Parallel Image Processing Report

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1 Introduction

An exploration probe belonging to a Chinese mining company has returned from a two year mission to the Orion Nebula with approximately 10 million images which have suffered both motion and Gaussian blur. The company has put out a tender for the restoration of these images using the iterative and computationally expensive Richardson-Lucy deconvolution algorithm. This report details a brief investigation of the time and money costs for a potential bid on this contract.

Test Rig All performance metrics, unless explicitly stated otherwise, were calculated on a Linux VM running on an AMD Deneb quad-core 3.2GHz CPU with 8 gigabytes of memory. The effects of running the program on other systems was not explored and it was assumed that no order-of-magnitude change could be attained. That said, non-trivial gains could definitely be achieved by upgrading from what is now a two year old architecture and also possibly by removing the overheads imposed by running a virtual machine.

2 Implementation

A single core working with a small point spread function kernel may complete ten iterations (enough to noticeably improve the image) on a single channel, 1024x1024 sized image in 2-10 seconds. Even at two seconds per image this would result in the entire dataset being processed in over 230 days, a delay which may be unacceptable to the clients. To improve on this time, a double pronged approach to parallelism has been taken leveraging multiple core CPUs and multiple computers in a cluster.

2.1 Class Descriptions

The task is split into two main classes, an IO class for reading and writing images and a filter class capable of efficiently restoring images using the Richardson-Lucy algorithm.

2.1.1 ImageQueue

The first is a producer class which reads the input directory and pushes the names of all the image files contained in that directory onto a stack. On request it pops a file name off the stack and reads the data contained into a buffer using the CFITSIO library. FITS is the flexible image transport system which is popular in scientific fields, especially astronomy, and is used in this project mostly for the simple way it handles double precision pixels and dynamic maximum/minimum values.

2.1.2 DeconvFilter

The second, and more important, class is the DeconvFilter consumer class. This class takes a PSF and allocates all the memory space it needs on construction so that processing a single image is done without any unnecessary overhead. For small kernel sizes (see discussion) the algorithm is as follows:

```
FOR iteration = 1 to niter
    temp  = image*psf
    temp  = original_image / temp;
    temp  = temp*psf
    image = temp.*image
ENDFOR
```

Where / is a per element division, * is the convolution operator and .* is a per element multiply.

2.1.3 FFT vs Direct Convolution

For large kernels the algorithm is equivalent however slightly more involved as convolution is achieved by performing a fast Fourier transform on both matrices, multiplying the matrices' elements (not the same thing as matrix multiplication) and then performing an inverse Fourier transform. The second option was not explored past a simple implementation using the FFTW (Fastest Fourier Transform in the West) library.

Direct convolution is $O(N^2)$ where N is the image size. However since the point spread function may be simplified to a small kernel of non-zero values this can be made $O(NM)$ where is M is the kernel size. This means the algorithm quickly slows past the speed of the FFT approach as the kernel size increases. That said, for small values of M this is still a much faster option.

The other option being fast Fourier transforms. According to the convolution theorem, the Fourier transform of a convolution is the pointwise product of Fourier transforms. This algorithm is $O(NlogN)$, a much more attractive option for large kernels and one that was implemented using the FFTW but not used or fully tested.

2.1.4 Further Work

File IO times are minimal in comparison to that that of the deconvolution filter however we do wish to shave as much time off as possible. Therefore the final implementation of this project would see a concurrent producer-consumer model implemented using a semaphore to ensure that a new image is always ready for the filter thread and that the algorithm is never waiting on a disk or network transfer. For this reason IO times are not considered in the calculations seen in the results section.

2.2 OpenMP

OpenMP is an API for Fortran and C/C++ which provides a simple yet powerful interface to both task and data parallelism. Worker threads are instantiated cheaply and inline with as little as a single line OMP directive such as:

```
#pragma omp parallel for private(...) shared(...)
```

Adding this directive to the convolution function expressed previously resulted in an execution speed 0.90*4 (quad-core) times faster than the single threaded implementation. The other steps of the algorithm were also parallelised in a similar manner however as they were all O(n) the effect of doing this was negligible.

2.3 MPI

Message Passing Interface is a popular standard for communication between processes in distributed memory systems such as cluster compute set ups.

It enables easy execution and communication between processes in the cluster which allowed the software to be converted into a distributed version with minimal effort. The system with MPI uses a master node which is responsible for the producer class and therefore is the node with direct access to the images. The rest of the nodes are workers which request an image, process it, then return it. As stated previously, the transfer times are short (theoretically they would take 8ms on an 8Gb/s Infiniband link) however in the final system these transfers would be made asynchronously and buffered so that execution time is dependent only on the deconvolution algorithm.

2.4 Unknown Variables

Before reading the next section it is important to note there are two unknown factors which may influence the results.

Kernel size The point spread function determined to be the cause of noise on the images may be described as a rectangular matrix of any size smaller than the image itself. When using Fourier transforms to perform convolution the size of the kernel is irrelevant. When performing convolution manually however increases in the kernel size result in the same increase in execution time. For example a 7x7 sized kernel will take 49/9 times longer to run than a 3x3. More information will be needed from the client in order to properly estimate the project requirements. Regardless, all execution times mentioned in this report are for a 3x3 kernel which produced visually adequate results.

Image channels The deconvolution filter currently treats a single buffer as one image, although it would be trivial to implement multiple buffers per image this was not done as the concept of RGB channels is not particularly relevant in astronomy. If the images are in fact 3 channel then all performance values will just need to be tripled. Again, please ask the client to clarify this.

3 Results

As previously explained all of the following results were obtained on a 3.2GHz quadcore running as a virtual machine. GCC compiled the program with full optimisation (-O3), a flag which roughly halved execution time and cut the number of instructions inside the most important loop down by almost two thirds. The kernel dimensions were 3x3 and 10 iterations were performed on single channel images. An example output from this is attached to this report.

The program was benchmarked by performing 1000 iterations with a total execution time of 32.7 seconds which translates into 32.7ms per iteration or 0.327 seconds for an image.

For 10 million images this means the running time for a single computer is just under 38 days. For a more reasonable time we spread the load over a number of computers using the MPI technique described above.

In order to maximise efficiency the controller thread may be run on the same machine as a worker, using just a single core as it is not computationally demanding. This configuration means the execution time will be $38/(N_{computers} - 0.25) seconds$.

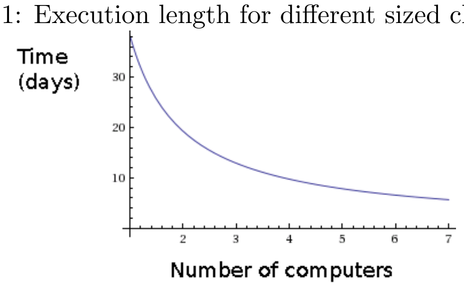
The only constraint on MPI based systems that has not yet been considered is the bandwidth requirement. For a typical network speed of 8Gbit/s, 128 images may be transferred per second. Since data must be returned to the controller node this value must be halved to 64 images processed per second. If the nodes can process an image in 0.327 seconds then an 8GBit/s connection limits us to a maximum of 21 nodes per master. Since this value is considerably more than would be required anyway (the entire job would finish in 1.8 days at that rate), and is an underestimate anyway due to the switched fabric topology of Infiniband, this will not cause a problem and was not investigated further.

4 Recommendations

If the PSF requires a large enough kernel to make the FFT method the faster option then it is recommended to purchase or hire a cluster GPU instance such as the US$100,000 prebuilt GPU Computing Kit from HP which should be able to complete the task within a week (although I have no data to back this up).

If not then a cheaper, cpu-heavy cluster should be bought or hired according to figure 1 and the client's preference.

Figure 1: Execution length for different sized clusters.



All of these figures will need to be re-evaluated depending on both caveats mentioned in the Unknown Variables section, the client's expectations for time till completion and the number and speed of cores in the purchased or hired computers.