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Anisotropic Diffusion Method for Speckle Noise Reduction in Breast Ultrasound Images

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Abstract: Breast ultrasound is an important technology for detecting breast lesions, but it faces a challenge in the form of speckle noise that negatively affects the quality of images. Effective methods are needed to eliminate this noise without compromising the image's fine edges and important features. In this work, we present a cutting-edge methodology based on a deep understanding of the dynamics of breast ultrasound images and the challenges of speckle noise. The method uses two separate stages of processing with two nonlinear filters. The first filter, the anisotropic diffusion filter, smooths out edges and boosts image contrast by lowering noise while keeping the tissue's structure. In the second stage, the SRAD filter is applied to remove residual noise and refine the image, increasing its clarity and improving the ability to visualize subtle lesions. This improved approach was evaluated using a comprehensive set of quantitative indices. The results confirmed the significant performance improvement provided, with the lowest MSE value of 0.2 and the highest PSNR of 59.3. Also, it reached the optimal value in the UQI and SSI, which indicates the robustness of the method in maintaining the quality of the structural image. The results confirm the value of the proposed approach and herald its promising potential for improving medical diagnostic results using breast ultrasound.

Keywords: Ultrasound images, Speckle noise, Linear filters, Non-linear filters, Anisotropic diffusion, SRAD.

1. Introduction

Women with abnormal mammography results often use breast ultrasound imaging as their main investigative tool. It is important to conduct a thorough breast examination using an ultrasound imaging system [1]. Because it is non-invasive, a trustworthy diagnosis technique, simple to use, non-toxic, and inexpensive, ultrasound is becoming increasingly important. Unfortunately, speckle noise is the main issue with ultrasound imaging [2]. The texture of such noise was formerly assumed to give important information about the histological properties of the tissue area; however, further analyses have proven that speckle noise is essentially an artifact brought on by system imaging. It reduces the contrast and reliability of medical images, making it harder to perform various tasks, such as feature extraction, segmentation, and registration[3, 4]. Moreover, it takes effort and time for doctors to separate essential information from noise-corrupted images. Speckle is a feature of images created using coherent sources; it manifests visually as a random granular texture. Ultrasonic waves are an example of a wave whose phase remains constant, making them ideal for use as a coherent source. Each particle's reflected wave will have a phase and amplitude directly related to its position. That's why the sum of the reflected waves might have a constructive or destructive interaction. When an irregular surface reflects a wave, the image is damaged by appearing speckled,' which is speckle noise. Speckle artifact is a significant contributor to image deterioration and contrast loss. It makes lesion identification more challenging. Consequently, speckle reduction filters are essential for boosting image quality and facilitating the detection of lesions. While suppressing speckle noise, preserving image borders and fine details is essential. A breast ultrasonography lesion is defined by various characteristics, including texture, shape, and boundary; preserving edges and details will enhance diagnostic accuracy [5]. In a review of previous studies, we find multiple attempts to address this problem. In 2019, an algorithm combining a Savitzky-Golay smoothing (SGS) filter and an SRAD filter was proposed. To reduce speckle noise and preserve edges. Experimental results show that the proposed algorithm outperforms traditional methods in noise reduction and edge preservation. Key challenges include computational complexity and the need to precisely define filter parameters to ensure optimal performance [6]. In 2020, a new method for filtering speckle noise in medical images was proposed. This method uses a phase-based measure (PAS) to detect and filter various edges of the image, in addition to reducing speckle noise. The main innovation in this study is the integration of fractional azeotropic dispersion and total diversity into a single framework, providing a significant performance improvement in terms of noise reduction and preservation of image details. However, this method is complex to apply due to its use of advanced techniques such as fractional total contrast and phase analysis [7]. In a 2022 study, a comparative analysis of wavelet conversion systems in ultrasound image denoising was done. This analysis focused on the effectiveness of wave conversion systems using real ultrasound images as well as artificial images contaminated with three types of noise. The study found that the effectiveness of filtering is highly dependent on the settings of the specific waveform conversion system, the type of ultrasound data, and the noise present. The results indicated that selecting appropriate waveform conversion settings is essential to obtain high image quality. A weakness of this study is the complexity associated with selecting and adjusting the appropriate waveform conversion settings for each specific case, which requires skill and experience to achieve the best results [8]. In 2023, a new approach to reduce point noise in medical ultrasound images using Cyclically Consistent Adversarial Neural Network (CycleGAN) was presented. This method involves mode transfer between the noisy data domain and the noise-free data domain to form a global bidirectional mapping. This model uses noise images and noise-free images as input, allowing outstanding results in noise reduction while preserving details. However, the study faces some challenges such as the possibility of instability in training and difficulty in dealing with severe noise, which may affect the accuracy of the results in some cases [9]. Finally, in 2023, an advanced framework for ultrasound image enhancement with an improved hybrid search algorithm and a new kinematic clustering processing chain is presented. This approach uses pre-position frames generated by the specialist before selecting the required diagnostic frame. These frameworks are applied to the improved modified three-step search (O-MTSS) algorithm to improve the final processed framework. The results showed significant improvement in noise reduction while preserving fine edges and details with good computation time for real-time scanning. However, some challenges were identified, such as the possibility of an error in the first step in the algorithm, which could lead to following a wrong path, and distortion of correlations between neighboring pixels. In some of the techniques used, this leads to poor performance with images that contain significant noise [10]. These results highlight the importance of continuous review and improvement of the methods used in processing ultrasound images.

In the field of medical image processing, traditional methods such as linear and nonlinear filters face major challenges in the need for a balance between image resolution and noise removal efficiency. Linear filters, although fast, fall short in preserving fine details and fail to deal with speckle noise effectively. On the other hand, although nonlinear filters are able to preserve edges and details, they have difficulties in handling high noise such as speckle noise [11]. To address these challenges, in this paper we propose to combine an anisotropic diffusion filter, which efficiently handles edges and fine details, but may struggle in the face of dense speckle noise, with an SRAD filter, which has a high ability to reduce noise including speckle noise but may cause Some loss of fine detail. By combining these two filters, we aim to create a balance that combines effectiveness in removing speckle noise while maintaining image quality and resolution. This approach seeks to achieve significant progress in the field of medical image processing, especially in breast ultrasound applications, where high accuracy and processing speed are urgently needed to improve diagnostic results.

Following is the summary of the paper’s content. Several filters for reducing speckle noise and proposed model are discussed in Section 2. The Reduction Filters Evaluation Metric is described in Section 3. Section 4 presents the implementation and quantitative assessment findings. In Section 5, the study’s findings are addressed.

2. Speckle reduction filters

Images often include different types of noise. Numerous operations, such as image acquisition, conversion, and compression, may create noise. Since there are several sorts of noise, it is necessary to give various solutions. Because the brain, heart, and other organs display temporal motion, speckle noise includes high-frequency components. Installing a low-pass filter is necessary to eliminate high-frequency noise. Speckle noise was taken out of breast ultrasound (BUS) images using the following linear and non-linear filters.

2.1 Linear speckle reduction filters

The majority of published solutions for filtering speckle reduction employ linear filtering, which is based on local statistics. Their operating concept may be summarized by a weighted average computation using subregion statistics to estimate statistical measures across distinct pixel windows ranging from $[3 \times 3]$ to $[15 \times 15]$ [12]. Statistical adaptive filters are simply smoothing filters constructed such that areas of an image that closely resemble the speckle statistics are replaced with a local mean value, whilst regions with characteristics that are least similar to speckle are left untouched. Using the following formula, the output of the filter is calculated:

$$f = \overline{W} + k(W - \overline{W}) \tag{1}$$

where k is the adaptive filter coefficient, which is determined based on local statistics, and the mean value within the filter window is represented by the symbol $\overline{W}$.

The average intensity of the mask is combined linearly with each neighborhood's center pixel intensity to create an image via the Lee filter. Local statistics based on a multiplicative speckle model are used in this strategy to conserve data. This filter employs the variance value. Smoothing is used when the resulting variation is slight and is not advised when the variance is large. Since image information may be maintained in low and high contrast, the filter has an adaptable character [13]. The mathematical model for the Lee filter is as shown:

$$I_{mg}(x, y) = I_m + W \times (C_P - I_m) \tag{2}$$

where W is the filter window, I_m is the mean intensity of the filter window, I_{mg} is the pixel value after filtering, C_P is the center pixel,

$$W = \delta^2(\delta^2 + \varepsilon^2), \tag{3}$$

where δ^2 is the variance of the pixel specified as, and ε is the additive noise variance.

$$\delta^2 = \frac{1}{W}\sum_{i=0}^{W-1}(X_i)^2, \tag{4}$$

where X_i is the pixel value at i, and W is the size of the window. The Lee filter is excellent at preserving fine details while reducing noise in images, especially in low-contrast areas. However, it may face challenges in high-contrast areas, where it performs less effectively at reducing noise. [14].

The Frost filter provides a computationally efficient adaptive filter approach to decrease speckle noise in the spatial domain. This filter preserves the important edge properties of the image. It is a minimum mean square error (MSE) convolutional filter for speckle removal. The Frost filter is a circularly symmetric exponentially damped filter that employs local statistics inside individual filter windows. The pixel being filtered is replaced with a value based on the filter's center distance, damping factor, and local variance . For the Frost filter, a damping factor is necessary. The value of the Damping Factor measures exponential damping. The lower the value, the better the filter's performance and smoothness. When the Frost filter is used to de-noised images, the edges become more distinct [15]. It is described as:

$$N = \sum_{m \times m} r\vartheta\, e^{-\vartheta|d|} \tag{5}$$

where, r is the filter parameter, $\vartheta = \left(\frac{4}{m\acute{\sigma}^2}\right)\left(\frac{\sigma^2}{I^2}\right)$, ϑ describes the location of the pixel after processing, m shows a moving kernel, σ represents values for local variance and $\acute{\sigma}$ represents image coefficient of variation. I definition of local mean and $|d|$ is the measurement of the distance from the pixel ϑ. Frost filter effectively preserves edge characteristics and increases image clarity. This filter works in a way that reduces noise while maintaining image quality, but it may be less effective at dealing with high-frequency noise[16].

Kuan filter is a local minimum MSE linear filter subject to multiplicative noise. Even though the signal model assumptions and derivations vary, the formulations of the Kaun and Lee filters are identical. This filter ensures consistency between the averages of comparable areas and detects the presence of edges and points. This stability is dependent on the moving window that contains the variation figure. It is far more sophisticated than the Lee filter because it does not use approximation. It transforms the multiplicative speckle model into the linear additive form. The expression for the weighted function W of the Kuan filter:

$$W = \frac{\left(1 - \frac{C_u}{C_i}\right)}{(1 + C_u)} \tag{6}$$

where, C_u= coefficient of estimated noise variation, $C_u = \sqrt{\frac{1}{ENL}}$, $ENL =$ equivalent noise looks, $C_i =$ image variation coefficient, $C_i = \frac{S}{m}$, $S =$ standard deviation inside the window filter. The Kuan filter efficiently detects edges and spots, which contributes to improving image quality. This filter stands out in areas of low to moderate noise, but its effectiveness may be affected by the severity of the noise in the image [14].

2.2 Non-linear speckle reduction filters

To remove noise from an image, non-linear filtering uses a linear scaling of pixel values and non-linear actions on neighboring pixels. The most homogenous region around each image pixel is the basis for several of the non-linear filters .

Perona and Malik introduced an anisotropic (PM) model for image augmentation and denoising based on a partial differential equation (PDE). PM improves edges by restricting diffusion along edges and promoting isotropic diffusion inside homogenous regions and smooths out images [17]. The mathematical description of this diffusion is shown:

$$\frac{\partial f(t)}{\partial t} = div[C(\|\nabla f(t)\| \times \nabla f(t))],$$
$$f(t = 0) = f \tag{7}$$

where the divergence operator is div, $(\|\nabla f(t)\|)$ is the image $f(t)$ gradient magnitude, $C(\|\nabla f(t)\|)$ is the diffusivity function or the diffusion coefficient and f is the original image. $C(\|\nabla f(t)\|)$ is a non-negative, monotonic, nonincreasing function in the anisotropic diffusion technique over the gradient magnitude. Consequently, the diffusion coefficient may adaptively regulate the diffusion speed, allowing for the differentiation of image edges and the reduction of diffusion in edge areas.

By linearly scaling the gray-level values, the image is despeckled. Calculate the average of all pixels in a moving window of 5×5 pixels whose difference between the grey level and intensity (the middle pixel) is less than or equal to a specified threshold. This filter stands out for improving the image by significantly reducing noise and enhancing edges. However, it requires careful parameter routing to achieve the optimal balance between noise reduction and detail preservation [18].

Median filtering is a non-linear technique that removes “speckle” noise from ultrasound images. It assigns each pixel the neighborhood’s median value. The median is calculated by arranging all of the nearby pixel values in numerical order and then swapping out the pixel value that is being examined for the middle one. Typically, median filters eliminate lines narrower than half the neighborhood’s width and may also round off corners. The hybrid median filter (HMF) is an improved median filter that may avoid these issues. It can eliminate more specks and retain edges and corners more effectively. The essential concept of an HMF is that it takes data from two kinds of windows. This filter, for example, suppresses noise in every 5×5 local windows of an image using the methods below: Step 1: Each 5×5 window's pixels are separated into two groups, with the first group consisting of pixels $45°$ degrees distant from the center pixel. This sub-neighborhood is denoted by the symbol “+” while the second sub-neighborhood consists of pixels positioned at $90°$ angles to the core pixel. This neighborhood is referred to as the “×” sub-neighborhood. m_+ is the median value of the first group, and $m_\times$ is the median value of the second group. In Step 2, the center pixel is replaced with the median of m_+, $m_\times$, and the original pixel [19]. The filtering procedure is shown in the diagram Fig. 1. Median filter effective at removing noise while preserving edges, but may have difficulty maintaining sharp edges in cases of extreme noise, which can sometimes lead to distortion.

In addition to the HMF, the relaxed median filter (RMF) may also be used as an alternative to the medium filter. By relaxing the order statistic for pixel replacement, this filter is achieved. RMF allows for the preservation of more image features than the median filter. This approach preserves tiny features, sharp corners, thin lines, and curved structures more effectively than the median filter. RMF operates as follows: lower (l) and upper (u) boundaries establish a sub list inside the $[W_i](.)$ that includes the grey levels that are enough non-noise to be considered acceptable. If the input corres ponds to the sub-list, it is not filtered; otherwise, the standard median filter is used. Let $m = N + 1$ and l, u such that $1 \leq l \leq m \leq u \leq 2N + 1$; otherwise, let the standard median filter be applied. RMF is defined as follows:

$$\{W_i\} = \begin{cases} X_i & if\ X_i \in [[W_i]_l, [W_i]_u]; \\ [W_i]_m & otherwise; \end{cases} \tag{8}$$

where $Y_i =$ Relaxed median= $\{W_i\}$, $[W_i]_m$ is the median value of the samples inside the window W_i.

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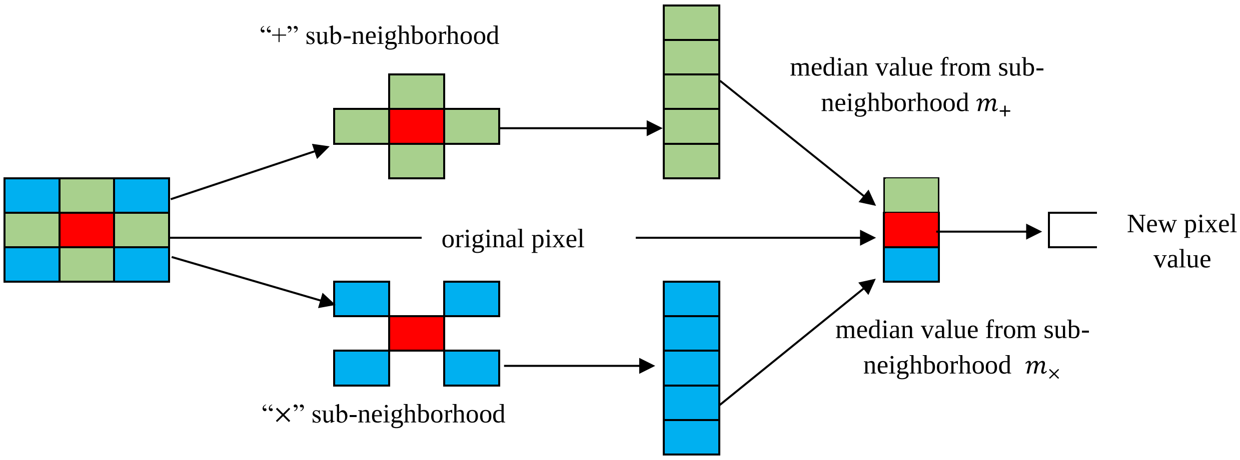

Figure. 1 Pictorial representation of HMF

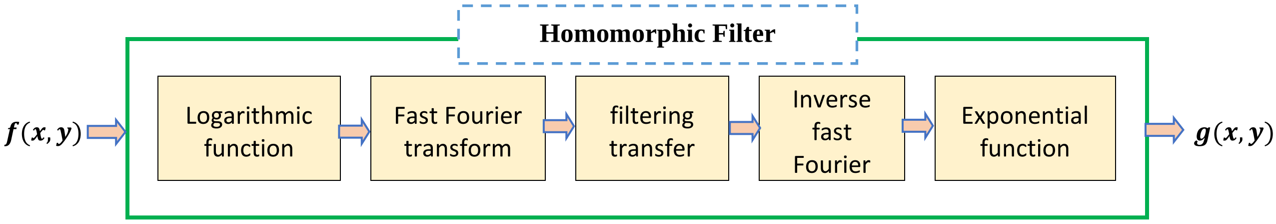

Figure. 2 Flow diagram of HF

To decrease the localization error caused by non-uniform illuminations, the homomorphic filter (HF) is a technique for enhancing images. As seen in Fig. 2, HF first transfers image(s) from the spatial domain to the frequency domain to enhance image brightness and contrast. After filtering, the image(s) are transported back to the spatial domain with decreased reflectance [20].

The Kuwahara filter, a non-linear filter type, is utilized to eliminate adaptive noise from the images. Better image smoothing is achieved with this filter. This filter can be built for a variety of window sizes. The technique will be explained for a window with a size of 3×3 for readability. As shown in Fig. 3, the filter window must be separated into four regions. Dark black color is usually used to indicate the center pixel. The following equation may be used to get the average and variance for all four regions:

$$Z_k = \frac{1}{(M+1)\times(M+1)} \times \sum_{(x,y)\in k} \varphi(i(x,y)) \quad (9)$$

$$\partial_k^2 = \frac{1}{(M+1)\times(M+1)} \times \sum_{(x,y)\in k} [\varphi(i(x,y)) - Z_k]^2 \quad (10)$$

were, $K \to \{0,1,2,3\}$, or four separate regions. The image function with (x,y) coordinates is $i(x,y)$. The function to determine a specific pixel value is φ. The number of pixels in the current region is

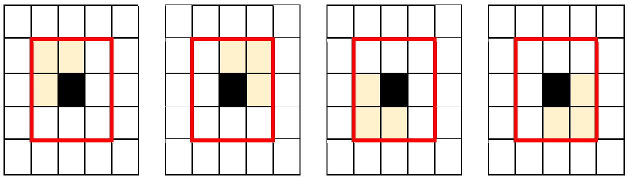

Figure. 3 Different areas of the Kuwahara filter

$(M+1)\times(M+1)$. Although a larger window size yields better results for the Kuwahara filter, the studied. Kuwahara filter effectively enhances and smoothes the image, preserving edges, but may produce unwanted effects in areas of sharp changes, requiring its careful use[21].

Lee developed a spatial filter based on the Gaussian distribution's Sigma probability. It is often compared to recent real-time noise-adaptive filters [22]. For noisy grayscale images, the sigma filter is used to detect noise by using the standard deviation measure defined as:

$$S = \sqrt{\frac{1}{m}\sum_{j=1}^{m}\left(x_j - \mu\right)^2} \quad (11)$$

In this case, we'll use a window of size m to calculate the mean μ of m sets of input data, $x_1, x_2, \dots \dots x_m$. We can characterize the sigma filter's output as follows:

$$y_{SF} = \begin{cases} f(x_1, x_2, \dots x_m) \; if \; \left|x_{(m+1)/2} - \mu\right| > tS \\ x_{(m+1)/2} \qquad\qquad\qquad otherwise \end{cases} \tag{12}$$

the median of the input set is used to create the smoothing function $f(.)$, where t is the smoothing parameter and $x_{(m+1)/2}$ is the center sample. The smoothing function $f(.)$ is applied to the input set if and only if the criterion $d_t\left|x_{(m+1)/2} - \mu\right| > tS$ is met, which indicates that the center sample is a probable noisy sample. No filtering is done if the center sample is devoid of noise. The filtering operation, from the uniformly smoothing filter operation $(t = 0)$ to the identity operation $(t \to \infty)$ Sigma filter excellent at detecting and removing noise while preserving detail, but care must be taken in choosing parameters to avoid removing important details from the image, especially in cases where noise is similar to real details .

The Gaussian pass filter removes parts with high regularity, ensuring that parts with low regularity are preserved. It helps with image kneading. It confines very high-frequency parts and retains low-frequency components to smooth the image.

$$G(u, v) = H(u, v).F(u, v) \tag{13}$$

where $F\,(u, v)$ is the original image's Fourier transform. $H(u, v)$: Filter mask Fourier Transform. The Gaussian filter helps improve brightness and contrast, making it ideal for softening an image and improving its overall quality.

The SRAD filter, known as speckle noise reduction anisotropic diffusion, is an advanced image processing technology, specifically designed to improve the quality of ultrasound images. This filter uses a partial differential equation, where the diffusion process is regulated based on a diffusion coefficient that depends on the magnitude of the gradient in the image. This parameter is applied to allow diffusion across homogeneous regions and restrict diffusion along edges, preserving sharp edges and reducing the effect of noise. The basic equation for this filter follows the formula:

$$f_{i,j} = g_{i,j} + \frac{1}{h_s}\operatorname{div}\left(c_{\text{srad}}\,(|\nabla g|)\nabla g_{i,j}\right) \tag{14}$$

where $f_{i,j}$ is the pixel value after filtering, $g_{i,j}$ is the original pixel value, h_s is the scaling factor, c_{srad} is the noise reduction filter coefficient defined by the following formula:

$$c_{\text{srad}}\,(|\nabla g|)^2 = \frac{1}{2\left|\nabla g_{i,j}\right|^2 + \frac{1}{16}\left(\nabla^2 g_{i,j}\right)^2 + \left(g_{i,j} + \frac{1}{4}\nabla^2 g_{i,j}\right)^2}$$

where $\nabla g_{i,j}$ is the gradient of the image, and $\nabla^2 g_{i,j}$ is the Laplacian of the image. The SRAD filter has a high ability to reduce speckle noise without negatively affecting image clarity and ensures that essential edge detail is preserved, making it ideal for applications requiring high clarity and fine detail. However, it requires careful parameter routing to ensure best performance, and can be more computationally complex than simpler filters[23].

2.3 Proposed model

In our constant pursuit of tangible progress in the field of breast ultrasound imaging, we present a proposed method based on combining an anisotropic diffusion filter with an SRAD filter. The selection of these two candidates did not come out of nowhere, but rather was the result of an in-depth study of their unique characteristics and how the capabilities of each can be enhanced when applied in conjunction.

The anisotropic diffusion filter has an excellent ability to preserve and enhance image edges, which is vital for differentiating between healthy and diseased tissue in breast images. On the other hand, the SRAD filter has a high ability to reduce speckle noise, which improves image clarity and facilitates the diagnosis process. Combining these two filters provides a comprehensive approach that takes advantage of the advantages of each filter for integrated image enhancement. The motivation for this choice lies in the perfect complementarity between the edge preservation provided by the anisotropic diffusion filter and the SRAD filter's ability to reduce noise with high precision. This integration allows us to achieve higher levels of accuracy in image analysis, making the proposed method able to deliver sharper and less noisy images, which is essential in capturing fine tissue properties. In this proposed method, an anisotropic diffusion filter is first used to smooth the image and identify edges, followed by an SRAD filter to purify the image from residual noise, including random specks that may hide vital details.

3. Evaluation Metric of Reduction Filters

The standard techniques of testing speckle reduction filters for ultrasound images are described in this section. We are evaluating the efficacy and improvement of image data of speckle noise reduction filtering algorithms. The quantity of variations between the input and the filtered image that may be found using MES is often employed. The disparity between the original and filtered images will vary more and less depending on the MSE value. In the case of identical images, MSE is equal to 0. For wholly different images, it is 255. It is determined as follows:

$$MSE = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(f_{i,j} - g_{i,j}\right)^2 \tag{15}$$

The N and M variables, respectively, represent the rows and columns of the input $f_{i,j}$ image and the filtered $g_{i,j}$ image [13].

In the presence of multiplicative noise, the signal-to-noise ratio (SNR) quantifies the decrease of speckles. It is determined by dividing the noise image by the filtered image. Higher SNR levels indicate that the filtering effect is more effective, and the quality of the de-noised image is much better. Decibels SNR is used to represent it as:

$$SNR = 10\log_{10}\left(\frac{\sigma^2}{\sigma_{error}^2}\right) \tag{16}$$

σ^2 is the original image's variance, and σ_{error}^2 is the error variance (difference between noise and de-noised image), i.e. $\left|f_{i,j} - g_{i,j}\right|$.

Peak signal-to-noise ratio (PSNR) is the performance assessment of speckle noise reduction. It is the maximum signal power achievable ratio to the noise image. The equation gives the PSNR in dB for 256 grey levels:

$$PSNR = 20\log_{10}\frac{2^n-1}{MSE}20\log_{10}\frac{\omega}{MSE} \tag{17}$$

where ω is the image's maximum intensity. Higher $PSNR$ values indicate a higher image quality. For identical images, $MSE = 0$ and $PSNR$ are undefined.

The three elements contrast distortions, brightness distortions, and correlation loss are combined to create the universal quality index (UQI), which assesses image distortions between two images. The given equation can be used to estimate the UQI:

$$UQI = \eta \times \psi \times \xi \qquad -1 < UQI < 1 \tag{18}$$

$$\eta = \frac{2\varepsilon_{\circ}\times\varepsilon_r}{\varepsilon_{\circ}{}^2+\varepsilon_r{}^2}, \psi = \frac{\tau_{or}}{\tau_o\times\tau_r}, \xi = \frac{2\tau_o\times\tau_r}{\tau_o{}^2+\tau_r{}^2} \tag{19}$$

where (η) is the mean luminance similarity between the noised image and the de-noised image, and (ψ) represents the correlation coefficient that assesses the similarity between the two images, and (ξ) the contrast similarity of the images. The standard deviation of the filtered and origin images is (τ_o) and (τ_r), respectively, and the covariance is (τ_{or}). ($\varepsilon_{\circ}$) and (ε_r) are the filtered and origin images' mean[24].

The structural similarity index (SSI) predicts the retention of structural information in de-noised images. SSI's formulation is explained as follows:

$$SSI = \frac{1}{N}\sum\frac{(2\mu_1\mu_2+a_1)(2\mu_{1,2}+a_2)}{(\mu_1^2+\mu_2^2+a_1)(\sigma_1^2+\sigma_2^2+a_2)} \tag{20}$$

where σ_1, σ_2 are the standard deviations and μ_1, μ_2 are mean of images. Constants a_1 and a_2 are supplied to strengthen the denominator. SSI has values ranging from $0\ to\ 1$; when it equals 1, images are structurally equivalent [25].

Laplacian mean squared error (LMSE) metric was created based on the edges measurement value. A high LMSE value indicates a low-quality image. Following is a definition of LMSE:

$$LMSE = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}[L(f(i,j))-L(g(i,j))]^2}{\sum_{i=1}^{I}\sum_{j=1}^{J}[L(f(i,j))]^2} \tag{21}$$

where $L(i,j)$ is laplacian operator:

$L(f(i,j)) = f(i+1,j) + f(i-1,j) + f(i,j+1) + f(i,j-1) - 4f(i,j)$[26].

4. Result and discussion

Image quality in medical imaging is a crucial factor in determining the accuracy of diagnoses, and from this standpoint, this study focused on analysing the performance of different noise filters in improving breast ultrasound (BUS) [27]. The experiments were performed on a dataset of 780 images of three different categories: normal, benign, and malignant with an average resolution of 500 x 500 pixels. Images are saved as PNG files. The images were divided into three categories: 133 normal, 487 benign, and 210 malignant, with a size of 1280×1024. Fig. 4 shows the fundamental structures of the approach used to reduce speckle noise on BUS. These filters were evaluated using a set of standard statistical metrics including MSE, SNR, PSNR, UQI, SSI, and LMSE.

The results, as shown in Tables 1 and 2, provide a clear indication of the marked superiority of nonlinear filters over their linear counterparts on most of the criteria used. Specifically, the anisotropic diffusion filter and SRAD filter stand out with advanced results, as they showed low MSE values

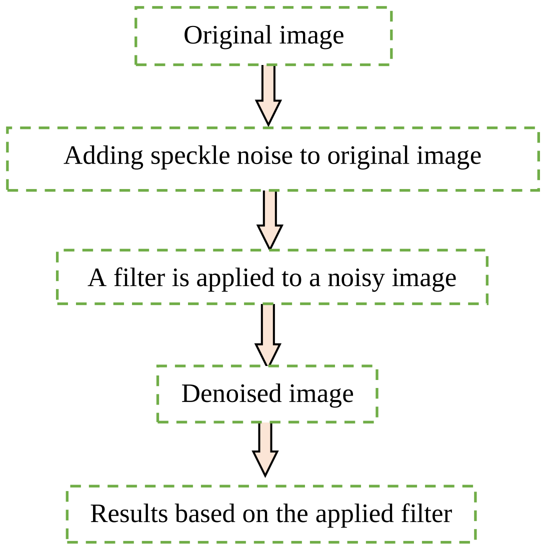

Figure. 4 Block diagram of the produced speckle noise reduction on BUS

indicative of reduced noise, while high SNR and PSNR values indicative of enhanced image quality. In addition, higher SSI values suggest effective preservation of structural features of the original image, which is critical for preserving fine clinically relevant details.

It is noteworthy that the proposed filter, which combines anisotropic diffusion filter and SRAD techniques, scored highest across almost all metrics, reflecting its outstanding effectiveness in achieving an ideal balance between noise reduction and maintaining structural clarity. These results are attributed to the strategy used in the proposed filter, where the diffusion is adjusted based on the image gradient, allowing edges and fine details to be preserved while effectively removing noise from homogeneous regions. This clearly shows how improved filters can contribute to improving the accuracy of diagnosis and screening of lesions in ultrasound imaging. Low values of LMSE in nonlinear filters indicate their high ability to preserve the structural quality of the image. On the other hand, high values of UQI and SSI indicate outstanding success in keeping the brightness, contrast, and overall image quality similar to the original image. The notable differences between linear and nonlinear filters in the table underscore the importance of choosing the appropriate image filtering method in clinical applications. Although some linear filters such as “Frost” and “Conditional Averaging” have shown acceptable results, they do not measure up to non-linear filters in providing an improved final image.

Table 1. Image quality evaluation metrics calculated for BUS based on statistical measurements of MSE, SNR, PSNR, UQI, SSI, and LMSE, for linear filters

Linear filters	MSE	SNR	PSNR	UQI	SSI	LMSE
Additive	9.1	33.2	41.5	0.97	0.99	0.98
lee	3.1	37.9	46.3	0.97	0.99	0.26
Frost	2.4	38.9	47.3	0.97	0.99	0.34
kuan	27.2	28.4	36.8	0.97	0.99	4.24
linear Skal	23.7	29.0	37.4	0.94	0.98	2.90
Conditional Averaging	4.2	36.6	44.9	0.97	0.99	0.60
Neighborhood Averaging	2.9	38.2	46.5	0.98	0.99	0.32
Log-Compressed	46.4	26.1	34.4	0.91	0.96	1.09

Table 2. Image quality evaluation metrics calculated for BUS based on statistical measurements of MSE, SNR, PSNR, UQI, SSI, and LMSE, for non-linear filters

Nonlinear filters	MSE	SNR	PSNR	UQI	SSI	LMSE
Anisotropic Diffusion	0.5	45.9	54.2	0.99	0.99	0.23
Linean Scaling	5.4	35.5	43.8	0.94	0.98	0.66
Hybrid Median	1.4	41.2	49.5	0.98	0.99	0.32
Relaxed Median	1.5	41.1	49.4	0.98	0.99	0.53
Homomorphic	9.7	32.9	41.3	0.89	0.96	1.55
kuwahara	33.5	27.6	35.9	0.89	0.93	3.11
sigma	2.4	39.0	47.3	0.97	0.99	0.36
Gaussian Smooth	6.3	34.8	43.1	0.98	0.99	0.77
SRAD	0.5	46.1	54.4	0.99	0.99	0.01
Proposed model	**0.2**	**51.0**	**59.3**	**1.00**	**1.00**	**0.003**

The strategy adopted in applying these filters is considered essential in achieving noticeable improvements. By dynamically adjusting the diffusion rate based on information extracted from image gradients, the filtering process is directed to be more sensitive in areas of high detail and less aggressive in homogeneous areas. This means that the filter does not act with the same force over the entire image, but rather adapts to the specific need of each part of the image, which contributes to preserving the structural quality and details vital for diagnosis. This adaptation significantly improves the final image quality, not only by reducing noise but also by enhancing structural clarity and contrast. Thus, this method allows doctors to see more clearly and accurately the lesions and fine details within the image, which enhances the diagnostic ability and helps in making treatment decisions based on reliable, high-quality information. In addition, the use of these filters contributes to improving the overall performance of breast ultrasound, opening new horizons for research and development in the field of

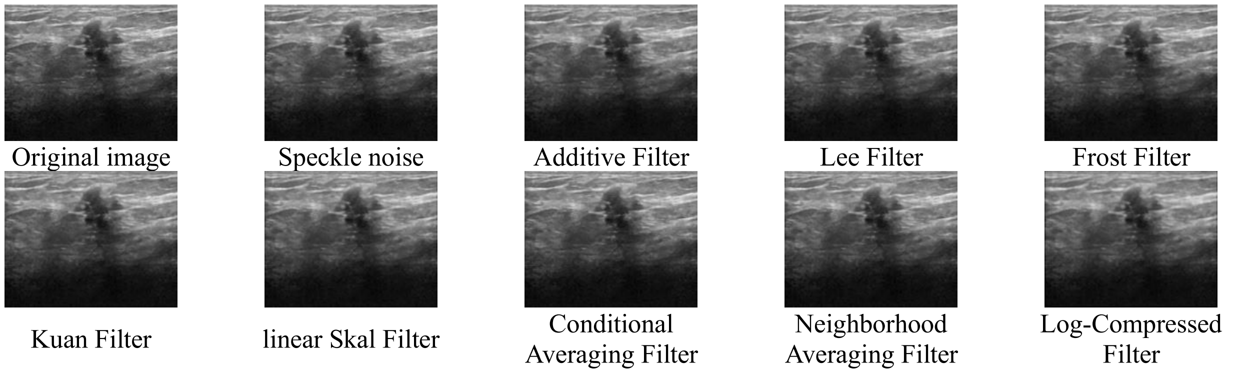

Figure. 5 Linear speckle reduction filters

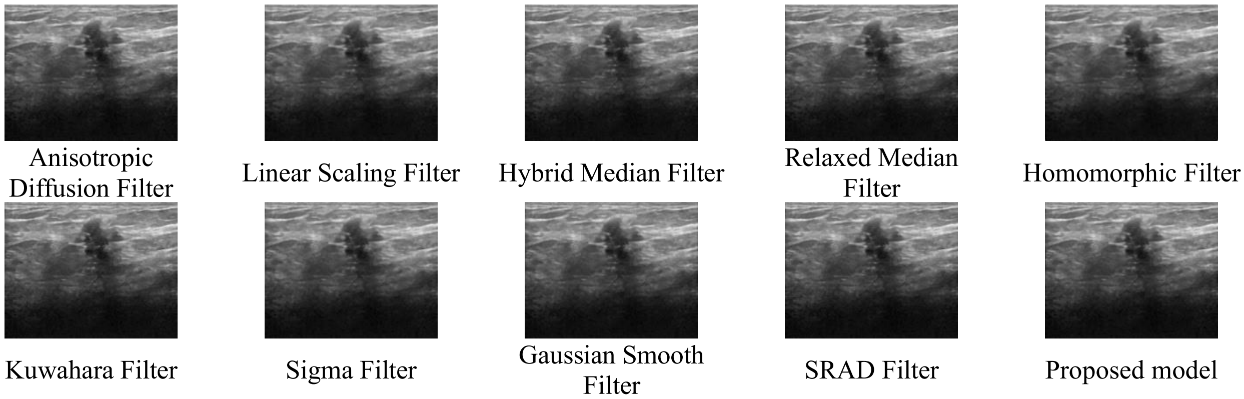

Figure. 6 Non-linear speckle reduction filters

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Table 3. Comparison of our proposed model to current models

Reference	MSE	SNR	PSNR	UQI	SSI	LMSE
Goyal [6]	0.01	-	22.9	-	0.8	-
Mei [7]	-	-	27.7	-		-
Vilimek [8]	-	-	23.8	-	0.6	-
Liu [9]	-	-	39.1	-	-	-
Elnokrashy [10]	1214.1	12.3	17.3	-	0.5	-
Proposed model	**0.2**	**51.0**	**59.3**	**1.0**	**1.0**	**0.003**

medical imaging. Thus, the method proposed in our research is an important step towards improving the quality of medical imaging and enhancing the accuracy of diagnosis.

In the context of comparison with other studies, it can be said that the method proposed in our research, which combines the anisotropic diffusion filter and SRAD techniques, has recorded a significant improvement in almost all the metrics used. Table 3 shows the results of comparing the proposed model with existing models, these results not only highlight the effectiveness of this method in reducing noise and improving structural clarity but are also attributable to the strategy adopted in applying the filtering, where the diffusion rate is adjusted based on the image gradient to preserve fine edges and details.

These results reinforce the conviction that advanced image filtering methods, especially those based on nonlinear principles, offer effective solutions to the challenges associated with ultrasound imaging. By striking a careful balance between reducing noise and preserving necessary structural information, these methods enable us to perform more accurate diagnostic assessments, which contributes to enhancing the efficiency of medical diagnosis.

5. Conclusions and future works

In this study, we comprehensively evaluated linear and nonlinear filters in breast ultrasound image processing, and our results yielded advanced techniques that achieve an optimal balance between removing noise and preserving vital structural features of images. The proposed method, which combines an anisotropic diffusion filter and SRAD filter, not only showed significant improvement in MSE, SNR, and PSNR metrics compared to existing methods, but also in UQI, SSI, and LMSE metrics, confirming its ability to enhance the overall quality of medical images. Our results show that the proposed model achieved the lowest mean square error (MSE) value of 0.2, the highest signal-to-noise ratio (SNR) value of 51.0, and the highest peak signal-to-noise ratio (PSNR) value of 59.3. In addition, the proposed model achieved the optimal value of Universal Image Quality Indicator (UQI) and Structural Attribute Index (SSI) of 1.00, and the LMSE value decreased to 0.003, demonstrating a significant improvement in the overall quality of medical images compared to the other techniques studied. From our findings, we conclude that the use of nonlinear filters can have a significant positive impact on medical image processing, paving the way for important improvements in the diagnosis of mammary lesions. The study also shows that effective integration of different techniques can lead to significant improvements in performance, which indicates the importance of a multi-faceted approach to medical image processing. Our findings open perspectives to explore the applicability of the proposed filter to a wide range of other medical applications, such as CT and MRI, where macular noise can be a pressing problem. Developing integrated image processing systems that use artificial intelligence to automatically recognize healthy and pathological patterns in medical images is one of the main goals of future research.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Methodology, formal analysis, data curation, writing—original draft preparation, and editing, Eman A. Radhi; supervision, software, validation, Mohammed Y. Kamil; all authors read and approved the final manuscript.

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