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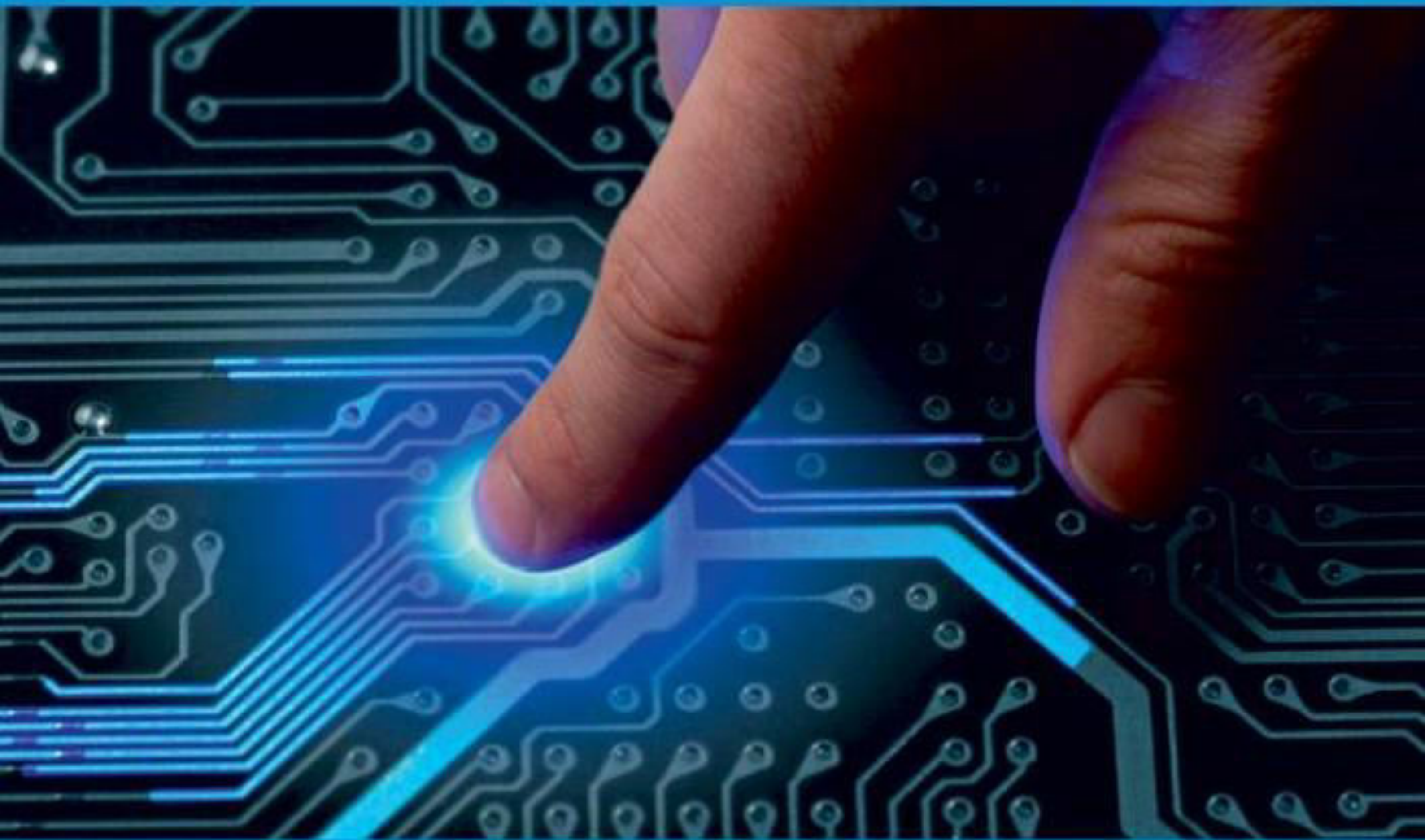

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Reducing Gaussian Noise in Bionics: Image Denoising using the DWT Technique

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ABSTRACT: This paper outlines a model for image denoising and Gaussian noise reduction using various wavelets in combination with Wiener and deconvolution filters. Wavelets represent a cutting-edge area of research in image processing and enhancement. The study compares Haar, Daubechies, and Biorthogonal wavelets for denoising biomedical images. Wavelet analysis employs a logical windowing technique with variable-sized regions, allowing for The application of shorter segments in areas where high-frequency information is desired. As biomedical images are often affected by corruption by Gaussian noise, image denoising is needed for accurate diagnosis.The research explores the 2-D Discrete Wavelet Transform (DWT) and develops an algorithm to denoise Images degraded by Gaussian noise. The results include both qualitative and quantitative analyses, demonstrating The efficiency of the DWT technique by comparing the denoised images with the original noisy images. Quantitative analysis involves evaluating the Mean Square Error (MSE) of the filtered images and estimating the processing time for different wavelets. Gaussian noise reduction is a key criterion for objectively determining image quality, and the Point Spread Function (PSF) of the restored image is used to assess distortion levels. Finally, a comparison table is provided, showcasing the performance analysis of Haar, Db2, and Biorthogonal wavelets in image denoising.

KEYWORDS: Discrete Wavelet Transform, Gaussian Noise Reduction, Image Noise Suppression, Wiener Filter

I. INTRODUCTION

In the contemporary era of modernization through inventions, Numerous methods have been created for the best image digitization, acquisition, and processing. Among these advancements, wavelet-based Techniques have attracted considerable focus because of their wide range of implementations in domains such as biomedical engineering, wireless and mobile communications, computer graphics, and turbulence analysis. Among the leading notable applications of wavelets is in image compression. The swift rise in the adoption of electronic imaging necessitates a systematic approach to designing image compression and denoising systems to ensure the quality of the image required for various applications.The effectiveness of an enhancement algorithm is often measured using Peak Signal-to-Noise Ratio (PSNR), which is a key indicator of image quality. The quality and compression efficiency can vary depending on the characteristics and content of the input image. In medical imaging, including MRI, Gaussian and speckle noise are common issues. Gaussian noise significantly degrades image quality and Is presented at various stages of image acquisition. This noise can originate from improper contact between transducer probes and the body, air gaps, or during beamforming, signal processing, and scan conversion processes.

Speckle noise, a specific type of noise affecting coherent imaging systems like medical and astronomical images, poses additional challenges. In Synthetic Aperture Radar (SAR) imaging, Gaussian noise is multiplicative, meaning it varies directly with the local grey level of the image. The noise and signal are statistically independent, and the local area variance and mean are centered on individual pixels, with these local statistics reflecting the overall image properties.Recent literature has explored signal denoising using nonlinear techniques to address speckle noise. Systematic image analysis typically involves three primary stages: pre-processing, data reduction, and image feature analysis. Noise removal is a crucial task in image processing, and various approaches exist depending on whether the noise is additive or multiplicative. Images affected by noise during acquisition and transmission, making denoising essential to retain maximum image features.Overall, advancements in image processing and denoising have significantly contributed to the domain of digital image enhancement, offering effective solutions for noise reduction and improved image quality.

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II. LITERATURE REVIEW

Digital image acquisition and processing techniques are crucial in modern medical diagnosis, utilizing modalities such as X-ray, Ultrasound, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI). Advanced digital image processing techniques are vital for enhancing image Quality through the elimination of noise, thus aiding in better diagnosis.. [1] Emphasizes the significance of using advanced digital image processing methods to enhance image quality by eliminating noise components, which improves diagnostic accuracy. [1] Also provides a review of various techniques used for denoising ultrasound images[1] Also shows a survey on different techniques used in ultrasound image denoising [2]. A comprehensive survey on ultrasound image denoising techniques highlights the efficacy of Wiener filtering in the wavelet domain combined with soft thresholding. This approach Is discovered to be superior when compared to five Classical speckle reduction filters are evaluated based on their performance using statistical measures such as Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE). The Wiener filtering combined with Bayes shrink thresholding technique in the wavelet domain shows superior performance based on these metrics and the visual quality of Ultrasound B-scan images.[3]. The study has been done onVarious filtration techniques, including Wiener and median filters, are compared with a newly proposed method that enhances the existing technique by refining the threshold function parameter K. This new approach yields results that adapt to different noise levels. Signal-to-mean square error is used as a metric to assess the quality of the denoising process [4]. Also some survey are made on various techniques used in ultrasound image denoising [5]. Some analysis in this regard has applauded the Wiener filtering in the wavelet domain, combined with soft thresholding, as an all-encompassing technique. Also,some comparison is done for the efficiency of wavelet based thresholding technique in highlighting information of the Medical ultrasound images are processed using five different classical speckle reduction filters [6]. The effectiveness of these filters is assessed using statistical metrics such as Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE). Based on these statistical metrics The visual clarity of Ultrasound B-scan images the wiener filtering the Wiener filtering technique combined with Bayes shrink thresholding in the wavelet domain performed better than the other filtering techniques [7]. It is observed that there is a great scope of Various filtering methods, including Wiener and median so in this regard many further novel approaches are proposed . These techniques extends the existing techniquesBy enhancing the threshold function parameters, such as K, the technique produces results that adapt to varying noise levels [8]. Signal-to-mean square error was used as a metric to assess the quality of the denoising process[9].

III. PROBLEM FORMULATION

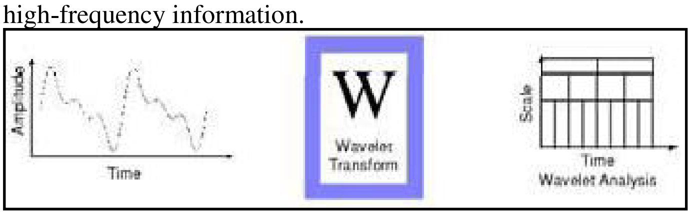
A model is designed and implemented for reducing noise in images using discrete wavelet transform with a multilevel decomposition approach. The denoised images are quantitatively evaluated using Mean Square Error estimation to assess image fidelity. Gaussian noise reduction is evaluated as a primary criterion for objective image quality. Additionally, the Point Spread Function (PSF) of the restored images is analyzed to gauge the level of distortion. Finally, a comparison table is constructed to illustrate the performance analysis of Haar, Db2, and Bio-orthogonal wavelets [10] for image denoising.

IV. RESEARCH METHODOLOGY

A. Discrete Wavelet Transform

Wavelet analysis takes the concept of windowing techniques further by utilizing variable-sized regions for analysis.
Wavelet **analysis allows**
Fig. 1: Wavelet Transform on a Signal: Wavelet Transform in contrast with the Time-Based, Frequency-Based, and Short-Time Fourier Transform (STFT) Views of a Signal [12]

the use of long time intervals where we want more precise low-frequency information, and shorter regions [11] where we want high-frequency information.



$$V(x, y) = g[u(x, y)] + \eta(x, y) \quad (1)$$

$$g[u(x,y)] = \iint h(x, y; x', y') u'(x', y') dx' dy' \quad (2)$$

$$D(x, y) = f[g(u(x, y))]\, \eta 1(x, y) + \eta 2(x, y) \ (3) \quad (3)$$

Here u(x, y) represents the objects (means the original image) and v(x, y) is the observed image. Here h (x, y; x', y') represents the impulse response of the image acquiring process. The term ŋ(x,

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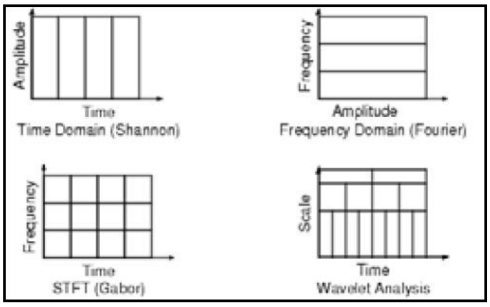

Fig. 2: Evaluation of various Trasform Techniques [13]

The Discrete Wavelet Transform (DWT) involves applying wavelet transforms to discretely sampled wavelets. This transform effectively localizes a function in both space and scale and offers advantages over the Fourier transform. One of its key benefits is the ability to compute the wavelet matrix more quickly than the Fourier matrix.The DWT is particularly useful for signal coding, leveraging its properties to represent a discrete signal in a more redundant form. This redundancy is often utilized as a preprocessing step for data compression, making the DWT a powerful tool in signal processing and compression applications.

B. Multilevel Decomposition

The wavelet decomposition tree is created through a step-by-step process where a signal is repeatedly decomposed into successive approximations. Each approximation is separated into more basic into lower resolution components, resulting in a hierarchical structure of decomposed signal layers [16]

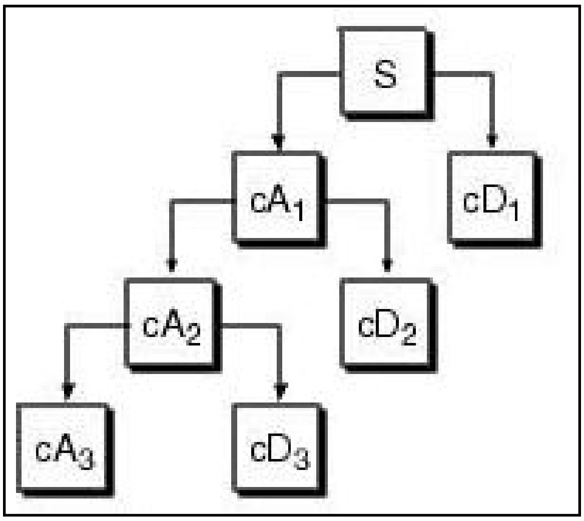

Fig. 3: Multilevel decomposition method used for wavelet

Mathematically the image noise can be represented with the help of these equations below:
y) represents the additive noise which has an image dependent random components f [g(w)] ŋ1 and an image independent random component ŋ2. Gaussian noise can be modeled as follow:
$V(x, y) = u(x, y)s(x, y) + \eta(x, y)$ (4)
Where the speckle noise intensity is given by s(x, y) and ŋ(x, y) is a white Gaussian noise [17]. The main objective of image-denoising techniques is to remove such noises while retaining as much as possible the important signal features.

C. Weiner Filter

The Wiener filter, a type of linear filter adopted for spectral domain filtering, adapts to local image variance during application. It minimizes smoothing where variance is high and increases it where variance is low [18], often yielding superior results compared to standard linear filters. This adaptive approach preserves edges and other high-frequency image details more effectively than comparable linear filters. However, it requires more computation time.

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Inverse filtering is a deconvolution restoration technique used when an image is blurred by a known low pass filter, allowing recovery through inverse or generalized inverse filtering. Yet, inverse filtering is highly sensitive to additive noise. Addressing each degradation separately allows for developing specific restoration algorithms that can be combined as needed. Wiener filtering achieves an optimal balance between inverse filtering and noise reduction by simultaneously removing additive noise and reversing blurring. It optimizes the mean square error, providing a linear estimation of the original image within a stochastic framework [20].

In the Fourier domain, the orthogonality principle expresses the Wiener filter as:

$$W(f_1, f_2) = \frac{H^*(f_1, f_2) S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)},$$

where $S_{xx}(f_1,f_2)$, $S_{nn}(f_1,f_2)$ are respectively power spectra of the original image and the additive noise, and $H(f_1,f_2)$ is the blurring filter [21]. The Wiener filter consists of two parts: inverse filtering (high-pass filtering) for deconvolution and noise reduction (low-pass filtering) through compression. This dual function effectively addresses additive white Gaussian noise, a prevalent high-frequency component in image wavelet coefficients, particularly challenging in recent multi-resolution image-processing efforts using wavelet transforms.

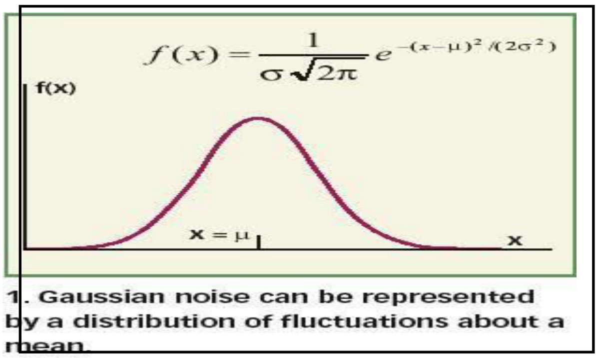

Fig. 4: Gaussian Noise can be illustrated by a Distribution of Fluctuations About the Mean

Gaussian noise significantly degrades the visual quality and perception of images, affecting various stages of image acquisition. Noise may result from inadequate contact or an air gap between the transducer probe and the body, during the beam forming process, and during signal processing. Additionally, interpolation during scan conversion can lead to information loss. Speckle noise, found in coherent imaging systems like medical and astronomical images, is another type of noise that impacts image clarity. In Synthetic Aperture Radar (SAR), Gaussian noise acts as a multiplicative factor, directly correlating with local grey levels. Notably, the signal and noise are statistically independent of each other. The mean and variance of a single pixel correspond to those of the surrounding local area centered on that pixel.

V. KINDS OF WAVELETS USED

A. Haar Wavelets

The Haar wavelet is known as the simplest and earliest wavelet. It exhibits discontinuity and has a shape similar to a step function. Interestingly, it shares the same wavelet function as the Daubechies db1 wavelet.

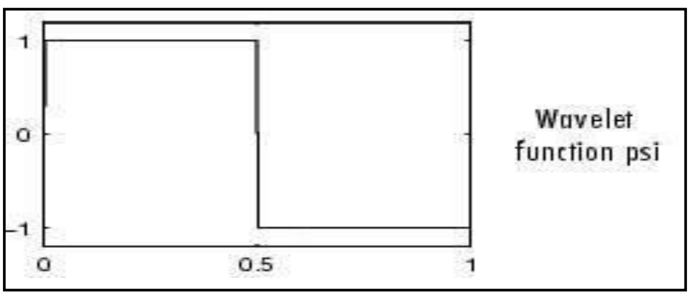

Fig. 5: Waveform of the Haar wavelet function

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B. Daubecheis Wavelet

Ingrid Daubechies, a prominent figure in wavelet research, pioneered the development of Orthogonal functions with compact support wavelets, thereby enabling practical applications of discrete wavelet analysis. The Daubechies family of wavelets is denoted by names like dbN, where N indicates the order and "db" serves as the wavelet's "surname." Notably, the db1 wavelet, also known as the Haar wavelet, shares the same wavelet function as the original Haar wavelet.

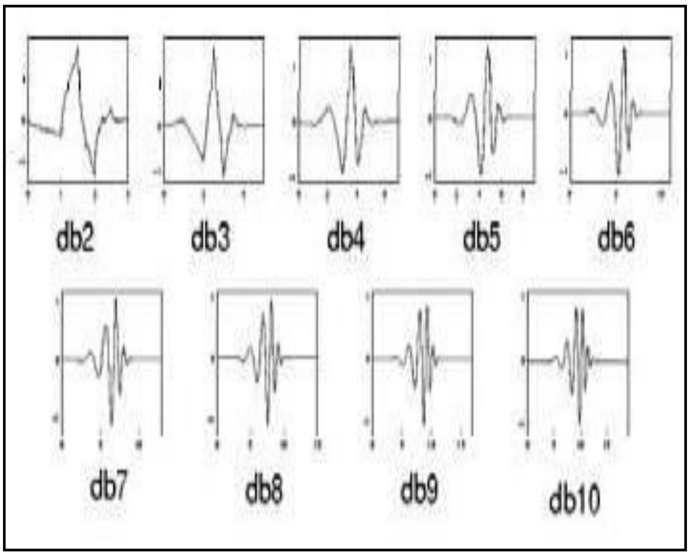

Fig. 6: Daubecheis Wavelet Functions Waveform

C. Bio-orthogonal Wavelet

This wavelet family demonstrates linear phase characteristics essential for signal and image reconstruction. Utilizing two distinct wavelets—one for decomposition (on the left side) and another for reconstruction (on the right side)—instead of a single wavelet yields intriguing properties and benefits.

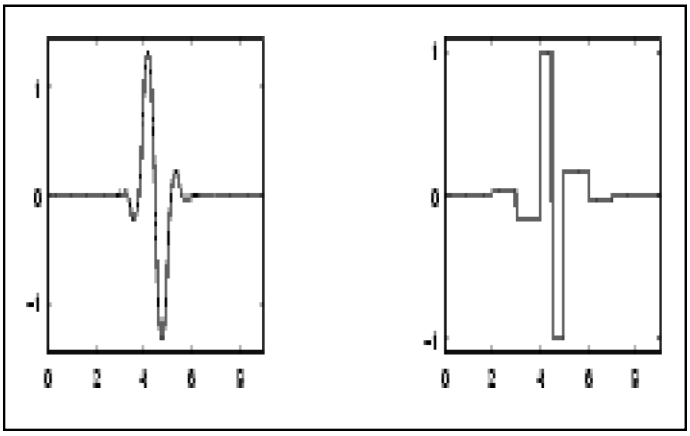

Fig. 7: Bior1.5 Wavelet Function Waveform

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VI. RESULTS

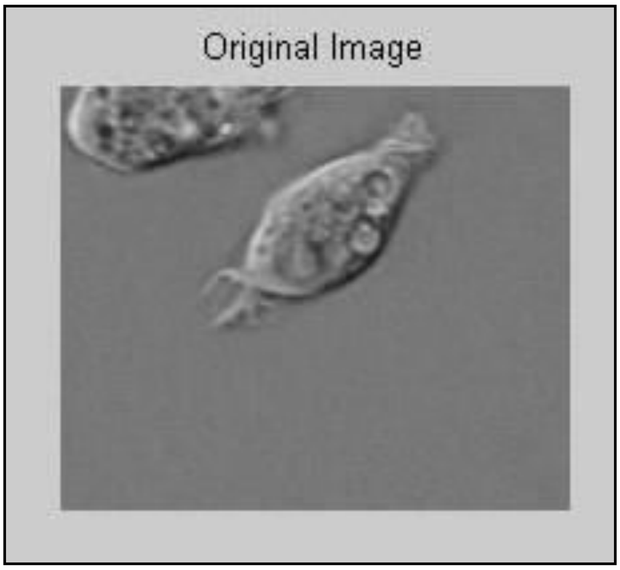

Fig. 8: Original Cell Image

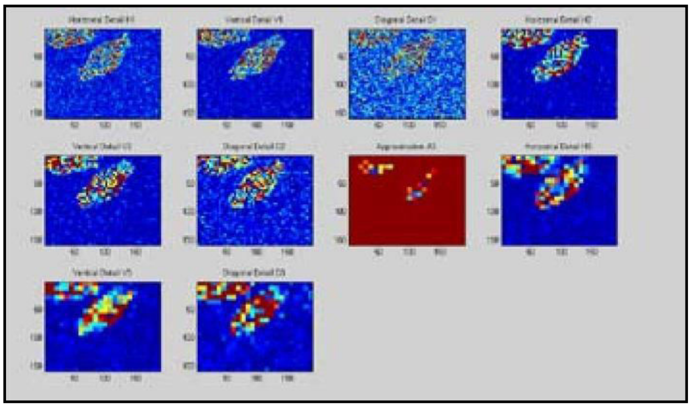

Fig. 9: Approximation and Coefficients capturing details after applying the wavelet transform Have Been Applied to Input Image

A. Noisy Image After Adding Additive Gaussian Noise Using Gaussian Noise Model

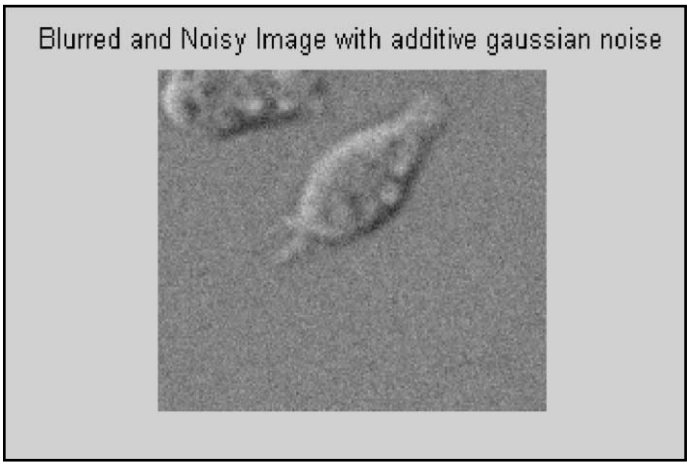

Fig. 10: Blurred and Image subjected to additive Gaussian noise

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B. Results Using Haar Wavelet And Weiner Filters

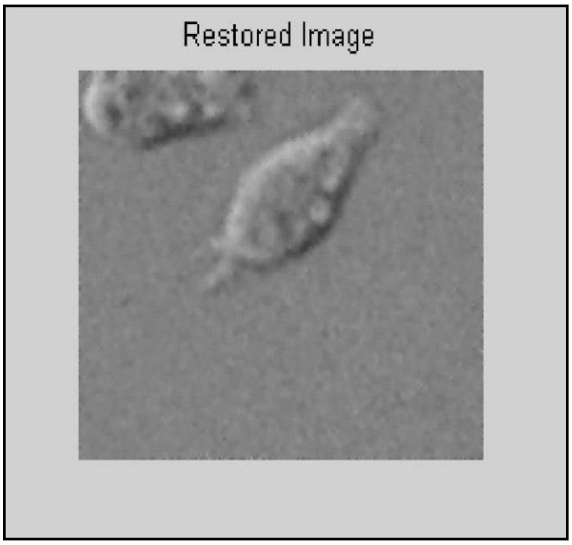

Fig. 11: Restored Image Using Weiner Filters and Haar Wavelet

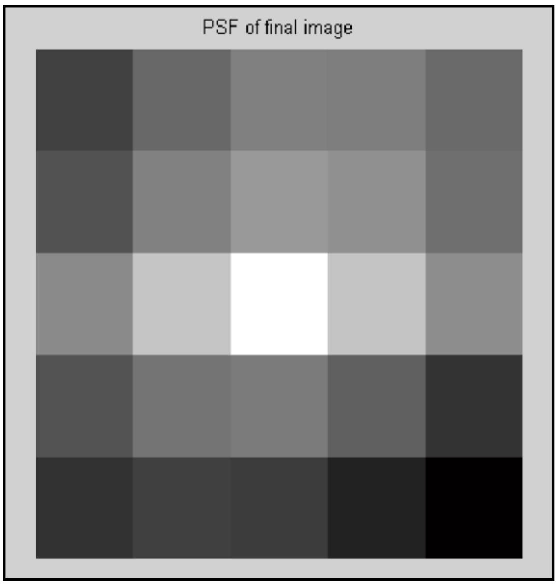

Fig. 12: PSF of Final Image

Mean Square Error = 0.3015
Elapsed time = 5.415113 seconds

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C. Results Using Daubecheis Wavelet And Weiner Filters

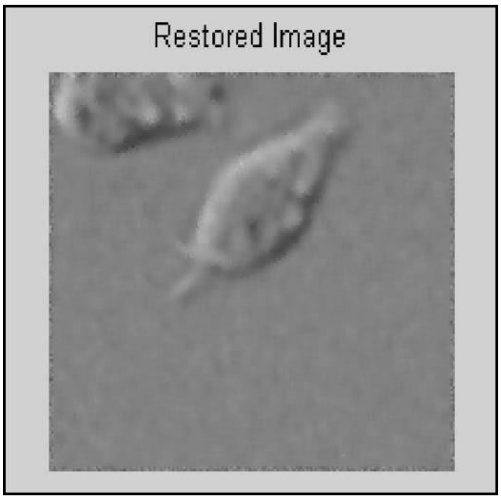

Fig. 13: Restored Image Using Weiner Filters and db2 wavelet

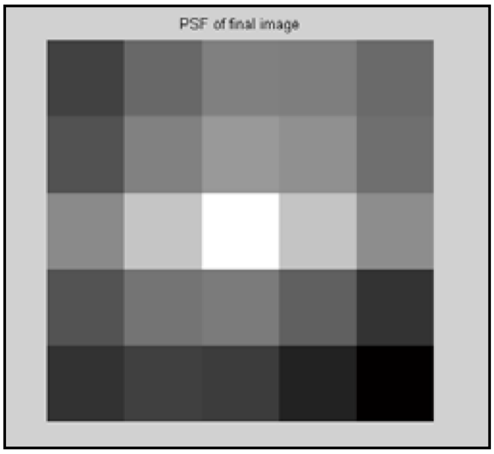

Fig. 14: PSF of Final Image

Mean Square Error = 0.5154
Elapsed time = 5.346064 seconds

D. Results Using Biorthogonal Wavelet and Weiner Filters

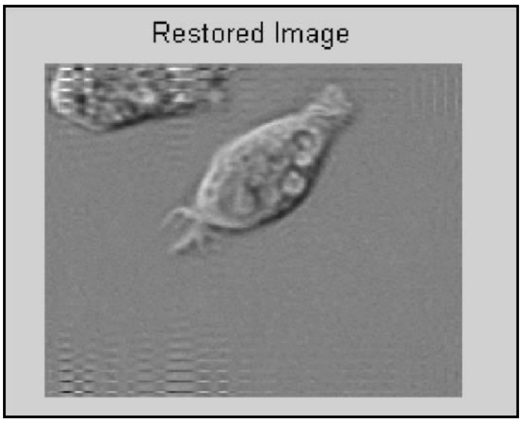

Fig. 15: Restored Image with Bior1.5 Wavelet and Weiner Filter

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(Shows Ringing Effect)

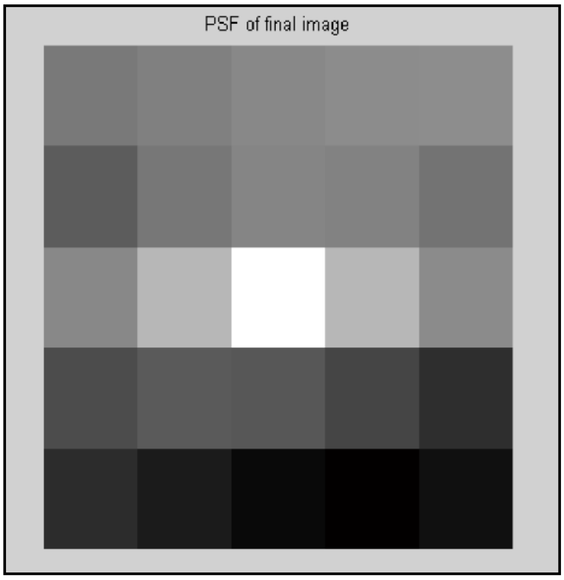

Fig. 16: PSF of Final Image

Mean Square Error = 0.7363
Elapsed time = 7.619770 seconds

VII. CONCLUSION

Image denoising has been successfully accomplished using a novel technique combining wavelet transform with Wiener filters. The results were evaluated subjectively through visual inspection of the restored images and objectively by assessing the Point Spread Function (PSF) of the final output restored images, which exhibited minimal distortion.Objective measurement the evaluation of image quality was carried out using the Mean Square Error (MSE)metric across different wavelets: Haar, Db2, and Bior1.5. The performance analysis included evaluation based on two parameters: MSE and processing elapsed time.

Table 1:

Parameter	Haar	DB2	Bior1.5
MSE	0.3015	0.5154	0.7363
Processing Time	5.415113	5.346064	7.619770

Based on the findings, it is evident that the Haar wavelet outperforms db2 and Bior1.5 from the perspective of MSE, overall picture quality, and processing time. However, the Bior wavelet, particularly Bior1.5, exhibits a ringing effect as observed in Figure 14.

VIII. FUTURE SCOPE

In the future, there is significant potential to expand the deployment of the multiresolutional analysis algorithm, as described in this thesis, to encompass other types of medical imaging modalities like CT scans, MRI, and EEG images. These modalities often encounter various types of noise, such as speckle and Gaussian noise, which degrade image quality and complicate accurate diagnosis.Additionally, there is an opportunity to put this algorithm into practice on a Field-Programmable Gate Array (FPGA) platform. FPGA technology offers advantages in developing intelligent denoising models tailored specifically for ultrasound images. This approach would involve optimizing resource utilization and minimizing operational constraints during the FPGA implementation process, ensuring efficient and

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real-time processing of ultrasound data.Further enhancements could involve exploring minor adjustments to the algorithmic code to improve its processing efficiency. This could include refining algorithms for noise reduction, enhancing feature extraction capabilities, or streamlining computational steps to achieve faster processing times without compromising accuracy.Overall, these future directions aim to extend the capabilitiesConcerning the use of multiresolutional analysis in medical imaging, leveraging advanced technologies like FPGA to enhance diagnostic accuracy and image quality across various imaging modalities.

IX. APPLICATIONS

Wavelets are crucial across various uses because they are capable of analyze both the scale and time aspects of signals and images. These aspects can be separated somewhat arbitrarily to better understand their roles. In the context of decomposition, denoising, and compression, wavelets are essential for simplifying and clarifying signals or images.

Studies have explored the utilization of wavelets in several medical and scientific applications. For example, wavelets are used to extract micro-potentials in electrocardiograms (EKGs) and to localize the electrical activity of the His bundle in the heart, which is crucial for ECG noise removal. In electroencephalograms (EEGs), wavelets help identify and localize rapid transitory signals that are often obscured by typical brain signals.Wavelets also play a significant role in enhancing mammograms, improving the differentiation between tumors and calcifications. Additionally, they are used in classifying Magnetic Resonance Spectra to investigate how the amount of fat in one's diet affects body fat levels composition without invasive sampling. In this application, each Fourier spectrum is characterized by selected wavelet coefficients, enhancing the encoding process and providing more precise analysis.Overall, wavelets are essential for improving the clarity and accuracy of various signals and images, making them invaluable in medical diagnostics and scientific research.
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