

# Implementation of CNN Hardware Accelerator based on Eyeriss structure

System-on-a-Chip
Design LAB  $-\sum$ 

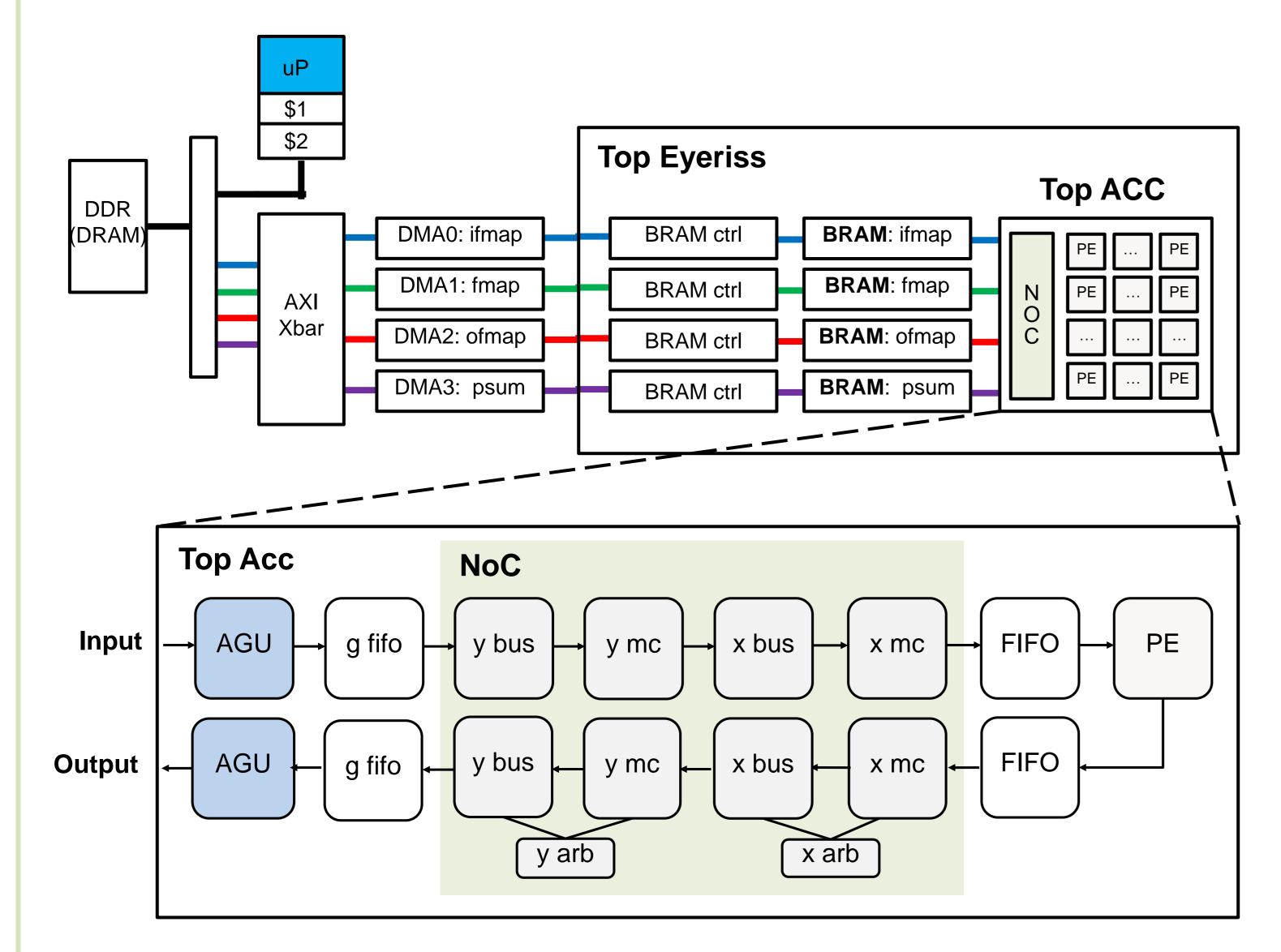
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## 1 Abstract

CNN operations require convolution operations, data loads, and storage. Accessing DRAM for all data significantly increases execution time and consumes energy. In order to reduce access to the DRAM where the data is stored, we used Processing Element (PE) proposed by Eyeriss. We also **designed the entire data flow**, such as network on chip (NoC), address generator unit (AGU) and buffer controller.

# 3 Structure



- It reduces DRAM access by storing required data in **BRAM**.
- The X-Y bus uses round robin arbitration to send calculation results from multiple mcs to the next element.

# 5 Processing Pass

The processing pass is a unit in which the accelerator performs an operation after loading data and stores the results back. In the following example, the input image data is loaded once per six processing passes.

| Lavor | CNN Shape Parameters | CNN

		Example:	Pro	cessin	g passes	s, conv.	layer 3.		CON		15	3	13	256	384	1	
				Pass0	Pass1	Pass2	Pass3	Pass4	Pass5	Pass	s6	Pass7	Pass8	1	Pa	ss383	► time
if	maps	fmap IDs channel IDs		1-4	1-4	1-4	1-4	1-4	1-4	5-8	_	5-8	<u>1</u> 5-8			1 3-256	
f	ilters	filter IDs channel IDs		1-64	65-128 1-4	129-192	193-256	2 <u>57-320</u> 1-4	3 <u>21-38</u> 4 1-4	1-6 <sup>4</sup> 5-8	_     -	5-8	129-192 5-8			1-384 3-256	
Of	fmaps	fmap IDs channel IDs		1-64	<u>1</u> 65-128	1 129-192	1 193-256	<u>1</u> 257-320	<u>1</u> 321-384	1-64	1 6	1 65-128	1 129-192		32	<u>1</u> 1-384	

## 8 Result

Model	Cycle	Time Required (s)	Comparison
SW	149,520,384	2.99	x1
HW(SB_t1)	15,604,224	0.312	x9.58
HW(SB_t4)	14,662,656	0.293	x10.12
HW(DB_t4)	5,408,167	0.108	x27.65

- \* SW : The plain convolution loop.
- \* HW(SB\_t1): Proposed accelerator with single buffer and parameter t=1.
- \* HW(SB\_t4) : Proposed accelerator with single buffer and parameter t=4.
- \* HW(DB\_t4): Proposed accelerator with double buffer and parameter t=4.

#### Comparison of execution speed of HW(SB\_t4) and SW on Zynq board. HW(SB\_t4) is 13.87 times faster than SW.

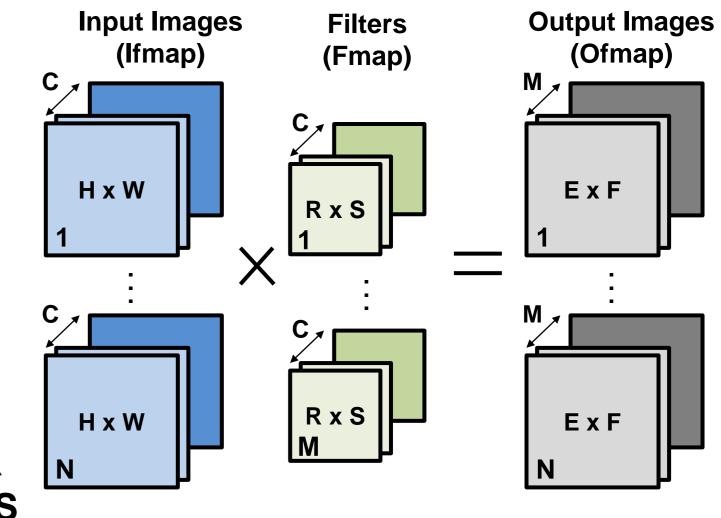
DMA - HW run time : 4098.216309 [us] SW run time : 56879.121094 [us] Difference of HW and SW result : 0

#### 2 CNN

CNN consists of multidimensional convolutions that require time and energy to calculate, load and store data. The worst case is accessing DRAM every time.

for n in N

for n in N
for c in C
for m in M
for e in E
for f in F
for r in R
for s in S



row 1

row 2

row 3

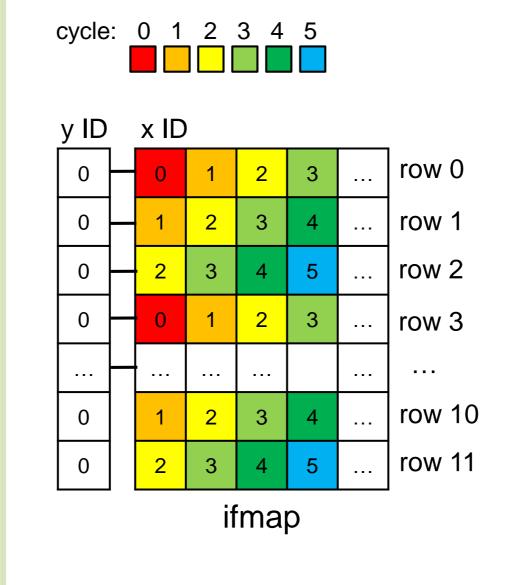
row 10

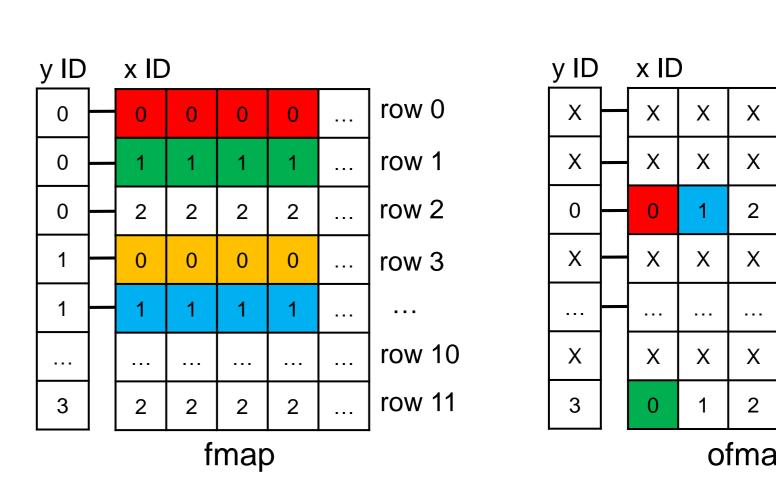
row 11

o[n][m][e][f] += I[n][c][e + r][f + s] \* W[m][c][r][s]

# 4 Using Data in Parallel

Each y mc(multicast controller) and x mc have an id. In AGU, a packet containing the y and x tags is attached to the data to be sent. The mc interprets the sent packet and gets the data if the tag matches its id.

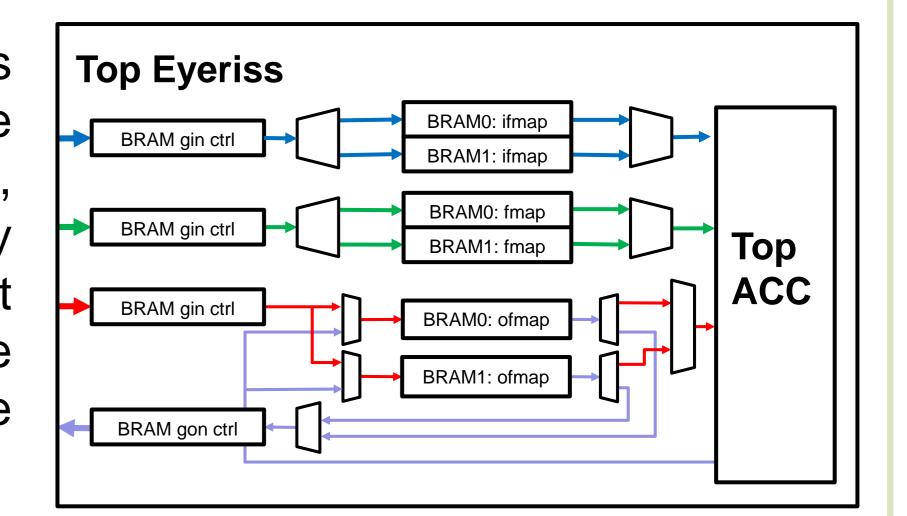




Example: mapping ids, conv. layer 3.

# 6 Double Buffer

As the example in the previous 5-Processing Pass, the same ifmap is used in six passes, and ofmap is repeated every six passes. Considering that ofmap is used repeatedly, we used a double buffer to reduce the number of ofmap loads.



## Experiment Environment

Xilinx Zynq 706

Alexnet Convolution Layer 3

- Size of ifmap: 15x15, fmap: 3x3, ofmap: 13x13
- Size of input channel C: 256, output channel W: 384

Eyeriss parameters of Layer 3

- p: 16, q: 4, r: 1, t: 4



## Conclusion

The proposed structure decreases DRAM access and reuses data to shorten execution time. The result of the Xilinx Zynq board and the simulation shows that the execution time is reduced by up to 27 times.

## \* Reference

Eyeriss: An Energy-Efficient Reconfigurable Accelerator for Deep Convolutional Neural Networks – ISSCC 2016