New Noise Reduction Technique for Medical Ultrasound Imaging using Gabor Filtering

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Abstract

Ultrasound (US) imaging is an important medical diagnostic method, as it allows the examination of several internal body organs. However, its usefulness is diminished by signal dependent noise known as speckle noise. Speckle noise degrades target detectability in ultrasound images and reduces contrast and resolution, affecting the ability to identify normal and pathological tissue. For accurate diagnosis, it is important to remove this noise from ultrasound images. In this study, a new filtering technique is proposed for removing speckle noise from medical ultrasound images. It is based on Gabor filtering. Specifically, a preprocessing step is added before applying the Gabor filter. The proposed technique is applied to various ultrasound images, and certain measurement indexes are calculated, such as signal to noise ratio, peak signal to noise ratio, structure similarity index, and root mean square error, which are used for comparison. In particular, five widely used image enhancement techniques were applied to three types of ultrasound images (kidney, abdomen and ortho). The main objective of image enhancement is to obtain a highly detailed image, and in that respect, the proposed technique proved superior to other widely used filters.

Keywords: Ultrasound Images, Speckle Noise, Edge Preservation, Performance Evaluation, Gabor Filter.

1. INTRODUCTION

Digital ultrasound (US) imaging is a widely used medical diagnosis technique, owing to its safe noninvasive nature, low cost, capability of generating real time images, and continuing improvement in image quality [1]–[4]. It is estimated that one out of every four medical diagnostic image studies (such as X-Ray, CT, MRI, PET, and US) in the world involves US techniques. Ultrasound imaging is used for visualizing muscles and several internal organs and thus revealing certain pathological abnormalities using real-time tomographic images [3], [4]. It is also used for visualizing the fetus during routine and emergency prenatal care. Obstetric sonography is commonly used during pregnancy. It has no known long-term side effects and rarely causes any discomfort to the patient. As it does not use ionizing radiation, ultrasound involves no risks to the patient. It provides live images from which the operator can select the most useful section, thus facilitating quick diagnoses.

The usefulness of ultrasound imaging is diminished by signal dependent noise known as speckle noise. This is multiplicative noise that degrades image quality; hence, it reduces the ability of an observer to discriminate fine details in diagnostic examination and renders treatment decision-making difficult. Edge preservation [5] and noise reduction are important for accurate diagnosis [6]–[9]. Speckle reduction is the process of removing speckle noise from US.

Speckle noise decreases the efficiency of further image processing such as edge detection [5], [6]. De-noising techniques should reduce speckle without blurring or changing the location of the edges, which are those points at which the luminous intensity changes sharply and usually reflect important changes in the properties of the image. Thus, edge detection is highly important in identifying and understanding the entire image. Edge detection is primarily the measurement and detection of gray change, and in ultrasound images, it is a difficult task because the related algorithms may be sensitive to noise [9], [10].

Speckle noise also degrades the speed and accuracy of US image processsing operations, such as segmentation and registration [11], [12]. Thus, the enhancement of image quality is an important and demanding research field, and this study aims at suppressing speckle noise by preserving edges in ultrasound images.

2. RELATED STUDIES

De-noising techniques for US images have been extensively studied, owing to the need for accurate diagnosis. Richard et al. [2] proposed a novel adaptation of median filters for boundary-preserving speckle reduction. Specifically, a set of short lines passing through the center of a square-shaped kernel was considered. Following the sticks technique, the median along each line was computed, and the largest median value was taken for the central pixel. Patider et al. [3] used median, mean, and Wiener filters for removing noise. In this regard, adaptive filter design has attracted considerable attention.

Bhattacharya et al. [4] demonstrated the pertinence of Gabor filtering in brain image segmentation, namely, the identification analysis of the output of noisy and filtered images by Gabor filtering. An algorithm was developed that implemented all filtering types on the input image, and arithmetic parameters were calculated according to the comparison between the output and input images. Negi et al. [5] proposed a Gabor based wavelet transform for edge detection in ultrasound as well as normal images. Gabor based detection performs filtering in different directions and scales to determine the edges of the texture at optimal frequency. To reduce the effect of noise, the edges were detected in smooth images instead of the original images, and it was demonstrated that Gabor wavelet-based edge detection is highly effective for preserving edges.

Karaman et al. [6] proposed an adaptive filtering technique for removing speckle pattern from ultrasound images. Smoothing operators (mean or median) are applied in regions where the tissue is assumed homogeneous. These regions are obtained by region growing that is constrained only by statistical properties and the distance from the central pixel. Similarly, Joseph et al. [7] proposed a new weighted linear filtering approach that uses local binary patterns (LBP) for reducing speckle noise in ultrasound images. This approach performs effective denoising without affecting image content. It uses LBP, which is a gray scale invariant that describes local primitives, such as curved edges, points, spot, and flat areas, and plays a vital role in texture analysis. It is widely used in various computer vision problems, such as face recognition, motion analysis, medical image analysis, fingerprint recognition, palmprint recognition, and vessel extraction in conjunctive imaging. In this process, the center pixel value is subtracted from that of each neighboring pixel. To generate the LBP code for a neighborhood, the weight assigned to each pixel is multiplied by a numerical threshold. The process is repeated for a set of circular samples.

Based on 2D homogeneity, Yanhui et al. [8] proposed directional averaging whereby homogeneity is checked for pixel values. Pixels with homogeneity above a certain threshold remain unchanged. Otherwise, they are processed by their directional average filter. Edge detection is followed by directional filtering along the edge with the highest edge-value (vertical or horizontal). This approach can effectively reduce speckle noise without adversely affecting textual information.

In conclusion, speckle noise reduction was performed in [2], [3], [6], and [7]; however, edge detection was not considered. In [4], signal to noise ratio and correlation were improved, but edge preservation was ignored. In [5], the Gabor wavelet transform was used for edge detection, but noise was not considered. The directional averaging technique was proposed in [8]; however, if averaging is performed in US images, then blur and edge degradation occur. Gabor filtering is suitable for edge preservation, but its performance in noise reduction from US images is poor. In the present study, a new technique for removing speckle noise from ultrasound images is proposed that also preserves edges and detail information.

3. SPECKLE NOISE MODEL

Speckle noise is multiplicative noise affecting all coherent imaging systems, including medical ultrasound [11]-[13]. The most critical part of developing a method for recovering a signal from its noisy environment is choosing a reasonable statistical (or analytic) description of the physical phenomena underlying the data-formation process. The availability of an accurate and reliable model of speckle noise formation is a prerequisite for the development of a valuable de-speckling algorithm [14], [15]. However, in ultrasound imaging, a unified definition of such a model remains arguable. Nevertheless, there exist several possible formulas whose potential has been empirically verified. A possible generalized model for speckle imaging is the following:

$$g(n,m) = f(n,m)u(n,m) + \xi(n,m) \tag{1}$$

where g, f, u, and ξ denote the observed image, original image, the multiplicative component, and the additive component of the speckle noise, respectively. (n, m) denotes the pair of axial and lateral indices of the image samples or, alternatively, the angular and range indices for B-scan images. In ultrasound images, only the multiplicative component of the noise is to be considered, and thus the model can be considerably simplified by disregarding the additive term. The simplified version of this equation thus becomes

$$g(n,m) = f(n,m)u(n,m) \tag{2}$$

4. GABOR FILTER

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter [4] used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

Its impulse response is defined by a harmonic function multiplied by a Gaussian function. Owing to the multiplication-convolution property (convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions. A Gabor filter can be represented as

$$g(x,y;\lambda,\theta,\Psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\Pi\frac{x'}{\lambda}+\Psi\right) \tag{3}$$

where $x' = x\cos\theta + y\sin\theta$ and $y' = -x\sin\theta + y\cos\theta$, λ denotes the wavelength of the cosine factor, θ denotes the orientation of the normal to the parallel stripes of the Gabor function, ψ is the phase offset, σ is the sigma of the Gaussian envelope, and γ is the spatial aspect ratio, which specifies the elasticity of the support of the Gabor function. The Gabor filter is the only filter with orientation selectivity that can be expressed as a sum of only two separable filters. If higher frequency information is chosen, the edge is maximized.

Gabor filters are directly related to Gabor wavelets, as they can be designed for a number of dilations and rotations. They are convolved with the signal, and this process is closely related to processes in the primary visual cortex [4], [5]. Gabor filters have received considerable attention because they can approximate the characteristics of certain cells in the visual cortex of some mammals. In addition, they have been shown to possess optimal localization properties in both the spatial and the frequency domain. Gabor filters have been used in various applications, such as texture segmentation, target detection, fractal dimension management, document analysis, edge detection, retina identification, and image coding and image representation.

5. PROPOSED TECHNIQUE

In ultrasound imaging, it is often desired to remove speckle noise for accurate diagnosis. Moreover, edge preservation is important in identifying and understanding the entire image. Edges are those points at which luminous intensity changes sharply [5]. Gabor filters use orientation selectivity; they choose higher frequency information and thus maximize edges. Their performance is poor for speckle reduction, and in this study, this limitation is removed. By modifying the traditional Gabor filter, a new speckle noise reduction technique for ultrasound images is presented. This is accomplished by adding certain preprocessing tasks. The steps of this technique are shown in Figure1**.**

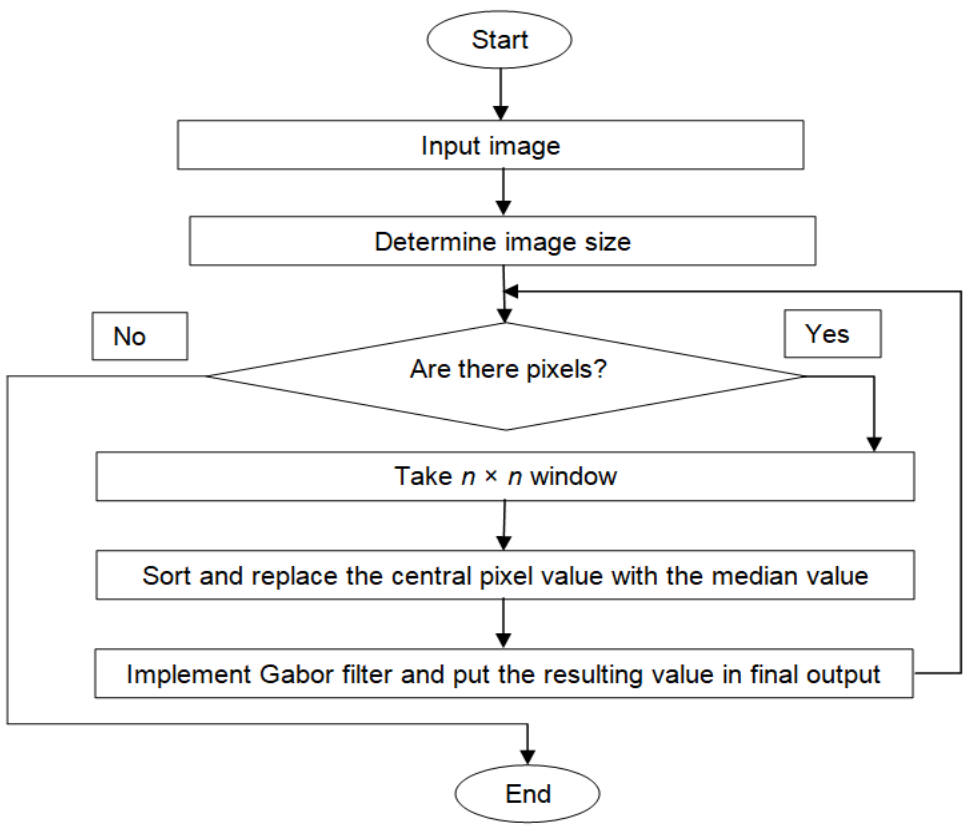

FIGURE 1: Flow Diagram of Filtering Technique.

The general approach of image denoising is to apply a function for processing each pixel of the image. A basic approach is based on the use of masks, which are also referred to as filters, kernels, templates, or windows. An *n* × *n* kernel is used for processing each pixel, where a kernel is a small 2-D array in which the values of the coefficients determine the nature of the filtering process, namely, image sharpening, edge detection, and smoothing. Filtering is performed to determine the central pixel value of the kernel. As *n* is normally an odd number, the size of the filter kernel is, for example, 3 × 3, 5 × 5, 7 × 7.

In Figure 1, an input image is first taken, and its size is calculated. Then, a two-dimensional window of size 3 × 3 is selected. This window is centered at each pixel of the corrupted image for performing the desired operations, as shown in Figure 2.

x-1,y-1	x-1,y	x-1,y+1
x,y-1	x, y	x,y+1
x+1,y-1	x+1,y	x+1,y+1

FIGURE 2: 3×3 Region of An Image.

The central pixel is replaced by the median value of the 3 × 3 region in the window; this preprocessing task is performed to remove noise. Then, the final output image is obtained by Eq.3.

6. RESULTS AND DISCUSSION

Simulation studies are usually the first step for quantitatively evaluating the performance of an estimation method. To validate the efficiency of the proposed filtering technique, a simulation study was carried out using the MATLAB and ImageJ software packages. Three ultrasound images (kidney, abdomen, and ortho) were used. An original noise-free image was first selected. Subsequently, an image contaminated with speckle noise (noise factor 0.04) was selected, and finally output images were obtained by image processing operations involving various types of filtering, namely, the existing and the proposed techniques.

Firstly, preprocessing was performed for various window sizes. For quantitative assessment, the image quality index (IMGQ) and the edge preservation factor (EPF) were used. IMGQ and EPF are the most important image quality measurement metrics. Based on the value of IMGQ and EPF the window size is selected for preprocessing.

IMGQ can determine the degree of distortion in terms of loss of correlation [16]. The dynamic range of IMGQ is between −1 and 1, and higher values indicate higher image quality. It is calculated by the following equation [16]:

$$IMGQ = \frac{4\sigma_{xx'}\overline{X}\,\overline{X}'}{[\sigma_x^2 + \sigma_{x'}^2][\overline{X}^2 + (\overline{X}')^2]} \tag{4}$$

where x, x' denote the original and filtered images, σ denotes the standard deviation, and $\overline{X}, \overline{X}'$ the mean value of original and filtered images.

The edge preservation factor (EPF) is one of the most important measurement metrics [17], [18], which is also used for selecting the window size. Edge preservation is important in the processing of medical images. Its value facilitates the selection of the best filter [17]. If EPF is higher, the technique is better. It is obtained by the following equation [17], [18]:

$$EPF = \frac{\sum(\Delta I - \overline{\Delta I})(\Delta I_d - \overline{\Delta I_d})}{\sqrt{\sum(\Delta I - \overline{\Delta I})^2 \sum(\Delta I_d - \overline{\Delta I_d})^2}} \qquad (5)$$

where Δ is the Laplace operator, i.e., the differential operator given by the divergence of the gradient of a twice-differentiable real valued function in the *n*-dimensional Euclidian space. ΔI, ΔI_d, $\overline{\Delta I}$, and $\overline{\Delta I_d}$ denote the action of the Laplace operator on the original image, the filtered image, the mean of the original image, and the mean of the filtered image, respectively.

Table 1 shows the quantitative performance for various window sizes. The corresponding images are shown in Figure 3. Here a 3 × 3 window was selected because larger windows, such as 5 × 5 or 7 × 7, result in over-smoothed images with degraded edges and yield low IMGQI and EPF values. If 3 × 3 windows are used, only the neighboring pixels are considered, and thus edges remain unchanged. As edge preservation is important for accurate diagnosis, a 3 × 3 window was selected for preprocessing.

TABLE 1: Quantitative Performance For Various Window Sizes.

Filter	Image	IMGQI			EPF		
		3 × 3 window	5 × 5 window	7 × 7 window	3 × 3 window	5 × 5 window	7 × 7 window
Proposed	Kidney	0.51	0.36	0.33	0.67	0.41	0.21
	Abdomen	0.52	0.40	0.36	0.71	0.45	0.26
	Ortho	0.57	0.38	0.33	0.74	0.39	0.20

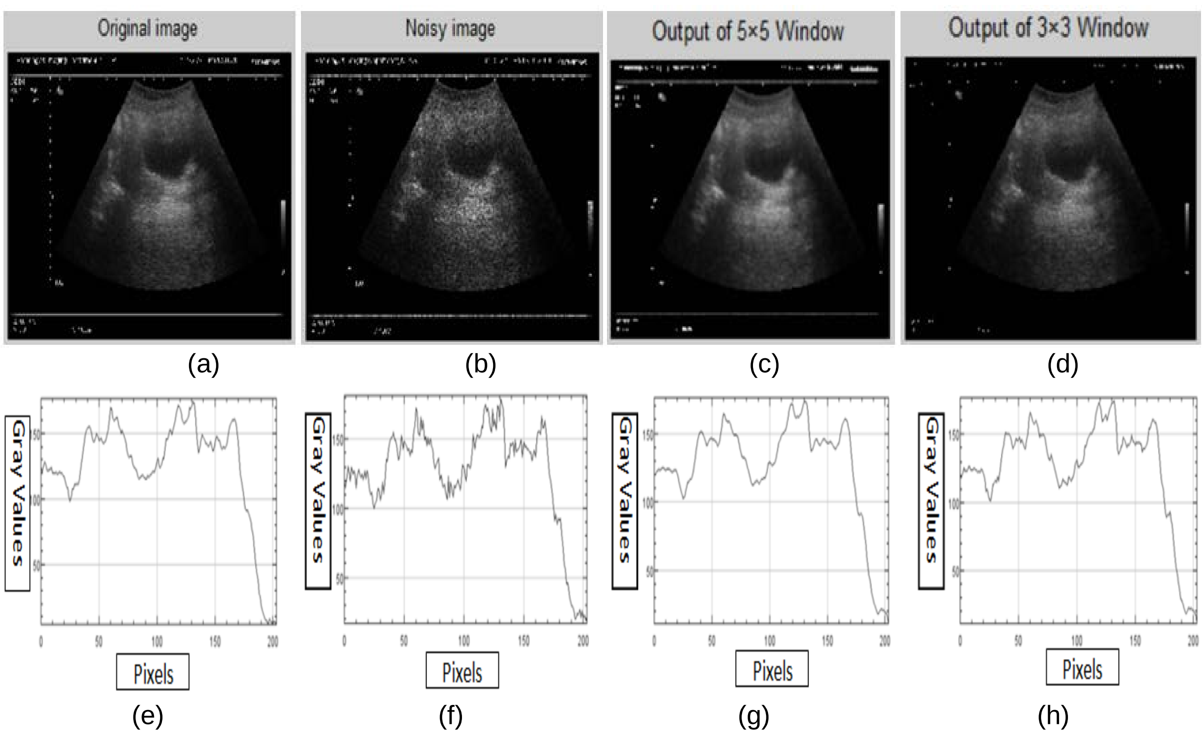

FIGURE 3: Abdomen image (noise factor is 0.04); a) original image, b) noisy Image, c) output of 5 **×** 5 window, d) output of 3 **×** 3 window, e) intensity profile of original image, f) intensity profile of noisy image, g) intensity profile of the output of 5 **×** 5 window, h) intensity profile of the output of 3 **×** 3 window.

By observing Table 1 and Figure 3, it can be seen that the 3 × 3 window yields better results in terms of speckle noise reduction and edge and detail preservation. Moreover, higher values of IMGQ and EPF are obtained. In Figure 3, (e), (f), (g), and (h) show the intensity profiles, that is, the sets of intensity values taken from regularly spaced points along a line segment or multiline path. The *improfile* function was used for creating the intensity profiles. For points that do not fall at the center of a pixel, the intensity values were interpolated.

In Figure 3, the output image (d), which is the output of the 3 × 3 window, approximates the input image (a), and the intensity plot profile (h) approximates the intensity plot profile of the original image. From the intensity plot profile of the output of the 5 × 5 window (g), it can be concluded that it is slightly smoother than original image; thus, the 3 × 3 window was selected for preprocessing.

Pictorial assessment of the performance of various filtering techniques for speckle noise reduction (with noise factor 0.04) in ultrasound images was performed for various images and is shown in Figures 4 and 5.

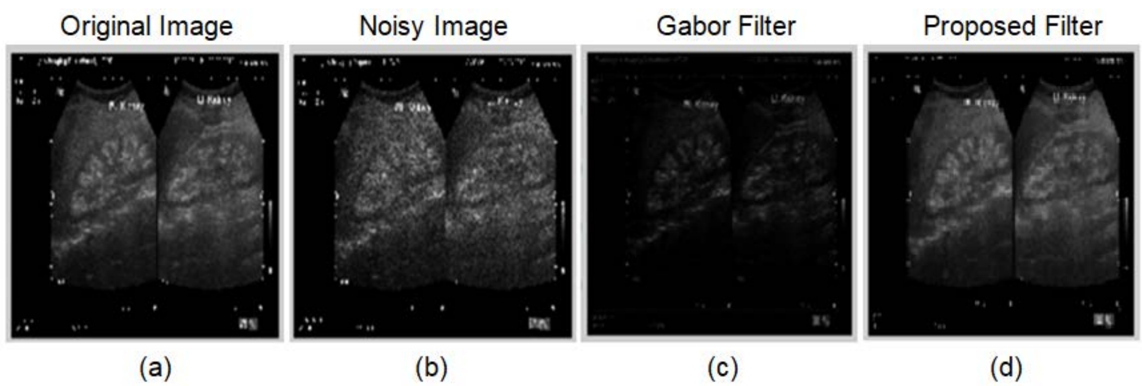

FIGURE 4: Input and Output of Kidney image for speckle noise (noise factor is 0.04).

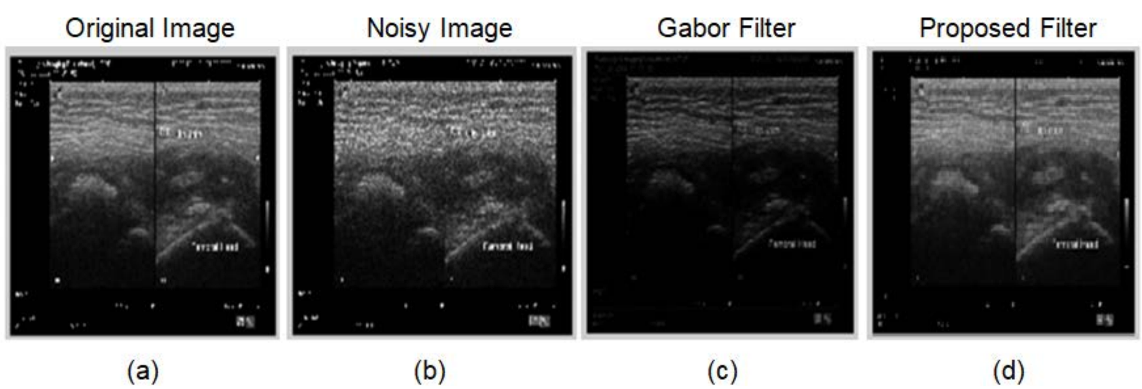

FIGURE 5: Input and Output of Ortho image for speckle noise (noise factor is 0.04).

Speckle noise is a multiplicative noise that has granular patterns and ultrasound speckle results from the coherent accumulation of random scatterings from the resolution cell. From the noisy image (b) of Figures 4 and 5 one can see that, speckle noise degrades the quality of US image badly. In this case it is very important to remove this noise from these images. Here despeckling is performed by using various well known denoising techniques. In this case, despeckling is expected to reconstruct the original image by preserving edges and other image details. The output of Gabor filter (c) is very poor, but, from Figures 4 (d) and 5 (d), it is clear that the proposed filtering technique provides better visual appearances in the case of removing speckle noise from ultrasound images.

Quantitative measurement of the performance of various filtering technique for removing speckle noise from ultrasound images are represented by the following Table 2. For the quantitative assessment, several performance measures were used to compare the performance of despeckling methods. This measurement is performed on basis of the values of signal to noise ratio (SNR), peak signal to noise ratio (PSNR), structure similarity index (SSIM), and root mean square error (RMSE).

Higher SNR and PSNR values indicate better image quality [16]–[25]. The luminance, contrast, and structure of two images are compared using SSIM. It can be regarded as a similarity measure between the images [16]. The standard value of SSIM is 1. SSIM can be calculated using the following equation:

$$SSIM(I, I_d) = \frac{(2\mu_I \mu_{I_d} + C_1)(2\sigma_{II_d} + C_2)}{(\mu_I^2 + \mu_{I_d}^2 + C_1)(\sigma_I^2 + \sigma_{I_d}^2 + C_2)} \tag{6}$$

RMSE is used for assessing the performance of image reconstruction relative to the original image. It represents the difference between original and denoised images. Higher values indicate large difference and lower values indicate smaller difference [16]. For identical images, it is zero. RMSE is calculated by the following equation [18]:

$$e_{rms} = \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [I(x,y) - I_d(x,y)]^2 \tag{7}$$

In (6) and (7), I and I_d denote the original image and the denoised image, respectively. μ_I and μ_{Id}, σ_I and σ_{Id} denote the average and the variance of I and I_d, respectively. σ_{IId} is the covariance of I and I_d. C_1 and C_2 are two variables for stabilizing the denominator. Rows and columns are denoted by x and y, respectively, and $M \times N$ is the image size.

TABLE 2: Performance Table For Various Filters.

Filter	Image	SNR		RMSE	PSNR	SSIM
		Original	Filtered			
Median	Kidney	12.09	11.61	0.08	98.22	0.69
	Abdomen	13.10	12.72	0.07	97.72	0.79
	Ortho	12.02	11.77	0.09	98.62	0.66
Average	Kidney	12.09	11.29	0.14	98.21	0.59
	Abdomen	13.10	12.56	0.13	97.70	0.72
	Ortho	12.02	11.49	0.15	98.60	0.55
Inverse	Kidney	12.09	6.66	0.17	98.23	0.43
	Abdomen	13.10	5.08	0.13	97.22	0.60
	Ortho	12.02	0.55	0.16	98.60	0.45
Wiener	Kidney	12.09	10.23	0.09	98.22	0.25
	Abdomen	13.10	11.18	0.10	97.72	0.12
	Ortho	12.02	11.51	0.11	98.62	0.29
Gabor	Kidney	12.09	1.36	2.40	98.23	0.36
	Abdomen	13.10	0.73	1.82	97.72	0.52
	Ortho	12.02	1.37	4.67	98.62	0.35
Proposed Method	Kidney	12.09	11.87	0.07	98.23	0.99
	Abdomen	13.10	12.86	0.07	97.73	0.99
	Ortho	12.02	11.89	0.09	98.62	0.99

From Figures 4, and 5, it is clear that the proposed filter yields better visual results and preserves more detail information. From Table 2, it can be seen that the proposed filter yields better results in terms of various measurement metrics as well. The Gabor filter uses orientation selectivity, ensuring edge preservation but not satisfactory speckle noise removal; thus, SNR is considerably low for that filter. By contrast, the corresponding value for the proposed filtering technique is significantly higher. Likewise, RMSE is also high for the Gabor filter, which indicates that the difference between the original image and the denoised image is high. However, the proposed technique has low RMSE, which implies that the output image approximates the original image. From Table 2, it is clear that the proposed filter has higher SNR and PSNR compared with existing filters. Moreover, its SSIM is close to 1, which indicates that the denoised image approximates the original image.

7. CONCLUSION AND FUTURE WORK

Human vision is sensitive to high-frequency information. Image details (e.g., corners and lines) have high frequency content and carry important information for visual perception. In this study, a new filtering technique was proposed for removing speckle noise from medical ultrasound images. In particular, a new method for enhancing the performance of the existing Gabor filtering method has been presented. Specifically, a simple preprocessing step was added with Gabor filter to establish a new technique. The performance of five well known despeckling methods was examined in the current study. Moreover, in all case the performance of the proposed technique for removing speckle noise from various ultrasound images was compared with that of various traditional speckle noise reduction techniques. In conclusion, it is clear that the proposed filter yielded better output for kidney, abdomen, and ortho images compared with existing filters.

It is noted that no attempt was made to compare the performance of proposed technique for segmentation or any other viewpoints. Performance evaluation of proposed method from a different number of viewpoints (e.g., computational efficiency, reliability of recovering different anatomical structures, and different tissue morphologies) well deserves a future study.

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