
Advanced computer architecture

Lab3: Memory management

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1 Introduction

In this lab we will venture into the memory of the GPU. Despite the fact that Numbu already uses some basic memory management in the background we will still experiment with it manually. By doing this we should see some improvements in execution times. We will first implement a kernel function that filters a certain signal with and without the use of memory pre-allocation. After that a function previously used will be implemented that can use the pre-existing data on the GPU.

The code repository can be found at:

<https://github.com/imstevenxyz/geavanceerde-computerarch>

2 Kolmogorov–Zurbenko filter

The first part of this lab consists of a Kolmogorov–Zurbenko filter that is implemented parallel in a kernel function as seen in code fragment 2.1. This function takes three important arguments, the original signal samples array, the filter coefficients and the result array. The variables that will hold the corresponding data will be transferred to the GPU memory, first alone and then all three together. This will be done using the `cuda.to_device()` method.

```

1 @cuda.jit
2 def kernel_filter_outputFocus(samples, coeffs, result):
3     # Calculate the thread's absolute position within the grid
4     x = cuda.threadIdx.x + cuda.blockIdx.x * cuda.blockDim.x
5
6     # Set stride equal to the number of threads we have available in
7     # either direction
8     stride_x = cuda.gridDim.x * cuda.blockDim.x
9
10    for i in range(x, result.shape[0], stride_x):
11        for j in range(coeffs.shape[0]):
12            result[i] += samples[i+j] * coeffs[j]
```

Codefragment 2.1: KZ-filter kernel function

The kernel execution timing results are:

- No memory management => 0.0027556300163269045
- Only the original signal samples transferred => 0.0024497437477111815
- Only the coefficients transferred => 0.002444329261779785
- Only the result transferred => 0.002314467430114746
- Everything transferred => 0.0017078185081481933

Of course the transfer of read-only data to the GPU memory also takes time:

- Transferring the original signal => 0.00028020620346069336
- Total execution time with transfer => 0.002650794982910156

By comparing these result we see that the execution time somewhat decreases when all data is transferred. But we should take into account that the transfer itself is not included in the result. When we add the transfer and execution time together we see that it is only faster by a small fraction. 0.00275 compared to 0.00265.

3 DFT

Now two kernel functions are implemented that are executed in sequence after each other that process the same memory transferred with `cuDevice.to_device()`. By doing this the data does not have to be transferred back to the CPU, this gives us of course less overhead. This is useful since both kernel function work hand in hand to calculate one end result and the data should not be transferred unnecessarily.

The timing results of the execution are:

- No memory management => 0.11401880025863648
- Memory management => 0.11228885889053344

There is a small decrease in execution time, but as seen in the previous section we have to take into account the transfer time of the data.

4 Conclusion

Overall we see that memory management has some improvements and ease of uses. The execution times mostly improve because the transfer is no longer timed directly. Furthermore, Numba itself already does a lot of memory management in the background, maybe not that efficiently. If needed, manual memory management can be used and can in theory greatly improve the execution times when possible and unnecessary data transfers will bottleneck the bus system. Since we use only a small set of samples, the data to transfer is not that big and does of course not create that much overhead. When memory management is used for a lot of data we should see good improvements in the timing results.