STRING ALGORITHM ON GPGPU

by

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Dedication

This thesis is dedicated to
my beloved parents,
family
and friends.

Acknowledgements

I would like to express my gratitude towards various people whom during this several months of my final year project, had provided me with great assistance. Without their help and support, this project would not have been completed on time.

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Abstract

Since the last decade, the concept of general purpose computing on graphics processors was introduced and has since garnered significant adaptation in the engineering industry. The use of a Graphics Processing Unit (GPU) as a many-core processing architecture for the purpose of general-purpose computation yields performance improvement of several orders-of magnitude. One example in leveraging a GPU for improved computational performance is the parallelization of string searching algorithms.

The string search algorithm is often required to be performed on large datasets. However, string algorithms are commonly optimised to be performed using a Central Processing Unit (CPU) and risks high levels of computational bottlenecks. As such, this dissertation first identifies these bottlenecks by analysing the design and implementation of a serial Bloom Filter algorithm. Based on the analysed results, a parallel Bloom Filter algorithm is proposed, which utilizes software threads (i.e., OpenMP) on a multi-core processor for data parallelism. Experimental results suggest that a multi-core driven (i.e., Using 8 logical processors) parallel Bloom Filter algorithm exhibits performance speed up of up to 3.3x for a set of 10 million strings.

The design and implementation of the parallel Bloom Filter algorithm is then extended into a GPU processor using the Compute Unified Device Architecture (CUDA) parallel computing platform. The proposed parallel Bloom Filter algorithm on CUDA segments the string list into blocks of words and threads in generating the bit table, which is used during the string matching process. This method maximizes the computational performance and sustains consistent string matching results. Experimental results suggest that a GPU driven (i.e., Using 256 CUDA cores) parallel Bloom Filter algorithm further extends the performance speed up to 5.5x for a set of 10 million strings.

In addition, this dissertation also analyses the searching drawback of a Bloom Filter algorithm in locating matching string positions. As such, an alternative parallel Quick Search string algorithm is designed, implemented and assessed in an effort to address this drawback.

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List of Abbreviations

1D	1-dimensional
2D	2-dimensional
3D	3-dimensional
ALU	Arithmetic logic unit
AP	Arash Partow
API	Application programming interface
CPU	Central processing unit
CUDA	Compute Unified Device Architecture
DRAM	Dynamic random-access memory
GDDR	Graphics Double Data Rate
GUI	Graphical user interface
GPGPU	General-purpose computing on Graphics Processing Unit
GPU	Graphics processing unit
IEEE	Institute of Electrical and Electronics Engineering
LFSR	Linear feedback shift register
NCAR	National Center for Atmospheric Research
OpenGL	Open Graphics Library
OpenMP	Open Multiprocessing
PDC	Parallel data cache
SM	Streaming multiprocessor
SMT	Simultaneous multithreading
SP	Streaming processors
WRF	Weather Research and Forecasting model

List of Mathematical Symbols

fpp	false positive probability
k	number of hash functions
m	size of bit array
n	number of elements
O($log\ n$)	logarithmic time complexity
O(n)	linear time complexity
t_s	time taken for a Bloom Filter in serial implementation
t_p	time taken for a Bloom Filter in OpenMP implementation
t_c	time taken for a Bloom Filter in CUDA implementation
$\mathbb{i}$	set of words in the word list
$\mathbb{O}$	set of resultant hash operations
$\emptyset$	empty set

CHAPTER 1: INTRODUCTION

1.1 Preamble

General-purpose computing on a Graphics Processing Unit (GPGPU) is the utilization of a Graphics Processing Unit (GPU) to handle computation in applications which are traditionally performed by the Central Processing Unit (CPU). It involves using a GPU along with a CPU with the aim of accelerating general-purpose scientific and engineering applications. The multicore architecture of a CPU encourages thread-level parallelism and data-level parallelism whereas a GPU contains hundreds of smaller cores with high efficiency and are designed for parallel performance. Hence, computation-intensive portions of the application which can be done in parallel are handled by the GPU while the remaining serial portion of the code by the CPU. This leads to applications which run considerably faster.

This project focuses on using GPGPU to develop a string manipulating algorithm. It is also compared with serial implementation as well as data-level parallel implementation on a CPU to verify its advantage over a CPU-only implementation.

1.2 Current Trend

Computing technology began with a single core processor, where only one operation could be performed at a time. Instruction pipelining was then introduced such that the processor's cycle time is reduced and throughput of instructions is increased [1]. Starting from 2005, CPU manufacturers have begun offering processors with more than one core. In recent years, 3-, 4-, 6- and 8-core CPU have been developed. Leading CPU manufacturers have also announced plans for CPUs with even more cores. The most recent development is the introduction of a new coprocessor, Intel

Xeon Phi, which has 60 cores and can be programmed like the conventional x86 processor core [2]. Continuous development on increasing CPU cores has proven that parallel computing is the current trend.

The first GPU served to support line drawing and area filling. Blitter, a type of stream processor, accelerates the movement, manipulation and combination of multiple arbitrary bitmaps [3]. The GPU was also equipped with a coprocessor which has its own instruction set, hence allowing graphics operations to be invoked without CPU intervention. In 1990s, GPU began supporting 2-dimensional (2D) graphical user interface (GUI) acceleration. Various application programming interfaces (APIs) were also created. By the mid-1990s, GPUs had begun supporting 3-dimensional (3D) graphics. NVIDIA became the first GPU company to produce a chip which could be programmed for shading, allowing each pixel and each geometric vertex to be processed by a program before being projected onto the screen. Continuous development in early 2000s led to the ability of pixel and vertex shaders to implement looping and lengthy floating point math [4]. The flexibility of GPUs had become increasingly comparable to that of CPUs. In recent years, GPUs have been equipped with generic stream processing units, allowing them to evolve into more generalized computing devices. The GPGPU has since been applied in applications which require high arithmetic throughput, and have shown better performance than conventional CPU.

1.3 Problem Statement

In the case of string search, large datasets may be processed using computer clusters. A computer cluster consists of several loosely connected computers which work together. However, using computer clusters for processing large string datasets proves to be costly. Hence, an alternative option is needed such that the processing of large string datasets can be efficient yet cost effective.

The rise of GPU computing is a good solution as an alternative option. Due to the high arithmetic throughput of GPUs, applications running on them will be less computationally expensive aside from being more cost effective as compared to traditional central processing technologies.

1.4 Motivation and Proposed Solution

This project is motivated by the need to increase the efficiency in processing large datasets, specifically strings. In recent years, the computing industry has been concentrating on parallel computing. With the introduction of NVIDIA's Compute Unified Device Architecture (CUDA) for GPUs in 2006, GPUs which excel at computation are created [5]. A GPU offers high performance throughput with little overhead between the threads. By performing uniform operations on independent data, massive data parallelism in application can be achieved. This provides an opportunity for data processing to be completed in less time. In addition, GPU requires lower cost and consumes less power compared to computers having similar performance. It is also available in almost every computer nowadays.

1.5 Objectives

a. Identify the computational bottleneck of a serial Bloom Filter implementation
b. Design and develop Bloom Filter string search algorithm based on data parallelism on a multicore processor architecture using Open Multiprocessing (OpenMP)
c. Extend the data parallelism design of the Bloom Filter string search algorithm to a many-core architecture using the CUDA parallel computing platform
d. Identify the searching limitation of the Bloom Filter algorithm
e. Propose and implement a Quick Search algorithm based on data parallelism both on a multicore and a many-core architecture

1.6 Report Structure

The report for this project consists of:

Chapter 2 presents background information on the different searching algorithms, namely Linear Sequential Search, Binary Search and Hash Tables. The chosen algorithm, Bloom Filter, is also discussed in this chapter. Background information on OpenMP and CUDA are provided in this chapter as well.

In **Chapter 3**, the detailed design of the project for a serial CPU implementation of the Bloom Filter algorithm is explained. The computational load of the algorithm is identified.

Chapter 4 proposes a parallel CPU implementation of the algorithm based on the serial version designed in Chapter 3. The difference in performance between the serial CPU and parallel CPU implementations is discussed as well.

In **Chapter 5**, the combined CPU and GPU implementation is proposed to further improve the time efficiency of the algorithm. Performance comparison is made between the serial CPU version and the CUDA version.

Chapter 6 proposes the deduction obtained from comparing the OpenMP implementation with the CUDA implementation. A performance analysis is also made between CUDA implementation on different graphic cards.

Chapter 7 suggests another string algorithm, Quick Search algorithm, to address the limitation of a Bloom Filter in location identification.

Lastly, **Chapter 8** provides a summary of the project and concludes the thesis. A recommendation section is included for future researches and designs.

CHAPTER 2: LITERATURE REVIEW

This chapter introduces several types of search algorithms. The description of the chosen string search algorithm for this project is also included. Information regarding OpenMP, CUDA, and CUDA C constitute parts of this chapter as well. Applications of CUDA and existing CUDA string algorithms are given before this chapter is concluded.

2.1 Search Algorithm

A search algorithm is used to find an element with specified properties among a collection of elements. Computers systems usually store large amount of data from which individual records are to be retrieved or located based on a certain search criterion. It may also be used to solely check for the existence of the desired element.

2.2 Linear Sequential Search

Linear search algorithm represents one of the earliest and rudimentary search algorithms. In this algorithm, the search starts from the beginning and walks till the end of the array, checking each element of the array for a match. If the match is found, the search stops. Else, the search will continue until a match is found or until the end of the array is reached [6]. Figure 2.1 illustrates this algorithm.

Apart from using arrays, this algorithm can be implemented using linked lists. The "next" pointer will point to the next element in the list. The algorithm follows this pointer until the query is found, or until a NULL pointer is found thus indicating that the query is not in the list. The advantage of linked list over array is that the former allows easy addition of entries and removal of existing entries.

This algorithm is useful when the datasets are limited in size as it is a straightforward algorithm. It also proves to be useful when the data to be searched is regularly changing. The weakness of this algorithm is that it consumes too much time when the dataset increases in size. This is because it is an O(*n*) algorithm [7].

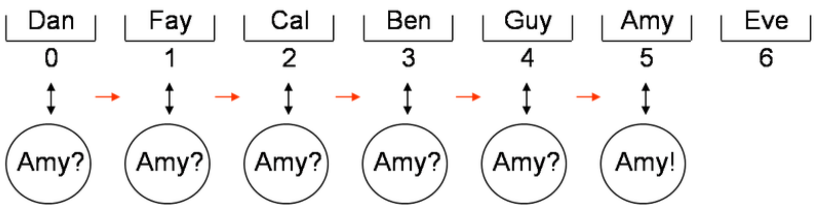


Figure 2.1: Linear Sequential Search for "Amy".

2.3 Binary Search

Searching a sorted dataset is a common task. When the data is already sorted, utilizing the binary search algorithm would be a wise choice. To begin, the position of the middle element is first calculated. A comparison is made between this element and the query. If the query is found to be smaller in value, the search will be continued on elements from the beginning until the middle. Else, the search will proceed onto elements after the middle until the end. The time complexity for binary search is O(*log n*) [8]. An example of binary search is given in Figure 2.2.

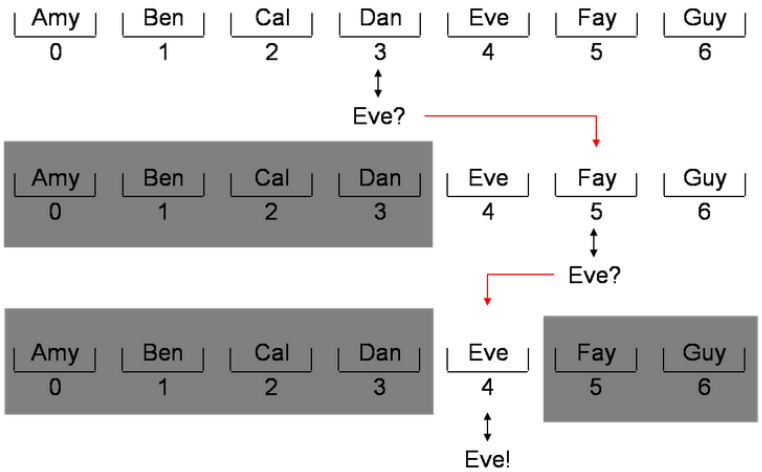


Figure 2.2: Binary Search for Eve.

In the case whereby the data is not sorted yet, a binary search tree would come in handy. A binary search tree is either empty or a key that fulfils 2 conditions can be found in each of its nodes [9]. The conditions are: the left child of a node contains a key that is less than the key in its parents, while the right child of a node contains a key that is more than the key in its parents. To search for an element in the binary search tree, the data at the root node is first inspected if it matches the query. If it doesn't match, the branches of the tree will be searched recursively. If it is smaller, then a recursive search is done on the left subtree. If it is greater, then the right subtree is searched. If the tree is null, it indicates that the query isn't found. If the data is already sorted and if the characters are entered in order, then the binary tree will become unbalanced and it degenerates into a linked list. This leads to the algorithm being inefficient. To avoid this problem, an efficient algorithm is needed to balance the binary search tree.

2.4 Hash Tables

A hash table is used to implement an associative array, a structure that maps keys to values. A hash function is used to convert the keys into numbers that are small enough to be practical for a table size [10]. To build a simple hash table, the key (database) is sent to the hash function. The value returned from the hash function then becomes the hash table index for storing the index of the key in the database. To search for a query, the query is sent to the hash function to obtain the hash table index. The element stored at that index will give the location of the key in the database. The information required from the database entry can then be retrieved as shown in Figure 2.3. A collision will occur when more than one key produce the same index after the hash function is performed. Collisions can be resolved by replacement, open addressing or chaining [11].

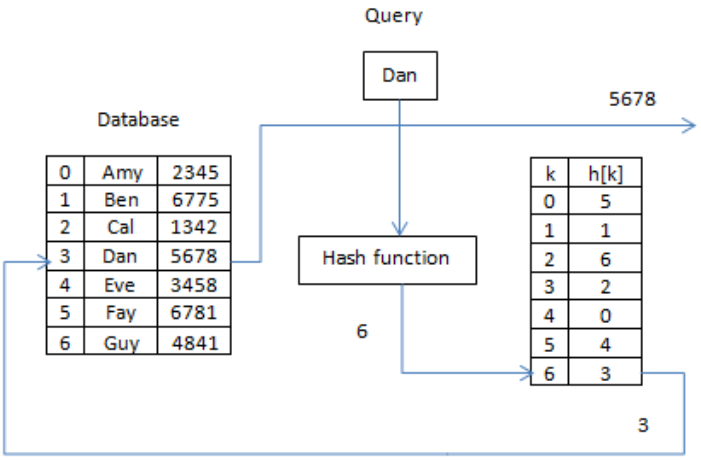


Figure 2.3: Using Hash Table to search for Dan's data.

Hash table proves to be a good choice when the keys are sparsely distributed. It is also chosen when the primary concern is the speed of access to the data. However, sufficient memory is needed to store the hash table. This will lead to limitations in the datasets as a larger hash table will be needed to cater for a larger dataset.

2.5 Bloom Filter

Bloom Filter was introduced in 1970, by Burton Howard Bloom [12]. It is a memory-efficient data structure which rapidly indicates whether an element is present in a set. A false positive indicates that a given condition is present when it is not while a false negative indicates an absence when it is actually present. In the case of Bloom Filter, false positives are possible, but not false negatives. Addition of elements to the set is possible, but not removal. Adding more elements to the set increases the probability of false positives, if the filter size is fixed.

2.5.1 Algorithm Description

A Bloom Filter is implemented as an array of *m* bits, all set to 0 initially. *k* different hash functions are defined; each will map or hash the set elements to one of the *m*

array positions [13]. The hash functions must give uniform random distributed results, such that the array can be filled up uniformly and randomly [14].

Bloom Filter supports two basic operations, which are *add* and *query*. To add (or i.e., insert) an element into the filter, the element is passed to each of the *k* hash functions and *k* indices of the Bloom Filter array are generated. The corresponding bits in the array are then set to 1. To check for the presence of an element in the set, in other words query for it, the element is passed to each of the hash functions to get indices of the array. If any of the bits at these array positions is found to be 0, then the element is confirmed not in the set. If all of the bits at these positions are set to 1, then either the element is indeed present in the set, or the bits have been set to 1 by chance when other elements are inserted hence causing false positive [15].

It is impossible to remove of an element from the Bloom Filter [16]. This is because if the corresponding bits of the element to be removed are reset to 0, there is no guarantee that those bits do not carry information for other elements. If one of those bits is reset, another element which happens to be encoded to the same bit will then give a negative result when it is queried, hence the term false negative. Therefore, the only way to remove the element from the Bloom Filter would be to reconstruct the filter itself sans the unwanted element. By reconstructing the filter, false negative will be eliminated.

2.5.2 False Positive Probability

As stated in Section 2.5, false positive occurs when a result indicates that a condition has been fulfilled although in reality it has not. This subsection describes the mathematical derivation of the false positive probability.

Assuming that the hash functions used are independent and uniformly distributed, the array position will be selected with equal probability.

Let *k* represent the number of hash functions,
m represent the number of bits in the array,

n represent the number of inserted elements, and

fpp represent the probability of false positive.

The probability that a certain bit is set to 1 by one of the hash functions during element insertion is $\frac{1}{m}$ [12]

Probability of a bit not set to 1 by a certain hash function $= 1 - \frac{1}{m}$ **(2-1)**

Probability of a bit not set to 1 by any of the hash functions $= (1 - \frac{1}{m})^k$ **(2-2)**

Probability of a bit not set to 1 after inserting *n* elements $= (1 - \frac{1}{m})^{kn}$ **(2-3)**

Probability of a bit set to 1 after inserting *n* elements $= 1 - (1 - \frac{1}{m})^{kn}$ **(2-4)**

When a false positive occurs, all the corresponding bits are set to 1; the algorithm erroneously claims that the element is in the set. The probability of all corresponding bits of an element being set to 1 is given as [17]

$$fpp = \left[1 - \left(1 - \frac{1}{m}\right)^{kn}\right]^k \approx (1 - e^{-kn/m})^k \quad \textbf{(2-5)}$$

Based on Equation 2.5,

when *m* decreases: $fpp \approx \lim_{m \to 0} \left(1 - \frac{1}{e^{kn/m}}\right)^k \cong 1$ **(2-6)**

when *n* increases: $fpp \approx \lim_{n \to \infty} \left(1 - \frac{1}{e^{kn/m}}\right)^k \cong 1$ **(2-7)**

Hence, it can be concluded that the probability of false positive increases when *m* decreases or when *n* increases. When the size of a dataset is large, *n* will be a large value. To minimize the false positive probability, *m* would need to be set to a large value (i.e., using a large Bloom Filter). Trade-off between false positive probability and memory space is thus required.

Figure 2.4 shows an empty Bloom Filter (all bits set to 0) with $m = 14$

Figure 2.4: An empty Bloom Filter.

3 hash functions are performed on an element ($k = 3$)

The corresponding bits (bits 2, 10 and 11) in the Bloom Filter are set to 1 (coloured)

Figure 2.5: The Bloom Filter after adding first element.

The hash functions are performed on a second element.

The corresponding bits (bits 0, 7 and 10) are then set to 1.

One of the bit positions (bit 10) is coincidently the same as for the first element.

Figure 2.6: The Bloom Filter after adding second element.

Hash functions are performed on a query (neither same as first nor second element). The bits at position 2, 7 and 11 are checked. Since the bits at these locations are set, the filter will indicate that the query is present in the dataset. However, the query is actually not part of the dataset as it differs from the first and second element. Hence, false positive has occurred.

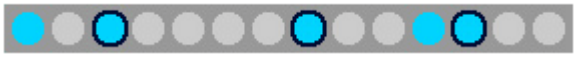


Figure 2.7: False positive in Bloom filter.

2.5.3 Advantages

The Bloom Filter algorithm shows a significant advantage in terms of space saving, as compared to other algorithms involving arrays, linked lists, binary search trees or hash tables. Most of these algorithms store the data items themselves, hence the number of bits required may vary depending on the type of data stored. Additional overhead for pointers is needed when linked list is used. Bloom Filter, on the other hand, requires a fixed number of bits per element regardless of the size of the elements. However, space saving comes at a price. The downside of Bloom Filter is the existence of false positive probability and no removal of elements once they are inserted. Despite so, these constraints are usually acceptable, making Bloom Filter a preferred option when the dataset is large and space is an issue.

A unique property of Bloom Filter is that the time taken to add an element or to check for the existence of an element in the set is a fixed constant, O(*k*) [18]. In other words, it is regardless of the number of elements already inserted in the set. The lookups in the Bloom Filter algorithm are independent of each other and thus can be performed in parallel.

Bloom Filter also proves to come in handy when privacy of data is preferred. In a social peer-to-peer network, Bloom Filter can be used for bandwidth efficient communication of datasets. Network users are able to send sets of content while having their privacy protected. The content may be the interests and/or taste of the peer [19]. Bloom Filter protects the privacy of the data as it does not literally present the content to the other peer. At the same time, the small filter size contributes to a narrow bandwidth requirement.

2.6 Parallel Processing

Parallel processing, also known as parallel computing, involves executing a program using more than one CPU or processor core. The computational speed of a program will increase as more engines are running it. Higher throughput can then be achieved. There are a few types of parallelism, namely bit-level parallelism, instruction-level parallelism, data parallelism and task parallelism [20]. Bit-level parallelism is achieved by increasing the processor word size. Instruction-level parallelism allows a few operations in a computer program to be performed simultaneously. Data parallelism can be achieved when each processor in a multiprocessor system performs the same task on different sets of data. Task parallelism, on the other hand, can be achieved when each processor executes different processes on the same or different data.

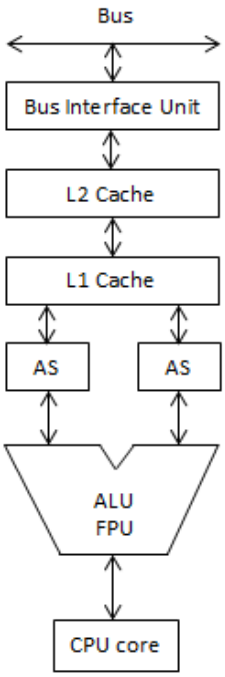


Figure 2.8: Hyperthreading Block Diagram.

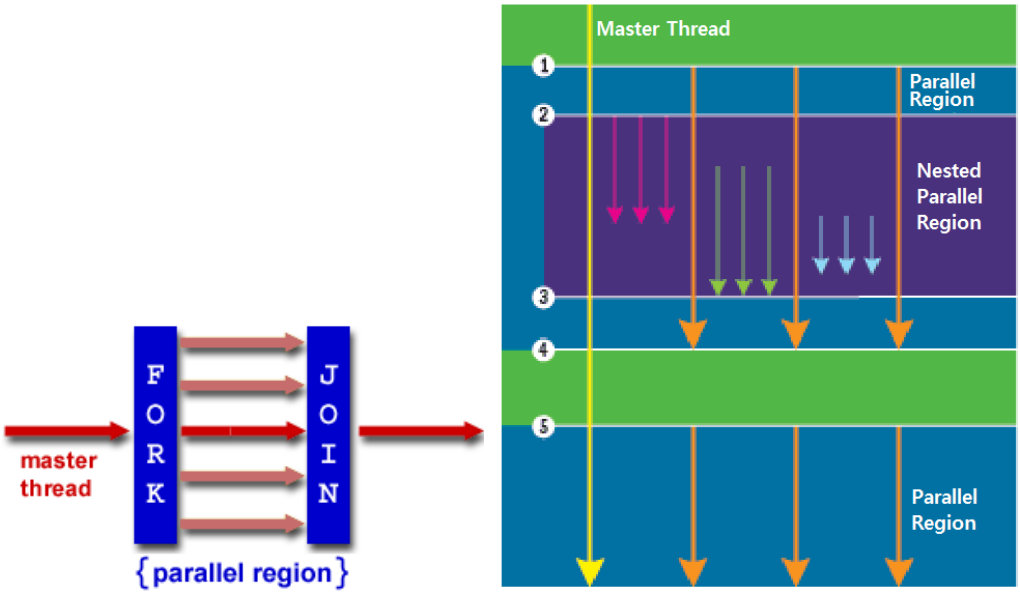
Hyper-threading, as illustrated in Figure 2.8, is Intel's version of simultaneous multithreading (SMT). For each physical processor core, 2 virtual cores are addressed by the operating system [21]. The main execution resources are shared. However, each virtual processor has its own complete set of Architecture State (AS). The operating system will be under the impression of having 2 logical processors; hence 2 threads or processes can be scheduled simultaneously.

2.7 OpenMP

OpenMP is an API that is designed to support multiprocessing programming (in terms of multithreading). It allows creation and synchronization of threads as designed in the program [22]. However, the thread is not seen in the code. **`#pragma`** directives are needed to inform the compiler that a certain part of the code can be parallelised. The way data can be accessed and modified may need to be clarified in the code.

The execution model used by OpenMP is the fork-join model. The program execution begins with a single-thread execution known as master thread [23]. The master thread forks into several threads when a parallel construct is encountered. The threads will execute the parallelized part independently and concurrently, and are allocated to different processors depending on the runtime environment. The threads will then be synchronized at the end of the parallel part and the program execution reverts back to only the master thread. This is illustrated in Figure 2.9(a).

Nested parallel regions are also possible, whereby each thread from the original parallel region forks into a team of threads. As shown in Figure 2.9(b), the master thread (yellow) splits into 4 threads (1 yellow, 3 orange) when the first parallel region is encountered at point 1. In the nested region starting from point 2, 3 out of the 4 threads split into new thread teams. At the end of the nested parallel region at point 3, threads from the same thread teams are synchronized. At point 4, the 4 threads are synchronized and the program continues the execution with only the master thread. Point 5 marks the beginning of another parallel region.



(a) (b)

Figure 2.9: OpenMP execution models [24].

2.8 CUDA

CUDA is a parallel programming paradigm that was released in November 2006 by NVIDIA [25]. Apart from being used to develop software for graphics processing, this architecture alleviates many of the limitations that previously prevented general-purpose computation from being performed legitimately by the graphics processor.

2.8.1 Architecture of a CUDA-capable GPU

Previous generations of GPU partitioned computing resources into vertex and pixel shaders, whereas the CUDA architecture included a unified shader pipeline. This enables every arithmetic logic unit (ALU) on the chip to be marshalled by a program intending to perform general-purpose computations [26]. The ALUs were also built to comply with the Institute of Electrical and Electronics Engineers (IEEE) requirements for single-precision floating-point arithmetic. The instruction set used by the ALUs are those tailored for general computations instead of those specifically for graphics. Apart from having arbitrary read and write access to memory, the execution units on the GPU have access to shared memory, a software-managed cache. The addition of these features allows the GPU to excel at general-purpose computation apart from performing traditional graphical tasks.

Figure 2.10 shows the architecture of a CUDA-capable GPU. The GPU is organized into an array of highly threaded streaming multiprocessors (SMs). 2 SMs form a building block for the GPU in Figure 2.10. However, different generations of CUDA GPUs may have different number of SMs in a building block. Each SM has a number of streaming processors (SPs) that share control logic and instruction cache [27]. The graphics double data rate (GDDR) DRAM, denoted as global memory in Figure 2.10, are different compared to those in a CPU motherboard. For computing applications, they function as very-high-bandwidth, off-chip memory, but with more latency than the typical system memory. If the application is massively parallel, then the higher bandwidth will make up for the longer latency.

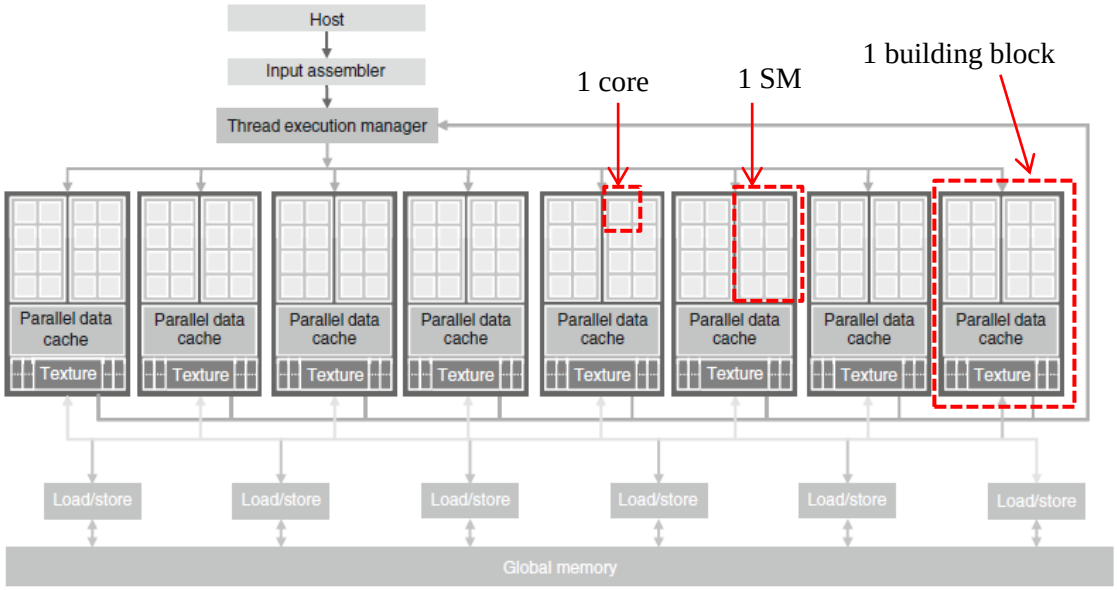


Figure 2.10: Architecture of a CUDA-capable GPU [28].

2.8.2 CUDA Programming Model

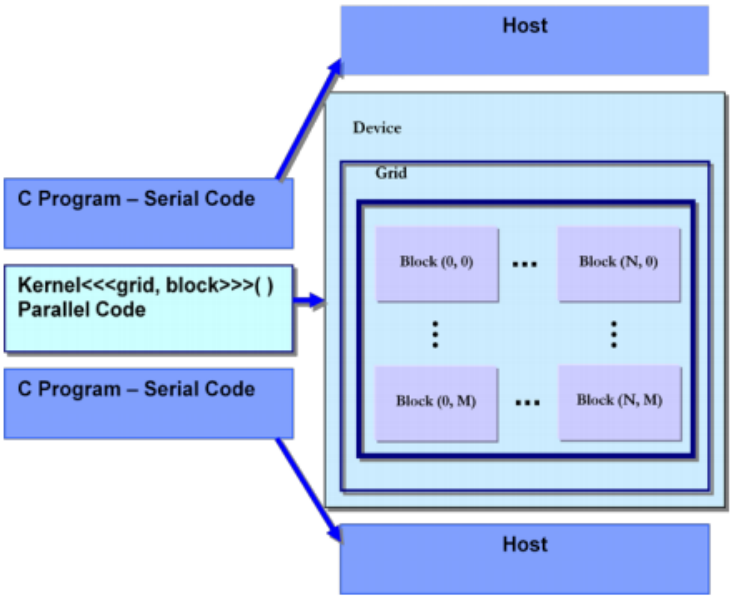


Figure 2.11: Heterogeneous architecture [29].

The CPU, known as the host, executes functions (or serial code as shown in Figure 2.11). Parallel portion of the application is executed on the device (GPU) as kernel. The kernel is executed as an array of threads, in parallel. The same code is executed

by all threads, but different paths may be taken. The threads can be identified by its IDs, for the purpose of selecting input or output data, and to make control decisions [4]. The threads are grouped into blocks, which in turn are grouped into a grid. Hence, the kernel is executed as a grid of blocks of threads. The grid and each block may be one-dimensional, two-dimensional or three-dimensional. The architecture is illustrated in Figure 2.12.

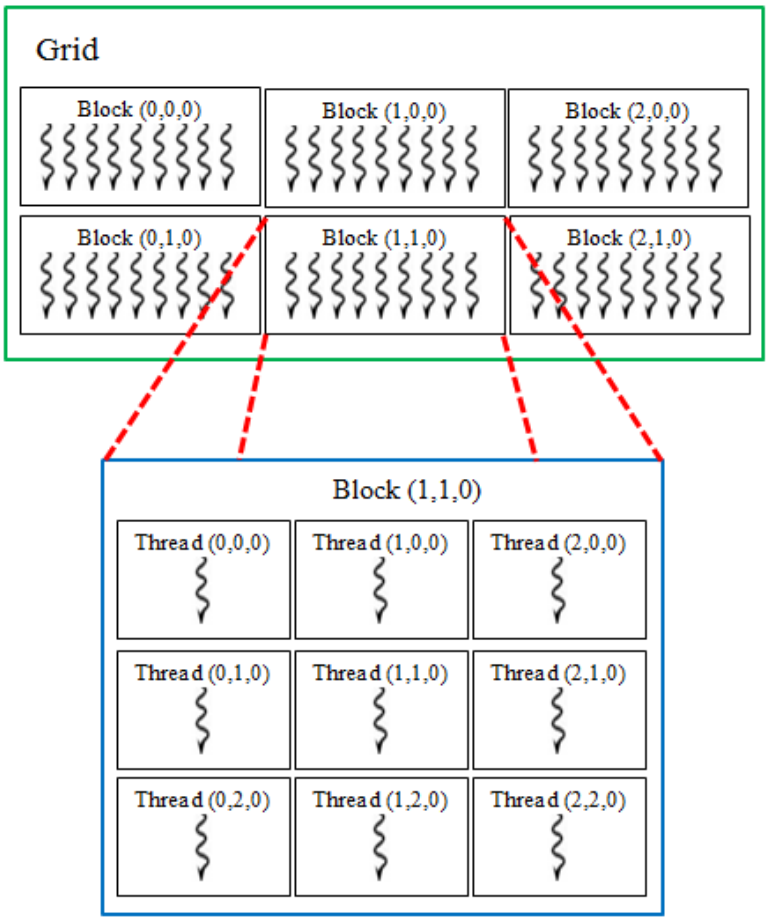


Figure 2.12: CUDA compute grid, block and thread architecture.

Cooperation among threads within a block may be needed for memory accesses and results sharing. Shared memory is accessible by all threads within the same block only. This restriction to "within a block" permits scalability [28]. When the number of threads is large, fast communication between the threads will not be feasible. However, each block is executed independently and the blocks may be distributed across an arbitrary number of SMs.

2.8.3 CUDA Memory Model

The host (CPU) and device (GPU) memories are separate entities. There is no coherence between the host and device [30]. Hence, in order to execute a kernel on a device, manual data synchronization is required. This is done by allocating memory on the device and then transferring the relevant data from the host memory to the allocated device memory. After device execution, the resultant data will need to be transferred back from the device memory to the host memory.

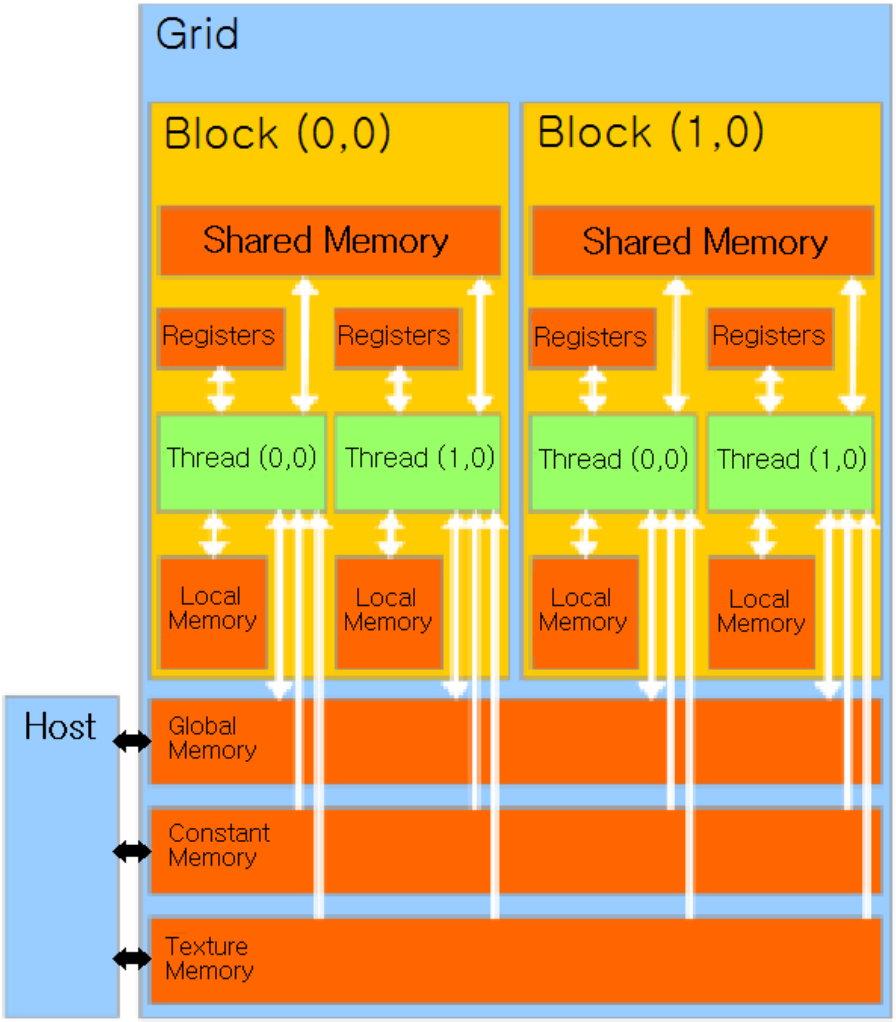


Figure 2.13: Cuda device memory model [31].

As shown in Figure 2.13, the global memory is a memory that the host code can transfer data to and from the device. This memory is relatively slow as it does not provide caching. Constant memory and texture memory allow read-only access by

the device code. API functions help programmers to manage data in these memories. Each thread has its own set of registers and local memory. Local variables of the kernel functions are usually allocated in the local memory [32]. Shared memory is shared among threads in the same block whereas global memory is shared by all the blocks. Shared memory is fast compared to global memory. It is also known as parallel data cache (PDC). All these memories (excluding constant memory) may be read and written to by the kernel.

2.8.4 CUDA Execution Model

As mentioned in Section 2.8.2, the main (serial) program runs on the host (i.e., the CPU) while certain code regions run on the device (i.e., the GPU). The execution configuration is written as **`<<< blocksPerGrid, threadsPerBlock >>>`**. The value of these two variables must be less than the allowed sizes depending on the device specifications. The maximum number of blocks and threads that can reside in a Streaming Multiprocessor depends on the compute capability of the device.

Figure 2.14 shows the architecture of a Streaming Multiprocessor (SM) for a device with CUDA compute and graphics architecture, code-named Fermi architecture. There are a total of sixteen load/store (LD/ST) units, allowing source and destination address to be calculated for sixteen threads per clock [33]. The four special function units (SFU) are used to execute transcendental instructions such as sin, cosine, reciprocal and square root. There are thirty-two cores in an SM, grouped into two groups of sixteen cores each. Each core has its own floating point unit (FPU) and arithmetic logic unit (ALU).

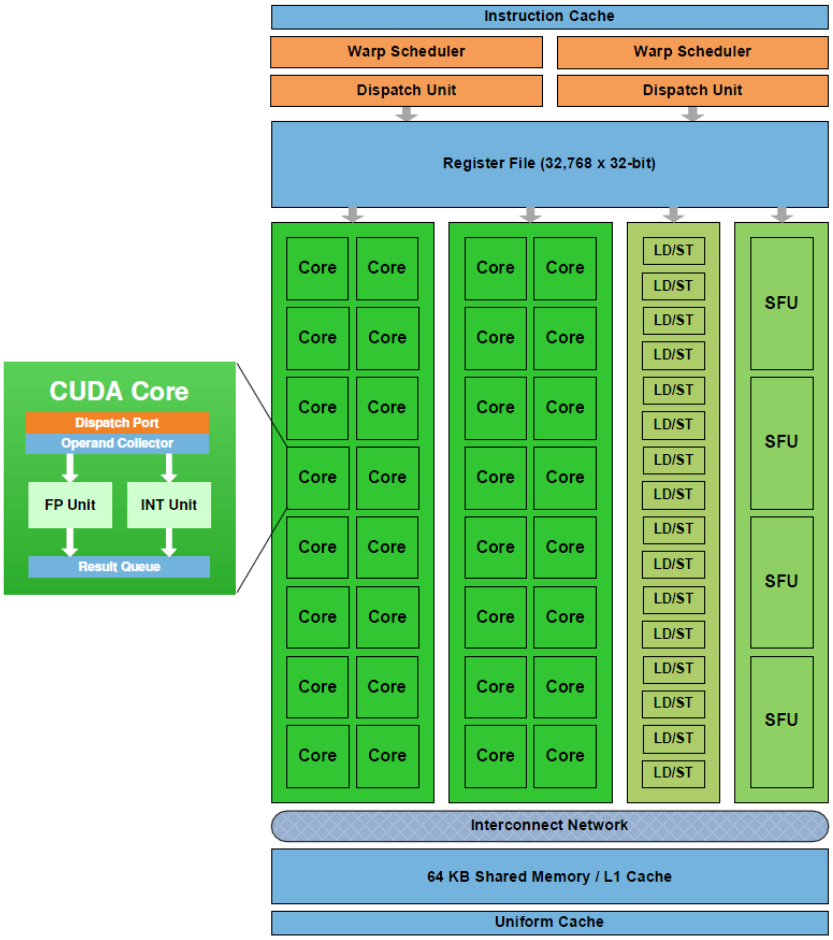


Figure 2.14: Architecture of a Streaming Multiprocessor (SM) [34].

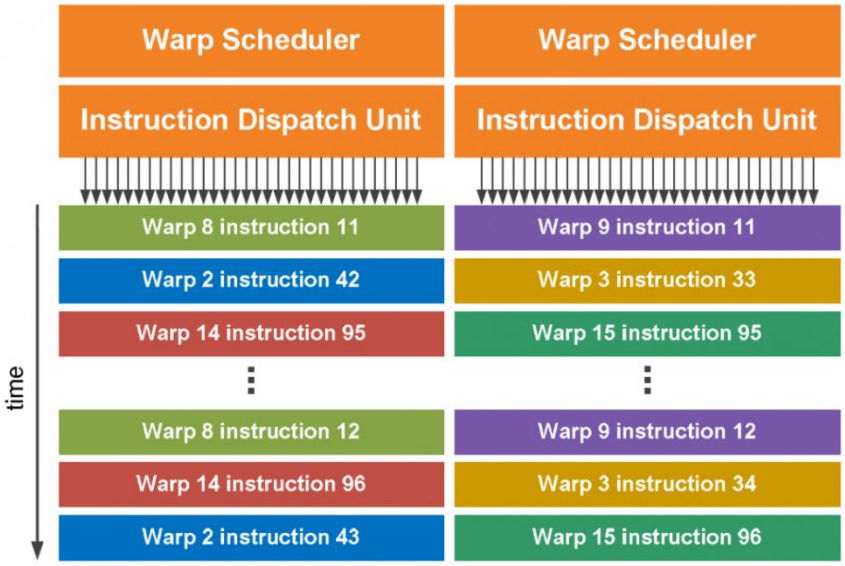


Figure 2.15: Dual Warp Scheduler in a Streaming Multiprocessor [34].

After a block has been assigned to an SM, it will be further divided into 32-thread units known as warps. All threads of a warp are scheduled together for execution. Each SM has two warp schedulers, as illustrated in Figure 2.15. Two warps can be issued and executed concurrently in an SM. The SM double-pumps each group of sixteen cores to execute one instruction for each of the two warps. If there are eight SMs in a device, a total of 256 threads will be executed in a clock.

When an instruction executed by the threads in a warp requires the result from a previous long-latency operation, the warp will not be selected for execution [28]. Another resident warp which has its operands ready will then be selected for execution. This mechanism is known as latency hiding. If there is more than one warp ready for execution, a warp will be selected for execution based on the priority mechanism. Warp scheduling hides the long waiting time of warp instructions by executing instructions from other warps. As a result, the overall execution throughput will not be slowed down due to long-latency operations.

As a conclusion for the execution model, each thread is executed by a core, each block is executed on a multiprocessor and several concurrent blocks may reside on a multiprocessor. Each kernel is executed on a device.

2.9 CUDA C

Prior to the introduction of CUDA C, Open Graphics Library (OpenGL) and DirectX were the only means to interact with a GPU. Data had to be stored in graphics textures and computations had to be written in shading languages which are special graphics-only programming languages [4]. In 2007, NVIDIA added a relatively small number of keywords into the industry-standard C for the sake of harnessing some of the special features of the CUDA Architecture, and introduced a compiler for this language, CUDA C. This has also made CUDA C the first language specifically designed by a GPU company to facilitate general-purpose computing on GPUs. A specialized hardware driver is also provided so that the

CUDA Architecture's massive computational power may be exploited. With all these improvements by NVIDIA, programmers no longer need to disguise their computations as graphic problems, nor do they require knowledge of OpenGL and DirectX.

2.9.1 Device Function

The number of blocks within a grid and number of threads per block must be specified when calling the kernel function. A Kernel function has a return type **`void`**. It also has a qualifier **`__global__`** to indicate that the function is called from the host code and it is to be executed on the device. The device functions are handled by NVIDIA's compiler where as the host functions are handled by the standard host compiler [35]. The input arguments of the kernel function must point to the device memory.

2.9.2 Basic Device Memory Management

a) To allocate the device global memory: **`cudaMalloc()`**
   i. Call this function from the host (CPU) code to allocate a piece of global memory (in GPU) for an object.
   ii. The first function argument is the address of a pointer to the allocated object.
   iii. The second function argument is the size of the allocated object in terms of bytes.
   iv. Example:

```
float* dev_a;
cudaMalloc ( (void**) &dev_a, sizeof (int) );
```

b) To copy from the host (CPU) memory to the device (GPU) memory and vice versa: **`cudaMemcpy()`**
   i. The first function argument is the pointer to the destination.

ii. The second function argument is the pointer to the source.

iii. The third argument indicates the number of bytes to be copied.

iv. The fourth argument indicates the direction of transfer (host to host, host to device, device to host, or device to device).

v. Example (host to device):
`cudaMemcpy ( dev_a, &host_a, sizeof (int), cudaMemcpyHostToDevice );`

vi. Example (device to host):
`cudaMemcpy (&host_a, dev_a, sizeof (int), cudaMemcpyDeviceToHost);`

c) To free the device memory: **`cudaFree()`**

i. Call this function from the host (CPU) code to free an object.

ii. The function argument is the pointer to the freed object.

iii. Example: **`cudaFree (dev_a);`**

2.9.3 Launching Parallel Kernels

a) Launching with parallel blocks

i. Example: **`kernel <<<N, 1>>> (dev_a, dev_b)`**

- There will be **`N`** copies of the **`kernel()`** being launched.
- **`blockIdx.x`** can be used to index the arrays whereby each block handles different indices

b) Launching with parallel threads within a block

i. Example: **`kernel <<<1, N>>> (dev_a, dev_b)`**

- There will be **`N`** copies of the **`kernel()`** launched.
- **`threadIdx.x`** is used to index the arrays

c) Launching with parallel threads and blocks

i. Example: **`kernel <<< M, N>>> (dev_a, dev_b)`**

- There will be **`M × N`** copies of **`kernel()`** launched.
- The unique array index for each entry is given by:

  `Index=threadIdx.x + blockIdx.x*blockDim.x`

- **`BlockDim.x`** refers to the number of threads per block

2.9.4 Shared Memory

Parallel threads have a mechanism to communicate. Threads within a block share an extremely fast, on-chip memory known as shared memory. Shared memory is declared with the keyword **`__shared__`**. Data is shared among threads in a block. It is not visible to threads in other blocks running in parallel.

2.9.5 Thread Synchronization

Parallel threads also have a mechanism for synchronization. Synchronization is needed to prevent data hazards such as read-after-write hazard [36]. The function used to synchronize thread is **`__syncthreads()`**. Threads in the block will wait until all threads have hit the **`__syncthreads()`** instruction before proceeding with the next instruction. An important point to note is that threads are only synchronized within a block.

2.10 Applications of CUDA

Various industries and applications have enjoyed a great deal of success by building applications in CUDA C. The improvement in performance is often of several orders-of-magnitude. The following shows a few ways in which CUDA Architecture and CUDA C have been put into successful use.

2.10.1 Oil Resource Exploration

The oil prices in the global market continue to rise steeply causing the urgent need to find new sources of energy. However, the exploration and drilling of deep wells are very costly. To minimize the risks of failure in drilling, 3D seismic imaging technology is now being used for oil exploration [37]. Such technology allows for a detailed look at potential drilling sites. However, terabytes of complex data are involved when imaging complex geological areas. With the introduction of faster and more accurate code by SeismicCity, the computational intensity of the algorithms has increased by 10-fold. Such algorithms would then require large number of CPUs setup, which is impractical. Running CUDA on NVIDIA Tesla server system solves this problem. The massively parallel computing architecture offers a significant performance increase over the CPU configuration.

2.10.2 Design Industry

Conventionally, physical cloth samples of the intended clothing line are needed for prototyping and to gain support from potential investors [38]. This consumes a lot of time as well as cost, causing wastage. OptiTex Ltd introduced 3-D technology which modernizes this process by allowing designers to simulate the look and movement of clothing designs on virtual models. By using a GPU for computation, the developers managed to obtain a 10-fold performance increase in addition to removing bottlenecks that occurred in the CPU environment. With the promising performance by the GPU computing solution, production costs and design cycle time has been greatly reduced.

2.10.3 Weather and Climate

The most widely used model for weather prediction is Weather Research and Forecasting Model (WRF). Despite having large-scale parallelism in these weather models, the increase in performance is due to the increase in processor speed instead of from increased parallelism [39]. With the development of National Center for

Atmospheric Research's (NCAR's) climate and weather models from Terascale to Petascale class applications, conventional computer clusters and addition of more CPUs prove to be no longer effective for speed improvement. To improve overall forecasting speed and accuracy of the models, the NCAR technical staffs have collaborated with the researchers at University of Colorado and came up with NVIDIA GPU Computing solutions. It is observed that there is a 10-fold improvement in speed for Microphysics after porting to CUDA. The percentage of Microphysics in the model source code is less than 1 per cent, but a 20 per cent speed improvement for the overall model is observed when converted to CUDA.

2.11 Existing CUDA String Algorithms

The simplest algorithm for string search is Brute-Force algorithm. The algorithm tries to match the pattern (query) to the text (input word list) by scanning the text from left to right. In the sequential form, a single thread will conduct the search and outputs to the console if a match is found. In the CUDA version, *N* threads can be used to conduct for the same search [40]. The difference lays in that each of the *N* parallel threads attempts to search for a match, in parallel. When the thread founds a match, the data structure used to store the found indices will be updated. The drawback of Brute Force algorithm is its incompetency in speed. Despite its implementation in CUDA, the text will need to be scanned from beginning till the end. Hence, this algorithm is more suitable when simplicity is of higher priority compared to speed.

Another algorithm which has been implemented in CUDA is QuickSearch, a variant of the popular Boyer-Moore Algorithm [41]. "Bad character shift" is precomputed for the pattern (query) before searching is performed. The main disadvantage is the space requirement. If the pattern and/or the text are long, more space will be needed.

A research paper by Raymond Tay [42] has explored the usage of GPUs to support batch oriented workloads by implementing the Bloom Filter algorithm. A

performance gain was obtained when the Bloom Filter algorithm was implemented using CUDA. Hence, Bloom Filter is chosen to be the implemented algorithm in this project, with the aim of achieving similarly positive results when large datasets are involved. Bloom Filter is also chosen as it requires a fixed number of bits per element irrespective of the size of the elements. In other words, less space will be required compared to the aforementioned algorithms when the input file is large. In addition to that, the time taken for the algorithm to check for an element is regardless of the number of elements in the set. The lookups are independent of each other and thus can be parallelized, providing an opportunity for the algorithm to be implemented using CUDA.

The following chapter thus investigates the performance limitation of a serial Bloom Filter in justifying the need for a parallel design, both on CPU and GPU domains.

CHAPTER 3: PERFORMANCE DRAWBACK OF A SERIAL BLOOM FILTER STRING SEARCH ALGORITHM

3.1 Introduction

The Bloom Filter algorithm is first implemented only on the CPU, using serial programming. This marks the simplest way of programming. It serves as a benchmark for performance comparison with parallel as well as GPGPU versions of the program.

3.2 Program Flow

By referring to Figure 3.1, the program begins with the loading of input word file into the CPU memory. If the word file is not found and it fails to be loaded, the console will show failure in loading file and the program terminates. The word file is then processed before the Bloom Filter is instantiated. The filter is inserted by setting the bits based on the hash functions performed on the strings in the word file.

After all elements have been inserted, the input query file is loaded into the CPU memory. Similar to the word file, failure in loading the file will result in program termination. Processing of queries is required before the filter is checked for the queries. If the query is in the word file, a message is printed on the console stating its presence. After all queries have been searched and the results have been printed, the program terminates.

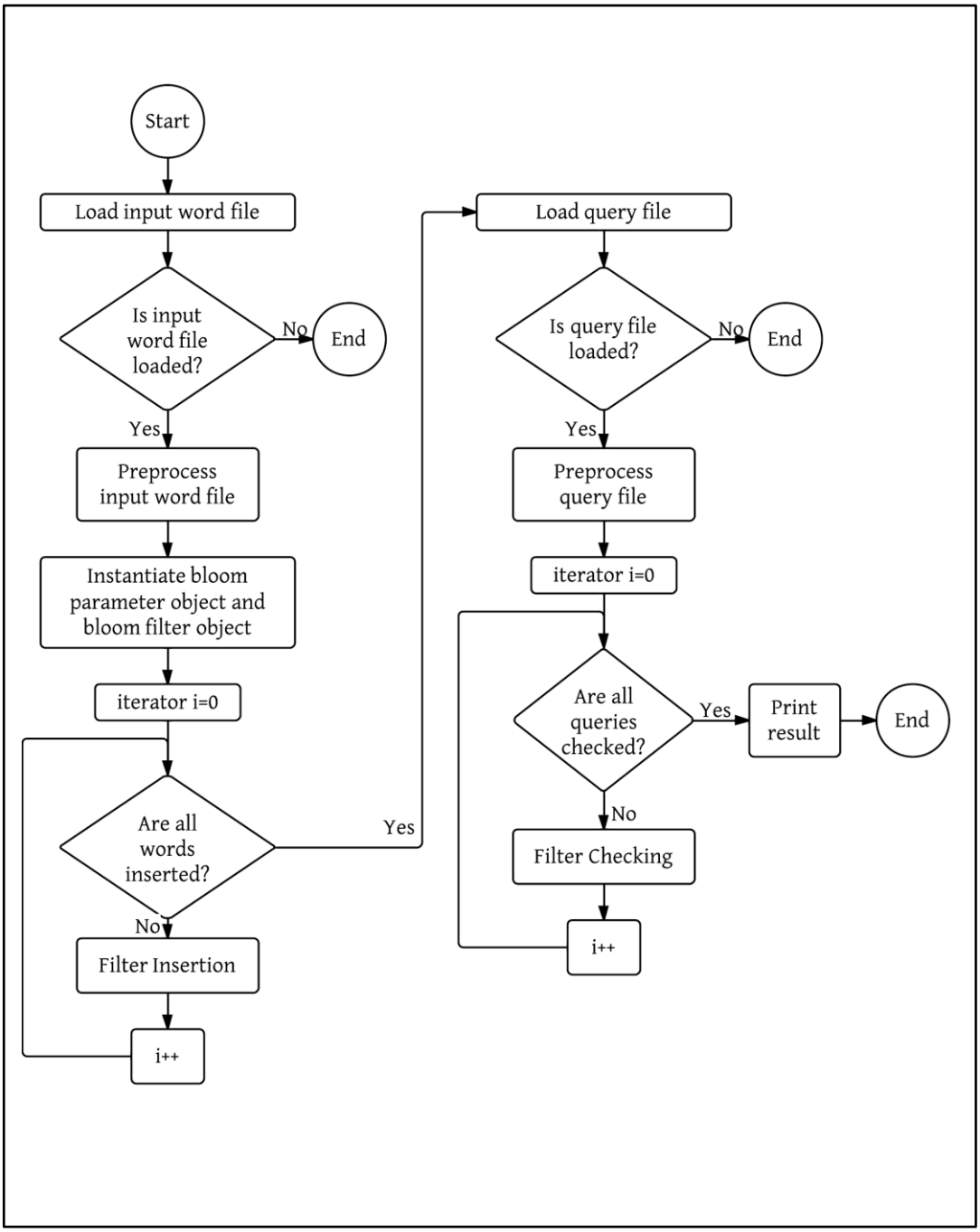


Figure 3.1: Flowchart for the main program.

3.2.1 Loading Input Files

Program Listing 3.1 describes the file-loading function used in this project. A character pointer-to-pointer for the word array and an integer pointer for the number of words are passed from the main function into the file-loading function as shown in Line 1. If the word file is successfully loaded, the integer pointer is updated based on the number of strings in the file. This is portrayed in Line 19. The pointer-to-pointer then points to an array of pointers. Each pointer points to a string in the word file. This relates to Lines 27-31. The same algorithm is used to read both input word file and query file.

```
1  bool load_word_list(int argc, char* pArgv[], char**
       &ppWord_list_ptr_array, int* pWordnum)
2  {
3      static const char wl_list[] = {"word-list-1k.txt"};
4      std::cout << "Loading list " << wl_list << ".....";
5
6      ifstream stream;
7      stream.open(wl_list, ios::in);
8      if (!stream)
9      {
10           std::cout << "Error: Failed to open file '" << wl_list
             << "'" << std::endl;
11           return false;
12     }
13
14     char temp[WORDLENGTH] = {'\0'};
15
16     while(!stream.eof())
17     {
18           stream.getline(temp,WORDLENGTH);
19           (*pWordnum)++;
20     }
21
22     ppWord_list_ptr_array = new char*[*pWordnum];
23
24     stream.clear();
25     stream.seekg(0);
26
27     for(int i=0; i<(*pWordnum); i++)
28     {
29           ppWord_list_ptr_array[i] = new char[WORDLENGTH];
30           stream.getline(ppWord_list_ptr_array[i],WORDLENGTH);
31     }
32
33     std::cout << " Complete." << std::endl;
34     return true;
35 }
```

Program Listing 3.1: Input file loading.

3.2.2 Data Pre-processing

There are typically 3 operations involved in data pre-processing, namely preparing and filling up index tables to indicate the starting position (offset from the beginning of the contiguous space) and the size of each string, allocating contiguous space (on host) for the input strings, and copying the strings into the allocated space. It can be illustrated in Figure 3.2.

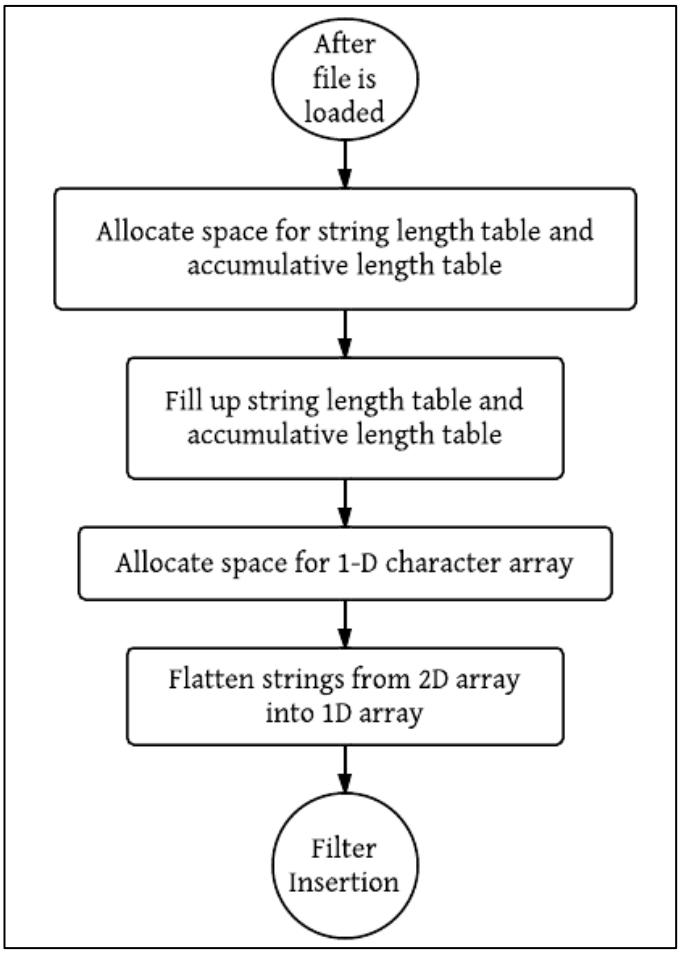


Figure 3.2: Pre-processing of input text file.

Data pre-processing is done for serial CPU programming as well, so that a fair comparison can be made when parallel programming and GPGPU are implemented. The performance comparison will be made solely based on the Bloom Filter algorithm, excluding the time taken for pre-processing the data.

3.2.3 Class Objects

Two classes are introduced in the program, namely **`CBloom_parameters`** and **`CSimple_bloom_filter`**. The members and functions of the **`CBloom_parameters`** class are described in Table 3.1 and Table 3.2, respectively.

Table 3.1: CBloom_parameters Class Members.

Class Member	Significance
`BP_fpp`	Indicates the false positive probability of an element
`BP_k`	Indicates the number of hash functions to be performed
`BP_n`	Indicates the number of elements in the filter
`BP_random_seed`	A value used in generation of salt
`BP_table_size`	Gives the size of the Bloom Filter

Table 3.2: CBloom_parameters Class Functions.

Function Name	Function
`BP_compute_parameters()`	Computes the size of the Bloom Filter
`CBloom_parameters()`	Class constructor which initializes the number of elements, the number of hash functions, *fpp*, value of random seed and calls the class function **`BP_compute_parameters()`**

The calculation of the size of Bloom Filter in the class function **`BP_compute_parameters()`** in Table 3.2 is deduced from Equation 2.5 (which shows the equation for *fpp*). The value of *fpp* is initially set at $\frac{1}{n}$. The size of the Bloom Filter is hence calculated based on the following equation:

$$m = \frac{-kn}{\log(1-fpp^{\frac{1}{k}})} \quad \textbf{(3-1)}$$

Table 3.3 describes the members of the **`CSimple_bloom_filter`** class.

Table 3.3: CSimple_bloom_filter Class Members.

Class Member	Significance
`BF_bit_table_`	Bit-table array with each element storing 8 bits
`BF_inserted_element_count_`	Gives the total number of string elements inserted into the Bloom Filter
`BF_random_seed_`	A random value used in generating salts for hash functions
`BF_raw_table_size_`	Size of **`BF_bit_table_`**
`BF_salt_count_`	Gives the number of hash functions used
`BF_table_size_`	Gives the actual size of the Bloom Filter (bit-table array size $\times 8$)
`salt_`	Each element of the array is used as an initial hash value (before the hash function is performed) such that the same hash algorithm will produce different results when performed on the same string element

The class member **`BF_bit_table_`** is set as a volatile variable such that the compiler reads the bit-table from its storage location (in memory) each time it is referenced in the program. If the **`volatile`** keyword is not used, the compiler might generate the code that re-uses previously read value from the register. In the case of serial programming, the possibility of cache miss is almost zero. However, in a multi-threaded program with the compiler's optimizer enabled, cache incoherency will lead to inaccurate results. This is because each processor has its own cache memory and change in one copy of the operand might not be visible to other copies. Hence the bit-table array is set to volatile in the serial implementation as well for a fair comparison.

The functions of the **`CSimple_bloom_filter`** class are described in Table 3.4.

Table 3.4: CSimple_bloom_filter Class Functions.

Function Name	Function
`~CSimple_bloom_filter()`	Class destructor
`compute_indices()`	Computes the indices of the bit table
`contains()`	Checks for the presence of a query
`CSimple_bloom_filter()`	Class constructor which initializes the number of elements, the number of hash functions, the value of random seed, an empty bit-table, the size of the bit-table and calls the class function **`generate_unique_salt()`**
`effective_fpp()`	Calculates the effective *fpp* of the Bloom Filter
`element_count()`	Indicates the total number of elements inserted into the filter.
`generate_unique_salt()`	Generates salts for the hash functions
`hash_ap()`	Performs hash function on the element
`insert()`	Inserts elements into the filter
`size()`	Gives the size of the Bloom Filter

3.2.4 Filter Insertion

To insert an element (string) into the Bloom Filter, the element and its length are passed into a class function called **`insert()`** as shown in Program Listing 3.2.

```
1  for (int i=0; i<g_Wordnumber; i++)
2   {
3
       filter1.insert(&(g_pTotalwordarray[g_pAccumulative_Wordlengt
       h[i]]), g_pWordlength[i]);
4
5   }
```

Program Listing 3.2: Serial filter insertion.

Figure 3.3 shows the algorithm for the **`insert()`** function. The iterator **`i`** is incremented after a single hash function is performed and one of the bits in the Bloom Filter is set to 1. After performing *k* number of hash functions and setting the Bloom Filter *k* number of times, one string element (word) is considered inserted. The hash algorithm will be described in detail in Section 3.3. The flow as portrayed in the flowchart below is repeated for all elements.

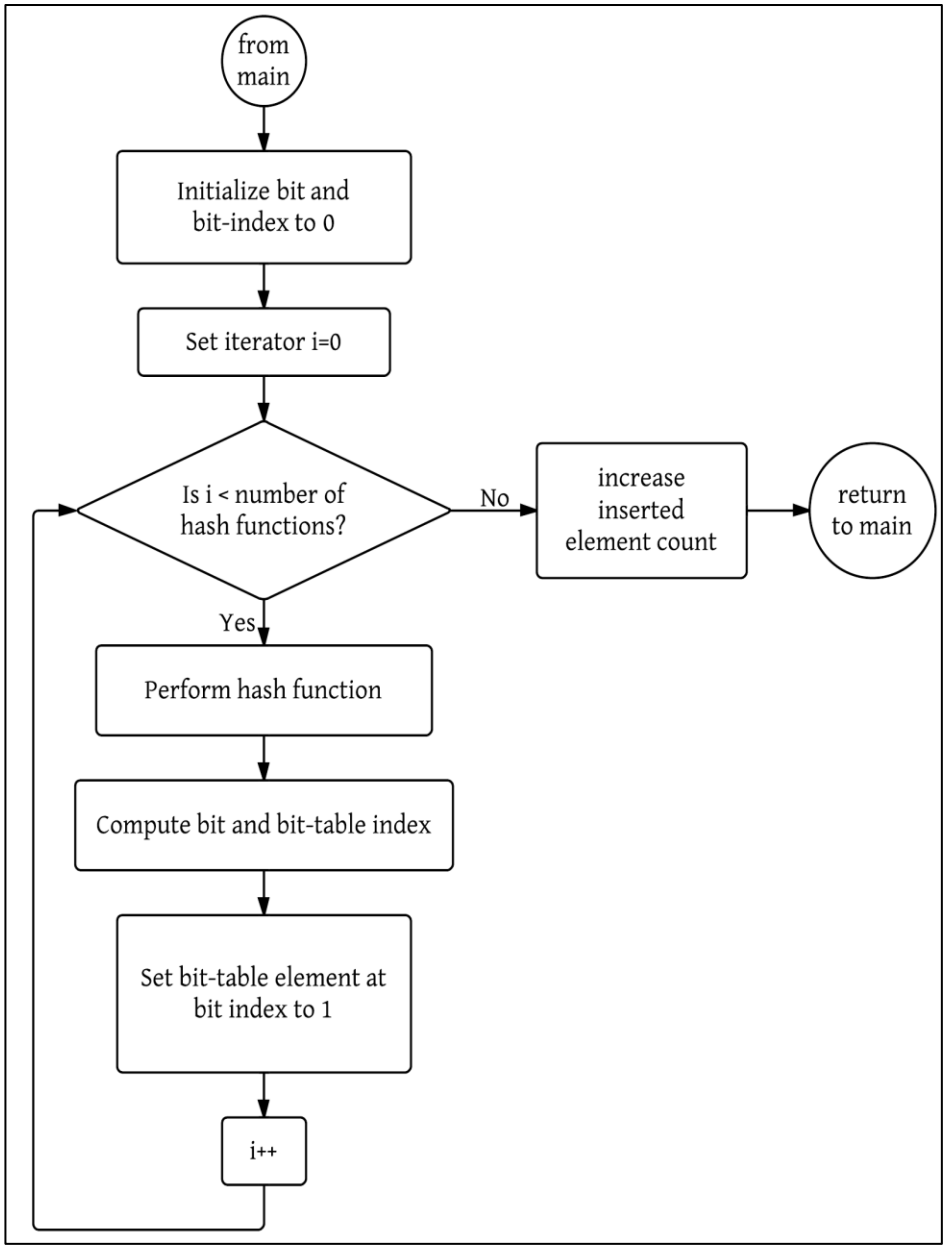


Figure 3.3: Flowchart for inserting one element.

To insert an element (string) into the Bloom Filter refers to setting certain values of the bit table to the value "1". A **`bit_mask`** array of size 8 is used in the program. Each element of the array consists of 8 bits. The reason for using a **`bit_mask`** array is to eliminate collision when 2 elements contribute the same bit index. Algorithm 1 shows the insertion for one element. Conversely, Program Listing 3.3 illustrates the code implementation.

Algorithm 3.1: Generate bit-table for one element

```
1  bit_index ← 0
2  bit ← 0
3  iterator i ← 0
4  While i <BF_salt_count_ do
5      perform hash function
6      bit_index = hash % BF_table_size_
7      bit = bit_index % 8
8      bit_table [bit_index/8]   |=  bit_mask[bit]
9      Increase the iterator
10 end
```

```
1   inline void insert(char* key_begin, int length)
2   {
3      unsigned int bit_index = 0;
4      unsigned int bit = 0;
5
6      for (unsigned int i = 0; i < BF_salt_count_; ++i)
7      {
8         compute_indices(hash_ap(key_begin,length,salt_[i]),
                          bit_index,bit);
9         BF_bit_table_[bit_index / bits_per_char] |=
                          bit_mask[bit];
10     }
11
12     ++BF_inserted_element_count_;
13  }
```

Program Listing 3.3: Filter insert function for one string element.

Example:

Originally, **`BF_bit_table_[20]`** stores 0x00

1. element "above" gives **`bit_index`** = 20, **`bit`** = 0;

Hence, **`BF_bit_table_[20]`** |= **`bit_mask[0]`**

0x00 |= 0x01

`BF_bit_table_[20]` now stores 0x01

2. element "beyond" gives **`bit_index`** = 20, **`bit`** = 5;

Hence, **`BF_bit_table_[20]`** |= **`bit_mask[5]`**

0x01 |= 0x20

`BF_bit_table_[20]` now stores 0x21

3.2.5 Filter Searching

To check for the existence of a query in the input word list, a similar process as filter insertion is performed. The same **`bit_mask`** array is used as in the case of bit-table generation. The query and its length are passed into a class function called **`contain().`** Algorithm 2 describes this function. The hash value and the table index are calculated as shown in Lines 5 to 8. The bit at the calculated position is checked for its Boolean value. If the **`bit_mask`** element is not retrievable, then the query is confirmed to be non-existent in the word-list. The function returns a **`false`** to the main program as shown in Line 10. If all hash functions have been performed and all respective **`bit_mask`** elements have been retrieved, then either the query is present in the word-list or a false positive has occurred. The function returns a **`true`** to the main program. The entire process as described in Algorithm 2 is repeated for *n* number of queries.

Algorithm 3.2: Checking bit-table for one element

1 *bit_index* ← *0*

2 *bit* ← *0*

3 *iterator i* ← *0*

```
4  While i <BF_salt_count_ do
5      perform hash function
6      bit_index = hash % BF_table_size_
7      bit = bit_index % 8
8      bit_table [bit_index/8]   &  bit_mask[bit]
9      if bit_mask element is not retrieved
10         return false to main function
11     Increase the iterator
12 end
13 return true to main function
```

Examples:

`BF_bit_table_[20]` stores 0x21 after all elements of the word-list have been inserted.

1. query "beyond" gives **`bit_index`** = 20, **`bit`** = 5;

Hence, **`BF_bit_table_[20]`** & **`bit_mask[5]`**

0x21 & 0x20

`bit_mask[5]` is retrieved, hence query is found.

2. query "tiger" gives **`bit_index`** = 20, **`bit`** = 7;

Hence, **`BF_bit_table_[20]`** & **`bit_mask[7]`**

0x21 & 0x80

`bit_mask[7]` is not retrieved, hence query is not found.

3.3 AP Hash Function

The chosen algorithm for the hash function is Arash Partow (AP) hash function. It is a hybrid rotative and additive hash function algorithm that resembles a simple Linear Feedback Shift Register (LFSR) [43]. When the feedback function of an LFSR is chosen appropriately, the output sequence of bits will appear random.

Therefore, by using AP hash algorithm, the calculated hash values (and hence bit table indices) will be random, collisions can be reduced. The hash algorithm is described as below:

Algorithm 3.3: Computes the hash value for a string

1 *loop* ← *0*
2 *iterator* ← *first character of the string*
3 *hash* ← *one of the elements of salt array*
4 ***While*** *word_length >=8* ***do***
5 *m* ← *first 4 characters pointed by iterator*
6 *n* ← *next 4 characters pointed by iterator*
7 *Increase the iterator*
8 $hash = hash_{i-1} \oplus (hash_{i-1} \times 2^7) \oplus \left[m_{i-1} \times \left(hash_{i-1} \times \frac{1}{2^3}\right)\right] \oplus$
9 $\sim\{(hash_{i-1} \times 2^{11}) + [n_{i-1} \oplus (hash_{i-1} \times \frac{1}{2^5})]\}$
10 *Word_length is reduced by 8*
11 ***end***
12 *p* ← *first 4 characters pointed by iterator*
13 ***While*** *word_length >=4* ***do***
14 ***If*** *(loop & 0x01):*
15 $hash = hash_{i-1} \oplus (hash_{i-1} \times 2^7) \oplus \left[p_{i-1} \times \left(hash_{i-1} \times \frac{1}{2^3}\right)\right]$
16 ***Else***
17 $hash = hash_{i-1} \oplus \sim\{(hash_{i-1} \times 2^{11}) + [p_{i-1} \oplus (hash_{i-1} \times \frac{1}{2^5})]\}$
18 *Word_length is reduced by 4*
19 *Increase the iterator*
20 ***end***
21 *x* ← *first 2 characters pointed by iterator*
22 ***While*** *word_length >=2* ***do***
23 ***If*** *(loop & 0x01):*
24 $hash = hash_{i-1} \oplus (hash_{i-1} \times 2^7) \oplus \left[x_{i-1} \times \left(hash_{i-1} \times \frac{1}{2^3}\right)\right]$

25 ***Else***

26 $hash = hash_{i-1} \oplus \sim\{(hash_{i-1} \times 2^{11}) + [x_{i-1} \oplus (hash_{i-1} \times \frac{1}{2^5})]\}$

27 *Word_length is reduced by 2*

28 *Increase the iterator*

29 ***end***

30 ***If*** *word_length=1:*

31 $hash = hash_{i-1} + [k_{i-1} \oplus (hash_{i-1} \times 0xA5A5A5A5)] + i$

32 ***Return*** *hash*

3.4 System Assessment

3.4.1 Assessment Environment

This project was implemented in the Microsoft Windows platform; the chosen software for development was Microsoft Visual Studio 2010. The CPU specifications are given as follows:

Table 3.5: CPU Specifications.

Processor	Intel Core™ i7-2700K at 3.50GHz
Installed Memory (RAM)	8.00 GB

3.4.2 Performance Assessment

The results were collected for different dataset sizes, ranging from 1000 strings to 10,000,000 strings. The length of each string in the word-list and query-list is no more than 20 characters. 500 hashes were performed on each string. The average values (of the time taken) after five runs were used to plot the following graphs. Figure 3.4 shows the time taken for inserting strings into the filter while Figure 3.5 shows the time taken to query for strings. The total time taken for the insertion and querying is illustrated in Figure 3.6. Time taken to print the search results was not

included in the performance measurement as this project emphasizes on the string algorithm itself.

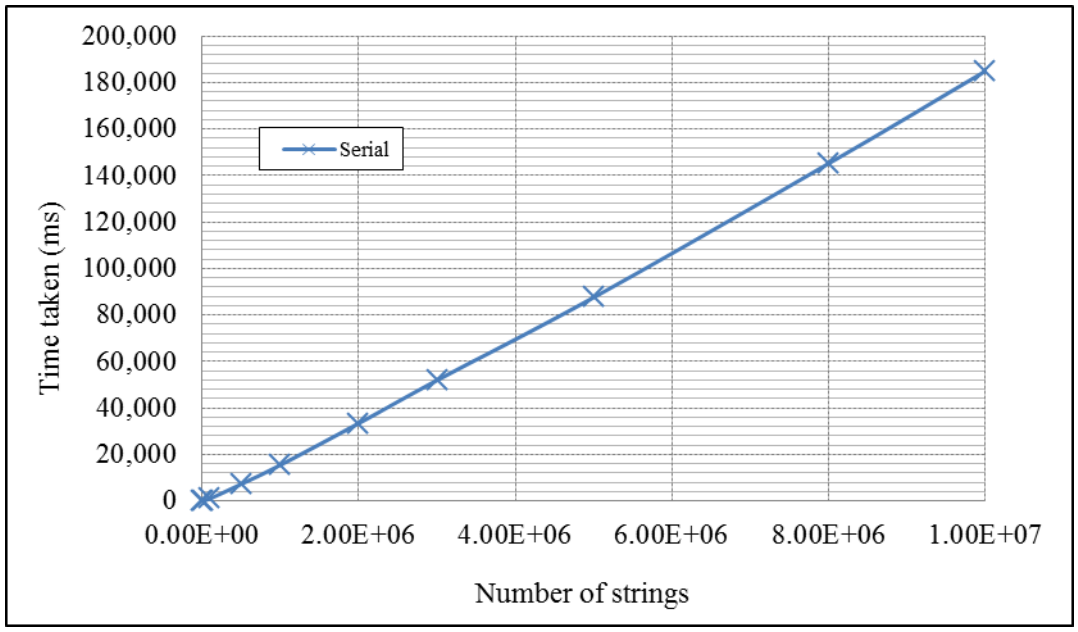


Figure 3.4: Time taken for Filter Insertion implemented using serial programming.

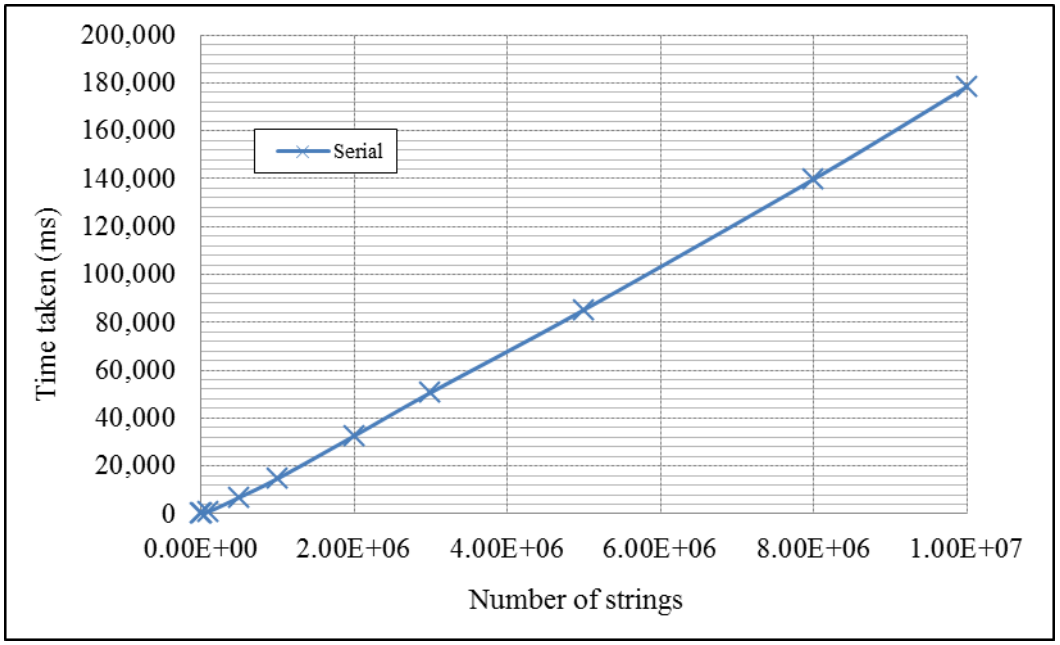


Figure 3.5: Time taken for Filter Search implemented using serial programming.

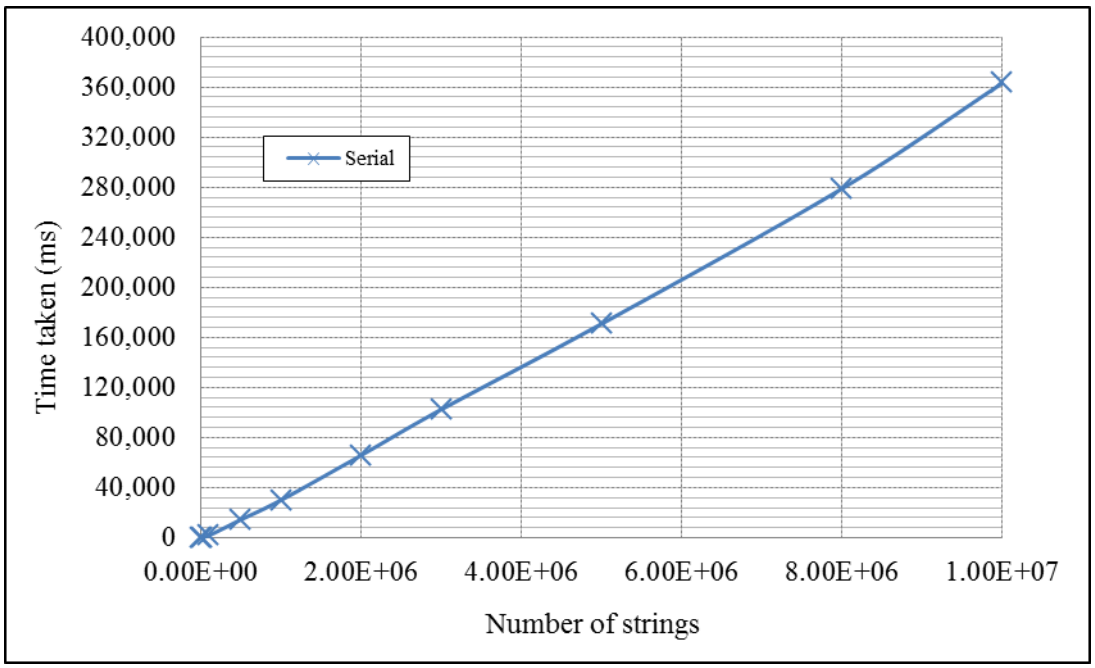


Figure 3.6: Total time taken for Bloom Filter algorithm (insert and search) implemented using serial programming.

All three figures have shown a linear increase in the processing time for the Bloom Filter algorithm when the data size was increased. As shown in Figure 3.4, approximately 180 seconds were needed to insert 10,000,000 strings into the filter. Similar amount of time was needed to search for 10,000,000 queries, as portrayed in Figure 3.5. Hence, the total amount of time taken for the Bloom Filter algorithm for a dataset size of 10,000,000 was approximately 360 seconds. Observation of the CPU utilization displayed only $\frac{1}{8}$ of the logical processors was used for executing the program. This has shown that the CPU was underutilized despite having a hardware that supports multicore and hyperthreading.

When the number of strings (n) increments by 1, the total number of hash functions to be performed increases by a factor of k. The computational load in this algorithm is hence identified as the hash functions performed on the strings. In order to reduce the execution time of the algorithm, a more time-efficient programming paradigm is needed.

The repetitive process of performing hash functions on different strings suggests that parallelisation may be applied. Hence, Bernstein's Conditions are examined to ensure that the hashings of strings are independent of each other.

Suppose that $\mathbb{I}$ represents a set of words in the word list,
$\mathbb{O}$ represents a set of resultant hash operations

Let $\mathbb{I}_o = \{a, b, o, v, e\}$ where $\mathbb{O}_o = X$; and
$\mathbb{I}_1 = \{b, e, l, o, w\}$ where $\mathbb{O}_1 = Y$; **(3-2)**

Since $\mathbb{I}_o \cap \mathbb{O}_1 = \emptyset$, and
$\mathbb{I}_1 \cap \mathbb{O}_0 = \emptyset$, and
$\mathbb{O}_0 \cap \mathbb{O}_1 = \emptyset$, **(3-3)**

The insertion process for both $\mathbb{I}_o$ and $\mathbb{I}_1$ can be executed concurrently.

By deduction,

$\mathbb{I}_i \cap \mathbb{O}_{i+1} = \emptyset$, and
$\mathbb{I}_{i+1} \cap \mathbb{O}_i = \emptyset$, and
$\mathbb{O}_i \cap \mathbb{O}_{i+1} = \emptyset$ **(3-4)**

Hence,

$\mathbb{I}_i \cap \mathbb{O}_{i+1} \cap \mathbb{O}_{i+2} \ldots \cap \mathbb{O}_{i+n-1} = \emptyset$, and
$\mathbb{I}_{i+1} \cap \mathbb{I}_{i+2} \ldots \cap \mathbb{I}_{i+n-1} \cap \mathbb{O}_i = \emptyset$, and
$\mathbb{O}_i \cap \mathbb{O}_{i+1} \cap \mathbb{O}_{i+2} \ldots \cap \mathbb{O}_{i+n-1} = \emptyset$ **(3-5)**

From Eq. (3.2), Eq. (3.3), Eq. (3.4) and Eq. (3.5), since all three Bernstein's Conditions are satisfied, it is proven that the data has no dependency on each other. Thus, is has been confirmed that the hashing algorithm for different strings can be executed concurrently. The next chapter discusses the implementation of the Bloom Filter algorithm using parallel programming by leveraging on the compute capabilities of a multicore processor.

CHAPTER 4: DATA PARALLELISATION OF A BLOOM FILTER USING OPENMP

The previous chapter has proven that data parallelisation of the Bloom Filter algorithm is in fact possible. Hence, this chapter describes the design and development of a parallel Bloom Filter string search algorithm on a multicore architecture.

4.1 Program Design

The program flow for the Bloom Filter algorithm implemented using OpenMP is similar to the serial programming implementation. The only changes made are on the Bloom Filter insertion and querying functions. Both functions involve performing the same tasks on different sets of data, thus providing an opportunity for data parallelism to be implemented.

Prior to implementing parallelisation in the program, the maximum number of threads that can run at a time was obtained by calling the library function **`omp_get_max_threads()`**. To set the number of parallel threads, the library function **`omp_set_num_threads()`** was called.

4.1.1 Filter Insertion

The algorithm for insertion using OpenMP is similar to that of using serial programming. Program Listing 4.1 illustrates the code implementation of **`insertProcess()`**. This function receives a pointer pointing to the input string

array (**`*pTotalwordarray`**), a pointer pointing to the table storing length of each input string (**`*pWordlength`**) and a pointer pointing to the table storing offsets of each string (**`pAccumulative_Wordlength`**). Atomic operation is required when updating the bit-table, as shown in Line 13 of Program Listing 4.1. This allows protection against simultaneous writes on the same bit-table location by different threads. Nested parallel region was not implemented as it introduces additional overhead. Since there is enough parallelism in the main program flow, it is more efficient to use all threads at this level rather than to create nested regions in the **`insertProcess()`** function. Figure 4.1 depicts the execution model for **`insertProcess()`** which relates to Program Listing 4.1 **.**

```
1  void insertProcess(int totalWords, char *pTotalwordarray,
           int *pAccumulative_Wordlength, int *pWordlength)
2  {
3     int j = 0;
4     #pragma omp parallel for private(j)
5     for (int i=0; i<totalWords; i++)
6     {
7           unsigned int bit_index = 0;
8           unsigned int bit = 0;
9           for (j = 0; j < BF_salt_count_; ++j)
10          {
11                compute_indices(hash_ap(&(pTotalwordarray
                        [pAccumulative_Wordlength[i]]),
                        pWordlength[i],salt_[j]),bit_index,bit);
12                {
13                      #pragma omp atomic
14                      BF_bit_table_[bit_index/bits_per_char] |=
                              bit_mask[bit];
15                }
16          }
17          ++BF_inserted_element_count_;
18    }
19 }
```

Program Listing 4.1 OpenMP Filter Insert Function.

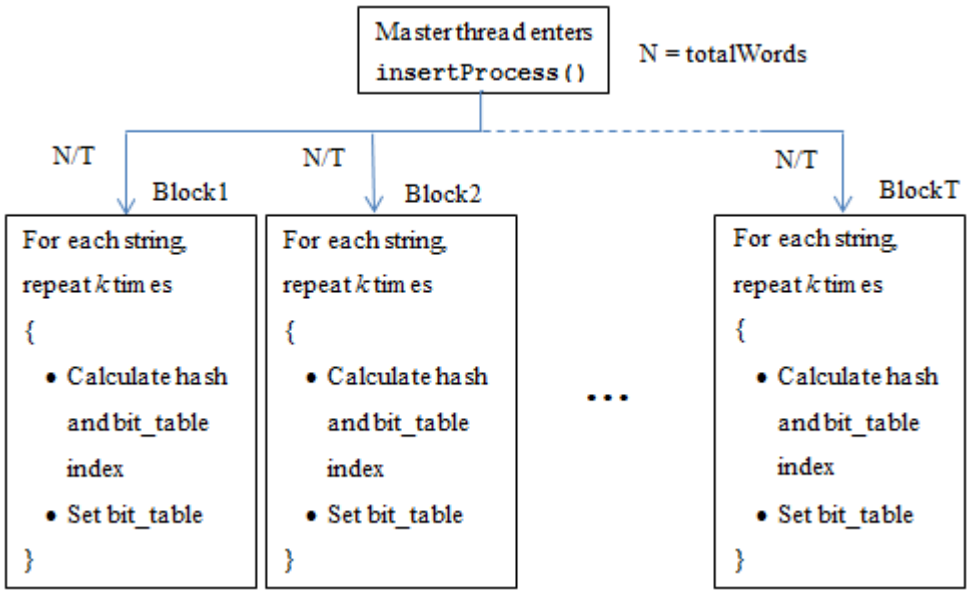


Figure 4.1: Execution Model for OpenMP Insert (T represents number of parallel threads).

4.1.2 Filter Searching

The algorithm for filter search using OpenMP is the same as that of using serial programming. Atomic operation is not required as parallel threads are only reading **`BF_bit_table_[]`** value from the memory, thus the memory content remains unchanged. Similar to filter insertion, there are a few blocks running in parallel, depending on the number of parallel threads set in the code. As seen in Line 1 of Program Listing 4.2, the function **`containsProcess()`** receives one additional argument compared to the function used for filter insertion. The additional argument is a Boolean pointer which points to an array (**`*existence2`**). The array is used to store the result of filter search. Atomic operation is not required when updating this array because each thread will write to a different location of the array as shown in Line 17. The execution model for **`containsProcess()`** which relates to Program Listing 4.2 is depicted in Figure 4.2**.**

```
1  void containsProcess(int totalQueries, char *pTotalqueryarray,
           int *pAccumulative_Querylength, int *pQuerylength,
           bool* existence2)
2  {
3     int j =0 ;
4
5     #pragma omp parallel for private(j)
6     for (int i=0; i<totalQueries; i++)
7     {
8           unsigned int bit_index = 0;
9           unsigned int bit = 0;
10
11          for (j = 0; j < BF_salt_count_; ++j)
12          {
13                compute_indices(hash_ap(&(pTotalqueryarray
                        [pAccumulative_Querylength[i]]),
                        pQuerylength[i],salt_[j]),bit_index,bit);
14
15                if ((BF_bit_table_[bit_index / bits_per_char] &
16                           bit_mask[bit]) != bit_mask[bit])
17                      existence2[i] = false;
18          }
19    }
20 }
```

Program Listing 4.2 OpenMP Filter Search Function.

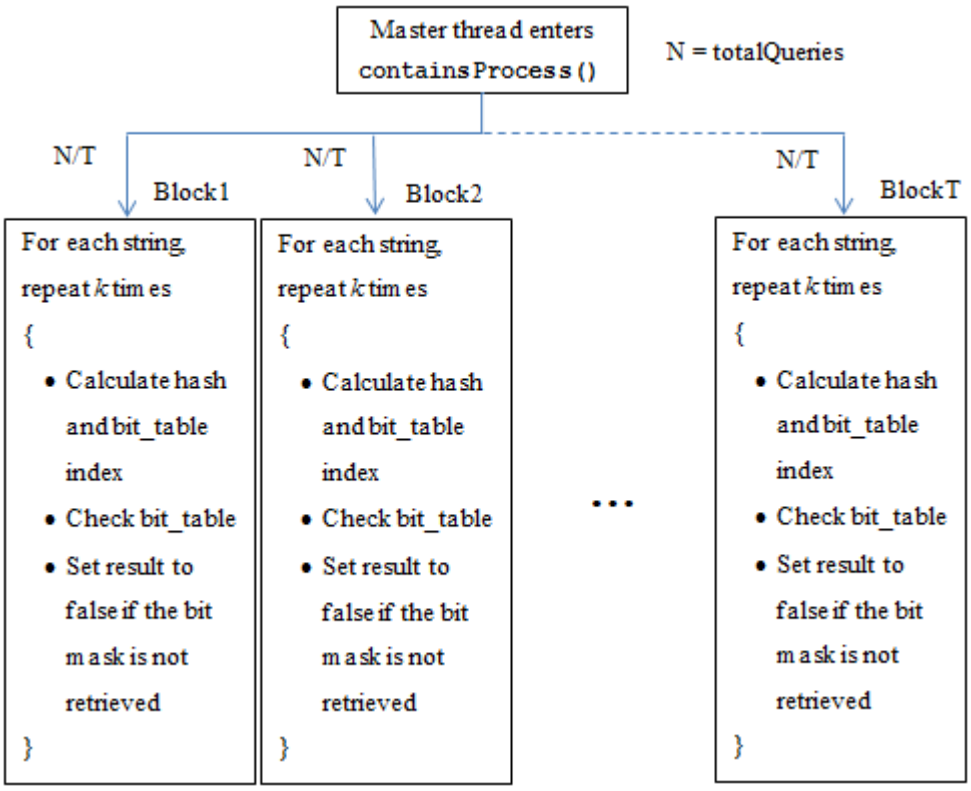


Figure 4.2: Execution Model for OpenMP Search (T represents number of parallel threads).

4.2 System Assessment

4.2.1 Assessment Environment

A similar test setup and sample data set from Section 3.4.1 is adapted here. For the OpenMP implementation, the function **`omp_get_max_threads()`** returned a value of 8 when it was called. This is because there are 4 cores on the machine, and each core allows hyperthreading. Hence, the number of parallel threads was set to 8 using the function **`omp_set_num_threads()`**.

4.2.2 Performance Assessment

Prior to results collection, the bit-table and result array obtained from OpenMP and serial implementations were compared. The comparison results confirmed that identical bit-tables and result arrays were obtained.

The performance of the Bloom Filter algorithm executed using OpenMP was measured against the same algorithm running in serial. The execution time was recorded for filter insertion and querying only, excluding the time to print the bit-table and the searching result to text files. The results for execution time were plotted using the average value of five runs. The performance gain of the OpenMP implementation over the serial implementation was also calculated and plotted in the graphs.

Let t_s represent the time taken for the Bloom Filter in a serial implementation

t_p represent the time taken for the Bloom Filter in an OpenMP implementation

The performance gain (or performance ratio or speedup factor) is calculated as:

$$Performance\ gain = \frac{t_s}{t_p} \quad \textbf{(4-1)}$$

Figure 4.3, Figure 4.4 and Figure 4.5 show the execution time and the performance gains for the Bloom Filter algorithm when it is executed using serial programming and OpenMP.

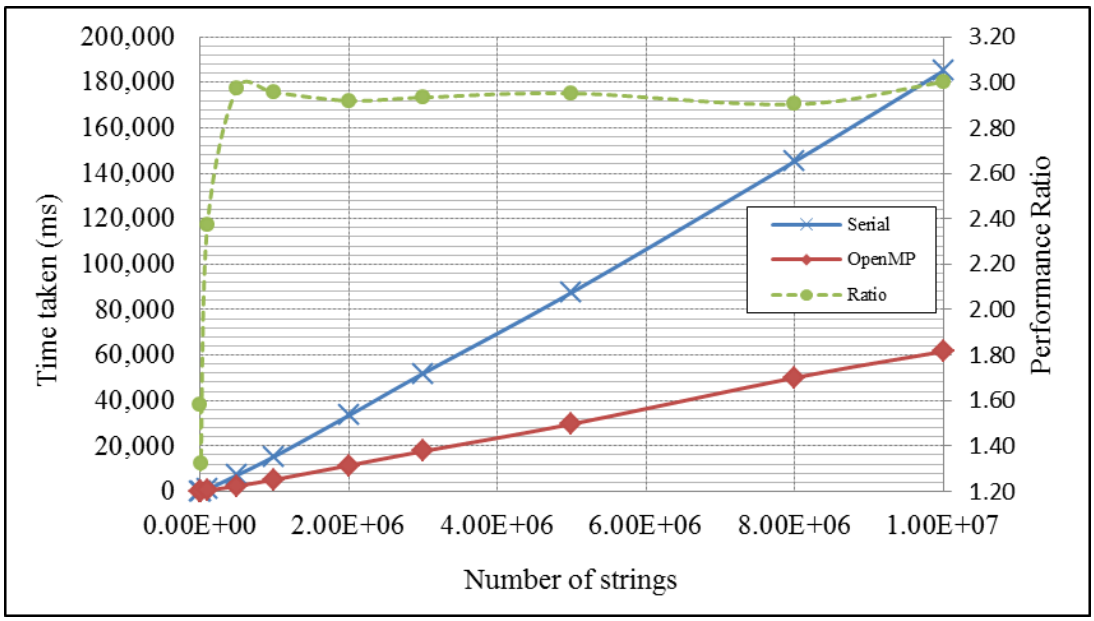


Figure 4.3: Time taken and performance gain for Filter Insertion when implemented using serial programming and OpenMP.

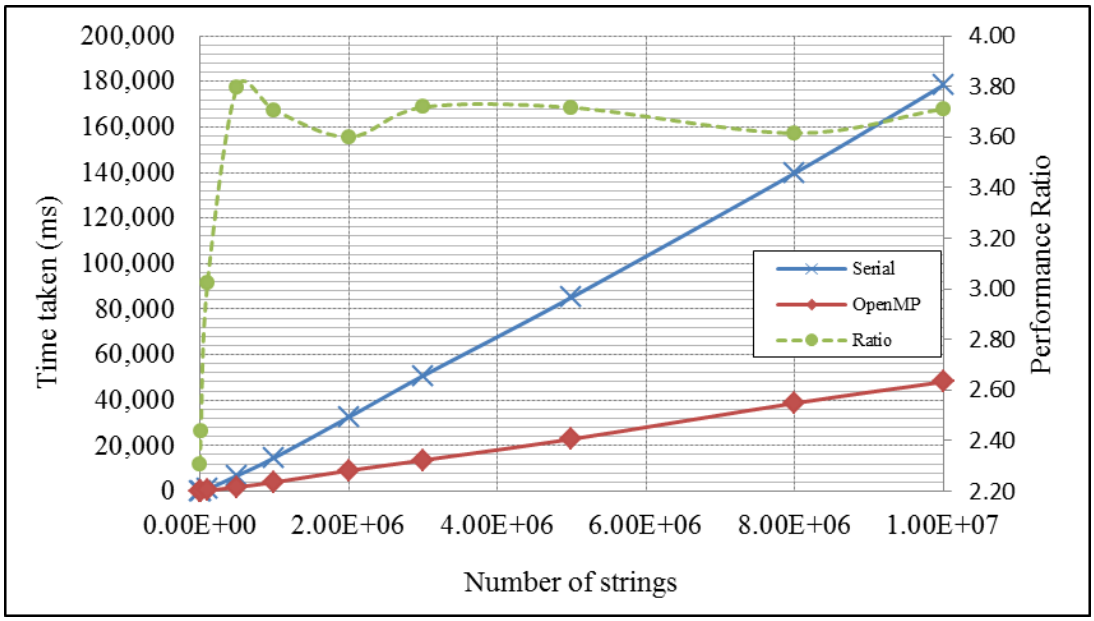


Figure 4.4: Time taken and performance gain for Filter Search when implemented using serial programming and OpenMP.

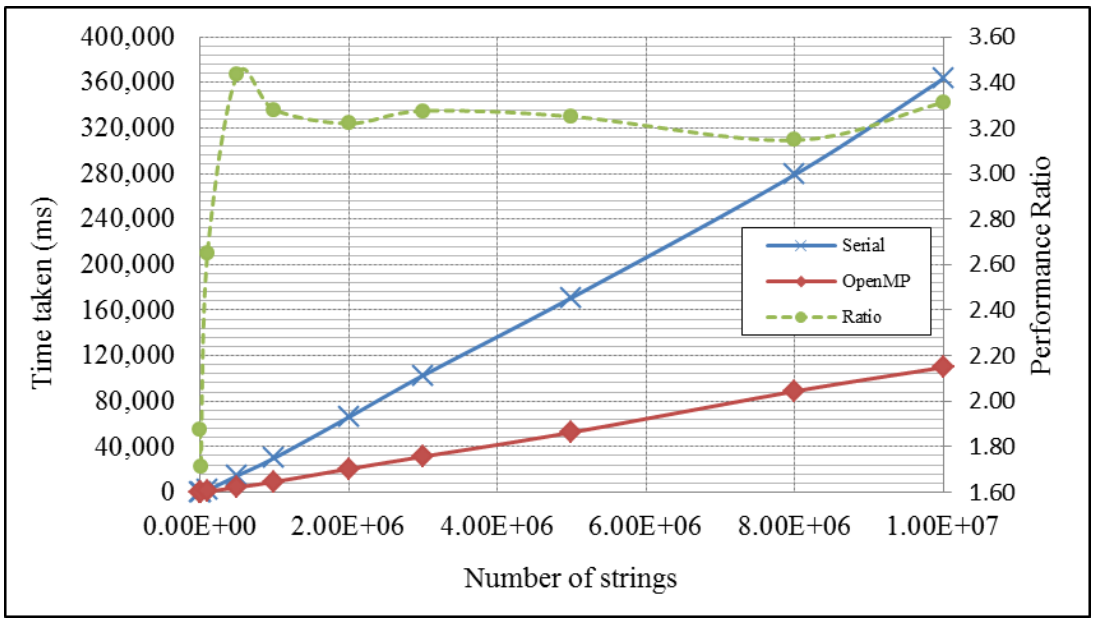


Figure 4.5: Total time taken and performance gain for Bloom Filter algorithm (insert and search) when implemented using serial programming and OpenMP.

As observed from Figure 4.3, Figure 4.4 and Figure 4.5, the processing time for the Bloom Filter was longer when serial programming was implemented as compared to OpenMP. When the size of the dataset was set at 10,000,000, the time taken for the serial filter insertion was approximately 180 seconds as compared to 60 seconds for OpenMP; hence a speedup of 3.0x was achieved. For filter search, the serial implementation took 180 seconds while the OpenMP implementation took approximately 48 seconds. A speedup factor of 3.8x was exhibited in Figure 4.4 for the dataset size of 10,000,000. Summation of the time taken for the filter insertion and the filter search led to a total of 360 seconds for the serial implementation and 100 seconds for the OpenMP implementation. Hence, a speedup of 3.3x was recorded for the dataset size of 10,000,000 strings. This can be observed in Figure 4.5. The reason for the performance gain in the OpenMP implementation over the serial implementation is there were 8 threads working (processing the strings) in parallel when the algorithm was implemented using OpenMP.

The performance gain of OpenMP over serial programming showed a steep increase when the input data is small in size. Data sizes greater than 500,000 strings show an almost constant speedup factor (approximately 2.9x for insertion, 3.7x for searching and 3.3x for overall). A reasonable explanation for this is the processing speed of the

CPU has reached its saturation point. Further speedup could only be obtained if more parallel threads were launched inline with the existence of more logical processors.

Since there were 8 threads running in parallel, theoretically the speedup factor should be 8.0x. However, the maximum speed up attained was less than 4.0x. A reasonable explanation for this is the bit-table insertion was not fully parallelisable. Atomic operation was introduced hence the insertion function degenerated into serial programming when more than 1 thread attempted to access the same bit-table element. Threading overhead also introduced delay to the algorithm.

Despite the inability to obtain the expected performance gain, the implementation of OpenMP had been very encouraging. It has proven that the performance of the Bloom Filter algorithm is better when it is implemented in a multicore architecture. However, with the advent of the many core processing technology, the performance of the parallel Bloom Filter algorithm can be further improved by leveraging on the compute capabilities of this technology. As such, the following chapter explores the design and implementation of a parallel Bloom Filter algorithm on a many core architecture.

CHAPTER 5: CUDA IMPLEMENTATION OF THE BLOOM FILTER STRING SEARCH ALGORITHM

As suggested in the previous chapter, the Bloom Filter algorithm is then implemented on a GPU, which offers a massively parallel architecture. This chapter describes the design and development of the Bloom Filter algorithm on the many-core architecture.

5.1 Program Design

Threads in the GPU do not have direct access to the CPU memory. Hence, explicit data transfer from the CPU memory to the GPU memory is required. A device pointer is first allocated using **`cudaMalloc()`**. **`cudaMemcpy()`** is then used for data transfer into the GPU global memory. Table 5.1 shows the data which are transferred only once (from CPU to GPU) throughout the entire program.

Table 5.1: Variables which are transferred once throughout the entire program.

Variable on host (CPU) memory	Pointer to device (GPU) memory
`filter2.salt_`	**`dev_pSalt_`**
`filter2.BF_table_size_`	**`dev_pTable_size`**
`filter2.BF_bit_table_`	**`dev_pBit_table`**
`bit_mask`	**`dev_pBit_mask`**

The size of memory available on the GPU is limited as compared to the CPU; it is approximately 25% that of the CPU memory. On Windows, the maximum allowable

run time for each kernel launch is five seconds. When the size of the data transferred is large, the blocks of threads are queued for execution; leading to a long execution time which might exceed the run time limit. As a result, data processing has to be performed in batches. For each batch of data, the device pointers are reallocated and the data are copied into the GPU global memory. The pointers are then freed after the kernel has completed its tasks. The variables which are transferred in batches are listed in Table 5.2 while Table 5.3 shows the associated device memory pointers.

Table 5.2: Values stored in each variable on the host memory.

Variable on host (CPU) memory	Significance
g_pTotalwordarray[]	1-Dimensional (1D) character array (input word)
g_pWordlength[]	Length of each input word
g_pAccumulative_Wordlength[]	Offset of each input word
g_offset	Total number of characters of previously processed strings
g_Remaining_words	Remaining number of strings when the data size is not an exact multiple of the batch size
g_pTotalqueryarray[]	1D character array (query)
g_pQuerylength[]	Length of each query
g_pAccumulative_Querylength[]	Offset of each query
g_Query_result[]	Array for storing search result

Table 5.3(a): Device pointers for variables which are transferred in batches.

Variable on host (CPU) memory	Pointer to device (GPU) memory
g_pTotalwordarray[]	**dev_pTotalwordarray**
g_pWordlength[]	**dev_pWordlengthtable**
g_pAccumulative_Wordlength[]	**dev_pOri_Accu_length**
g_offset	**dev_pOffset**
g_Remaining_words	**dev_pNum**
g_pTotalqueryarray[]	**dev_pTotalqueryarray**

Table 5.3(b): Device pointers for variables which are transferred in batches.

g_pQuerylength[]	**dev_pQuerylengthtable**
g_pAccumulative_Querylength[]	**dev_pOri_Query_accu_length**
g_Query_result[]	**dev_pQuery_result**

As aforementioned, the batch size of the data is limited due to the Windows "watchdog" timer as well as the size of the GPU memory. Hence, for both filter insertion and searching, the batch size is chosen as 50,000 strings. Smaller batch size is feasible but not recommended. This is because additional constant overhead is generated each time data transfer is invoked. Hence, fewer invocation of copy operation is preferred. A performance comparison was made between the batch size of 8 and 50,000. This will be explained in detail in Section 5.2.2.

5.1.1 Offset Calculation

Since batch processing is performed, the values stored in the respective offset tables (for words and queries) will be invalid for the subsequent batches of data. A CUDA kernel is launched in order to calculate the offset position of each string in each data batch. Another piece of GPU memory is allocated and the pointer to this memory (**dev_pAccu_length** for input word or **dev_pQuery_accu_length** for query) is passed in as one of the kernel arguments. The actual offset of each string (of the current batch) would then be: the value in the original offset table minus the total length of previously processed strings.

To maximize the utilization of the CUDA cores, the number of threads per block is set to the maximum allowable value (i.e., 1024 for Quadro 4000). The variable **BLOCK** is a global constant, fixed at 50,000. The number of blocks for kernel invocation is set to **(BLOCK+1023)/1024** (for each data batch of 50,000 strings) or **(g_Remaining_words+1023)/1024** (for the remaining strings when the total data size is not an exact multiple of 50,000) in order to prevent too few threads from being launched whenever **BLOCK** or **g_Remaining_words** is not an exact

multiple of 1024. Program Listing 5.1 describes the kernel functions used for offset calculations. **`offset1()`** (Line 8 to Line 14) is invoked to calculate for 50,000 strings while **`offset()`** (Line 1 to Line 6) is invoked to calculate for the remaining strings when the total number of strings is not an exact multiple of 50,000. As can be seen from the code, **`offset()`** receives one extra argument, **`dev_pNum`**, compared to **`offset1()`**. This argument indicates the number of remaining strings. The index of each thread is calculated in Line 3 (and Line 10). The condition checking in Line 4 (and Line 11) is needed so that the calculations in Line 5 (and Line 12) will not be performed when the thread index overshoots the end of the array.

```
1   __global__ void offset (int* dev_pAccu_length,
              int* dev_pOffset, int* dev_pNum,
              int* dev_pOri_Accu_length)
2   {
3      int tid = threadIdx.x + blockIdx.x * blockDim.x;
4      if (tid < (*dev_pNum))
5            dev_pAccu_length[tid] = dev_pOri_Accu_length[tid] -
                                     (*dev_pOffset);
6   }
7
8   __global__ void offset1 (int* dev_pAccu_length,
              int* dev_pOffset, int* dev_pOri_Accu_length)
9   {
10     int tid = threadIdx.x + blockIdx.x * blockDim.x;
11     if (tid < BLOCK)
12           dev_pAccu_length[tid] = dev_pOri_Accu_length[tid] -
                                     (*dev_pOffset);
13
14  }
```

Program Listing 5.1 Kernel functions for offset calculations.

5.1.2 Filter Insertion

The kernel function to insert string elements into the Bloom Filter receives several pointers to the device memory, which are **`dev_pTotalwordarray`**, **`dev_pWordlengthtable`**, **`dev_pAccu_length`**, **`dev_pSalt_`**, **`dev_pTable_size`**, **`dev_pBit_mask`**, and **`dev_pBit_table`**.

As mentioned in Section 5.1.1, the value for **`BLOCK`** is 50,000, which is the chosen batch size. **`K`** is also a global constant, with the value of 500. It is the number of hash functions to be performed on each string. There will be **`BLOCK×K`** copies of the **`insert()`** function being launched for each batch of data. As for the remaining strings, **`g_Remaining_words×K`** copies of the aforementioned function are launched.

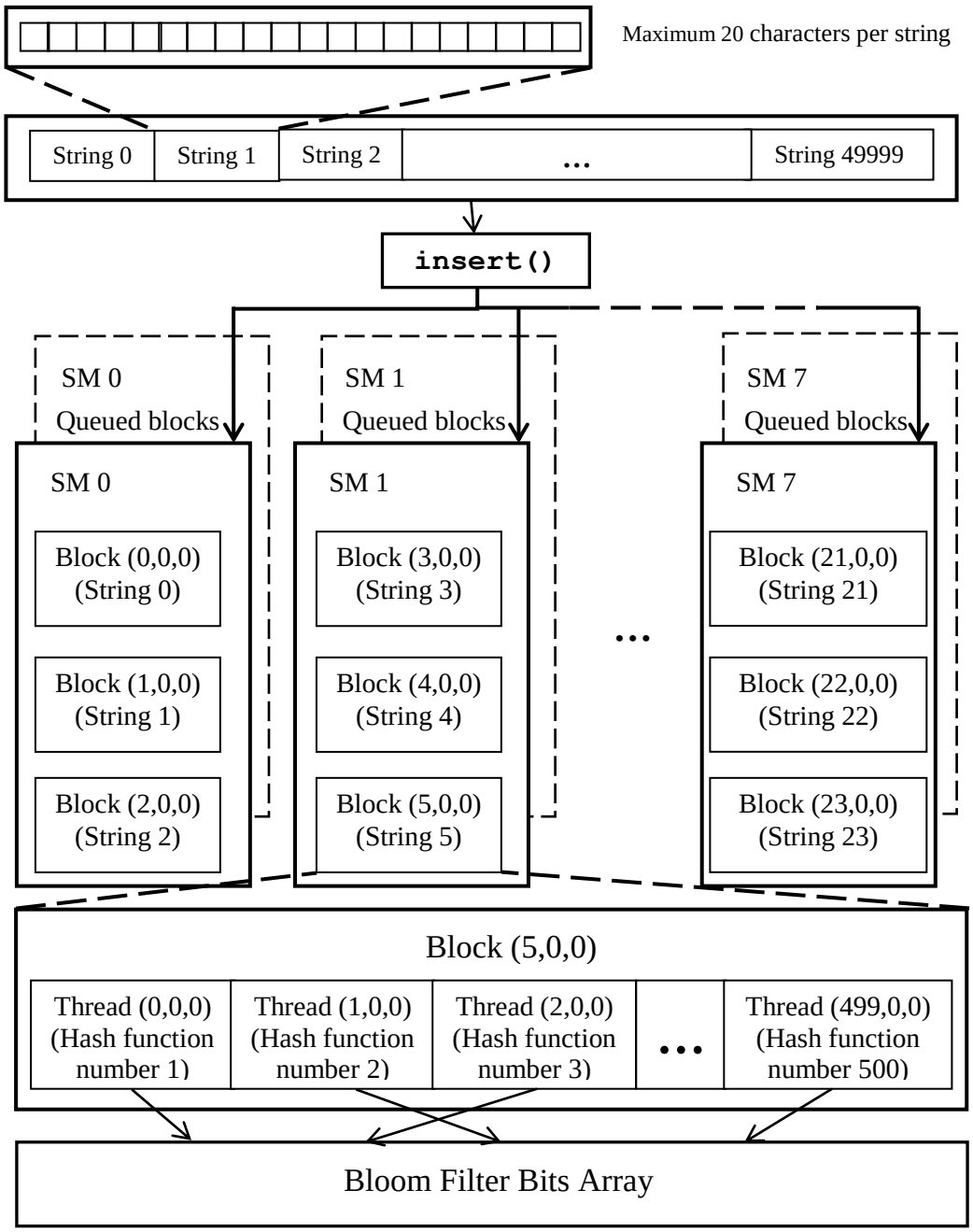


Figure 5.1: Execution Model for `insert()` function (for one batch of data with batch size of 50,000).

Figure 5.1 illustrates the execution model for the **`insert()`** function for one batch of strings. Conversely, Program Listing 5.2 illustrates the code implementation. If the total number of strings is not an exact multiple of the batch size, the filter insertion will be executed on the device using the similar model but with fewer blocks. The number of threads per block remains the same (500).

As illustrated in Figure 5.1, after invoking the kernel, each block will process one string. The string is copied from the GPU global memory into the shared memory to allow faster memory access by each thread within the block. Hence, the ID of the block is used to obtain the string (and its length) that it to be processed by the block. This is shown in Lines 4 and 9 of Program Listing 5.2.

Figure 5.1 has also shown that each thread within a block will perform a different hash function on the same string. Each thread will then set one of the elements in the Bloom Filter bit-table (referred to as bit array in Figure 5.1) after calculating the associated index. Therefore, the ID of the thread is used to obtain the associated salt element which is used as the initial hash value, as shown in Line 15.

Similar to the OpenMP implementation of the Bloom Filter algorithm, atomic operation has to be performed when setting the bit-table (as shown in Line 58). By using atomic operation, race condition is avoided as the operation is performed without interference from other threads.

Figure 5.1 has shown 3 resident blocks in each SM. There are also queued blocks for each SM. The justification for this is provided in Section 5.2.2.

```
1   __global__ void insert(char* pDev_totalwordarray,
       int* pDev_wordlengthtable, int* pDev_accu_length, unsigned
       int  *pDev_salt_,  unsigned  long  int  *pDev_table_size,
       unsigned int *pDev_bit_mask, unsigned int *pDev_bit_table)
2   {
3       __shared__ char* itr;
4       int remaining_length = pDev_wordlengthtable[blockIdx.x];
5
```

Program Listing 5.2(a) CUDA Insert Function.

```
6     if (threadIdx.x == 0)
7     {
8           itr = (char*)malloc(remaining_length*sizeof (char));
9           memcpy(itr,
      (char*)pDev_totalwordarray+(pDev_accu_length[blockIdx.x]),
      remaining_length * sizeof (char));
10    }
11
12    __syncthreads();
13    int position = 0;
14    unsigned int loop = 0;
15    unsigned int value = pDev_salt_[threadIdx.x];
16    while (remaining_length >= 8)
17    {
18          const unsigned int& i1 = *(reinterpret_cast
                  <const unsigned int*>(itr + position));
19          position += sizeof(unsigned int);
20          const unsigned int& i2 = *(reinterpret_cast
                  <const unsigned int*>(itr + position));
21          position += sizeof(unsigned int);
22          value ^= (value <<  7) ^  i1 * (value >> 3) ^
                  (~((value << 11) + (i2 ^ (value >> 5))));
23          remaining_length -= 8;
24    }
25
26    while (remaining_length >= 4)
27    {
28          const unsigned int& i = *(reinterpret_cast
          <const unsigned int*>(itr + position));
29          if (loop & 0x01)
30                value ^=    (value <<  7) ^  i * (value >> 3);
31          else
32                value ^= (~((value << 11) + (i ^(value>> 5))));
33          ++loop;
34          remaining_length -= 4;
35          position += sizeof(unsigned int);
36    }
37
38    while (remaining_length >= 2)
39    {
40          const unsigned short& i = *(reinterpret_cast
                  <const unsigned short*>(itr + position));
41          if (loop & 0x01)
42                value ^=    (value <<  7) ^  i * (value >> 3);
43          else
44                value ^= (~((value << 11) + (i ^(value>> 5))));
45          ++loop;
46          remaining_length -= 2;
47          position += sizeof(unsigned short);
48    }
49
50    if (remaining_length)
51    {
52          value += ((*(itr + position)) ^ (value * 0xA5A5A5A5))
          + loop;
53    }
```

Program Listing 5.2(b) CUDA Insert Function.

```
54
55    int bit_index = value % (*pDev_table_size);
56    int bit = bit_index % 0x08;
57
58    atomicOr ( &(pDev_bit_table[bit_index / bits_per_char]) ,
                  pDev_bit_mask[bit] );
59
60    if (threadIdx.x == 0)
61          free (itr);
62  }
```

Program Listing 5.2(c) CUDA Insert Function.

5.1.3 Filter Searching

The kernel function to query the Bloom Filter for string elements receives several pointers to the device memory, which are **`dev_pTotalqueryarray`**, **`dev_pQuerylengthtable`**, **`dev_pQuery_accu_length`**, **`dev_pSalt_`**, **`dev_pTable_size`**, **`dev_pBit_mask`**, **`dev_pBit_table`**, and **`dev_pQuery_result`**.

As stated in Table 5.2 and Table 5.3, **`dev_pQuery_result`** points to the array (in the GPU global memory) which stores the result of the **`contain()`** function. Prior to invoking the kernel, the entire array is set to a Boolean value of **`true`**.

Figure 5.2 illustrates the execution model for this function for one batch of queries. If the total number of queries is not an exact multiple of the batch size, the filter searching will be executed using the similar model but with fewer blocks. The number of threads per block remains the same (500).

Similar to the **`insert()`** function, each block performs searching for one query and each thread within the block performs a hash function on the same query. Each thread also computes the bit-table index and checks the bit-table. If any of the threads within the block finds that the bit-table is not set, the result array at the index position indicated by the block ID will be set to **`false`**. In example, by referring to Figure 5.2, if Thread(2,0,0) of Block(5,0,0) detects that the bit-table is not set, then **`dev_pQuery_result[5]`** will be set to **`false`**.

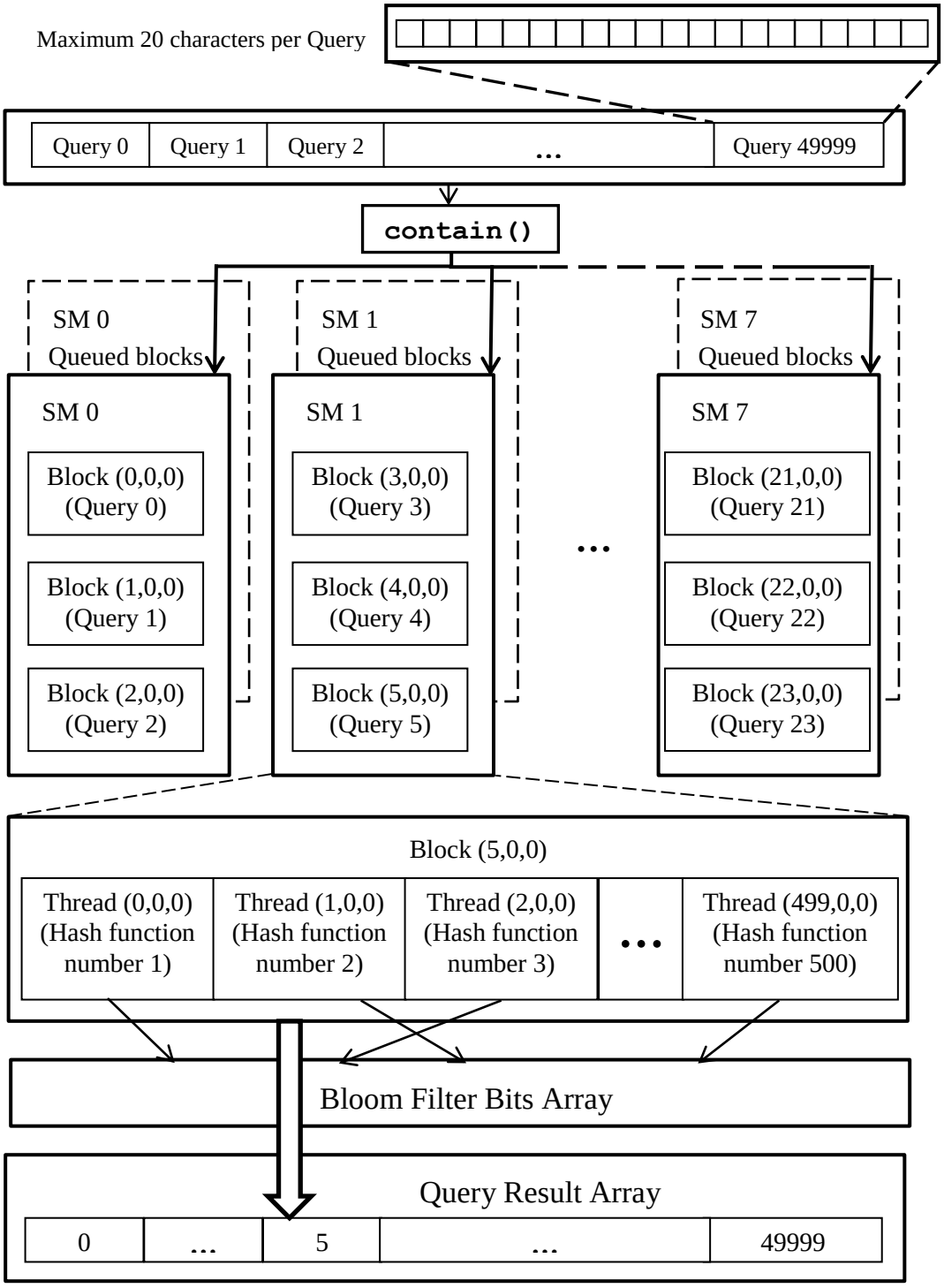


Figure 5.2: Execution Model for `contain()` function (for one batch of data with batch size = 50,000).

Atomic operation is not needed for this kernel function because only threads within the same block will write to the same array location and the value written is the same (which is **`false`**) regardless of which thread is writing to it. The results are then copied from the GPU memory to the CPU memory after the kernel has finished executing.

5.2 System Assessment

5.2.1 Assessment Environment

Prior to implementing this project using GPGPU, the environment for development has to be set up. The CUDA toolkit was installed and the necessary settings were chosen for the Microsoft Visual Studio project. The project was implemented as a combination of code running on a CPU and on a GPU. The compute-intensive part that can be parallelized was implemented on the GPU using CUDA C programming.

Table 5.4: Device Properties.

Device Model	Quadro 4000
CUDA compute capability	2.0
Global memory size	2048 Mbytes
Number of multiprocessors (SM)	8
Number of CUDA Cores/SM	32
Number of threads/warp	32
GPU clock rate	0.95 GHz
Maximum number of threads per multiprocessor	1536
Maximum number of threads per block	1024
Maximum number of warps per multiprocessor	48
Maximum number of block per multiprocessor	8

5.2.2 Performance Assessment

By referring to the GPU device property in Table 5.4, the maximum number of resident blocks per SM is 8 due to its compute capability. However, since each block is launched with 500 threads, only 3 blocks can reside in an SM due to the maximum limit of resident threads per SM (1536), hence the execution models are as illustrated in Figure 5.1 and Figure 5.2. Since there are 8 SMs for this device, a maximum of 24 blocks are being executed concurrently. The rest of the blocks will be in queues. Threads in each block are grouped into warps of size 32. Hence, there are 16 warps in a block, giving a total of 48 warps in an SM. The SM is thus considered to have achieved maximum occupancy. The execution of a warp is scheduled by the warp schedulers in the SM.

In order to verify that the algorithm was correctly ported over to the CUDA architecture, a comparison was made between the bit-table and the result array obtained from the CUDA implementation and those obtained from the serial implementation. The comparison results confirmed that identical bit-tables and result arrays were obtained.

To measure the performance of the algorithm in the different implementations, the execution time was recorded for the filter insertion and searching only. The time taken to print the bit-table and the searching results to text files was excluded. The average values of five runs (for all dataset sizes) were used to plot the graphs in this section.

As mentioned in Section 5.1, the performance of the Bloom Filter algorithm implemented on CUDA was compared when the batch size was fixed at 8 and when it was fixed at 50,000. Figure 5.3 shows the total time taken for the insertion and searching of the Bloom Filter.

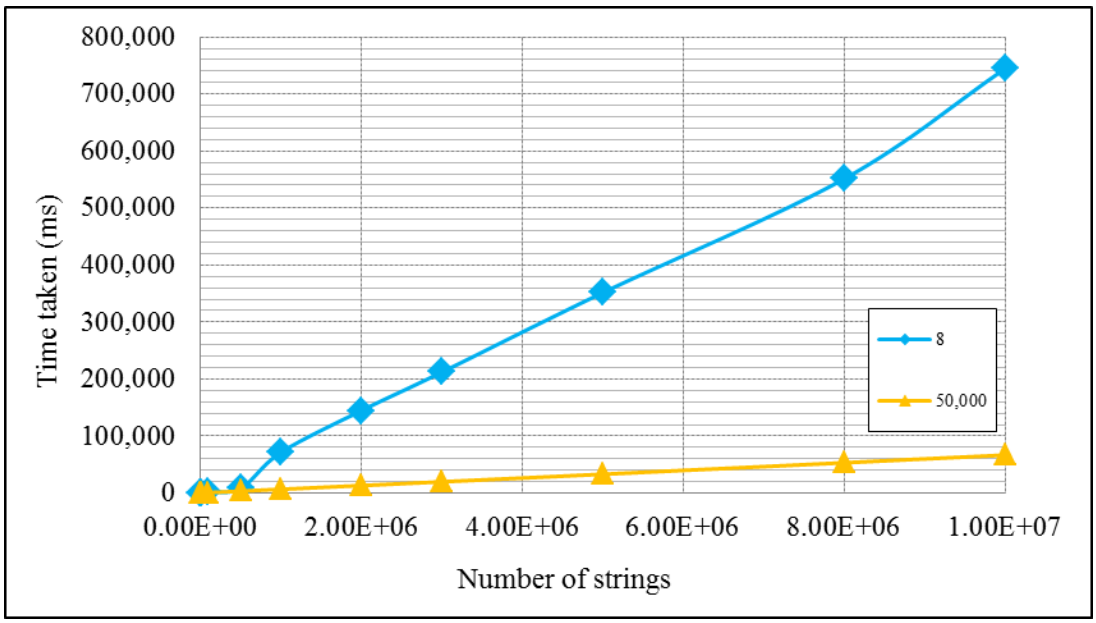


Figure 5.3: Total time taken for Bloom Filter (insert and search) when implemented on CUDA using different batch sizes (8 and 50,000).

As observed from the figure, the total time taken when the batch size was fixed at 50,000 was much less compared to when it was fixed at 8. When the size of the dataset was 10,000,000, approximately 750 seconds were needed for the case of the batch size being set to 8. In contrast, less than 100 seconds were needed when the batch size was set to 50,000. As such, it is proven that a larger batch size gives a better performance for the Bloom Filter algorithm. Longer total execution time was taken for a smaller batch size because more invocations of data transfer were needed. Apart from this, the number of warps residing in each SM was 16, which is one third of the maximum allowable value; hence the SM was not fully occupied. GPU-Z, an application for monitoring the GPU resources had also shown that the GPU load was less than 30% when the batch size was set at 8. On the contrary, a GPU load of 99% was achieved when the batch size was set at 50,000. Therefore, the batch size was chosen as 50,000.

After setting the batch size, the performance of the Bloom Filter algorithm executed using CUDA was measured against the same algorithm running in serial. The performance gain of the CUDA implementation over the serial implementation was calculated and then plotted as shown in Figure 5.4, Figure 5.5 and Figure 5.6.

Let t_c represent the time taken for the Bloom Filter in a CUDA implementation. The performance gain (or performance ratio or speedup factor) is calculated as:

$$Performance\ gain = \frac{t_s}{t_c} \quad \textbf{(5-1)}$$

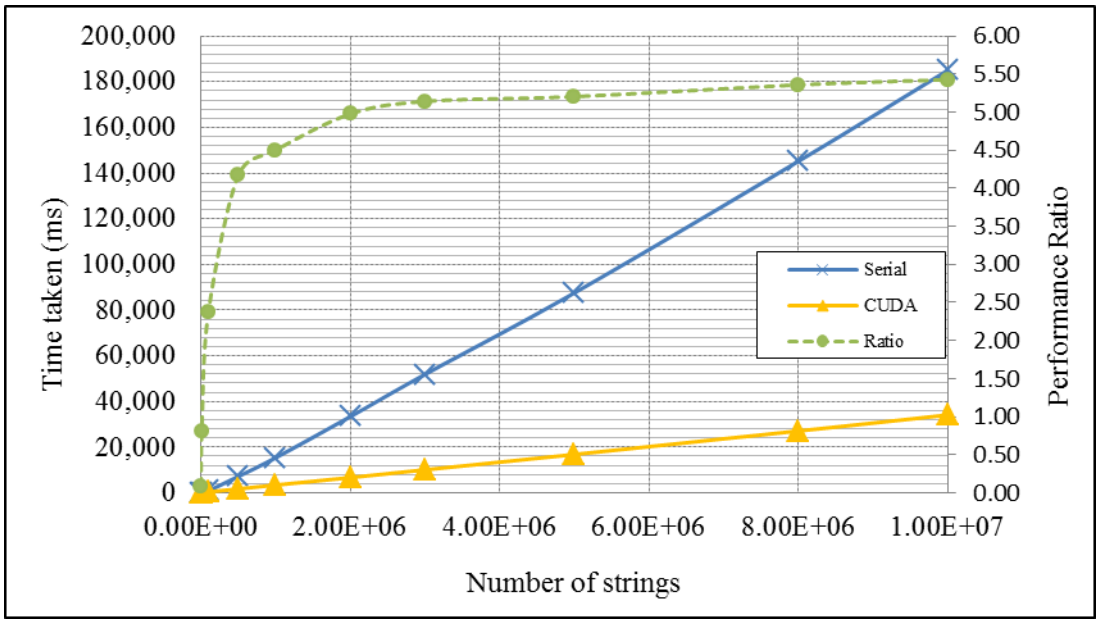


Figure 5.4: Time taken and performance gain for Filter Insertion when implemented using serial programming and CUDA.

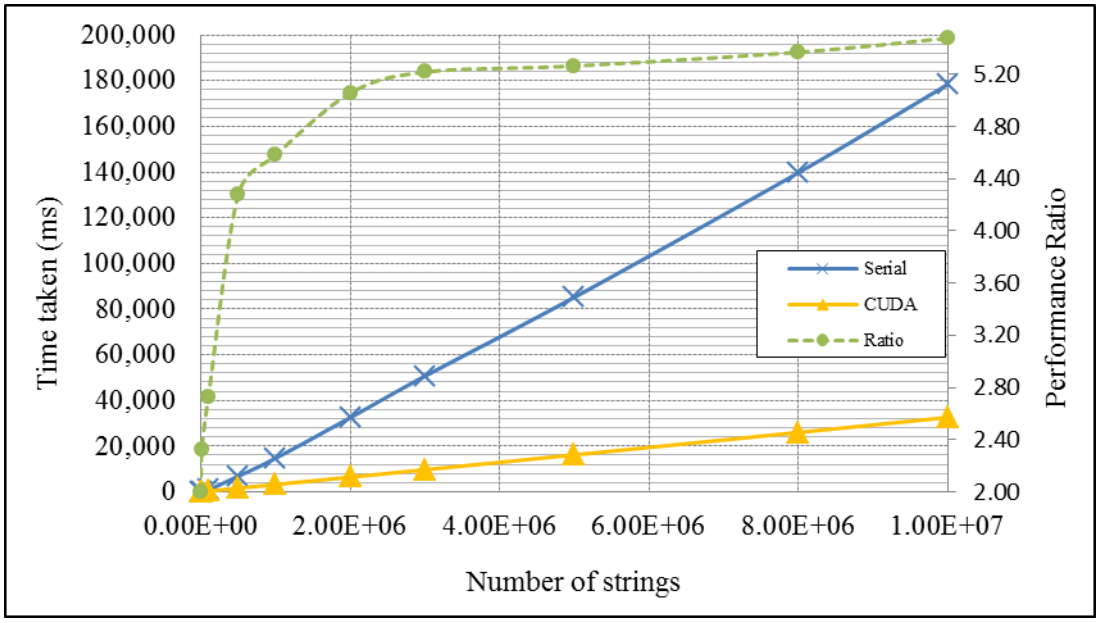


Figure 5.5: Time taken and performance gain for Filter Search when implemented using serial programming and CUDA.

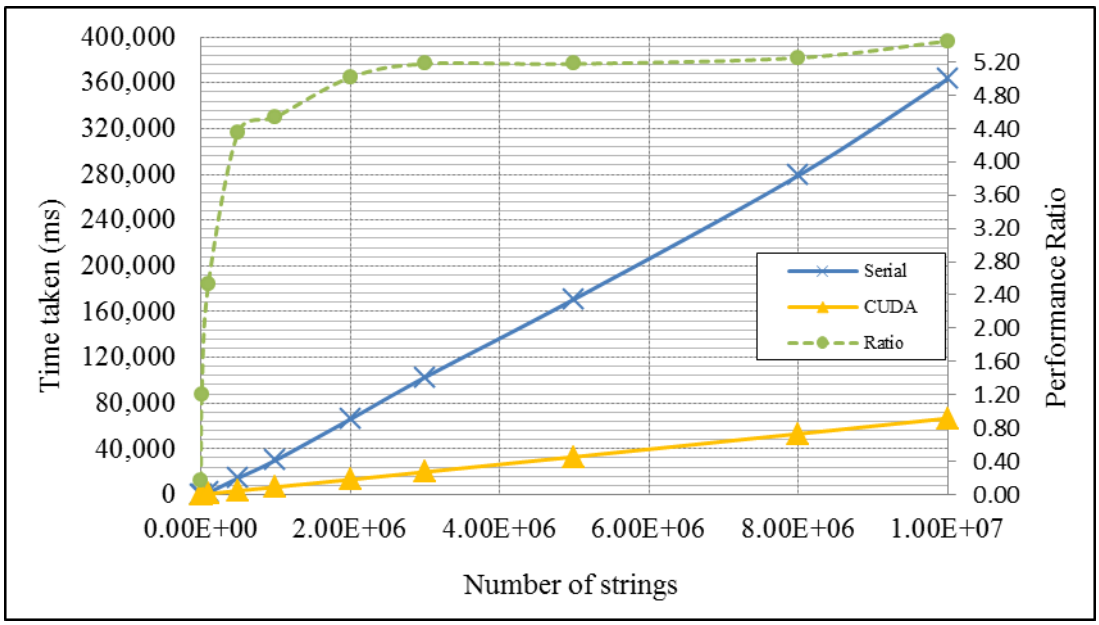


Figure 5.6: Total time taken and performance gain for Bloom Filter (insert and search) when implemented using serial programming and CUDA.

Figure 5.4, Figure 5.5 and Figure 5.6 show the execution time and the performance gains for the Bloom Filter algorithm when it was executed using serial programming and CUDA. As observed from the three figures, the processing time for the Bloom filter was longer when serial programming was implemented as compared to the CUDA implementation. Approximately 35 seconds were needed for inserting 10,000,000 strings into the CUDA filter whereas 180 seconds were needed by the serial filter; hence a performance speedup of 5.5x was achieved. The filter search for 10,000,000 strings (queries) exhibited an almost similar amount of time and speedup. As a result, a speedup factor of approximately 5.5x can be observed from Figure 5.6 as well, whereby the serial filter took 360 seconds for the algorithm while the CUDA filter took 69 seconds.

For a more in-depth assessment, it can be observed that the performance gain of CUDA over serial programming showed a dramatic increase when the size of the input data was small. By referring to Figure 5.6, CUDA implementation of the algorithm took slightly less amount of execution time when there were 10,000 strings, contributing to a speedup factor of 1.2x. When the size of the dataset was increased to 100,000, the speedup factor increased to approximately 2.6x. A speedup factor of 4.4x was achieved when the dataset consisted of 500,000 strings. However,

the increase in performance gain slowed down upon reaching this data size. For data size greater than 3,000,000 strings, the speedup factor increased at an even slower rate. The speedup factor was approximately 5.2x for 3,000,000 strings and 5.5x for 10,000,000 strings. The declination of the increase rate of speedup factor could be due to resource limitation (number of CUDA cores and SMs).

For the case of filter insertion, atomic instruction was involved when the bit-table was updated by more than one thread. Each atomic write to the global memory location was performed in a serial manner. This introduced delay as the program could not be entirely parallelised when such condition occurs.

In the filter querying function, there is a conditional branch statement to check if the bit-table element has been set. In the case whereby the threads within a warp diverged due to the conditional statement, each branch path would be executed serially by the warp. After all paths have been completed, the threads would converge back to the same execution path. The divergence thus introduced delay into the algorithm.

CUDA implementation of the algorithm has shown a positive performance speedup whereby it reached approximately 5.5x. Despite having a maximum of 256 threads executing in parallel in one clock, the performance speedup did not reach 256x. This is because the time taken for copying the data from the CPU memory to the GPU memory was included in the performance measurement. Although the algorithm has already exploited the use of shared memory with the purpose of reducing the computational time, the bit-table remained in the GPU global memory. This is because updates to the bit-table must be visible to all threads. Consequently, the performance of the algorithm was affected due to the low global memory bandwidth. In spite of that, there has been an overall improvement for the CUDA implementation of the algorithm compared to the serial CPU implementation.

CHAPTER 6: FURTHER DEDUCTIONS FROM PERFORMANCE COMPARISON

In the previous chapters, serial implementation of the Bloom Filter algorithm has served as the benchmark for comparison. This chapter investigates the performance comparison between parallel programming on a CPU and on a GPU. An analysis was also done to compare the performance of the algorithm when executed on different GPUs.

6.1 Performance Assessment for Parallel CPU and GPU Implementations

Theoretically, the GPU execution will consume less time compared to the parallel CPU execution as a GPU has a massively parallel structure. The results collected from this project support this theory. The size of the datasets ranges from 1,000 strings to 10,000,000 strings. The average values after five runs were used to plot the graphs. The performance gain is calculated as the ratio of the time taken by the CUDA implementation (using Quadro4000) to the time taken by the OpenMP implementation (with 8 parallel threads).

Figure 6.1, Figure 6.2 and Figure 6.3 show the time taken for the filter insertion, filter search and the total time (insert and search) for the algorithm, respectively.

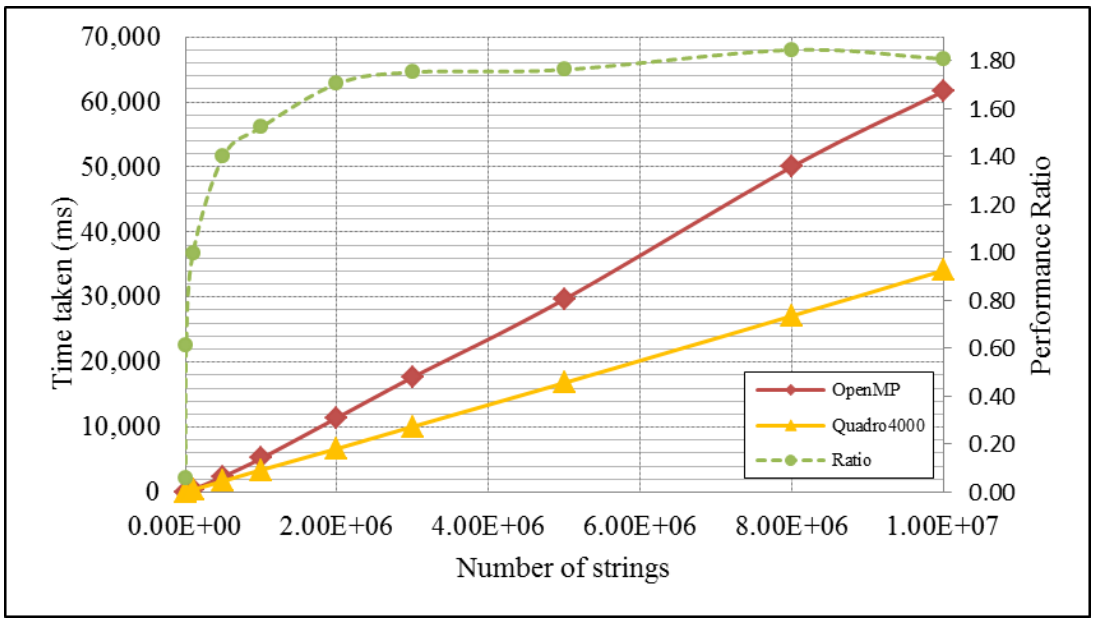


Figure 6.1: Time taken and performance gain for Filter Insertion when implemented using OpenMP and CUDA (Quadro4000).

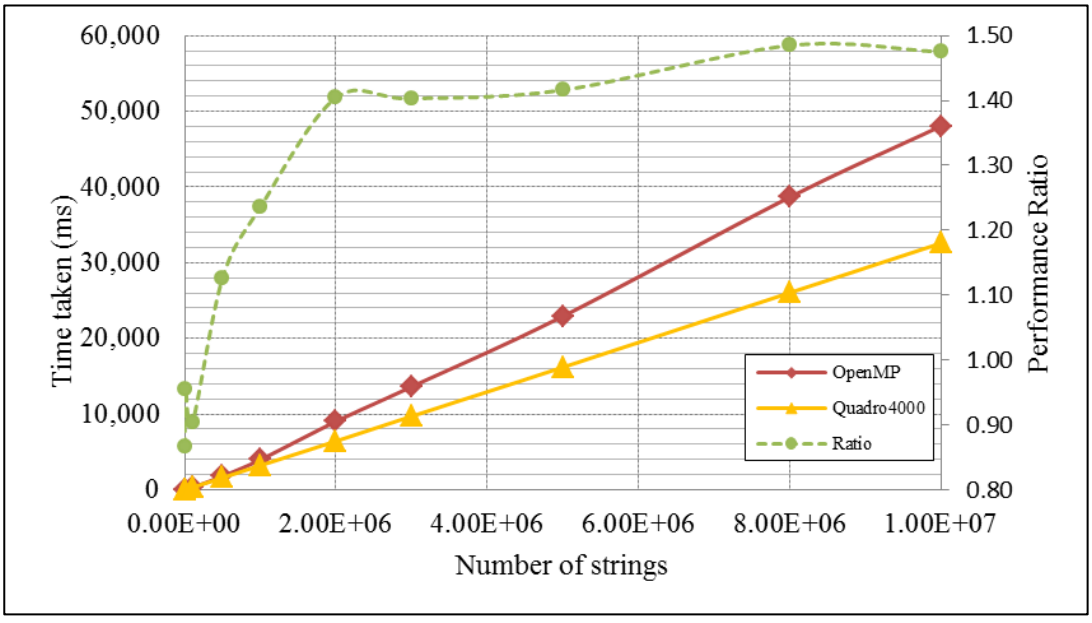


Figure 6.2: Time taken and performance gain for Filter Search when implemented using OpenMP and CUDA (Quadro4000).

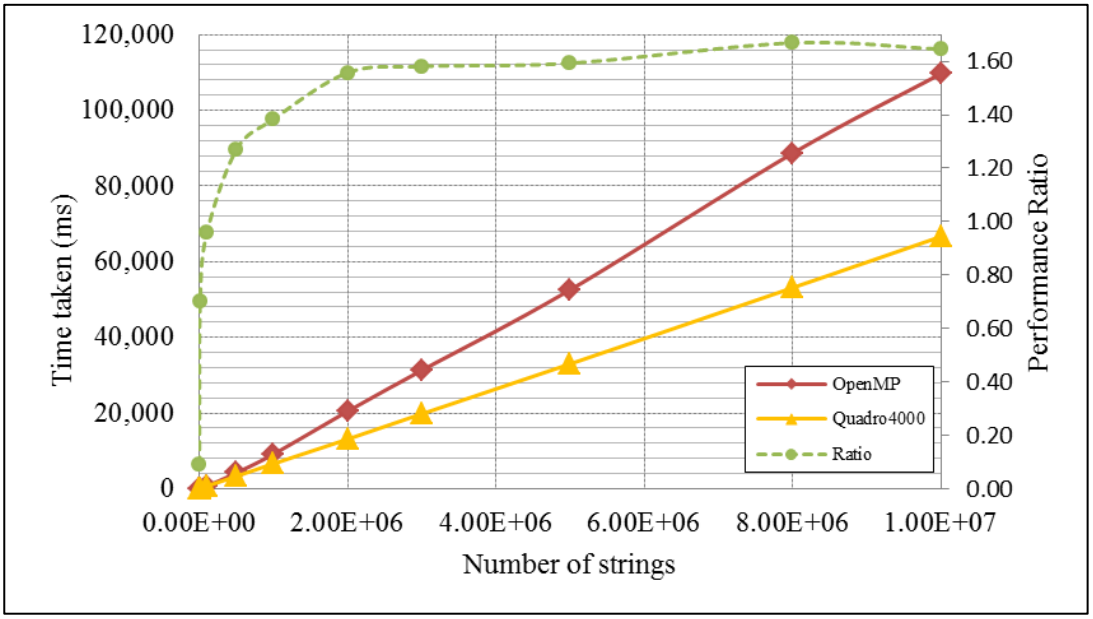


Figure 6.3: Total time taken and performance gain for Bloom Filter (insert and search) when implemented using OpenMP and CUDA (Quadro4000).

A similar trend can be observed in all three figures. Figure 6.1 recorded a 1.8x speedup for the filter insertion when the number of strings was 10,000,000, whereby the OpenMP implementation took approximately 62 seconds while the CUDA implementation took roughly 35 seconds. In Figure 6.2, a gain of 1.48x was recorded when searching was performed for 10,000,000 strings. 48 seconds were needed for OpenMP whereas 34 seconds were taken by CUDA. Therefore, the speedup factor for the total time taken was recorded as approximately 1.65x, as portrayed in Figure 6.3.

Figure 6.3 has also shown that the OpenMP and CUDA implementations took approximately equal amount of time when the number of strings was 100,000 in both input word list and query list. The speedup factor for the CUDA implementation then increased from 1.3x (for 500,000 strings) to 1.5x (for 2,000,000 strings). This marks a substantial increase in the performance speedup when the data size was smaller than 2,000,000. As the data size increased further, the performance speedup increased in a slow but steady manner. At 10,000,000 strings, the performance speedup reached approximately 1.65x. A possible explanation for this decreasing speedup factor is the GPU resources have reached an almost saturated

point. In addition, more copy operations were invoked when the data size increases, hence incurring more overheads since the data were processed in batches.

6.2 System Assessment for the GPGPU Implementation on Different GPUs

6.2.1 Assessment Environment

Table 6.1: Device Properties.

Device Model	GeForce 530	Quadro4000
CUDA compute capability	2.1	2.0
Global memory size	1024 MBytes	2048 Mbytes
Number of multiprocessors (SM)	2	8
Number of CUDA Cores/SM	48	32
GPU clock rate	1.40 GHz	0.95 GHz
Maximum number of threads per multiprocessor	1536	1536
Maximum number of threads per block	1024	1024
Total number of registers available per block	32768	32768

Table 6.1 shows the comparison of specifications between the 2 GPUs used in the performance assessment, namely GeForce 530 and Quadro4000. The compute capabilities affect the throughput of the native arithmetic instructions. Compute capability 2.1 generally allows more operations per clock cycle per multiprocessor. However, there are more multiprocessors in Quadro4000, hence providing an advantage over GeForce 530. The total number of CUDA cores in Quadro4000 is also higher compared to GeForce 530, allowing more operations to be performed in parallel. The GPU clock rate for Quadro4000 is less, thus the performance gain of Quadro4000 over GeForce 530 is expected to be less obvious.

6.2.2 Performance Assessment

For the Quadro4000 performance assessment, the results were taken from Section 5.2.2. The Bloom Filter algorithm was executed on the GeForce 530 device and the time taken for the algorithm was recorded. The algorithm was executed for five times for each dataset size. The average values were then used to plot the graphs in Figure 6.4, Figure 6.5 and Figure 6.6. The performance gain is calculated as the ratio of the time taken when executed on a Quadro4000 device against the time taken when executed on a GeForce 530 device.

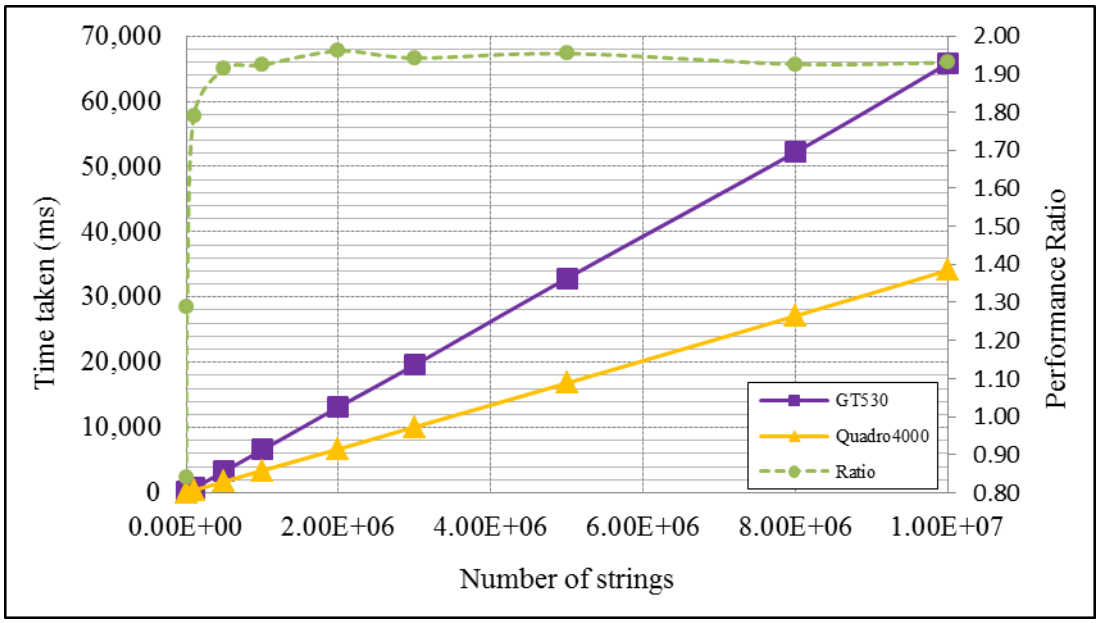


Figure 6.4: Time taken and performance comparison for Filter Insert when executed using GeForce 530 and Quadro4000.

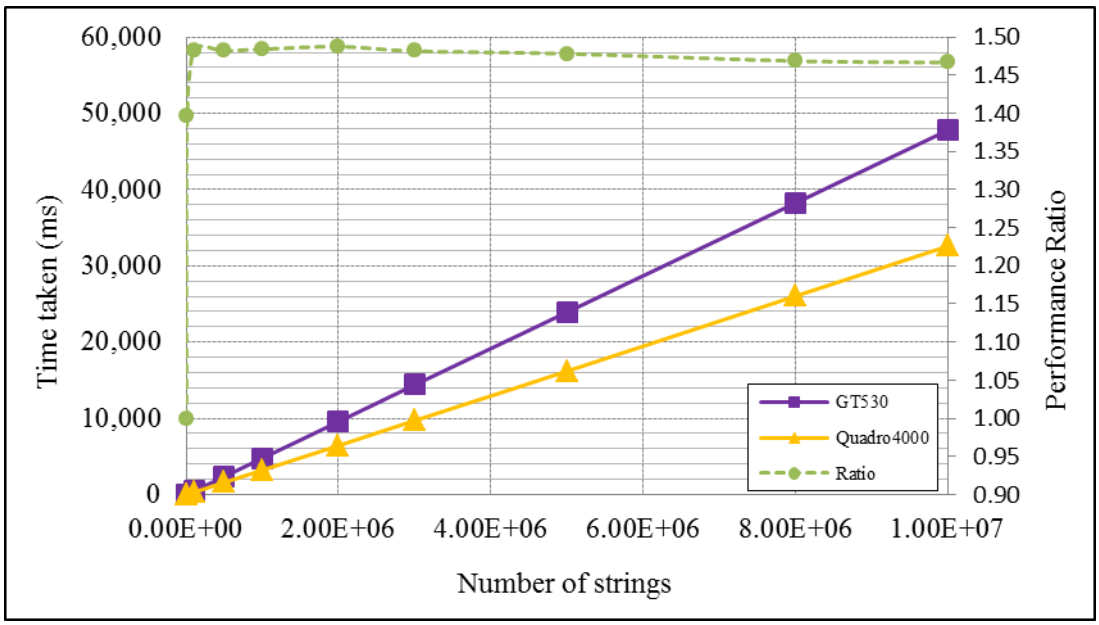


Figure 6.5: Time taken and performance comparison for Filter Search when executed using GeForce 530 and Quadro4000.

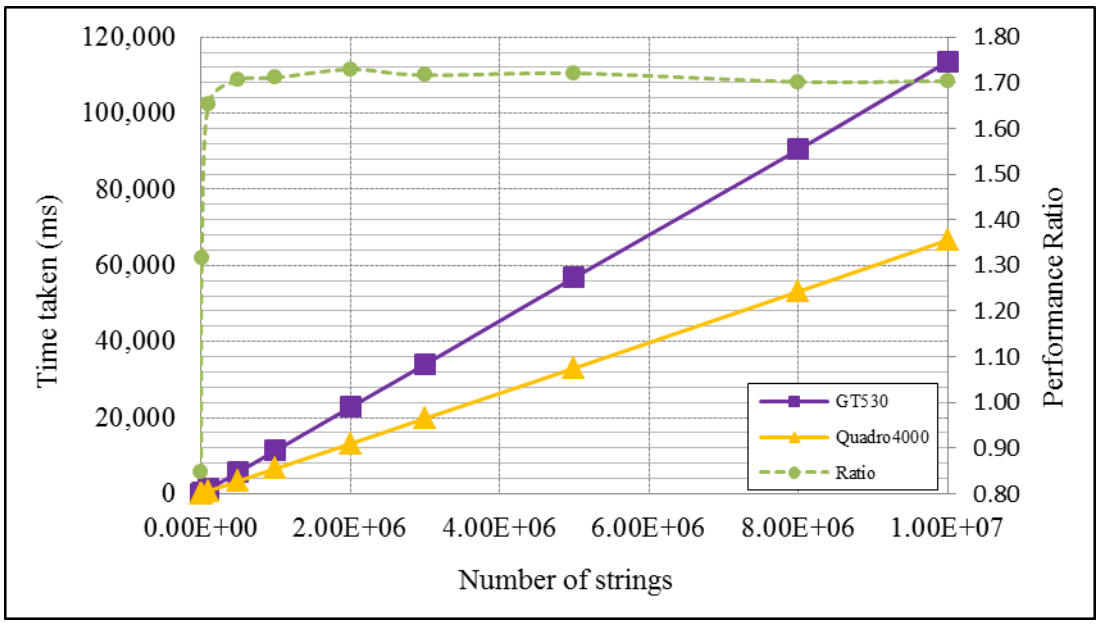


Figure 6.6: Total execution time and performance gain when executing the Bloom Filter algorithm (insert and search) on GeForce 530 and Quadro4000.

Figures 6.4, 6.5 and 6.6 illustrate the results collected for different dataset sizes after executing the same program on different GPUs. The collected results correspond to the expectation of Quadro4000 providing a computational edge over GeForce 530. The curvature for the performance gain in all three figures is similar. By referring to

Figure 6.4, a speedup of 1.9x was achieved for inserting 10,000,000 strings into the filter, whereby GeForce 530 took 66 seconds while 35 seconds was recorded for Quadro4000. To search the filter for 10,000,000 queries, 48 seconds were needed by GeForce 530 while 34 seconds were needed by Quadro4000. This relates to a speedup factor of 1.45x as shown in Figure 6.5.

Based on the total execution time (filter insertion and search) as shown in Figure 6.6, Quadro4000 has shown a performance gain of approximately 1.3x when the dataset consist of about 10,000 strings. A gain of 1.65x was achieved when the size of the dataset was increased to 100,000. Upon reaching the dataset size of 2,000,000 strings, the gain in performance reached its peak of slightly more than 1.7x. When the number of strings was increased further, the performance gain suffered a minimal decrease. For a dataset size of 10,000,000, GeForce 530 took approximately 115 seconds while Quadro4000 took roughly 69 seconds, exhibiting a performance gain of 1.7x. The decrease in the performance gain could be due to the limitation of resources in both devices causing the processing of data blocks to be queued. The higher clock rate of GeForce 530 could be accounted for this decrease in performance gain.

The encouraging results from this project have proven that the implementation of the Bloom filter algorithm using GPGPU is feasible. However, this algorithm does not support locating the query in the input word-list. This is because hash algorithm has been performed on the input strings. The location of each string in the word-list was not stored and was irretrievable from the hash value.

Figure 6.7 shows part of the bit-table after 1000 strings were inserted into the Bloom Filter. The entire bit-table is not shown for brevity purpose.

…	187	56	31	65	192	201	…

Figure 6.7 Part of the bit-table for 1000 strings.

As seen in the figure, the resultants of the OR operation in the algorithm constitute the elements of the bit-table array. As such, it is evident that no information

regarding the string location was inserted into the bit-table. Consequently, location identification of the strings is impossible. Hence, another string searching algorithm is investigated in the following chapter, with the aim of addressing this drawback.

CHAPTER 7: QUICK SEARCH ALGORITHM FOR LOCATION IDENTIFICATION

This chapter discusses the implementation of the Quick Search algorithm for location identification. It attempts to address the limitation of Bloom Filter in finding the position of query in input word-list.

7.1 Algorithm Description

The Quick Search algorithm is adapted from the Boyer-Moore algorithm, whereby it utilizes only the bad-character shift table [44]. The query string is known as pattern. The algorithm attempts to find the location of the pattern in the text (the input word file). Pre-processing is done on the pattern, so that sections of the text can be skipped when searching is performed. This results in lower constant factor compared to other string search algorithms. A longer pattern length usually reduces the searching time as longer sections of the text may be skipped.

The algorithm begins by aligning the first character of the pattern with the first character of the text. A character-by-character comparison is made between the pattern and the text, starting from the right-most character of the pattern. If a mismatch is found, then the pattern is shifted right by a number of positions depending on the bad character rule. If the beginning of the pattern is reached, it indicates that the pattern has been found in the text. Searching of pattern (in text) can be resumed by proceeding with a new alignment, and repeating the entire process until the alignment has past the end of text.

7.1.1 Bad Character Rule

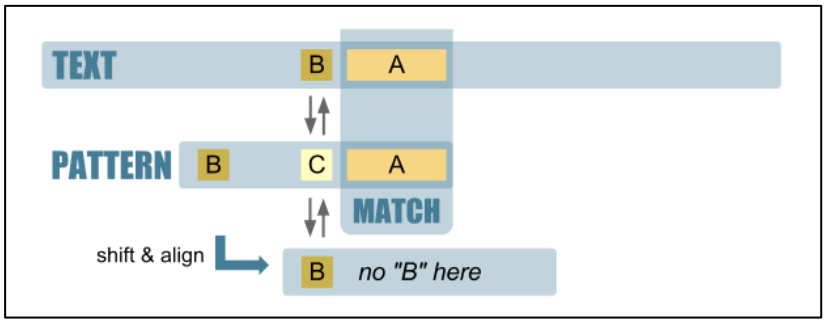


Figure 7.1: Mismatch character is found in pattern [45].

Figure 7.1 depicts that the mismatched character “B” in the text exist in earlier part of the pattern. Hence, the pattern may be shifted to the right until both “B” in the text and the pattern are aligned. Character comparisons will resume after the new alignment is done. If the mismatch character does not exist in the pattern at all, the entire pattern may be shifted forward. This is illustrated in the following figure.

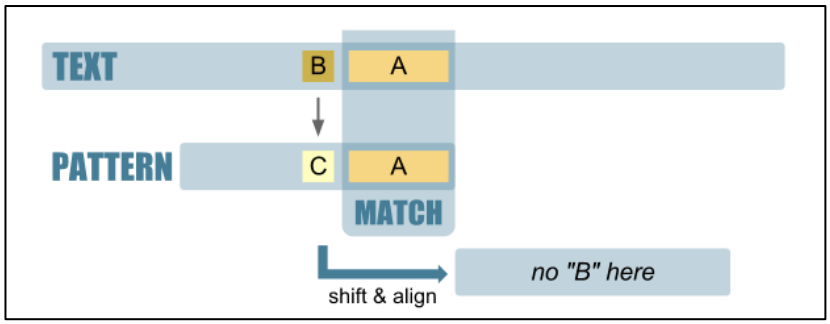


Figure 7.2: Mismatch character is absent in pattern [45].

7.2 Program Design

As illustrated in Figure 7.3, the program begins with loading the input word file and processing all the strings into a 1D character array (text). The query (pattern) file is then loaded and flattened into a 1D character array as well. An integer array is created to store the results of the Quick Search algorithm. Each element of the array corresponds to the location for one pattern in the text. The Quick Search algorithm is performed for all the patterns and the results are printed to a *.txt* file.

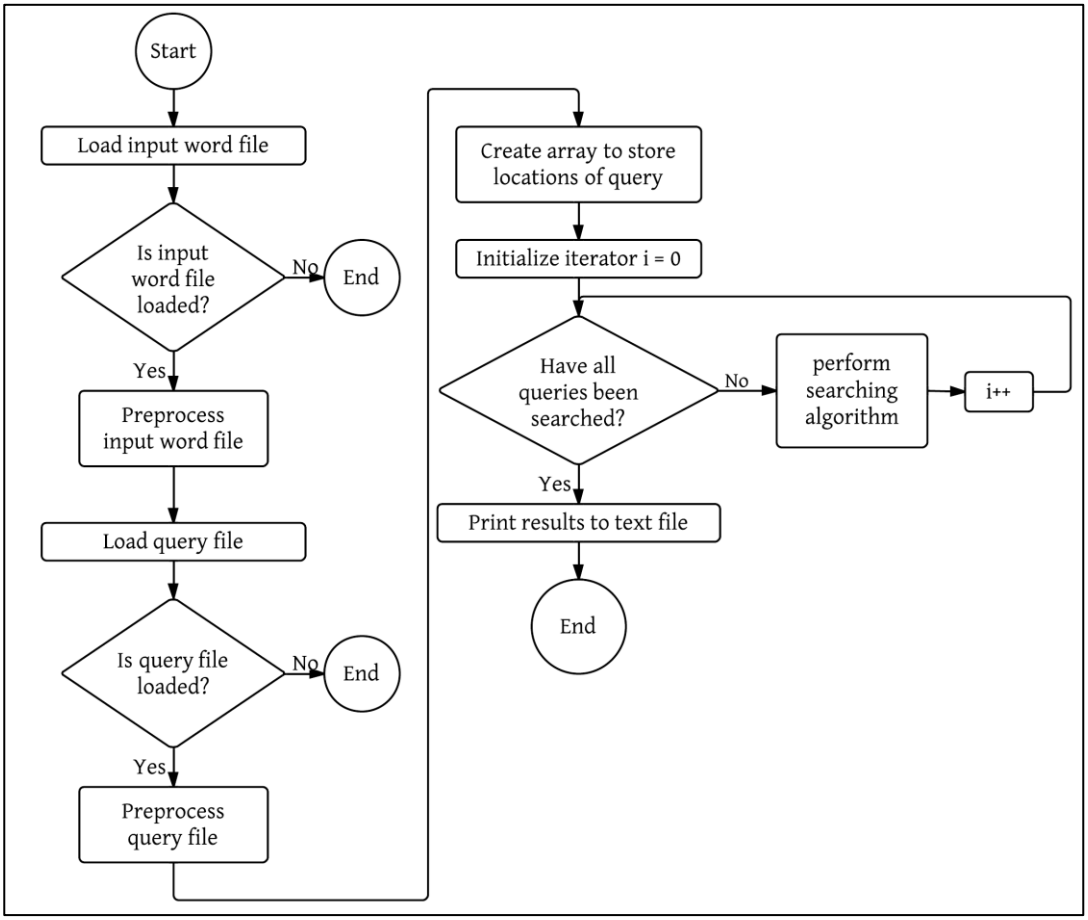


Figure 7.3: Quick Search Algorithm.

7.2.1 Serial Implementation

As suggested from the flowchart in Figure 7.3, the QuickSearch algorithm is performed on one pattern at a time. Each time the function **`boyer_moore()`** is called, one element in the result array is updated. The function **`boyer_moore()`** receives 7 arguments from the main function. At line 15 of Program Listing 7.1, the function **`badcharshift()`** is called. This function creates the bad-character-shift array of size 255 by setting each element to the value of $patternlength - 1$. The ASCII value of each character in the pattern is used as an array index. Array element at that index is then set to the value of displacement of the corresponding character from the last character of the pattern. This is done at Lines 5-9 of Program Listing 7.1.

After the bad-character-shift table is built, the search for pattern location begins. The pattern (referred as **pat** in the code) is compared with the text (referred as **string** in the code). If the pattern and text do not match, the pattern is shifted by a number of positions depending on the bad-character-shift table. Line 32 shows the shifting step. If the pattern and text matches, the location of the pattern in the text is found by comparing the offset in the text (**ind**) with the value stored in the offset table (pointed by **g_pAccumulative_Wordlength**). This is portrayed in Line 25. If a match is found, the element of the result array (pointed by **g_location**) is updated with the location.

```
1  void badcharshift(char *pat, int patlen, int bc[])
2  {
3     int i;
4
5     for (i=0; i < ALPHABET_LEN; ++i)
6           bc[i] = patlen+1;
7
8     for (i=0; i < patlen; ++i)
9           bc[pat[i]] = patlen - i;
10 }
11
12  void boyer_moore (char *pat, int patlen, char *string,
                  int stringlen, int* g_pAccumulative_Wordlength,
                  int g_Wordnumber, int* g_location)
13  {
14    int bc[ALPHABET_LEN];
15    badcharshift(pat, patlen, bc);
16
17    int ind=0;
18
19     while (ind < (stringlen-patlen) )
20    {
21          if (memcmp (pat, string+ind, patlen) == 0)
22          {
23                for (int a=0; a<g_Wordnumber; a++)
24                {
25                      if (g_pAccumulative_Wordlength[a]==ind)
26                      {
27                            (*g_location) = a+1;
28                            a=g_Wordnumber;
29                      }
30                }
31          }
32          ind += bc[string[ind+patlen]];
33    }
36    return;
37  }
```

Program Listing 7.1 Generating bad-character-shift table and searching for query.

7.2.2 OpenMP Implementation

The number of parallel threads has been set to 8 by calling the function **`omp_set_num_threads()`**. Figure 7.4 illustrates the execution model for the OpenMP implementation. Each thread will perform searching for one query and then it will update the associated element of the result array. The design of the program is similar to that of the serial implementation. The only difference is **`#pragma`** directives are added in the main function, as shown in Line 1 and Line 3 of Program Listing 7.2. The search function remains the same as that of in the serial implementation.

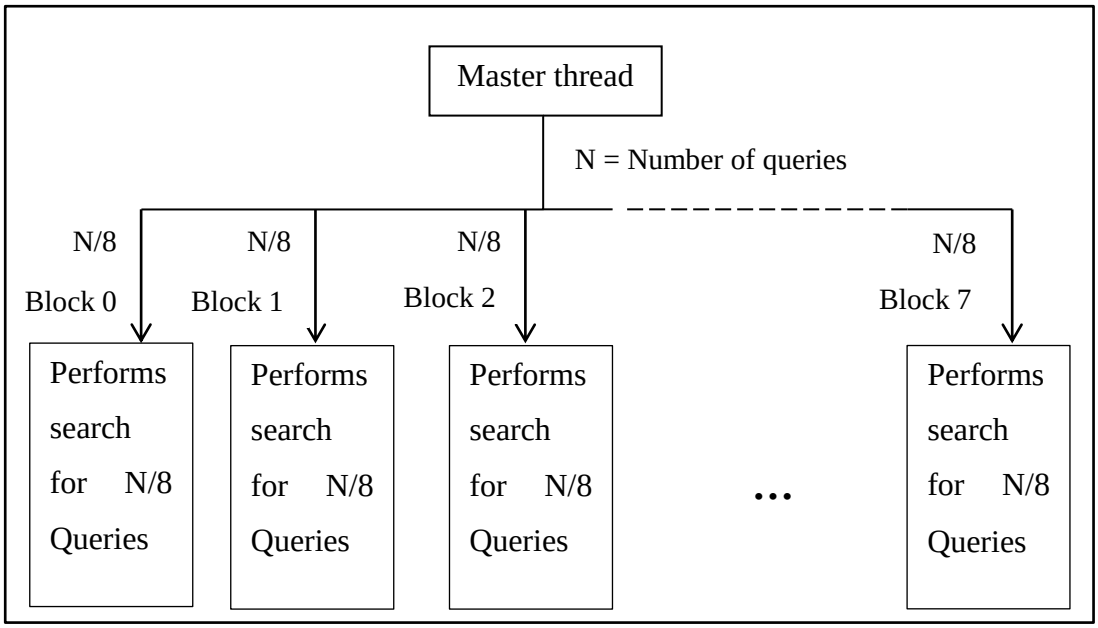


Figure 7.4: OpenMP Execution Model for `boyer_moore()` function when 8 parallel threads are launched.

```
1  #pragma omp parallel
2  {
3     #pragma omp for
4     for (int i=0; i<g_Querynumber; i++)
5     {
6           boyer_moore(g_ppQuery_list_ptr_array[i],
                  g_pQuerylength[i], g_pTotalwordarray,
                  g_Totalwordlength,  g_pAccumulative_Wordlength,
                  g_Wordnumber, &(g_location[i]));
7     }
8  }
```

Program Listing 7.2 Calling `boyer_moore()` function in the main program.

7.2.3 CUDA Implementation

After loading and processing the input word file and the query file, the text and the pattern must be copied from the CPU memory into the GPU memory. Due to the limitations in the GPU resources and the maximum allowable kernel execution time, only 2000 patterns can be passed into the kernel for processing in one invocation. Hence, searches are performed in batches when the number of patterns exceeds 2000. The kernel function is invoked by calling

```
cuda_boyer_moore<<< BLOCK, THREAD >>>
      (dev_pTotalWordArray, dev_pTotalWordLength,
      dev_pTotalWordnum, dev_pAccumulative_Wordlength,
      dev_pTotalQueryArray, dev_pQuerylength,
      dev_pTotalQuerynum, dev_pAccumulative_Querylength,
      dev_pResults);
```

The value for **BLOCK** is set at 63, while the value for **THREAD** is set at 32. Since each SM can have a maximum of 8 resident blocks and there are 8 SMs in the device used, it is speculated that all blocks will be residing in the SM at the same time. There will be no queuing of blocks. The device pointers passed into the kernels serve the same purposes as in the Bloom Filter algorithm.

Each thread in each block performs the complete Quick Search algorithm for one pattern. The index of the result array is calculated as:

$$index = blockID \times threads\ per\ block + threadID \quad \textbf{(7-1)}$$

The associated element of the result array is then updated by each thread. This is illustrated in Figure 7.5. The kernel function is identical to the **boyer_moore()** function in serial and OpenMP implementations.

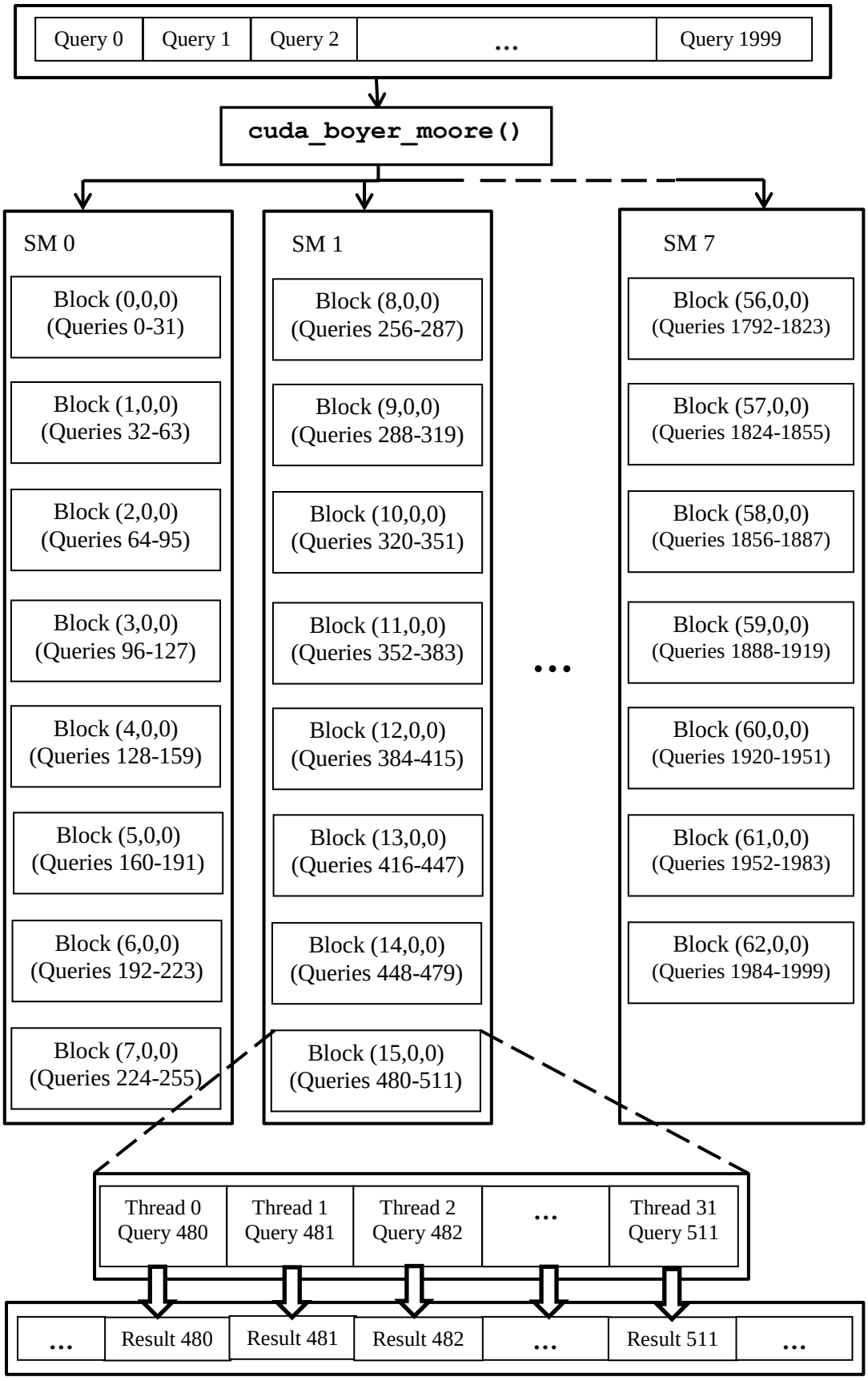


Figure 7.5: CUDA execution model for `cuda_boyer_moore()` function with 2000 queries.

7.3 System Assessment

7.3.1 Assessment Environment

The CPU specifications are as stated in Table 3.5 of Section 3.4.1. The OpenMP implementation utilizes 8 threads for the parallelised region of the code. Quadro4000 was used as the GPU device for the CUDA implementation.

7.3.2 Performance Assessment

For each dataset size, the Quick Search algorithm was executed 5 times on each implementation (serial, OpenMP and CUDA). The average values were then used to plot the graphs in this section. The performance gain for the OpenMP implementation over the serial implementation is calculated as the ratio of the time taken when implemented in a serial program against the time taken when implemented in a data-parallelised CPU program. The ratio of the time taken in the serial implementation over the time taken in the CUDA implementation gives the performance gain for the CUDA implementation over the serial implementation.

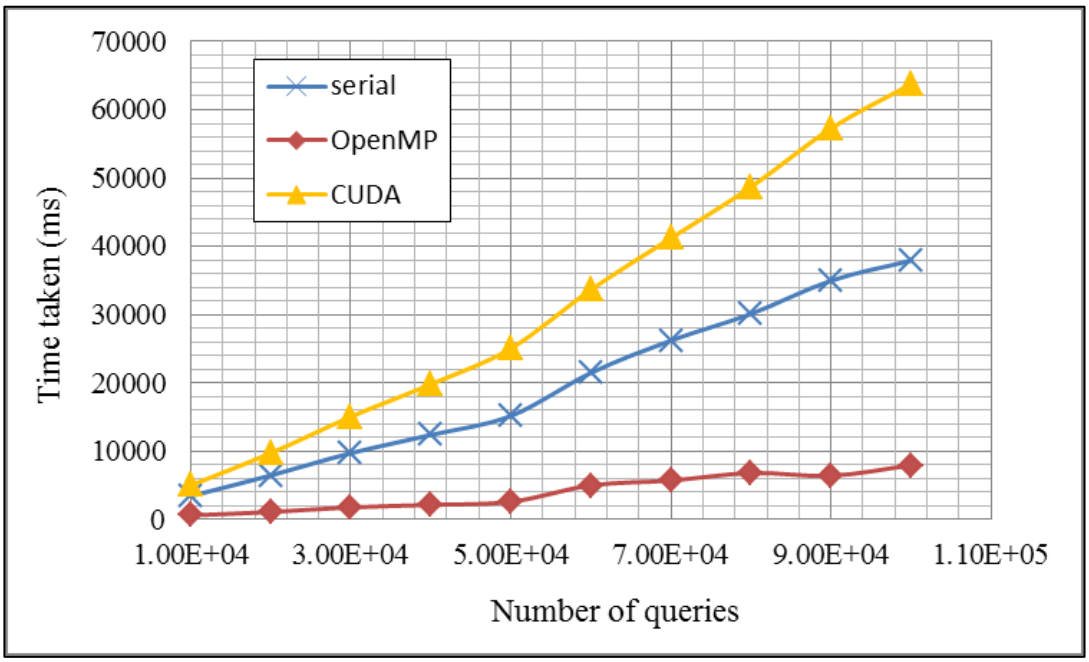


Figure 7.6: Time taken for Quick Search when the size of the input word list is fixed at 110,000.

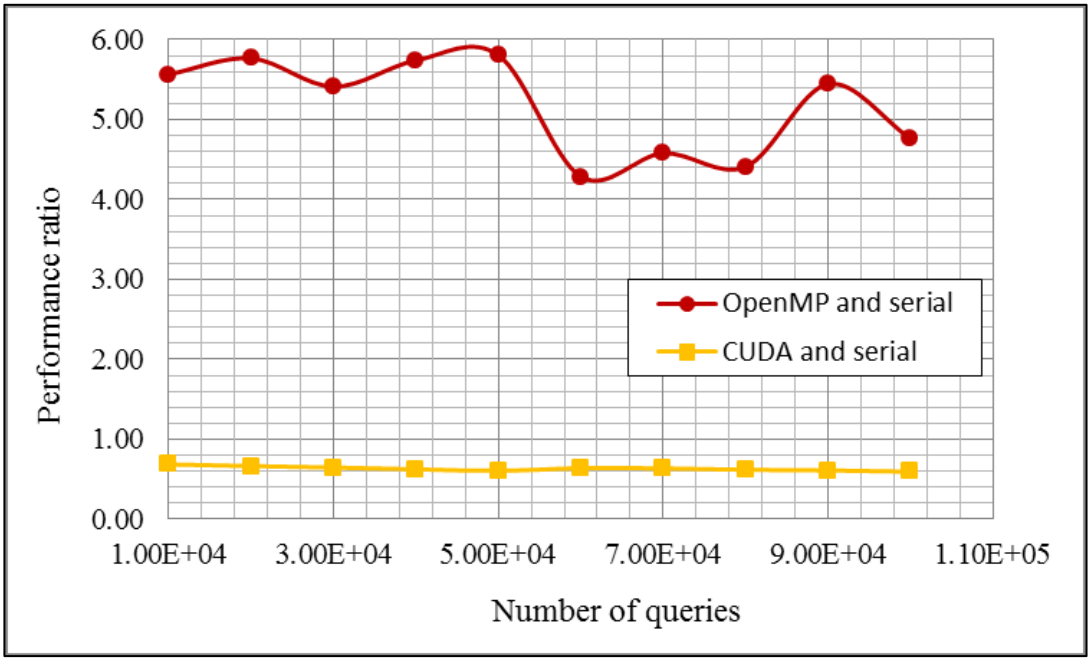


Figure 7.7: Performance ratio when the size of the input word list is fixed at 110,000.

Figure 7.6 depicts the total time taken for the Quick Search algorithm when the input word list was fixed at 110,000 strings while the number of queries was varied from 10,000 to 100,000. As observed from the figure, when the number of queries was increased, the time taken for searching increased as well. The total time recorded for searching 100,000 strings are 38 seconds, 8 seconds and 63 seconds for the serial, OpenMP and CUDA implementations, respectively.

For the case of OpenMP implementation, the increase in the searching time was less obvious compared to the serial and CUDA implementations. This is because the increment in the data size was shared among 8 parallel threads. A peak gain of 5.8x was recorded when the algorithm was performed for 50,000 queries. As shown in Figure 7.7, the speedup factor for the OpenMP implementation was inconsistent. The inconsistency in the CPU runtime may have contributed to the fluctuating results.

As observed in Figure 7.6, the CUDA implementation of the Quick Search algorithm took a much longer time compared to the serial version. This is portrayed in Figure 7.7 as well, whereby the ratio of the CUDA implementation over the serial

implementation was less than 1 for all sizes of the query list. A performance ratio of approximately 0.6x was recorded. A possible explanation is the approach taken in the CUDA implementation was not fully optimized. The text (input word list) and the queries were located in the global memory of the device; hence long latency was generated when the character comparison was made between the queries and the text. In addition, since the algorithm had to be performed in batches when the number of queries exceeds 2000, more invocations of the copy operation were performed. This led to more data transfer overheads, thus consuming more time.

The performance for each implementation of the Quick Search algorithm was also recorded when the number of queries was fixed at 2,000 while the number of strings in the word list was varied from 10,000 to 100,000. Figure 7.8 and Figure 7.9 illustrates the results obtained.

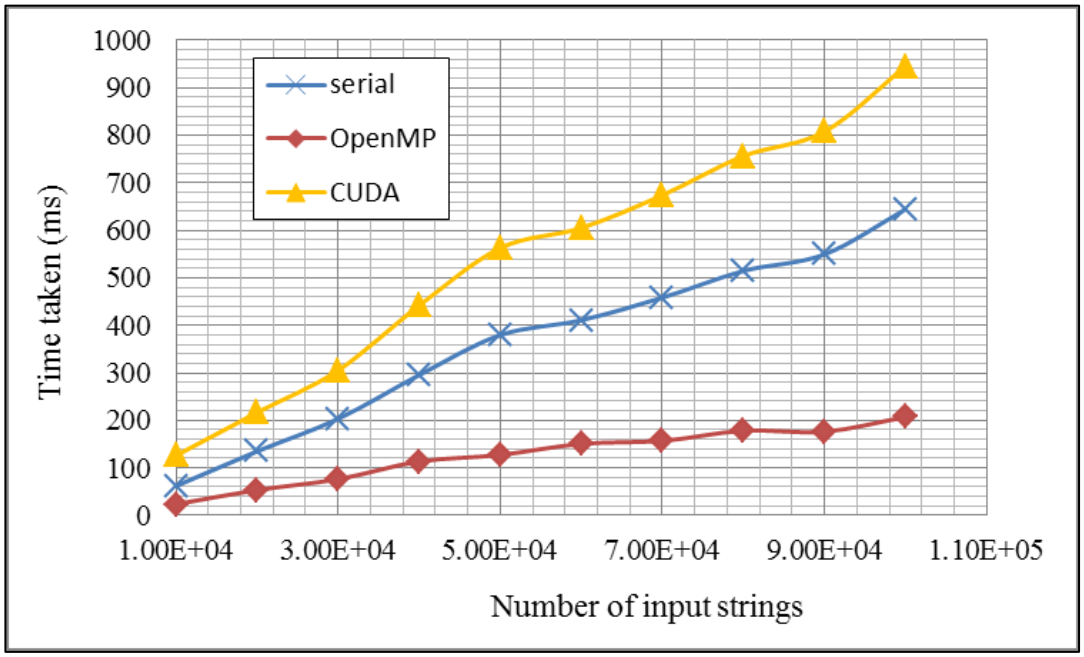


Figure 7.8: Time taken for Quick Search when the size of the query list is fixed at 2000.

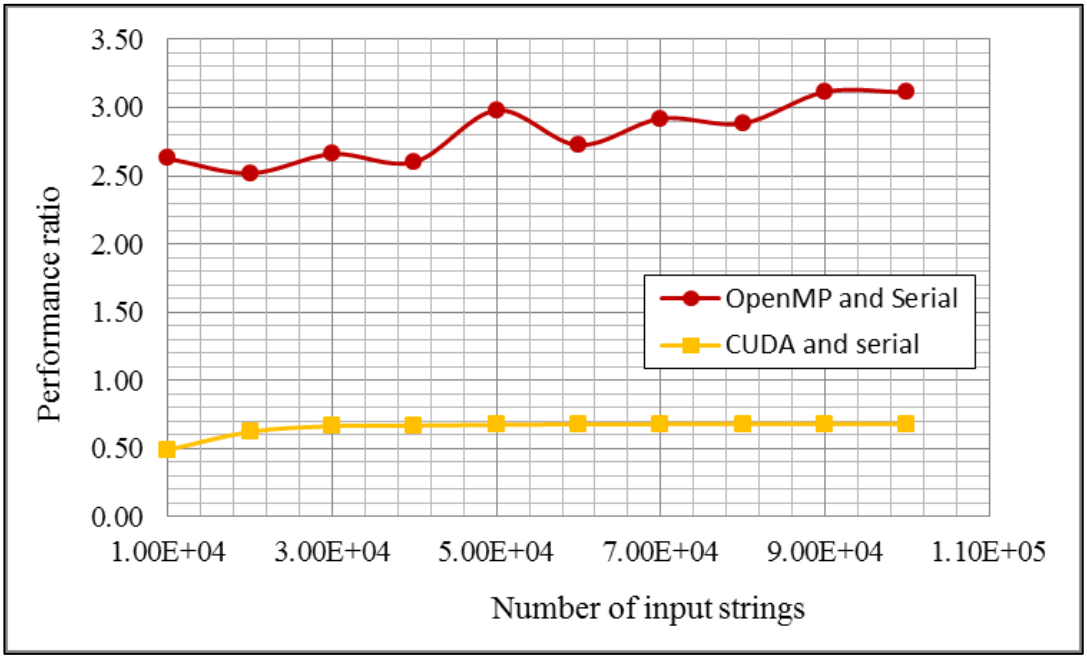


Figure 7.9: Performance ratio when the size of the query list is fixed at 2000.

The higher number of strings in the word list implies a longer text length was involved in the Quick Search algorithm. Hence, more time was needed for the algorithm when the length of the text was longer. This corresponds to the results shown in Figure 7.8, whereby the time taken for searching 2,000 queries in a 100,000 word list was 640 milliseconds for the serial implementation, 200 milliseconds for the OpenMP implementation and 900 milliseconds for the CUDA implementation.

From Figure 7.9, it is observed that the performance gain for the OpenMP implementation over the serial implementation showed a gradual increase (but with minimal fluctuations) when the input word list was increased in size. The gain in performance was less dramatic compared to the case when the size of the query list was varied. This is because parallelisation was distributed based on the number of queries. Hence, the increase in the computational load due to the word list size would have less impact on the improvement ratio of the OpenMP implementation.

The CUDA implementation has again showed worse result when it was compared to the serial implementation. As shown in Figure 7.9, there was a slight increase from

0.5x for 10,000 input strings to almost 0.7x for 40,000 input strings. However, the performance ratio remained constant at 0.7x upon reaching 50,000 input strings. No further performance improvement could be obtained. This could be due to the storage of the text and the queries in the global memory of the device; thus inducing delay when the data were fetched (for character comparisons) due to the narrow memory bandwidth.

The Quick Search algorithm has managed to overcome the drawback of the Bloom Filter algorithm in location identification. The OpenMP implementation of the algorithm has shown the best performance among the three implementations whereas the CUDA implementation obtained the worst performance. A hypothesis deduced here is the usage of the global memory for storing the constantly-used data will result in an inefficient algorithm due to the long memory access latency. An attempt to imitate the CUDA implementation of the algorithm based on the abstract submission by Raymond Tay was unsuccessful due to the lack of information given in the paper. The current implementation adapted in this project does not show the advantage of the CUDA implementation over the serial implementation. As such, a different strategy in designing would be required for a performance improvement, which is recommended as part of the future work.

CHAPTER 8: CONCLUSIONS AND FUTURE WORK

8.1 Summary of Work

One of the objectives of the project is to identify the computational bottleneck of the serial implementation of the Bloom filter. The repetitive hashing procedures has been proven to be the main contributor of the hash computational load. Hence, data parallelisation by using OpenMP has been implemented as part of this project. The main objective of this project is to design and develop a string searching algorithm using GPGPU. Implementation of Bloom Filter using CUDA has proved to be feasible and has given positive results. The limitation of the Bloom Filter algorithm has been identified as its inability to locate the position of the query in the input word list. Quick Search algorithm was then investigated to overcome the drawback of Bloom Filter.

8.2 Conclusions

The massively parallel computing architecture of a GPU provides an opportunity for string searching algorithms to be implemented using CUDA. Thus, Bloom Filter has been chosen to be implemented in this project. The research of this project also includes designing and developing a parallel CPU implementation of the algorithm. A performance speedup of 3.3x was attained for the dataset size of 10,000,000. The performance of the Bloom Filter algorithm using the CUDA implementation was also benchmarked. For 10,000,000 strings, a gain of 5.5x was obtained in the performance of the algorithm. Hence, it can be concluded that utilising a GPU to perform a computationally expensive algorithm improves the performance of the program. However, the improvement in performance is affected by the architecture

and the compute capability of the GPU. The Bloom Filter algorithm offers space and time efficiencies; however it is not suitable if location identification is needed. Quick Search would be a more appropriate algorithm if space efficiency is not a primary concern.

8.3 Future Work

The Bloom Filter algorithm implemented in this project has limited the number of hash functions to a specific value. The amount of space required for storing the bit-table and the false positive probability are calculated based on that value. Optimization can be performed in order to obtain the optimal number of hash functions such that the size of the bit-table can be reduced without increasing the false positive probability.

Implementation of Quick Search algorithm using CUDA can be investigated further by restructuring the algorithm when it is ported over to CUDA architecture. Improvement in performance will be obtained if the algorithm is optimised for processing on a GPGPU.

The algorithm developed in this project is implemented on a single card within a single machine. Future work can be done to improve the performance by running the algorithm using multiple cards within a single machine or across several machines (i.e., GPU clusters).

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