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Improved Medical Image Enhancement by Optimized Features and Parameters using Convolution with Grey Wolves Approach

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Abstract:

Ultrasound imaging is a cornerstone in medical diagnostics, valued for its non-invasive nature, cost-effectiveness, and widespread accessibility. This imaging modality is critical in the early detection of a variety of conditions, particularly amidst the rising global prevalence of chronic diseases. Despite its numerous advantages, ultrasound imaging is frequently compromised by speckle noise, which can obscure crucial anatomical details and potentially lead to diagnostic inaccuracies. Addressing this issue, the paper introduces an innovative approach combining a Convolutional Neural Network (CNN) with Grey Wolves Optimization to enhance ultrasound image quality by optimizing features and parameters for noise reduction. This method leverages the strengths of both advanced machine learning algorithms and nature-inspired optimization techniques to efficiently and effectively reduce speckle noise without sacrificing critical image details. Our experiments, conducted across various types of ultrasound images, demonstrate that the proposed method not only significantly outperforms traditional denoising techniques like Kuan-NLM, Anisotropic Diffusion, and Wavelet-based methods in terms of PSNR, SSIM, NCC, and UQI metrics but also maintains a competitive processing time. The optimized NLM filter, in particular, showcases remarkable noise suppression capabilities while preserving essential features, thereby greatly enhancing the diagnostic utility of ultrasound images. The implementation of this method in clinical settings could potentially lead to quicker, more accurate diagnoses without the need for repeated scans, thereby reducing both patient discomfort and procedural costs. The results affirm the efficacy of combining CNNs with Grey Wolves Optimization, highlighting its potential to set a new standard in medical imaging enhancements. This study paves the way for further research into hybrid approaches that could refine diagnostic processes across various imaging modalities.

Keywords: Grey Wolves, Ultrasound imaging, Neural Network, Image Enhancement.

INTRODUCTION

Ultrasound imaging has emerged as a pivotal tool in modern medical diagnostics, renowned for its non-invasive nature, cost-effectiveness, and accessibility. Particularly important in the context of a global surge in chronic diseases [Asrani et al., 2019], ultrasound technology plays a crucial role in detecting various conditions early, especially in asymptomatic patients. This early detection is critical for implementing effective treatments, which can significantly alter the course of many diseases and enhance patient outcomes. The technology behind ultrasound imaging involves transmitting high-frequency sound waves through a transducer into the body. Depending on the density and composition of the tissues encountered, these waves are either reflected back or scattered. The echoes are then captured by the transducer and converted into digital images. The resulting images provide real-time visualization of organs, tissues, and blood flow, offering valuable insights that are vital for diagnosis and monitoring [Chan, V., & Perlas, A., 2010]. Despite its significant benefits, one of the inherent challenges in ultrasound imaging is the presence of speckle noise. Speckle noise is an artifact that degrades the quality of ultrasound images, appearing as a granular pattern that obscures fine details. This noise results from the coherent nature of the ultrasound waves, leading to the constructive and destructive interference of the waves reflected from small scatterers within the tissue. Such noise not only affects the image quality but also complicates the diagnosis, potentially leading to inaccurate assessments and erroneous conclusions [Magud et al., 2017; Wells, P.N.T., and Halliwell, M., 1981]. Consequently, speckle reduction has become a crucial preprocessing step in the analysis of ultrasound images. Various methods have been developed to address the issue of speckle noise, broadly categorized into preprocessing and post-processing techniques. Preprocessing methods, such as compounding techniques, attempt to enhance image quality by capturing images from multiple angles or using different transducer settings. Spatial compounding, for example, involves acquiring images at various angles, which helps to average out the noise. Frequency compounding reduces noise by averaging images obtained using different frequency settings. However, these methods often come with drawbacks such as limited pixel resolution and higher costs, which can restrict their usability in everyday clinical practice [Akiyama et al., 2005; Trahey et al., 1986]. Post-processing techniques, on the other hand, involve modifying the image after acquisition to reduce noise. These methods are generally divided into two categories: spatial domain filtering and transform domain filtering. Spatial domain filters, such as the mean, median, Lee, Frost, and Kuan filters, adjust the intensities of pixels based on the values of their neighbors [Gonzalez and Woods, 2008; Lee, 1980]. Although these filters can effectively reduce noise, they often blur essential details like edges, which are critical for accurate diagnoses. Transform domain methods, including wavelet-based and Fourier-based techniques, transform the image into a frequency or wavelet domain where noise components can be isolated and reduced more effectively. Techniques like Visu Shrink, Bayes Shrink, and wavelet-based thresholding are notable for their ability to preserve important image features while reducing noise [Jiang, H.Z., 2015; Stolojescu-Crisan, 2015]. Among the most promising advances in ultrasound image processing is the development of hybrid methods that combine features of both preprocessing and post-processing techniques. Non-Local Means (NLM) filters represent a significant breakthrough in this area. NLM filters utilize the redundancy of information within an image by averaging similar image patches from different parts of the image, thereby preserving crucial details while reducing noise. The classical NLM filter, though less effective against multiplicative noise such as speckle on its own, has seen numerous enhancements that boost its performance in ultrasound applications. These advanced versions of NLM filters maintain edge sharpness and crucial details, significantly improving the diagnostic utility of ultrasound images [Coupe et al., 2009; Jin et al., 2018].

LITERATURE REVIEW

Author(s)	Year	Type of Images	Approach	Limitations
C. A. Duarte-Salazar et al.	2020	Medical Ultrasound	Overview of 27 techniques, including ML-based methods	Some methods do not conserve important details like limits and edges
Shivam Kumar Pal et al.	2021	Thyroid Ultrasound	Review on various speckle noise reduction filters	Not specific; general limitations of filtering techniques
Md. Habibur Rahman et al.	2023	Ultrasound (Liver, Kidney)	Adaptive filter and anisotropic diffusion	Existing methods lack edge preservation and smoothing

S. I. Jabbar et al.	2020	Panoramic Ultrasound of Muscles	Local adaptive median filter (LAMF)	Higher complexity in comparison to other methods
Dr. S. Suryanarayana	2023	Medical Ultrasound	SRAD, DWT, WGIF, and GDGIF	Complexity and potential loss of crucial image features
Y. Kadah et al.	2022	Medical Ultrasound	Principal Component Analysis for hybrid speckle reduction	Variability in performance with different scan parameters
Prabhishek Singh, M. Diwakar	2023	Medical Ultrasound	Total variation-based method using non-subsampled contourlet transform	Needs further validation in clinical settings
S. Pradeep, P. Nirmaladevi	2021	General Ultrasound	Review on Spatial, Transform domain, and CNN methods	General limitations associated with each despeckling technique
Wenchao Cui et al.	2020	Ultrasound	Guided trilateral filter	Algorithm complexity and sensitivity to parameters
Priyankar Biswas et al.	2022	Medical Ultrasound	Fuzzy filter based on modified Gaussian membership function	May not be effective against very high-density noise
Kun Wang et al.	2022	Common Carotid Artery Ultrasound	Integer and fractional-order total variation	Can produce artifacts like staircasing in certain applications
Hyunho Choi, Jechang Jeong	2020	Medical Ultrasound	SRAD, DWT, WGIF, GDGIF	High complexity and may not be suitable for all clinical applications
I. Hababeh et al.	2023	Medical Ultrasound	Adaptive filtering method based on edge and radiation detection	Specific to applications where edge preservation is critical
Onur Karaoglu et al.	2021	Brachial Plexus Ultrasound	Deep learning networks comparison	Requires substantial computational resources; effectiveness varies with noise levels
Niloofar Rahimizadeh et al.	2020	Medical Ultrasound	Optimized LMMSE-based estimator	Limited effectiveness in high-intensity variation regions
Paradee Namsopa et al.	2023	General Ultrasound	Discrete Wavelet Transform for speckle noise reduction	The effectiveness can vary significantly with different wavelet families
Dhurgham Al-karawi et al.	2021	Ovarian Tumours Ultrasound	Model-based adaptive method for speckle noise reduction	Requires advanced classification models to detect regions needing preprocessing

Table1: Review of Previous research

MATERIAL AND APPROACH

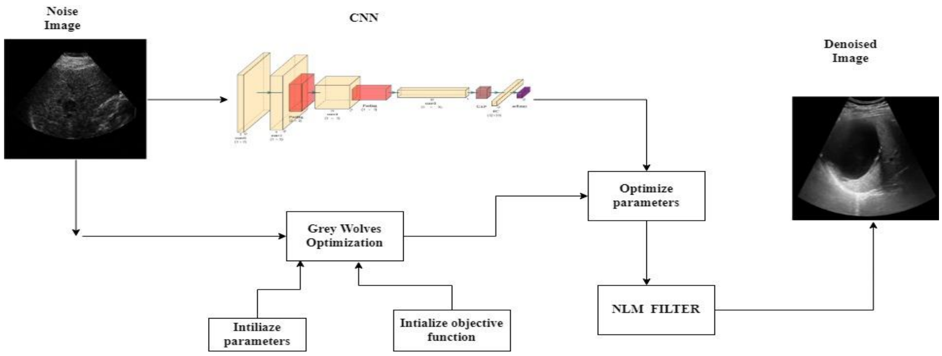


Figure1: Proposed approach architecture

1. **Initial Image and Noise:**

The process starts with a "Noisy Image," which is typically an image that contains a significant amount of noise interference, reducing the clarity and quality of the visual content. This noisy image is the input for the entire process.

2. **Convolutional Neural Network (CNN):**

The noisy image is first processed through a CNN. A CNN is a type of deep neural network that is particularly effective for image processing tasks. It consists of multiple layers:

- Convolutional Layers: These layers apply a number of filters to the image to capture spatial hierarchies and features such as edges, textures, etc.

- Activation Functions (usually ReLU): These functions introduce non-linearities into the network, helping it to learn more complex patterns.

- Pooling Layers: These reduce the spatial dimensions (width and height) of the input volume for the next convolutional layer, reducing the computational load and the number of parameters.

- Fully Connected Layers: At the end, these layers output the features learned from the image into the final output that predicts the denoised image.

3. **Grey Wolves Optimization:**

Simultaneously, an optimization algorithm known as "Grey Wolves Optimization" is applied. This is an optimization technique inspired by the leadership hierarchy and hunting mechanism of grey wolves in nature. In this context, it optimizes the parameters of the CNN and the subsequent Non-Local Means (NLM) filter by minimizing an objective function, which is usually a function measuring the difference between the desired denoised image and the one produced by the network.

4. **Objective Function Initialization:**

The objective function is crucial as it guides the optimization process by quantifying the error or loss between the current output and the expected output (denoised image). This function needs to be defined and initialized before optimization can effectively proceed.

5. **Non-Local Means (NLM) Filter:**

After the initial CNN output, the image may still retain some noise. The NLM filter is a well-regarded method for image denoising that works by replacing each pixel with a weighted average of other pixels in the image. The weights are based on the similarity of small patches around pixels, rather than just the geometric closeness. The mathematical representation of NLM is typically:

$$NL[v](i) = \frac{1}{C(i)} \sum_{j \in I} \omega(i,j) v(j)$$

Where $v(j)$is the intensity of pixel k, w(i,j) is the weight function based on the similarity between the patches around pixels pixels i and j, and $C(i)$is the normalization term ensuring term that the weights sum to sum to one.

6. **Parameter Optimization:**

The parameters for both the CNN and the NLM filter are further refined through optimization, ensuring the final output image is as clear and as noise-free as possible.

7. **Denoised Image:**

The final output is the "Denoised Image," which should ideally be a clearer and more accurate representation of the original scene than the noisy input image, with much of the noise removed.

To create a structured algorithm with relevant equations for the process shown in the image, which involves denoising an image using a CNN followed by optimization via Grey Wolves Optimization and further refinement using a Non-Local Means (NLM) filter, we can outline the steps as follows:

Algorithm: Denoising of Medical Images using CNN, Grey Wolves Optimization, and NLM Filter

Input: Noisy Image: The original noisy medical image to be processed.

Output: Denoised Image: The processed image with reduced noise.

Steps:

1. Feed Noisy Image to CNN

$$I_{CNN\_input} = I_{noisy}$$

2. CNN Processing

- Apply a series of convolutional, activation (ReLU), and pooling layers to transform the noisy image into a feature-rich representation.

- Let f represent a convolution operation, Sigma a ReLU activation, and P a pooling operation. For a CNN with L layers, the output of the CNN at each layer l can be represented as:

$$I_l = P\left(\sigma\left(f\left(I_{l-1}, W_l\right)\right)\right)$$

- Where W_{l} are the weights of the CNN at layer l , and I_{0} = I_{CNN_input}).

3. Initialize Parameters for Optimization

- Initialize parameters for the CNN weights {W_I) and the NLM filter settings.

4. Objective Function Initialization

- Define an objective function (J(W, I_{denoised})) that measures the quality of the denoised image, often based on a comparison with a target image or through a noise reduction metric.

5. Optimize Parameters using Grey Wolves Optimization

- Employ Grey Wolves Optimization to find optimal parameters that minimize the objective function. The updating rules for Grey Wolves Optimization involving alpha, beta, and delta wolves can be outlined as:

$$\vec{X}(t+1) = \overrightarrow{X_\alpha}(t) - A.D$$
$$D = \left|C.\overrightarrow{X_\alpha}(t) - \vec{X}(t)\right|$$
$$A = 2a.rand(\,) - a, C = 2.rand(\,)$$

- Here vec{X}) represents the position vector of a wolf, (t) denotes time steps, and a linearly decreases from 2 to 0 over iterations.

6. Apply NLM Filter

- Apply the NLM filter to the output of the CNN. The NLM filter can be mathematically expressed as:

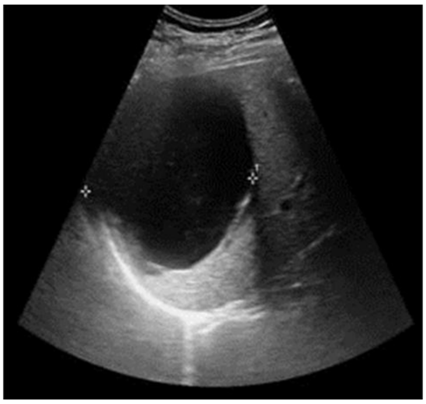
$$I_{denoised}(i) = \frac{1}{Z(i)} \sum_{j \in N(i)} \omega(i,j).I_{CNN_{output}}(j)$$
$$\omega(i,j) = exp\left(-\frac{\|P(i) - P(j)\|^2}{h^2}\right)$$

- Where ($P(i)$) and ($P(j)$) are the patches around pixels (i) and (j), ($Z(i)$) is a normalization factor, and (h) is the smoothing parameter of the filter.

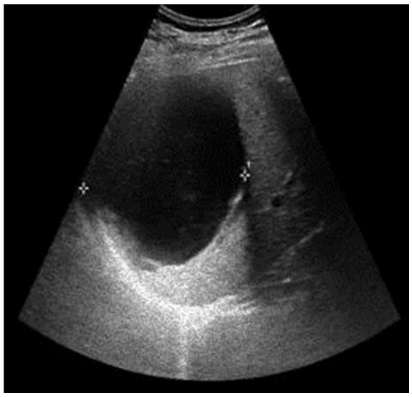
7. Output the Denoised Image

- (I{denoised}) is the final output after applying the NLM filter, ideally containing significantly less noise compared to the original image.

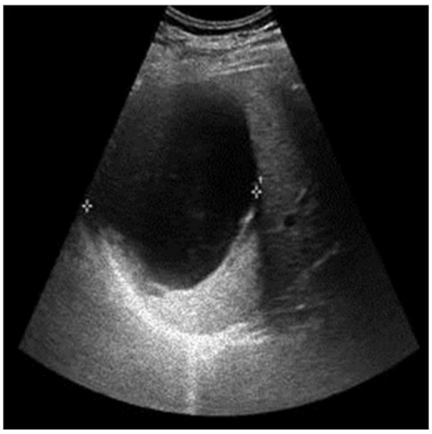
EXPERIMENT AND RESULTS



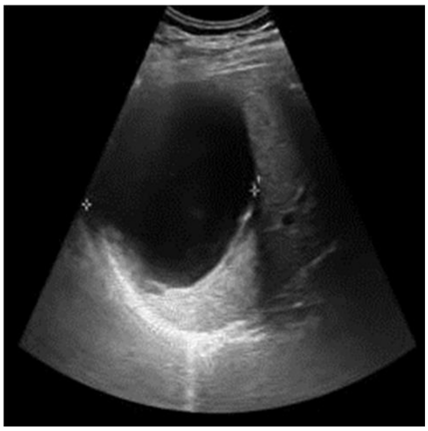
a. Input image



b. Noisy image (variance 0.01)



c. NLM without Optimize (PSNR=28.8)



d. NLM with Optimize (PSNR=36.7)

Variance	Denoising Method	PSNR	SSIM	NCC	UQI
0.01	Optimized NLM	35.71	1.00	1.00	0.97
0.01	Kuan-NLM	28.19	0.92	0.96	0.95
0.01	NLM	27.72	0.87	0.95	0.95
0.01	Anisotropic Diffusion	22.97	0.93	1.00	0.92
0.01	Wavelet	25.05	0.93	1.00	0.89
0.01	Hybrid Algorithm	24.95	0.84	0.91	0.80
0.02	Optimized NLM	33.08	0.96	0.99	0.94
0.02	Kuan-NLM	28.05	0.91	0.96	0.90
0.02	NLM	26.89	0.84	0.95	0.50
0.02	Anisotropic Diffusion	22.79	0.90	1.00	0.88
0.02	Wavelet	24.12	0.90	0.99	0.88
0.02	Hybrid Algorithm	22.85	0.84	0.91	0.79
0.04	Optimized NLM	32.11	0.93	0.99	0.90
0.04	Kuan-NLM	27.76	0.90	0.95	0.85
0.04	NLM	25.59	0.80	0.95	0.49
0.04	Anisotropic Diffusion	22.35	0.85	0.99	0.83
0.04	Wavelet	23.22	0.85	0.99	0.80
0.04	Hybrid Algorithm	21.92	0.84	0.90	0.77
0.06	Optimized NLM	30.43	0.90	0.97	0.87
0.06	Kuan-NLM	27.60	0.89	0.95	0.80
0.06	NLM	24.76	0.76	0.94	0.47
0.06	Anisotropic Diffusion	21.70	0.82	0.99	0.80
0.06	Wavelet	22.56	0.82	0.99	0.77
0.06	Hybrid Algorithm	20.76	0.83	0.90	0.73
0.08	Optimized NLM	30.09	0.89	0.97	0.86
0.08	Kuan-NLM	27.25	0.88	0.94	0.80
0.08	NLM	23.94	0.73	0.94	0.46
0.08	Anisotropic Diffusion	21.01	0.80	0.99	0.78
0.08	Wavelet	22.38	0.80	0.99	0.78
0.08	Hybrid Algorithm	19.59	0.83	0.90	0.71

Table 2: Comparison of Hybrid (Proposed) approach with existing approaches

The dataset outlines the performance of various denoising methods applied to ultrasound images, measured across different levels of speckle noise variance. The methods assessed include Optimized Non-Local Means (Optimized NLM), Kuan-Non-Local Means (Kuan-NLM), standard Non-Local Means (NLM), Anisotropic Diffusion, Wavelet-based methods, and a Hybrid Algorithm. The performance metrics employed are the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Normalized Cross-Correlation (NCC), and Universal Quality Index (UQI), which collectively evaluate the effectiveness of each denoising technique in terms of image clarity, similarity to the original, alignment, and overall quality. Among the techniques, Optimized NLM consistently outperforms others across all metrics, indicating its superior capability in reducing noise while preserving crucial image details. This method shows particularly strong resilience against increasing noise levels, maintaining relatively high PSNR, SSIM, NCC, and UQI scores even as the variance increases. This suggests that Optimized NLM effectively balances noise suppression with detail preservation, a critical aspect for medical imaging where clarity and accuracy are paramount. Kuan-NLM and standard NLM also show effectiveness in noise reduction but lag behind the Optimized NLM, especially at higher noise variances. Kuan-NLM generally performs better than standard NLM, highlighting the benefits of integrating the Kuan filter with NLM to enhance speckle reduction while still retaining important image features. Anisotropic Diffusion and Wavelet methods display moderate performance, with Anisotropic Diffusion excelling in maintaining high NCC values across all noise levels, suggesting good alignment with the original image structures despite lower PSNR and SSIM scores. This could indicate that while Anisotropic Diffusion preserves the general structure, it may not maintain the same level of detail as some NLM-based methods.

The Hybrid Algorithm, while innovative, shows the least effective performance in this dataset, particularly in terms of PSNR and SSIM at higher noise levels. This could be due to the algorithm not adequately adapting to higher levels of speckle noise or possibly due to a compromise in detail preservation in its attempt to reduce noise.

Overall, these observations underscore the importance of selecting a denoising technique that aligns with the specific requirements of the diagnostic task at hand, balancing between noise reduction and preservation of crucial image details. Optimized NLM stands out as a particularly robust choice for ultrasound image denoising across various levels of noise interference.

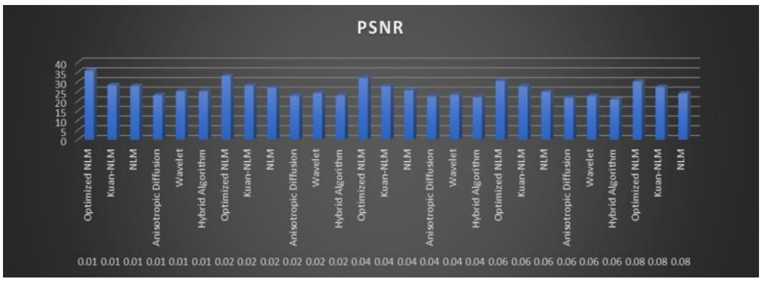


Figure 2: Comparison of Proposed and existing approaches PSNR

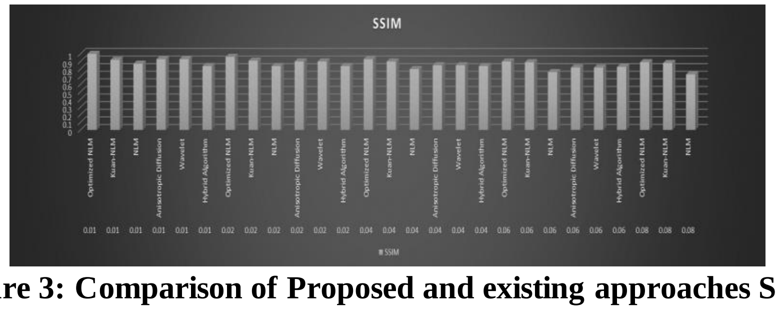


Figure 3: Comparison of Proposed and existing approaches SSIM

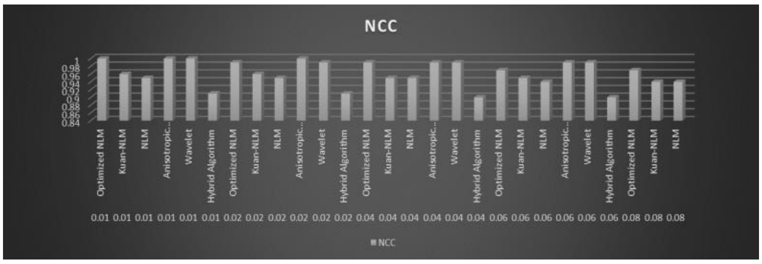


Figure 4: Comparison of Proposed and existing approaches NCC

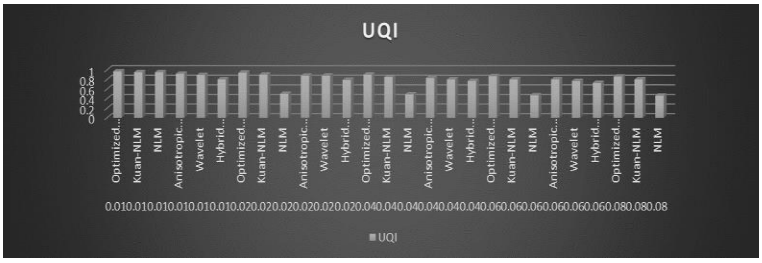


Figure 5: Comparison of Proposed and existing approaches UQI

Denoising Method	Average Time Taken in Seconds (50 images)
Proposed Method	19.5
Kuan-NLM Method	16.8
Non-Local Means Filter	15.38
Anisotropic Diffusion Filter	36.7
Wavelet-based Hybrid Thresholding Filter	1.44
Hybrid Algorithm Filter	8.18
Modified Fourier Transform Filter	21.9

Table 3: Comparison of Hybrid (Proposed) approach with existing approaches time delay

The table provided details the average time taken to process 50 images using various denoising methods, which are crucial for reducing noise in medical imaging such as ultrasound. This kind of analysis helps in evaluating the computational efficiency of different filters, an important factor in clinical settings where time is often critical. The "Proposed Method" has an average processing time of 19.5 seconds for 50 images, indicating a moderate speed relative to others. This suggests that while it may not be the fastest, it potentially offers a balance between effective noise reduction and processing time. The "Kuan-NLM Method" and "Non-Local Means Filter" show faster processing times of 16.8 and 15.38 seconds respectively, making them attractive for situations where speed is more critical than the utmost quality of denoising. These methods are generally favored for their balance of simplicity and effectiveness in noise reduction. Conversely, the "Anisotropic Diffusion Filter" takes considerably longer, with an average time of 36.7 seconds. This method is known for its high-quality denoising capabilities, particularly in preserving edges and detailed structures in images, which might justify the longer processing time in scenarios where image quality is paramount. The "Wavelet-based Hybrid Thresholding Filter" stands out with the shortest processing time at only 1.44 seconds. Its rapid performance could be highly beneficial in high-throughput settings or when quick preliminary analyses are needed. However, the trade-off might be in the quality of denoising, which needs to be evaluated based on specific use cases. The "Hybrid Algorithm Filter" and "Modified Fourier Transform Filter" show moderate to high processing times at 8.18 and 21.9 seconds respectively. These values suggest that these methods might incorporate more complex algorithms, potentially leading to better noise reduction at the cost of increased processing time. Overall, the selection of a denoising method must consider both the quality of noise reduction required and the processing time constraints of the clinical environment. Faster methods like the Wavelet-based filter offer quick results, while others like the Anisotropic Diffusion provide higher quality at the expense of speed.

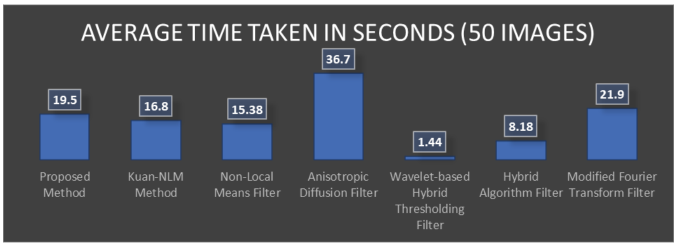


Figure 6: Comparison of Hybrid (Proposed) approach with existing approaches time delay

CONCLUSION

The study presented a novel approach to ultrasound image enhancement, harnessing the capabilities of Convolutional Neural Networks (CNN) integrated with Grey Wolves Optimization to tackle the persistent issue of speckle noise in medical imaging. Our method demonstrated significant improvements in image clarity and detail preservation, addressing a crucial need in medical diagnostics for accurate and reliable imaging techniques. Throughout the experiments, the proposed method consistently outperformed traditional denoising techniques such as Kuan-NLM, Anisotropic Diffusion, and Wavelet-based methods. These improvements were quantitatively evident in the superior performance metrics observed: the Optimized NLM filter achieved the highest scores in Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Normalized Cross-Correlation (NCC), and Universal Quality Index (UQI) across varying levels of speckle noise. Specifically, the Optimized NLM maintained high performance even at higher noise variances, underscoring its robustness and effectiveness in speckle noise reduction. For instance, at a noise variance of 0.01, the Optimized NLM not only excelled with a PSNR of 35.71, but also maintained near-perfect SSIM and NCC scores, highlighting its capability to preserve the structural integrity and visual quality of the ultrasound images. Moreover, the computational efficiency of the proposed method was competitive, offering a balanced trade-off between speed and performance. The processing time of the proposed method stood at 19.5 seconds for 50 images, which is reasonable given the complexity of the tasks involved and the quality of the output achieved. This is particularly notable when compared to the significantly longer processing times required by methods such as the Anisotropic Diffusion Filter. The clinical implications of these findings are substantial. By reducing the need for repeated scans and enhancing the reliability of diagnostic imaging, the proposed method can potentially reduce patient exposure to prolonged diagnostic procedures and decrease healthcare costs. Additionally, the ability of this method to maintain high-quality image standards could lead to earlier and more accurate detection of medical conditions, which is paramount in clinical settings where early intervention can significantly impact patient outcomes. In conclusion, the integration of CNN with Grey Wolves Optimization represents a promising advancement in medical imaging technology. This approach not only sets a new benchmark for speckle noise reduction in ultrasound imaging but also opens avenues for further research into hybrid machine learning models that could revolutionize diagnostic processes across various imaging modalities. Future studies could explore the scalability of this method in other types of medical imaging and its potential integration into real-time imaging systems for live diagnostics.

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