

# ENGINEERING PRACTICE ADVANCED (EIEN6709P)

## **FPGA IMAGE PROCESSING**

**SUBMITTED** 

 $\mathbf{BY}$ 

TEAM 1

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#### **Abstract**

This report discusses the implementation and optimization of a Sobel edge detection algorithm for image preprocessing on an FPGA platform. With the MNIST dataset of handwritten digits as the main experimental setup, this report illustrates how hardware acceleration can be used to greatly enhance the performance and efficiency of image preprocessing tasks, which are typically regarded as bottlenecks in computer vision workflows. The Sobel filter was first developed and tested in the Python development environment, translated to C++, and implemented in Xilinx Vitis HLS for execution on an FPGA on a Xilinx ZedBoard. Optimizations at the hardware level, including loop pipelining and reduction of bit-width, were added to maximize throughput and minimize latency. The synthesized design was integrated into a system-level environment in Vivado, and host software was created in Vitis for managing data flow and execution routines.

The evaluation results show that the FPGA-based implementation provides a considerable acceleration of processing time, while also providing stable and accurate edge detection on MNIST images. Furthermore, a user-friendly graphical interface was developed to facilitate visualization of the results. This work demonstrates the practical benefits of applying FPGA-based acceleration to preprocessing tasks and highlights an extensible approach to traditional vision algorithm implementation on hardware platforms.

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#### 1. Introduction

As the computer vision field keeps expanding, the performance of image preprocessing has increasingly become the key enabler of real-time and low-latency applications. As the essential initial step in the majority of vision pipelines, this preprocessing operation improves the quality of input images by minimizing noise and accentuating important features, directly affecting machine learning model accuracy. But, software implementations of these kinds of preprocessing algorithms typically lag behind the high throughput and low power demands, particularly in embedded or edge computing setups.

In this work, the implementation and optimization of a Sobel edge detection filter, a very popular preprocessing algorithm, on an FPGA platform are analyzed. The target hardware of this work is the Xilinx ZedBoard, which is known for its favorable combination of flexibility and processing power. For a test and evaluation platform, for the purposes of testing and evaluation, the MNIST dataset, which includes thousands of 28×28 grayscale images of handwritten digits [1], is utilized as the benchmark.

The project entails an end-to-end pipeline beginning with algorithm prototyping carried out in Python, followed by translation and optimization executed in C++ with Vitis HLS, then implemented into a hardware system in Vivado and ultimately targeted onto the FPGA. A graphical user interface-based interface was also created to enable interactive testing on MNIST samples. By leveraging hardware-aware optimizations such as pipelining and loop unrolling, the design seeks to showcase considerable performance gains over conventional CPU-centric methods.

## 2. Background and Motivation

Image preprocessing is a significant step in computer vision systems that is frequently accountable for the conversion of raw input data into a more helpful format by refining edges, moderating noise, and readying images for feature extraction or classification. Edge detection is a prevalent and efficient method used in preprocessing, which reduces image content while preserving structural information. Among the numerous approaches available, the Sobel filter is particularly popular because of its simplicity and effectiveness at emphasizing intensity gradients in images [2].

The Sobel filter detects edges by convolving the image with two 3×3 kernels that respond maximally to edges running vertically and horizontally. Sobel filters uses small matrices called

**kernels (or filters)** to calculate the gradient across an image. A **convolution kernel** slides across the image, computing a weighted sum of pixels in a small neighborhood (e.g.,  $3\times3$ ).

- This allows **local analysis** of how intensity changes.
- Different kernels are designed to detect different patterns (e.g., vertical or horizontal changes).
- $G_x$ : Detects **horizontal** intensity changes (edges that are vertical).

$$egin{bmatrix} -1 & 0 & 1 \ -2 & 0 & 2 \ -1 & 0 & 1 \end{bmatrix}$$

•  $G_y$ : Detects **vertical** intensity changes (edges that are horizontal).

$$egin{bmatrix} -1 & -2 & -1 \ 0 & 0 & 0 \ 1 & 2 & 1 \end{bmatrix}$$

Sobel filters also use Gradient Magnitude and Direction. A gradient measures how much the pixel intensity changes in a specific direction. In image terms a high gradient means a sharp change, likely an edge and a low gradient means little change to a smooth region. We compute the gradient at each pixel to find these intensity changes.

After convolution, two images are obtained Gx and Gy. From these, we compute the magnitude:

$$G=\sqrt{G_x^2+G_y^2}$$

Though software implementations of the Sobel filter are simple, they are confronted with scalability and processing limitations when realized with big datasets or in real-time computing setups. It is especially true in edge computing setups, where low latency, energy efficiency, and compact form factor are prime considerations. Conventional CPUs, designed for sequential workloads, are not well placed to fully exploit the intrinsic parallelism inherent in image processing applications. In contrast to this, FPGAs offer tremendous advantages by enabling massive parallelism and user-defined data paths, which facilitate real-time image processing efficiently [3]. FPGAs are programmable compared to fixed-function GPUs or ASICs, which makes it more convenient for designers to architect the hardware for specific workloads like the Sobel filter. All these advantages make them ideal to implement preprocessing algorithms in systems where performance, flexibility, and power efficiency are priority [3].

The MNIST data set [1], commonly utilized in image classification and pattern recognition research, presents itself as a suitable test case since it is simple, well-annotated, and has a standard 28×28 grayscale format. The purpose of this project is to critically analyze the design, implementation, and optimization of the Sobel filter in FPGA hardware with MNIST as the benchmark data set.

The inspiration for this project is the bridging of the gap between algorithm-level design and successful hardware implementation. By following a disciplined development process and FPGA optimizations, the project highlights the practical benefits and challenges of applying conventional image preprocessing algorithms to reconfigurable hardware platforms.

#### 3. Methodology

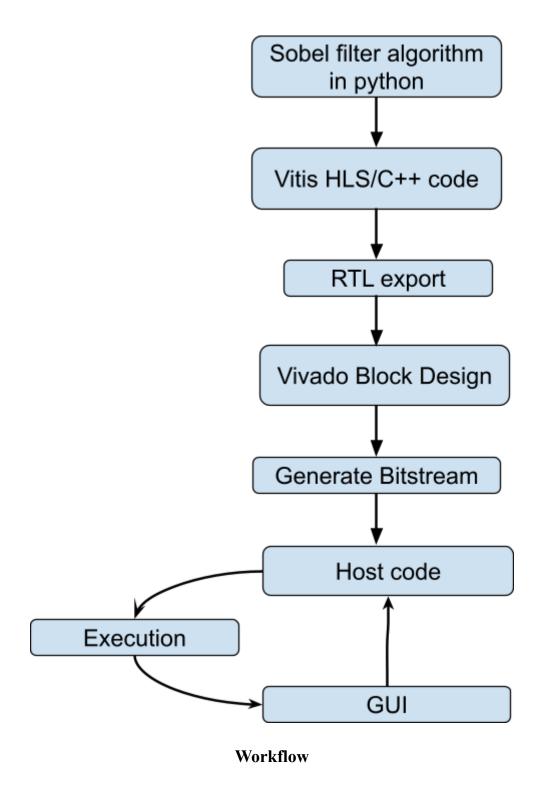
This section explains the end-to-end process used for implementation and optimization of the Sobel edge detection algorithm on an FPGA platform using the MNIST dataset. The method involves software prototyping, hardware implementation through High-Level Synthesis (HLS), system-level design, and host-side integration. The methodology is broken down into a number of steps to promote accuracy, efficiency, and simplicity of demonstration.

## 3.1 Project Workflow Overview

The process of development was organized into a series of basic stages:

- i. Algorithm Prototyping: Sobel edge detection was initially developed and tested in Python. This step ensured that the underlying logic appropriately detected edges in 28×28 grayscale MNIST images and provided a helpful baseline to which the FPGA implementation could be compared.
- **ii. HLS Conversion and Optimization:** The verified Python algorithm was then translated to C++ for synthesis using Xilinx Vitis HLS. FPGA-specific optimization directives such as loop pipelining, loop unrolling, and bit-width reduction were applied to enhance throughput and reduce resource utilization. The design was particularly tuned for the fixed image sizes intrinsic to the MNIST dataset. We evaluated the result of the test bench with the python result.
- **iii. FPGA Hardware Design:** The IP core created with HLS was then incorporated into a Vivado block design. The ZYNQ Processing System (PS) was set up to communicate with the Programmable Logic (PL), thereby enabling correct interaction via AXI interfaces. After system verification, the bitstream was created and exported for deployment on the Xilinx ZedBoard.
- iv. Software-Hardware Integration: Host-code software was developed using the Xilinx Vitis IDE platform to establish communication between the ARM processor on the ZedBoard and the Sobel accelerator in the PL. The software handled operations such as reading MNIST image data, writing pixel arrays to the accelerator, reading processed outputs, and handling user interaction.
- v. GUI Development: A simple graphical user interface was realized to enable demonstrations. The interface supports importing MNIST images, display of the input

and the output generated through edge detection, and filtering parameter adjustment. The GUI plays a central role in illustrating processing potential of the FPGA and provides a more interactive experience for demonstration purposes.



#### 4. Prototyping Algorithms with Python

The primary objective of this stage was to realize and verify the Sobel edge detection filter in a software framework prior to moving on to the hardware design. Python was selected since it is easy, has rich image processing library support, and allows visualization. The MNIST handwritten digit dataset was employed to verify the efficacy of the filter on low-resolution grayscale images.

#### Methodology:

With Python and the help of libraries such as NumPy, Matplotlib, and OpenCV, the MNIST digit images, which have a size of 28×28 pixels, were loaded and processed. The Sobel operator in horizontal and vertical directions was applied to detect gradient changes and hence to highlight the edges of the digits.

Each picture went through the following process:

- i. Image loading and normalization to ensure consistent pixel intensity scaling.
- ii. Convolution with Sobel kernels in the X and Y directions.
- iii. Calculation of the gradient magnitude to produce a final edge map.
- iv. Visualization of both the original and processed images to assess the accuracy of edge detection.

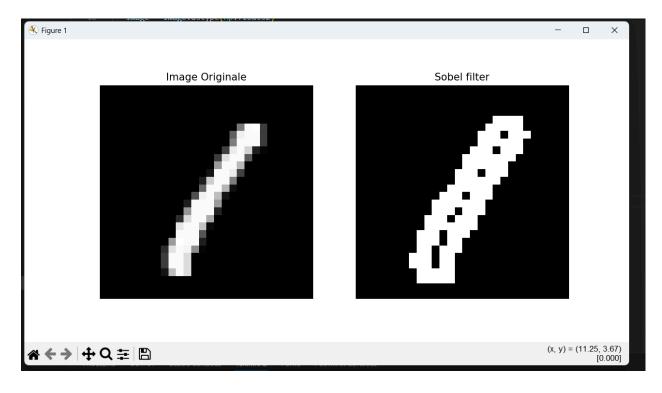
## **Python Code Snippet:**

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.ndimage import convolve
def sobel filter(image, threshold=None):
  sobel x = np.array([[-1, 0, 1],
                      [-1, 0, 1]]
  sobel y = np.array([[-1, -2, -1],
  image = image.astype(np.float32)
     grad_x = convolve(image, sobel_x, mode='constant', cval=0.0)
     grad y = convolve(image, sobel_y, mode='constant', cval=0.0)
  grad mag = np.hypot(grad x, grad y)
  max val = grad mag.max()
```

```
grad mag /= max val
  if threshold is not None:
             grad_mag = (grad_mag > threshold).astype(np.float32)
  return grad mag, grad x, grad y
def load mnist(csv path):
  data = pd.read_csv(csv_path)
  labels = data.iloc[:, 0].values
    images = data.iloc[:, 1:].values.reshape(-1, 28, 28) / 255.0
  return images, labels
def plot results(original, filtered, title="Filtered image"):
  plt.figure(figsize=(10, 5))
  plt.subplot(1, 2, 1)
  plt.title("Image Originale")
  plt.imshow(original, cmap='gray')
  plt.axis('off')
```

```
plt.subplot(1, 2, 2)
  plt.title(title)
  plt.imshow(filtered, cmap='gray')
  plt.axis('off')
  plt.show()
  images, labels = load mnist("test/mnist train.csv")
  print(len(images))
  sample idx = 3
  original image = images[sample idx]
       filtered_image, grad_x, grad_y = sobel filter(original image,
threshold=0.2)
  plot results(original image, filtered image, "Sobel filter")
  plt.figure(figsize=(15, 5))
    plt.subplot(1, 3, 1).imshow(grad x, cmap='gray').set title('Gradient
    plt.subplot(1, 3, 2).imshow(grad y, cmap='gray').set title('Gradient
                   plt.subplot(1,
                                               3).imshow(filtered image,
cmap='gray').set title('Magnitude du Gradient')
```

#### **Outcome:**



Both original and processed image visualizations in order to ascertain the degree of accuracy in edge detection.

## 5. High-Level Synthesis (HLS) with C++

The objective in this stage was to port the Sobel edge detection algorithm previously verified in Python to C++, then synthesize it into hardware using Xilinx Vitis High-Level Synthesis (HLS) to enable the implementation of the algorithm as a custom hardware accelerator on the FPGA that was optimized for the fixed image dimensions of the MNIST dataset.

#### Methodology:

The Sobel edge detection algorithm originally developed in Python was re-implemented in C++ with hardware design considerations, such as efficient memory access, appropriate data types, and modular code structure. The implementation was organized into three core files: **sobel.cpp**, containing the main functional logic; **sobel.h**, defining data types and function prototypes; and **sobel\_tb.cpp**, serving as the testbench for simulation and verification. The C++ design was synthesized into a Register Transfer Level (RTL) description using Xilinx Vitis HLS, targeting the programmable logic (PL) of the ZedBoard based on the **xc7z020clg484-1** Zynq-7000 SoC.

To improve the performance and hardware efficiency of the design, several high-level synthesis (HLS) optimization directives were employed:

- i. **Loop Pipelining:** Enabled concurrent processing of adjacent pixels by overlapping iterations of loops, thus reducing initiation intervals and overall latency. For example we use #pragma HLS PIPELINE II=1 and #pragma HLS PIPELINE II=2 to reduce latency and allow concurrent processing.
- ii. **Loop Unrolling:** Applied to inner convolution loops to increase parallelism and throughput, especially during the horizontal and vertical gradient calculations. We used #pragma HLS UNROLL that significantly boosts throughput during the 3×3 Sobel kernel gradient calculations.
- iii. **Fixed-Point Arithmetic:** Floating-point operations were replaced with fixed-point equivalents where precision loss was negligible, leading to reduced hardware complexity and faster synthesis.
- iv. Array Partitioning and Dataflow: These directives allowed simultaneous memory access and concurrent execution of independent processing stages, facilitating higher parallelism and better resource utilization. The input image was handled as a two-dimensional matrix, and careful management of boundary conditions ensured valid memory access during kernel operations. Intermediate values, such as the horizontal and vertical gradients, were buffered internally to enable efficient pipelined processing throughout the filter stages.

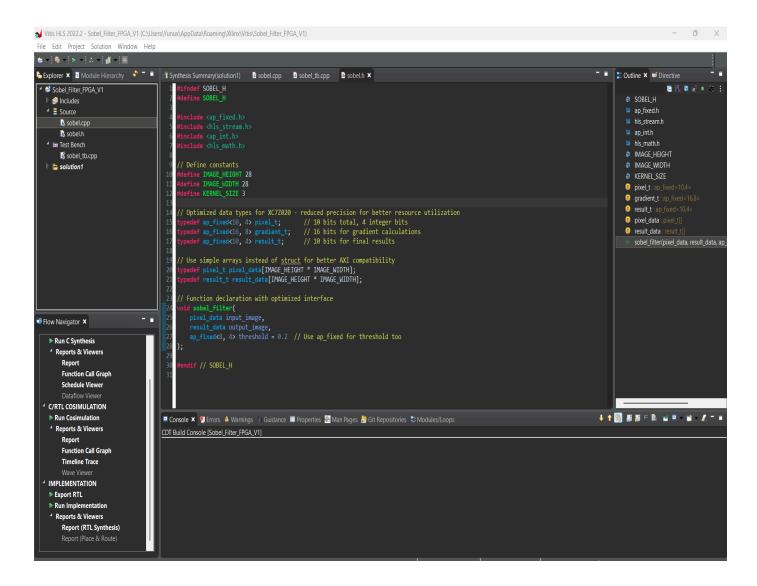
The code below allows **parallel access to multiple elements** in the same row, important for Sobel 3×3 filtering

```
#pragma HLS ARRAY_PARTITION variable=Gx complete dim=0
#pragma HLS ARRAY_PARTITION variable=Gy complete dim=0

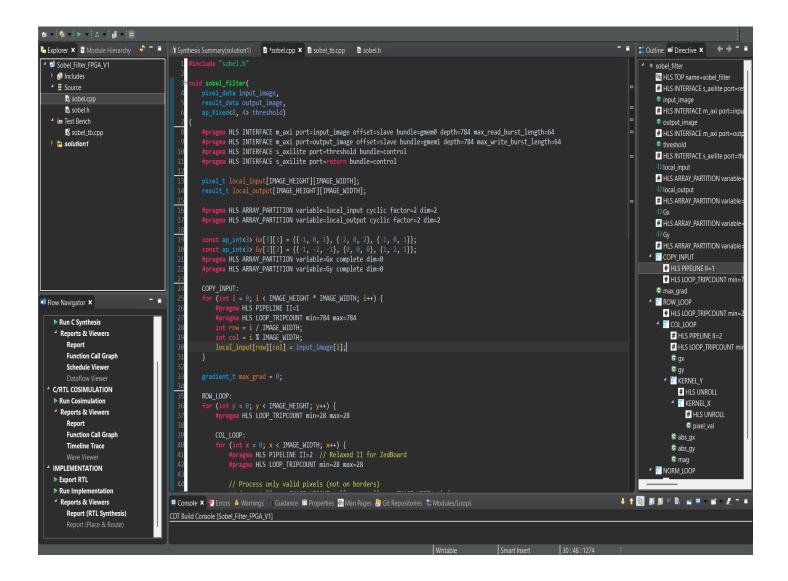
#pragma HLS ARRAY_PARTITION variable=local_input cyclic factor=2 dim=2
#pragma HLS ARRAY_PARTITION variable=local_output cyclic factor=2 dim=2
```

To illustrate the HLS-based implementation, key excerpts from each of the three C++ source files are presented below.

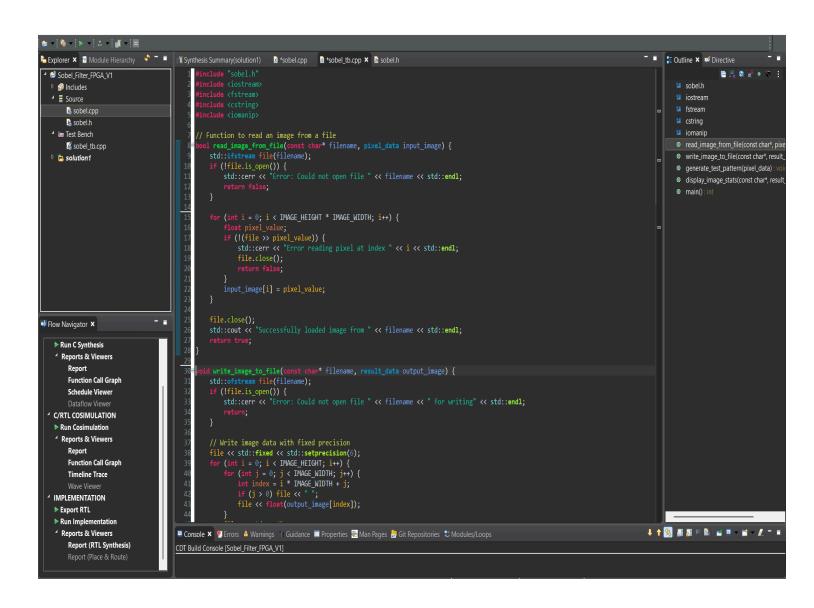
(a) **sobel.h** - **Header File:** This file defines data types, image dimensions, and the function prototype for the Sobel filter.



**(b) sobel.cpp** – **Main Function Implementation:** This file contains the actual implementation of the Sobel edge detection algorithm, written for synthesis using HLS-friendly constructs.



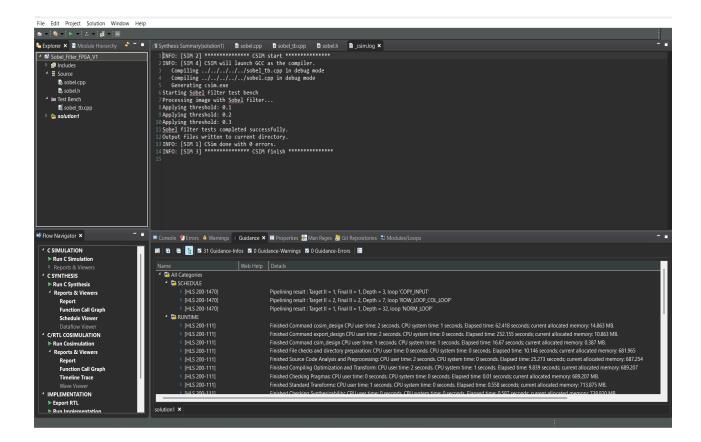
(c) sobel\_tb.cpp - Testbench for Verification: This testbench file was used to simulate and verify the correctness of the Sobel filter before synthesis.



#### HLS Simulation, Verification, RTL Export and Report Analysis:

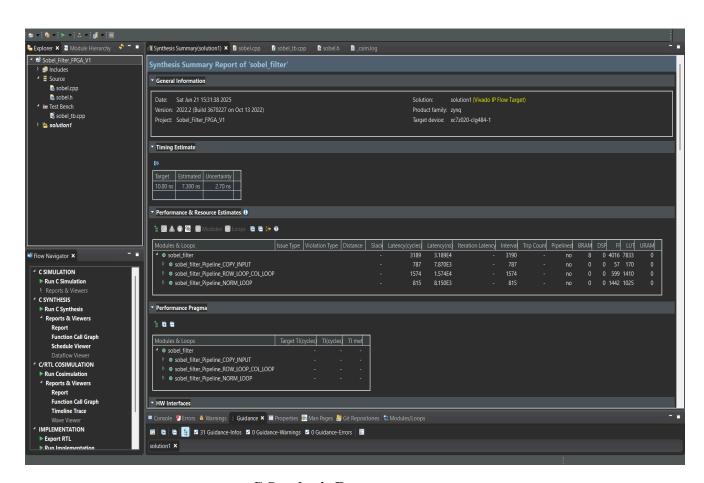
Following the building and creation of the Sobel filter algorithm using C++, a full series of simulation and synthesis steps were carried out using Xilinx Vitis HLS to establish correctness, examine performance, and ready the design for implementation in hardware. This phase merges the results of the next phases: C Simulation, C Synthesis, Co-Simulation, and RTL Export.

C **Simulation:** The first half involved simulating the C++ version to verify that the algorithm was giving accurate results when applied to sample MNIST images. The testbench (sobel\_tb.cpp) read in a sample image, executed the filter, and printed out the output values for comparison.



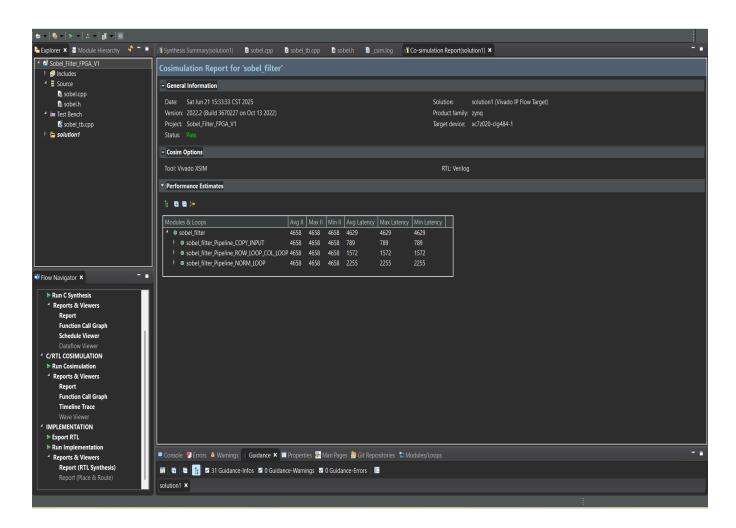
**C Simulation Report** 

C Synthesis: The second step was to take the validated C++ implementation and convert it to Register Transfer Level (RTL) hardware in Vitis High-Level Synthesis (HLS). In this step, synthesis reports were created that gave us estimates of latency, initiation interval (II), and FPGA resource utilization. This is to verify the validity and correctness of the algorithm before hardware synthesis.



**C** Synthesis Report

**Co-Simulation:** Co-simulation was run to ensure that the RTL model produced the same behavior as the original C++ model. The comparison was done by comparing the output of both simulations at the bit level. This is to provide bit-for-bit correspondence in between the hardware and software models.

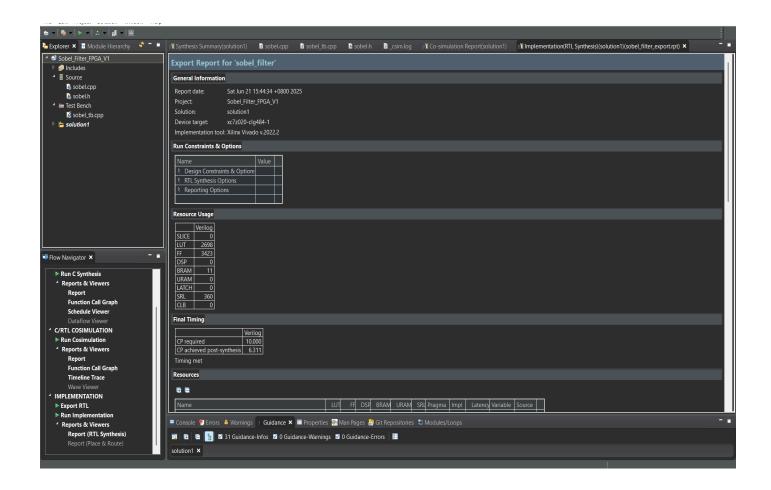


**Co-Simulation Report** 

RTL Export: Upon successful verification and synthesis, the final step was exporting the design into an IP core. The IP core, along with Verilog/VHDL files, interface definitions, and configuration metadata, was packaged for use in Vivado. This is to develop the synthesized architecture to incorporate in the programmable logic (PL) of the Zynq-7000 system-on-chip (SoC) on the ZedBoard platform. The exported IP was later imported into Vivado for system-level integration and bitstream generation.

#### **Generated Files:**

- i. RTL (Verilog/VHDL) code
- ii. IP metadata (component.xml)



**Export Report** 

#### 6. FPGA Hardware Design in Vivado

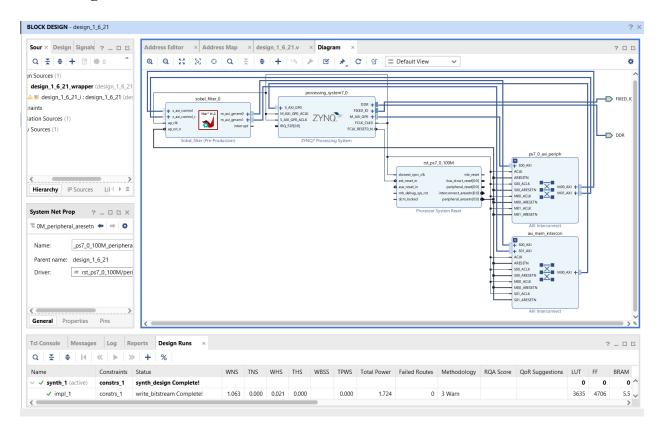
The goal of this phase was to integrate the custom Sobel filter synthesized as an IP core using Vitis HLS into a complete hardware platform using Xilinx Vivado. The platform was built on the **ZedBoard** (xc7z020clg484-1). The procedure that was used to implement and design the hardware system is as follows:

- i. **Vivado Project Creation:** A new project in Vivado was created, and the ZedBoard (ZYNQ-7000 SoC, part number XC7Z020CLG484-1 was targeted. Default board presets were enabled to simplify the configuration of peripherals and the processing system.
- ii. **Importing the Sobel HLS IP Core:** The custom Sobel edge detection module, previously exported from Vitis HLS, was added to the Vivado IP catalog and instantiated within the block design.
- iii. **Including the ZYNQ7 Processing System (PS7):** The ZYNQ7 PS block was included to serve as the central controller. Configuration settings were updated to:
  - Enable UART1 for serial communication with a host PC.
  - Enable DDR3 RAM for storing MNIST image data.
- iv. Connected the Sobel IP to the PS7 via AXI-Lite and AXI interfaces: AXI Interconnects were used to route communication between the PS and the Sobel IP block. Proper memory address ranges were assigned to the IP core using the Address Editor to ensure software-level access via Vitis.
- v. Validated the design and generated the bitstream: Once the block design was completed, the system was validated using Vivado's integrated tools to ensure all connections were correctly made and that the design met interface and timing requirements. Any missing connections or unassigned addresses were resolved during this phase.

#### After successful validation:

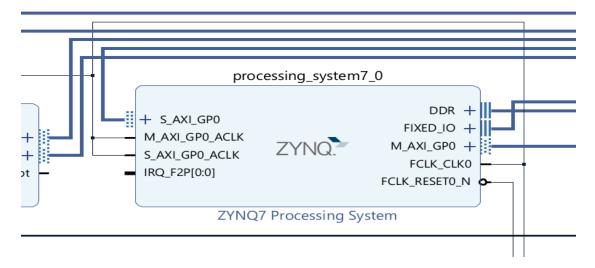
- i. The block design was wrapped in a top-level HDL wrapper.
- ii. Synthesis and Implementation were performed.
- iii. The final bitstream file (.bit) was generated and exported along with the hardware platform description (.xsa) for use in the Vitis software development environment (Hostcode).

## **Block Design:**



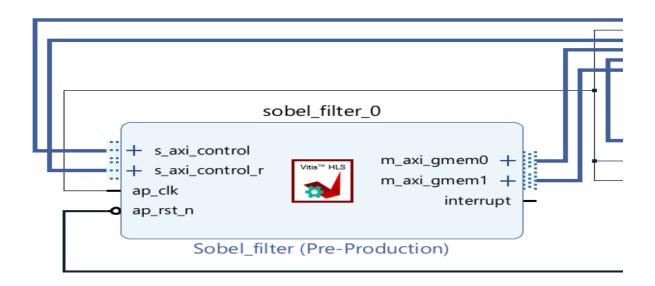
**IP Block Diagram** 

i. **processing\_system7\_0 - ZYNQ Processing System (PS7):** Manages control, memory access, and data I/O.



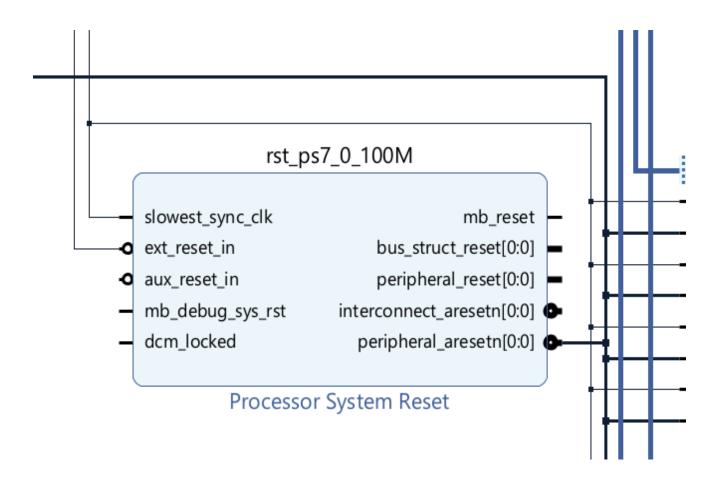
**ZYNQ Processing System (PS7)** 

ii. **sobel\_filter\_0 - Custom HLS IP Core:** Performs edge detection on images using the Sobel filter.



**Custom HLS IP Core** 

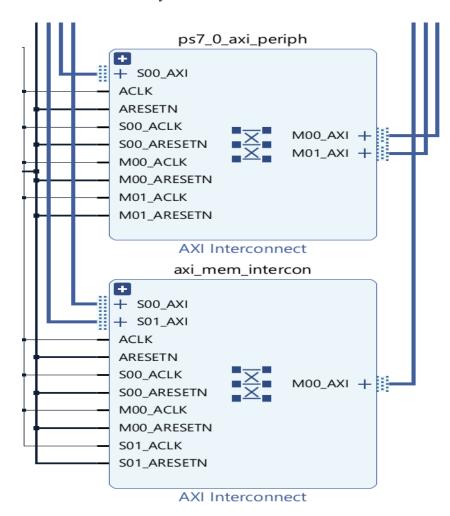
iii. rst\_ps7\_0\_100M - Processor System Reset Block: Handles system reset synchronization.



**Processor System Reset Block** 

- iv. **AXI Interconnect Blocks:** There are two AXI interconnects in this design:
  - Ps7\_0\_axi\_periph: Routes AXI-Lite transactions from PS7 to the Sobel IP control interface.
  - Axi\_mem\_intercon: Routes AXI full transactions for image data transfer between DDR and the Sobel IP (m\_axi\_gmem0).

They enable seamless communication between PS and PL, with address decoding and port arbitration handled internally.



**AXI Interconnect Blocks** 

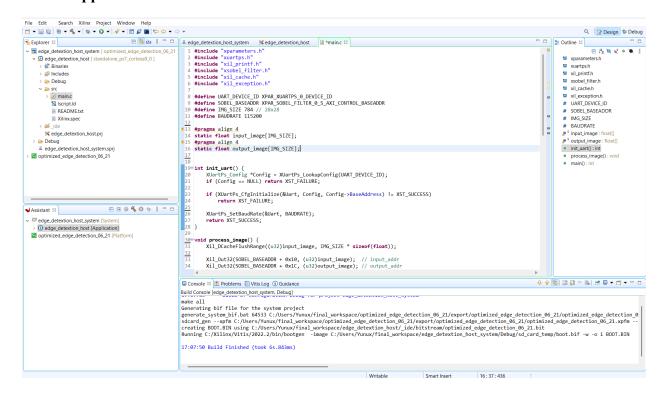
## 7. Integration of Software-Hardware in Vitis IDE (Host Code)

The main goal of this phase was to create host-side software that is designed to facilitate data communication between the ARM Processing System and the Sobel hardware accelerator realized in the programmable logic (PL). The software reads MNIST images, loads them to the FPGA, initializes the Sobel filter module, and gets back resulting edge maps for visualization

#### **Process:**

- i. **Exporting the Hardware Platform:** The hardware design, including the Sobel IP core and processing system, was exported from Vivado as an **.xsa file**. This file describes the platform's hardware structure and is used to configure the Vitis workspace.
- ii. **Creating the Vitis Application Project:** A new application project was created in the Vitis IDE, targeting the exported hardware platform. The project was based on a C application template designed for bare-metal execution on the Zynq ARM core.
- iii. **Writing the Host Application Code:** The host application was redesigned to facilitate PC-to-FPGA communication via UART while maintaining hardware acceleration. The software performs these critical tasks:
  - i. Image Acquisition via UART: MNIST images are transmitted from the PC GUI as serialized 32-bit floating-point arrays. The host code reconstructs these into 28×28 matrices in aligned DDR memory.
  - ii. Memory Management: Image buffers are allocated in DDR with explicit cache control. The ARM processor flushes input data to ensure coherence before acceleration and invalidates output buffers to retrieve processed results.
  - iii. Sobel IP Configuration:The accelerator is programmed through AXI-Lite registers:
    - Input/output buffer addresses are set to shared DDR locations
    - Threshold values are configured in normalized fixed-point format
    - Processing is initiated via a start command
  - iv. Execution Monitoring: The host polls the IP's status register to detect completion, ensuring synchronization between software and hardware execution.
  - v. Result Retrieval: Processed edge maps are read from DDR and transmitted back to the PC via UART, enabling visualization and validation on the host machine.

# **Code Snippet:**



Hostcode

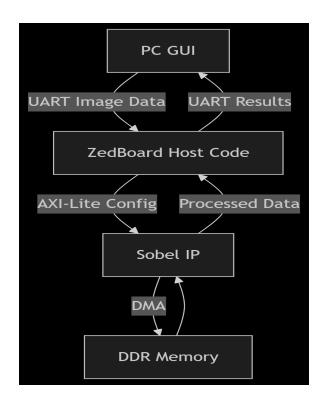
#### 8. GUI Development

The goal of this stage was to design a simple and interactive graphical user interface (GUI) that allows users to select MNIST images, configure Sobel filter parameters, and visualize both the original and processed images. The GUI acts as a bridge between the user and the FPGA system, simplifying demonstration and testing.

#### **Process:**

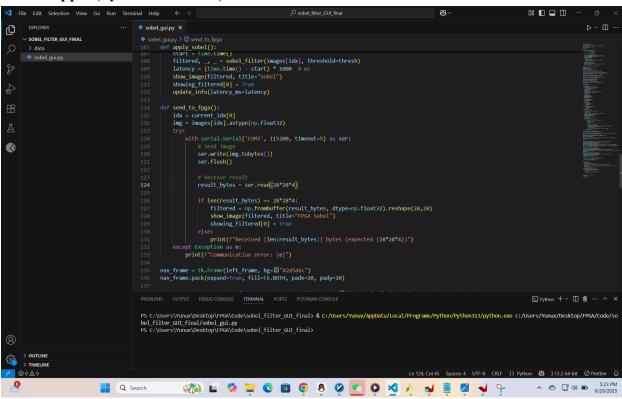
A lightweight GUI was developed in Python using the Tkinter library, which is well-suited for rapid prototyping and cross-platform compatibility. The interface was designed to integrate seamlessly with the host software and hardware setup. The GUI provides the following core functionalities:

- Dataset Access and Image Selection: The application loads the MNIST dataset from local storage and presents a user-friendly way to browse or randomly select a digit image (28×28 pixels).
- ii. Parameter Configuration: Users can adjust key processing parameters such as the Sobel threshold, allowing control over edge sensitivity. This value is later passed to the FPGA through the host code.
- iii. **Initiating FPGA Processing:** Upon clicking the "**Run FPGA**" button, the selected image is sent to the FPGA via the host software. The GUI communicates with the Vitis-built host application, which in turn configures the Sobel IP and retrieves the output.
- iv. **Result Visualization:** The GUI displays the edge-detected result returned by the FPGA. Images are rendered using the Matplotlib library, which integrates smoothly with Tkinter to deliver clear, high-quality visual output.

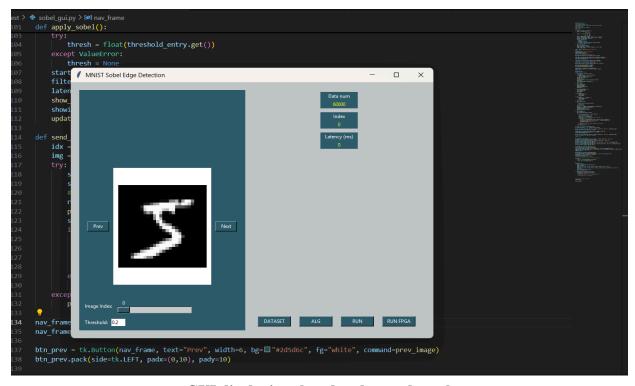


**Execution Flow** 

## **Code Snippet (Python + Tkinter):**



# **GUI Code**



GUI displaying the edge-detected result

## Reference

- [1] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.
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- [3] Y. Zhang and V. K. Prasanna, "High-performance and energy-efficient image processing using FPGAs," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 23, no. 11, pp. 1810–1823, 2013.