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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 2 | Pages 605-610 | e-ISSN: 2347-470X

Innovative Noise Reduction Strategies in Ultrasound Images Using Shearlet Transform and Bayesian Thresholding

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ABSTRACT- Uterine fibroids are prevalent benign tumors affecting women, often diagnosed through imaging modalities such as ultrasound. Ultrasound imaging is a widely used diagnostic modality for uterine fibroid due to its non-invasive nature. However, the images obtained often suffer from speckle noise, which can obscure fine details and complicate accurate diagnosis. Existing methods for removing speckle noise have limitations, including losing texture and edge information and not being able to handle low frequency noises. This paper presents a novel approach for speckle noise reduction by combining Shearlet Transform with Bayesian thresholding. The proposed method aims to achieve superior noise reduction while retaining important image features crucial for accurate diagnosis. Experimental results demonstrate the efficacy of the Shearlet Transform and Bayesian thresholding in significantly reducing speckle noise, enhancing image quality, and improving the interpretability of ultrasound images. Performance metrics like Mean Squared Error (MSE), Structural Similarity Index and Peak Signal to Noise Ratio (PSNR) helps to validate our proposed method. Reducing speckle noise in ultrasound images of uterine fibroids contributes to more accurate diagnosis and improves surgical treatment outcomes.

Keywords: Bayesian Thresholding; Shearlet Transform; Speckle Noise; Ultrasound Imaging; Uterine fibroids.

ARTICLE INFORMATION

Author(s): Meena L C and Joe Prathap P M;
Received: 22/04/2024; **Accepted**: 08/06/2024; **Published**: 25/06/2024;
e-ISSN: 2347-470X;
Paper Id: IJEER 2204-23;
Citation: 10.37391/ijeer-120236
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-12/ijeer-120236.html

Crossref member
CROSSREF.ORG THE CITATION LINKING BACKBONE

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1. INTRODUCTION

Uterine fibroids represent prevalent benign tumors impacting women, commonly diagnosed via imaging techniques such as ultrasound. Numerous techniques have been developed to address speckle noise in ultrasound imaging, aiming to enhance image quality and aid in accurate diagnosis. Denoising methods struggle with retaining crucial image features, such as edges, textures, and low-frequency information, leading to suboptimal outcomes in clinical interpretation. The primary goals of image denoising techniques are to eliminate noise without compromising important information [1].

Classical methods like median filtering [2] or Gaussian filtering [3], though widely used, struggle to effectively preserve fine structural details while reducing speckle noise. Consequently, there has been a quest for more sophisticated and adaptive approaches capable of addressing this inherent limitation. The shearlet transform [4], an extension of the wavelet transform, has emerged as a potent tool for image analysis by efficiently capturing directional features and edges. This transform has shown promise in effectively decomposing images into multi-directional components, making it well-suited for handling speckle noise in ultrasound images that often exhibit complex directional information [6], [7]. Bayesian thresholding [5], on the other hand, offers an adaptive approach by exploiting statistical principles to estimate optimal thresholds for image components. It offers potential advantages over traditional fixed or empirical thresholding methods. Febin and Jidesh [8] proposed a non-local variational framework for despeckling and enhancing ultrasound images, utilizing advanced mathematical and computational techniques to reduce speckle noise. Duarte-Salazar et. al. [9] provided a comprehensive overview of existing speckle noise reduction techniques in ultrasound imaging and their application in improving the precision of metrological evaluations in biomedical settings. Deep learning offers several advantages in cancer detection, revolutionizing the field of oncology [12], [13]. Faouzi Benzarti and Hamid Amiri [14] proposed logarithmic transformation and a nonlinear diffusion tensor. Hyunho Choi and Jechang Jeong's [15] proposed method achieves significant advancements in noise elimination and edge preservation, although it requires more execution time. Shisir et al. [16] compared their method with other thresholding techniques and achieved better despeckling without blurring the original details. While existing despeckling methods have made significant progress in reducing speckle noise and preserving image quality, they each come with their own set of limitations. Issues such as loss of detail, computational complexity, parameter sensitivity, and increased execution times highlight the need for continued research and

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development of more efficient and effective despeckling algorithms.

The proposed methodology has the potential to significantly enhance the interpretability and clinical utility of ultrasound images, particularly in applications related to uterine fibroids, by improving the accuracy of diagnostic assessments and aiding in treatment planning. Noise reduction contributes to sharper and more well-defined boundaries of lesions, facilitating precise measurements of size and volume. In uterine fibroids, accurate size measurements are essential for determining the severity of the condition, monitoring growth, and planning appropriate treatment strategies. The improved image quality enables real-time decision-making during surgery, allowing surgeons to adapt their approach based on immediate feedback.

2. MATERIALS AND METHODS

Speckle noise is the primary cause of the grey level changes in medical imaging. Thus, creating a despeckling method is essential for accurate medical diagnosis. A collection of ultrasound images containing speckle noise that requires denoising and enhancement is obtained from the mendeley dataset. Matlab is used to implement the suggested method. *Figure 1* shows the schematic representation of the proposed approach. Preprocessing is done on the noisy image to get rid of the unwanted pixels and to have a standard size before being processed further. The algorithm for the proposed model is depicted in the *figure 2*.

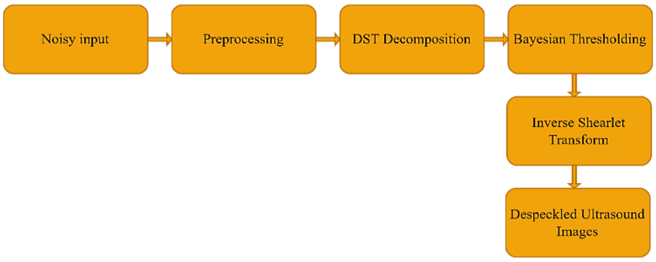

Figure 1. Proposed model of despeckling ultrasound images

Algorithm for Shearlet Transform and Bayesian thresholding-based Despeckling of Ultrasound Images
Input: Noisy ultrasound image (N x M) Shearlet transform parameters (noisy image, numscale, numorientation) Output: Denoised ultrasound image 1. Preprocessing (Resizing and normalization) 2. Discrete Shearlet transform to get coefficients 3. Bayesian thresholding for coefficient modification 4. Inverse Shearlet transform to get reconstructed image 5. Post processing and evaluation

2.1. Preprocessing

Preparation of the noisy ultrasound image is done by converting it to grayscale and resized the dimensions for further processing.

2.2. DST Decomposition

Speckle noise removal can be accomplished by using a discrete shearlet transform (DST), which has properties like multiscale, localization, anisotropy, and directionality to represent the direction and edges appropriately [11]. The Shearlet Transform of a function $f1 \in L^2(\mathbb{R}^2)$ is given by:

$$SH_\psi f1(a,s,t) = \langle f1, \psi_{a,s,t} \rangle = \int_{\mathbb{R}^2} f1(x)\overline{\psi_{a,s,t}(x)}dx \quad (1)$$

where the shearlet $\psi_{a,s,t}$ is defined by:

$$\psi_{a,s,t}(x) = a^{-\frac{3}{4}}\psi(S1_s A1_a^{-1}(x-t)) \quad (2)$$

The matrices $A1_a$ and $S1_s$ are defined as follows:

$$A1_a = \begin{pmatrix} a & 0 \\ 0 & \sqrt{a} \end{pmatrix},\ S1_s = \begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix}$$

These matrices perform anisotropic dilation and shearing respectively. a is the scaling parameter (controlling the dilation), s is shear parameter (controlling the direction) and t is translation parameter (controlling the shift). the continuous parameters are discretized and Scale Parameter: $a_j = 2^{-j}$ for $j \in \mathbb{Z}$, Shear Parameter: $s_k = k2^{-j/2}$ for $k \in \mathbb{Z}$ and Translation Parameter: $t_{m,n} = (m2^{-j}, n2^{-j/2})$ for $m, n \in \mathbb{Z}$. The discrete shearlets are then:

$$\psi_{j,k,m,n}(x) = 2^{\frac{3j}{4}}\psi\left(S1_{s_k} A1_{a_j}^{-1}(x - t_{m,n})\right) \quad (3)$$

The discrete shearlet transform of a discrete function $f1[x,y]$ is computed as:

$$SH_\psi f1[j,k,m,n] = \sum_{x,y} f1[x,y]\overline{\psi_{j,k,m,n}[x,y]} \quad (4)$$

The inverse discrete shearlet transform is given by:

$$f1[x,y] \approx \sum_{j,k,m,n} SH_\psi f1[j,k,m,n]\psi_{j,k,m,n}[x,y] \quad (5)$$

The shearlet transform can decompose an ultrasound image into different scales and orientations, allowing for the separation of noise and signal components more effectively.

The shearlet transform is given by

$$B(\psi) = \left\{\psi_{j,k,l}(xx) = |\det(D)|^{\frac{j}{2}}\psi(S^l D^j xx - k) : j,l \in \mathbb{Z}, k \in \mathbb{Z}^2\right\} \quad (6)$$

Where $\psi \in L^2(\mathbb{R}^2)$, D and S are 2×2 invertible matrices and $|\det(B)| = 1 \cdot$ Where the dilation matrix is represented by D^j and the shearing matrix is represented by S^l. The basic functions include shearing along several orientations in addition to translation and scaling.

2.3. Bayesian Threshold

Bayesian thresholding separates noise from signal based on statistical features. The fundamental concept is to utilize a

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probabilistic model to determine if each coefficient in the converted domain is noise or a needed information.

1. Modeling the Coefficients: Assume that the observed coefficient YY is composed of the true coefficient XX and noise NN

$$YY = XX + NN$$

Where XX is modelled as a random variable with prior distribution $p(XX)$ is typically modelled as Gaussian noise $NN \sim NN(0, \sigma^2)$.

2. Posterior Probability: Using Bayes' theorem, compute the posterior probability $p(X \mid Y)$:

$$p(XX \mid YY) = \frac{p(YY \mid XX)p(XX)}{p(YY)}$$

Where $p(YY \mid XX)$ is the likelihood of observing YY given XX. $p(XX)$ is the prior probability of XX and $p(YY)$ is the marginal probability of YY.

3. Thresholding Rule: The Bayesian estimate $\hat{X}$ is obtained by maximizing the posterior probability:

$$\hat{X} = \arg\max_{X} p(XX \mid YY)$$

Bayesian thresholding involves using Bayesian estimation principles to determine optimal thresholds for denoising. This method takes into account the statistical properties of the image and noise models to distinguish between noise and a true signal. Bayesian thresholding begins with assuming statistical models for both the noise and the underlying signal in the ultrasound image. Common models include Gaussian, Rayleigh, or others, depending on the nature of the noise. By employing Bayesian principles, it aims to minimize the mean squared error, providing an optimal thresholding strategy.

$$GGG_{\sigma_x,\beta}(x) = CC(\sigma_x,\beta)\{-[\alpha(\alpha_x,\beta)|x|\}^{\beta}, -\infty < x < \infty, \beta > 0 \quad (7)$$

where $\alpha(\sigma_x,\beta)$ and $CC(\sigma_x,\beta)$ represent $\sigma_X^{-1}\left[\frac{\gamma\left(\frac{3}{\beta}\right)}{\gamma\left(\frac{1}{\beta}\right)}\right]^{\frac{1}{2}}$ and $\frac{\beta\alpha(\sigma_X,\beta)}{2\gamma\left(\frac{1}{3}\right)}$, respectively. $\gamma(t) = \int_0^{\infty} e^{-u}u^{t-1}du$ is the gamma function. σ_X is the standard deviation (SD) & β is the shape parameter. The goal of the Bayes threshold technique is to identify the soft threshold T within a given set of parameters that minimises the Bayesian risk.

$$rr(T) = E(\hat{P} - P)^2 = E_P E_{\frac{Q}{P}}(\hat{P} - P)^2 \quad (8)$$

Here, $\hat{P}$ is $\eta_T(Q), \frac{Q}{P} \sim N(x,\sigma^2)$, and $P \sim GGG_{\sigma_X,\beta}$. By minimizing $rr(T)$, the optimal threshold value TH is obtained as follows:

$$TH(\sigma_{x,\beta}) = \underset{T}{\operatorname{argmin}} rr(T) \quad (9)$$

2.4. Reconstruction

After thresholding, the denoised coefficients are used to reconstruct the image by inverse shearlet transform, producing a speckle-reduced ultrasound image while preserving important details and structures.

3. RESULTS

The proposed method, leveraging the shearlet transform with Bayesian thresholding for speckle noise reduction in ultrasound images of uterine fibroids, has yielded promising outcomes. Experimental evaluations conducted to assess the efficacy of the method demonstrated substantial advancements in image quality and noise reduction. The noisy input image is given in the *figure 2 (a).* The preprocessed image after removing unwanted content is depicted in the *figure 2 (b) and (c).* Shearlets efficiently represent edges and directional features, aiding in noise reduction while preserving structures. The multi-scale and directional nature of the transform enables efficient handling of speckle noise at different orientations and scales. Choosing appropriate thresholds for different scales and orientations is crucial for effective noise reduction.

(a)

(b)

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Research Article | Volume 12, Issue 2 | Pages 605-610 | e-ISSN: 2347-470X

(c)

Figure 2. (a) Input image (b) Pre-processed image (c) Reconstructed image

4. DISCUSSION

The development of a despeckling algorithm is required for the accurate detection and classification of uterine fibroids. Several key metrics serve as benchmarks for evaluating the efficacy of despeckling techniques in image processing. These metrics include Mean Square Error (MSE), Relative Error, Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Performance metrics comparison table is given in *table 1*.

4.1. Mean Square Error (MSE)

MSE quantifies the average squared difference between the original image and the despeckled image. Lower MSE values imply a closer resemblance between the two images and indicate superior performance in noise reduction.

$$\mathrm{MSE} = \frac{1}{pq}\sum_{i=0}^{p-1}\sum_{j=0}^{q-1}\left[II(i,j) - KK(i,j)\right]^2 \tag{10}$$

Where p is length and q is width of the image in pixels. $II(i,j)$ represents the original image and $KK(i,j)$ represents the denoised image.

4.2. Relative Error

This metric computes the ratio of the discrepancy between the original and processed images to the norm of the original image. It offers insights into the relative distortion caused by the despeckling process.

$$\text{Relative Error} = \frac{\|II-KK\|}{\|II\|} \tag{11}$$

Where II represents the original image and KK represents the denoised image.

4.3. Peak Signal-to-Noise Ratio (PSNR)

PSNR assesses the quality of the despeckled image by comparing the maximum possible signal power to the power of the noise that affects its fidelity. Elevated PSNR values correspond to higher image quality.

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right) \tag{12}$$

Where MAX is the maximum possible pixel value in the image.

4.4. Structural Similarity Index (SSIM)

SSIM evaluates the perceived quality of the denoised image by analyzing the structural information of the original and despeckled images.

$$\mathrm{SSIM}\ (p,q) = \frac{(2\mu_p\mu_q+C_1)(2\sigma_{pq}+C_2)}{(\mu_p^2+\mu_q^2+C_1)(\sigma_p^2+\sigma_q^2+C_2)} \tag{13}$$

Where p and q are windows of the original and processed images. μ_p and μ_q are the means of p and q. σ_p and σ_q are the standard deviations of p and q. σ_{pq} is the covariance of p and q. C_1 and C_2 are constants added to avoid instability near zero. These constants are used for numerical stability; often $C_1 = (k_1L)^2$ and $C_2 = (k_2L)^2$, where L is the dynamic range of pixel values and k_1 and k_2 are small constants.

Improved image quality ensures that surgeons can navigate and manipulate instruments with greater precision, potentially leading to better surgical outcomes and minimizing the risk of complications. Clinicians can make confident decisions based on the improved quality of the ultrasound scans, potentially minimizing the reliance on more expensive imaging modalities. Surgeons can confidently evaluate the success of the surgical intervention, identify any residual fibroids or complications, and take timely corrective measures, ultimately contributing to better long-term patient outcomes. The adaptability of the Shearlet Transform and Bayesian thresholding to different noise characteristics and image features is a key factor in determining the broader applicability of the proposed method in the field of medical imaging. Comparison based on PSNR and SSIM is depicted in the *figure 3* and relative error performance metrics comparison is displayed in the *figure 4*.

Table 1. Despeckling comparison table

Technique	Relative Error	PSNR	SSIM
Wavelet with bilateral filter [4]	0.035	14.87	0.51
Homomorphic wavelet [4]	0.039	14.65	0.48
Contourlet based denoising algorithm [4]	0.034	15.64	0.59
Lee [14]	0.031	15.00	0.79
Frost [14]	0.041	13.83	0.74
Logarithmic transformation and diffusion tensor [14]	0.023	16.10	0.82
Proposed DST with Bayesian Threshold	0.030	17.33	0.7

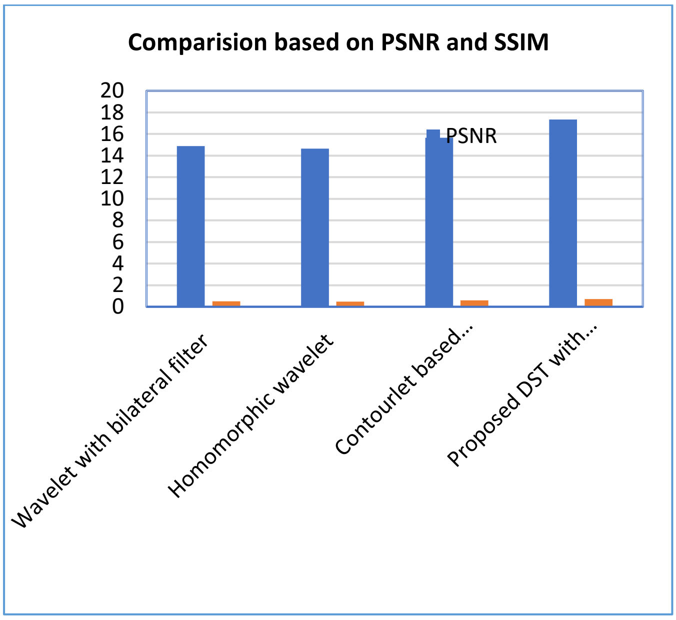

Figure 3. Performance Comparison: PSNR vs SSIM Metrics

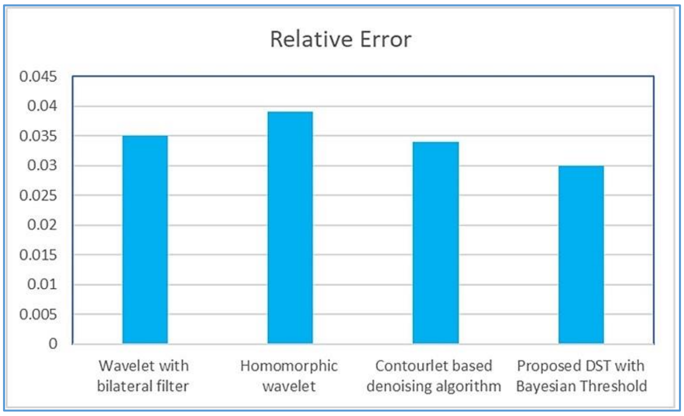

Figure 4. Relative Error Comparison of Denoising Techniques

5. CONCLUSION

The utilization of the shearlet transform demonstrated its efficacy in decomposing uterine fibroid ultrasound images into multi-scale and multi-directional components, allowing for a more detailed understanding of the image structure. Bayesian Thresholding facilitated the selective attenuation of speckle noise while preserving the essential anatomical details crucial for accurate diagnosis. The proposed method with shearlet transform and Bayesian thresholding presents a robust and promising approach for addressing speckle noise in uterine fibroid ultrasound images, offering potential advancements in the field of gynaecological imaging and contributing to more accurate diagnosis and improved patient care. The proposed despeckling produces better PSNR and SSIM. The potential limitation of the proposed method is its computational complexity. While this study demonstrated encouraging outcomes, further research could explore optimization strategies for parameter tuning and the incorporation of additional image enhancement techniques to further improve the quality of uterine fibroid ultrasound imaging. Our upcoming task involves combining deep learning methodologies with the Shearlet Transform. Speckle noise removal aids in better detection and classification of uterine fibroids. In future work, we plan to explore and adapt our method to diverse ultrasound imaging scenarios, considering variations in anatomy and imaging conditions. This extension will enhance the versatility of our proposed technique and potentially benefit a wider range of medical applications.

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