Reconstruction of a Multiscale Filter for Edge Preserving Speckle Suppression of Ultrasound Images

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Abstract

Speckle noise tends to reduce the diagnostic value of ultrasound imaging modalities by degrading image quality. Edge-preserving noise-suppression can play an important role for accurate diagnosis.Therefore edge-preserving speckle suppression is the ultimate demand for accurate diagnosisby healthcare industries. In this study, a new hybrid filtering technique, namely, multiscale filter is proposed and analyzed to suppress the speckle noise in ultrasound images by preserving the image edges. Linear filtering speeds are high, but cannot preserve the edges of images efficiently, and this is a major limitation. Conversely, nonlinear filtering can handle edges more effectively; a Gabor filter preserves edges well but fails at suppressing noise. The method proposed here combines the concept of three linear and nonlinear filters with a Gabor filter to counter the limitations. In particular, when it is filtered, a 3×3 image kernel is divided into three segments and three linear and non-linear techniques are applied to each segment. Finally, the results of each section are integrated and processing is performed with a Gabor filter to obtain the results. The performance of the multiscale filter is analyzed for various ultrasound images of kidney, breast, abdomen, prostrate, orthopedic, and liver. The proposed multiscale filter provides superior results than other widely used de-speckling filters.

Keywords: Linear Filter, Non-linear Filter, Speckle Noise, Gabor Filter, Medical Images.

1. INTRODUCTION

Physicians and radiologists recognize ultrasound (US) imaging as the most used and powerful screening and diagnostic tool among the currently available medical imaging modalities. US imaging has certain major advantages over other medical imaging modalities such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), and positron-emission tomography (PET) (Talukder et al., 2018). US imaging is accurate, painless, harmless to the body, and cost-effective. In addition, ultrasound has no long-term side effects, it involves no risks and normally patient does not feel any discomfort. Ultrasound is effective for quick diagnosis because it provides live images from which it is easy to select the most useful section for diagnosing Therefore, ultrasound imaging is one of the most popular tool in sophisticated diagnostic procedures. However, ultrasound imaging has some unique challenges, such as low image quality caused by speckle noise; the usefulness of ultrasound imaging is diminished by this noise (Talukder et al., 2018).

Speckle noise is a multiplicative noise that is an inherent property of medical ultrasound imaging systems. Speckle noise tends to degrade image quality and obscure image details, thereby reduce the reliability, and usefulness of ultrasound images in medical diagnosis (Negi & Mathur, 2014; Karaman et al., 1995). Image preprocessing [Khan et al., 2020, Nadji et al. 2023], de-noising [Yang et al., 2019, Rahman et al. 2014, Rahman et al. 2012], image enhancement [Iswardani et al., 2018, PK et al., 2014], image edge preservation [Ruhaiyem et al., 2021] helps the physicians to identify each object uniquely because image edges represent the sharp changes in the properties of the image. For this reason, edge preservation is important in identifying and understanding the whole image for proper diagnosis. Therefore, speckle suppression method is the ultimate demand for removing speckle noise by preserving edges to increasing the diagnostic potential of ultrasound imaging.

Various different methods are used to suppress noise from images. Traditionally, linear and nonlinear filtering methods are used for removing noise (Patidar et al., 2010). Linear filters perform processing based on linear mapping that replaces the central pixel of the processing kernel according to a linear equation (Patidar et al., 2010; Church et al., 2008). Linear filtering speed is higher but these filters cannot efficiently preserve the edges of images, which is a major problem (Patidar et al., 2010; Church et al., 2008).Conversely, nonlinear filters can better handle edges compared with linear filters (Patidar et al., 2010). The median filter is a widely used nonlinear filter (Church et al., 2008; Sivakumar et al., 2010; Kumarpatidar et al., 2014; Gupta et al., 2013), that is used to removes speckle noise.

This work aims to propose a new edge preserving noise filtering technique, namely, multiscale filter. Multiscale filter is propose by combining the concept of both linear and nonlinear techniques and removing the limitations of various linear and nonlinear techniques. Propose method uses the concept of a midpoint filter, a median filter, and a mean filter with the processing kernel of a Gabor filter. Performance of the proposed method is compared with different widely used de-speckling methods by calculating the signal to noise ratio (SNR), edge preservation factor (EPF), and structure similarity index (SSIM). From results, it is founded that the proposed method provides superior results compared to other methods.

2. RELATED WORKS

Different methods such as linear and nonlinear filtering and wavelet-based de-speckling have been proposed to reduce noise. Based on median filtering, (Czerwinski et al., 1995) proposed adaptive median filter called the directional median filter that is used for speckle reduction by preserving boundaries. This filter can remove the speckle patterns from the images by preserving the edges. Sticks technique is used for processing; specifically, at the time of filtering, a set of short lines is passed through the center of a square-shaped kernel and the median along each line is computed. A set of median values was computed at every point of the original image, each corresponding to a differently oriented stick, and the median of the pixel intensities that lay along every stick was computed. Finally, the output image was reconstructed by selecting the largest median value for the central pixel at each point. This work improved noise reduction, but edges are not considered.

Karaman et al., 1995 presented an adaptive speckle suppression filtering technique. Here, no limitation on kernel shape is imposed; each kernel effectively fits an arbitrarily shaped homogeneous region containing the processed pixel. Each kernel is grown in a region that employs local image statistics as its criteria. To choose a suitable window size to represent the speckle statistics, the local mean and variance of the speckle areas with no resolvable details are measured for different sized square windows. If the local variance-to-mean ratio is larger than that of the speckle, then the corresponding pixel can be considered a resolvable object. Otherwise, this pixel is considered as a part of the homogeneous region and mean or median filters are applied in this homogeneous regions.

Dutt et al., 1996 proposed an adaptive speckle reduction filter for medical ultrasound images. They presented a statistical analysis to quantify the extent of the speckle formation for log-compressed images. This statistical analysis is based on the k-distribution model that is used to design an unsharp masking filter for speckle noise reduction.

Park et al. 2007 proposed a cellular neural network architecture for speckle reduction and boundary enhancement on ultrasound images. At the point of speckle reduction, templates of cellular neural network are selected. Then, boundary strengthening is performed by an infinite impulse response filter for the learning of neural networks to determine the template. This technique can detect tumors efficiently by preserving edges.

Yu et al., 2002 proposed a nonlinear anisotropic diffusion technique to reduce speckle noise. They outline a partial differential equation (PDE)-based approach for speckle removal. The PDE-based approach allows the generation of an image scale space without the bias due to filter window size and shape. By this technique, edges are enhanced by inhibiting diffusion across edges. This new technique can remove speckle noise by preserving the edges of the images.

Patider et al., 2010 used various filtering techniques for different types of noise. They used a median filter, mean filter, wiener filter, and wavelet transform to remove noise patterns. In this regard, adaptive filter design has attracted considerable attention.

Xu et al., 1994 introduced a spatially selective noise filtration technique to remove noise from various images. This technique is based on the direct spatial correlation of the wavelet transform at several adjacent scales. Direct spatial correlation of wavelet transforms contents at several adjacent scales are used to detect the location of edges and other significant features accurately. This correlation improves the accuracy of locating important edges in signals and images.

Randhawa et al., 2017 used median filter, wiener filter, wavelet-based, and Speckle Reducing Anisotropic Diffusion (SRAD) methods for removing noise from the ultrasound images of liver. They show that if noise variance is low then SRAD method is effective but fails in the cases of high noise variance. They also observed that wiener filter performs well from the ultrasound images of liver in both low and high noise variances.

Guo et al., 2009 proposed a directional average filter for speckle noise reduction. This method works by checking the homogeneity of pixel values. Pixels values remain unchanged if the value is above a certain threshold value. Otherwise, pixel values are processed using directional averaging. This method can suppress speckle noise by preserving textual information; however, due to averaging, the image becomes smooth.

Zong et al., 1998 presented a multiscale nonlinear filter for speckle reduction and contrast enhancement in echocardiographic images. Within a multiscale wavelet analysis framework, contrast enhancement was performed by log transform and discrete wavelet transform. They applied a wavelet shrinkage technique to remove noise by preserving the sharpness of salient features and used nonlinear processing to enhance contrast within local surface boundaries and along object boundaries. For instance, they used a window of size 3×3 to smooth wavelet coefficients at the first level before applying wavelet shrinkage. The shrinkage of wavelet coefficients was performed via soft thresholding, which was carried out on coefficients of logarithmically transformed images.

Bhattacharya et al., 2013 performed the segmentation in brain image using Gabor filtering technique. Different segments of the noisy and filtered images is identified using Gabor filter. Joseph et al., 2013 proposed a weighted linear filter for speckle pattern suppression from ultrasonic images. This approach can remove noise without affecting the image content. Negi et al., 2014 developed a wavelet transformation method that is based on Gabor filter. Proposed method is used for detecting image edges in ultrasound images and different normal images. Image smoothing is performed to reduce the effect of noise. After smoothing the edges detection is done using the smooth images instead of the original one.

Gupta et al., 2017 proposed a linear smoothing method for removing noise from various images. Their proposed method combined an edge preserving method and an image smoothing method. This method can remove noise from various artificial images by preserving edge. Abd El-Gwad et al., 2017 used various linear and nonlinear filtering techniques for removing noise from the ultrasound image of prostrate. Garg at al., 2018 proposed a linear spatial filtering method for removing noise from various artificial images and ultrasound images of gallbladder. This method can remove noise effectively from the ultrasound images of gallbladder but cannot preserve edges properly.

A large body of existing studies explained that speckle noise affects all coherent imaging systems, including medical ultrasound images (Joseph et al., 2013; Duarte-Salazar et al., 2020; Roomi et al., 2011; Njeh et al., 2011; Farnandez-Caballero et al., 2008; Das et al., 2018; Sudha et al., 2009; Narayanan et al., 2009); as a results, proper diagnosis become difficult. Speckle noise reduction from ultrasound images is a challenge to select accurate diagnosis plan (Pregitha et al., 2012; Yue et al., 2007; Pradeep et al., 2021; Talukder et al., 2015; Talukder et al., 2013; Mia et al., 2023; Rahman et al., 2013). These related studies provide information about a large corpus of existing research that has addressed the problem of de-noising ultrasound images. Based on this knowledge, a new multiscale filter is proposed to suppress speckle noise from ultrasound images by preserving image edges.

From related study it was found that most of the methods are either noise reduction methods or edge preservation methods; however, proposed method performs both edge preservation and noise reduction. In case of the proposed method processing kernel is divided into three small regions and three regions are processed independently, finally results are integrated to obtain the final results. This is also a major difference between theproposed and existing methods.

3. PROPOSED METHODOLOGY

Multiscale filter is proposed by combining the concepts of the median, mean, and midpoint filter with those of a Gabor filter. In particular, at the time of filtering a 3×3 image kernel is divided into three segments, and three linear and non-linear filtering techniques are applied to each segment and finally integrated to acquire the results. For each window, we find the value of the central pixel from the entire window. Noise reduction of ultrasound images using any linear or non-linear method is challenging. This is because the total region of the processing kernel is considered for the processing of a single pixel and image become smooth; as a results edge clarity can be reduced which reduce the diagnosis accuracy. Edge preserving noise suppression is important to understand all the organs clearly from the entire image which is possible if one can calculate one pixel value by considering the smallest portion of the processing kernel instead of the whole. This article proposed multiple filter based on this concept.

At the time of using multiscale filtering technique, the processing kernel is divided into three segments and three different linear and non-linear filters e.g., the midpoint, median, and mean filters are applied to each segment respectively. Thereafter, the results of three segments are combined, and the final value of the central pixel of the processing window is calculated followed by a Gabor kernel. Gabor wavelet can effectively preserve image edges and linear filters can suppress noise; therefore, proposed multiscale filtering method is effective for edge preserving speckle suppression.

3.1 Theoretical Explanation of the Hybrid Filter

If a 3×3 window that contains 9-pixel values is considered, and the entire window is divided into three sections, then each section is processed individually. The window is as shown in Fig.1.

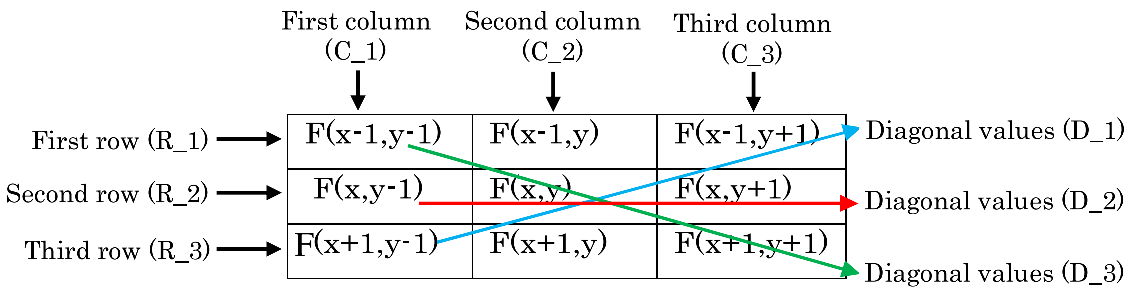

FIGURE 1: A 3×3 regionof an input image.

At the time of implementing multiscale filter, this window is divided into three parts as indicated in Fig. 1, and the filtering is performed as follows

Step-1: From the 3×3 region of an input image as shown in Fig.1, the three image coefficients of the first row (R_1) or the first column (C_1) or the diagonal values (D_1) are taken in an array and the ***Midpoint*** value is calculated by averaging the maximum and minimum values ofthese three image coefficients pixel values (Gonzalez, 2009); finally, each value is replaced by this value.

Step-2: The three values of the second row (R_2) or the second column (C_2) or the diagonal values (D_2) are taken in an array. Sorting is performed and these three values are replaced by calculating the ***Median*** value of those values (Benkrid et al., 2002; Penney et al., 2004; Buades et al., 2005; Pitas et al., 1992).

Step-3: The image coefficient values of the third row (R_3) or the third column (C_3) or the diagonal values (D_3)are taken in an array and the ***Mean*** value is calculated using the mean filter (Gonzalez, 2009); thereafter each value is replaced by this value.

Step-4: The above mentioned three arrays are merged and sorting is performed. The central pixel of the window shown in Fig.1 is replaced by the median value. Finally, the output pixel is calculated by using the following equation of the Gabor filter (Talukder et al., 2018).

$$g(x, y;\ \lambda, \theta, \Psi, \sigma, \gamma) = exp\left(-\frac{\acute{x}^2+\gamma^2\acute{y}^2}{2\sigma^2}\right) cos(2\pi\frac{\acute{x}}{\lambda} + \ \Psi) \qquad (1)$$

In this equation, $\acute{x} = x\cos\theta + \ y\sin\theta$ and$\acute{y} = -x\sin\theta + \ y\cos\theta$. Further, λ, θ, Ψ, σ, and γdenotes the wavelength of the cosine factor, the orientation of the Gabor function, the phase offset, the sigma of the Gaussian envelope, and the spatial aspect ratio, respectively.

The working procedure of the proposed filtering technique is comprehensively shown in the flowchart in Fig. 2. At the time of processing, first, an ultrasound image is taken as input, and calculated the size of the image. Desired operation is executed to remove speckle pattern using a loop from the first image coefficient to the last image coefficient of the image. A two-dimensional window of size 3 × 3 is selected for preprocessing; this window is centered on the processed pixel in the noisy image as shown in Fig. 1. Preprocessing is done by using a midpoint filter, a median filter, and a mean filter. The resultant output image is calculated by using the equation of the Gabor filter(Talukder et al., 2018). A well-known nonlinear method is the median filter that is efficient for removing speckle pattern from images (Gonzalez, 2009; Benkrid et al., 2002; Penney et al., 2004; Buades et al., 2005; Pitas et al., 1992). The mean filtering is a linear technique that is widely used to reduce intensity variation from one pixel to the next (Gonzalez, 2009). Midpoint filter is capable to remove speckle pattern from the images using the midpoint value of the processing kernel (Gonzalez, 2009). The Gabor filter is effective for edge preservation (Talukder et al., 2018); for these reasons, this article combines the concepts of median, mean, and midpoint filtering with that of the Gabor filter.

Proposed method is analyzed using the concepts of deductive methodology, for example, after data collection, the proposed method and some existing popular methods are applied to various type of ultrasound images and finally experimental results are compared and analyzed.

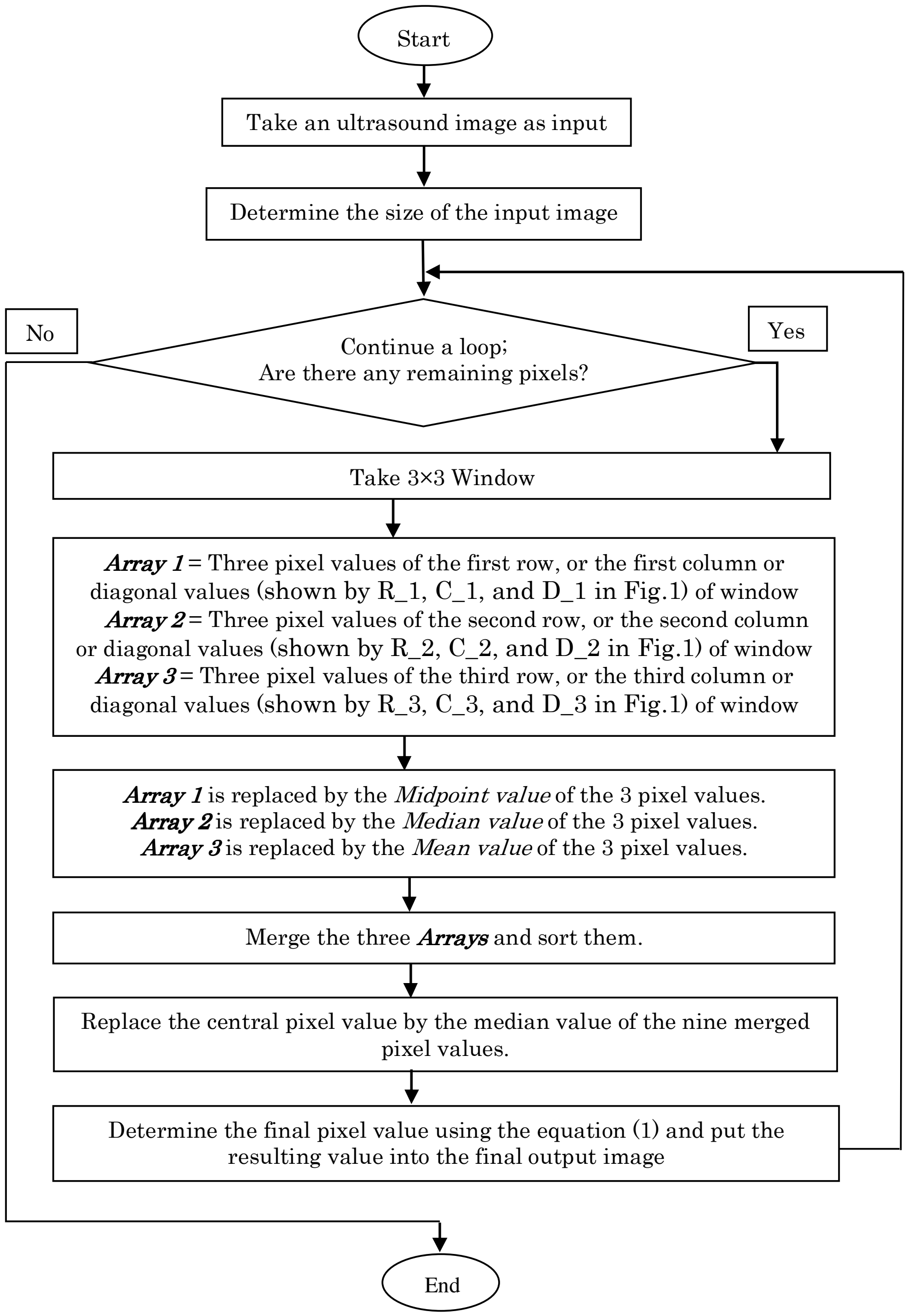

FIGURE 2: Proposed filtering technique flow diagram.

4. NUMERICAL EXPERIMENTS

Numerical experiments are conducted using the MATLAB Toolbox and the ImageJ Toolbox. De-speckling is performed using the proposed filtering method and various well-known filtering methods. For the validation of the proposed method, experimental results of the proposed method is compared with the results of various well-known methods.

In the validation process, the quality measure of the proposed method was verified using 51 real kidney, abdomen, breast, orthopedic, liver, and prostrate US images that were collected from the National Institute of Traumatology & Orthopaedic Rehabilitation, Bangladesh. First, an original noise-free image and an image contaminated with speckle noise (noise factor 0.04) are selected. Various existing and proposed filtering techniques are applied to find the results.

For the experiment, the proposed filter variously processed a 3×3 region of the image. Three filters were applied in rows, columns and diagonally and the results were tested. First, results were tested by implementing linear, and nonlinear filters in the diagonal direction but the results of this approach were poor. This was because in the case of diagonal processing, the central image coefficient value was recorded several times. Therefore, if the central image coefficient value is noisy, then this degrades the performance because this noisy value is considered for all processing steps. Linear, and nonlinear filters was also implemented in columns and rows. The processing directions are shown in Fig. 3.

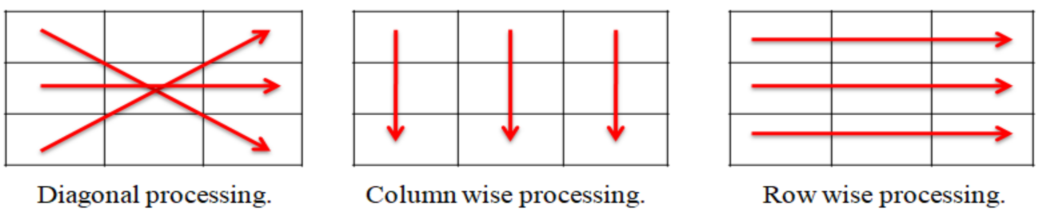

FIGURE 3: Processing in various directions**.**

The signal-to-noise ratio (SNR) and the edge preservation factor (EPF) were used as quantitative assessment metrics for selecting the processing direction (i.e., row, column, or diagonal). SNR and EPF are the most important image quality measurement metrics. SNR is calculated by measuring the ratio of signal to noise power (Karaman et al., 1995; Bhattacharya et al 2013; Rahman et al., 2013). A higher SNR indicates better quality. Edge preservation helps to understand all the objects clearly; therefore, EPF is important for medical images processing. Higher EPF represents that the technique is more effective. EPF is calculated using the equation (2):

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

In this equation,Δ represents the Laplace operator; *I,* and I_d, represent the input image, and the filtered image, respectively.

Filter Name	Image Name	SNR	EPF
Row-wise processing	Kidney	11.9	0.66
	Abdomen	12.9	0.75
	Ortho	11.9	0.63
Column-wise processing	Kidney	11.9	0.64
	Abdomen	12.6	0.70
	Ortho	11.8	0.63

Diagonal processing	Kidney	11.1	0.51
	Abdomen	12.01	0.63
	Ortho	11.03	0.48

TABLE 1: Quantitative measurements of three filters in various directions.

Table 1 represents the quantitative values of SNR and EPF obtained for the proposed filtering technique in various directions (i.e., row, column, or directional).

Normally, noise reduction performance of any filtering method varies based on the characteristics of input image. From Table 1 it is observed that the results of row and column-wise processing provides almost the same for some images; however, it can be seen that in most of the case processing by row-wise provides better results in terms of SNR and EPF. Therefore, row-wise is used for speckle suppression from ultrasound images using multiscale filtering method.

Pictorial assessment is performed for ultrasound images (with a noise factor of 0.04) using various speckle-noise reduction techniques. Representative results for the kidney, abdomen, and orthopedic ultrasound images are demonstrated in Figs. 4, 5, and 6. In these figures, (a), (b), and (c) represents the original ultrasound images, noisy images with a noise factor of 0.04, and the de-noised images using the proposed filtering method, respectively. Further, (d), (e), and (f) represents the 3D interactive plot of the original, noisy, and filtered images, respectively. In 3D plot, X and Y is the spatial co-ordinates, and Z represent brightness values of the pixels. Comparatively higher value is obtained (in Z direction) from speckle noise contaminated pixels.

In the case of pictorial assessment two task was performed. First, speckle suppression was performed in MATLAB toolbox. Preservation of image details by preserving image edges was expected at the time of speckle reduction. Second, the ImageJ toolbox was used to visualize 3D interactive plot of the original, noisy, and the filtered images.

By comparing the images (a), (b), and (c) of Figs. 4, 5 and 6, it is observed that the better clarity was obtained using the proposed method for speckle suppression. By observing the images (d), and (e), it was found that the image co-efficient values were for (e) compared with (d); as mentioned previously that speckle represent higher values, therefore, (e) contain speckle noise. The 3D plot of the filtered image (f) was almost similar to the noise free image (d); therefore, it can be concluded that the proposed method can suppress speckle pattern from the ultrasound images effectively.

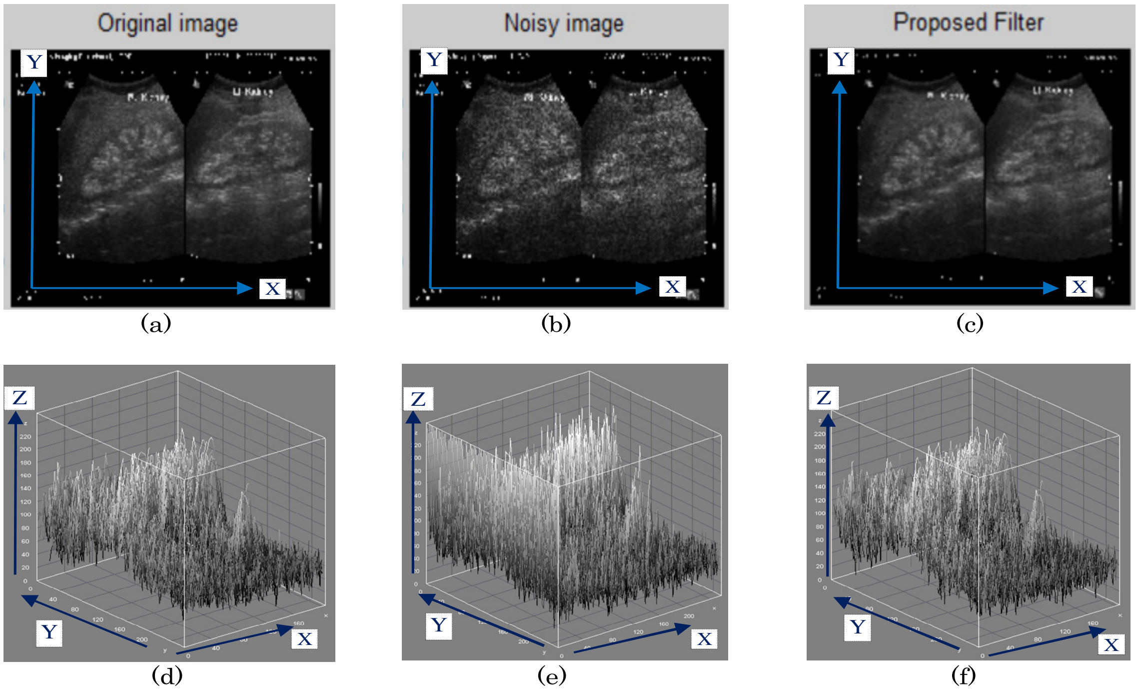

FIGURE 4: Ultrasound image of Kidney: a) Original, b) Noisy, c) Filtered using the proposed method, d) 3D interactive plot (original), e) 3D interactive plot, (noisy), and f) 3D interactive plot (filtered).

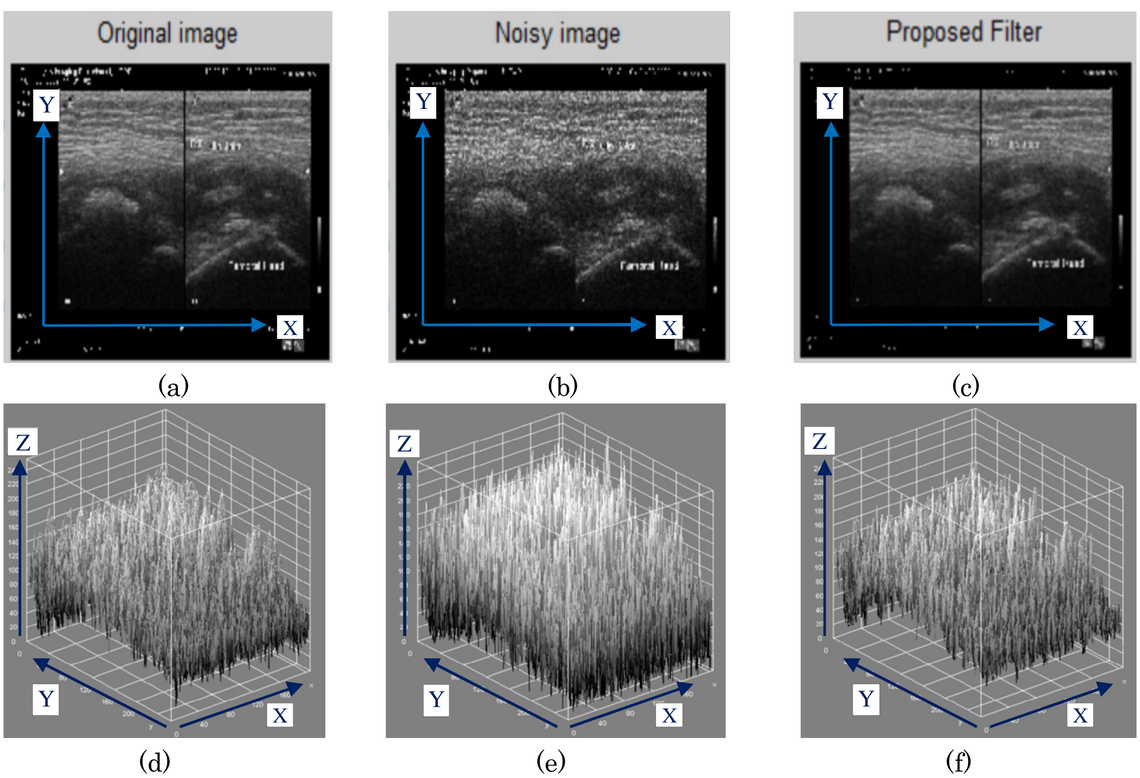

FIGURE 5: Ultrasound image of Abdomen: a) Original, b) Noisy, c) Filtered using the proposed method, d) 3D interactive plot (original), e) 3D interactive plot, (noisy), and f) 3D interactive plot (filtered).

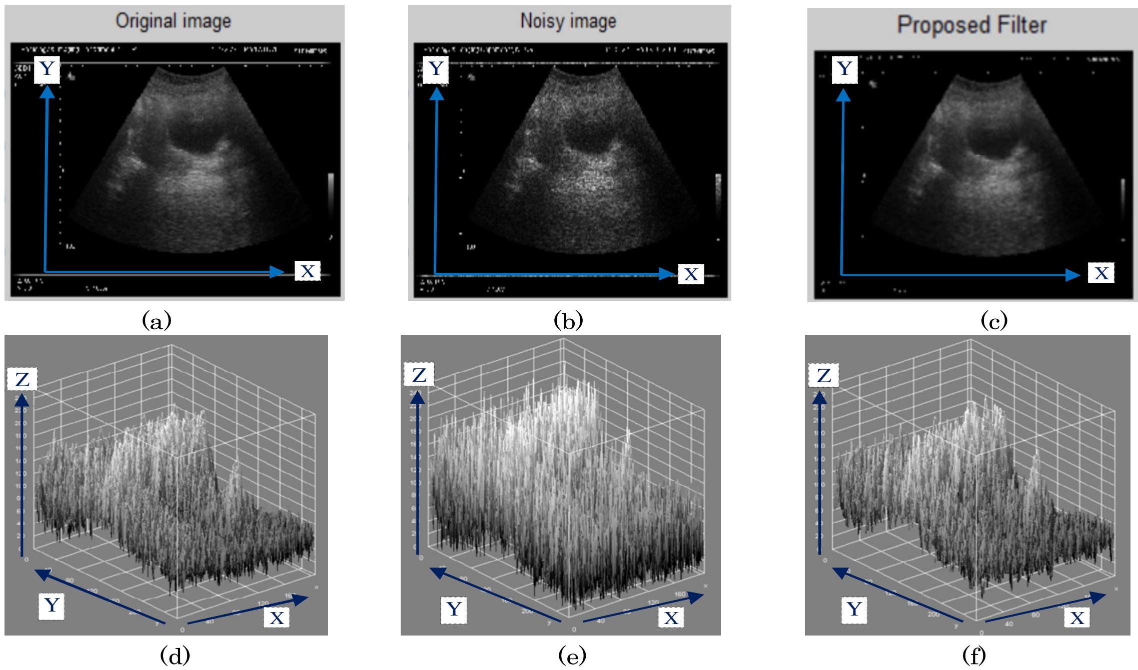

FIGURE 6: Ultrasound image of Ortho: a) Original, b) Noisy, c) Filtered using the proposed method, d) 3D interactive plot (original), e) 3D interactive plot, (noisy), and f) 3D interactive plot (filtered).

For the validation of the proposed method, the performance was compared with five popular speckle reduction methods. Quantitative evaluation and comparison was performed by calculating the values of the SNR, EPF, and structure similarity index (SSIM).

SSIM is used to compare the image structure to calculate the similarities between two images. The range of SSIM is from 0 to 1. When the value of SSIM is close to 1 for two images this means that the structure of these two images are similar with respect of luminance, contrast, and other values. SSIM between two images is calculated using equation (3):

$$SSIM\ (I, I_d) = \frac{(2\mu_I \mu_{I_d} + C_1)(2\sigma_{II_d} + C_2)}{(\mu_I^2 + \mu_{I_d}^2 + C_1)(\sigma_I^2 + \sigma_{I_d}^2 + C_2)} \tag{3}$$

In this equation, I and I_d respectively denote the original and the denoised images. μ_I and μ_{Id}, $\sigma_I$and σ_{Id} denote the average and variance of I and I_d, respectively. σ_{IId} is the covariance of I and I_d. C_1 andC_2 are variables for stabilizing the denominator.

A total of 51 different US images comprised of 11 kidney images, 10 abdomen images, 10 breast images, 10 orthopedic images, 5 liver images, and 5 prostrate images were used for quantitatively measuring the performance of various filtering technique. For each filtering technique, a separate box plot was generated to compare the performances. The results of the box plot analysis for the SNR, EPF, and SSIM are presented in Figs. 7, 8, and 9 respectively. The quantitative measurement results of the various filtering techniques' performance are represented in Table 2. In Table 2, the average values of the SNR, EPF, and SSIM values for 51 different US images using various filtering techniques are represented.

Median filtering is widely used for image denoising (Gonzalez, 2009; Benkrid et al., 2002; Penney et al., 2004; Buades et al., 2005; Pitas et al., 1992). Median filtering is good for removing noise and provides good SNR values, and this is its main advantage but median filtering cannot preserve the edges of image effectively and its EPF values are sub-optimal, and this is its main limitation. The Gabor filter is widely used for edge preservation and provides good EPF values (Talukder et al., 2018; Negi et al., 2014)]; but fails at noise reduction; this is the major limitation of Gabor filtering. The proposed filter removes the limitations of the median and Gabor filters.

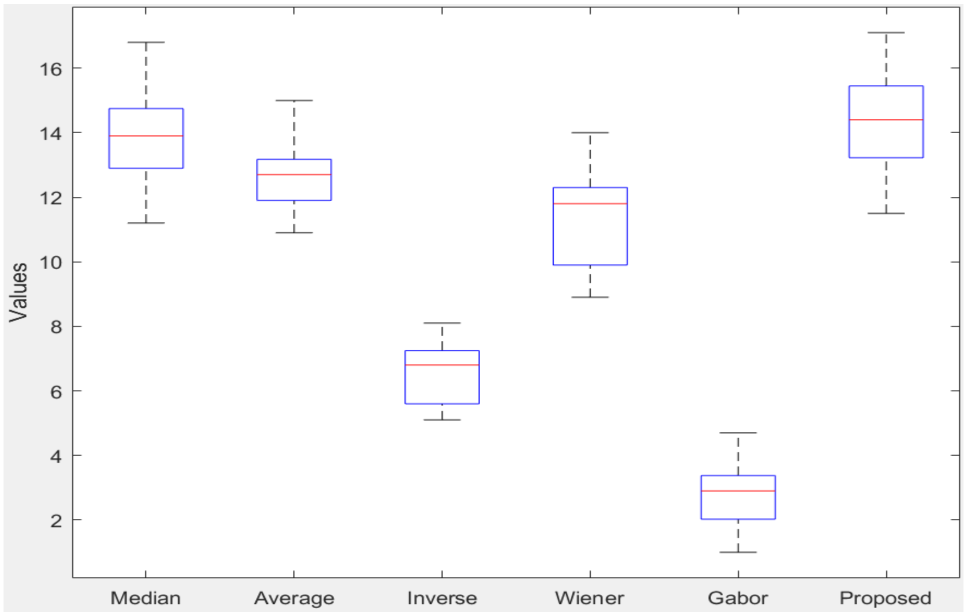

FIGURE 7: SNR box plot for different filtering techniques.

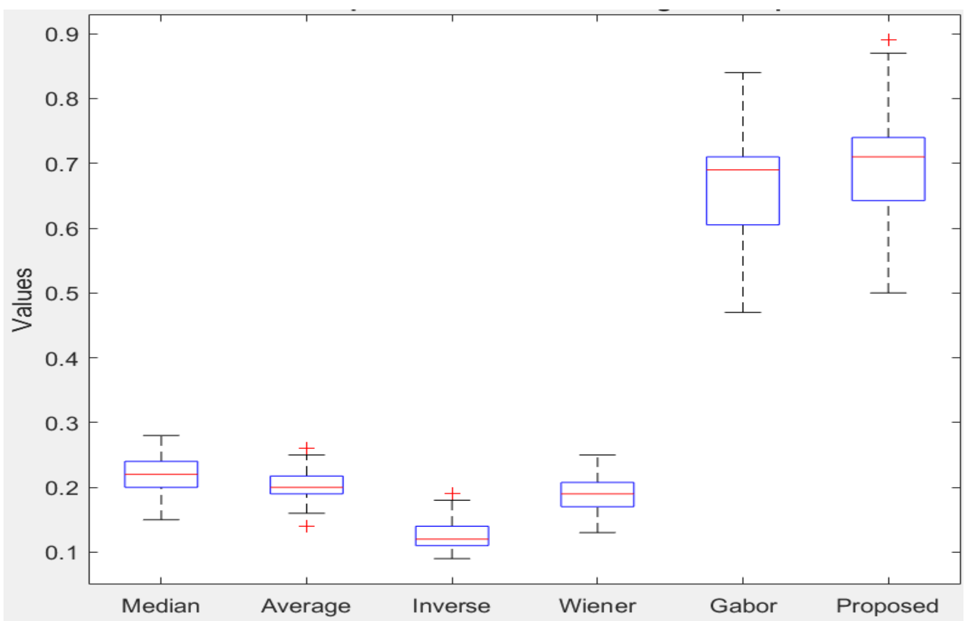

FIGURE 8: EPF box plot for different filtering techniques.

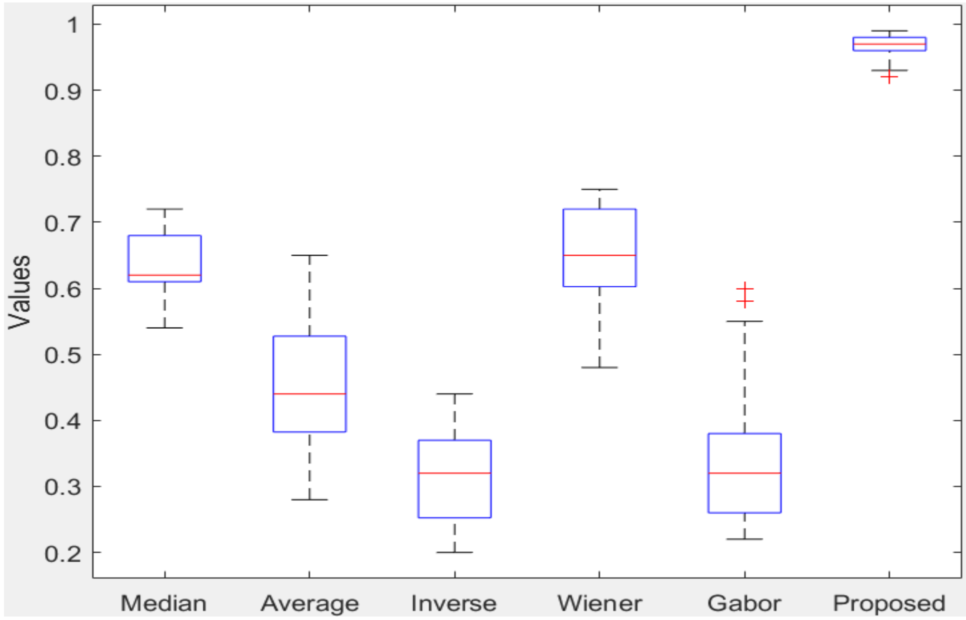

FIGURE 9: SSIM box plot for different filtering techniques.

From Fig. 7 and 8, it can be said that the SNR values provided by median filtering are acceptable but that the EPF values are poor. On the contrary, Gabor filtering is very good for edge preservation and provides good EPF values (from Fig. 8); but Gabor filtering is sub-optimal for noise reduction and provides the very poor SNR values seen in Fig. 7. The proposed hybrid filter is good for both noise reduction and edge preservation. The SNR value of the proposed filter is higher than the median filter and the EPF value of the proposed filter is higher than that of the Gabor filter.

From Fig. 9, one can see that the SSIM values provided by the proposed filtering method are close to 1. The SSIM value being close to 1 means that, the proposed filter removes noise efficiently by preserving edges.

The proposed filter removes the limitations of the median and Gabor filtering techniques by combining the concept of both linear and nonlinear filtering techniques and provides higher SNR values and higher EPF values. From Fig. 7, it is clear that proposed filtering technique slightly improves the SNR values compared with the median and other filters. The EPF values provided by the proposed filtering method are higher than the EPF values of the Gabor and other filters as is seen in Fig. 8. The purpose of this study was to achieve edge preservation and noise reduction, which the proposed method does by improving both the noise reduction and edge preservation parameters.

Filter Name	SNR	EPF	SSIM
Median	13.8	0.22	0.63
Average	12.6	0.20	0.44
Inverse	5.9	0.12	0.31
Wiener	11.4	0.19	0.64
Gabor	2.8	0.67	0.34
Proposed Method	14.5	0.70	0.97

TABLE 2: Quantitative measurements of the performance of various filtering technique.

From Table 2, it is clear that the proposed filtering technique provides superior results. One can observe the significant improvement of the value of speckle-SNR, by applying the proposed filtering technique. Among the existing methods, median filtering provides higher SNR at a value of 13.8. The proposed filter provided a value of 14.5, which is higher than the median and any other method. The Gabor filter provides a higher EPF value among the existing methods. The EPF value for Gabor filtering is 0.67 and the EPF value for the proposed filter is 0.70, which is higher than for any other method. The SSIM value is 0.97 for the proposed method and is much higher than for the existing methods.

5. DISCUSSION

The performance of the proposed filtering technique was qualitatively (Figs. 4, 5, and 6) and quantitatively (Fig. 7, 8, and Table 2) measured. The proposed filtering technique provides superior results when compared with existing methods. All traditional noise removal techniques considered the entire kernel area for processing each pixel. This hampered the image edges and smoothed the image. The proposed method removes this problem by considering the smallest kernel region when processing each pixel.

In Table 2, it can be seen that the proposed filter provided SNR, EPF, and SSIM values that are higher than those of the existing filters. The SNR value increases when noise is effectively removed. A high EPF value means that the method preserves edges properly. For two identical sets of data the SSIM value is 1. The median filter is optimal for noise reduction and for this reason its SNR value is higher but it cannot preserve the edges properly and provides a poor EPF value. Gabor filtering is good for edge preservation and provides good EPF values of but it fails for noise reduction. The average SNR, EPF, and SSIM values for the proposed method are 14.5, 0.70, and 0.97 respectively. The SNR, EPF, and SSIM values of the proposed method are higher than for other existing methods meaning that the proposed method removes noise and preserves edges better than existing methods.

Median filtering can remove noise, mean filtering can reduce the intensity variation from one pixel to the next; midpoint filtering can remove randomly distributed and uniform noise. Conversely, Gabor filtering is the only type with orientation selectivity that maximizes and preserves the edges in images sufficiently. The proposed filter combines noise reduction filtering e.g., median, mean, and midpoint filtering with Gabor filtering. For this reason, the proposed filter is good for both noise reduction and edge preservation; which are the main advantages of our proposed method. Because the proposed filter combines three linear and nonlinear filters with the Gabor filter, the processing time of the proposed filtering technique is little higher than for the existing linear and nonlinear methods.

6. CONCLUSION

High frequency information is crucial in human vision because it carries details that are important for visual perceptions. Images with a high frequency content (e.g., corners and lines) are more sensitive to discernment. The presence of noise degrades the target detectability in the images and reduces contrast and resolutions, which affects the identification of normal and pathological tissue. Ultrasound images are automatically affected by speckle noise. If this noise can be removed from ultrasound images,it willfacilitate diagnoses. De-noising by preserving the edges has become a crucialrequirementfor ensuring correct diagnoses using such images. The demand from the healthcare industries is for the preservation of useful diagnostic information that includes minimal noise.

Accordingly, a new multiscale filter is proposed by this study that integrates the qualities of linear and nonlinear filtering methods. The proposed method is used for speckle noise suppression from medical ultrasound images and the results are compared with five well-known and widely used speckle suppression methods. The experimental results prove that the proposed method produces images that are clearer and smoother than those of the other methods. In case of the proposed method, edge enhancement is also performed with noise reduction; therefore, better results were obtained compared to the existing methods.

In conclusion, from the measurements, it is clear that the proposed filter de-specklesvarious ultrasound images by preserving the edges more effectively than existing filters. Clear image generation through speckle noise-suppression by preserving edge is important for proper diagnosis. Therefore, this research work will help the physician to perform accurate diagnosis using medical ultrasound images. As well as, general people will be benefited through this research in the case of ultrasound imagediagnosis.The validity of this study was checked by employing US images. In future research the validity of the proposed method will be checked using computed tomography*(*CT)*,* magnetic resonance (MRI), and Positron-emission tomography *(*PET*)* image-types.

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