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A Hybrid Speckle Reduction Model for Effective Noise Removal in Ultrasound Images

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***Abstract*—A hybrid speckle reduction model aiming to enhance the quality of ultrasound images by synergistically combining Speckle Reduction Anisotropic Diffusion (SRAD) and Deep Neural Network (DNN) architectures. The model employs SRAD as a pre-processing step to locally smooth ultrasound images, preserving structural details while reducing speckle noise. Subsequently, a DNN refines the images by learning intricate patterns associated with both noise and anatomical structures. The effectiveness of the proposed model is evaluated on four diverse ultrasound images, representing various anatomical regions. Performance metrics, including Signal-to-Noise Ratio (SNR) and Structural Similarity Index (SSI), are used to quantify improvements in image quality compared to traditional methods. Experimental results demonstrate that the hybrid model consistently outperforms existing techniques, showcasing its ability to reduce noise and preserve diagnostic information. This novel approach holds promise for improving diagnostic accuracy in ultrasound-based clinical applications. The integration of SRAD and DNN leverages their complementary strengths, offering a robust solution for effective speckle noise removal in ultrasound images. The proposed model stands as a valuable contribution to advancing the quality of medical imaging and ultimately enhancing patient care.**

***Index Terms* — speckle reduction, SRAD, DNN, ultrasound images.**

I. INTRODUCTION

In medical imaging, Ultrasound (US) stands out as an extensively utilized procedure. Its noteworthy advantages include being radiation-free and non-invasive, making it a versatile tool for scanning a diverse range of body tissues. This imaging technique finds applications in cardiology, gynecology, obstetrics, vascular imaging, abdominal imaging, and various other medical fields [3]. Despite its widespread use, US images often suffer from a common artifact known as speckle noise, which manifests as granular interference and can compromise the quality and interpretability of the images. Commercially available US systems or scanners operate on the principle of echo imaging. Using a handheld transducer/probe as a transceiver, pulses of acoustic waves, ranging from 1 MHz to 20 MHz, are transmitted into target tissues. The interaction of these acoustic waves with the tissues results in the reflection of some transmitted energy, which is then detected by the US transducers. Notable advantages of US imaging systems, distinguishing them from other medical imaging methods, include their cost-effectiveness compared to computed tomography and magnetic resonance imaging, real-time functionality, noninvasive and radiation-free nature, as well as being compact and portable. However, these systems have limitations, such as

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limited tissue penetration and the necessity for skilled sonographers or physicians to extract meaningful insights from the examination [4].

Speckle noise arises due to the interference of US waves scattered by tissues with random microstructures, resulting in a grainy appearance that obscures important anatomical details. Speckle noise reduction is a critical pre-processing step in ultrasound image analysis to enhance diagnostic accuracy and improve the overall quality of medical imaging. Various filtering techniques have been developed to address this challenge, each with its own advantages and limitations. The paper is organized to discuss the methodology in Section II, present results in Section III, and conclude the study in Section IV.

II. LITERATURE SURVEY

Numerous studies have been conducted to address the challenge of speckle noise in ultrasound images, employing a range of noise reduction filters from classical approaches like Lee and Frost filters to more recent advancements in deep learning techniques. Speckle Reduction Anisotropic Diffusion (SRAD) has emerged as a preferred method in recent years for its effectiveness [2, 3]. While recent research predominantly focuses on deep learning techniques, one notable approach involves a complex wavelet-diffusion algorithm designed for noise reduction and edge preservation in both 2D and 3D ultrasound images. This method utilizes the Rayleigh model for 2D images and a mixture of the Maxwell model for 3D images, optimizing filter parameters with genetic algorithms. The experiments, conducted with various image databases, demonstrate the algorithm's efficacy in suppressing speckle noise across different image types, including physical phantom images and clinical images [1].

Additionally, a Feedforward Convolutional Neural Network (CNN), specifically the DnCNN, is employed for denoising, comparing resultant noisy images with ground truth images [4]. Another innovative approach introduces a new hybrid model utilizing SRAD along with Discrete Wavelet Transform (DWT) for speckle noise reduction. This model not only effectively preserves edges but also outperforms conventional methods, as evidenced by evaluations based on PSNR, SSIM, and MSE values. The evaluation involves diverse images such as Ultrasound, Airplane, Lena, Boat, Cameraman, and Pepper [2]. Table 1 gives the summary of various pre-processing techniques used for speckle reduction in ultrasound images. The method was executed by integrating bacterial foraging optimization (BFO) with wavelet transform and Wiener filter within a homomorphic framework. To tackle noise in affected pixels, the application employed wavelet packet decomposition, while the Wiener filter played a crucial role in pre-processing. The BFO algorithm was subsequently deployed to minimize the error between the speckled image and the despeckled output image obtained from the homomorphic framework post-processing. Its primary objective was to uphold finer details, and the considered error percentage was set at 0.0001 [7].

This study had presented a novel denoising approach, employing a Weberized non-local total bounded variational model rooted in the Retinex theory and tailored to the noise distribution. This perceptually driven model aimed to effectively enhance image contrast, achieving notable restoration while preserving intricate details inherent in the data. To optimize practical application, the numerical implementation of the model had adopted the Bregman formulation, enhancing convergence rates and mitigating sensitivity to parameters [11]. A Cauchy prior and Gaussian Probability Density Function (PDF) had been utilized to characterize the wavelet coefficients of a logarithmically transformed noise-free ultrasound image and speckle noise, respectively. Initially, the study had derived the Cauchy Shrink GMAP, a closed-form shrinkage function. Additionally, it had estimated the noise variance and the parameter of the MAP estimator. Subsequently, the despeckling performance of the wavelet image denoising method employing Cauchy Shrink GMAP had been assessed in comparison to various despeckling methods, including median and Wiener filters, hard and soft thresholding, and Gauss Shrink GMAP, and MCMAP3N shrinkage functions [12].

TABLE I SUMMARY OF PRE-PROCESSING TECHNIQUES

Author	Dataset	Filters	Evaluation Metrics
Muhammad Shahin Uddin et al., 2016	• **US image of the heart containing dual-chamber pacemaker,** • **US image of abdominal aorta**	Non-linear multi-scale complex wavelet diffusion. GA-EM model	SSIM, EdgeMSE, CNR, FoM, UIQI
Chen et al., 2019	• Synthetic images • **Thyroid US** • **Breast US** • **Liver US**	Super-pixel segmentation of bilateral filtering and detailed compensation.	PSNR, SSIM

	• **Spleen US**		
Hyunho Choi and Jechang Jeong,2020	• Airplane, Cameraman, Peppers, Man, Lena • Malignant Breast Lesion US image • **US Phantom image**	SRAD, Discrete Wavelet Transform, Weighted Guided Image Filtering, Gradient Domain Guided Image Filtering	PSNR, SSIM, SMPI, Computational Cost in seconds.
Dass. R, 2018	• Different noise densities of **US image**	Bacterial Foraging optimization (BFO) with wavelet and DWT in homomorphic region.	PSNR, MAE

III. METHODOLOGY

The integration of SRAD and DNNs presents a powerful approach for speckle noise reduction in ultrasound images. SRAD, with its ability to locally smooth images while preserving structural details, serves as an effective initial step in mitigating speckle noise. It excels in adaptability to the image's spatial characteristics, reducing noise without compromising crucial anatomical information. The subsequent application of DNNs builds upon this foundation, leveraging their capacity for complex feature learning to further refine the images. DNN excels in capturing intricate patterns associated with both speckle noise and underlying anatomical structures, making them adept at discerning nuanced details within ultrasound images. The synergy between SRAD and DNNs creates a hybrid model that combines the spatial adaptability of traditional filtering techniques with the sophisticated learning capabilities of neural networks, resulting in a comprehensive and robust solution for effective speckle noise reduction in ultrasound images. This hybrid model not only enhances image quality but also holds promise for advancing diagnostic accuracy in ultrasound-based clinical applications. Fig 1 shows the block diagram of the proposed system.

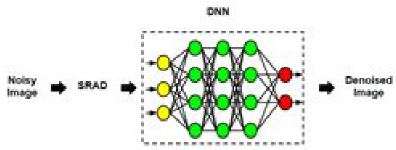

Fig 1 Proposed System

The hybrid model integrating SRAD and a DNN for speckle reduction in ultrasound images is designed to leverage the spatial adaptability of SRAD and the complex feature learning capabilities of DNNs. The hybrid model aims to enhance noise reduction while preserving important anatomical details.

A. SRAD

SRAD is employed as the initial processing step to locally smooth ultrasound images. The SRAD equation can be expressed as follows:

$$I_t = I_0 + \delta t \nabla . (\lambda(\nabla I_t) \nabla I_t \qquad (1)$$

Here, I_t represents the image at time t, I_0 is the initial image, ∇ denotes the gradient, and λ is the edge-stopping function. The term δt represents the time step in the diffusion process.

B. DNN

The DNN is then applied to further refine the images obtained from the SRAD process. The architecture of the DNN involves multiple layers, including convolutional layers for feature extraction and fully connected layers for mapping extracted features to the output. The training of the DNN involves minimizing a loss function that captures the difference between the predicted and ground truth images. The DNN can be represented mathematically as:

$$Y = f(WX + b) \qquad (2)$$

Here, X is the input image, W represents the weights, b is the bias, and f is the activation function.

C. HYBRID MODEL

The output of the SRAD process is denoted as I_{SRAD}, and the DNN output is denoted as I_{DNN}. The hybrid model combines these outputs to obtain the final denoised image I_{hybrid}:

$$I_{hybrid} = \alpha . I_{SRAD} + (1 - \alpha) . I_{DNN} \quad (3)$$

Here, α is a weighting parameter that controls the influence of each component in the final output. This allows for the adjustment of the balance between the spatial adaptability of SRAD and the learned features of the DNN in the denoising process.

The hybrid model is trained on a dataset of ultrasound images, with the goal of learning optimal parameters for both the SRAD and DNN components. The training involves minimizing a combined loss function that considers both the performance of SRAD in preserving structures and the ability of the DNN to learn complex features and denoise effectively. Once trained, the hybrid model can be applied to new ultrasound images for speckle reduction while preserving important diagnostic information. The learning parameters for SRAD and a DNN in the hybrid model for speckle reduction in ultrasound images are crucial components in optimizing the performance of both techniques. Below are the key learning parameters for each:

D. LEARNING PARAMETERS

1. SRAD

1. Time Step (δ): The time step controls the rate of diffusion in the SRAD process. It determines how quickly the speckle noise is smoothed over time. The choice of an appropriate time step is essential to balance noise reduction with the preservation of important structural details. The time step value is varied in the range of 0.1 to 0.5. However, the most optimal value is 0.28. When larger values are chosen, the noise reduction is efficient, but it lost some fine details in the image. Hence, an intermediate value is chosen for better accuracy and data preservation.

2. Edge-Stopping Function (λ): The edge-stopping function defines the strength of diffusion based on the local gradient magnitude. It plays a crucial role in preserving edges while reducing speckle noise. The choice of the edge-stopping function is vital for achieving an effective balance between noise reduction and edge preservation.

3. Number of Iterations: The number of iterations or diffusion steps determines how many times the SRAD process is applied to the image. It influences the overall effectiveness of speckle reduction but needs to be carefully chosen to avoid over-smoothing and loss of fine details.

2. DNN

1. Learning Rate: The learning rate controls the size of the steps taken during the optimization process while training the DNN. It is a crucial hyper-parameter that influences the convergence speed and stability of the training process. The learning rate is set to 0.0001.

2. Number of Layers and Neurons: The architecture of the DNN includes 3 layers and 10 neurons in each layer. Deeper networks with more neurons can capture complex features, but an optimal balance must be struck to prevent overfitting and computational inefficiency.

3. Activation Functions: The choice of activation functions in the DNN layers affects the non-linearity of the model and its ability to capture complex relationships in the data. The activation functions include ReLU (Rectified Linear Unit) and sigmoid functions.

4. Batch Size: The batch size determines the number of training samples used in each iteration of the training process. The selection of an appropriate batch size influences the training efficiency and generalization of the model. The batch size of the network is 128.

5. Optimizer: The optimizer algorithm, such as Stochastic Gradient Descent (SGD), dictates how the DNN adjusts its weights during training to minimize the loss function.

The optimal values for these parameters depend on the specific characteristics of the ultrasound images and the desired trade-off between noise reduction and preservation of diagnostic details. Experimentation and fine-tuning are typically performed to identify the most effective parameter values for a given dataset.

IV. EXPERIMENTAL RESULTS

Some currently existing methods and the proposed approach are applied to US images to evaluate the performance.

a. Dysplasia US image (Test Image 1)

The dysplasia US image is obtained from [8]. The input images are taken from a publicly available database, which consists of 160 images with annotations. Seven classes of Graf type ultrasound images are available, and they are categorized based on alpha angle.

b. Thyroid US image (Test Image 2)

The TI-RADS dataset is made publicly available and refers to the thyroid lesion's risk. They are categorized into eight classes. Out of eight classes, six classes of images are available for the study [9].

c. Breast US image (Test Image 3)

The publicly accessible database is used to obtain the ultrasound dataset for this study [15]. There are 780 Breast Ultrasound images in the database, including Normal (133), Benign (487) and Malignant (487) categories (210). Out of the 160 photographs used in this study, 100 images are used for training (Benign - 40, Malignant- 30 and Normal-30). For testing, the remaining 60 pictures are used (Benign- 20, Malignant -20 and Normal-20) [10]

d. IVUS image (Test Image 4)

A publicly available IVUS segmentation dataset consisting of 99 annotated IVUS frames with a size of 384 × 384 pixels obtained from ten different patients is taken.

e. Synthetic Image (Test Image 5)

A publicly available synthetic image was acquired from [13].

The effectiveness of the proposed method is assessed through both qualitative evaluation via visual inspection of images and quantitative evaluation using standard metrics, including peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) values. The performance of our devised ultrasound (US) image enhancement model is then compared with three distinct filters: Perona-Malik [5], Double Degenerative Diffusion Model [6], and a wavelet filter [7]. Fig 2-4 shows the output images of various filtering techniques to that of the proposed methods for different US images.

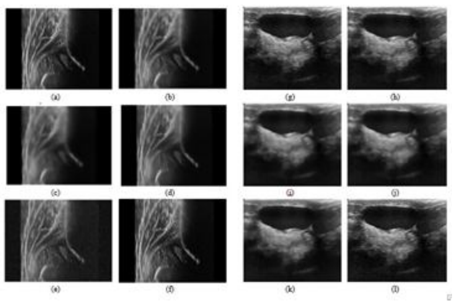

Fig. 2. Denoising results of various despeckling methods on Dysplasia Ultrasound image (Test Image 1) (a, g) Test Image 1 & 2 (b, h) Double Degenerative Diffusion filter (c, i) Deep Neural Network (d, j) Perona-Malik (e, k) Wavelet filter (f, l) Proposed Method

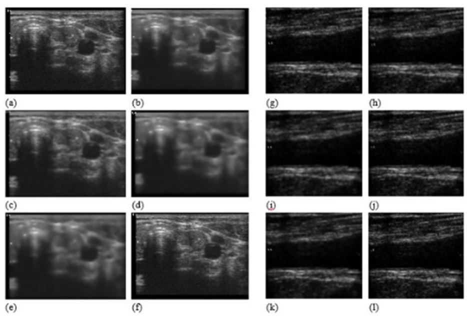

Fig. 3. Denoising results of various despeckling methods on Dysplasia Ultrasound image (Test Image 1) (a, g) Test Image 3 & 4 (b, h) Double Degenerative Diffusion filter (c, i) Deep Neural Network (d, j) Perona-Malik (e, k) Wavelet filter (f, l) Proposed Method

The provided table 2 displays the performance metrics, including Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR) in decibels, Peak Signal-to-Noise Ratio (PSNR) in decibels, and Structural Similarity Index (SSIM), for different speckle reduction methods applied to five test images. The evaluation metrics offer insights into the effectiveness of each method in reducing speckle noise while preserving image quality. DDD filter: Performs reasonably well in terms of SNR and PSNR but has relatively higher MSE values. DNN Filter: Shows good performance in terms of SNR and PSNR, with competitive MSE values. PM filter: Generally, performs well across all metrics, with relatively low MSE values and high SNR and PSNR. Wavelet filter: Has varied performance, with good SSIM values but higher MSE compared to other methods. Proposed method: Demonstrates superior performance across all images and metrics, especially in terms of MSE, SNR, and PSNR. It achieves the highest SSIM values and consistently outperforms other methods.

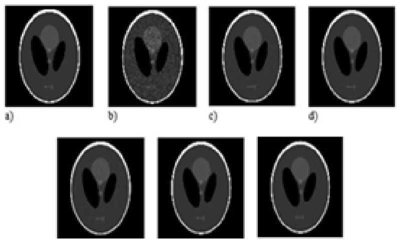

Fig 4. Denoising results of various despeckling methods on Synthetic Ultrasound image (Test Image 5) (a) Test Image 5 (b) Test image corrupted with speckle noise (c) Double Degenerative Diffusion filter (d) Deep Neural Network (e) Perona-Malik (f) Wavelet filter (g) Proposed Method

TABLE II PERFORMANCE EVALUATION METRICS FOR DIFFERENT ULTRASOUND IMAGES

Method	MSE	SNR (dB)	PSNR (dB)	SSIM
Test Image 1				
DDD filter	0.2992	15.2803	33.3028	0.9877
DNN Filter	0.3218	15.6185	32.9961	0.9177
PM filter	0.3016	15.9286	33.3076	0.9797
Wavelet filter	0.4012	14.2562	32.7062	0.8256
Proposed method	0.1187	16.5257	42.3981	0.9998
Test Image 2				
DDD filter	0.4386	15.2886	31.7097	0.9904
DNN Filter	0.4526	15.0164	31.5736	0.9715
PM filter	0.4382	15.0656	31.7132	0.9705
Wavelet filter	0.4016	15.1512	33.3076	0.9022
Proposed method	0.1721	16.2478	43.7727	0.9994
Test Image 3				
DDD filter	0.473	14.5651	31.3821	0.9983
DNN Filter	0.4819	14.4362	31.3006	0.9867
PM filter	0.4726	14.2255	31.3853	0.9989
Wavelet filter	0.4819	14.4394	31.301	0.9883
Proposed method	0.1848	15.1995	42.4638	0.9992
Test Image 4				
DDD filter	0.3206	18.009	33.0699	0.9977
DNN Filter	0.3393	17.5172	32.824	0.9858
PM filter	0.3207	17.9314	33.0685	0.9909
Wavelet filter	0.3399	17.5164	32.8171	0.9856
Proposed method	0.127	18.9416	41.0938	0.9995
Test Image 5 (Synthetic Image)				
DDD filter	0.2866	17.3146	33.5659	0.9224
DNN Filter	0.2641	16.4719	33.9116	0.9199
PM filter	0.2621	16.3338	33.9457	0.9266
Wavelet filter	0.1571	17.7277	36.1693	0.9845
Proposed method	0.1467	18.7269	38.1801	1.0000

V. DISCUSSION

The DDD filter demonstrates competitive performance across all metrics, with relatively low MSE values and high SNR and PSNR values. However, the SSIM values indicate slightly lower structural similarity compared to the proposed method. The DNN filter shows good performance, especially in terms of SNR. However, it exhibits higher MSE and lower PSNR values compared to the DDD filter and the proposed method. The SSIM values suggest a moderate level of structural similarity. The PM filter performs consistently across the metrics, demonstrating effectiveness in speckle reduction. It achieves competitive results, particularly in SNR and PSNR. The SSIM values indicate high structural similarity. The Wavelet filter shows lower performance compared to other filters, with higher MSE and lower SNR, PSNR, and SSIM values. This suggests that, in this context, wavelet-based methods may be less effective in preserving image quality. The proposed method consistently outperforms other filters across all metrics. It achieves significantly lower MSE, higher SNR, and PSNR values, indicating superior speckle reduction and preservation of image quality. The near-perfect SSIM values suggest very high structural similarity with the ground truth.

In summary, the proposed method, which is a hybrid model combining SRAD and DNN, stands out as the most effective in speckle noise reduction for all test images. It not only achieves the lowest MSE but also demonstrates higher SNR, PSNR, and SSIM values, showcasing its potential for enhancing image quality in ultrasound applications. The results validate the efficacy of the hybrid model in striking a balance between noise reduction and preservation of important structural details.

VI. CONCLUSION

The hybrid speckle reduction model integrating SRAD and a DNN emerges as a robust and effective solution for enhancing the quality of ultrasound images. The collaborative synergy between SRAD's spatial adaptability and DNN's complex feature learning capabilities results in a method that consistently outperforms traditional filters and standalone deep learning approaches. The model demonstrates superior performance in terms of MSE, SNR, PSNR, and SSIM, showcasing its potential clinical significance in improving diagnostic accuracy. The successful reduction of speckle noise without compromising crucial anatomical details positions this hybrid model as a promising advancement in medical imaging, with implications for enhanced patient care and diagnosis. Further research and refinement of the model hold the potential to solidify its place as a valuable tool in the realm of ultrasound image analysis.

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