

# SPECKLE REDUCTION IN ULTRASOUND IMAGES USING NEIGHSHRINK AND BILATERAL FILTERING

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## ABSTRACT

Speckle is a random multiplicative noise which obscures the perception and extraction of fine details in ultrasound images and speckle reduction is necessary to improve the visual quality of ultrasound images for better diagnosis. This study aims at introducing an algorithm by hybridizing bilateral filter with NeighShrink. The bilateral filter is applied before decomposition and after reconstruction of the image using discrete wavelet transform to improve the denoising efficiency and preserve the edge features effectively. The wavelet thresholding scheme NeighShrink is used for thresholding of wavelet coefficients. The algorithm is tested with synthetically speckled and real ultrasound images. Quality evaluation metrics such as Peak Signal to Noise Ratio (PSNR), Edge Preservation Index (EPI) and Correlation Coefficient (CoC) are used to assess the performance of the proposed method. Experimental results show that the proposed scheme improves the visual quality of ultrasound images by suppressing the speckle noise while retaining edges.

**Keywords:** Speckle Noise, Ultrasound Image, NeighShrink, Bilateral Filter

## 1. INTRODUCTION

Ultrasonography (US) is one of the widely used diagnostic imaging tools, it is non invasive and does not use X-rays or radiation. US has achieved excellent patient acceptance because it is safe, fast, painless and relatively inexpensive when compared with the other imaging modalities. One of the major drawbacks of the ultrasound image is poor image quality due to speckle noise (Loizou and Pattichis, 2008). Only skilled radiologist can make effective diagnosis and hence limiting its use over a wide network. In addition the presence of speckle complicates the image processing tasks like segmentation (Hiransakolwong *et al.*, 2003), feature extraction and classification. Hence, speckle suppression is essential to improve the visual quality and possibly the diagnostic potential of ultrasound imaging. Many noise reduction techniques have been developed for removing speckle noise and retaining edge details in ultrasound images. Most of the standard filters (Lee, 1981; Frost *et al.*, 1982;

Kuan *et al.*, 1987) use a defined filter window to estimate the local noise variance and perform the individual unique filtering process. The result is generally a greatly reduced noise level in areas that are homogeneous. But the image is either blurred or over smoothed due to losses in detail in non-homogenous areas like edges or lines. To overcome the drawbacks of spatial domain techniques, wavelet thresholding techniques have been proposed for denoising of medical images. The soft thresholding technique proposed by Donoho (1995) is used for denoising of medical images (Fourati *et al.*, 2005), in which the main critical task is the selection of threshold. VisuShrink (Donoho, 1995), SUREShrink (Donoho and Johnstone, 1995) and BayesShrink (Chang *et al.*, 2000) are the different methods proposed for the selection of threshold value. Chen *et al.* (2004) proposed a wavelet thresholding scheme based on wavelet coefficients within a neighborhood and its improved version NeighShrinkSURE was proposed by Dengwen and

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Wengang (2008). In SmoothShrink (Mastriani and Giraldez, 2005) a Directional Smoothing (DS) function is used to reduce the speckle noise in Synthetic Aperture Radar (SAR) images. The main strength of the wavelet thresholding technique is the capability to treat the different frequency components of an image separately but the problem experienced in this is generally smoothening of edges. The bilateral filter was proposed as an alternative to wavelet thresholding (Tomasi and Manduchi, 1998). Bhonsle *et al.* (2012) used bilateral filter for denoising of medical images and the filter performed well in the case of Additive White Gaussian Noise (AWGN) compared to speckle noise. To improve the efficiency of wavelet thresholding techniques, efforts have been taken to hybridize with spatial domain filters. Wavelet domain Total Variation (TV) denoising is one such hybrid technique presented for suppressing both Gaussian noise (Bhoi and Meher, 2008) and speckle noise (Abraham *et al.*, 2012). This method works well but the number of iterations of TV denoising lead to blurring effect. Multi-resolution property of the wavelet and bilateral filter are combined, for the removal of Gaussian noise (Zhang and Gunturk, 2008) and speckle noise (NagaPrudhviRaj and Venkateswarlu, 2012). In this framework based on the application, the image is decomposed into multilevel and at each level the bilateral filter is applied to the approximation subband and also after reconstruction of the image. Wavelet thresholding is applied to the detail subbands. Due to multilevel processing the computational complexity is high. Roy *et al.* (2010) proposed a new model based on the hybridization of soft thresholding and bilateral filter for denoising of variety of noisy images including ultrasound image.

This study aims at introducing a novel method which uses bilateral filter and the wavelet thresholding scheme NeighShrink to enhance the visual quality of ultrasound images for better diagnosis.

## 2. MATERIALS AND METHODS

### 2.1. Wavelet Thresholding

In wavelet based denoising methods the image is first decomposed into approximation (LL) and detail (LH, HL, HH) subbands. The smaller coefficients of detail subbands are processed via hard or soft thresholding and the modified coefficients are used to reconstruct the image.

The general wavelet based denoising involves three steps:

- Compute the wavelet transform of the noisy image
- Apply a threshold to the detail subband coefficients

- Reconstruct the image using the modified detail subband coefficients

The hard and soft thresholding functions are described as in Equation (1 and 2):

$$T_{\text{hard}}(w) = \begin{cases} w, & |w| > T \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$T_{\text{soft}}(w) = \begin{cases} w - T, & \text{if } w > T \\ w + T, & \text{if } w < -T \\ 0, & \text{if } |w| < T \end{cases} \quad (2)$$

where,  $T$  is the threshold value and  $w$  is the wavelet coefficient. In hard thresholding the wavelet coefficient is unaltered if the absolute value of it is greater than the threshold, otherwise it is set to zero as in (1). The soft thresholding given in (2) is an extension of the hard thresholding and in which the coefficients whose absolute values are lower than the threshold are set to zero and if the absolute value is greater the coefficients are modified by subtracting  $T$  from  $w$ . The selection of threshold plays an important role in wavelet denoising. The first category of threshold selection uses a universal threshold, in which the threshold is common for all the wavelet coefficients of the noisy image and whereas the second category is subband adaptive in which the threshold value is estimated for each subband separately. Most of the wavelet domain speckle suppression filters (Sudha *et al.*, 2009) apply first logarithmic transformation to convert multiplicative noise to AWGN. The transformed image is then denoised by wavelet thresholding or by Bayesian shrinkage. The medical ultrasound devices often include internal data pre-processing like a logarithmic compression of the dynamic range of the data (Loizou and Pattichis, 2008). Noise in the resulting image is not purely multiplicative and additional logarithmic transformation prior to speckle filtering seems less appropriate. Also, the wavelet based homomorphic filtering is computationally expensive due to logarithmic and exponential operations. In a non-homomorphic wavelet domain technique (Thakur and Anand, 2005) for the effective speckle reduction in ultrasound images, the noisy image is decomposed up to five levels. This may increase the computational complexity, hardware requirement and also cost. The proposed algorithm is a non-homomorphic approach and the noisy image is subjected to one level of decomposition.

### 2.2. NeighShrink

The wavelet-domain image thresholding scheme NeighShrink (Chen *et al.*, 2004) incorporates neighboring wavelet coefficients. In Neighshrink the magnitude of the squared sum of all the wavelet coefficients within the neighborhood window is taken into account for thresholding. The neighborhood window size should be odd; i.e., it can be 3×3, 5×5, 7×7, 9×9. But, through the results the authors suggested that the window sizes of 3×3 and 5×5 are good choices for NeighShrink and the shrinkage function for any arbitrary 3×3 window, depicted in **Fig. 1** centered at (i, j) is given by Equation (3):

$$\beta_{i,j} = \left( 1 - \frac{T_u}{S_{i,j}^2} \right)_+ \tag{3}$$

In NeighShrink the universal threshold  $T_u$  is estimated as in Equation (4):

$$T_u = \sigma_n \sqrt{2 \log L} \tag{4}$$

where, L is the size of the image and the noise standard deviation  $\sigma_n$  is estimated using Equation (5):

$$\sigma_n = \frac{\text{median}[\{w_{i,j} : i,j \in HH\}]}{0.6745} \tag{5}$$

The squared sum  $S_{i,j}^2$  of all the wavelet coefficients within the neighborhood window is computed according to Equation (6):

$$S_{i,j}^2 = \sum_{m=i-1}^{i+1} \sum_{n=j-1}^{j+1} w_{m,n}^2 \tag{6}$$

The ‘+’ sign in the formula indicates to keep the positive values and when it is negative it is set to zero. The centre wavelet coefficient  $\hat{w}_{i,j}$  is then estimated from the noisy wavelet coefficient  $w_{i,j}$  as in Equation (7):

$$\hat{w}_{i,j} = \beta_{i,j} w_{i,j} \tag{7}$$

### 2.3. Bilateral Filter

The bilateral filter proposed by (Tomasi and Manduchi, 1998) is a nonlinear, edge preserving filter. The filter replaces each pixel by the weighted average of the pixels in the neighborhood. Let  $g(i, j)$  be the current processing pixel in the selected window  $w$  of size  $(2n+1)$ , where  $n$  is the span of the filter. The

output of the bilateral filter  $y(i, j)$  is computed as in Equation (8):

$$y(i, j) = \frac{\sum_{s=i-n}^{i+n} \sum_{t=j-n}^{j+n} W_d(s, t) W_r(s, t) g(s, t)}{\sum_{s=i-n}^{i+n} \sum_{t=j-n}^{j+n} W_d(s, t) W_r(s, t)} \tag{8}$$

where,  $W_d$  and  $W_r$  are the domain and range weights, which are described as in Equation (9) and (10):

$$W_d(s, t) = \exp\left(-\frac{(i-s)^2 + (j-t)^2}{2\sigma_d^2}\right) \tag{9}$$

$$W_r(s, t) = \exp\left(-\frac{\|g(i, j) - g(s, t)\|^2}{2\sigma_r^2}\right) \tag{10}$$

The domain and range parameters  $\sigma_d$  and  $\sigma_r$  control the behaviour of weights. The bilateral filter is used in the proposed algorithm since it is non iterative and simple.

### 2.4. Proposed Method

The proposed method is a combination of bilateral filtering and wavelet thresholding and is illustrated in **Fig. 2**. In this method the image is first denoised using bilateral filter. Daubechies-8 wavelet is used to decompose the image into four subbands. The wavelet shrinkage technique NeighShrink is applied on the detail subband coefficients and the image is reconstructed using modified wavelet coefficients. Finally bilateral filtering is applied to get the despeckled image.

#### Algorithm:

- Step 1: The noisy image is processed using bilateral filter
- Step 2: The processed image is decomposed to one level using discrete wavelet transform, which gives rise to four subbands (approximation subband LL, detail subbands LH, HL and HH) and wavelet thresholding technique NeighShrink is used to threshold the wavelet coefficients of the detailed subbands
- Step 3: The inverse wavelet transform is applied on the modified wavelet coefficients to reconstruct the image
- Step 4: The bilateral filter is applied at the last stage to get the despeckled image

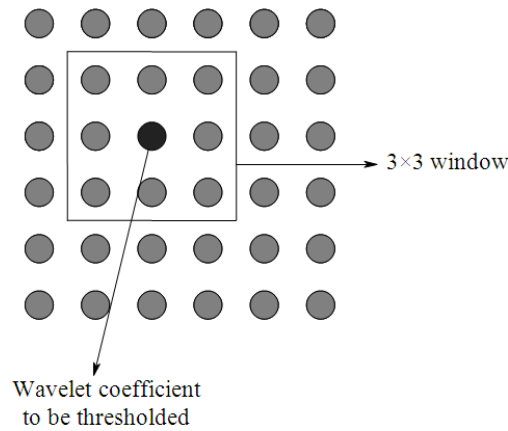


Fig. 1. Illustration of the neighborhood window

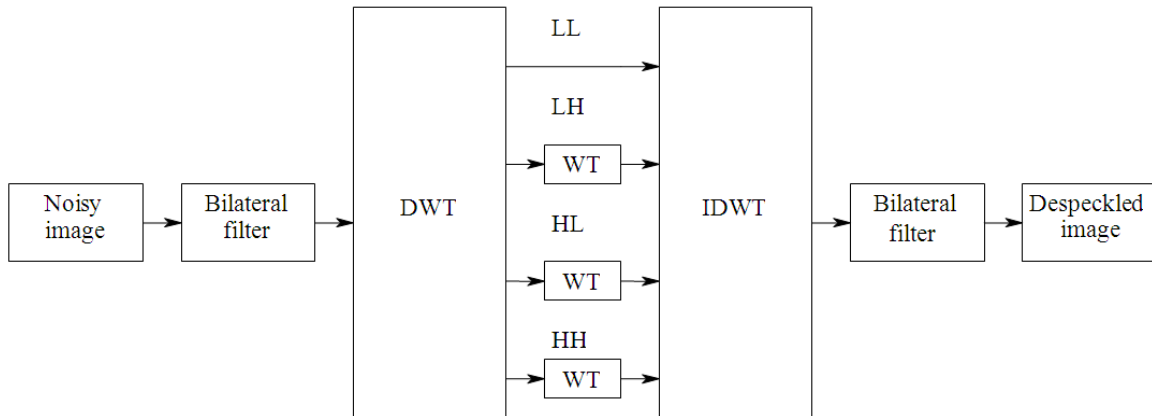


Fig. 2. Proposed method

The performance of the proposed method mainly depends on the parameters of the bilateral filter. The parameters are window size  $w$ , domain and range parameters  $\sigma_d$  and  $\sigma_r$ . The optimal values of these parameters are obtained by performing experiments on both synthetically speckled images and ultrasound images. The window size  $w$  of the bilateral filter for denoising of synthetically speckled images is  $11 \times 11$  and for ultrasound images, it is  $3 \times 3$ . The value of  $\sigma_d = 1.8$  for both the type of images and  $\sigma_r = k\sigma$  where  $\sigma$  is the noise standard deviation estimated using robust median estimator. The value of  $k$  is tuned to get the optimal performance.

### 2.5. Quality Metrics

The performance of various speckle reduction techniques is evaluated using the following standard image quality assessment metrics.

Peak Signal to Noise Ratio (PSNR) (Sakrison, 1997) is computed as in Equation (11):

$$PSNR = 10 \log_{10} \left( \frac{255^2}{MSE} \right) [dB] \tag{11}$$

Root Mean Square Error (RMSE) (Gonzalez and Woods, 2008), which is the square root of the squared error averaged over  $M \times N$  window is given by Equation (12):

$$RMSE = \sqrt{\frac{1}{M \times N} \sum_{i=1}^m \sum_{j=1}^n (x_{i,j} - y_{i,j})^2} \tag{12}$$

$M \times N$  is the size of the image and  $x, y$  represents the original and denoised images respectively.

Edge Preservation Index (EPI) (Sattar *et al.*, 1997) is computed according to Equation (13):

$$EPI = \frac{\sum(\Delta x - \overline{\Delta x})(\Delta y - \overline{\Delta y})}{\sum(\Delta x - \overline{\Delta x})^2(\Delta y - \overline{\Delta y})^2} \tag{13}$$

where,  $\Delta x$  and  $\Delta y$  are the high pass filtered versions of images  $x$  and  $y$ , obtained with a  $3 \times 3$  pixel standard approximation of the Laplacian operator. The  $\overline{\Delta x}$  and  $\overline{\Delta y}$  are the mean values of the high pass filtered versions of  $\Delta x$  and  $\Delta y$  respectively.

Correlation Coefficient (CoC) (Sattar *et al.*, 1997) is computed as in Equation (14):

$$CoC = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2(y - \bar{y})^2}} \tag{14}$$

where,  $\bar{x}$  and  $\bar{y}$  are the mean of the original and denoised image respectively. The CoC is used to measure the similarity between the original image and despeckled image.

### 3. RESULTS AND DISCUSSION

To test the efficiency of the proposed algorithm both synthetic and real ultrasound images are used. The ultrasound image of liver was obtained from the

public medical image database Medison available at <http://www.medison.Ru/uzi/eho240.htm>. The quantitative evaluation is problematic as there is no reference image without speckle. So, for quantitative evaluation the noise is added artificially to two types of images using MATLAB command. The first type is the synthetic image which consists of regions with uniform intensity and sharp edges (Test image-1). The second category is ultrasound image (Test image -2, Healthy brain; Sagittal view) in which the speckle noise was previously suppressed. The proposed approach is implemented in MATLAB and to compare the performance of the proposed method with the existing techniques, the results are presented in **Table 1 and 2**. The value of  $k$  used in computing  $\sigma_r$  ranges from 2 to 20 and it is obtained with different trials.

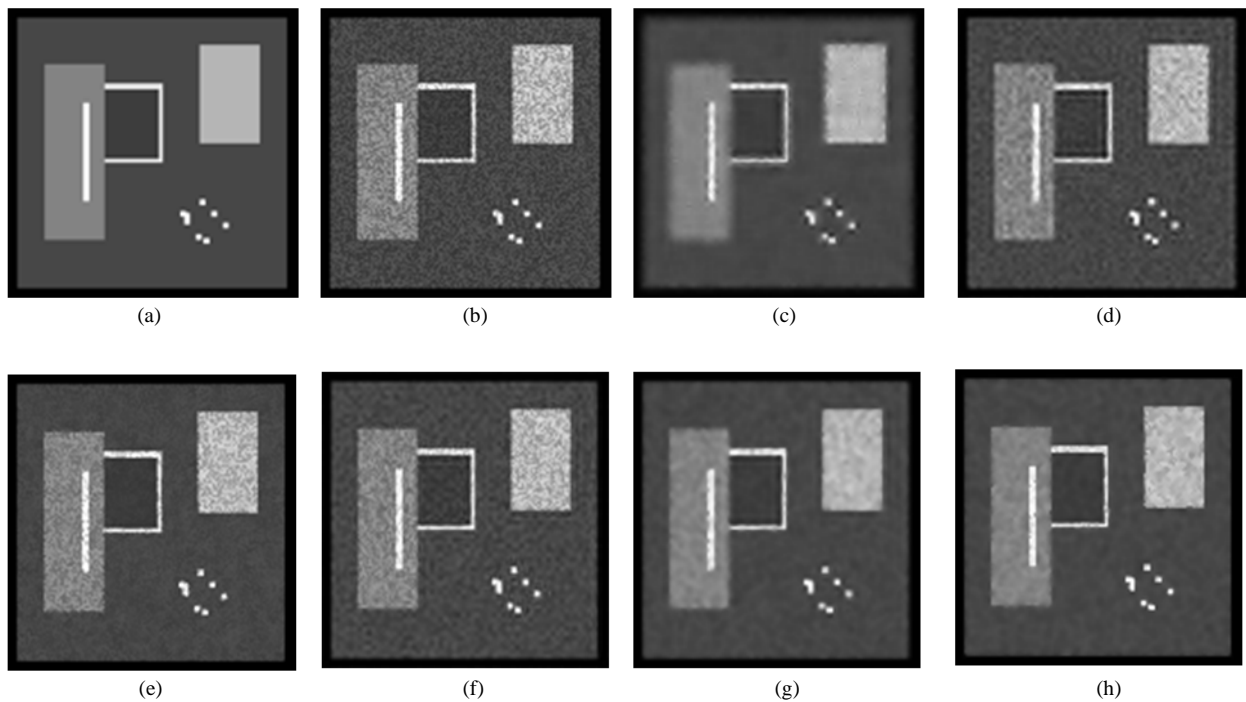
**Table 1** summarizes the PSNR, RMSE, EPI and CoC of various methods at two different levels of noise variance ( $\sigma^2 = 0.02, 0.06$ ) for the synthetic image (Test image-1). The quality metrics obtained for ultrasound image (Test image-2) with noise variance of  $\sigma^2 = 0.03$  and  $0.05$  are given in **Table 2**. For qualitative analysis the despeckled images are shown in **Fig. 3-5**.

**Table 1.** Image quality measures obtained by various denoising methods tested on synthetic image at two different noise levels ( $\sigma^2 = 0.02, 0.06$ )

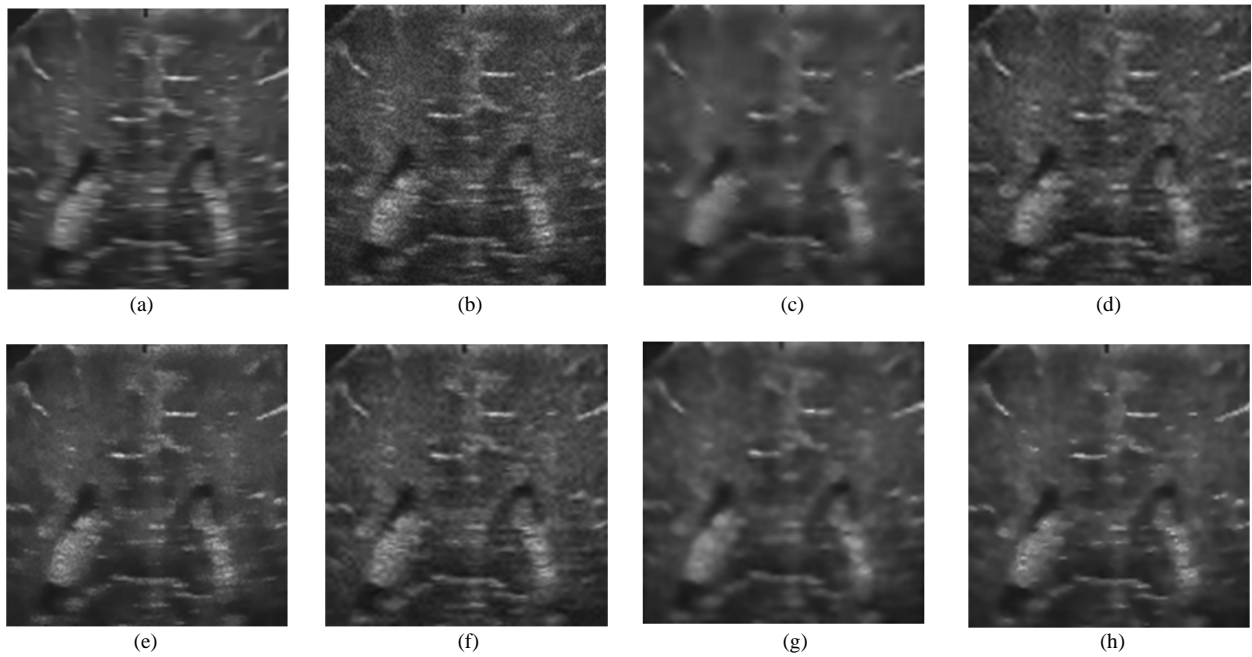
Method	Quality measures			
	PSNR (dB)	RMSE	EPI	CoC
Speckled input image (Test image-1) $\sigma^2 = 0.02$	28.99	0.0502	0.6427	0.9662
Soft thresholding	31.29	0.0385	0.6718	0.9794
BayesShrink	30.62	0.0417	0.7101	0.9762
NeighShrink	32.23	0.0346	0.7832	0.9834
Wiener filter in wavelet domain	30.61	0.0417	0.7500	0.9768
Bilateral Filter	31.91	0.0359	0.7707	0.9823
Soft thresholding and bilateral filter	35.26	0.0267	0.9181	0.9913
TV and Wavelet	33.29	0.0314	0.8228	0.9831
Proposed method	36.55	0.0230	0.9272	0.9931
Speckled input image (Test image-1) $\sigma^2 = 0.06$	24.21	0.0871	0.4259	0.9058
Soft thresholding	28.30	0.0544	0.4833	0.9589
BayesShrink	26.83	0.0644	0.4863	0.9438
NeighShrink	28.39	0.0538	0.5586	0.9596
Wiener filter in wavelet domain	29.01	0.0501	0.5617	0.9655
Bilateral Filter	28.76	0.0516	0.5820	0.9628
Soft thresholding and bilateral filter	29.73	0.0504	0.7286	0.9676
TV and Wavelet	29.92	0.0471	0.6413	0.9609
Proposed method	30.29	0.0473	0.7431	0.9707

**Table 2.** Image quality measures obtained by various denoising methods tested on ultrasound image (Test image-2) at two different noise levels ( $\sigma^2 = 0.03, 0.05$ )

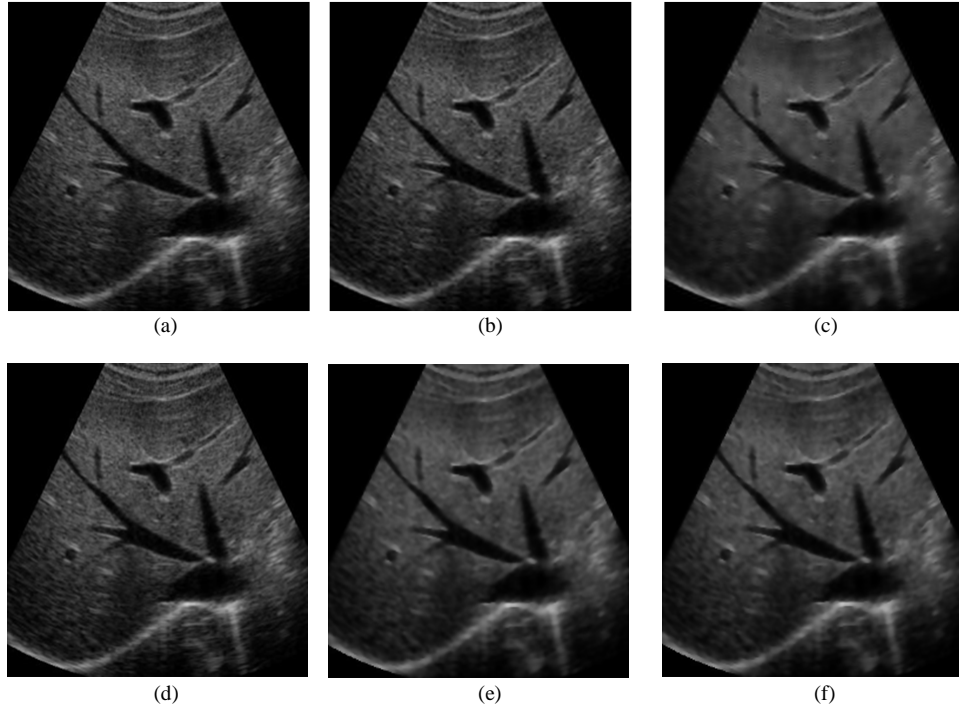
Method	Quality measures			
	PSNR (dB)	RMSE	EPI	CoC
Speckled input image (Test image-2) $\sigma^2 = 0.03$	28.39	0.0481	0.6427	0.8702
Bilateral Filter	31.08	0.0352	0.5928	0.9190
Soft thresholding	31.73	0.0328	0.4461	0.9267
BayesShrink	31.49	0.0337	0.5936	0.9256
NeighShrink	32.24	0.0309	0.5951	0.9358
Wiener filter in wavelet domain	31.75	0.0327	0.4574	0.9249
Soft thresholding and bilateral filter	32.69	0.0294	0.4872	0.9392
TV and Wavelet	31.99	0.0318	0.4466	0.9303
Proposed method	33.33	0.0273	0.6019	0.9475
Speckled input image (Test image-2) $\sigma^2 = 0.05$	26.21	0.0619	0.4027	0.8038
Bilateral Filter	30.17	0.0392	0.5148	0.9002
Soft thresholding	30.39	0.0382	0.3644	0.9023
BayesShrink	30.04	0.0398	0.4781	0.8982
NeighShrink	30.50	0.0378	0.5173	0.9080
Wiener filter in wavelet domain	31.31	0.0344	0.3805	0.9158
Soft thresholding and bilateral filter	31.68	0.0392	0.4106	0.9227
TV and Wavelet	30.51	0.0377	0.3712	0.9040
Proposed method	32.15	0.0312	0.5222	0.9306



**Fig. 3.** Denoising results of various speckle filtering methods on  $128 \times 128$  artificial speckle simulated synthetic image (Test image-1), (a) Test image-1, (b) Speckle Simulated, (c) Wiener-Wavelet, (d) Soft Thresholding, (e) Bilateral Filter, (f) NeighShrink, (g) Soft thresholding and bilateral filter, (h) Proposed Method



**Fig. 4.** Denoising results of various speckle filtering methods on 128×128 ultrasound speckle simulated image (Test image-2), (a) Test image-2 (b) Speckle Simulated (c) Wiener-Wavelet (d) Soft Thresholding (e) Bilateral Filter, (f) NeighShrink (g) Soft thresholding and bilateral filter (h) Proposed Method



**Fig. 5.** Results of various methods on real ultrasound image (a) Original image- Liver (b) Soft thresholding (c) Wiener-wavelet (d) NeighShrink (e) Soft thresholding and bilateral filter (f) Proposed Method

#### 4. CONCLUSION

From the quantitative results in **Table 1 and 2**, it may be observed that the proposed method outperforms the spatial domain filter (Bilateral filter), wavelet thresholding techniques (Soft thresholding, BayesShrink and NeighShrink), Wiener filter in wavelet domain (Rangsanseri and Prasongsook, 2002), soft thresholding and bilateral filter (Roy *et al.*, 2010) and TV and wavelet (Abraham *et al.*, 2012).

The higher values of EPI indicates that the combination of the wavelet thresholding technique NeighShrink and bilateral filter preserves edges better than the soft thresholding and bilateral filter. The significant improvement in the other quality metrics (PSNR, CoC) indicate the usefulness of the proposed method interms of denoising and feature preservation. The results (**Fig. 3-5**) show that the visual quality of the images has also been improved by the proposed method.

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