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Original Article

Design a Hybrid Filter for Image Denoising in Ultrasound Images Integrating SRAD, Wavelet Decomposition, and Guided Filtering

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Abstract: A frequent issue in US images is noise, named as speckle which noticeably lowers the resolution of image by making it look grainy, decreasing clarity, and creating obstacles to accurate evaluation. This paper explores a hybrid filtering approach (i.e., an algorithm) to address the challenge by combining three techniques: Speckle Reducing Anisotropic Diffusion (SRAD), Wavelet Decomposition, and Guided Filtering. The algorithm begins with utilizing SRAD for noisy US images as an initial filtering stage, which effectively reduces speckle noise while maintaining essential aspects of the image. Next, SRAD-processed image undergoes wavelet decomposition, that divides it into high-frequencies and low-frequencies subbands. Finally, Gradient Domain Guided Image Filtering (GDGIF) is integrated into high freq. subbands for suppressing noise, while Weighted Guided Image Filtering (WGIF) is integrated into low freq. subbands for improving feature preservation of ultrasound images. In the end we evaluated how well this method works by measuring two key factors: Peak Signal-to-Noise Ratio (PSNR) and Root Mean Squared Error (RMSE). Results showing values of PSNR greater than 35dB and RMSE approximately zero which makes ultrasound images clearer by minimizing the speckle noise more effectively than conventional filters while protecting key image elements. This method could assist doctors in reaching accurate and reliable diagnosis.

Keywords: Speckle noise, Ultrasound images, SRAD, Wavelet decomposition, Guided filtering, Image denoising, PSNR, RMSE.

1. Introduction

Devices used in Ultrasound are widely acknowledged for their reliability, affordability with portability relative to other imaging approaches such as X-ray, Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI). Although new research work under digital signal processing has boosted the quality of ultrasound scans, their standard still falls short to other medical imaging modalities. One major reason for this limitation is the existence of speckle noise [1], a grainy pattern naturally occurring in ultrasound images. Speckle noise is a multiplicative type of noise, which makes it very difficult to remove. This noise significantly affects US image clarity and can hinder the accurate diagnosis of lesions and other medical conditions [11]. Therefore, to achieve clearer and more reliable ultrasound images, effective speckle noise reduction techniques are essential in medical image processing.

Over the past several decades, numerous approaches have been introduced to tackle a speckle noise. There are three types of filtering methods: Linear filtering, Nonlinear filtering, and Hybrid filtering. Linear filtering models, namely Gaussian filter and Mean filter can denoise the image, but they have the problem of blurred edges. To overcome that problem, nonlinear filtering methods have been proposed. These techniques such as Non-local Means (NLM) filter [15] [16], Anisotropic Diffusion (AD) filter, and Bilateral filter have been designed to eliminate speckle noise and minimize degradation of the edge region. Still, these approaches help in preserving edges, they are not highly efficient in eliminating speckle noise completely because they do not fully consider the unique way noise appears in ultrasound scans.

To overcome these limitations of conventional single method approaches, hybrid filtering techniques have been explored. For instance, Yang et al. [2] developed a hybrid denoising method that integrates the statistical properties of speckle noise with the Non-Local Means (NLM) filter, enhancing noise suppression. Similarly, Zhang et al. [3] proposed a technique that combines wavelet filtering with guided filtering, achieving improved speckle noise reduction. Furthermore, Coupe et al. [4] utilized a Bayesian framework to modify the NLM filter for better noise removal. Despite these advancements, existing hybrid filtering methods still have limited edge preservation and performance in noise reduction, limiting their clinical applicability in ultrasound imaging [14]. Thus, there is a need for innovative frameworks that can effectively remove speckle noise while upholding edge information and refining diagnostic accuracy.

In this work, we forward a hybrid filtering approach [1][9] that integrates Speckle Reducing Anisotropic Diffusion (SRAD) [5], Wavelet Decomposition [6], and Guided Filtering [7] to enhance ultrasound image quality. SRAD is employed for its edge-preserving capabilities after noise reduction, significantly attenuating speckle noise while upholding crucial structural attributes. Wavelet decomposition performs multi-resolution analysis, transforming the image into frequency subbands. By converting multiplicative speckle noise into an additive form, it facilitates easier noise elimination. Finally, Guided filtering further refines the image by reducing residual noise and enhancing important features. This integrated approach demonstrates great performance in both noise suppression and edge preservation compared to conventional methods such as the Lee, Kuan, and Frost filters**.**

2. Proposed Algorithm

This proposed algorithm integrates Speckle Reducing Anisotropic Diffusion (SRAD), Wavelet Decomposition, and Guided Filtering to effectively remove speckle noise while preserving critical structural details in ultrasound images. The algorithm is implemented in sequential steps, as illustrated in the flowchart (Fig.1). Below is a detailed description of the proposed algorithm:

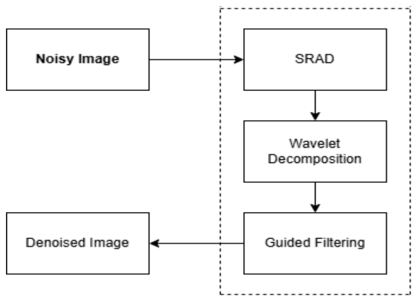

Fig 1. Flowchart of the proposed algorithm

A. Speckle Reducing Anisotropic Diffusion

The Speckle Reducing Anisotropic Diffusion (SRAD) is a variation of the anisotropic diffusion technique that specifically works for speckle noise reduction in ultrasound images. Unlike regular anisotropic diffusion, SRAD [12] uses the statistical properties of speckle noise, like the instantaneous coefficient of variation (ICOV), to control the smoothing process. This helps in reducing noise in uniform areas while keeping edges and important details intact. SRAD works by slowly adjusting each pixel's intensity based on the surrounding pixels. It calculates a special value called the ICOV [17], which helps in distinguish between edges and noise, ensuring that only noise is reduced while important details are preserved [17]. The mathematical formulation of SRAD is given by:

$$\frac{\partial I(x,y,t)}{\partial t} = \nabla \cdot \Big(c\big(q(x,y,t)\big) \cdot \nabla I(x,y,t)\Big) \quad [1]$$

where $I(x,y,t)$ represents the image at time t, ∇ is the gradient operator, $\nabla.$ is the divergence operator, and c(q) is the diffusion coefficient dependent on the ICOV $q(x,y,t)$. The ICOV, q is given by:

$$q = \frac{\sqrt{Var[I(x,y)]}}{Mean[I(x,y)]} \quad [2]$$

where Var and Mean are calculated within a local neighborhood of the pixel. The diffusion coefficient c(q) is defined as:

$$c(q) = \frac{1}{1+q^2} \quad [3]$$

The SRAD filter is particularly effective in reducing noise in the same type of region without blurring edges. By using SRAD as a pre-processing step, the noisy ultrasound image becomes clearer and smoother while keeping important details like edges and textures safe.

B. Wavelet Decomposition

After SRAD filtering, the image undergoes wavelet decomposition for further removal of residual speckle noise. Wavelet decomposition is a multi-resolution analysis technique that transforms the image into high frequency and low frequency subbands, allowing selective noise suppression in US images. Since speckle noise is multiplicative, it is first converted into additive noise using a logarithmic transformation:

$$log(f(x,y)) = log(g(x,y)) + log(n(x,y)) \quad [4]$$

where f(x,y) is the observed noisy image, g(x,y) is the original noise-free image, and n(x,y) represents the speckle noise.

The log-transformed image is then decomposed into four subbands (LL, LH, HL, HH) using discrete wavelet transform (DWT). The LL subband represents low-frequency components, capturing smooth variations in the image, while the other subbands capture high-frequency details such as edges and noise [18]. This decomposition enables targeted filtering of specific subbands. High-frequency subbands, which are heavily impacted by noise, can be denoised using advanced techniques without affecting the low-frequency components. The result is a more refined image with reduced speckle noise and preserved structural details.

C. Guided Filtering

Guided filtering is the final step in the hybrid approach, used to refine the outputs from wavelet decomposition. Two types of guided filters are applied:

Gradient-Domain Guided Image Filtering (GDGIF): This filter is applied to high-frequency subbands to suppress residual noise. GDGIF leverages the gradient information of a guidance image to ensure that fine details such as edges and textures are preserved during filtering. The guided filter assumes a linear relationship between the guidance image and the output, ensuring edge-aware smoothing. The output for each pixel is calculated as:

$$q_i = a_i I_i + b_i \quad [5]$$

where a_i and b_i are linear coefficients computed locally in a window centered on i, I_i is the guidance image, and q_i is the filtered output. The coefficients are optimized to minimize the difference between the filtered output and the input image.

Weighted Guided Image Filtering (WGIF): Applied to the low-frequency subband (LL), WGIF focuses on preserving the overall smoothness and suppressing low-frequency noise. The weighting mechanism incorporates local statistics of the image, ensuring that smoothing does not blur significant features. The filtered output is computed similarly to GDGIF but with additional weights to handle low-frequency noise effectively [13]. By combining GDGIF for high-frequency subbands and WGIF for the low-frequency subband, the guided filtering stage ensures comprehensive noise suppression while maintaining the structural details intact and accuracy in diagnostic quality of the ultrasound image.

3. Experimental Setup

In this experimental setup, the proposed hybrid filtering technique is tested on ultrasound images with artificially added speckle noise in it. The noise is introduced using MATLAB's built-in noise function with the 'speckle' option, ensuring a controlled and reproducible testing environment. Alternatively, a custom speckle noise model can be implemented for greater control over noise intensity and distribution. The filtering process is modularized, with separate functions for each filter integrated into a central program, allowing for easy testing, comparison, and optimization. The performance of the hybrid filter is evaluated using Root Mean Squared Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR), which measure noise reduction effectiveness and image quality preservation. These metrics provide a quantitative assessment of the filter's ability to suppress noise while retaining essential image details.

4. Dataset Description

The data set used in this research consists of ultrasound images, including both real and synthetic noisy images. Real ultrasound images are sourced from publicly available medical image databases (i.e.,https://www.kaggle.com/code/ darsh22blc1378/abdominal-ultrasound-segmentation-using-u-net). Synthetic noisy images are generated by adding speckle noise to clean ultrasound images using a multiplicative noise model. This approach ensures a controlled testing environment, allowing a direct comparison between the denoised results and ground truth (noise-free images). The speckle noise can be mathematically represented as:

$$I(x,y)=I_{original}(x,y) \cdot N(x,y) \quad [6]$$

where I(x,y) is the noisy image, $I_{original}$(x,y) is the clean image, and N(x,y) is the multiplicative speckle noise modeled using a Rayleigh distribution [1] [10]. The probability density function (PDF) of a Rayleigh-distributed random variable is given by:

$$f(x) = \left(\frac{x}{\sigma^2}\right) e^{-\left(\frac{x^2}{2\sigma^2}\right)} \,, x \geq 0 \qquad [7]$$

where, σ: scale parameter, which determines the spread of the distribution. x: Intensity values of the noisy image. The function is defined for $x \geq 0$, meaning that intensity values cannot be negative. The implementation of the hybrid filtering approach and its evaluation are conducted using MATLAB, leveraging its robust computational and visualization capabilities. The quantitative performance of the proposed hybrid filter is measured by two widely used image quality metrics named as: Peak Signal-to-Noise Ratio (PSNR) and Root Mean Squared Error (RMSE). These metrics show which extent of the proposed hybrid filter can effectively suppresses speckle noise while preserving essential image details.

Peak Signal-to-Noise Ratio (PSNR): PSNR is a significant metric used for evaluating the quality of a denoised image in terms of ratio, it is the ratio between the maximum possible power of the signal and the power of noise which affects image quality. A higher PSNR value indicates that the denoised image retains more structural similarity with the original ground truth image, implying better noise suppression [1] [8]. It is calculated as:

$$PSNR=10 \cdot log_{10}(MAX^{2} / MSE) \qquad [8]$$

where, MAX: Maximum possible pixel intensity, MSE: Mean Squared Error, computed as:

$$\mathrm{MSE} = \left(\frac{1}{\mathrm{N}}\right) \sum_{i=1}^{N} (I_i - \tilde{I}_i)^2 \qquad [9]$$

Root Mean Squared Error (RMSE): RMSE provides an alternative measure of image quality by measuring the absolute difference between the ground truth and the filtered image. Unlike PSNR, which is a logarithmic measure, RMSE represents error which is easier to interpret with a definitive scale. A lower RMSE indicates better noise suppression and image quality [1] [8]. It is defined as:

$$RMSE = \sqrt{\left(\frac{1}{N}\right) \sum_{i=1}^{N} (I_i - \tilde{I}_i)^2} \qquad [10]$$

where, I_i: Ground truth pixel intensity, $\tilde{I}_i$: Filtered image pixel intensity, N: Total number of pixels in the image.

Evaluation Results and Analysis

The proposed hybrid filtering approach was quantitatively and qualitatively evaluated to demonstrate its effectiveness in speckle noise reduction compared to classical methods, including Lee, Kuan, and Frost with SRAD filters. The evaluation focused on metrics such as Peak Signal-to-Noise Ratio (PSNR) and Root Mean Squared Error (RMSE) to measure noise suppression and image quality preservation.

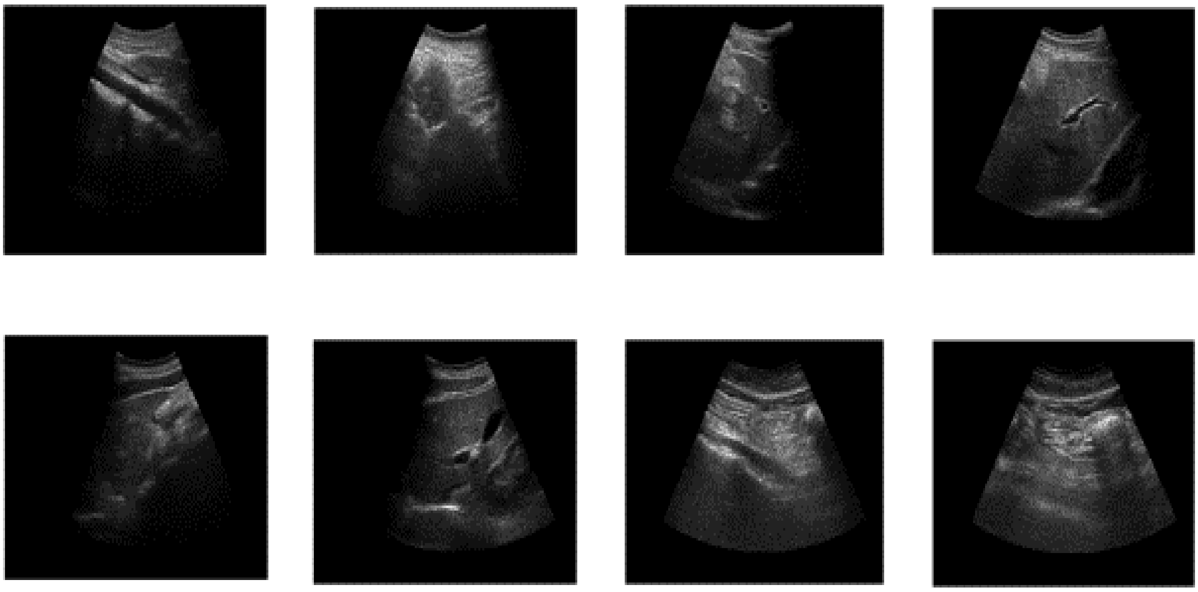

Fig 2. Different Ultrasound Images at the noise variance of 0.04dB

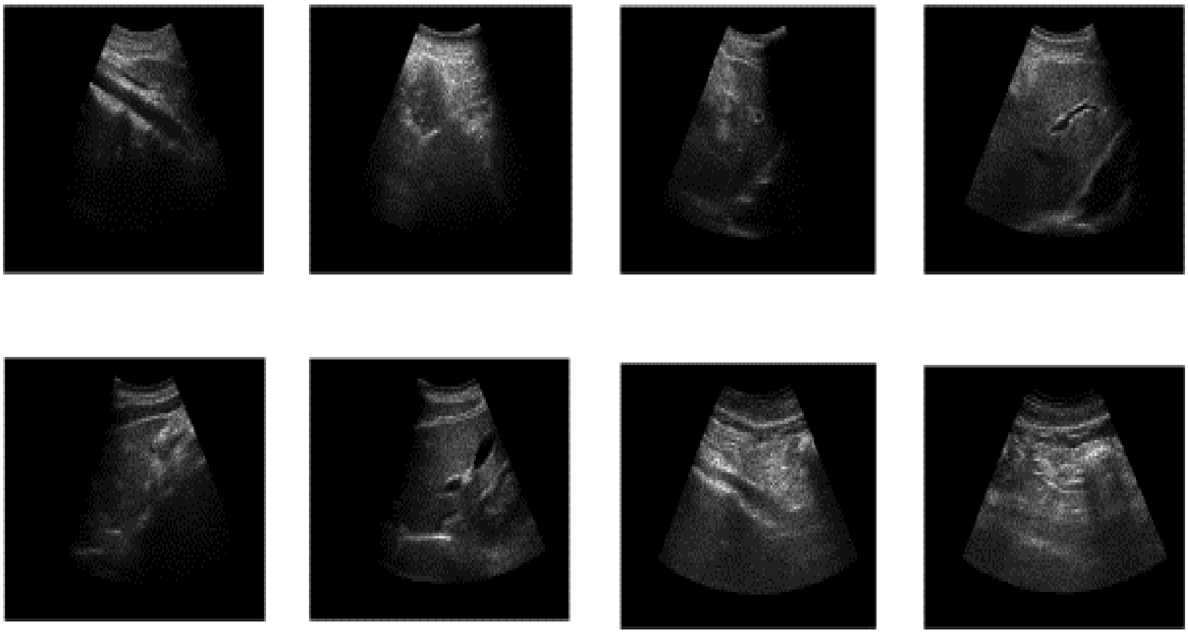

Fig 3. Different Ultrasound Images at the noise variance of 0.08dB

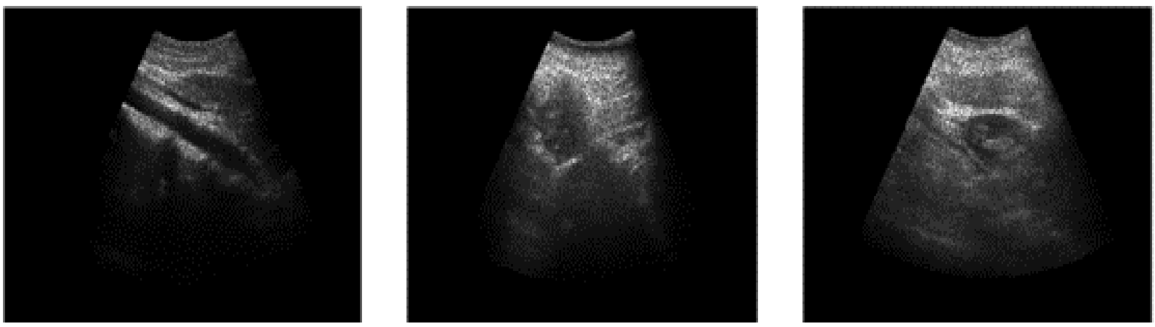

Fig 4. Lee Filtered Images from the noise variance of 0.08dB

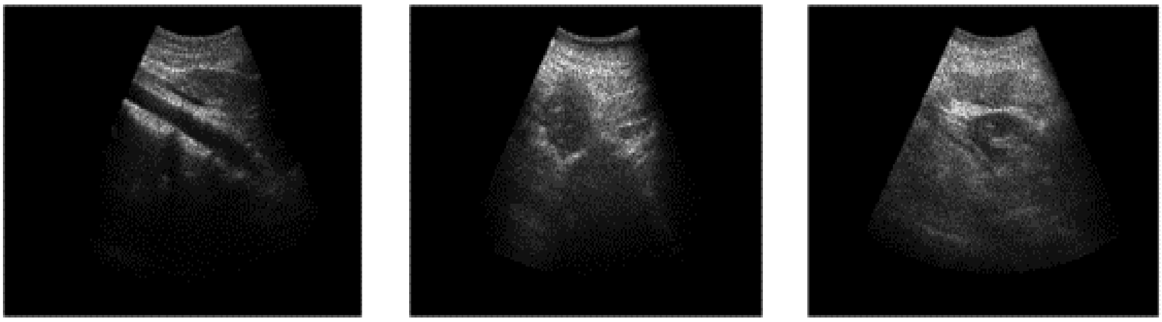

Fig 5. Kuan Filtered Images from the noise variance of 0.08dB

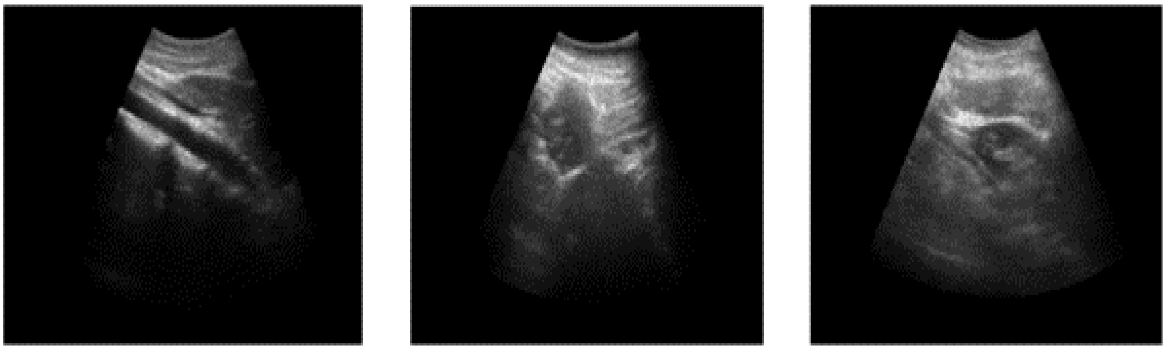

Fig 6. Frost Filtered Images from the noise variance of 0.08dB

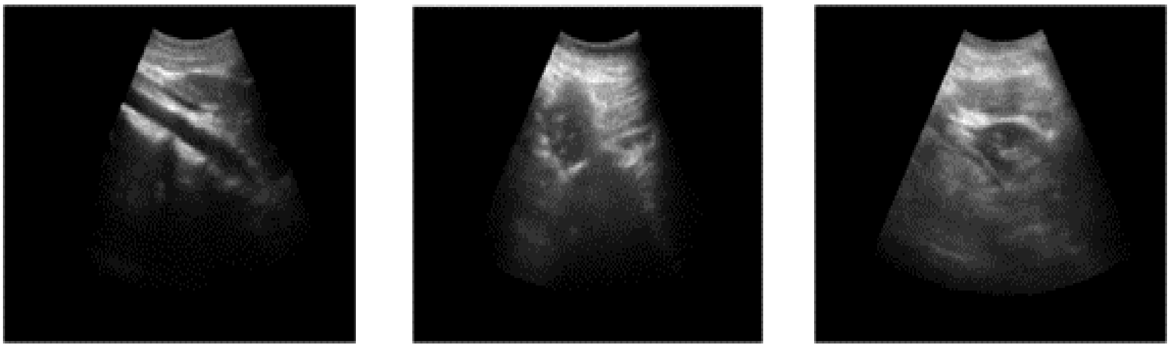

Fig 7. SRAD Filtered Images from the noise variance of 0.08dB

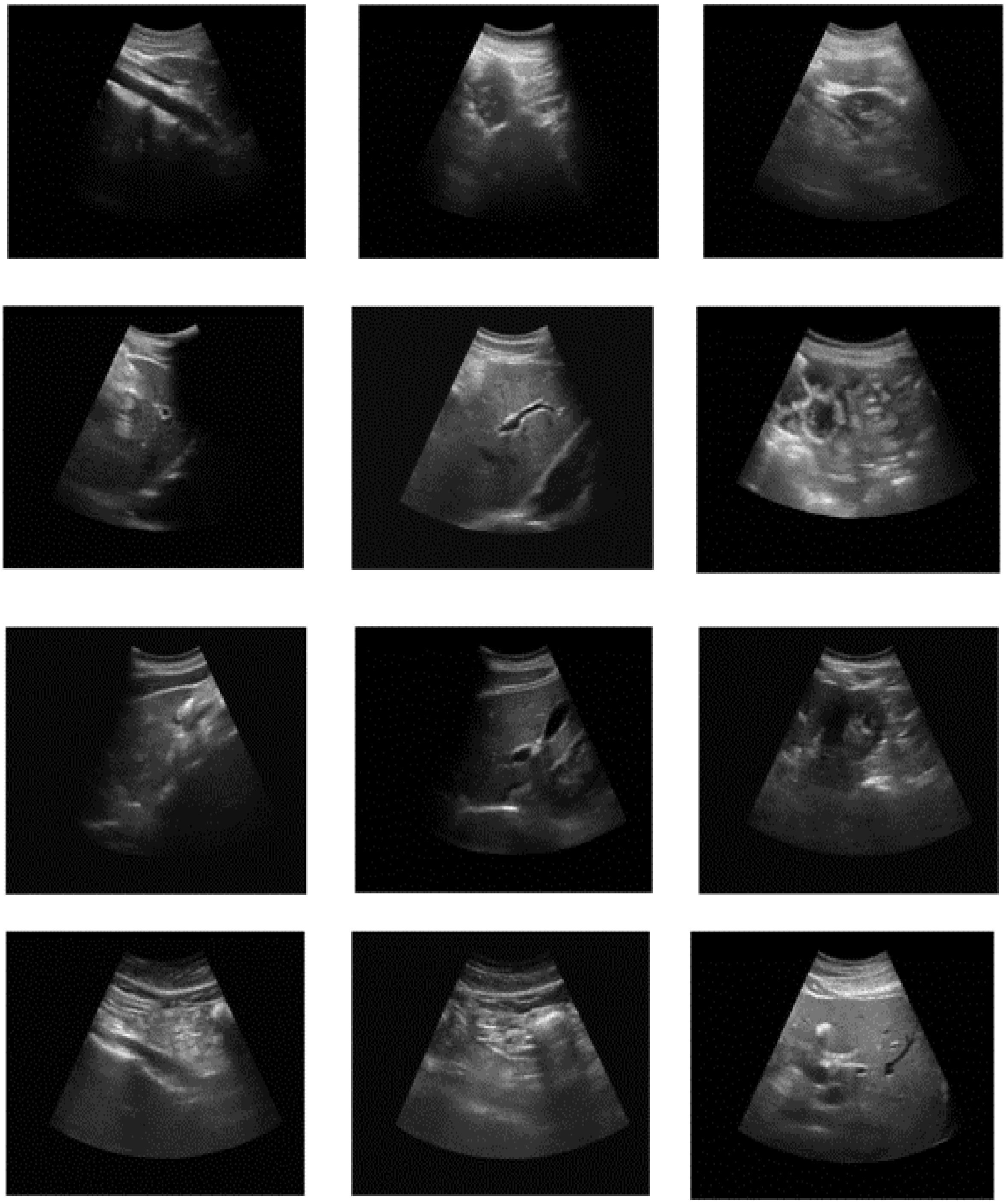

Fig 8. Proposed Hybrid Filtered Images from the noise variance of 0.08dB

Table 1: PSNR Metrics Table for Different Ultrasound Images

Image No.	Lee Filter (PSNR) in dB	Kuan Filter (PSNR) in dB	Frost Filter (PSNR) in dB	SRAD (PSNR) in dB	Hybrid Filter (PSNR) in dB
Image 1 (a1)	31.5	31.25	39.56	40.08	41.57
Image 2 (a12)	28.97	28.39	37.52	38.07	39.53
Image 3 (a24)	28.2	27.2	36.43	36.94	38.62
Image 4 (b1)	32.95	32.5	39.86	40.56	41.95
Image 5 (b12)	31.01	30.09	37.59	38.32	39.83
Image 6 (b24)	26.84	25.47	35.07	35.76	37.55
Image 7 (g1)	32.75	32.3	39.8	40.44	41.88
Image 8 (g12)	31.97	31.16	38.07	38.9	40.55
Image 9 (g24)	32.18	31.25	38	39.09	40.14
Image 10 (h1)	28.37	27.26	35.47	36.29	37.8
Image 11 (h12)	28.9	27.62	35.46	36.12	37.87
Image 12 (h24)	28.03	26.8	35.75	36.28	37.91

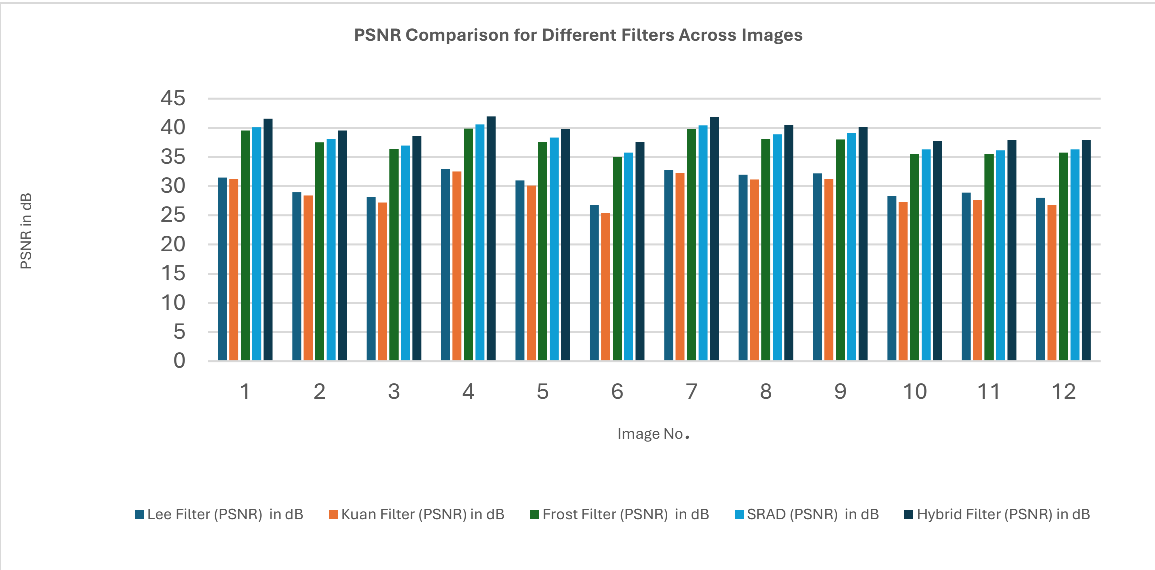

Fig 9. Bar Graph for Different Ultrasound Images

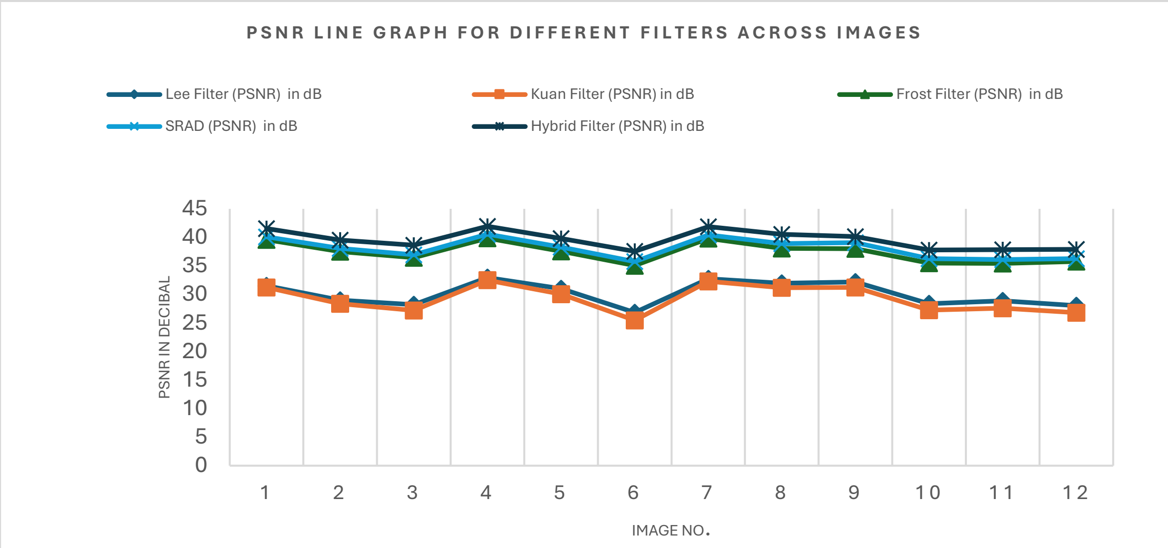

Fig 10. Line Graph for Different Ultrasound Images

Table 2: RMSE Metrics Table for Different Ultrasound Images

Image	Lee Filter (RMSE)	Kuan Filter (RMSE)	Frost Filter (RMSE)	SRAD (RMSE)	Hybrid Filter (RMSE)
Image 1 (a1)	0.02662	0.02737	0.01052	0.00983	0.00835
Image 2 (a12)	0.03561	0.03805	0.01331	0.01248	0.01056
Image 3 (a24)	0.03892	0.04363	0.01509	0.01423	0.01173
Image 4 (b1)	0.02251	0.02371	0.01016	0.00937	0.00799
Image 5 (b12)	0.02817	0.03129	0.0132	0.01213	0.0102
Image 6 (b24)	0.04551	0.05327	0.01764	0.0163	0.01326
Image 7 (g1)	0.02304	0.02428	0.01023	0.0095	0.00805
Image 8 (g12)	0.02522	0.02766	0.01249	0.01135	0.00939
Image 9 (g24)	0.02459	0.02738	0.01259	0.01111	0.00985
Image 10 (h1)	0.03817	0.04336	0.01685	0.01532	0.01288
Image 11 (h12)	0.03587	0.04158	0.01687	0.01563	0.01278
Image 12 (h24)	0.03967	0.04572	0.01632	0.01535	0.01272

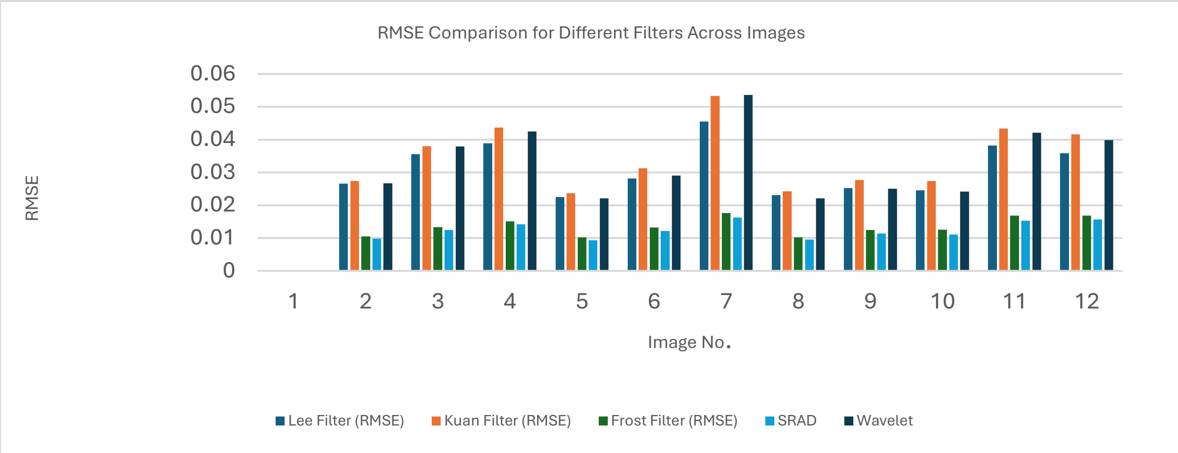

Fig 11. Bar Graph of RMSE for Different Ultrasound Images

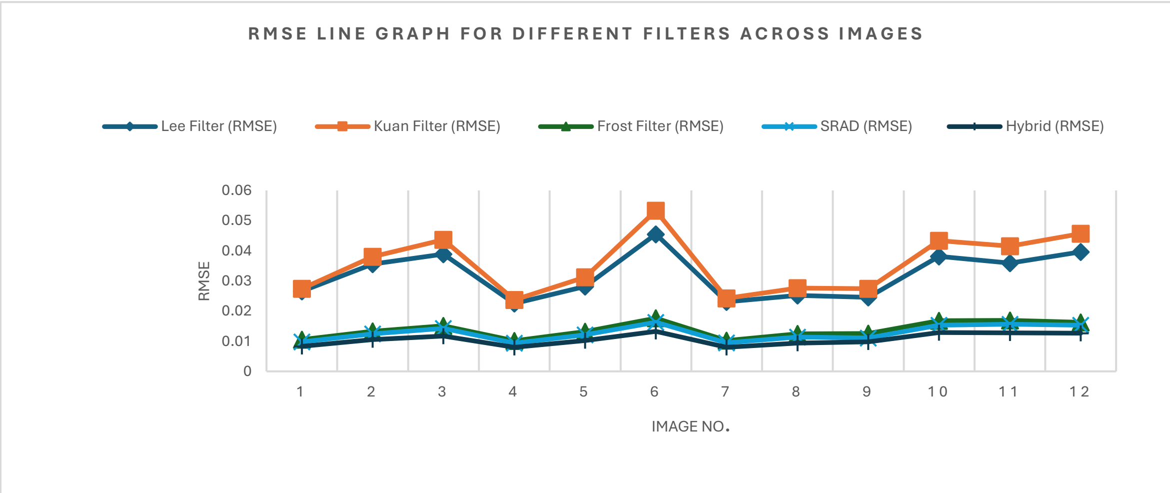

Fig 12. Line Graph of RMSE for Different Ultrasound Images

5. Conclusion and Future Work

This research introduces a hybrid filtering approach that combines Speckle Reducing Anisotropic Diffusion (SRAD), Wavelet Decomposition, and Guided Filtering to effectively reduce speckle noise in ultrasound images. The results demonstrate that the proposed method significantly suppresses speckle noise while preserving crucial image details. Quantitative evaluations using PSNR and RMSE confirm its superior performance compared to conventional and single filtering techniques such as Lee, Kuan, Frost, and SRAD. The hybrid approach enhances noise reduction, improves image clarity, and maintains edge details, which are essential for accurate medical diagnoses. This study contributes to biomedical image processing by addressing the limitations of standalone filtering techniques and providing a more robust and efficient solution for speckle noise reduction in ultrasound imaging.

The scope of this study can be expanded through several promising directions. Firstly, integrating the proposed hybrid filter with deep learning models like Convolutional Neural Networks (CNNs) [1] can enhance its adaptability and performance by leveraging data-driven learning mechanisms. Additionally, extending the application of this filter to 3D ultrasound imaging could provide solutions for volumetric noise suppression, which is essential for modern imaging techniques. Future efforts could also focus on optimizing the hybrid filter for real-time implementation using hardware acceleration techniques such as GPU computing. Finally, exploring the hybrid filter's applicability to other imaging modalities like MRI or CT scans could reveal its potential for broader use in medical diagnostics, making it a versatile tool for advanced biomedical imaging challenges.

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Data Availability

The source code and related materials for this research are publicly available on GitHub at: https://github.com/shubham310703/Speckle_noise_reduction_using_various_filters.git. This repository is intended to support further exploration and development in the field of biomedical image processing.

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