Research Article

Kaitheri Thacharedath Dilna and Duraisamy Jude Hemanth*

Novel image enhancement approaches for despeckling in ultrasound images for fibroid detection in human uterus

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Abstract: Ultrasonography is an extensively used medical imaging technique for multiple reasons. It works on the basic theory of echoes from the tissues under consideration. However, the occurrence of signal dependent noise such as speckle destroys utility of ultrasound images. Speckle noise is subject to the composition of image tissue and parameters of image. It reduces the effectiveness of many image processing steps and decreases human perception of fine details from ultrasound images. In many medical image processing methods, despeckling is used as the preprocessing step before segmentation and feature extraction. Many speckle reduction filters are proposed but while combining many techniques some speckle diagnostic information should be preserved. Removal of speckle noise from ultrasound image by preserving edges and added features is a great challenging task in ultrasound image restoration. This paper aims at a comprehensive description and comparison of reduction of speckle noise of ultrasound fibroid image. Many filters are applied on ultrasound scanned images and the performance is marked in terms of some statistical measures. Even though several despeckling filters are there for speckle reduction, all are not good for ultrasound scanned images. A comparison of quality measures such as mean square error, peak signal-to-noise ratio, and signal-to-noise ratio is done in ultrasound images in despeckling.

Keywords: fibroid, uterus, ultrasonic imaging, despeckling, filters

1 Introduction

Ultrasound image system uses high frequency of sound wave to get an image of uterus fibroid. Ultrasound waves travel through soft tissues but it produces echoes on solid objects. Each ultrasound wave covers a spatial volume defined by the smallest of detectable structures, called as resolution cells. Fibroid appears as well-defined solid mass and it appears as hypoechoic. These hypoechoic objects become visible as dark images, as they have low echogenicity, and bright image becomes visible as it has high echogenicity and is called hyperechoic. There have been many speckle reduction methods documented earlier. A nonlinear processing technique like logarithmic compression on ultrasound B scan images is described by Loupas et al. [1] and designed some parameters to defuse speckle in this paper. A comparative survey of spatial filtering techniques is seen in ref. [2]. This report gives awareness about the different aspects placed in the deduction of noise from ultrasound fetal images.

Lie and Chen [3] propose a compounding technique to improve target detectability by acquiring a sequence of ultrasound images with different angles, which is taken from a same target. A composite image is formed by averaging the images pixel values. Speckle reduction based on ratio of local variance to local mean that alter the quantity of smoothing is described in ref. [4]. Here denoising is improved in homogenous section where speckle appears abundantly and is seen as lowered down or even eluded in other areas to reserve details as such. The region growing speckle reduction scheme based on spatial filtering has been proposed in ref. [5]. In these methods, spatial filtering is accomplished depending on the information content of the image extracted from groups of the pixel which are formed based on similar gray level and connectivity. This is according to the local statistics of adaptive region, which is determined from size and shape. A drawback of region growing-based technique is the difficulty in designing suitable similarity criteria.

* Corresponding author: Duraisamy Jude Hemanth, Department of ECE, Karunya Institute of Technology and Sciences, Coimbatore, India, e-mail: judehemanth@karunya.edu

Kaitheri Thacharedath Dilna: Department of ECE, Karunya Institute of Technology and Sciences, Coimbatore, India; Department of ECE, College of Engineering and Technology, Payyanur, India

A work on speckle reduction by minimization of total variation in ultrasound images is described in ref. [6]. This approach adopted total variation minimization method suggested by Khalifa Djemal. The modification of smoothing level subjected to the statistics of log compressed images is described in ref. [7] by unsharp masking filter. However, this method fails in reducing speckle near or at edges of images. A relationship formed for image smoothing in continuous domain for isotropic scattering is given [8]. However, in images with speckle, isotropic diffusion advances flicker. Thus anisotropic diffusion model such as edge sensitive speckle reducing anisotropic diffusion (SRAD) method is described in ref. [9]. In this method, speckle is reduced but edge information is preserved. Modified SRAD filter, detail preserving anisotropic diffusion (DPAD) that depends on Kaun filter was established in ref. [10].

A different approach in reducing speckles using soft thresholding in wavelet filtering is proposed by Donoho [11]. However, this method lacks translation invariance. This drawback is eliminated using stationary wavelet method [12]. Lee filter [13] accomplishes filtering action on the image area that is having little variance. Lee filter fails in despeckling in the region's nearby edges and lines. A simplification of Lee filter is Kaun filter [14]. It is clear that speckle is observed as a major basis of noise in ultrasound image and should be eliminated without disturbing any important features. In this work different despeckling filters are applied on ultrasound fibroid images to denoise and to segment fibroid area to detect structural features of prescribed fibroid. The performance of every filter on these fibroid images is measured to find the best despeckling filter that can be

used in the segmentation of fibroid from ultrasound image.

Section 2 discusses about the materials and methods. Section 3 focuses on the various speckle reduction filters. Section 4 discusses about the performance analysis parameters used in this paper and details the result and discussion. Section 5 provides the conclusion.

2 Materials and methods

Ultrasound scanning is the preferred imaging technique to spot fibroids. The uterus ultrasonography is performed either abdominally or transvaginally. Ultrasound adverts to sound waves, which cannot be sensed by human ear. Proportional to the acoustic impedance of every soft tissue, sound waves are transmitted. This acoustic impedance is related to sound transmission velocity and density of tissue. Sound waves are reflected when there is a change in acoustic impedance. This occurs when two dissimilar density tissues placed next to each other. Therefore, ultrasound imaging is a noble tool for soft tissues. Reflected sound waves are absorbed by transducer located directly on the skin, and it converts the echoes to electrical signal. These signals are then demodulated and compressed to outfit for display devices. Fibroid in ultrasound image is commonly appearing as distinct, solid hypo echoic masses in ultrasound images. In this work, 256×256 gray level images are used with intensity ranges between 0 and 255. Figure 1 shows some sample data set with uterus fibroids.

Figure 1: Sample data set.

Certain useful information are faded or even lost during compression stage. The noise that occurs in medical image would be during acquisition and transmission usually. Speckle is a multiplicative noise that appears on B-Scan, which reduces quality of image. Speckle is an unwanted modification of desired signal. Speckle destroys the target detectability in scanned images and reduces resolution and contrast, which help human to differentiate typical and diseased tissue. It also cut down the speed and accuracy of segmentation of ultrasound image. Despeckling of scanned image is a challenging task. This paper put forward a comparison of different filters applied on ultrasound image involved in the detection of uterus fibroids. A structural outline is given in Figure 2.

3 Despeckling approaches

Speckle noise has granular pattern and is multiplicative in nature. Because of the temporal movement of organs, speckle noise in scanned images consists of high frequency components. Speckle noise has gamma distribution in nature.

$$G = \frac{g^{\alpha-1}}{(\alpha-1)!a^{\alpha}} e^{-\frac{g}{a}}, \quad (1)$$

where a^{α} is the variance and g is the gray level. Signal and noise are statistically independent and maintain proportional relationship in gray level in all areas. As it contains high frequency components, low pass filters can be applied on images. Some despeckling filters are described in this section.

3.1 Scalar filters

Scalar filters are used to maintain the valuable features in homogeneous region of an image. Speckle in this region is fully technically improved and compressed considerably in the other regions of the image. Two categories of scalar filters are mean filter and median filters.

3.1.1 Mean filter

Main application of spatial mean filter [14] is noise reduction and blurring. A predefined mask is applied on the image. Box filter is when all coefficients in the mask are equal. This method takes the average value of the neighborhood and replaces the value of every pixel in the image. With that it does not reduces the speckle noise as a whole but diminishes to some extent.

Figure 2: Frame work of proposed approach.

$$F(x, y) = \frac{1}{mn} \sum_{(s,t) \in Sxy} g(s, t), \quad (2)$$

where Sxy is the set of coordinates in a rectangular mask with $m \times n$ size.

3.1.2 Median filter

It is a nonlinear filtering technique to reduce noise by preserving edge characteristics. Median filtering [15] can be calculated by sliding a window over the image. It replaces value of middle pixel by median in the window by sorting values of pixels from the window into numerical order. The median filter produces less blurred images. This filter tends to destruct edges of image and yield false edges in the presence of small signal-to-noise ratio (SNR). For median filtering, we should specify the mask size to get noble result.

$$F(x, y) = \text{median}\{g(s, t)\}. \quad (3)$$

3.2 Adaptive filters

This method is used to bring back image without distorting the structures in the image. The two statistical measures that an adaptive filter presumes on are mean and variance with a defined $m \times n$ window region. Some filters that are having adaptive nature are discussed.

3.2.1 Wiener filter

Weiner filter [16] is a significant technique to reduce noise affected by linear motion or unfocussed optics. This is also known as least mean square filter. This method reduces noise on the comparison of preferred noiseless image. This filter computes local image variance and smoothing is done according to this. When local variance of the image is enormous, the smoothing is done in lesser amount and if it is small it executes more smoothing. Simultaneously, it eliminates the additive noise and overturns the blurring. The Wiener filtering is ideal in terms of mean square error, that is, it minimizes the overall mean square error, which is given as

$$e^2 = E\{(f - \hat{f})^2\}. \quad (4)$$

The method is centered on a stochastic background

$$G(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + \frac{P_n(u, v)}{P_s(u, v)}}, \quad (5)$$

$$G(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + K}, \quad (6)$$

where K is the constant chosen by the noise level; $H(u, v)$ is the Fourier transform of point spread function; $P_n(u, v)$ is the power spectrum of noise; and $P_s(u, v)$ is the power spectrum of signal.

3.2.2 Lee filter

Lee filter produces output image by working out on linear combination of the central pixel intensity in a neighborhood with the average intensity of mask. This method conserve details using local statistics and works based on multiplicative speckle model. This filter [17] works on the value of variance. Smoothing operation is executed if the resultant variance is low and is not recommended for high variance. Filter has an adaptive nature since image details can be preserved both in low and high contrast.

$$\text{Img}(x, y) = \text{Im} + W \times (\text{Cp} - \text{Im}), \quad (7)$$

where Img is the pixel value after filtering, Im is the mean intensity of filter window, Cp is the center pixel, and W is the filter window.

$$W = \sigma^2(\sigma^2 + \rho^2), \quad (8)$$

where ρ is the additive noise variance and σ^2 is the variance of the pixel given as

$$\sigma^2 = \frac{1}{N} \sum_{j=0}^{N-1} (X_j)^2, \quad (9)$$

where N is the size of the window and X_j is the value of pixel at j .

3.2.3 Kaun filter

It is a local linear minimum mean square error filter under multiplicative noise. The formulations arrived by Kaun [18] and Lee filter are same, even though the signal model assumption and derivations are different. This filter maintains stability between results of averages in similar regions and detect where edges and point features exist. This stability depends on the moving window which has the figure of variation inside. It is an advanced technique of Lee filter and it converts the multiplicative speckle model into the additive linear form.

Weighting function W is

$$W = \frac{1 + \frac{C_u}{C_l}}{1 + C_u}, \quad (10)$$

where C_u is the estimated noise variation coefficient and C_i is the variation coefficient of image.

$C_u = \sqrt{1/ENL}$, where ENL is the equivalent noise.

$$ENL = \frac{\bar{K}}{\sigma_k}, \quad (11)$$

where σ_k is the standard deviation and $\bar{K}$ is the mean intensity value.

3.2.4 SRAD filter

Anisotropic diffusion is a denoising technique without eradicating important parts of image content like edges or lines. SRAD filter [19] is an anisotropic denoising algorithm which is used to improve edges in an image. Even if the noise is detected or edge is not detected, filter will not enhance or smoothen the edge. Therefore the performance of SRAD is delicate to the selection of threshold value [20].

3.3 Wavelet filter

The wavelet filter [21] particularly highlights or de-emphasizes image details (high-frequency, mid-frequency, or low-frequency detail) in a definite spatial frequency domain. The foremost benefit of wavelet basis is that this can perfectly reconstruct functions even though having irregular shape with linear and higher order polynomial shapes, such as rectangle, triangle, and second order polynomials.

3.4 Homomorphic filtering

Speckle noise is multiplicative in nature. Homomorphic filtering [22] is used to eliminate the multiplicative noise by log and exponential operations. It transmutes multiplicative noise into additive. This filter mends gray scale image by simultaneous intensity range compression and contrast enhancement. An image can be represented by two components as illumination components $I(x,y)$ and reflectance components $R(x,y)$.

$$f(x, y) = I(x, y) \times R(x, y). \quad (12)$$

When illumination components vary slowly reflectance components tend to vary quickly. Consequently, intensity variation can be reduced by putting on a frequency domain filter. Before applying Fourier transform, multiplication should change to addition by taking logarithm.

$$g(x, y) = \ln(I(x, y)) + \ln(R(x, y)). \quad (13)$$

Then take FFT (Fourier Transform) and apply a proper Fourier filter function. To get the resultant image, take inverse transform and exponential function. Figure 3 shows the steps of homomorphic filtering.

3.5 Smoothing frequency domain filters

Frequency domain filters focus on image frequency and are used for smoothing and sharpening by removing low and high frequency components. Low pass filter passes low frequency components in an image, resulting in smoothened image by attenuating high frequency components. There are three types of low pass filters.

3.5.1 Ideal low pass filter (ILPF)

Transfer function of ILPF is

$$H(u, v) = \begin{cases} 1, & \text{if } D(u, v) \leq D_0 \\ 0, & \text{if } D(u, v) > D_0 \end{cases} \quad (14)$$

Figure 4: Despeckled image using mean filter.

Figure 3: Block diagram of homomorphic filter.

Table 1: MSE, SNR, and PSNR for mean filter on fibroid ultrasound image for different window size

Window size	MSE	PSNR	SNR
3	0.014	16.711	9.330
5	0.014	16.643	8.771
8	0.016	16.551	8.362
10	0.016	16.522	8.187

where D_0 is the cutoff frequency, D is the identified non-negative quantity, and distance from (u,v) is denoted as $D(u,v)$ in frequency domain

$$D(u, v) = \sqrt{\left(u - \frac{M}{2}\right)^2 + \left(v - \frac{M}{2}\right)^2}. \quad (15)$$

We can see that blurring effect decreases as cutoff frequency increases.

3.5.2 Butterworth low pass filter (BLPF)

Transfer function of BLPF with cutoff frequency D_0 and order “ n ” is

$$H(u, v) = \frac{1}{1 + (D(u, v)/D_0)^{2n}}. \quad (16)$$

One advantage of this filter is sharpness control and can be adjusted by order “ n .” The result of BPLF is smooth transition in blurring, as a function of increasing cutoff frequency.

Table 2: MSE, SNR, and PSNR for median filter on fibroid ultrasound image for different window size

Median filter			
Window size	MSE	PSNR	SNR
3	0.00069	19.0021	15.0524
5	0.00406	17.1608	11.3367
8	0.00957	16.2748	9.38251
10	0.01053	16.1766	9.14961

Figure 6: Median filter performance with different window size.

3.5.3 Gaussian low pass filter (GLPF)

GLPF is given by

$$H(u, v) = e^{-D(u,v)^2/2\sigma^2}, \quad (17)$$

where σ is a measure of the spread of Gaussian curve. GLPF has smooth transition between low and high frequencies. As the sigma becomes larger, the more variance

Figure 5: Median filtering result with various window size. (a) Window size = 3, (b) window size = 5, (c) window size = 8, and (d) window size = 10.

Figure 7: Resultant image after despeckling using (a) Weiner filter, (b) Kaun Filter, (c) Lee filter, and (d) SRAD.

Table 3: MSE, SNR, and PSNR for the adaptive filters

Filter	MSE	PSNR	SNR
Weiner filter	45.63	11.66	14.81
Lee filter	45.46	29.06	14.91
Kaun filter	44.5	26.21	15.03
SRAD filter	0.87	28.19	14.69
Mean filter	0.18	11.06	15.01
Median Filter	0.000685	19.02	15.05

allowed around mean, and as the sigma becomes smaller, the less variance allowed around mean.

4 Experimental results and discussions

Ultrasound scanned uterus fibroid image is used as input image and it is transformed into gray scale. Two different scalar filters (mean filter and median filter), four adaptive filter methods (Weiner filter, SRAD, and Lee and Kaun filter), wavelet transformation filter, and homomorphic filter are applied on transformed fibroid image. The experiments were carried out in a HP PC with processor Intel® Core™i3 7020U CPU and 4 GB RAM. Filter performance improvements are compared and quantified with certain performance evaluation parameters like mean square error (MSE), SNR, and peak SNR (PSNR). Comparative analysis is executed with the help of MATLAB simulation for easiness in the determination of statistical parameter.

Figure 8: Comparison of performance of different adaptive filters.

Table 4: MSE, SNR, and PSNR for the wavelet filters

Band	MSE	PSNR	SNR
Wavelet filter level = 1			
HL	0.00044	19.4682	16.0409
LH	0.00066	19.0351	15.1748
HH	2.08×10^{-6}	24.996	27.1398
Wavelet filter level = 2			
HL	0.08471	14.0204	6.63175
LH	0.08312	14.04	6.63841
HH	0.08481	14.0192	6.73183

The quality change between input image and filtered image is measured using MSE. The SNR signifies the magnitude of error comparative to the original image and if SNR is more it specifies that filtering effect is good. PSNR indicates the size of the error proportionate to the peak value of the signal and is figured with the size of the error proportionate to the average squared value of the signal. The quality of the image is detected by PSNR after preprocessing. High value PSNR specifies a better reduction in noise and hence makes sure that a good image enhancement is done and is expressed in decibels (dB). High value of PSNR means that image having additional valued signal than the noise.

$$MSE = \frac{1}{MN} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} [I(x, y) - \hat{I}(x, y)]^2, \quad (18)$$

where $I(x, y)$ is the original image where filter is supposed to apply and $\hat{I}(x, y)$ is the original image after filtering

$$SNR = 10 \log_{10} \frac{\frac{1}{MN} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} [I(x, y)]^2}{MSE}, \quad (19)$$

$$PSNR = 10 \log_{10} \frac{(2^N - 1)^2}{MSE}. \quad (20)$$

Figure 9: Filtered image using wavelet filter; band eliminated (a) HL, (b) LH, and (c) HH.

Figure 10: PSNR and SNR interpretation over different wavelet bands.

4.1 Result of mean filter

Figure 4 shows the filtered image using arithmetic mean filter. This filter changes non-noisy pixels, thus eliminating some adequate details of the image. Edges are not recuperated and are suitable only for low level noise. Table 1 provides the quantitative measure MSE, PSNR, and SNR by applying mean filter on fibroid image, and result shows that 3×3 window results in better performance because it has high PSNR and low MSE values.

4.2 Result of median filter

Median filter is the perfect nonlinear despeckling filter and it produces less blurred images. It works more

on nonuniform region. Figure 5 illustrates the result of median filtering with various window size. Performance of this filter with different window size depends on noise density. With low noise density, small window size provides improved performance. Table 2 shows the quantitative results of MSE, PSNR, and SNR with different window size. It shows that SNR and PSNR are high for small window size. The quantitative results are given in Figure 6. Window size 3 gives low MSE and high PSNR value, and thus window size 3 is adoptable in median filtering (Figure 7).

4.3 Result of adaptive filter

Lee filter produces the highest speckle suppression but it smooth out edges and textures. SRAD filter removes speckle without altering required image information and without affecting the important image edge features. Table 3 and Figure 8 detail the result with PSNR, SNR, and MSE values. It is clear that Lee filter and SRAD filter give better performance than the other filters.

4.4 Result of wavelet filter

Table 4 illustrates the quantitative result of denoising using wavelet filter with level 1 and level 2 decomposition. Level 1

Figure 11: Filtered image using homomorphic ideal filter. (a) $F_c = 10$, (b) $F_c = 20$, and (c) $F_c = 30$.

Figure 12: Filtered image using homomorphic wavelet filter HL, LH, and HH.

approximation image had enhanced performance than level 2 approximation. The results indicate that wavelet transforms despeckled images more effectively. After reconstruction the wavelet transform maintains the image constancy (Figures 9 and 10).

4.5 Result of homomorphic filter

Homomorphic filtering is applied on fibroid image with ideal, Butterworth with different cutoff frequency and homomorphic wavelet filter. Response is described in Figures 11 and 12. It is clear that performance is poor and it loses image information.

4.6 Result of frequency domain filter

Different frequency filtering techniques are applied on input image with various cutoff frequencies. Filtering is

applied with ideal low pass, Butterworth, and Gaussian low pass smoothing filter. Figures 13 and 14 illustrate the result of despeckling with various cutoff frequencies. Figure 14 shows the result of Gaussian filtering with different sigma values. It shows that image information is lost in this type of filtering. With lowest cutoff frequency image information are completely lost and increase in cutoff frequency results in improvement on images. This can be seen in Tables 5 and 6. High cutoff frequency gives in high PSNR value (Table 7).

4.7 Result analysis

The aforesaid tables show that SRAD filter and Lee filter have highest PSNR values and thus they work well on the ultrasound fibroid uterus images. SRAD filter is having 28.19 PSNR value and Lee filter is having PSNR value 29.06. Even though wavelet filter gives good result, it cannot work better on multiplicative noise. From these conclusions, Lee filter has the best performance and it

Figure 13: Filtered image using ILPF and Butterworth low pass filter with (a) $F_c = 10$, (b) $F_c = 20$, (c) $(F_c = 10) F_c = 30$, and (d) $F_c = 40$.

Figure 14: Filtered image using GLPF with various σ values.

Table 5: MSE, SNR, and PSNR for the homomorphic filters

Homomorphic wavelet filter			
Band	MSE	PSNR	SNR
HL	0.000485	19.35971	15.78599
LH	0.000733	18.93163	14.92983
HH	1.86×10^{-5}	22.73329	22.63681

Table 6: MSE, SNR, and PSNR for the ILPF

Fourier ideal filter			
Cutoff frequency	MSE	PSNR	SNR
10	0.0151	15.8036	7.83012
20	0.01195	16.0458	8.7199
30	0.00992	16.2381	9.25312
40	0.00894	16.3456	9.64849

Table 7: MSE, SNR, and PSNR for the BLPF

BLPF			
Cutoff frequency	MSE	PSNR	SNR
10	0.01424	15.8641	7.78238
20	0.01109	16.1225	8.73072
30	0.00929	16.3059	9.25078
40	0.00803	16.4569	9.65897

can reduce noise effectively without losing information about edges. This filter results in an improved contrast of the image and it smoothens homogenous regions and sharpens the edges and features in the image. Many metrics are used to evaluate the performance of these filters. The mean and standard deviation are measured in this paper to quantify the results of different spatial domain filters, frequency domain filters, wavelet filters and adaptive filters. Both the quantities are measured

on filtered image. Table 8 depicts the mean and standard deviation for the various filtered images with speckle noise, and Figure 15 gives the performance evaluation based on these values.

4.8 Comparative analysis

Author name	Method	PSNR
Hiremath et al. [19]	Wavelet transform and contourlet transform	23.877
Prasanna Kumar and Srinivasan [26]	Total variation model	19.85
Ratha Jeyalakshmi and Ramar [23]	Morphological image cleaning algorithm (MMIC)	—
Lehana et al. [25]	Median filtering	—
Proposed method	Lee filter	29.06

Table 8: Mean and standard deviation of fibroid image with different filters

Filter	Mean	Standard deviation
Weiner filter	0.2127	0.0373
Lee filter	0.2094	0.0438
Kaun filter	0.2084	0.0465
SRAD filter	1.0000	0.1787
Mean filter	0.2108	0.0419
Median filter	0.0007	0.0415
Ideal low pass filter (ILPF)	0.0089	0.0481
Butterworth low pass filter	0.0080	0.0475
GLPF	0.2126	0.0391
Wavelet filter	0.0848	0.0700
Homomorphic wavelet filter	0.0284	0.0385

Figure 15: Comparison chart of mean and standard deviation.

5 Conclusion

For developing an efficient and effective denoising technique for ultrasound images, many factors have to be considered. This paper provides the results of evaluation of many speckle reduction filters for application to fibroid ultrasound image. The experimental outcome of this study presents techniques that unveiled the finest denoising performance for speckle noise in ultrasound images. As a future work, different hybrid approaches can be tried out to eliminate the noises in the ultrasound images. These methods will aid in accurately identifying the fibroids in human uterus images.

Conflict of interest: Authors state no conflict of interest.

Data availability statement: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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