General-purpose Computing on Graphics Processing Units for Real-time Analysis of Scanning Electron Microscope Images

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Abstract

Chapter 1

Introduction

The scanning electron microscope (SEM) is a type of microscope that produces images using signals generated from the interaction between electrons and the surface under observation. It has higher resolutions than traditional optical microscopes—an SEM can have a resolution lower than one nanometre, whereas that of an optical microscope is limited to a few hundred nanometres. This has benefited a variety of fields by allowing scientists to see micro-details of objects that were previously impossible to observe. For example, the SEM can be used to study structures of semiconductor devices [1] and to view changes in bacterial cells [2].

Fig. 1.1 illustrates how an SEM works. The electron gun generates an electron beam, which is transformed into an electron probe after passing through the condenser lens and objective lens. It is then scanned across the specimen under the effect of the scanning coil. As a result of the interaction between the incident electrons and the specimen, some electrons (which are called secondary electrons) are emitted from the specimen. The detector collects the secondary electrons and generates signals based on their energy levels. The display unit uses the signals to produce one image after each complete scan of the specimen.

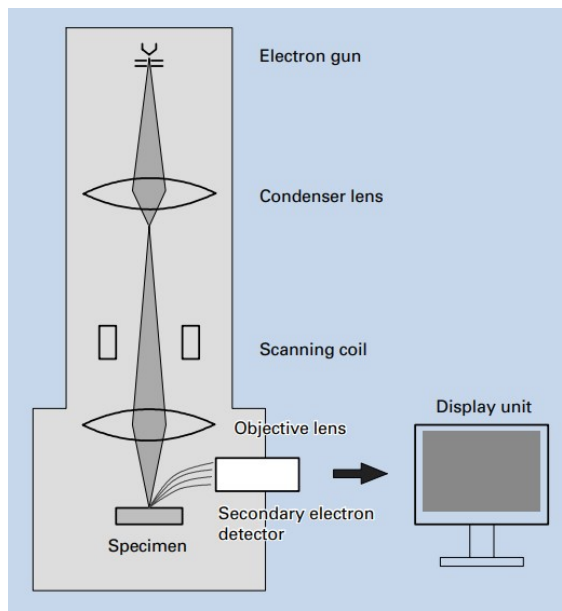


Figure 1.1: Basic construction of an SEM [3].

Many image analysis methods have applications in the field of SEM, and the fast Fourier transform is an especially popular one since it can be used to evaluate the focusing and astigmatism of an SEM [see section 3.3]; however, due to the complexity of the algorithm and a lack of fast hardware, real-time analysis had been either impossible or impractical in the past. In 1997, with an advanced central processing unit (CPU)—the Pentium Pro, it was only possible to achieve a refresh rate of 0.6 frames per second for 8-bit 1024×1024 input images [4]. Although the enhancement of CPUs has enabled faster computations throughout the years, what really brings the speed to a different level is the development of graphics processing units (GPUs).

The GPU used to be a highly specialised hardware that was designed to excel in rendering complex, high-resolution, real-time 3D scenes for games; however, its special architecture has made it outperform CPUs in many other areas and resulted in the birth of the idea of general-purpose computing on graphics processing units (GPGPU) [5], where GPUs are used to perform computations that are traditionally handled by CPUs.

A key characteristic of GPUs is massive parallelism. Depending on their positions, pixels in a 3D scene often require different processing to achieve effects such as lighting, blurring, and fogging. GPUs do this by breaking down the scene into fragments and manipulating each fragment individually. Modern GPUs have thousands of parallel processor cores each running tens of parallel threads to meet the the high requirement for parallelism. For example, the NVIDIA GeForce GTX 1060 has 1280 cores and each of them is capable of running 16 threads; a similarly prices CPU—the Intel i7-7700—has only 4 cores each running 8 threads. It is worth mentioning that the processing cores on a GPU are not as sophisticated as a full CPU and run at a lower clock frequency. The processor clock frequency of the GTX 1060 is 1708 MHz whereas the i7-7700 has a base processor frequency of 3600 MHz. This means that GPGPU is more useful for applications that involve simple, repetitive, parallel tasks. A recent example is deep learning, where computations that follow the same logical sequence of control need to be performed on a deep network of nodes. Typical deep learning networks in 2015 consist of about one million nodes [6], which means that the computations cannot be done efficiently on a CPU.

This report investigates the gain in calculation speeds from the use of GPUs, and presents a diagnostic tool developed based on GPGPU, which can perform real-time histogram equalisation and FFT on images captured by an SEM. The tool was used to implement an automatic focusing and astigmatism correction algorithm, and the results are discussed.

Chapter 2

The gain in calculation speeds from the use of GPUs

2.1 GPU computing

The GPU is designed to meet the high demand in parallelism for fast rendering of scenes on displays. For example, a 1080p display refreshing at 60 Hz requires $60 \times 1920 \times 1080 = 124,416,000$ values to be computed in each second, which cannot be done efficient enough in the sequential manner used by the CPU. It describes an image using graphics primitives as shown in Fig. 2.1. To construct the image, the primitives are passed through the graphics pipeline of the GPU, which can be divided into the following stages:

- Vertex generation. A list of vertices are generated to represent the image as a 3D triangle mesh, as illustrated by Fig. 2.2.

- Triangle generation. The vertices are assembled into triangles, which are the fundamental hardware-supported primitive in modern GPUs.

- Fragment generation. The triangles are mapped to blocks of pixels on the screen; each block is called a "fragment".

- Fragment processing. The fragments are shaded based on colour and texture information to determine their final colour.

- Composition. A final image is created by assembling the fragments.

The processing of primitives within each stage follow the same logical sequence of control, but the data are different. This pattern is called "single instruction multiple data" (SIMD). The GPU has a large array of SIMD, multi-threaded processing cores sharing the same global memory, and it divides the cores among the stages such that the pipeline is divided in *space*, not time. Each primitive is processed by a thread of one of the processors.

The parallel structure of the GPU can also provide a significant speed improvement in general-purpose computing. Take the addition of two vectors of size N as an example:

$$\boldsymbol{v_3} = \boldsymbol{v_1} + \boldsymbol{v_2}$$

A single-threaded CPU divides the task in

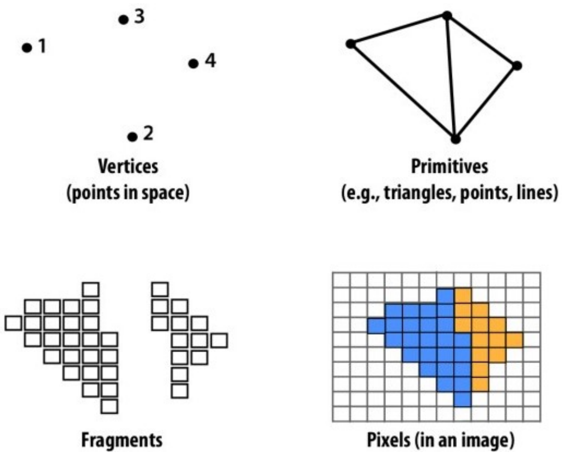


Figure 2.1: Graphics primitives [7].

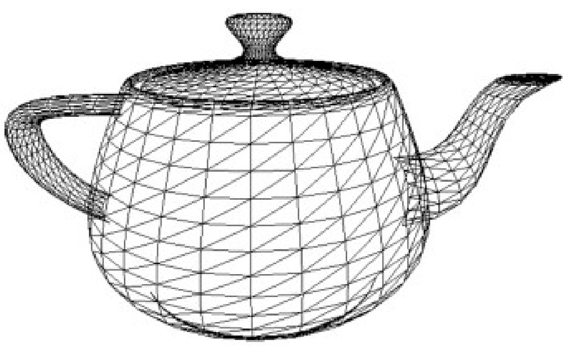


Figure 2.2: Representing an image as a 3D triangle mesh [7].

time and does:

$$\begin{aligned}&\text{Time 1: } \boldsymbol{v_3}[0] = \boldsymbol{v_1}[0] + \boldsymbol{v_2}[0]\\&\vdots\\&\text{Time n: } \boldsymbol{v_3}[n] = \boldsymbol{v_1}[n] + \boldsymbol{v_2}[n]\end{aligned}$$

This results in a time complexity of $O(N)$. The GPU can in theory achieve a time complexity of $O(1)$ by dividing the task in space, i.e. among threads, and doing:

$$\text{Time 1: } \begin{cases}\text{Thread 1: } \boldsymbol{v_3}[0] = \boldsymbol{v_1}[0] + \boldsymbol{v_2}[0]\\ \vdots\\ \text{Thread n: } \boldsymbol{v_3}[n] = \boldsymbol{v_1}[n] + \boldsymbol{v_2}[n]\end{cases}$$

The task is an SIMD task—the program takes one element from each of the vectors and perform addition on them, but the data handled by each thread is different, it can therefore make full use of the SIMD cores of the GPU. When N is small, the overhead in allocating the resources means that the speed improvement is negligible; as N grows larger, the reduction in time complexity quickly compensates for the overhead and makes the GPU much faster than the CPU; however, when N is too big, the GPU will run out of resources, which sets a cap to its performance.

Prior to 2007, to use GPUs for general-purpose computing, the user must write programs using the graphics application programming interface (API) since it was the only interface to GPU hardware. The programming model can be summarised as below:

- The user specifies geometry that covers a region on the screen.
- The user sets parameters of the pipeline (e.g., "lighting" and "texture" information).
- The user provides the fragment processing program (kernel).
- The GPU produces an output "image" and stores it in global memory.

This was a major problem in GPGPU because many general-purpose tasks have nothing to do with graphics and are difficult to implement using the graphics API.

The introduction of CUDA changed the situation by providing a more natural, direct, non-graphics interface. The new programming model can be summarised as below:

- The user defines the computation as a structured grid of threads.
- The GPU executes each thread and stores the results in global memory.

This model allows the user to directly define threads that are run on the processing cores of the GPU, eliminating the complexity in translating the program into graphics pipeline language, which makes it easier for the user to take full advantage of the GPU's power. The following section describes an experiment conducted to determine the gain in calculation speeds from using CUDA.

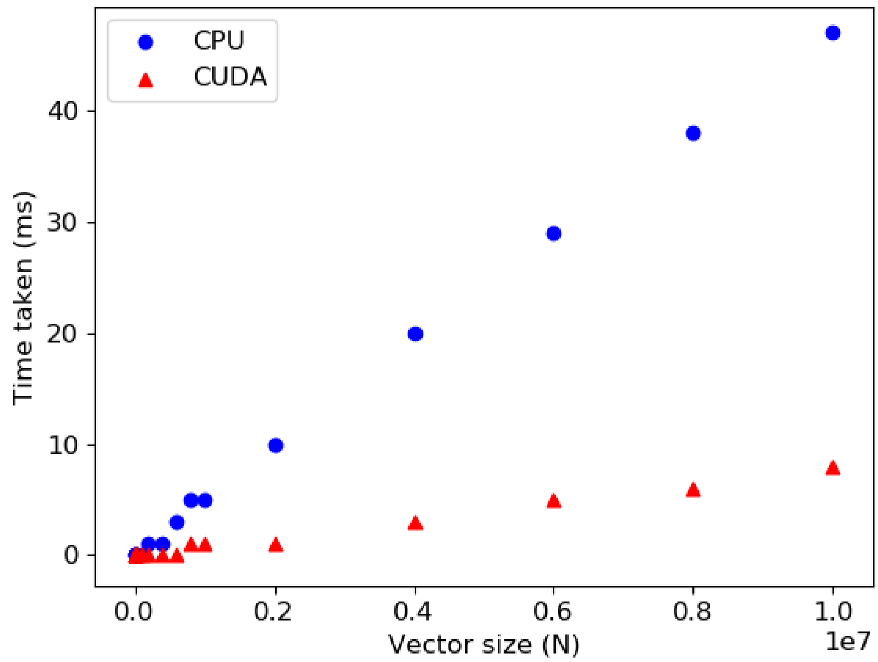
2.2 Experiment, results and discussions

An experiment was set up to compare the performance of a middle-range GPU—the NVIDIA GeForce GTX 1060—and a similarly priced CPU—the Intel Core i7-7700, for the following operations:

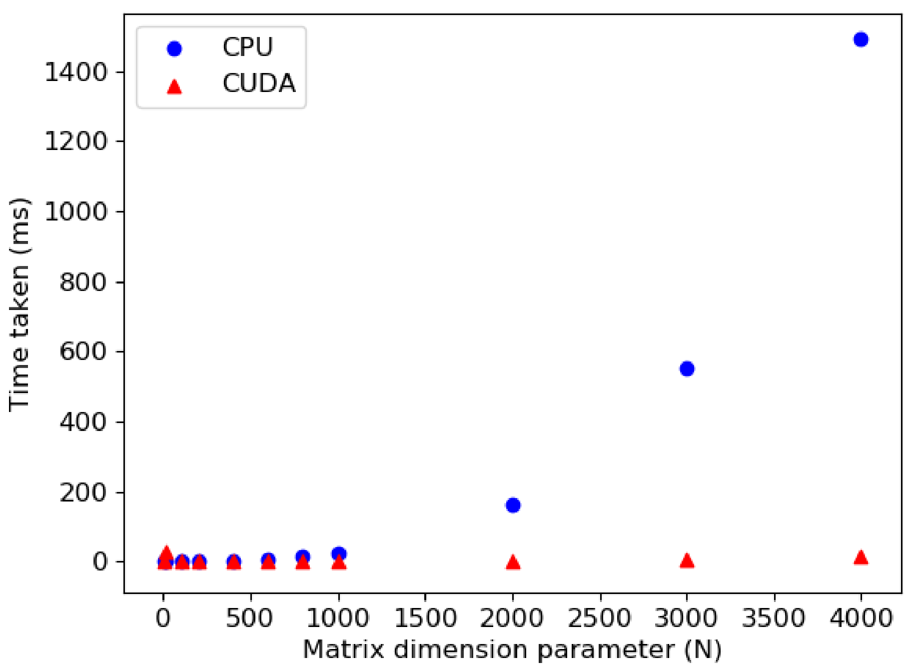
- Addition of two random vectors of size N, which has a time complexity of $O(N)$ if done without parallelism, as described in the previous section.
- Multiplication of two random matrices of dimension $N \times N$, which has a time complexity of $O(N^3)$ if done without parallelism (and without using special algorithms such as the Coppersmith-Winograd algorithm).

Ten test samples were taken for each set of parameters and the average results are shown in Fig. 2.3. As can be seen, the GPU provides a significant improvement on calculation speeds when there are a few millions of elements to be processed (which is typical in image processing).

This has allowed the development of a real-time diagnostic tool for the SEM with useful framerates, which is discussed in the next chapter.



(a) Vector addition.



(b) Matrix multiplication.

Figure 2.3: Performance test results of the GPU and the CPU

Chapter 3

Real-time diagnostic tool for SEMs

3.1 Design of the software

3.2 Real-time histogram equalisation for improving image contrast

3.3 Real-time fast Fourier transform for evaluating image focusing and astigmatism

Chapter 4

Automatic focusing and astigmatism correction algorithm

Chapter 5

Conclusions

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