Self-Paced Learning 4

Floating Point Matrix Multiplication

Github Link: matrix multiply hls R08943129 羅宇呈

1. Brief introduction of the system

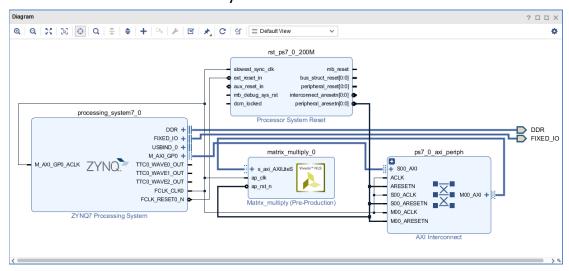


Fig.1 System Block Diagram

這個 Lab 我實作的是 3x3 的浮點數矩陣乘法運算,浮點數的矩陣乘法經常在影像處理或者線性代數運算器中出現,因此在大量需要矩陣運算的演算法中,這個 IP 非常重要,在介面的選擇上,Kernel Function 所使用的 Interface 都是 AXI-SLAVE,並且讓 ZYNQ 的 Processing System 作為 MASTER 讀寫 IP。

Fig. 2 Source Code

2. Optimization Flow (Observation)

我先對 Iteration 的 for loop 加上 pipeline II=1 直接 Synthesis,卻發現 II 的 Constraint 發生 Violation,後來打開 Analysis 發現原因是因為浮點數的乘法和加法並沒有連貫的串在一起

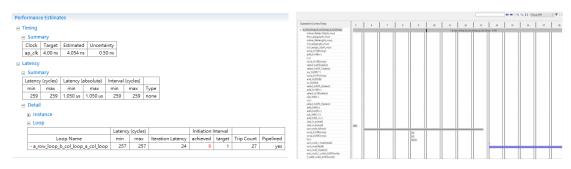


Fig. 3 II Violation of Baseline Design

```
a_row_loop: for (int r = 0; r < MULTIPLIER_TRAITS::RowsATrans; r++) {
  b_col_loop: for (int c = 0; c < MULTIPLIER_TRAITS::ColsBTrans; c++) {
    a_col_loop: for (int k = 0; k < MULTIPLIER_TRAITS::ColsATrans; k++) {
    #pragma HLS PIPELINE II = 1
    cast_in_a = GetMatrixElement<TransposeFormA,RowsA,ColsA,InputType>(A, r, k);
    cast_in_b = GetMatrixElement<TransposeFormB,RowsB,ColsB,InputType>(B, k, c);
    mult [k] = cast_in_a * cast_in_b;
}
sum_mult = mult [0];
acc_loop: for (int k = 0; k < MULTIPLIER_TRAITS::ColsATrans; k++) {
    #pragma HLS PIPELINE II = MULTIPLIER_TRAITS::INNER_II
    #pragma HLS dependence variable=sum_mult inter false
    sum_mult = mult [k] + sum_mult;
}
C [r][c] = sum_mult;
}
</pre>
```

Fig. 4 Modified Code

因此我將 Code 改寫,試圖把乘法和加法**分開成兩個 loop**,先將乘法的部分暫存起來再累加,期望可以讓兩個 loop 各自優化成 II=1,然而發現雖然 Timing 有改善,但是 Timing Violation 仍然發生。

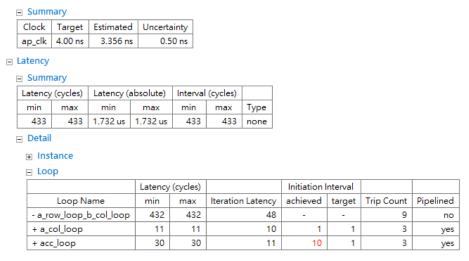


Fig. 5 Timing Violation of Modified Design

最後我再修改 Code,將累加的每個值都暫存起來,**讓整個電路的 Topology 變成 Linear**,並加上 Dependency 的 Pragma 將 Interloop Dependency 設為 False,另外 我也將這些暫存值的 Array Partition 展開成 DFF,最後將每個 Loop 都設上 pipeline II=1

```
a_row_loop: for (int r = 0; r < MULTIPLIER_TRAITS::RowsATrans; r++) {
  #pragma HLS PIPELINE II = 1
  b_col_loop: for (int c = 0; c < MULTIPLIER_TRAITS::ColsBTrans; c++) {</pre>
    #pragma HLS PIPELINE II = 1
    a_col_loop: for (int k = 0; k < MULTIPLIER_TRAITS::ColsATrans; k++) {</pre>
      #pragma HLS PIPELINE II = 1
      cast in_a = GetMatrixElement<TransposeFormA,RowsA,ColsA,InputType>(A, r, k);
      cast_in_b = GetMatrixElement<TransposeFormB,RowsB,ColsB,InputType>(B, k, c);
      mult [k] = cast_in_a * cast_in_b;
    sum_mult [0] = mult [0];
    acc_loop : for (int k = 0; k < MULTIPLIER_TRAITS::ColsATrans; k++) {</pre>
        #pragma HLS PIPELINE II = MULTIPLIER_TRAITS::INNER_II
        #pragma HLS dependence variable=sum_mult inter false
        sum_mult [k] = mult [k] + sum_mult [k-1];
    C [r][c] = sum_mult [MULTIPLIER_TRAITS::ColsATrans-1];
}
```

Fig. 6 Final Design

Performance Estimates

□ Timing

Summary

Clock	Target	Estimated	Uncertainty		
ap_clk	4.00 ns	3.356 ns	0.50 ns		

■ Latency

■ Summary

Latency	(cycles)	Latency (absolute)	Interval		
min	max	min	max	min	max	Type
44	44	0.176 us	0.176 us	44	44	none

Detail

■ Loop

	Latency (cycles)			Initiation I	nterval		
Loop Name	min	max	Iteration Latency	achieved	target	Trip Count	Pipelined
- a_row_loop	42	42	41	1	1	3	yes

Fig. 7 All Loop Meet Constraints

最後終於成功將所有的 loop 都展開成 II=1,而且相較 Baseline Design,Latency 大大降低,原先為 259 個 cycle,最終 Design 為 42 個 cycle 即可做完。

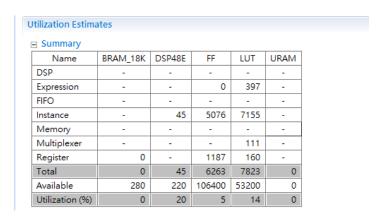


Fig. 8 Hardware Utilization

3. C/RTL Cosimulation

Cosimulation Report for 'matrix_multiply_top'

Result									
		Latency			Interval				
RTL	Status	min	avg	max	min	avg	max		
VHDL	NA	NA	NA	NA	NA	NA	NA		
Verilog	Pass	79	79	79	NA	NA	NA		

Export the report(.html) using the Export Wizard

Fig. 8 Cosimulation Pass

4. IP Python Verification

Fig. 9 Functionality Pass