Computer Architecture Lab Three

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1 Introduction

This report contains code—and rigorous analysis of said code—written using normal C++ and using the Cuda framework in an effort to build a solid understanding on the differences between vector processors and ordinary processors. A program that calculates the matrix equation shown in 1 is run on both at different matrix sizes. Additionally, profiling has been used to observe each function's timing to know what kind of operation consumes time in each version of the program. All code, profiling output files, and screenshots can be found in the project's Github repository.

$$R = C(A \times B + B \times A) \tag{1}$$

2 Prerequisites

This section contains the host system specifications used to run the two versions of the code, as well as a quick summary of the steps I followed in order to get my setup ready to compile Cuda code.

2.1 Host System Specifications

My setup is as shown in figure 1.

```
| New | New
```

Figure 1: Host System Specifications

The GPU used is a GTX980ti: a flagship GPU released in 2015. The specifications relevant to this report are:

- Streaming Multiprocessor Count (SMC): 22 (each clocked at 1216MHz)
- CUDA Core Count (CCC): 2816 (SMC \times 128)
- Cache: 48 KB (L1 per SM) & 3 MB (L2)
- Memory: 6GB of DDR5 (clocked at 1800 MHz)
- Memory Bus: 384 bit
- Memory Bandwidth: 345.6 GB/s

Understanding the GPU specifications is crucial for optimizing the block size and number of threads passed to the kernel—more on that later.

2.2 Installation Process

The process of installing Cuda was as follows:

1. Install cuda using

sudo pacman -S cuda

2. To make sure it was installed successfully:

- 3. Export Cuda library directory into '.bashrc' as an environment variable.
- 4. Add the following library in the .cu program:

2.3 Compilation Settings

Since this lab's main purpose is to compare CPU and GPU performance in executing the same operation, CPU memory allocation has been avoided when defining the variables holding the matrix and the stack is instead used to make the comparison as fair as possible. Bare in mind that the default stack size would not be able to hold the matrices at large values of N which would result in a segmentation fault; so, the following command was used to extend the stack size—which is not a best practice but it is purely for testing purposes:

When compiling the C++ version, I used gprof as a profiling tool to get a good estimate for how long does each function take to execute. So, the C++ code is compiled as follows:

The program then have to at least be run once in order to extract timing information using the following command:

When compiling the Cuda version, nvcc is used as the compiler and, luckily, Nvidia's provided nvprof tool grants way more accurate timing information even without extra flags. To compile, simply run:

To analyse using nvprof, run:

In the previous command, the shell command 'time' is used to give me the program's total runtime.

3 CPU Version of The Program

In this section, the CPU version of the program will be explained function-by-function. Additionally, runtime and profiling information will observed at different values of N. Note that gprof is a bit inaccurate since its lowest time unit is 0.01s; ergo, at low values of N, information gathered by gprof will not be provided.

3.1 Program Code

The program simply generates 3 square matrices—as well as 2 empty matrices: one as a temporary variable and one to store the final result—of size NxN and populates them with random numbers between 0 and 49. The generated matrices, as well as the matrix resulting from the operation are all written in comma separated (csv) files for debugging purposes.

```
#include <iostream>
#include <cstdlib>
#include <ctime>
#include <fstream>

using namespace std;

#define N 5000 // matrix row/col
```

Code Snippet 1: Included Libraries & Macro

```
void populateMatrix(unsigned int (&matrix)[N][N])
1
2
       for (int i = 0; i < N; i++)
3
4
           for (int j = 0; j < N; j++)
5
6
                matrix[i][j] = rand() % 50; // Generate random numbers
7
                   between 0 and 49 (inclusive)
           }
8
9
       }
10
```

Code Snippet 2: Function to Populate Matrices with Random Values

```
void printMatrix(const unsigned int (&matrix)[N][N])
1
2
        for (int i = 0; i < N; i++)
3
4
            for (int j = 0; j < N; j++)
5
6
                 cout << matrix[i][j] << "\t";</pre>
7
8
            cout << endl;</pre>
9
        }
10
11
```

Code Snippet 3: Function to Print Matrix (For Testing Only)

```
void addMatrix(const unsigned int (&matrixA)[N][N], const unsigned int
1
      (&matrixB)[N][N], unsigned int (&matrixC)[N][N])
2
   {
       for (int i = 0; i < N; i++)
3
4
           for (int j = 0; j < N; j++)
5
6
                matrixC[i][j] = matrixA[i][j] + matrixB[i][j];
7
8
           }
9
       }
10
   }
```

Code Snippet 4: Function to Add Two Matrices

```
void multMatrix(const unsigned int (&matrixA)[N][N], const unsigned int
1
      (&matrixB)[N][N], unsigned int (&matrixC)[N][N])
2
       for (int i = 0; i < N; i++)
3
4
5
           for (int j = 0; j < N; j++)
6
                matrixC[i][j] = 0;
7
                for (int k = 0; k < N; k++)
8
9
10
                    matrixC[i][j] += matrixA[i][k] * matrixB[k][j];
11
           }
12
13
       }
14
```

Code Snippet 5: unction to Multiply Two Matrices

```
void csvMatrix(const unsigned int (&matrix)[N][N], const char *filename)
2
3
       std::ofstream file(filename);
       for (int i = 0; i < N; i++)
4
5
       {
            for (int j = 0; j < N; j++)
6
7
                file << matrix[i][j];</pre>
8
9
                if (j < N - 1)
10
                     file << ",";
11
12
13
            file << "\n";
14
15
       file.close();
16
```

Code Snippet 6: Write Matrix in CSV File

```
int main()
1
2
       // random number generation shenanigans
3
       srand(time(NULL));
4
5
       // define matrices
6
       unsigned int matA[N][N];
7
       unsigned int matB[N][N];
8
       unsigned int matC[N][N];
9
       unsigned int matRes[N][N];
10
       unsigned int matTemp[N][N];
11
12
       // populate matrix A && B
13
14
       populateMatrix(matA);
       populateMatrix(matB);
15
       populateMatrix(matC);
16
17
       // output matrix A && B as csv files for references
18
       csvMatrix(matA, "MatrixA.csv");
19
       csvMatrix(matB, "MatrixB.csv");
20
       csvMatrix(matC, "MatrixC.csv");
21
22
       // C * ((A * B) + (B * A))
23
       multMatrix(matA, matB, matRes); // A * B = res
24
25
       multMatrix(matB, matA, matTemp); // B * A = temp
26
27
       addMatrix(matRes, matTemp, matTemp); // res + temp = temp
28
29
       multMatrix(matC, matTemp, matRes); // C * temp = res
30
31
       // output matrix C result for reference
32
       csvMatrix(matRes, "Result.csv");
33
34
       return 0;
35
36
```

Code Snippet 7: Main Function Implementation

3.2 Runtime & Profiling Results

In this section, runtime and profiling information will be observed for 6 values of N: 50, 100, 500, 1000, 2000, and 5000.

Figure 2: Runtime at N = 50

Figure 3: Runtime at N = 100

Figure 4: Runtime at N = 500

```
Each sample counts as 0.01 seconds.

% cumulative self self total

time seconds seconds calls ms/call ms/call name

97.95 1.10 1.10 3 365.70 365.70 multMatrix(unsi
0.89 1.11 0.01 1 10.02 10.02 addMatrix(unsig
0.00 1.11 0.00 4 0.00 0.00 csvMatrix(unsig
0.00 1.11 0.00 3 0.00 0.00 populateMatrix(
```

Figure 5: Function Timing at N = 500 (gprof)

Figure 6: Runtime at N = 1000

Each sa	mple count	s as 0.01	seconds.			
% C	umulative	self		self	total	
time	seconds	seconds	calls	s/call	s/call	name
98.45	9.08	9.08		3.03	3.03	multMatrix(unsi
0.11	9.09	0.01	4	0.00	0.00	csvMatrix(unsig
0.11	9.10	0.01		0.01	0.01	addMatrix(unsig
0.00	9.10	0.00		0.00	0.00	populateMatrix(

Figure 7: Function Timing at N = 1000 (gprof)

```
ComputerArchitecture_Playground/Lab_3 on main
) time ./nocuda

real 1m29.660s
user 1m29.257s
sys 0m0.175s
```

Figure 8: Runtime at N = 2000

```
Each sample counts as 0.01 seconds.

% cumulative self self total

time seconds seconds calls s/call s/call name

99.30 87.95 87.95 3 29.32 29.32 multMatrix(unsi-
0.03 87.98 0.03 4 0.01 0.01 csvMatrix(unsignos)

0.02 88.00 0.02 3 0.01 0.01 populateMatrix(
0.01 88.01 0.01 1 0.01 0.01 addMatrix(unsignos)
```

Figure 9: Function Timing at N = 2000 (gprof)

```
ComputerArchitecture_Playground/Lab_3 on main
) time ./nocuda

real    35m43.403s
user    35m39.282s
sys    0m0.613s
```

Figure 10: Runtime at N = 5000

```
Each sample counts as 0.01 seconds.

* cumulative self self total

time seconds seconds calls s/call s/call name

99.46 1470.95 1470.95 3 490.32 490.32 multMatrix(unsign o.01 1471.12 0.17 4 0.04 0.04 csvMatrix(unsign o.01 1471.26 0.14 3 0.05 0.05 populateMatrix(unsign o.00 1471.32 0.06 1 0.06 0.06 addMatrix(unsign o.00 1471.35 0.03 __init
```

Figure 11: Function Timing at N = 5000 (gprof)

3.3 Observation

At low values of N, the CPU code is blazing fast and outperforms the GPU in everything. But, once N crosses the 500 mark, the performance shifts in favour of GPU because the multMatrix function simply takes too long to execute. Additionally, the time taken at values of N higher than 2000 is immense. Figure 12 shows the exponential growth that happens at very high values of N^1 .

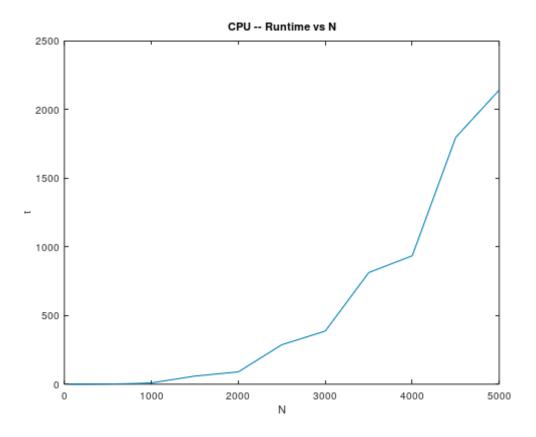


Figure 12: CPU – Runtime vs N

 $^{^{1}}$ Graph was plotted using Matlab at N = 50, 100, 250, 500, 750, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, 5000.

4 GPU Version of The Program

In this section, the GPU version of the program will be explained function-by-function. Additionally, runtime and profiling information will observed at different values of N.

4.1 Program Code

The program is mostly the same in many areas to its CPU counterpart—same csvMatrix and populateMatrix. But, the main difference is in how the GPU handles addition and multiplication, which will be explained later.

```
#include <cuda_runtime.h>
```

Code Snippet 8: Included Cuda Library

An addition to the code is determining the operation used based on 'enums' defined to ease code readability and simplify the used logic.

```
// available matrix operations
typedef enum
{
    ADD = 1,
    MUL = 2
} matOp;
```

Code Snippet 9: Defined Operations as Enums

The main change in the main function implementation is an entirely rewritten function to perform either addition of multiplication based on the passed enum operation. This function contains all the preparations for the GPU kernel functions for addition and multiplication.

Code Snippet 10: Main Function Implementation

The CUDA wrapper function takes two 2D arrays, one 2D array to store the result, and an enum that tells the function which operation to execute.

```
void matrixOperationCudaWrapper(const unsigned int (&h_matrixA)[N][N],
    const unsigned int (&h_matrixB)[N][N], unsigned int
    (&h_matrixRes)[N][N], unsigned char operation)
```

Code Snippet 11: Matrix Operation Wrapper Function

The first thing this function does is to define pointers that will be used to store memory addresses.

```
// create pointers to gpu
unsigned int* d_cudaA = 0;
unsigned int* d_cudaB = 0;
unsigned int* d_cudaRes = 0;
```

Code Snippet 12: Pointers to GPU Memory

```
// defining size
size_t sizeInBytes = N * N * sizeof(unsigned int);
```

Code Snippet 13: Required GPU Memory Size

There are two ways to allocate GPU memory using CUDA: cudaMalloc and cudaMallocManaged. cudaMalloc was ultimately chosen because it was easier to understand its syntax and the benefits cudaMallocManaged brought was too advanced to understand.

```
// allocate memory in gpu
cudaMalloc((void**)(&d_cudaA), sizeInBytes);
cudaMalloc((void**)(&d_cudaB), sizeInBytes);
cudaMalloc((void**)(&d_cudaRes), sizeInBytes);
```

Code Snippet 14: GPU Memory Allocation

Here, the passed matrices to the function are copied to the allocated GPU memory. This copying process represents a huge overhead in the program and can be optimized by using cudaMallocManaged which eliminates the need to use cudaMemory completely.

```
// copy vectors into gpu
cudaMemcpy(d_cudaA, h_matrixA, sizeInBytes, cudaMemcpyHostToDevice);
cudaMemcpy(d_cudaB, h_matrixB, sizeInBytes, cudaMemcpyHostToDevice);
```

Code Snippet 15: Copying Data From CPU Memory to GPU Memory

The number of threads and block size are chosen based on the GPU's hardware. Through trial and error, the best performance was achieved at a thread count of 32 and a block size of 128. It is important to keep both numbers a power of two to optimize performance. The type dim3 outputs The vector thread indices (X, Y, Z) suitable for the defined block size and thread count; this will be used in the kernel function.

```
// defining threads and block size
int threads = 32;
int blocks = 128;

// setting up kernel launch parameters
dim3 BLOCKS(blocks, blocks);
dim3 THREADS(threads, threads);
```

Code Snippet 16: Choosing Number of Threads and Block Size

Depending on the chosen operation, the corresponding kernel is launched by this obscurely complex syntax.

```
// launch kernel for chosen operation
1
2
       if (operation == ADD)
3
           matrixAddCUDA<<<BLOCKS, THREADS>>>(d_cudaA, d_cudaB, d_cudaRes);
       else if (operation == MUL)
4
           matrixMulCUDA<<<BLOCKS, THREADS>>>(d_cudaA, d_cudaB, d_cudaRes);
5
       else
6
7
       {
8
           cout << "chotto matte!" << endl;</pre>
9
           return; // do not continue this mess!
       }
10
```

Code Snippet 17: Launching Appropriate Kernel Based on Passed Operation

The kernel function for addition is fairly simple. The vector thread indices will be used to index the memory locations to perform summation. The tricky part is to index a 2D array correctly using 1D array indexing. It is important to make sure that a thread operates within the array bounds.

```
global__ void matrixAddCUDA(unsigned int* matrixA, unsigned int*
      matrixB, unsigned int* matrixRes)
2
       // Compute each thread's global row and column index
3
       int rowIndex = blockIdx.y * blockDim.y + threadIdx.y;
4
       int colIndex = blockIdx.x * blockDim.x + threadIdx.x;
5
6
       if (rowIndex < N && colIndex < N)</pre>
7
8
       {
9
           // simply add
           matrixRes[rowIndex * N + colIndex] = matrixA[rowIndex * N +
10
               colIndex] + matrixB[rowIndex * N + colIndex];
       }
11
12
```

Code Snippet 18: Matrix Addition CUDA Kernel Function

The kernel function for multiplication is a bit more complex. Like the previous function, it uses the vector thread indices to correctly index the arrays and perform a boundary check before executing any operation. It is important to initialize the result's element to 0 before accumulating the results of multiplying A and B.

```
global__ void matrixMulCUDA(unsigned int* matrixA, unsigned int*
      matrixB, unsigned int* matrixRes)
2
   {
       // Compute each thread's global row and column index
3
       int rowIndex = blockIdx.y * blockDim.y + threadIdx.y;
4
       int colIndex = blockIdx.x * blockDim.x + threadIdx.x;
5
6
       // Iterate over row, and down column
7
       if (rowIndex < N && colIndex < N)</pre>
8
9
           matrixRes[rowIndex * N + colIndex] = 0;
10
           for (int k = 0; k < N; k++)
11
12
13
               // Accumulate results for a single element
               matrixRes[rowIndex * N + colIndex] += matrixA[rowIndex * N +
14
                   k] * matrixB[k * N + colIndex];
15
           }
       }
16
17
```

Code Snippet 19: Matrix Multiplication CUDA Kernel Function

After the operation is done, the results are copied from GPU memory to CPU memory.

```
// copy result from gpu memory
cudaMemcpy(h_matrixRes, d_cudaRes, sizeInBytes,
cudaMemcpyDeviceToHost);
```

Code Snippet 20: Copying Data From GPU Memory to CPU Memory

Finally, free all the allocated GPU memory to avoid any memory leaks.

```
// free allocated gpu memory
cudaFree(d_cudaA);
cudaFree(d_cudaB);
cudaFree(d_cudaRes);
```

Code Snippet 21: Free Allocated GPU Memory

4.2 Runtime & Profiling Results

In this section, runtime and profiling information will be observed for 6 values of N at two thread counts (16 and 32): 50, 100, 500, 1000, 2000, and 5000.

Figure 13: Program Timing Information at N = 50 (Thread Count of 16)

Figure 14: Program Timing Information at N = 100 (Thread Count of 16)

Figure 15: Program Timing Information at N = 500 (Thread Count of 16)

Figure 16: Program Timing Information at N = 1000 (Thread Count of 16)

Figure 17: Program Timing Information at N = 2000 (Thread Count of 16)

Figure 18: Program Timing Information at N = 5000 (Thread Count of 16)

Figure 19: Program Timing Information at N = 50 (Thread Count of 32)

Figure 20: Program Timing Information at N = 100 (Thread Count of 32)

Figure 21: Program Timing Information at N = 500 (Thread Count of 32)

Figure 22: Program Timing Information at N = 1000 (Thread Count of 32)

Figure 23: Program Timing Information at N = 2000 (Thread Count of 32)

```
ComputerArchitecture_Playground/Lab_3 on main [#19]
) time nyprof ./cuda
==20774== NVPROF is profiling process 20774, command: ./cuda
==20774== Profiling application: ./cuda
==20784== Profiling application:
```

Figure 24: Program Timing Information at N = 5000 (Thread Count of 32)

4.3 Observation

At low values of N, the GPU code is ridiculously slow: the amount of time taken to copy data between GPU and CPU memory outweighs any gains in execution time of actual operations. Once N passes the 500 mark, actual gains start to appear. At values of N higher than 2000, the performance difference is staggering and the memory overhead is out shined by the speedup obtained in the multiplication operation. Figures 25 and 26 show the runtime at different values of N^2 at thread count 16 and 32 respectively. It is noticed that the slope of the second graph is more forgiving and that the runtime is considerably lower at the higher thread count.

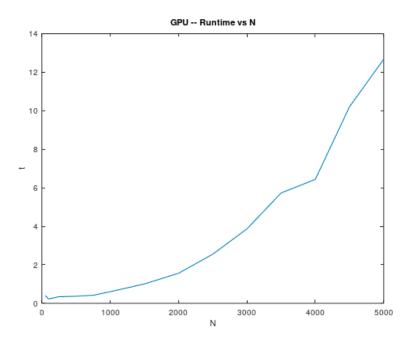


Figure 25: GPU – Runtime vs N (Thread Count of 16)

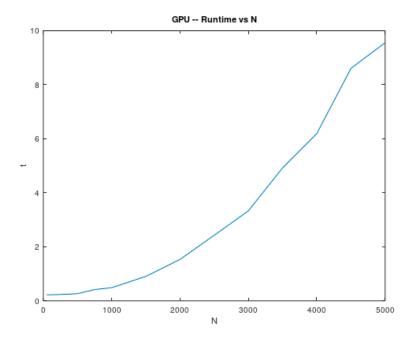


Figure 26: GPU – Runtime vs N (Thread Count of 32)

²Graph One and graph two were plotted using Matlab at N = 50, 100, 250, 500, 750, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, 5000.