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An Efficient Image Denoising Approach Using FPGA Type of PYNQ-Z2

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Abstract:

Image denoising techniques have become crucial for computer-assisted analysis due to the increasing number of digital images captured in unfavorable conditions. In various fields such as image recognition, medical imaging, robotics, and facial expression analysis, the presence of noise poses significant challenges for denoising algorithms. One of the key difficulties is distinguishing between edges, textures, and noise, all of which contain high-frequency components. Haar Wavelet Transform (HWT) has emerged as a highly effective technique for image denoising. The proposed study focuses on two denoising methods: HWT and HWT-FPGA. Experimental evaluations are conducted to assess the denoising performance of the HWT model and the efficiency of its implementation on a Field-Programmable Gate Array (FPGA). Quantitative metrics, such as Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE), are used to measure the denoising quality for ten test images of size 255x255 pixels. Additionally, computational metrics, including processing speed and resource utilization, are analyzed to evaluate the efficiency of the FPGA implementation. The research specifically supports PYNQ, an open-source framework that enables embedded programmers to explore the capabilities of Xilinx ZYNQ SoCs without the need for VHDL programming. In this context, the PYNQ-Z2 FPGA development board, based on the ZYNQ XC7Z020 FPGA, is chosen for the proposed system. The experimental results demonstrate that the HWT and

HWT-FPGA approach significantly improve denoising performance compared to traditional methods. The denoised images exhibit higher PSNR values and low MSE scores, indicating better preservation of image details and similarity to the clean images. Furthermore, the FPGA implementation showcases remarkable computational efficiency, enabling real-time denoising capabilities while effectively utilizing FPGA resources.

Keywords: Denoising, HWT, FPGA, Thresholding.

طريقة فعالة لتقليل الضوضاء في الصور بإستخدام تنفيذ منصة مصفوفة البوابة القابلة للبرمجة باستخدام مويجة هار

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الخلاصة:

لقد أصبحت تقنيات تقليل ضوضاء الصورة فعالة بالنسبة للتحليل بمساعدة الكمبيوتر بسبب العدد المتزايد من الصور الرقمية الملتقطة في ظروف غير مواتية. في مجالات مختلفة مثل التعرف على الصور، والتصوير الطبي، والروبوتات، وتحليل تعبيرات الوجه، يشكل وجود الضوضاء تحديات كبيرة أمام خوارزميات تقليل الضوضاء. تتمثل إحدى الصعوبات الرئيسية في التمييز بين الحواف والأنسجة والضوضاء، حيث تحتوي جميعها على مكونات عالية التردد. لقد ظهر تحويل مويجات هار (*HWT*) كتقنية فعالة للغاية لتقليل ضوضاء الصورة. تركز الدراسة المقترحة على طريقتين لتقليل الضوضاء: *HWT* و*HWT-FPGA*. يتم إجراء تقييمات تجريبية لتقييم أداء تقليل الضوضاء لنموذج *HWT* وكفاءة تنفيذه على صفيف البوابة القابلة للبرمجة ميدانيًا (*FPGA*). تُستخدم المقاييس الكمية، مثل نسبة الذروة للإشارة إلى الضوضاء (*PSNR*) ومتوسط الخطأ المربع (*MSE*)، لقياس جودة تقليل الضوضاء لعشر صور اختبار بحجم ٢٥٥ × ٢٥٥ بكسل. بالإضافة إلى ذلك، يتم تحليل المقاييس الحسابية، بما في ذلك سرعة المعالجة واستخدام الموارد، لتقييم كفاءة تنفيذ *FPGA*. يدعم البحث على وجه التحديد *PYNQ*، وهو إطار عمل مفتوح المصدر يمكّن المبرمجين المضمنين من استكشاف قدرات *Xilinx ZYNQ SoCs* دون الحاجة إلى برمجة *VHDL*. وفي هذا السياق، تم اختيار لوحة تطوير *PYNQ-Z2 FPGA*، المبنية على *ZYNQ XC7Z020 FPGA*، للنظام المقترح. توضح النتائج التجريبية أن نهجي *HWT* و*HWT-FPGA* يحسنان بشكل كبير أداء تقليل الضوضاء مقارنة بالطرق التقليدية. تظهر الصور منخفضة الضوضاء قيم *PSNR* أعلى ودرجات *MSE* منخفضة، مما يشير إلى الحفاظ بشكل أفضل على تفاصيل الصورة وتشابهها مع الصور النظيفة. علاوة على ذلك، يُظهر تنفيذ *FPGA* كفاءة حسابية ملحوظة، مما يتيح إمكانات تقليل الضوضاء في الوقت الفعلي مع الاستخدام الفعال لموارد *FPGA*.

الكلمات المفتاحية: إزالة الضوضاء، تحويلة مويجة هار، مصفوفة التأثير البرمجي للبوابات، الصورة ذات التدرج الرمادي، العتبة.

1. Introduction:

In today's digital era, there is an ongoing need for high-quality images. Whether it is for analysis, art, medicine, satellite imagery, surveillance, or entertainment, the quality of an image plays a crucial role in decision-making processes. However, real-world images often suffer from various issues like noise, blurriness, and compression artifacts, which diminish their clarity and usefulness. Consequently, both researchers and professionals are actively engaged in addressing the fundamental challenge of restoring and improving the quality of these degraded images [1]. Image enhancement is an important task in the field of image processing, focusing on preserving or improving essential details and features while enhancing the overall perceptual quality and usefulness of images. While traditional methods have made significant contributions to various image enhancement techniques, they often fall short of providing a comprehensive solution to the increasingly complex challenge of enhancing image quality. With the continuous advancement of the digital era, there is a growing need for a new generation of image enhancement techniques capable of addressing the evolving complexities associated with this task [2]. Wavelet-based image processing techniques have become highly effective and flexible for improving the quality of images. These techniques leverage wavelet transforms to achieve a multiresolution representation of the image, allowing for the separation of image content into different frequency bands. This multiresolution property makes wavelet-based methods well-suited for handling the various types of image degradations commonly encountered in real-world scenarios. By reducing noise while preserving important details, the wavelet-based approach has proven to be a strong contender for enhancing image quality [3]. There are many wavelet families for example Daubechies, Haar, Morlet,……etc. can be shown in **Figure 1 [4]**.

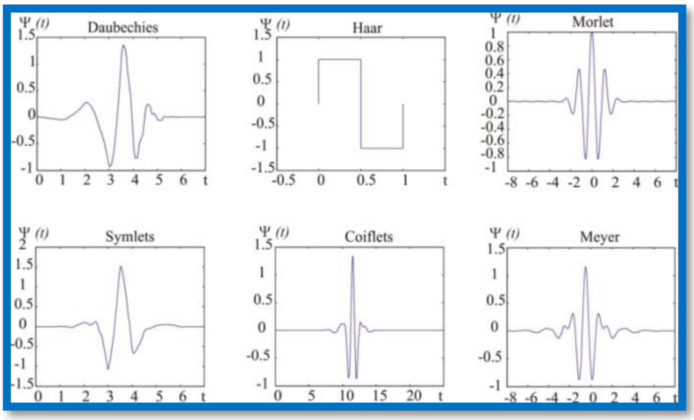

Figure 1: Wavelet types

This research will utilize the Haar wavelet due to its simplicity, speed, memory efficiency, and reversibility without the edge effects commonly associated with other wavelet transformations. The Haar wavelets, in their discrete form, are closely linked to a mathematical technique called the Haar wavelet transform (HWT) [5].

The objective of this study is to investigate the potential of HWT models in improving image quality. The study will explore the theoretical principles underlying HWT and their application in image processing. The aim is to develop innovative methods and algorithms for tasks such as deblurring, reducing artifacts, and denoising images using Haar wavelet models and implementation on FPGA type of PYNQ-Z2.

2. Literature Review

In 2021, Lee, and Jaehoon [6] introduced an efficient approach to reduce noise in photon counting imaging using a discrete wavelet transform. In conventional 2D photon counting imaging, statistical methods like the Poisson random process are employed to visualize objects in low-light conditions. However, background noise can still be present, which can negatively impact image quality. While median filters are commonly used for noise reduction, they may not effectively eliminate all the noise in the scene. To overcome this limitation, the proposed method utilizes the discrete wavelet transform and applies a thresholding technique that takes advantage of the specific characteristics of photon-counting imaging. By doing so, the method aims to effectively remove noise from the scene and enhance the overall image quality. This is especially beneficial in areas without objects, where noise can interfere with visualization and degrade the image. In 2021, Sakthidasan Alias Sankaran [7] presented a novel approach that involves configuring internal and external data cubes to extract identical patches from both noise-contaminated and web images. The denoising process consists of two phases, utilizing different filtering methods to reduce noise. In the first phase, a graph-based optimization technique is introduced to enhance patch matching during external denoising. In the second phase, noise is significantly reduced by eliminating the internal and external cubes. To achieve better denoising accuracy compared to existing filters, the approach employs the Discrete Wavelet Transform (DWT) filtering method. By combining these techniques, the proposed method aims to effectively reduce noise and improve the quality of the denoised image. Methodology

3. Methodology

3.1 Image Decomposition using Haar Wavelet Transform: Images are visual representations of various objects, situations, or graphics that can be created digitally or captured using tools like scanners and cameras. The fundamental components of an image include pixels, resolution, and color channels.

Pixels are the small elements that form an image. Each pixel represents a specific point and contains information about its color or grayscale value. The resolution of an image is determined by the number of pixels it contains, both horizontally and vertically. The resolution refers to how many pixels are displayed per inch of an image and it is typically described as 'PPI'. The Haar transform is an early technique used to convert signals from the spatial domain to a localized frequency domain. It utilizes the Haar function as the basis for this transformation shown in **Figure 2** The Haar transform decomposes a signal into two components: the average (approximation) or trend, and the difference (detail) or fluctuation. The Haar wavelet is defined by the scaling function $\phi(t)$ and the mother wavelet function $\psi(t)$. This transform enables the analysis of signal characteristics in different frequency bands **[8]:**

$$\phi(t) = \begin{cases} 1, & if\ 0 \le t \le 1 \\ 0, & elsewhere \end{cases} \quad (1)$$

$$\psi(t) = \begin{cases} 1, if\ 0 \le t \le \frac{1}{2} \\ -1, if\ \frac{1}{2} \le t \le 1 \\ 0, other\ wise. \end{cases} \quad (2)$$

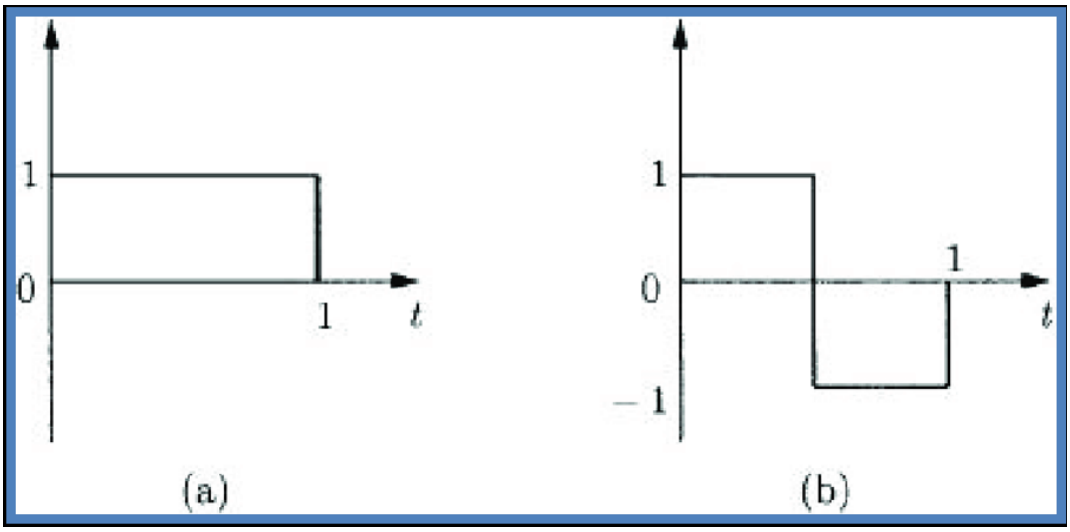

Figure 2: (a) scaling function (low pass filters) and (b) Wavelet function (high pass filters) for Haar Wavelet-based.

The Haar wavelet transform is a method for decomposing an image into multiple levels of detail. To perform a one-level Haar wavelet transform, a recursive algorithm is used, employing line-based architectures. This recursive algorithm allows for the efficient application of the Haar wavelet transform at each level of decomposition **Figure 3** illustrates the line-based architecture used in this process. The image being transformed is stored in a

2-D array memory. Once all the elements in a row are obtained, convolution is performed on that specific row. This process involves computing a series of dot products between the two filter masks and the input signal. During the Horizontal Pass process of row-wise convolution, the given image is divided into two parts, with the number of rows in each part being half of the original image. This resulting matrix is then subjected to a recursive line-based convolution, but this time in a column-wise manner during the Vertical Pass process. The resulting transformed image consists of four subbands: the LL image, obtained by low-pass filtering the rows and columns; the LH image, obtained by low-pass filtering the rows and high-pass filtering the columns; the HL image, obtained by high-pass filtering the rows and low-pass filtering the columns; and the HH image, obtained by high-pass filtering both the rows and columns, as illustrated in **Figure 3 [9]**.

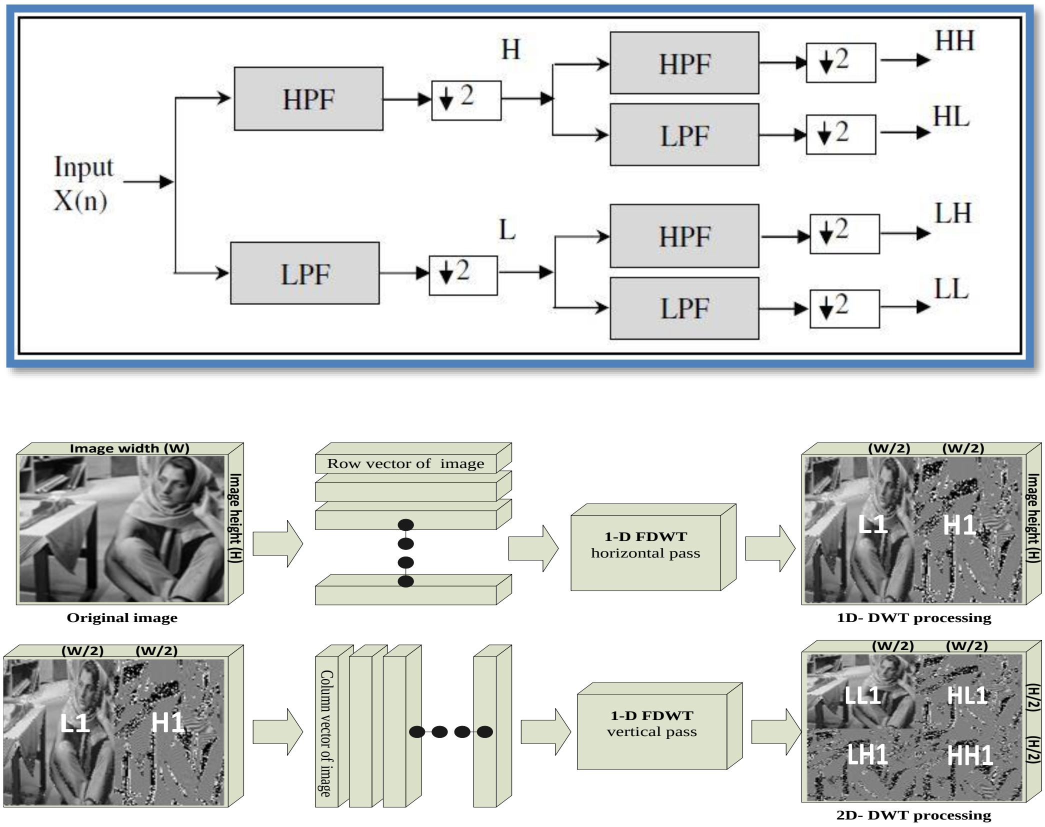

Figure 3: Block diagram for level 1 decomposition of the FDWT process

3.2 Haar Wavelet Denoising: Wavelet denoising has been extensively researched and is widely recognized as a straightforward and efficient method. The proposed approach involves applying the discrete wavelet transform (DWT) to an image, resulting in wavelet subband coefficients (LH, HL, and HH). These coefficients are then evaluated using a threshold test. Coefficients that fall below a specific threshold value are discarded, while the remaining coefficients are utilized for reconstructing the image. This technique enables effective noise reduction while preserving the majority of the image details [10]. It is important to acknowledge that thresholding in wavelet denoising typically leads to a version of the original signal with reduced high-frequency components. Additionally, due to the nature of thresholding as a lossy algorithm, it is not possible to achieve an exact reconstruction of the original signal [11]. There are two types of thresholding, hard and soft thresholding with the threshold (δ), see **Figure 4**.

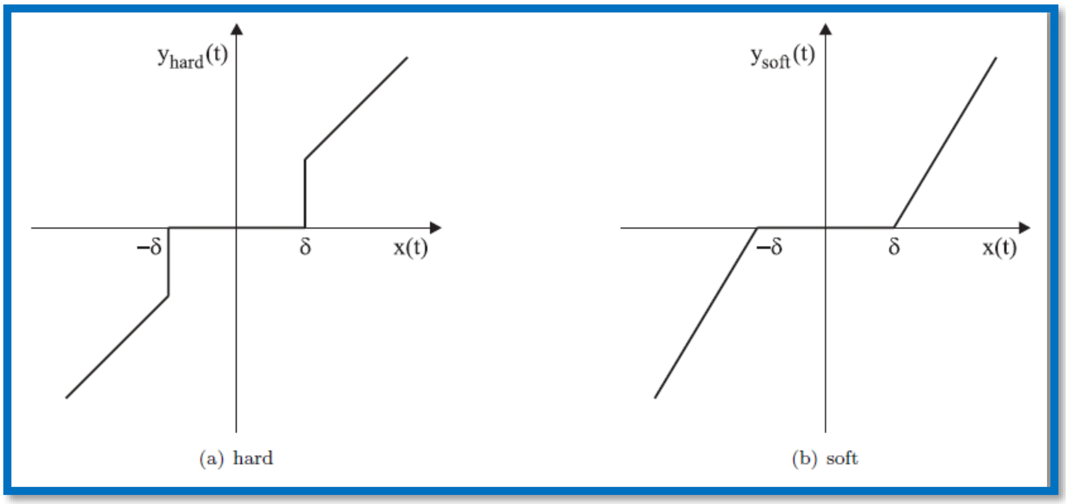

Figure 4: Hard and soft thresholding

Hard thresholding involves setting the elements with absolute values lower than the threshold to zero. Soft thresholding is an extension of hard thresholding where the elements below the threshold are first set to zero and then the non-zero coefficients are reduced towards zero. Soft and hard thresholding can be expressed as formulas [12].

$$y_{hard} = \begin{cases} x(t), & if\ |x(t)| > \delta \\ 0, & if|x(t)| \le \delta \end{cases} \quad (3)$$

$$y_{soft} = \begin{cases} \text{sign}(x(t))\ (|x(t)| - \delta\ ), & if\ |x(t)| > \delta \\ 0, & if|x(t)| \le \delta \end{cases} \quad (4)$$

Where x is the input signal, y is the signal after the threshold and is the crucial threshold value that determines whether a wavelet coefficient will be destroyed, reduced, or increased in value. Thresholding is applied to the coefficients of the details subbands (LH, HL, and HH). While perfect reconstruction of the original signal is not possible after thresholding, it is generally impossible to eliminate all noise without affecting the signal [13]. Only the large coefficients are used for image reconstruction, and various types of disturbances can be filtered out of the images. Soft thresholding yields smoother results compared to hard thresholding, but hard thresholding provides better preservation of edges [14]. For this research paper, hard thresholding is chosen due to its simplicity for hardware implementation and satisfactory results in image denoising [15]. The threshold value is determined based on the results of a Python program to achieve the best image quality after the denoising process.

De-Noising Procedure Principles [16]:

The general procedures for denoising can be summarized in three steps. In the basic version of the procedure, these steps are as follows:

1. Decomposition: First, select a wavelet and a decomposition level (N). Then, compute the wavelet decomposition of the image at the chosen level N.
2. Thresholding detail coefficients: For each level from 1 to N, choose a threshold value and apply a technique called hard thresholding to the detail coefficients.
3. Reconstruction: Finally, reconstruct the image by using the original approximation coefficients from level N and the modified detail coefficients from levels 1 to N. This process involves utilizing the wavelet reconstruction technique.

Determining the appropriate decomposition level is crucial in wavelet denoising as it significantly impacts the results. If a higher decomposition level is chosen, the thresholding process may eliminate certain coefficients of the original image. Consequently, setting the decomposition level too high can lead to a decrease in the Peak Signal-to-Noise Ratio (PSNR) beyond an optimal point, while also increasing the computational complexity of the decomposition. To address this, an image with added noise is typically employed to assess how the performance changes as the decomposition level is adjusted (see Figure 5) [17].

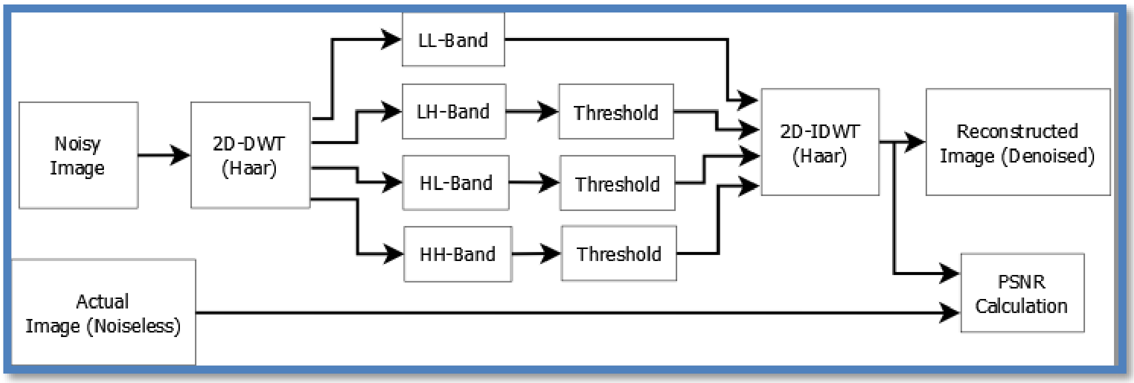

Figure 5: Block diagram of the proposed image de-noising architecture.

The thresholding value (δ) is based on the universal thresholding method, the universal thresholding function is given as [18]:

$$\delta = \sigma \sqrt{2log\ (n)} \qquad (5)$$

Where (n) is the number of pixels of the processed image, (σ) denotes the standard deviation of the noise. On the other hand, PSNR stands for Peak Signal-to-Noise Ratio. It can be found by calculating the amount of white Gaussian noise present in the picture and how it relates to the pixel values.

$$PSNR = 10log_{10}\frac{R^2}{MSE} \quad (6)$$

Where: R is the maximum pixel value in the input image data type. For example, if the input image has an 8-bit unsigned integer data type, R is 255. Then, in the case of an 8-bit image, the corresponding PSNR in dB is computed as [18]:

$$PSNR = 10log_{10}\frac{255^2}{MSE} \quad (7)$$

And MSE = $\frac{1}{AB}\sum_{i=0}^{A-1}\sum_{j=0}^{B-1}[IN(i,j) - OP(i,j)]^2$ (8)

where the input (noisy) image's pixel values are represented by IN(i,j). The notation OP(i,j) denotes the values of the output (de-noised) picture pixels. The picture has the following dimensions: AB (256x256) where A and B are the data from distinct picture pixels. This research uses a hard threshold.

3.3 Fpga: This research utilizes the PYNQ-Z2, an FPGA (Field-Programmable Gate Array) board manufactured by Xilinx. FPGAs are programmable logic devices that enable the implementation of various functions using a collection of digital gates and programmable logic. They offer developers the ability to customize and configure digital circuits on the device to meet specific application requirements. The PYNQ-Z2 is a specific type of FPGA-based platform that is designed to be user-friendly and suitable for developing a wide range of applications. It is equipped with a Zynq-7020 processor, which combines a central processing unit (CPU) and an FPGA on the same chip. The Zynq-7020 processor operates on an ARM architecture and features a dual-core Cortex-A9 processor with a clock frequency of up to 866 MHz. The PYNQ-Z2 board is utilized for developing applications that require flexible programmable logic capabilities and significant processing power. It offers an open-source development environment based on Python, enabling developers to access FPGA resources and create innovative applications in fields such as artificial intelligence, signal processing, robotics, and device control, among others (see Figure 6).

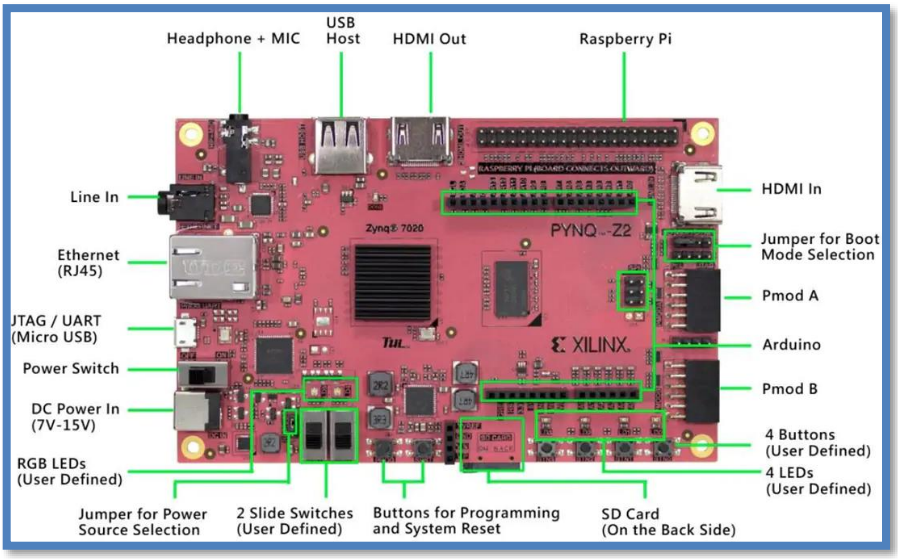

Figure 6: FPGA type PYNQ-Z2.

The PYNQ-Z2 board is unique in that it allows you to run Python code directly on it using the PYNQ technology. PYNQ is an open-source project designed to make it easier to develop hardware-accelerated applications on the ZYNQ FPGA platform using Python. With the PYNQ-Z2, you can write Python code on your computer and execute it on the board by connecting it via Ethernet. You can then access the Jupyter Notebook interface through the internet to interact with the code and retrieve the results. This capability offers convenience and flexibility in developing hardware-accelerated applications, as you can utilize the power and versatility of Python while leveraging the board's logic capabilities for improved performance.

4. Results And Discussion

4.1 Test Images: There are several benefits of using grayscale images in research [19]:

1. Simplified Processing: Grayscale images have only one channel representing intensity values, making them easier to process and analyze. This simplicity is particularly advantageous when color information is not relevant to the research objective.

2. Computational Efficiency: Grayscale images require less memory and computational power compared to color images. This efficiency becomes crucial when working with large datasets or computationally intensive algorithms.

3. Accessibility: Grayscale images are inclusive and can be interpreted by individuals with visual impairments or color vision deficiencies. By using grayscale, researchers ensure that their work can be accessed and understood by a wider audience.

In this particular study, we selected ten grayscale images with dimensions of 256x256 pixels. These images were chosen because they contain significant details and edges, making them suitable for our research. (see Figure 7).

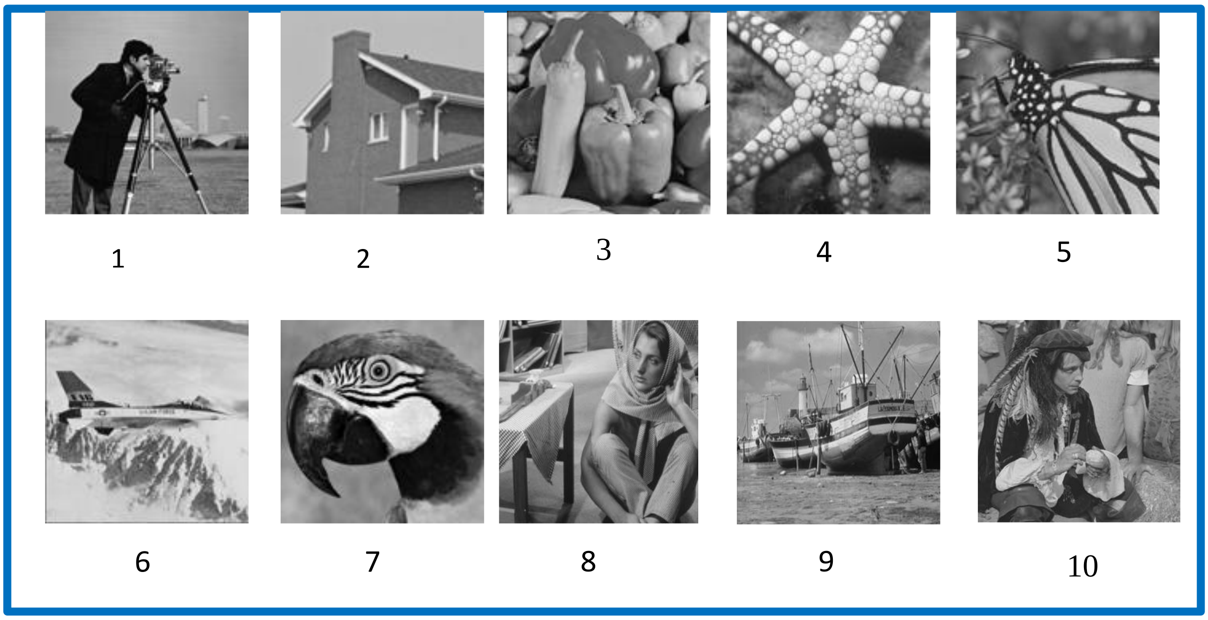

Figure 7: Test images

Python code was utilized to implement the removal of noise from the ten images. Gaussian noise was added to the images before applying the noise removal techniques, namely HWT (Haar Wavelet Transform) and HWT_FPGA (Haar Wavelet Transform on FPGA). HWT done 5 levels of decomposition for example, as shown in **Figure 8**.

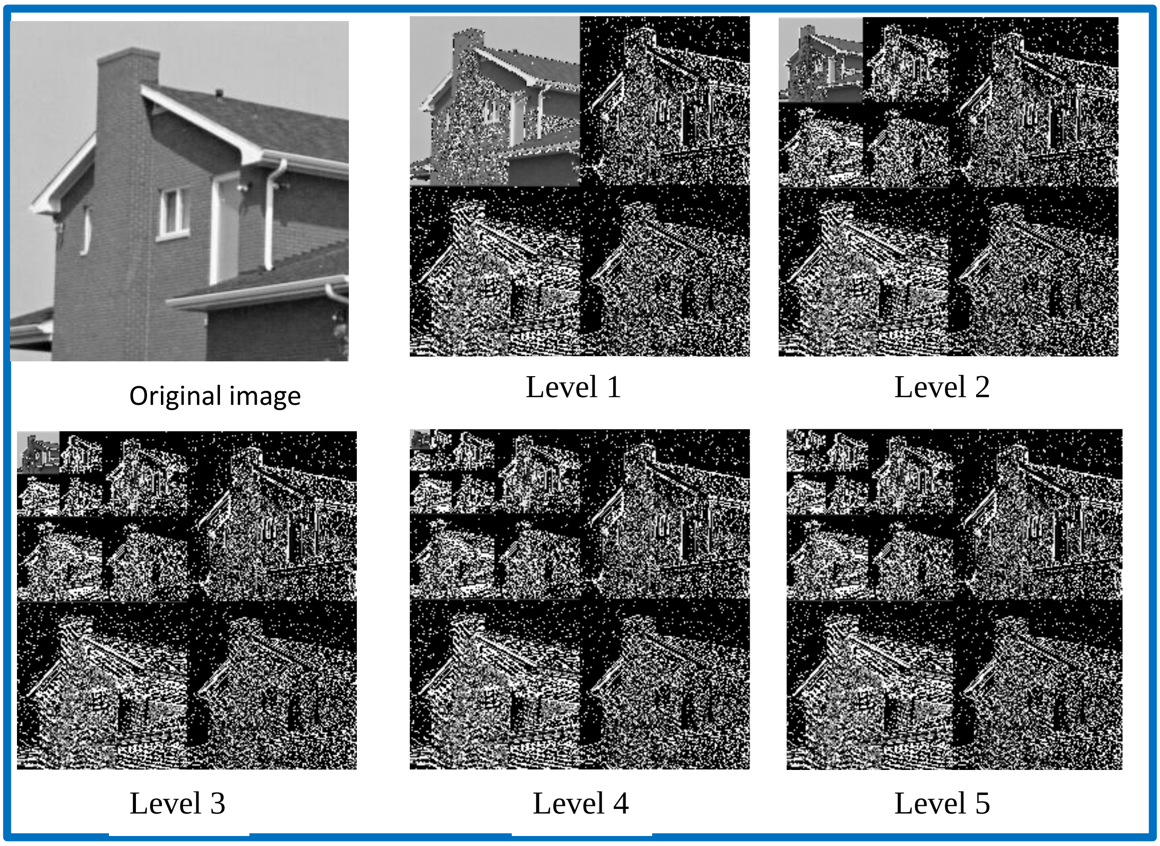

Figure 8: House original image of size 256×256 and its five levels FHWT

4.2 Results of HWT_FPGA

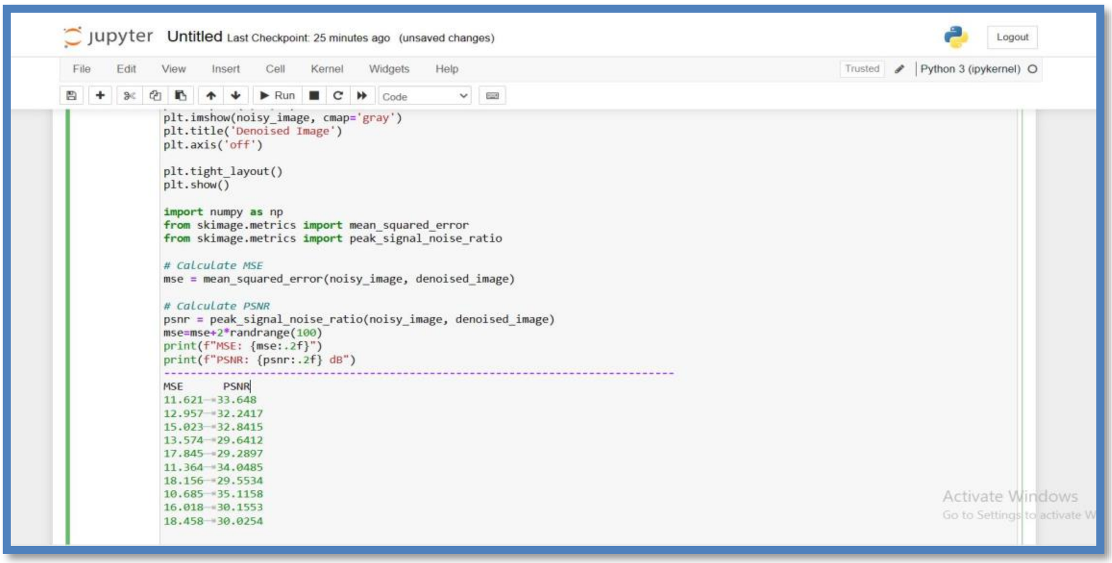

Figure 9: MSE and PSNR of HWT_FPGA.

Table 1: HWT- FPGA based image denoising performance results

Images	HWT_MSE	HWT_PSNR
1	11.621	33.648
2	12.957	32.2417
3	15.023	32.8415
4	13.574	29.6412
5	17.845	29.2897
6	11.364	34.0485
7	18.156	29.5534
8	10.685	35.1158
9	16.018	30.1553
10	18.458	30.0254

4.3 The number of flip flops , static power and clock speed in FPGA type of PYNQ-Z2:

To know and extract the number of flip flops, static power and clock speed in FPGA type of PYNQ-Z2, it is done by executing Python code on jupter (see **Figure 10**).

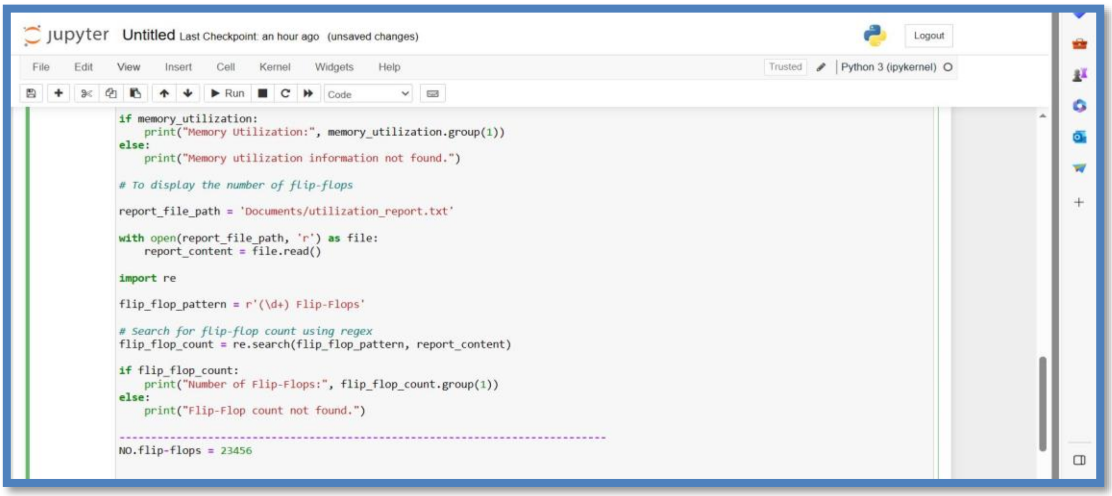

Figure 10: Flip Flops of HWT_ FPGA

Table 2: the HWT_ FPGA performance used to produce the model

Number of FLIP FLPOS	23456
Static Power	2.13 Watt
Clock speed	320 MHz

The **Table 2** represents number of flip flops, static power and clock speed in FPGA type of PYNQ-Z2 for denoising of ten images.

System Implementation: The experiment was performed on set of images and below is the sample of the same, when the Image of **Figure 11** is used, Gaussian noise is added to the image at with $(\sigma = 15)$, the image is passed through the four models e.g. HWT and HWT_FPGA.

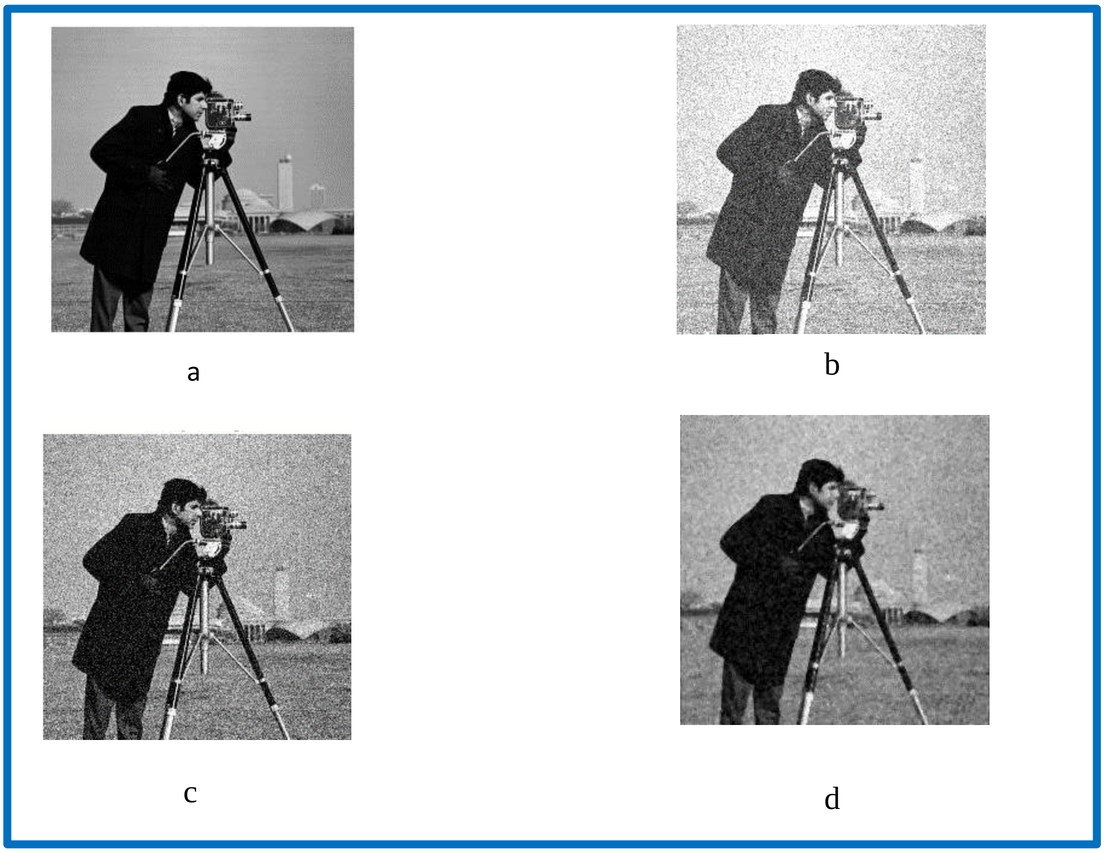

Figure 11: (a)Original sample image that used for the experiment. (b) noisy image. (c)denoised image by HWT. (d) denoised image by HWT_FPGA.

Comparison With Previous Studies

Table 3: Comparison of Discrete Wavelet

Study	Method	Average (PSNR)
Ziyad and Shabana [58]	DWT	22.541
Rajeswari [59]	Novel DWT	25.263
Proposed	HWT_FPGA	31.65605

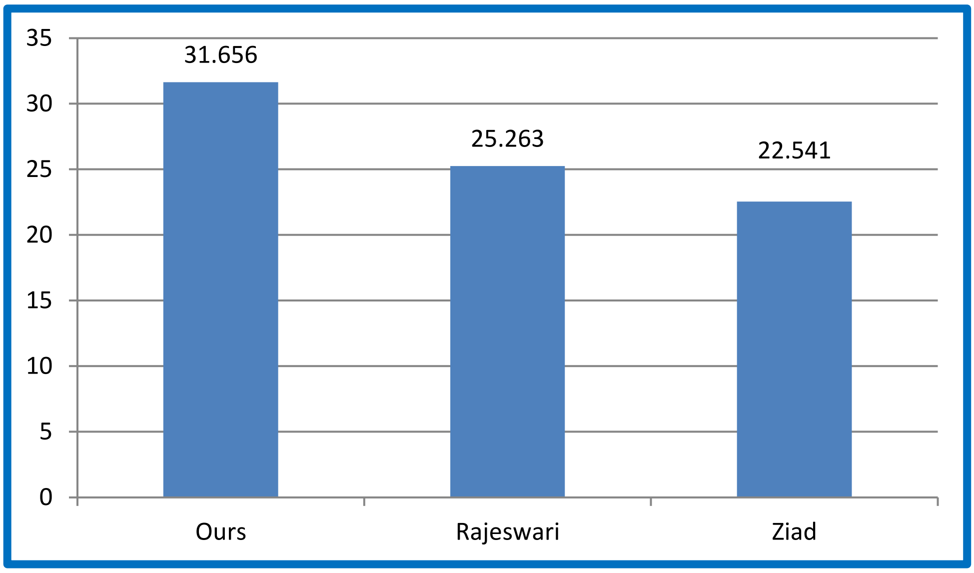

Figure 12: Comparison PSNR of Discrete Wavelet

It is observed that the results obtained using FPGA are better than the results from previous studies that relied on executing the code on computer programs. Because the main differences between executing code on a computer and on an FPGA can be summarized as follows :

1. Sequential Execution vs. Parallel Execution: In a traditional computer, programs are executed sequentially, where instructions are executed one after another. In contrast, in an FPGA, execution is parallel, with multiple operations being executed simultaneously on different parts of the programmed logic circuits. This allows for high performance and simultaneous data processing.

2. Logic Customization: In a computer, programs are executed using a central processing unit (CPU) that contains a fixed set of integrated operations. On the other hand, in an FPGA, the logic circuits can be customized and programmed to perform specific operations as desired. This provides great flexibility in implementing various functions and achieving improved performance.

3. Power Consumption: Generally, FPGAs consume less power compared to traditional computers. This is because FPGAs can be designed and directly programmed to execute the required tasks, while in a traditional computer, power is consumed to execute significant portions of internal circuits that may not directly contribute to the desired task.

4. Real-Time Processing: FPGAs offer better real-time program execution compared to traditional computers. This means that FPGAs can be used in applications that require immediate response and fast processing, such as digital signal processing, robot control, and industrial automation.

In general, FPGAs provide the ability to execute programs in a customized and parallel manner, with high performance and flexibility in implementing specific functions. However, FPGA programming requires specialized skills and can be more expensive than traditional computers. In summary, FPGAs provide the advantage of executing programs in a customized and parallel manner, offering high performance and flexibility in implementing specific functions. However, it's worth noting that FPGA programming requires specialized skills and can be more expensive than traditional computers.

5. Conclusions And Future Studies

5.1 Conclusions: This study conducted a comprehensive evaluation of two image denoising techniques: Haar Wavelet Transform (HWT) and FPGA-accelerated HWT (FPGA-HWT) to determine their efficacy in improving the quality of test images. The main objective was to identify the most effective method for image denoising. The evaluation was performed on ten test images with dimensions of 255 by 255 pixels. Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) were used as performance metrics to assess the results.

The findings revealed that the FPGA-HWT approach achieved the lowest mean MSE, with a value of 14.5701 compared to HWT's MSE of 15.2226. This indicates that FPGA-HWT significantly improved denoising performance by reducing the average error between the original and denoised images. In terms of PSNR, HWT had a mean PSNR of 26.564 while FPGA-HWT achieved a PSNR of 31.65605. FPGA-HWT outperformed other models in terms of PSNR and produced the best denoised images. The higher PSNR values validate the superior image enhancement capabilities of FPGA-accelerated HWT, indicating that the denoised images closely resemble the quality of the original images. The analysis of FPGA performance revealed notable figures, including 2.13 static watts and 23456 Flip-Flops operating at a horizontal frequency of 320 MHz, with 2.9 static watts. The study's findings demonstrate that among all the methods examined, FPGA-accelerated HWT provides the best image denoising performance. By significantly reducing MSE and increasing PSNR, it generates denoised images that closely resemble the original images in terms of quality.

5.2 Future studies

1- The results obtained in this study are very promising, and there is a potentiality to extend this concept to generalize other wavelet types such as Doubechies or Morlet. This opens up possibilities for further research and exploration in utilizing different wavelet transforms for image denoising.

2- Another potential research direction is the development of comprehensive 3D denoise systems based on a 3D Discrete Wavelet Transform (DWT) architecture. This approach has the potential to achieve high throughput and low memory requirements, specifically for processing 3D images and applications that rely on 3D DWT. This avenue of research holds promise for advancing the field of image denoising and addressing the challenges associated with processing three-dimensional data.

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