

# ECE 8893 Parallel Programming for FPGAs

## Lab 1

### Matrix Multiplication Acceleration on FPGA

#### 1. Introduction:

This aim of this Lab is to design an accelerator for matrix multiplication. In the base implementation shown below, the dimension of matrix A is M x N (100 x 200) and that of matrix B is (N x K) 200 x 300.

```
29 // Compute the matrix multiplication
30 for(int i = 0; i < M; i++) {
31     for(int j = 0; j < K; j++) {
32
33         for(int p = 0; p < N; p++) {
34             MatC[i][j] += MatA[i][p] * MatB[p][j];
35         }
36     }
37 }
38 }
```

The latency and resource utilization for the base implementation are:

```
=====
== Utilization Estimates
=====
* Summary:
```

Name	BRAM_18K	DSP	FF	LUT	URAM
DSP	-	5	-	-	-
Expression	-	-	0	649	-
FIFO	-	-	-	-	-
Instance	2	0	758	1074	-
Memory	200	-	0	0	-
Multiplexer	-	-	-	611	-
Register	-	-	1092	128	-
Total	202	5	1850	2462	0
Available	432	360	141120	70560	0
Utilization (%)	46	1	1	3	0

```
=====
```

Fig 1.1 Utilization estimates of base matrix mul

```
+ Latency:
* Summary:
```

Latency (cycles)		Latency (absolute)		Interval		Pipeline
min	max	min	max	min	max	Type
6380037	6380037	63.800 ms	63.800 ms	6380038	6380038	none

```
+ Detail:
* Instance:
  N/A

* Loop:
```

Loop Name	Latency (cycles)		Iteration	Initiation	Interval	Trip	Pipelined
	min	max	Latency	achieved	target	Count	
- VITIS_LOOP_15_1_VITIS_LOOP_16_2	20002	20002	4	1	1	20000	yes
- VITIS_LOOP_21_3_VITIS_LOOP_22_4	60002	60002	4	1	1	60000	yes
- VITIS_LOOP_27_5_VITIS_LOOP_28_6	30002	30002	4	1	1	30000	yes
- VITIS_LOOP_34_7_VITIS_LOOP_35_8	6240000	6240000	208	-	-	30000	no
+ VITIS_LOOP_37_9	201	201	3	1	1	200	yes
- VITIS_LOOP_45_10_VITIS_LOOP_46_11	30004	30004	6	1	1	30000	yes

Fig 1.2 Performance estimates of base matrix mul

## 2. Acceleration Techniques:

- 1. Loop reordering:** It can be observed from the above estimates that the innermost loop (VITIS\_LOOP\_37\_9) in the base matrix multiplication is not pipelined due to loop-carry dependency as `MatC[i][j]` result must be populated before reading the result which takes more than 1 cycle. Hence, reordering the loop is beneficial in this case to eliminate the II violation.

```

31      // Compute the matrix multiplication
32      for(int i = 0; i < M; i++) {
33          for(int p = 0; p < N; p++) {
34
35              for(int j = 0; j < K; j++) {
36                  #pragma HLS PIPELINE II=1
37                  MatC[i][j] += MatA[i][p] * MatB[p][j];
38              }
39          }
40      }

```

From figure 2.1 below, it can be observed that loop reordering helps in pipelining the innermost loop in matrix multiplication and helps in reducing the latency by **239,996 cycles**.

```
+ Latency:
* Summary:
```

Latency (cycles)		Latency (absolute)		Interval		Pipeline
min	max	min	max	min	max	Type
6140041	6140041	61.400 ms	61.400 ms	6140042	6140042	none

```
+ Detail:
* Instance:
N/A

* Loop:
```

Loop Name	Latency (cycles)		Iteration Latency	Initiation achieved	Interval target	Trip Count	Pipelined
	min	max					
- VITIS_LOOP_15_1_VITIS_LOOP_16_2	20002	20002	4	1	1	20000	yes
- VITIS_LOOP_21_3_VITIS_LOOP_22_4	60002	60002	4	1	1	60000	yes
- VITIS_LOOP_27_5_VITIS_LOOP_28_6	30002	30002	4	1	1	30000	yes
- VITIS_LOOP_34_7_VITIS_LOOP_35_8_VITIS_LOOP_37_9	6000004	6000004	6	1	1	6000000	yes
- VITIS_LOOP_45_10_VITIS_LOOP_46_11	30004	30004	6	1	1	30000	yes

Fig. 2.1 Performance estimate after loop reordering

- Loop Tiling:** Loop reordering gives an opportunity to unroll the inner most loop, provided matrices A, B, and C are partitioned. However, due to large size of the matrices, partitioning and unrolling causes scalability issues. Hence, loop tiling technique is used to achieve parallelism within smaller tiles. Matrices A, B, and C are partially and cyclically partitioned based on the dimension of the tile as shown below:

```
29 #pragma HLS array_partition variable=MatA dim=1 factor=25 cyclic
30 #pragma HLS array_partition variable=MatB dim=2 factor=10 cyclic
31 #pragma HLS array_partition variable=MatC dim=1 factor=25 cyclic
32 #pragma HLS array_partition variable=MatC dim=2 factor=10 cyclic
33 // Compute the matrix multiplication
34 for(int i = 0; i < M; i += D)
35 {
36     for(int p = 0; p < N; p++)
37     {
38         for(int j = 0; j < K; j += W)
39         {
40             #pragma HLS PIPELINE II=1
41             for(int ii = 0; ii < D; ii++)
42             {
43                 FIX_TYPE a = MatA[i + ii][p];
44                 for(int jj = 0; jj < W; jj++) {
45                     MatC[i + ii][j + jj] += a * MatB[p][j + jj];
46                 }
47             }
48         }
49     }
50 }
```

Loop tiling technique helps in achieving a speedup of  $D \times W$  ( $D$  = depth,  $W$  = width of the tile). For example, when  $D = 25$  and  $W = 10$ , the number of cycles for matrix

multiplication is reduced to 24004 from 6000004, thus giving a **250x speedup for matrix multiplication**.

```
+ Latency:
* Summary:
```

Latency (cycles)		Latency (absolute)		Interval		Pipeline
min	max	min	max	min	max	Type
164074	164074	1.641 ms	1.641 ms	164075	164075	none

```
+ Detail:
* Instance:
  N/A

* Loop:
```

Loop Name	Latency (cycles)		Iteration	Initiation	Interval	Trip	Pipelined
	min	max	Latency	achieved	target	Count	
- VITIS_LOOP_18_1_VITIS_LOOP_19_2	20009	20009	11	1	1	20000	yes
- VITIS_LOOP_24_3_VITIS_LOOP_25_4	60011	60011	13	1	1	60000	yes
- VITIS_LOOP_30_5_VITIS_LOOP_31_6	30011	30011	13	1	1	30000	yes
- VITIS_LOOP_41_7_VITIS_LOOP_43_8_VITIS_LOOP_45_9	24004	24004	6	1	1	24000	yes
- VITIS_LOOP_60_12_VITIS_LOOP_61_13	30012	30012	14	1	1	30000	yes

Fig 2.2 Performance estimates after loop tiling ( $D = 25$ ,  $W = 10$ )

- 3. Loop Fusion:** In Fig 2.2 above, it can be observed that computation is no longer a bottleneck. The read/write operations from DRAM to BRAM take 85% of the cycles while actual computation takes 15% of the cycles. This is because loading matrices A and B and initializing matrix C happens in a sequential manner. Different DRAM ports can be used for all three matrices to allow parallel access and loop fusion can be applied to reduce the DRAM to BRAM transfer latency.

```
18  int max_m_n = ((M >= N) ? M : N);
19  int max_n_k = ((N >= K) ? N : K);
20  for(int i = 0; i < max_m_n; i++)
21  {
22      for(int j = 0; j < max_n_k; j++)
23      {
24          if((i < M) && (j < N))
25          {
26              MatA[i][j] = MatA_DRAM[i][j];
27          }
28
29          if((i < N) && (j < K))
30          {
31              MatB[i][j] = MatB_DRAM[i][j];
32          }
33
34          if((i < M) && (j < K))
35          {
36              MatC[i][j] = 0;
37          }
38      }
39  }
```

```
+ Latency:
* Summary:
```

Latency (cycles)		Latency (absolute)		Interval		Pipeline
min	max	min	max	min	max	Type
114044	114044	1.140 ms	1.140 ms	114045	114045	none

```
+ Detail:
* Instance:
  N/A

* Loop:
```

Loop Name	Latency (cycles)		Iteration Latency	Initiation achieved	Interval target	Trip Count	Pipelined
	min	max					
[- VITIS_LOOP_20_1_VITIS_LOOP_22_2	60011	60011	13	1	1	60000	yes
[- VITIS_LOOP_46_3_VITIS_LOOP_48_4_VITIS_LOOP_50_5	24004	24004	6	1	1	24000	yes
[- VITIS_LOOP_66_8_VITIS_LOOP_67_9	30012	30012	14	1	1	30000	yes

Fig 2.3 Performance estimates after loop fusion ( $D = 25$ ,  $W = 10$ )

From Fig 2.3 above, it can be observed that loop fusion leads to further reduction of **50,030 cycles**.

#### 4. Optimized Latency and resource utilization of the final design:

The final design achieves parallelism in tiles of  $D = 25$ ,  $W = 10$ . The performance and utilization estimates can be seen below:

```
+ Latency:
* Summary:
```

Latency (cycles)		Latency (absolute)		Interval		Pipeline
min	max	min	max	min	max	Type
114044	114044	1.140 ms	1.140 ms	114045	114045	none

```
+ Detail:
* Instance:
  N/A

* Loop:
```

Loop Name	Latency (cycles)		Iteration Latency	Initiation achieved	Interval target	Trip Count	Pipelined
	min	max					
[- VITIS_LOOP_20_1_VITIS_LOOP_22_2	60011	60011	13	1	1	60000	yes
[- VITIS_LOOP_46_3_VITIS_LOOP_48_4_VITIS_LOOP_50_5	24004	24004	6	1	1	24000	yes
[- VITIS_LOOP_66_8_VITIS_LOOP_67_9	30012	30012	14	1	1	30000	yes

Fig 4.1 Performance estimates for final design (Tile size  $D = 25$ ,  $W = 10$ )

The latency of the optimized design is **114044**. Thus, an overall speed up of **55.94** ( $6380037/114044$ ) is gained as compared to the base implementation.

```
=====
== Utilization Estimates
=====
```

\* Summary:

Name	BRAM_18K	DSP	FF	LUT	URAM
DSP	-	64	-	-	-
Expression	-	-	0	21229	-
FIFO	-	-	-	-	-
Instance	6	0	2599	12848	-
Memory	420	-	0	0	-
Multiplexer	-	-	-	11326	-
Register	-	-	17981	2848	-
Total	426	64	20580	48251	0
Available	432	360	141120	70560	0
Utilization (%)	98	17	14	68	0

Fig 4.2 Utilization estimates for final design (Tile size D = 25, W = 10)

## 5. Design Space Exploration:

In order to analyze the tradeoff between latency and resource utilization, depth and width of the tiles can be changed. The following table summarizes the latency and resource utilization for different depth and width combinations:

Depth (D)	Width (W)	Latency (cycles)	BRAM (%)	DSP (%)	FF (%)	LUT (%)
5	10	210044	61	6	4	18
10	15	130044	73	10	5	41
25	10	114044	98	17	14	68
10	30	110044	107	15	13	72
20	20	105044	135	17	17	95

It can be observed from the above table that although high depth and width give a lower latency, they have a very high resource utilization which is not an optimal solution. Design selection should be made depending on which metric out of latency and area we care about.

## 6. Effect of quantization:

The following table summarizes the effect of quantization on resource utilization:

AP Fixed Type	Depth (D)	Width (W)	Latency (cycles)	BRAM (%)	DSP (%)	FF (%)	LUT (%)
<32, 10>	25	10	114044	98	17	14	68
<24, 8>	25	10	114044	91	156	13	70
<32, 10>	10	15	130044	73	10	5	41
<24, 8>	10	15	130044	63	94	5	42

While quantization does reduce the result precision, from the above table it can be observed that lower quantization also results in slightly lower BRAM usage at the cost of extremely high DSP usage while latency remains the same for a given <D, W> pair.

## 7. Observations:

While tiling helps in achieving a speedup of  $D \times W$  for matrix multiplication, it can be observed that after a point increasing  $D$  and  $W$  does not result in high speed up as memory becomes a bottleneck. Even after loop fusion, about 78.9% of the cycles (90,023 cycles) are spent in loading and storing data from DRAM to BRAM whereas only 21.06% cycles (24004 cycles) are spent in the actual computation. Thus, further optimization techniques such as data streaming can be applied to reduce the memory overhead – i.e., begin computation as soon as first few elements of  $A$  and  $B$  are available instead of waiting for all elements of  $A$  and  $B$  to be loaded in BRAM.

Secondly, in the current design fanout is high as  $D$  elements from matrix  $A$  are multiplied with  $W$  elements in matrix  $B$ , which can be improved.

Finally, for an  $M \times K$  matrix,  $D$  and  $W$  must be factors of  $M$  and  $K$  respectively to maintain functional correctness. Thus, there is a lot of constraint in the incremental step size of  $D$  and  $W$ . Moreover, if  $M$  and  $K$  are not factorizable, tiling becomes slightly complicated.