

Αρχιτεκτονική Προηγμένων Υπολογιστών και Επιταχυντών Lab 3 Report

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1 Introduction

Lab3 improves on Lab2 by:

- Vectorizing the input/output decreasing the memory accesses
- Storing the input/output to different banks achieving parallelized memory access

2 Application changes

To be able to vectorize the pixels correctly we utilize 512 bit unsigned integers which contains 16 integers each.

$$\frac{512}{\text{sizeof}(int)} = \frac{512}{32} = 16$$

Compared to lab2's code, here we cannot simply add 3 buffers containing a row and its neighboring element since we are using another layer of abstraction among the list of: - chunks and - buffers.

This extra layer is the unsigned 512 bit integer which another entity that can contain our pixel.

The solution we came up with involves creating a single buffer which contains $BUFFER_SIZE + (WIDTH/VECTOR_SIZE)*2$ 512bit elements. This added quantity allows us to always carry the furthest element ,towards the front or rear end of the buffer, that we might need. These two elements are:

- the up element of the buffer's first element and
- the down element of the buffer's last element.

The real matrix's width divided by how many 32 bit integers are inside a 512 bit integer essentially tells us how many 512bit elements to the right or to the left our sought after up and down elements are.Adding two times that covers both edge cases.

Now that we have all the info that we need in our C_local buffer we can continue by loading it to our intermediate variables which are used to apply sharpening and clipping. Ultimately they are stored in the C_filt output pointer argument and the cycle continues until C_filt is fully populated.

3 New Pragmas

There are two new pragmas used on this lab:

```
#pragma HLS DATAFLOW
#pragma HLS stream variable = A_local depth = 64
```

Dataflow enables parallelization through pipelining but on a task level which lies in contrast with $PIPELINE$ which works on an instruction level. On the other side stream is applied on an array, for example variable A from the code sample, and is used when that array is consumed or produced in a sequential manner. Then a FIFO loop is used instead of RAM achieving more efficient communication.

4 Data comparison

4.1 Kernels & Compute Units

Kernel Execution	lab2	lab3
Enqueues	1	1
Total Time (ms)	0.513	0.042
Min Time (ms)	0.513	0.042
Avg Time (ms)	0.513	0.042
Max Time (ms)	0.513	0.042

4.2 Kernel Data Transfers

Top Kernel Data Transfer	lab2	lab3
Number of Transfers	15079	1329
Avg Bytes per Transfer	8.000	110.000
Transfer Efficiency %	0.196	2.691
Total Data Transfer (MB)	0.121	0.146
Total Write (MB)	0.033	0.066
Total Read (MB)	0.088	0.081

Top Kernel Data Transfer	lab2	lab3
Total Transfer Rate (MB/s)	872.740	12063.900

4.3 Host Data Transfer

Host Transfer	lab2	lab3
Number of READs	1	1
Number of WRITEs	2	2
READ Transfer Rate (MB/s)	0.761	3.118
WRITE Transfer Rate (MB/s)	1.185	5.253
READ Average Size (kB)	32.768	131.072
WRITE Average Size (kB)	40.960	163.840

4.3.1 Comments:

Using the vectorization method we achieved an acceleration of **1221%**. Note that the performance increase is even higher due to the fact that this implementation uses **128*128** matrices and the lab2's used **64*64** matrices. Also writing and reading, of the kernel/host to and from global memory, is evidently a lot faster this time thanks to the more compact way the data is transmitted.

5 Screenshots

Kernels & Compute Units					
Kernel Execution (includes estimated device times)					
Kernel	Enqueues	Total Time (ms)	Min Time (ms)	Avg Time (ms)	Max Time (ms)
⚡ imageDiffPosterize	1	0.042	0.042	0.042	0.042

Figure 1: kernel-compute-units

Top Kernel Transfer								
Compute Unit	Device	Number of Transfers	Avg Bytes per Transfer	Transfer Efficiency (%)	Total Data Transfer (MB)	Total Write (MB)	Total Read (MB)	Total Transfer Rate (MB/s)
⚡ imageDiffPosterize_1	xilinx_u200_gen3x16_xdma_2_202110_1-0	1329	110.000	2.691	0.146	0.066	0.081	12063.900

Figure 2: kernel-data

Host Data Transfers							
Host Transfer							
Context: Number of Devices	Transfer Type	Number of Buffer Transfers	Transfer Rate (MB/s)	Avg Bandwidth Utilization (%)	Avg Size (KB)	Total Time (ms)	Avg Time (ms)
context0:1	READ	1	3.118	N/A	131.072	N/A	N/A
context0:1	WRITE	2	5.253	N/A	163.840	N/A	N/A

Figure 3: host-data

6 Zip Contents

- lab3.cpp
 - lab3's kernel.
- tb_lab3.cpp
 - The host which manages the lab3's kernel.
- lab3.pdf
 - This report