CMPE 691 – Reconfigurable System Design PROJECT

 \mathbf{ON}

MATRIX CONVOLUTION HARDWARE ACCELERATOR

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1. Introduction

Matrix convolution is a core computation generally applied in a broad range of applications including images processing, machine learning, computing vision and many more. Especially in convolution neural networks, matrix convolution plays an important role in feature extraction and pattern recognition. While convolution operations are very useful, such operations are computationally expensive, and it is a challenge to implement these operations for real-time performance on general purpose processors [1].

The challenges mentioned above can benefit from the hardware acceleration methodology as it provides ability to offload the computations. Specifically, the field-programmable gate arrays (FPGAs) supply the needed flexibility and parallelism for accomplishing convolution calculations.

This paper deals with the design and architecture of Matrix Convolution Hardware Accelerator with reference to the Finite State Machine with Datapath. The hardware module is designed to have the Avalon-MM interface to allow direct communications with a processor through memory map interconnect. As a reference point C based software-only implementation matrix convolution was also implemented and results were compared with hardware assisted convolution.

The primary objectives of this project are to prove that the hardware accelerator is functionally correct. The first objective is to prove that the achieved results outperform reference software-only implementation. To explain the benefits of the approaches based on collaboration with hardware to solve problems of computational complexity.

This paper describes the system design approach, hardware and software interface, and the quantitative characterization of the performance, with reference to the main advantages of the FPGA implementation of the matrix convolution operations.

2. Background Work

2.1 Matrix Convolution Overview

Matrix convolution is defined as a mathematical operation to yield a third matrix from two matrices signifying the localized interaction between them. The operation involves sliding a smaller matrix known as kernel over an input matrix and summing the multiplication of elements in the kernels that overlap with respective elements of an input matrix [2]. This operation is stored in an output matrix. For example, applying a 3x3 kernel to a 5x5 input matrix result in a 3x3 output matrix. The computation at each position in the output matrix is given by:

0	1	2	3	4								
5	6	7	8	9		1	0	1		36	42	48
10	11	12	13	14	*	1	0	1	=	66	72	78
15	16	17	18	19		1	0	1		96	102	108
20	21	22	23	24								

Input Matrix Kernel Matrix Output Matrix

The computation at first position in the output matrix is shown below. The respective elements will be calculated in the same process.

O
$$[0][0] = (0.1) + (1.0) + (2.1) + (5.1) + (6.0) + (7.1) + (10.1) + (11.0) + (12.1)$$

O $[0][0] = 0 + 0 + 2 + 5 + 0 + 7 + 10 + 0 + 12 = 36$

2.2 Need for Hardware Acceleration

The main concern unique to matrix convolution is the high computational requirement of the technique. This organization makes efficient use of the processor impossible on general-purpose processors because the sequential nature of the computation means that large datasets cannot be utilized in order to reduce processing time or that applications that require real-time processing are slowed considerably by large matrices. But sometimes, due to a large number of parallel operations required and frequent data reuse optimization, hardware accelerators, especially those on FPGAs, are an efficient solution.

As for matrix convolution, there are more benefits that flow from using hardware accelerators, which include the ability to perform multiple kernel operations at a go; thereby improving of high throughput and scalability [1].

2.3 FSM-Based Hardware Design

Finite State Machines (FSMs) are a reliable basis for supervising sequential processes in hardware. In this project, an FSM based design was used to coordinate the input phase, the computational phase, and the output phase of the moving-average matrix convolution. It evolves through states like IDLE, LOAD, COMPUTE, and DONE, to check for great resource usage.

Due to this approach, the design unknowns are reduced while at the same time addressing the flexibility and scalability issues. The FSM collaboratively operates with the data path to execute the multiply-accumulate (MAC) that convolution entails to deliver reliable computations.

2.4 Relevance of Related Work

The work done by Cao et al. (2019) titled "FPGA-based Accelerator for Convolution Operations" show how FPGA-based design can be used to facilitate convolutional tasks. Their work also concentrates on getting benefits with FPGA resource to increase more throughput while minimizing the latency. But as their design targets systolic arrays [1], this project follows a much simpler FSM design intended for matrix convolution applications.

This distinction makes the hardware accelerator applicable to a wider perspective of other computations other than neural networks. In addition, the design integrates with an Avalon-MM interface to provide clear visibility by displaying it if it needs to communicate with software applications, adding to its flexibility.

3. Design and Implementation

3.1 FSM Design for Matrix Convolution

The flow of the operations at the hardware accelerator was controlled based on the Finite State Machine (FSM) approach. The FSM consists of the following states:

- IDLE: Wait for a write or read signal to start operations.
- LOAD: Reads the input matrix elements from the processor and saves them into internal memory of the system.
- COMPUTE: Computes the output matrix by iteratively passing through the input matrix and the kernel to do the matrix convolution.
- DONE: Indicates the end of convolution process and goes back to the IDLE state.

This FSM based design further ensures that the different blocks of the hardware work in harmony with minimal clock cycles being utilized. Every state changes according to control signals like start and done. Fig 1 depicts the state machine used for matrix convolution with a 3x3 input matrix and a 2x2 kernel matrix. It highlights the four main states IDLE, LOAD, COMPUTE, and DONE that coordinate the operations efficiently. This file is attached as "matrix convolution3 3.sv".



Fig 1: State Machine for Matrix Convolution for 3*3 Input Matrix and 2*2 Kernel Matrix

Fig 2 shows the state machine for matrix convolution with a 5x5 input matrix and a 3x3 kernel matrix. It illustrates the scalability of the FSM design, showcasing its ability to handle larger matrices by adjusting states and operations to maintain efficiency. This file is attached as "matrix convolution5 5.sv".

Fig 2: State Machine for Matrix Convolution for 5*5 Input Matrix and 3*3 Kernel Matrix

3.2 Integration with Avalon-MM Interface

Communication between the matrix convolution module and the processor was facilitated by implementing an Avalon-MM interface for the module. This interface contemplate a memory mapping communication that facilitates the data interchange between the FPGA and the CPU. Address decoding was used while integrating, WRITE logic was equally included, and READ-back was part of the integrating procedure.

Key Functionalities of the Integration:

• Write Operation:

In the following, when avs_s1_write is 1, the elements in the input matrix and control signals are stored in the internal registers.

By specifying the behavior of internal register avs_s1_address it is possible to direct data transfer towards the desired location.

• Read Operation:

In the second stage, when avs_s1_read is asserted, a corresponding element in the result matrix, done signal and status register address are read. This makes it easy for the processor to access computed results when the need arise.

• Control and Status Signals:

A control register exists to control the convolution computation while a status register is used to give information concerning the computation.

• A dummy delay pipeline is implemented for some illustrations in order to synchronize control and output signals correctly.



Fig 3: Avalon-MM interface for the module Matrix Convolution for 3*3 Input Matrix and 2*2

Output Matrix

Fig 3 illustrates the Avalon-MM interface implemented for the matrix convolution module. It shows the memory-mapped communication protocol, detailing the flow of read and write operations between the processor and FPGA. Control signals and address decoding are used to ensure proper data transfer. This file is attached as "matrix_convolution_avalon_interface.sv". In this project, we used 3*3 input matrix module for Hardware software codesign.

Signal	Direction	Description
avs_s1_write	Input	Write enable for input data
avs_s1_read	Input	Read enable for output data
avs_s1_address	Input	Specifies the target register
avs_s1_writedata	Input	Input data for the convolution
avs_s1_readdata	Output	Output data (convolution result)

3.3 Custom Component Creation

The netlist description of the matrix convolution accelerator was implemented with the help of Intel Quartus Prime to obtain the custom component. The design included the following steps:

- FSM Implementation: The FSM and associated data path were described in system verilog to implement the functionality of convolution.
- Avalon-MM Interface Integration: It became necessary to map signals to the Avalon-MM protocol.
- System Integration: This was implemented in the Platform Designer (Qsys) and memory mapped was initialized with a base address.
- Header File Generation: The .socinfo file was further used to create another header point for the software application to use, the macros included concerned memory-mapping.

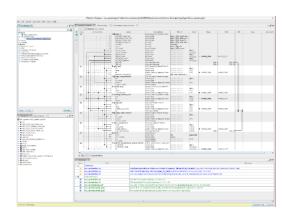


Fig 4: Custom Component Creation for Matrix Convolution

Fig 4 shows the process of custom component creation for the matrix convolution module. It highlights the steps taken in Intel Quartus Prime, including FSM implementation, Avalon-MM integration, and system-level configuration, to create a functional hardware component.

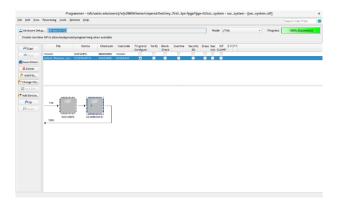


Fig 5: FPGA is programmed successfully

Fig 5 confirms the successful programming of the FPGA for executing matrix convolution operations. It demonstrates the completion of hardware configuration, readying the system for validation and testing.

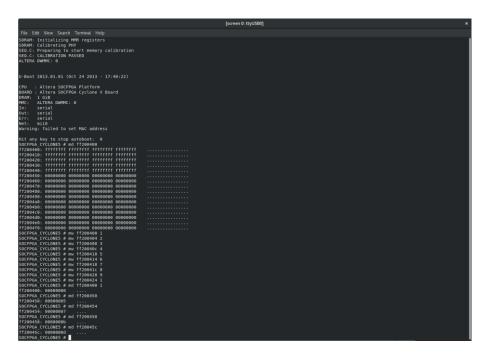


Fig 6: Writing and Reading into registers using U-Boot terminal

Fig 6 shows the writing and reading of data into registers using the U-Boot terminal. It provides an example of how input data is stored and output data is retrieved, illustrating the interaction between hardware and software components.

3.4 Software Hardware Codesign

The specific software application also known as main.c was completed and designed to directly operate with the hardware accelerators. It performed the following operations:

- Writing Input Matrix: The processor stored this input matrix with 3 rows and 3 columns to the hardware through the memory-map I/O.
- Triggering Computation: After accepting the input, the hardware went to the COMPUTE state on its own accord.
- Reading Output Matrix: The processor also got the computed 2*2 output matrix from the hardware.

Fig 7 depicts the software and hardware integration code (main.c). It demonstrates the functions for writing input matrices, triggering computation, and reading output matrices via the Avalon-MM interface, ensuring smooth operation of the hardware accelerator. The file is attached as "main.c".

Fig 7: Software and Hardware Integration Code (main.c)

3.5 Testbench and Validation

To demonstrate the implementation of the FSM and the data path, a system verilog testbench has been created and implemented. The testbench simulated across a input scenario and captured waveform to verify:

- Proper state transition in the FSM has been verified.
- Proper calculation of the given convolution operation is done.
- Avalon-MM interface to FSM and vice versa must exchange the correct data.
- Waveform analysis shows that the design meets functional and timing specifications.
- Here, two testbenches are written, one for 3*3 input matrix and 2*2 output matrix. On the other hand, another testbench is for 5*5 input matrix and 3*3 output matrix. Those results are shown below respectively.

```
// Testbooms for module of 300 Norths consolution
module thatis, consolution;
logic clk;
logic creat;
logic creat;
logic creat;
logic clini) input_marks_0, input_marks_1, input_marks_2;
logic (1):01 input_marks_0, input_marks_1, input_marks_2;
logic (1):11 input_marks_0, input_marks_1, input_marks_2;
logic (1):11 input_marks_0, input_marks_1, input_marks_2;
logic (1):12 input_marks_0, input_marks_1, input_marks_2;
// Establish andput_marks_0, input_marks_1, input_marks_1;
// Establish andput_marks_0, input_marks_1,
// Establish andput_marks_0, input_marks_1,
// Establish andput_marks_0, input_marks_1,
// Establish andput_marks_0, input_marks_1(input_marks_1),
.stark(stark),
.stark(stark),
.stark(stark),
.stark(stark),
.stark(stark),
.docident_incl(input_marks_0),
.
```

Fig 8: Testbench for Matrix Convolution module for 3*3 Input Matrix and 2*2 output Matrix

Fig 8 presents the SystemVerilog testbench for the matrix convolution module with a 3x3 input matrix and a 2x2 output matrix. It validates the FSM and datapath, checking for proper state transitions and correct data exchange through the Avalon-MM interface. This file is attached as "matrix_convolution3_3tb.sv".

Fig 9 shows the simulation results for the 3x3 input matrix and 2x2 output matrix. It verifies the

correctness of the matrix convolution module by comparing the expected output with the computed results.

Fig 9: Simulation Results for Matrix Convolution module for 3*3 Input Matrix and 2*2 output Matrix

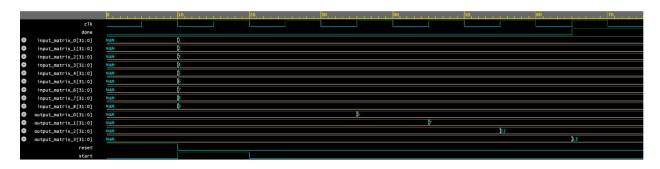


Fig 10: Waveform for Matrix Convolution module for 3*3 Input Matrix and 2*2 output Matrix

Fig 10 displays the waveform for the matrix convolution module with a 3x3 input matrix and a 2x2 output matrix. It confirms the proper timing and functional behavior of the FSM and data path during the computation process.

3.6 Clock Cycle Analysis

The clock cycle waveform demonstrates the behavior of the FSM-based matrix convolution hardware. The analysis is as follows:

1. Input Matrix Loading (WRITE MATRIX):

- All input matrix elements (input_matrix_0 to input_matrix_8) are loaded simultaneously within a single clock cycle.
- Total Clock Cycles for Input Load: 1 clock cycle.

2. Convolution Computation (COMPUTE):

• The computation phase processes all output elements together and completes in just 2 clock cycles.

• Total Clock Cycles for Computation: 2 clock cycles.

3. Output Matrix Generation (READ OUTPUT):

- The output matrix elements (output_matrix_0 to output_matrix_3) are produced sequentially, one per clock cycle.
- For **4 output elements**, the total time for the readout phase is: 4elements×1clock cycle/element = 4clock cycles.

4. Total Execution Time:

Summing up all phases, the total clock cycles required are:

• Input Write: 1 clock cycle

• Computation: 2 clock cycles

• Output Read: 4 clock cycles

Total Execution Time: 7 clock cycles

The total execution time for the matrix convolution operation is **7 clock cycles**, demonstrating an optimized and efficient hardware implementation.



Fig 11: Testbench for Matrix Convolution module for 5*5 Input Matrix and 3*3 output Matrix

Fig 11 depicts the testbench for the matrix convolution module with a 5x5 input matrix and a 3x3 output matrix. It expands on the design's scalability and demonstrates accurate computation for larger data sizes. This file is attached as "matrix_convolution5_5tb.sv".

```
Kernel Matrix:
1 0 1
101
101
Starting to write input matrix...
Input Matrix:
0 1 2 3 4
5 6 7 8 9
10 11 12 13 14
15 16 17 18 19
20 21 22 23 24
Waiting for computation...
Computation completed.
Output Matrix:
36 42 48
66 72 78
96 102 108
Testbench completed.
Simulation complete via $finish(1) at time 455 NS + 0
./testbench.sv:103
                           $finish;
```

Fig 12: Simulation Results for Matrix Convolution module for 5*5 Input Matrix and 3*3 output

Matrix

Fig 12 presents the simulation results for the 5x5 input matrix and 3x3 output matrix. It validates the hardware's functionality and ability to compute matrix convolutions for larger input data efficiently.



Fig 13: Waveform for Matrix Convolution module for 5*5 Input Matrix and 3*3 output Matrix

Fig 13 shows the waveform for the matrix convolution module with a 5x5 input matrix and a 3x3 output matrix. It illustrates the FSM's timing behavior and verifies the correctness of state transitions and output generation.

3.7 Implementation with only software

To set up a performance baseline, a C program for software only implementation for matrix convolution operation was designed. This implementation performed the following steps:

• Input Matrix: The 3*3 input matrix and 2*2 kernel were described in the program.

- Convolution Operation: Kernel sliding over the input matrix and performing the dot product computation was implemented using nested loop architecture.
- Output Matrix: To validate the outputs, they were saved in a 2*2 matrix output section.
- Here, two software implementations are written, one for 3*3 input matrix and 2*2 output matrix. On the other hand, another is for 5*5 input matrix and 3*3 output matrix. Those results are shown below respectively.

```
# crotupe cation he

# crotupe
```

Fig 14: Software only Implementation of Matrix Convolution for 3*3 Input Matrix and 2*2 output Matrix

Fig 14 depicts the software-only implementation for matrix convolution using a 3x3 input matrix and a 2x2 kernel matrix. It highlights the C code structure used to perform the operation and sets the baseline for hardware comparison. This file is attached as "software3 3.c".

```
Input Matrix:
1 2 3
4 5 6
7 8 9

Kernel Matrix:
1 0
1 0

Output Matrix:
5 7
11 13

Execution Time: 0.000002 seconds

...Program finished with exit code 0

Press ENTER to exit console.
```

Fig 15: Results for Software only Implementation of Matrix Convolution for 3*3 Input
Matrix and 2*2 output Matrix

Fig 15 shows the results of the software-only implementation for the 3x3 input matrix and 2x2 kernel matrix. It validates the correctness of the output generated by the software approach.

Fig 16: Software only Implementation of Matrix Convolution module for 5*5 Input Matrix and 3*3 output Matrix

Fig 16 depicts the software-only implementation for a 5x5 input matrix and a 3x3 kernel matrix. It demonstrates the nested loop structure used to perform convolutions on larger matrices. This file is attached as "software5_5.c".

```
Input Matrix:
0 1 2 3 4
5 6 7 8 9
10 11 12 13 14
15 16 17 18 19
20 21 22 23 24

Kernel Matrix:
1 0 1
1 0 1
1 0 1
Output Matrix:
36 42 48
66 72 78
96 102 108

...Program finished with exit code 0

Press ENTER to exit console.
```

Fig 17: Results for Software only Implementation of Matrix Convolution for 5*5 Input
Matrix and 3*3 output Matrix

Fig 17 shows the results of the software-only implementation for the 5x5 input matrix and 3x3 kernel matrix. It verifies the accuracy of the output and establishes a baseline for larger matrix convolutions.

4. Benchmarking and Validation

4.1 Software-Only Implementation Results

The software-only implementation was executed on a general-purpose processor to calculate the matrix convolution. The execution time is 0.000002 seconds.

```
Input Matrix:
1 2 3
4 5 6
7 8 9

Kernel Matrix:
1 0
1 0

Output Matrix:
5 7
11 13

Execution Time: 0.000002 seconds

...Program finished with exit code 0

Press ENTER to exit console.
```

Fig 18: Results for Software only Implementation of Matrix Convolution for 3*3 Input
Matrix and 2*2 output Matrix

Fig 18 presents the results of the software-only implementation for the 3x3 input matrix and 2x2 output matrix, highlighting the minimal execution time and correctness of the operation.

4.2 Hardware-Accelerated Implementation Results

The hardware accelerator was implemented on FPGA and validated using hardware-software codesign. The software interacted with the hardware via the Avalon-MM interface, using memory-mapped I/O to transfer input and output data.

Performance Metrics:

• **Input Write Time:** 0.000138 seconds

• Computation Time: 0.010058 seconds

• Output Read Time: 0.000053 seconds

• **Total Execution Time:** 0.010249 seconds

Fig 19: Results for Software Hardware Codesign Implementation of Matrix Convolution for 3*3 Input Matrix and 2*2 output Matrix using Uboot Terminal

Fig 19 shows the results of the software-hardware co-design implementation using the U-Boot terminal. It demonstrates the hardware-accelerated matrix convolution results, comparing execution times with the software-only implementation and showcasing the benefits of offloading computation to hardware.

The benchmarking process evaluated the correctness and performance of both software-only and hardware-accelerated implementations. The software implementation produced the correct output with minimal execution time due to the small matrix size, completing the convolution

operation in 0.000002 seconds. However, the hardware accelerator, while introducing overhead due to data transfer, demonstrated the capability to offload computation effectively. Future benchmarks with larger input sizes are expected to highlight the FPGA's parallel processing advantage.

4.3 Performance Comparison

Metric	Software Only	Hardware Accelerated
Execution time (seconds)	0.000002	0.010249
Correctness	Matched	Matched
Communication overhead	N/A	Present
Scalability	Limited	High for larger matrices

4.4 Analysis and Discussion

The results indicate that software only approach is slightly faster for this specific small matrix size (3x3 output). This is due to the following factors:

- Communication Overhead: Sending data between the CPU and FPGA adds delay and destroys performance for finer tasks creating hardware fewer than elaborate projects.
- Problem Size: Program in the hardware accelerator does not show its advantages with small matrices, as with them, the modern processor calculates the lightening fast.
- Setup Overhead: Synchronization at the first use of additional hardware and access via a memory-mapped range have an unavoidable cost.

However, hardware acceleration offers significant advantages for:

- Larger Matrices: It should also be noted that the present work has demonstrated that as matrix size increases (e.g., 100 x 100 or 1000 x 1000), the parallel FPGA architecture will offer better performance than a CPU.
- Repeated Computations: For real time or repeated processing, the hardware accelerator cuts CPU load and improves operating efficiency.

5. Conclusion

This project successfully demonstrated designing and implementing a hardware accelerator for matrix convolution operations. The FSM based design in integrated with Avalon-MM interface provided effective interconnection between the processor and FPGA. However, because of low computational complexity, the software-only implementation proved faster than the hardware design for small matrix sizes except for the spatial design where the proposed hardware accelerator achieved functional correctness and is capable of offloading computation.

The results suggest FPGA-based hardware acceleration is very efficient for computational-only tasks particularly at large problem sizes. In more detail, the approach of the hardware accelerator is to rely on the possibility of parallel processing for larger matrices and repetitive calculations.

6. Future Work

Future improvements to this project could focus on:

- Scalability for Larger Matrices: Benchmarking the hardware accelerator with larger input sizes (e.g., 100x100 or 1000x1000) to demonstrate its parallel processing advantage.
- **Pipelined Design:** Introducing pipelining in the FSM to reduce latency and improve throughput.

References:

- [1] Cao, Y., Wei, X., Qiao, T., & Chen, H. (2019, December). FPGA-based accelerator for convolution operations. In 2019 IEEE International Conference on Signal, Information and Data Processing (ICSIDP) (pp. 1-5). IEEE.
- [2] Snytsar, R. (2023). Sliding window sum algorithms for deep neural networks. *arXiv preprint* arXiv:2305.16513.