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RESEARCH ARTICLE – COMPUTER SCIENCE

Comparative Study of Discrete Wavelet Transforms in image Processing using LabVIEW 2023

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Abstract

Image processing plays an important rule of the modern emerging research areas that based on discrete wavelet transforms due to their abilities to represent images at multiple resolutions efficiently. This multiple resolution analysis is so useful in many applications such as image compression, denoising, texture analysis, and feature extraction.

In this work, A newfound proposed LabVIEW2023 simulation is designed to produce a comparative study between several test images using different types of the most common discrete wavelet transforms (DWT).

The comparison is based on calculation of the total evaluation time needed for process and in addition making a study for image edge detection in terms of different threshold ratios. The discrete wavelets transform (DWT) that used to achieve these comparisons analysis are the orthogonal and biorthogonal wavelets families.

The new LabView 2023 simulation design enviroments exemplified that it is a simple, typical and speedy tool to give the best of the desired results. The final results showed the effectiveness of biorthogonal wavelet transform (bior6-8) over the other discrete wavelets transforms.

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***Keywords**: Image decomposition; Edge Detection; Orthogonal Wavelets; Biorthogonal Wavelets; LabVIEW Environments*

1. Introduction

Wavelets are very important in wide fields like seismology, signal analysis and processing. The signals representation in terms of little computable function with efficiency is so complicated and difficult. In fact, the term wavelets are related to filtering term. The evaluation of multi-resolution in continuous time has some propinquity with means sub band filtering having discrete time of filter bank. Processing of data means generating the functions that are based on the construction of the set. This permits a sharp, an operant and explicative prescribe of the signal. The basic signal can be selected depending on the signal [1]. The exponentials of Fourier complex satisfy the benefits of the smoothly signal but still its performance is tedious for the discontinuous signals in the low and high frequencies regions. Wavelets are very small window that is so easy for processing. Therefore, the wavelet transformations recently played very important roles in many cases [2]. There are many of wavelet families that are

available like orthogonal, biorthogonal and reverse bi-orthogonal wavelets, Haar wavelets, Daubechies wavelets, Coifflets, Symlets and Discrete Meyer wavelets. The different discrete wavelets transforms are useful in data reconstruction because they demonstrate the linear phase property [3]. For signal processing, orthogonality is a very important attribute because it gives a simple and easy approach in building languages for data structures and controls.
Because of its very simple nature; orthogonality has many designs with less forecasts, with this feature, human can learn, read and write any aspects of the different programming languages. The features' meanings of orthogonality are independent for each context [4].

2. The Discrete Wavelet Transform

The Discrete Wavelet Transform represents the mathematical tool for the pyramidal image decomposition and by varying the frequency of a signal and its limited duration, the signal will be analyzed into small waves which facilitates the transformation. The original signal "reference signal" that contains the location information and wavelet transformation parameters will be degraded, and by using IDWT "Inverse Discrete Wavelet Transform", the reconstruction of original signal can be completely obtained depending on these coefficients [5]. First of all, the discrete wavelet transform will analyze the image into sub-images or sub-ranges (LL, LH, HL, and HH). Fig..1 shows the sub-bands within the DWT for an image (M×N) pixel.

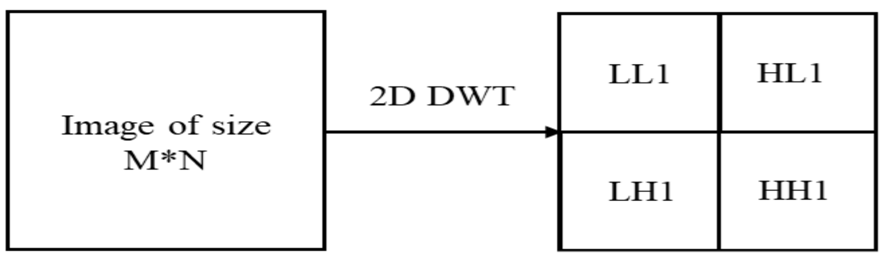


Fig. 1 The formed Sub-bands after One-level DWT. [5]

Where:

- LL (Approximation sub-band): has low-frequencies within the level and vertical directions. It represents the coarser approximation of the original image and retains the significant features and energy of the image.
- LH (Horizontal detail sub-band)**:** has low-frequencies within the even heading and high- frequencies within the vertical direction. It highlights the vertical edges and details of the original image.
- HL (Vertical detail sub-band)**:** has high-frequencies within the level direction and low frequencies within the vertical direction. It highlights the horizontal edges and details of the original image [6].
- HH (Diagonal detail sub-band)**:** has high-frequencies in both the horizontal and vertical directions. It highlights the diagonal edges and fine details of the image. All the sub-bands have Size $= \frac{M}{2} \times \frac{N}{2}$. (For an image size (M×N) pixel [7].

The LL (Approximation sub-band) tape is the foremost vital tape because it contains most vitality of the analyzed image which gives ideas to the image estimation. Since the ranges of high-frequency detail sub-bands (LH, HL, and HH) are less sensitive to human vision, the watermarks can be involved in these sus-bands. To increase the watermark strength, bars computations and counting are performed, without giving any extra effects on image quality [8]. In sequencing, the primary discrete wavelet transform is executed within the vertical direction, then within level direction. The primary level of deteriorating will give four sub-bands: LL1, LH1, HL1, and HH1. The LL sub-band from the primary level will be utilized as input for each sequential level of decay. Again, this LL sub-band will be divided into another four multi-resolution sub-bands for taking after coarse wavelength coefficients and this process will be repeated many times depending on the specific application requirements [9]. One of DWT features; it describes many locations of the image spatially by highlighting those areas and then effectively hiding any disturbing details and bad effects. This procedure is not limited for images, it is also useful in other applications like Clamour evacuation, sound and video compressions, because the first image will not identify the watermark. For image advanced levels of compression, each photo watermark will consist of two forms to simplify the incorporating between watermark and data at the moment extraction [9].Another feature of DWT is the localization ability of time and frequency, which give more advantages for separate wavelet transformation over Fourier transform transformation and simplify the process steps of image compression [10].

2.1 The Wavelets Transform for image processing

With the fast growth of multimedia data like images and their transmission across unsecured communication channels [11], a secured approach is needed. Preprocessing is a set of operations used to prepare an image for segmentation, such as image enhancement and de-nosing [12]. The Wavelets transform is the technique that used with signal analysis and processing. Generally, Wavelets are considered as the perfect method to analyze and represent information of images, image compression and segmentation. Wavelet transform has similar properties to Fourier transform but the difference is localized in both frequency and time domain, while the standard Fourier transform is only localized the frequency domain [13].

The wavelet transforms provides a convent description of color images and also it is very useful for edges' description, especially the lines that are highly localized. The wavelets could be getting it from a signal prototype wavelet (mother wavelet), by shifting and dilations. Wavelet transform can analyze the signal into a set of basic functions [14]. As we said before, the Wavelet transform is affected in wide aspects of signal processing especially image analysis and image compression [15]. The basic idea of Wavelet Transform comes by repeating filtering of the image coefficients on a column-by-column and a row-by-row basis [16]. As shown the Fig. 2.

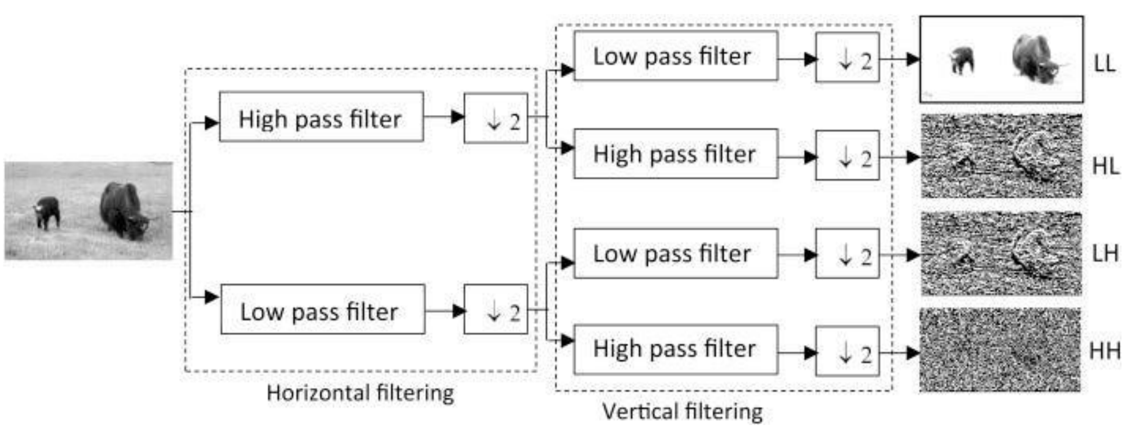


Fig. 2. Decomposition of an image 2-D discrete wavelet transform (2-D DWT) [17]

The approximation band (LL) is used for the segmentation purpose, and basically has interesting data of the original image. Finally, any image had been decomposed on one of the wavelet decomposition techniques would be analyzed with assorted levels of decomposition, and each level has four sus-bands (LL, LH, HL and HH). The work of (DWT) basically depends on time-scale representation which gives very good multi- resolution sub band decomposition of signals [18].

2.1.1 Image Pyramid

The image pyramid is a powerful simple structure for representing images at many levels of resolution. It is a collection of decreasing resolution images arranged as a pyramid's shape as shown in the Fig. 3. [19].

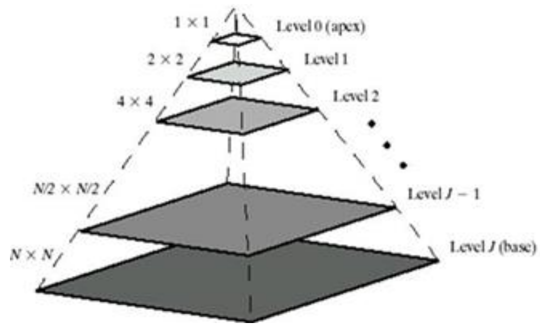


Fig. 3. The image pyramid. [19]

The base of the pyramid contains the high-resolution representation of the processing image; while the apex contains the low-resolution approximation. By moving up the pyramid, both image size and resolution decrease and we can create multi-resolution pyramids of images as given in Fig.3. The Wavelets are the most general way to represent and analyze multi-resolution images. For this, wavelets are exceptionally appropriate for the applications such as data compression, noise reduction, and singularity detection in signals [20]. Discrete wavelet transform is a high-speed linear operation on a data vector, with an integer power of 2. The DWT is orthogonal and invertible. The inverse transform expressed as a matrix is the transpose of the transform matrix and the orthonormal basis or wavelet basis can be defined as

$$\Psi_{(j,k)}(x) = 2^{\,j}/_{2}\;\; \Psi(2^{j}\, x - k) \qquad (1)$$

And the scaling function is given as

$$\Phi_{(j,k)}(x) = 2^{\,j}/_{2}\;\; \Phi(2^{j}\, x - k) \qquad (2)$$

Where:

- Ψ represents the wavelet function.
- j and k are the integers represent the wavelet basis scaling and dilation,
- The factor "j" represents width scale index,

- And the factor "k" represents the position.

The wavelet function dilation is achieved with powers of two and j translated by the integer k. Another form for wavelet equation is in terms of the wavelet coefficients:

$$\Psi\,(x) = {}^{n-1}{}_{k}\sum g_k\,(\sqrt{2\Phi\,(2x - k)} \qquad (3)$$

Where g_0 and g_1 represent the high pass wavelet coefficients. These Wavelet coefficients are calculated by a wavelet transform represent the change in the time series at a specific resolution [21].

2.2 Edge Detection

Recently, the images' edges detecting topic is considered one of the basic and most common subjects in digital image processing because of various and wide fields applications. The classical methods used for detecting edges in digital images still give excellent results if the threshold is chosen correctly [22]. Generally, the definition of an image edge can be summarized as the high frequencies of the image or the frontier that separates two different regions or scenes in the same image [23]. Also, some of important features for edge detection, it considered as a kind of image segmentation [24], and reducing the image size [25]. Reducing image size is very useful in data compression, image segmentation, and matching processes. Also, edge detection can be used for pattern recognition and scene anatomy. The discrimination ability of the human eye to lines is more understandable than a normal image, besides, there are clearer details that can be seen and noticed in converting from the original image to an edge image [26].

There are several algorithms on edge detection, Canny, Sobel, Roberts and Prewitt, for many scientists, "Canny" is the best. Bin and Yeganeh called "Canny" is considered as the ideal edge detection because of its great influence on obtaining results. The feature of Canny algorithm that it can detect the edges of the noisy images even if the noise was not removed from the image [27].

Chandrasekar and Shrivakshan worked on many edge detection algorithms, but they concluded that the Canny algorithm produces better results than other algorithms in case of choosing the setting parameters accurately [28].

2.3 The Orthogonal and Biorthogonal wavelets Families

The Wavelet families can be divided into two main and basic categories, orthogonal and bi-orthogonal wavelets, which have various properties of the basic functions. Generally, Orthogonality eliminates the transform coefficients by minimizing redundancy [29]. Symmetry gives linear phase and minimize border arti-facts. The other significant properties of the wavelet functions in image compression applications are symmetry, compact support, degree of smoothness and regularity [30]. In addition, the orthogonality is considered as an important aspect related to signal processing since it is a simple method in languages for building controls and data structures. Because of its simple nature, it has many orthogonal designs with less expectations [1],[2]. Orthogonality always reflects the right angles, i.e., 90°. The orthogonal wavelet is related to the wavelet transform, and they are orthogonal to each other. Orthogonality has the advantages of avoiding the interference so that the error-free output can be obtained. Because of this feature, it is mostly preferable method in signal processing.

The orthogonal wavelets are considered as the wavelet transform's adjoints. But when this condition fails, they result in biorthogonal wavelets. At this point, biorthogonal wavelets are formed and orthogonality of wavelets get vanished. In other words, an orthogonal wavelet means using a single wavelet with a single-scaling function. While the biorthogonal wavelet means generating one wavelet and also one scaling function for image decomposition process and additional one wavelet with one scaling function for image reconstruction process. The both scaling functions are responsible for generating different multi-resolution analyses. Generally, the biorthogonal wavelet is more advanced than the orthogonal wavelet [31]. However, it requires extra time-consuming and effort to accomplish the computation process. The basic difference between the orthogonal and the biorthogonal wavelets is the variation in wavelet's length during the analysis and the synthesis process. In orthogonal wavelets, the same length filters are used and in the biorthogonal wavelet, different lengths filters are used [32].

2.3.1 The Orthogonal Wavelets Families

There are several types of orthogonal wavelets with a brief explanation on these types.

2.3.1.1 The Haar Wavelet

In 1909 Alfréd Haar proposed The Haar wavelet is a sequence of rescaled (square-shaped) functions that together form a basis or wavelet family. The Haar sequence is now considered as the first known wavelet basis. It is considered the simplest type. It is discontinuous and resembling a step function. Also, it represents the same as Daubechies db1 wavelet. The basic technical disadvantage of the Haar wavelet is not continuous not differentiable wavelet, but this property can, considered as an advantage for signals analysis with sudden transitions (discrete signals) [33]. The Fig. 4. shows the Haar wavelet psi.

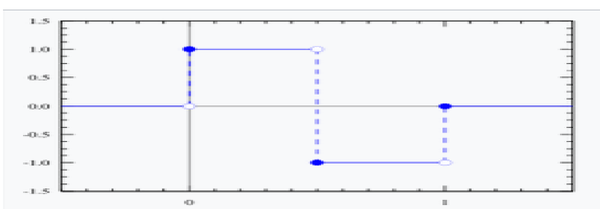


Fig. 4. The Haar Wavelet psi [33]

2.3.1.2 The Daubechies Wavelets

The Daubechies wavelets were built by Ingrid Daubechies, they considered as the one of the brightest stars in the world of wavelet research that contrivance "compactly supported orthonormal wavelets", which make the discrete wavelet analysis practicable. The names of the Daubechies family wavelets are written dbN, where N is the order (N=2 to 10), and db is the wavelet's surname. The db1 wavelet, is considered as the Haar wavelet [34]. As shown in Fig.5.

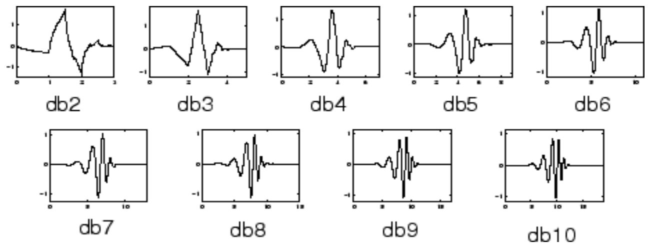


Fig. 5. The Daubechies wavelet psi [34]

2.3.1.3 The Coiflets Wavelets

Coiflets are considered as discrete wavelets that designed by Ingrid Daubechies, at the request of Ronald Coifman, to have scaling functions with vanishing moments. This wavelet is almost considered as symmetric. The wavelet function has $2N$ moments equal to 0 and the scaling function has $2N$-1 moments equal to 0. The two functions have a support of length $6N$-1(1-5) [34]. Fig. 6 shows The Coiflets wavelet psi.

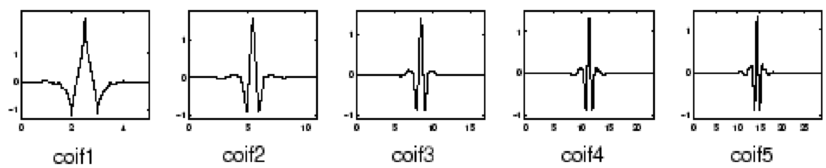


Fig. 6. The Coiflets wavelet psi [34]

2.3.1.4 The Symlets Wavelets

The symlets wavelets are also considered as nearly symmetrical wavelets that proposed by Daubechies as the continuous modifications to the db family. The both wavelet families have similar properties. Fig. 7. shows the Symlets functions psi [34].

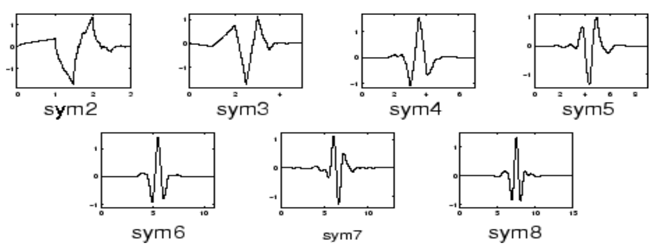


Fig. 7. The Symlets wavelet psi. [34]

2.3.2 The Biorthogonal Wavelets

This wavelets family offers the property of linear phase, which is useful in image reconstruction process. Two wavelets will be used in image processing, one for image decomposition (on the left side) and the other wavelet for image reconstruction (on the right side) instead of using the same one single. So, many interesting properties are derived. Designing biorthogonal wavelets allows more degrees of freedom than orthogonal wavelets. One additional degree of freedom is the possibility to construct symmetric wavelet functions [32]. Fig. 8. shows the biorthogonal wavelets psi.

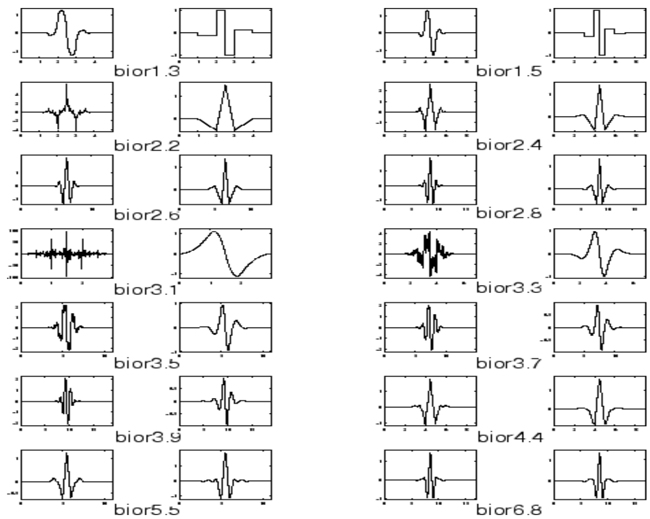


Fig. 8. The biorthogonal wavelets psi [33]

3 Methodology

In this work, LabVIEW 2023 (Laboratory Virtual Instrumentation Engineering Workbench) is used, two proposed simulation design systems are used to evaluate the complete comparison requirements for the image decomposition and image edge detection for many image pyramid levels. The comparison is made using two test images of different sizes, Camera Man test image1 (256 ×256) pixel and two can2 test image2 (280×420) pixel. In General, The LabView 2023 Enviroments produced asimple, typical and speedy tool to give the best results for image decomposition and image edge detection in many image pyramid levels.

Each simulation design system had two main windows: the front panel window and the block diagram windows [35].

3.1 The Image Decomposition LabVIEW 2023 Simulation System

The First Simulation Design System is for the image decomposition, as shown in Fig. 9 a and b.

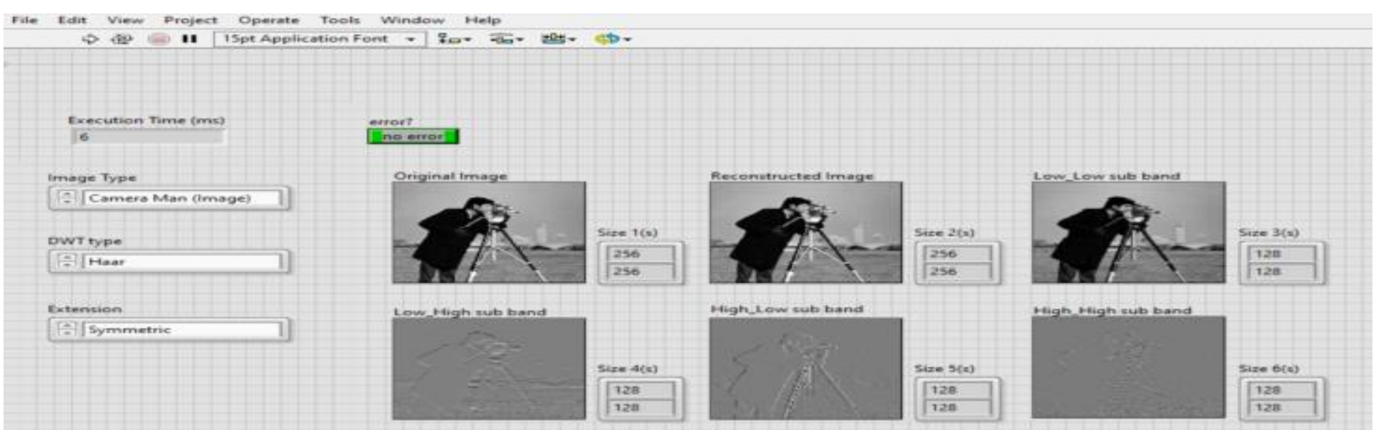


Fig. 9-a. The front panel of LabVIEW 2023 simulation design for image decomposition

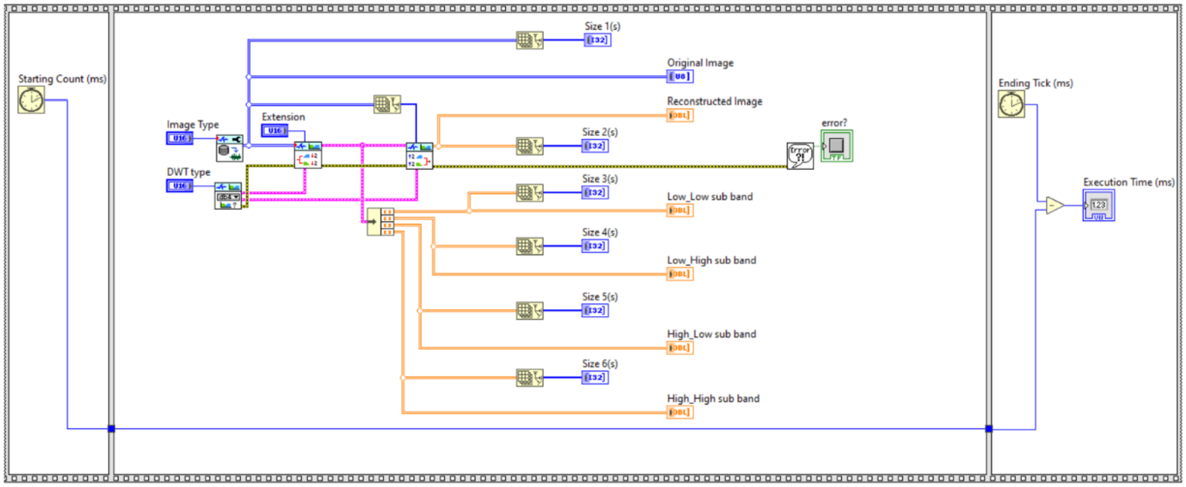


Fig. 9-b. The block diagram and of LabVIEW 2023 simulation design for image decomposition

All the following steps are done using the flat sequence structure to calculate the total evaluated time for the image decomposition process.

3.1.1 The Image Loading Step:

An image acquisition is achieved by loading the test images from file saved in the data base with adjusting the image size, orientation, scaling to a standard format and removing noise from the original test image is by applying filters (e.g., Gaussian blur). As shown in Fig. 10.

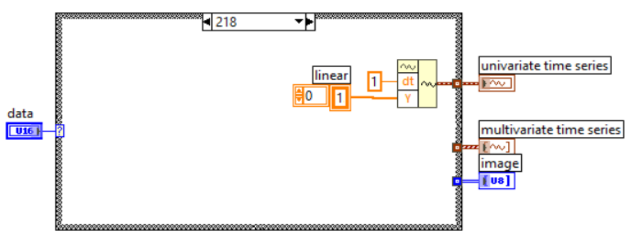


Fig. 10. The Image Loading Step

3.1.2 Applying the Discrete Wavelet Transform (DWT) to the original test image step:

A wavelet is selected (Haar, Daubechies, Symlets, etc.) to achieve the comparison requirements and involves a convolving of the original test image with the wavelet function and its scaling function to achieve down sampling. As shown in Fig. 11.

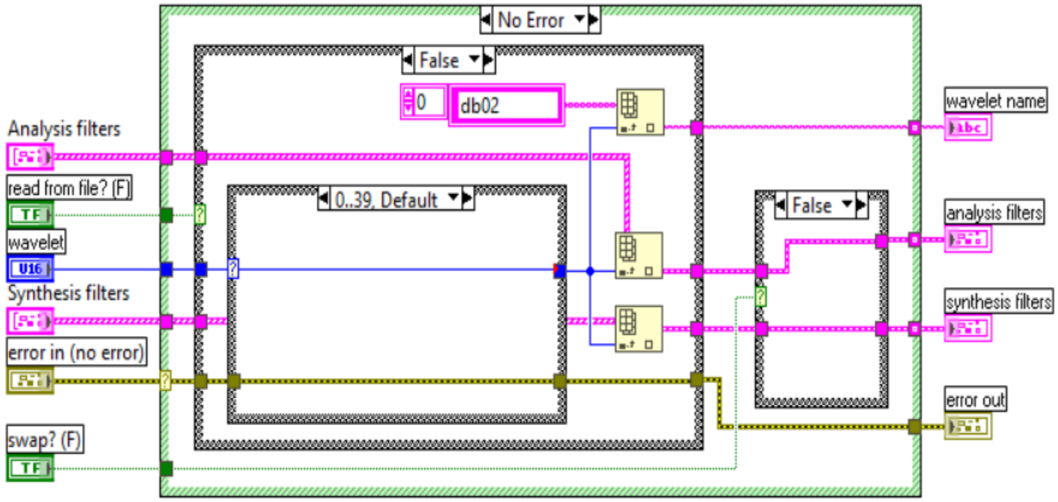


Fig. 11. Applying the discrete wavelet transform (DWT) to the original test image step

3.1.3 Decomposition the original test image into Sub-bands step:

In a single decomposition level, an original test image is decomposed into four sub-bands using filter banks (i.e. Analysis filters and Synthesis filters); (LL) Low-frequency components for capturing the coarse details, (LH) High-frequency components in the horizontal direction, (HL) High-frequency components in the vertical direction and (HH): High-frequency components in both vertical and horizontal directions. This process steps are repeated in multi decomposition level on the approximation sub-band (LL) to further sub-bands and breaking down the image into finer levels of detail. As shown in Fig. 12.

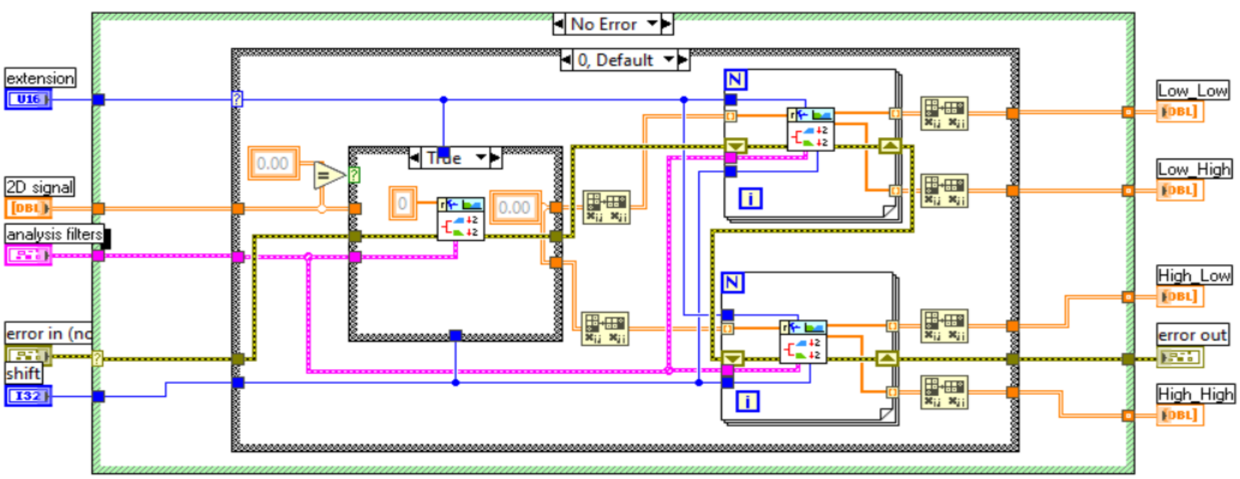


Fig. 12. Decomposition the original test image into Sub-bands step

3.1.4 The Image Reconstruction Step:

Applying the inverse discrete wavelet transform (IDWT) to reconstruct the image from its sub-bands. This begins from the coarsest level (lowest resolution LL and its corresponding LH, HL, and HH sub-bands) using filter banks (Analysis filters and Synthesis filters). For iterative reconstruction level, an image is reconstructed using the inverse DWT, up sampling, and convolving with the inverse wavelet functions. Combining the reconstructed sub-bands to form (LL), the approximation sub-band for the next finer level. The final reconstruction involves repeating the process until reaching the finest level, obtaining the fully reconstructed image, applying image enhancement techniques to improve the visual quality of the decomposed or reconstructed image, visualize the decomposed sub-bands for analysis and interpretation and finally image evaluation which means assess the quality of the decomposition using metrics like PSNR (Peak Signal-to-Noise Ratio).

The reconstructed image will be displayed as shown in Fig. 13.

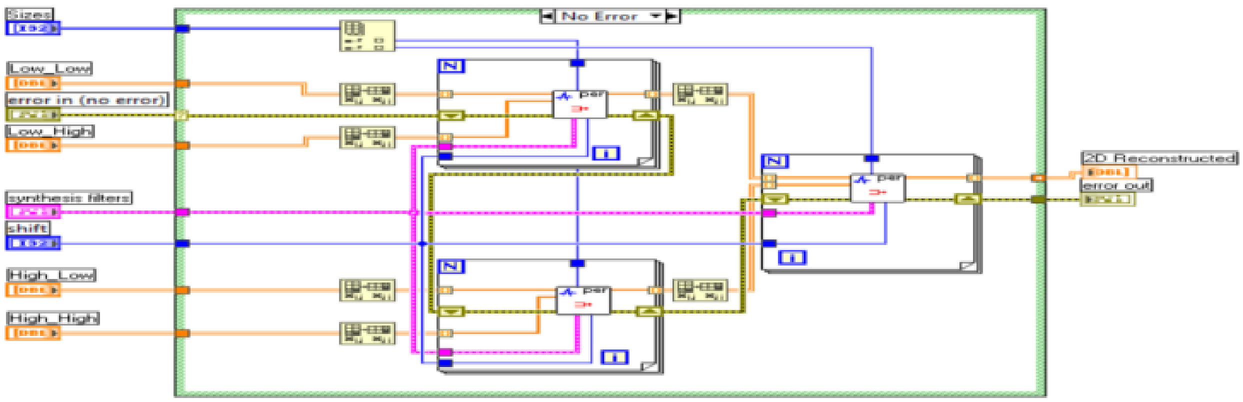


Fig. 13. The Image Reconstruction Step

3.2 The Image Edge Detection LabVIEW 2023 Simulation System

The Second Simulation Design System is for the image edge detection, as shown in Fig. 14 a and b.

Fig. 14-a. The front panel of LabVIEW 2023 simulation design for image edge detection

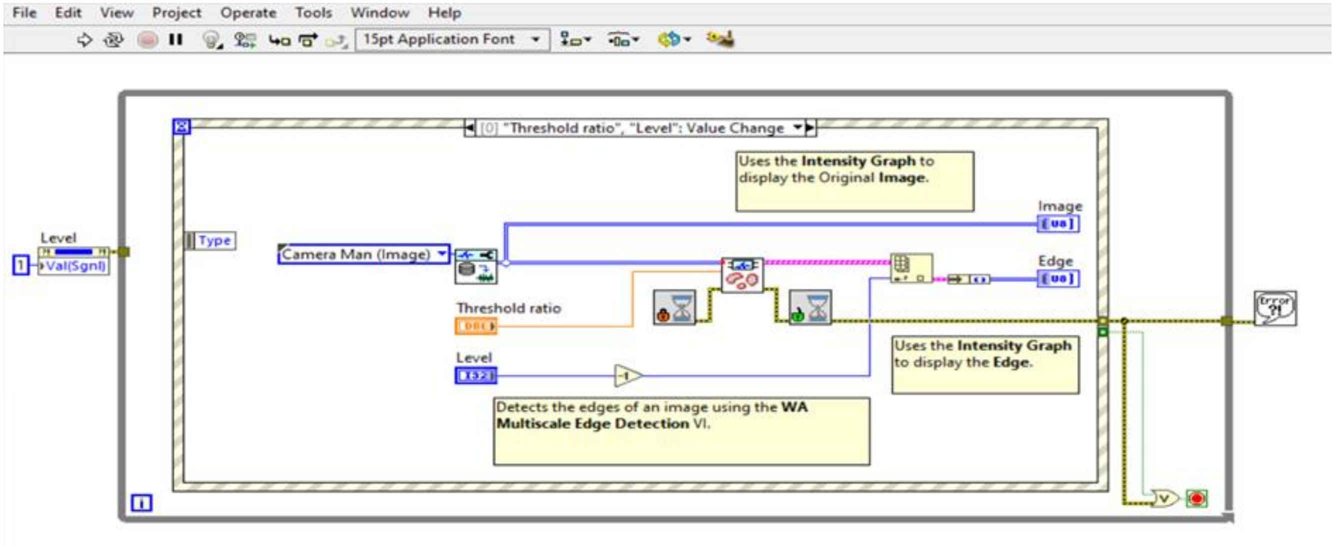


Fig. 14-b. The block diagram of LabVIEW 2023 simulation design for Image Edge Detection

3.2.1 The Image Loading Step:

An image acquisition is achieved by loading the test images from file saved in the data base with adjusting the image size, orientation, scaling to a standard format and removing noise from the original test image is by applying filters (e.g., Gaussian blur). As shown in Fig. 10.

3.2.2 Applying the Discrete Wavelet Transform (DWT) to the original image step:

A wavelet is selected (Haar, Daubechies, Symlets,..etc) to achieve the comparison requirements and involves a convolving of the original test image with the wavelet function and its scaling function to achieve down sampling. As shown in Fig. 11.

3.2.3 The Extract High-Frequency Components step:

An extraction of the high-frequency components from the wavelet sub-bands (LH, HL, HH).

3.2.4 Combining Edge Information Step:

The Computing the edge magnitude by combining the high-frequency sub-bands. The steps (3.2.3) and (3.2.4) are shown in Fig. 15.

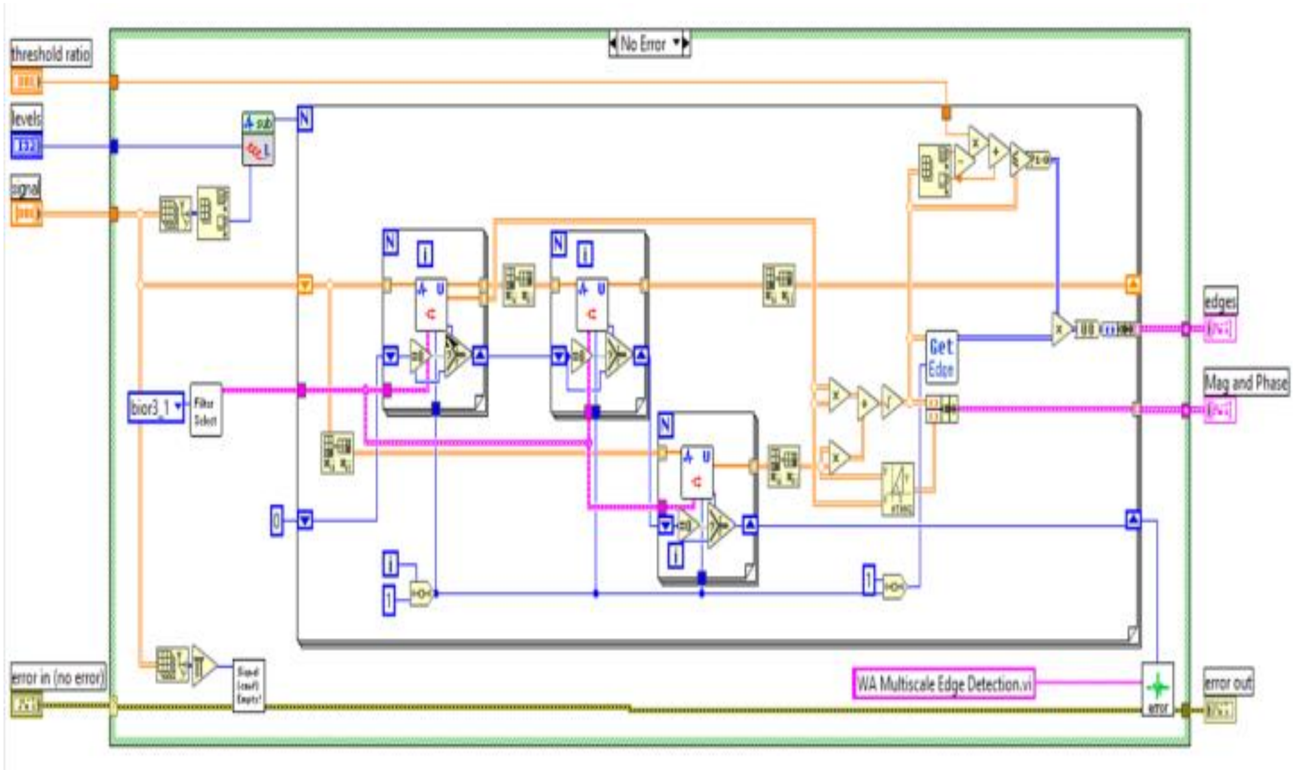


Fig. 15. Computing of the edge magnitude.

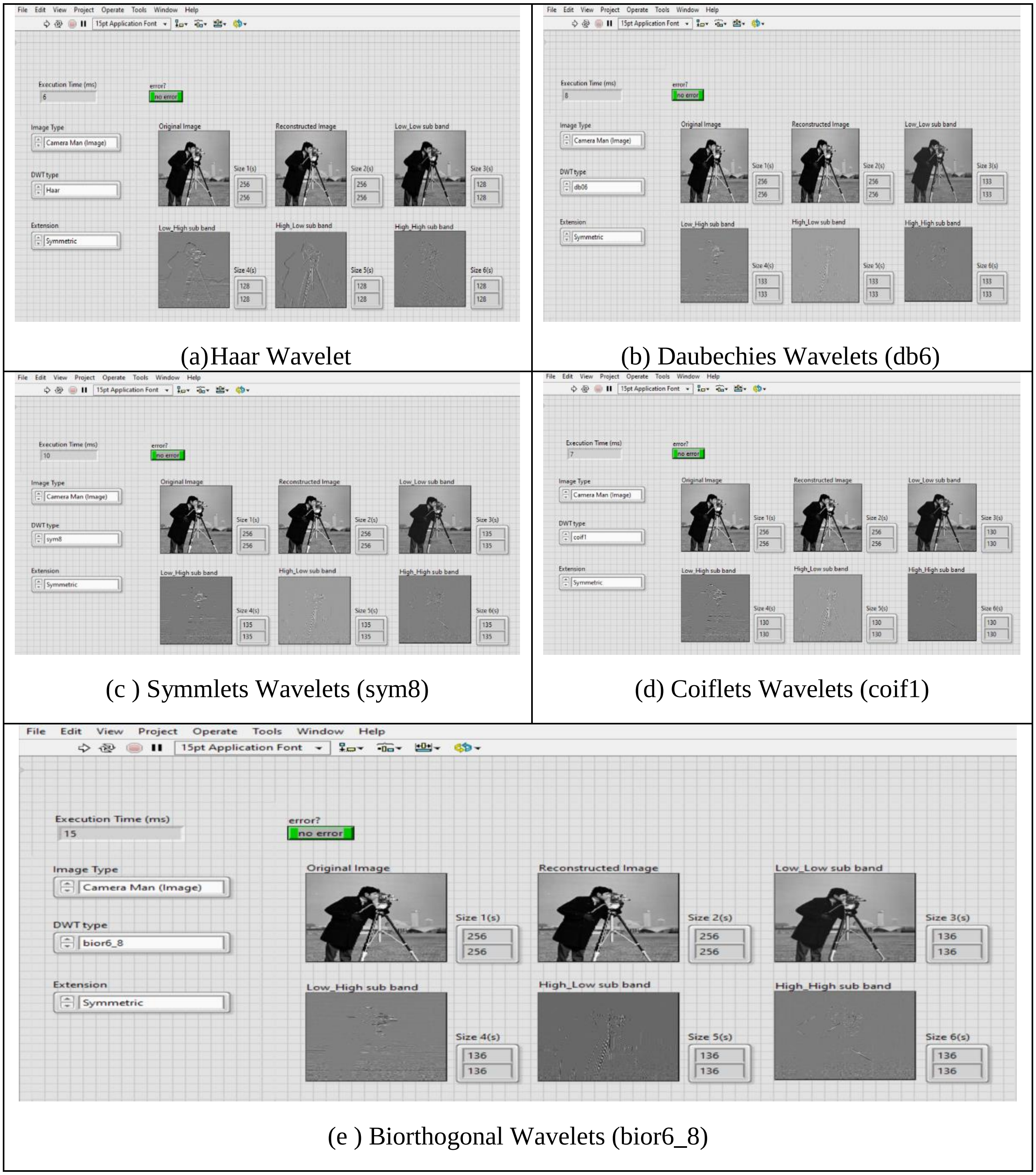
4. Results and Discussion

4.1 The image decomposition LabVIEW 2023 simulation system results

To achieve the LabVIEW simulation design results:

- Choosing two test images that different in size in order to get distinctly results that support the use of this design, the two images are:
    - ➢ Camera Man test image1 (256×256) pixels.
    - ➢ Two Can image test image2 (280×420) pixels.
- Choosing different discrete wavelets transforms:
    - ➢ The Orthogonal Wavelets Families:
        - o The Haar Wavelet (≈ db1)
        - o The Daubechies Wavelets (db2, db3,…., db14).
        - o The Symmlets Wavelets (sym2, sym3, ., sym8).
        - o The Coiflets Wavelets (coif1, coif2, … coif5).
    - ➢ The Biorthogonal Wavelets (bior1_3, bior1_5, bior2_6, bior2_8, bior3_1, bior3_3, bior3_5, bior3_7, bior3_9, bior4_4 (FBI), bior5_5 and bior6_8).

In Fig. 16, the obtained practical results from the Image Decomposition LabVIEW Simulation Design for image test1: Camera Man, Level One in terms of symmetric extension technique.



(a)Haar Wavelet

(b) Daubechies Wavelets (db6)

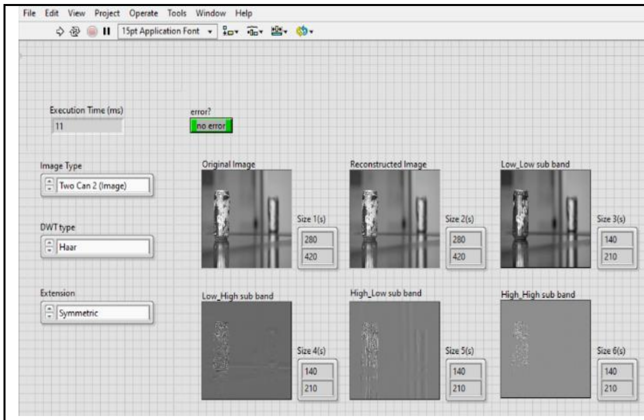
(c) Symmlets Wavelets (sym8)

(d) Coiflets Wavelets (coif1)

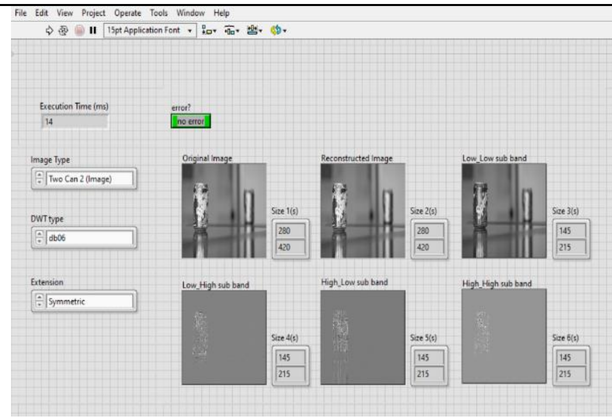
(e) Biorthogonal Wavelets (bior6_8)

Fig. 16. The front panels of the Image Decomposition LabVIEW simulation design for image test1: Camera Man, Level One

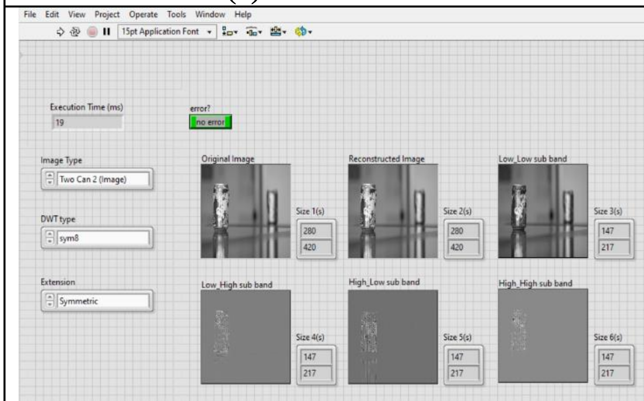
In Fig. 17, The practical obtained results from the Image Decomposition LabVIEW Simulation Design for image test2: Two Can2, Level One in terms of symmetric extension technique.



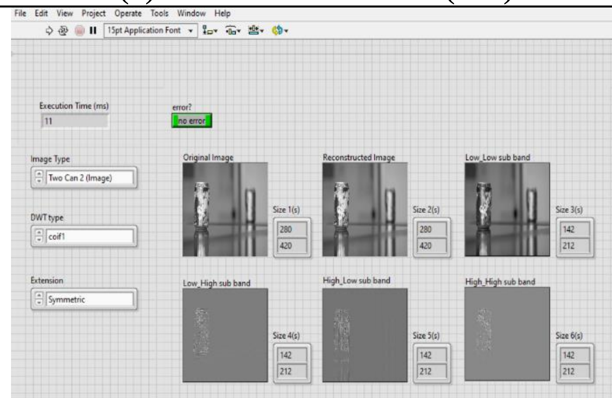
(a) Haar Wavelet



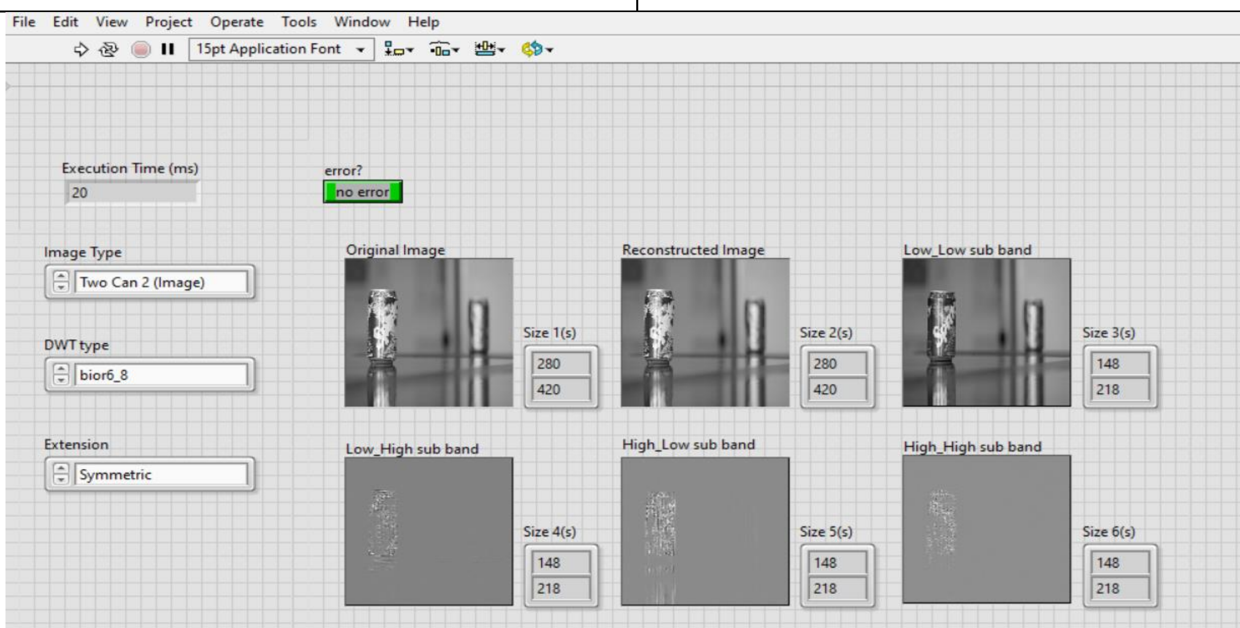
(b) Daubechies Wavelets (db6)



(c) Symmlets Wavelets (sym8)



(d) Coiflets Wavelets (coif1)



(e) Biorthogonal Wavelets (bior6_8)

Fig. 17. The front panels of the Image Decomposition LabVIEW simulation design for image test2: Two Can2, Level One

After choosing the test image and the DWT type with symmetric extension in the front panel fields, after the running step, instantly the execution time value appears in Execution Time (ms) field. We noticed that Haar wavelets have the least time (6 and 11 msec) to compute the decomposition process, it is the simplest wavelet that's is usually used in simple structure systems. In spite of the long time (15 and 20 msec) for Bior 6_8 to finish computing the decomposition process, due to the longer filter length and more complex calculations, but it is the best wavelet choice in giving perfect results for the resulted reconstructed image because it provides smoother results with fewer artifacts.

In Details, the performance results of each wavelet in image decomposition in terms of the required evaluated time (in msec) to complete the image decomposition process based on using two different test images sizes is shown in the table 1.

Table 1. The Evaluated time results of two test images using different discrete wavelets transforms

The Wavelets families	The Wavelet Name	Camera Man test image1 Evaluated Time (ms)	Two Can test image2 Evaluated Time (ms)
Haar Wavelet	Haar	6	11
The Daubechies Wavelets	db2	6	9
	db3	7	10
	db4	7	11
	db5	8	12
	db6	8	14
	db7	9	15
	db8	10	15
	db9	10	18
	db10	11	21
	db11	12	22
	db12	13	22
	db13	14	25
	db14	17	27
The Symmlets Wavelets	sym2	5	9
	sym3	6	10
	sym4	7	10
	sym5	8	12
	sym6	8	13
	sym7	9	15
	sym8	10	19
The Coiflets Wavelets	coif1	7	11
	coif2	9	16
	coif3	11	19

	coif4	14	24
	coif5	18	28
The Biorthogonal Wavelets	bior1_3	6	12
	bior1_5	8	13
	bior2_6	11	22
	bior2_8	13	17
	bior3_1	6	10
	bior3_3	8	14
	bior3_5	9	15
	bior3_7	10	16
	bior3_9	12	18
	bio4_4 (FBI)	9	14
	bior5_5	11	16
	bior6_8	15	20

From the table 1,

Generally, the speed of a discrete wavelet transform depends on the length of the filter. So, shorter filters (Haar, db2, sym2, coif1 and bior1_3) typically lead to least evaluated time and faster computations compared to the longer filters (db14, sym8, coif5 and bior6_8). The reason absolutely belongs to the computational complexity that increases with filter's length.

- The clear difference the in the readings results of the different discrete wavelets transforms in image decomposition process using two different size test images. Increasing the size (width × height) of the test image will increase the total evaluated time.

This can be shown clearly in Fig. 18.

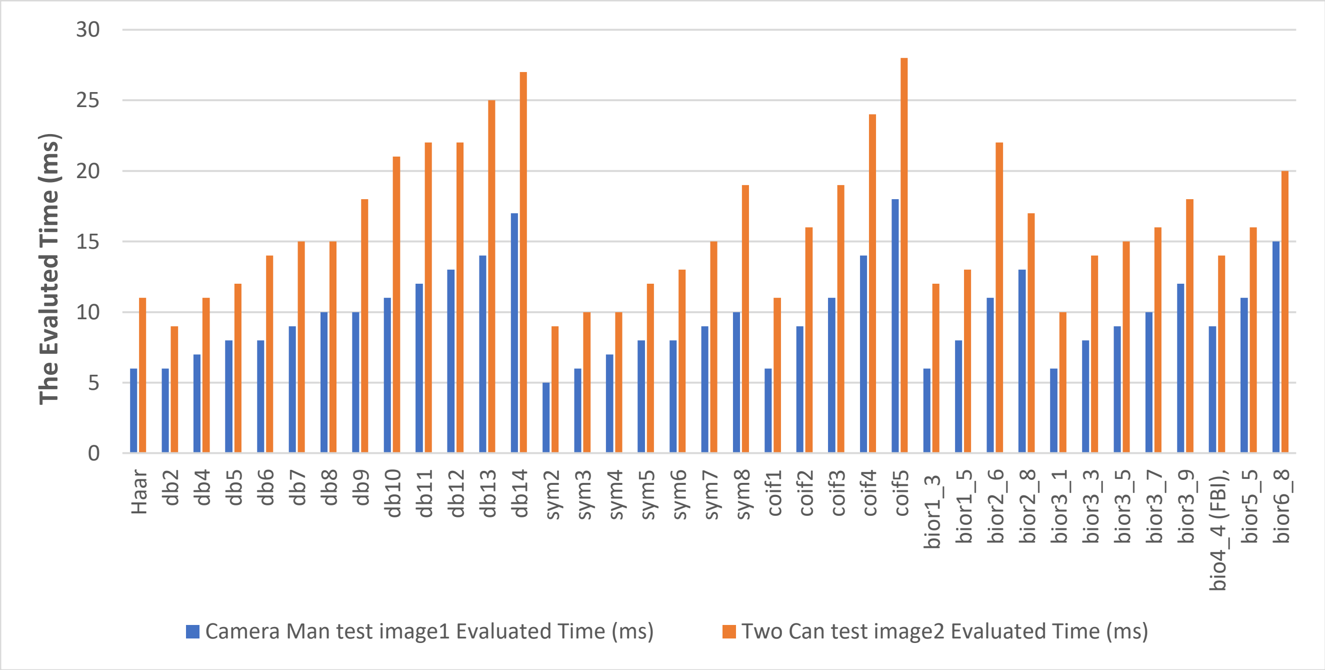
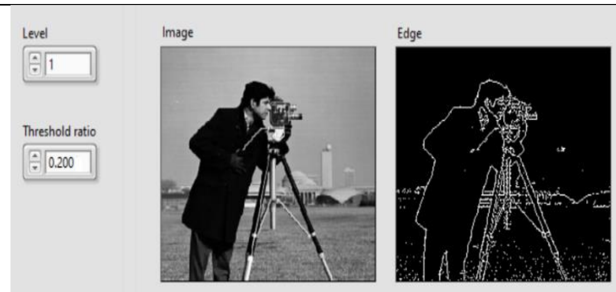


Fig. 18. The performance of different (DWT) in image decomposition of Two test images.

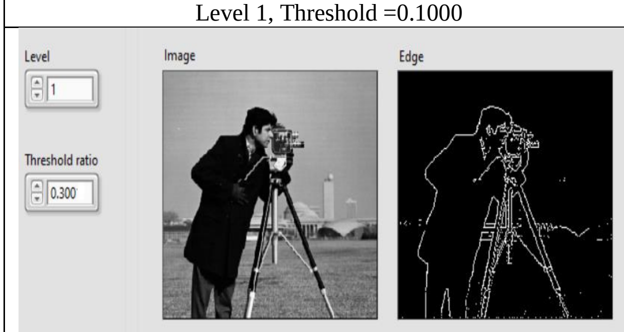
4.2 The Edge Detection LabVIEW 2023 Simulation System Result

In the edge detection LabVIEW 2023 simulation system, by choosing different discrete wavelets and by changing the threshold ratio during edge detection process, this widely affects on the resulting reconstructed image. The lower threshold means the minimum threshold value for edges detecting, while the upper threshold means the maximum threshold value for edges detecting. In this simulation design, The Canny algorithm relies on thresholding to identify significantly the intensity changes that represent edges. Fig. 19 shows the obtained results from Edge Detection LabVIEW 2023 Simulation System with different threshold ratios and sus-bands level 1.

Level 1, Threshold =0.1000

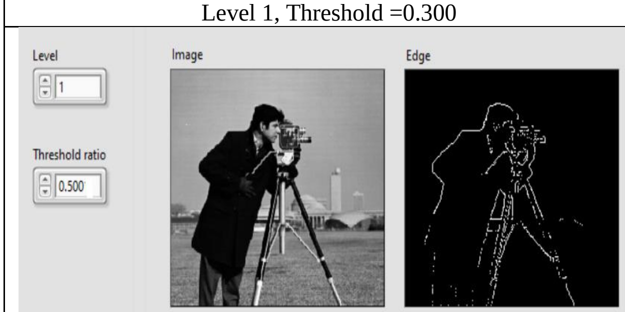


Level 1, Threshold =0.2000

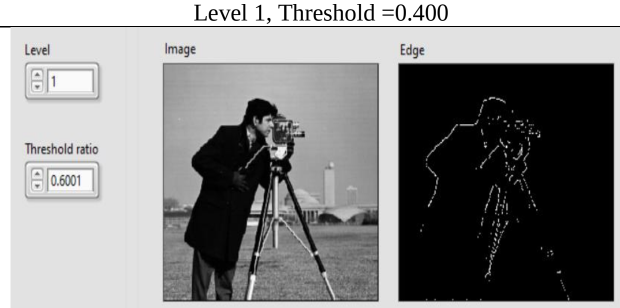


Level 1, Threshold =0.300

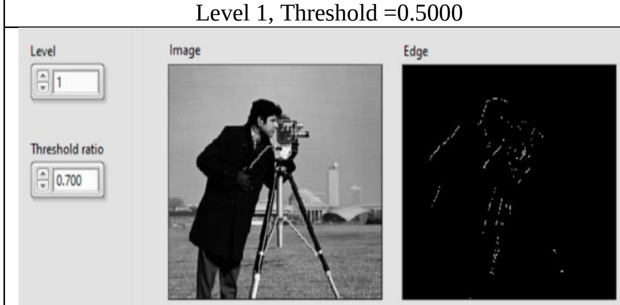
Level 1, Threshold =0.400



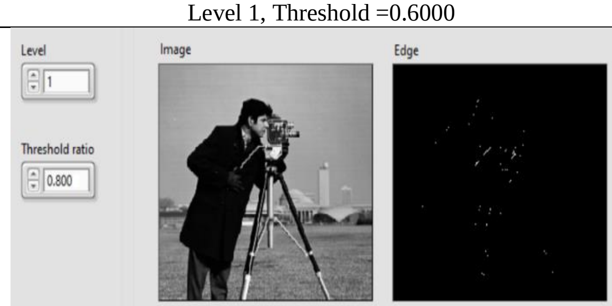
Level 1, Threshold =0.5000



Level 1, Threshold =0.6000



Level 1, Threshold =0.7000



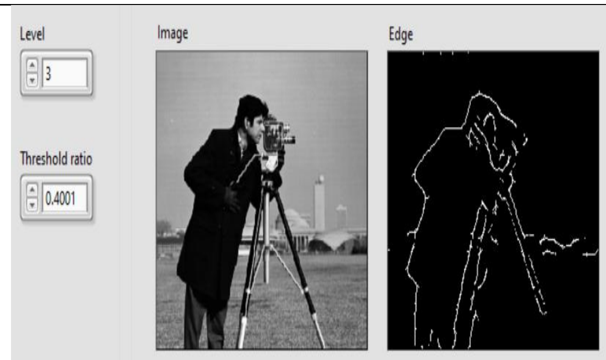
Level 1, Threshold =0.8000

Level 1, Threshold =0.9000

Fig. 19. The front panel results from edge detection LabVIEW 2023 simulation system with different threshold ratios

In Fig. 20, the results of Edge detection with different sus-bands levels and threshold ratio=0.4001

sus-band Level 2



sus-band Level 3

sus-band Level 4

sus-band Level 5

sus-band Level 6

Fig. 20. The front panel results of Edge detection with different sus-bands levels and threshold ratio=0.4001

As we see from Fig. 19 and Fig. 20, the higher threshold value gives fewer edges detected, which means identified only the most prominent edges and it is effectively reduces noise because it minimizes false edges due to a noise or minor the intensity variations. By choosing a lower threshold value, a more and more edges will be detected, capturing finer details and also minor edges. But in other side, the noise will increase and more susceptible to noise, and frequently leading to the detection of spurious edges. By increasing the sub-band levels in image edge detection system, this will perform a multi-level wavelet decomposition on the image and each level of decomposition will capture different frequency components, that improves the ability to detect edges at different scales.

5. Conclusions

- The New LabVIEW 2023 Simulation System for image processing give us a new, fast, typical and simple approach to calculate the total image decomposition time that achieved the calculations with a one Run command.
- The increasing size of the test image will increase the total evaluated time.
- All the types of discrete wavelets transforms are suitable for image decomposition and image edge detection in spite of different required time for the reconstructed image decomposition process.
- The New LabVIEW 2023 Simulation System allows the symmetric extension with orthogonally techniques.
- Biorthogonal wavelets provided more freedom and least limitations than the orthogonal wavelets in image processing process.
- Increasing the number of sub-band levels (decomposition levels) allows for the image edge detection to get the finer details and edges. These higher levels of decomposition will segment the image into more granular frequency components, which can be useful for detecting invisible image edges.
- Although, orthogonal wavelet sometimes is preferred for their simplicity and efficiency, which make it suitable for applications requiring precise feature localization, but the biorthogonal wavelet, with their symmetry and smoother reconstructions, generally offer a better performance for image decomposition and denoising, particularly for natural images.
- The choice between orthogonal and biorthogonal wavelets depends on the specific requirements of the image processing task and the nature of the images being processed.

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