioned above and that gives us the assurances we desired.

VII. RESULTS, ANALYSIS AND DISCUSSION

In this section we will talk about the results we obtained in the phase of the work assignment and also talk about some tests we conducted and some metrics we think are valuable analyzing.

In this work assignment, we design and ran two different tests to see how our CUDA solution worked under some different circumstances. The tests were:

- Changing the value of N in both the sequential and CUDA versions
- Changing the number of threads per block in the CUDA version
- Comparing the time and percentage of time for each hotspot function in both versions

A. Test 1

For the first test we conducted had a very simple principle. We wanted to see how the execution time changed in both the CUDA and the C++ versions when we changed the value of N, or in other words, we changed the number of particles. We tested 6 different numbers: 1000, 2000, 5000, 7500, 10000 and 15000 for both the sequential version(fig 5) and the CUDA version (fig 6).

We can see the results of the execution time of both versions in the graph (fig 4) and TABLE I

TABLE I EXECUTION TIME FOR BOTH VERSIONS

N =	1000	2000	5000	7500	10000	15000
	2.0309s					
Sequential	2.43169s	9.71843s	59.8467s	137.473s	187.933s	604.508s

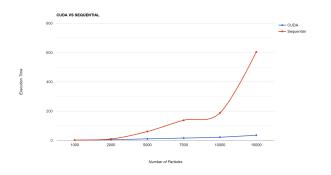


Fig. 4. Graph of execution time of CUDA and Sequential versions with different number of particles

By at looking and analyzing both of these we can see very easily, that as the value of the number of particles increases so does the difference in execution time between both versions. But we can get the full picture by calculating the speedup. Remembering the concept of speedup, it is a metric that indicates the performance gain achieved by utilizing parallelism compared to a sequential implementation. So will we use to really grasp, the difference between both versions.

In TABLE II, we can take a look at results of the calculations made to get this metric for each different value of N. Speedup is obtained by dividing the sequential time for parallel time, we can see the formula be applied in exemple below.

$$N = 5000: 59.8467/10.2138 = 5.8594$$

N =	1000	2000	5000	7500	10000	15000
SpeedUP =	1.1973	2.2052	5.8594	8.9308	8.8606	16.9101

We can notice once again, by analyzing this metric, that the difference rises with the number of particles (with the exception of 7500 and 10000). If talk about complexity, we can assess that the sequential version was a complexity of about $O(N^2)$ for both the **Potential** and the **computeAccelarations**

functions, while in the CUDA version the complexity of doing the same operations lowers to about O(N), and so, with the input set at 'ar', this means each function is called about 200 times. So that this means that while in the CUDA version, the rise is pretty much linear, in the sequential version it's quadratic.

Let's talk about scalability analysis, where we examine how the performance of a system changes as the problem size or workload increases and what we can conclude with this test of changing the value of N. In the CUDA, execution time increases gradually as N increases, indicating a relatively good scalability. While in the sequential version, the execution time increases significantly as N increases, demonstrating poor scalability. The rate of increase is much steeper compared to the CUDA version. This shows us that the CUDA version is able to handle the workload more efficiently, whereas the sequential version struggles and becomes increasingly inefficient. Furthermore, upon observing the values presented for the number of particles, specifically 7500 and 10000, it is evident that they are quite close, with a slight decrease in the metric. Upon closer analysis, it becomes apparent that this decrease is part of a variation considered normal. This phenomenon typically precedes the next significant leap in Speedup, which is expected to occur between 10000 particles and 150000 particles.

The analysis consistently reveals that the CUDA approach demonstrates superior efficiency, particularly when dealing with considerably large values, aligning well with our intended goals. This finding underlines the scalability of our solution, highlighting that Speedup rises with the rise of the number of particles (N).

B. Test 2

The second test was changing the number of threads used in our CUDA version, with the number of particles set at 5000. We did this by changing the value of the variable 'TB_SIZE' in both **computeAccelerationsPrepare** and **PotentialPrepare**, which is the variable that defines the number of threads per block in our solution. The values we tested were: 64, 128, 256, 512 and 1024. 256, was the number that was delivered in the final code. It's important to mention that the number of threads is directly influences the number of blocks.

```
Example
const int TB_SIZE = 256;
int GRID_SIZE =
ceil((N * 1.0) / (TB_SIZE * 1.0));
// GRID_SIZE = 20
computeAccelerations
<<<GRID_SIZE, TB_SIZE>>>
```

Another quick thing worth mentioning is that in CUDA, we should always run the numbers of thereds as a multiple of 32 since GPU hardware is designed to perform operations in parallel in warps of 32 threads. If we have a total number of threads that is not a multiple of 32, the GPU will still execute the threads, but there will be a number of "ghost threads" that

will be filled in to complete a warp. These additional threads may not be efficiently utilized and can result in some resource wastage. It's something that we have to be careful about when managing threads.

TABLE III
EXECUTION TIME IN RELATION TO NUMBER OF THREADS

N° of Blocks	78	39	20	10	5
Threads per Block	64	128	256	512	1024
Execution Time	10.07s	10.15s	10.21s	10.45s	12.21s

Analyzing Table III we can see that the execution time is lower in the cases with more blocks and fewer threads, but they all remain around the 10 seconds mark, with the notable exception being the last example, where we run 1024 threads per block, with 5 blocks where it rises to 12 seconds. 1024 threads is the maximum amount we can run in a single block. We believe that the reason this case is such an outlier in this test is that the huge amount of threads in this block causes a slight overhead when trying to synchronize them all. In regards to the other values, as we just noted as well, they aren't that far apart from each other. We can attribute the fact the execution time is lower with more blocks to a couple of potential reasons. With a lower number of threads per block, it is possible that the GPU is using available resources more efficiently. This may occur because the GPU can allocate and manage blocks more effectively, avoiding underutilization of its resources. Another reason that may cause this, is that a lower number of threads per block can lead to better load balancing, ensuring that each thread has a significant amount of work to perform which can be important to avoid situations where some threads finish quickly while others are still processing, which could result in delays, and we believe these two reasons are why we obtained the results we did in regards to this specific test.

C. Test 3

Our goal with this third test is to do a more detailed comparison of the sequential version of the code with our CUDA solution in order to have a more in depth comprehension of how the implementations we made really affects performance. In this test, we compare the time taken by each hotspot function, taking into consideration as well the percentage of time taken regarding the total execution time. They are the only two relevant functions to analyze since, they are the only ones that were changed and also are the ones that have a relevant impact in the execution time of the program, in both versions. To do this test we used the command 'gprof' for the sequential version (fig 17) and for the CUDA version we analyzed the profiling results, while in TABLE IV we have the values for time taken by each hotspot function, while in TABLE V we have the percentage of time each function in regards to the total time ((please note that in the CUDA version the value for 'Potential' includes both Potential_Map and Potencial Reduce).

As we have discussed before, the total time between both versions is very different, with the parallel version being

TABLE IV
TIME TAKEN COMPARISON

	Potential	computeAccelarations	Total Time
Sequential Version	30.61s	29.24s	59.86s
CUDA Version	2.4387s	7.75105s	10.2138s

TABLE V PERCENTAGE COMPARISON

	Potential	computeAccelarations	Total Time
Sequential Version	on 51.16%	48.87%	59.86s
CUDA Version	23.89%	75.89%	10.2138s

almost 6 times faster than the sequential one. However, this is not the point of this test and taking a look at both tables there is one thing that stands out immediately, that being the fact that while in the sequential version both functions take almost similar times (30.61s and 29.24s) and because of that the percentage of both is almost 50/50, in the CUDA version, there is a very big difference. The combination of both Potential functions that run on GPU (**Potential_Map** and **Potencial_Reduce**) only takes 23.89% of the total execution time, while **computeAccelarations** takes 75.89% of the time.

This can be explained by how both functions were implemented. Our implementation of the computeAccelarations function, works well and does exactly what it's required, and guarantees the absence of data races, but like we discussed in the previous section, isn't the most efficient solution possible, since it uses ourAtomicAdd and ourAtomicMinus devices that, while they are a good and safe way to guarantee functionality, it comes at a performance cost. By contrast, our **Potential** solution, implemented via **Potential Map** and Potencial_Reduce (and of course PotencialPrepare), is very efficient. This is a lot due to the fact, that in both functions that run on the GPU, we don't really have any "critical zones", because it's extremely parallel, and adding the fact that we use shared memory while in the reduce function, it's going to come at a very good performance gain, explaining why it gives us such a low execution time.

VIII. CONCLUSION

To conclude this phase 3 and final report in regards to this work assignment, we feel like the work we did on this project as a whole, helped us understand a lot better how parallel programming works and how we can improve it and that we should be aware of when working on it. We faced a lot of difficulties during the whole work assignment, but we believe that these helped us see first hand what to avoid doing and what mistakes can happen. We feel that this final phase has helped us to better consolidate our knowledge in the realm of CUDA and to gain a deeper understanding of how this aspect of programming operates.

ATTACHMENTS



Fig. 5. Results of C++ version with different Number of Particles

```
19. No. 1000
19. No. 1000
19. State of the control of the control
```

Fig. 6. Results of CUDA version with different Number of Particles

Fig. 7. ourAtomicAdd e ourAtomicMinus

Fig. 8. computeAccelarations CUDA Alternative

```
construction of the property o
```

Fig. 9. computeAccelarationsPrepare

```
| The content of the
```

Fig. 10. Potencial Prepare

```
double power(double base, int expoent){
  double res = 1.;
  int i = 0;
  while (i < expoent){
    res *= base;
    i++;
  }
  return res;
}</pre>
```

Fig. 11. Power

```
__device__ double power_cuda(double base, int expoent) {
    double res = 1.0;
    int i = 0;
    while (i < expoent) {
        res *= base;
        i++;
    }
    return res;
}
```

Fig. 12. Power Cuda

```
AVERAGE TEMPERATURE (K): 131.4550641593

AVERAGE PRESSURE (Pa): 131001228.4507508728

PV/NT () * mol^-1 K^-1): 28.4727885201

PERCENT ERROR of pV/NT AND GAS CONSTANT: 242.4490409666

TOTAL VOLUME (m^3): 2.3721986292e-25

NAMBER OF PARTICLES (unitless): 5000

20738= Profiling result:

Type Time (%) Time Calls Avg Min PMax Name
PU activities: 75.65% 7.67180s 202 37.979ms 37.925ms 38.026ms computeAccelerations(double*, double*, double
```

Fig. 13. Results of changing to 64 threads

```
28 4727885201
PERCENT ERROR of pV/nT AND GAS CONSTANT: 242.4490490666
TOTAL VOLUME (m^3):
                                    2.3721986292e-25
Calls Avg Min Max Name
202 38.056ms 37.995ms 38.117ms computeAccelerations(double*, double*, double
```

Fig. 14. Results of changing to 128 threads

```
- 🗆
pq52689@search7edu2:~/testescuda
      VERAGE PRESSURE (Pa):
                                                                                                                          131001228.4507598877
                                                                                                                           3.4244904654
      OTAL VOLUME (m^3):
     NUMBER OF PARTICLES (unitless):
20584== Profiling result:
Type Time(%) Time
70 activities: 76.3d% 7.983875
7, double*, double*, int)
23.40% 2.446925
Le*, int, double)
                                                                                                                  Calls Avg Min Max Name
202 39.520ms 39.435ms 39.603ms computeAccelerations(double*, double*, do
                                                                                                                    2217 8.8860us 7.9680us 17.376us [CUDA memcpy Htt0]
807 6.5620us 6.6480us 7.5520us [CUDA memcpy DttH]
201 20.4650us 19.584us 21.480us Potential_Reducc(double*, double*, int)
3024 3.4771ms 16.739us 39.753ms cudaMemcpy
217 122.42us 2.5920us 216.59ms cudaMemcpy
217 21.115us 2.5490us 154.29us cudaFree
604 12.694us 6.8795us 87.485us cudaLounchKernel
1 570.57us 570.57us 570.57us cudeviceTotalPme
1 13.6278us 390ms 142.18us cudeviceCettAtTribute
1 219.97us 219.37us 219.57us 219.50us cudeviceCettAtTribute
1 14.886us 41.886us 41.886us cudeviceCettCtBusId
```

Fig. 15. Results of changing to 512threads

```
AVERAGE TEMPERATURE (K):
                                                                                                                                                            131.4550641503
PERCENT ERROR of pV/nT AND GAS CONSTANT: 242.4490490666
NUMBER OF PARTICLES (unitless):

orfiling application: //bin/stencil

20660= Profiling result:

Type Time(%) Time

GPU activities: 79.70% 9.7324ds

", double", double", int)

20.07% 2.45087s

le", int, double) 9.15% 17.908ms
                                                                                                                                              Calls Avg Min Max Name
202 48.180ms 48.084ms 48.266ms computeAccelerations(double*, double*, double*,
                                                                                                                                                    201 12.193ms 12.075ms 12.254ms Potential_Map(double*, double*, double*,
                                                                                                                                                2217 8.0790us 7 9.580us 17.760us [CUDA memcpy Hcol]
807 6.7030us 6.0490us 7.8730us [CUDA memcpy Hcol]
201 21.391us 20.060us 22.720us Potential_Reduce_dos
202 1.395us 20.890us 23.6.240us 0.290us
2217 130.70us 2.8090us 236.240us 0.290us
2217 130.70us 2.8090us 236.240us 134.32us cudeMemcpy
2217 130.70us 2.5430us 154.32us cudememcpy
2218 25.270us 7.4290us 78.324us cudelulloc
2218 20.800us 411.20us 411.20us cudecefotalMem
2219 23.80890us 20.79us 124.80us cudeviceGetAteribut
23.379us 23.379us 23.379us cudeviceGetAteribut
24.0390us 457ns 1.6210us cudeviceGetClosme
25.379us 45.379us 26.220us cudeviceGetClosme
26.379us 457ns 1.6210us cudeviceGetClosme
27.389us 457ns 1.6210us cudeviceGetClosme
28.380us 280us 26.220us cudeviceGetClosme
29.39us 457ns 1.6210us cudeviceGetClosme
21.780us 798ns 798ns cudeviceGetCluid
```

Fig. 16. Results of changing to 1024 threads

```
seconds.

self total
calls ms/call ms/call name
Potential()
101 145.46 145.46 computeAccelerations()
VelocityWerlet(double, int, _IO_FILE*)
```

Fig. 17. gprof for sequential version