Wavelet Thresholding Techniques in Despeckling of Medical Ultrasound Images

R.Vanithamani [#1], G.Umamaheswari [*2]

[#] Biomedical Instrumentation Engineering Department, Faculty of Engineering, Avinashilingam University for Women, Coimbatore, Tamil Nadu, India

[1] vaniraj123@yahoo.co.in

[*] Electronics and Communication Engineering Department, PSG College of Technology, Coimbatore, Tamil Nadu, India

[2] umabhaskar@yahoo.co.in

Abstract— **This paper presents a review of wavelet thresholding techniques for despeckling of medical ultrasound images. An ultrasound image is first transformed into wavelet domain and then the wavelet coefficients are processed by different wavelet thresholding techniques. The denoised image is obtained by taking the inverse wavelet transform of the modified wavelet coefficients. The performance of the techniques reviewed in this paper is evaluated using the image quality assessment parameters such as Peak Signal to Noise Ratio (PSNR), Edge Preservation Index (EPI) and Correlation Coefficient (CoC).The practical implementation of this work is to determine the effective wavelet thresholding technique that compromises between edge preservation and noise suppression.**

Keyword- speckle noise, wavelet thresholding, ultrasound image, despeckling

I. INTRODUCTION

Ultrasound imaging has become an important and widely accepted modality for non invasive imaging of the human body because of its ability to produce real time images, its low cost and low risk to the patients. One of the major drawbacks of this imaging is poor image quality due to speckle noise [1]. 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 [2], feature extraction and classification. Hence, speckle suppression is essential to improve the visual quality and possibly the diagnostic potential of ultrasound imaging. Speckle reduction filters in both spatial and transform domain are discussed in [1].The spatial domain techniques may result in some problems such as blurring of edges, destroying lines and other important image information [3]. To overcome the drawbacks of spatial filtering, a wavelet based denoising method is introduced [4]. The soft thresholding technique [4] is used for denoising of medical images ([5], [6]). The noise reduction in the wavelet domain is called wavelet shrinkage or wavelet thresholding. In wavelet thresholding the image is first decomposed into approximation (low frequency) and detail subbands (high frequency). The coefficients of the detail subbands are processed via hard or soft thresholding. The selection of threshold plays an important role in wavelet denoising. There are two basic threshold selection categories. The first category of threshold selection uses a universal threshold method, in which the threshold is common for all the wavelet coefficients of the noisy image and whereas the second category is subband adaptive and in which the threshold value is estimated for each subband separately. The various threshold selection schemes proposed are VisuShrink [4], SUREShrink [7] and BayesShrink[8]. In NeighShrink [9] neighbor wavelet coefficients are taken into account for thresholding. NeighShrinkSURE, an image denoising method which is an improved version of NeighShrink [10]. The NeighShrink uses a suboptimal universal threshold and identical window size in all the wavelet subbands, whereas the improved version of it determines an optimal threshold and neighbouring window size for every subband by using SURE. SmoothShrink proposed in [11] applies a Directional Smoothing (DS) function on the wavelet coefficients of the detail subbands to reduce the speckle noise in Synthetic Aperture Radar (SAR) images.

In this paper, the different wavelet thresholding schemes are compared for ultrasound image denoising based on the image quality assessment parameters.

II. WAVELET THRESHOLDING

The properties which make wavelet transform attractive for denoising are multi-resolution and sparsity, and as the wavelet transform is good at energy compaction, the smaller coefficients represent noise and larger coefficients represent the important image features. The smaller coefficients present in the detail subband are modified using wavelet thresholding techniques while the larger coefficients of the approximation subband are unaltered. The Discrete Wavelet Transform of an image is implemented by filtering with a pair of quadrature mirror filters along the rows and columns alternatively, followed by down sampling by a factor of two in each direction. This filtering operation decomposes the image into four subbands (LL,HL,LH and HH) as shown in

Fig.1(a).The LL subband contains the low frequency components in both the directions, where as HL, LH and HH subbands contain the detail components in horizontal, vertical and diagonal directions respectively. The above filtering process is iterated on the LL subband splitting into four subbands in the same way, and is given in Fig. 1(b).

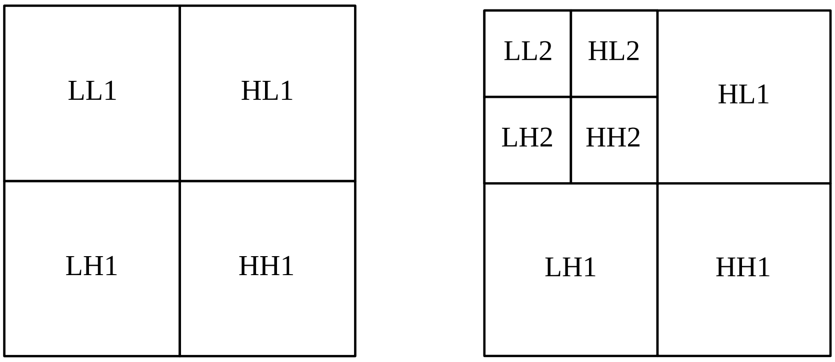


Figure1. Two dimensional Discrete Wavelet Transform- (a) First level of decomposition (b) Second level of decomposition

The general wavelet based denoising involves three steps

i) Compute the wavelet transform of the noisy image
ii) Apply a threshold to the detail subband coefficients
iii) Reconstruct the image using the modified detail subband coefficients

The main task of wavelet thresholding is the selection of threshold value and the effect of denoising depends on the selected threshold. A bigger threshold will throw off useful information and noise components at the same time while a smaller threshold cannot eliminate the noise effectively. The two thresholding functions frequently used are hard and soft thresholding. The hard thresholding eliminates coefficients that are smaller than a threshold; the soft thresholding shrinks the coefficients that are larger than the threshold as well.The hard and soft thresholding functions are given by (1) and (2).

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

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

where T is the threshold value and w is the wavelet coefficient.

A. VisuShrink

VisuShrink [4] uses universal threshold given in (3)

$$T_u = \sigma_n \sqrt{2 \log L} \tag{3}$$

where σ_n the noise standard deviation and L is the total number of pixels in an image. This technique yields overly smoothened images with less preserved details. This is due to the fact that the universal threshold with high probability yields an estimate that is at least as smooth as the signal. So the threshold value tends to be high for large values of L, and that may kill many signal coefficients along with noise. Hence this does not adapt good with discontinuities in the signal.

B. SUREShrink

A subband adaptive thresholding selection technique based on Stein's Unbiased Risk Estimate (SURE) is proposed in [7]. It attempts to select thresholds (T_{SURE}) that minimize mean square error. The threshold parameter T_{SURE} is estimated using

$$T_{SURE} = \arg\min_{T_h} \left(SURE\left(T_h; W\right) \right) \tag{4}$$

$SURE(T_h;W)$ is defined by

$$SURE\left(T_h;W\right)=\sigma_n^2-\frac{1}{L}\times\left(2\sigma_n^2.\#\left\{i:\left|W_i\right|\leq T_h-\sum_{i=1}^{L}\min\left(\left|W_i\right|,T_h\right)^2\right\}\right) \quad (5)$$

where, σ_n^2 is the noise variance

L is the total number of wavelet coefficients in a particular subband

W_i is a wavelet coefficient in a particular subband

$T_h \epsilon \left[0,T_u\right]$, T_u is the universal threshold

C. BayesShrink

The BayesShrink [8] method is effective for images corrupted by Gaussian noise, which uses an adaptive data driven threshold. It performs soft thresholding, and the threshold is determined for each subband by modeling the wavelet coefficients within each subband as random variables with Generalized Gaussian distribution (GGD). The Bayes threshold is given by (6)

$$T_B=\frac{\hat{\sigma}_n^2}{\hat{\sigma}_F} \quad (6)$$

$$\sigma_n=\frac{median\left[\left\{w_{i,j}:i,j\right\}\in HH\right]}{0.6745} \quad (7)$$

Where, $\hat{\sigma}_n^2$ is estimated noise variance by robust median estimator (7) and $\hat{\sigma}_F$ is the estimated signal standard deviation in wavelet domain.

The signal standard deviation is estimated as in (8)

$$\sigma_F=\sqrt{\max\left(\left(\hat{\sigma}_w^2-\hat{\sigma}_n^2\right),0\right)} \quad (8)$$

where $\hat{\sigma}_w^2$ is the variance of w. Since w is modeled as zero mean, $\hat{\sigma}_w^2$ can be calculated as

$$\hat{\sigma}_w^2=\frac{1}{n^2}\sum_{i,j=1}^{n}w^2{}_{i,j} \quad (9)$$

when, $\hat{\sigma}_n^2>\hat{\sigma}_w^2$, σ_F will become zero and T_B becomes ∞. For this case

$$T_B=\max\left(\left|w_{i,j}\right|\right) \quad (10)$$

D. SmoothShrink

SmoothShrink [11] is proposed to remove speckle noise from Synthetic Aperture Radar (SAR) images. It uses a Directional Smoothing (DS) filter that performs spatial filtering in a square moving window to protect edges from blurring while smoothing. The speckled SAR image is first decomposed into four wavelet subbands: Approximation (LL), Diagonal detail (HH), vertical detail (LH) and Horizontal detail (HL) respectively. Then DS function is applied on the wavelet coefficients of the detail subbands, and the coefficients of approximation subband are unaltered. Finally the SAR image is reconstructed using the modified coefficients. The size of the window can range from 3x3 to 33x33, but the studies show that the 3x3 gives better results.

Algorithm

Step 1: The average of the wavelet coefficients in four directions as in Fig.2 (d1, d2, d3, d4) is calculated.

Step 2: The absolute difference between the centre wavelet coefficient and each directional average is calculated as:

$$D\left(n\right)=abs\left(d\left(n\right)-w\left(i,j\right)\right),n=1,2,3,4 \quad (11)$$

where $d(n)$ is the average of wavelet coefficients in n^{th} direction and $w(i, j)$ is the centre wavelet coefficient.

Step 3: The directional average which gives minimum absolute difference is found out as given in (12).

$$\Gamma = \min(D) \tag{12}$$

Step-4: The estimated center wavelet coefficient is replaced with the minimum directional average obtained in Step-3 and it is given in Equation (13).

$$\hat{w}_{i,j} = \Gamma \tag{13}$$

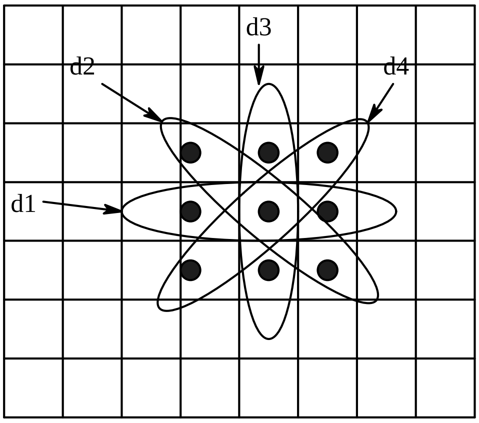


Figure2: 3x3 window for directional smoothing

E. NeighShrink

The wavelet-domain image thresholding scheme NeighShrink [9] incorporates neighboring wavelet coefficients.

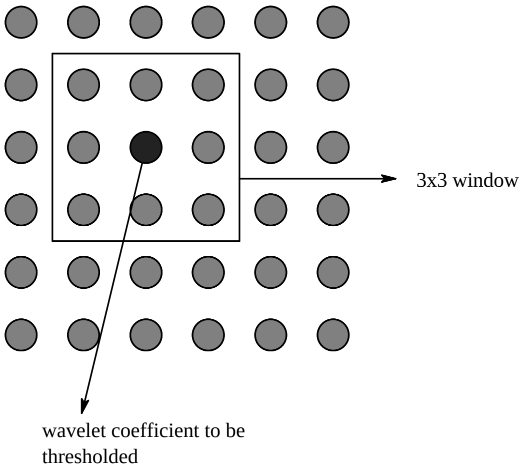


Figure 3: Illustration of the neighborhood window

It takes into account the magnitude of the squared sum of all the wavelet coefficients within the neighborhood window for thresholding. The neighborhood window size should be odd; i.e.it can be 3x3, 5x5, 7x7, 9 x 9 etc. But, through the results the authors suggested that the window sizes of 3x3 and 5x5 are good choices for NeighShrink, and the shrinkage function for any arbitrary 3x3 window, depicted in Fig.3 centred at (i, j) is given in Equation (14).

$$\beta_{i,j} = \left(1 - T_u^2 / S_{i,j}^2\right)_+ \tag{14}$$

where, T_u is the universal threshold and the squared sum $(S_{i,j}^2)$ of all the wavelet coefficients within the neighborhood window is estimated using (15).

$$S_{i,j}{}^{2} = \sum_{m=i-1}^{i+1} \sum_{n=j-1}^{j+1} w^{2}{}_{m,n} \tag{15}$$

The' +' sign in the formula indicates to keep the positive values, while setting it to zero when it is negative.

The estimated centre wavelet coefficient $\hat{w}_{i,j}$ is then obtained from the noisy wavelet coefficient $W_{i,j}$ using (16).

$$\hat{w}_{i,j} = \beta_{i,j} w_{i,j} \tag{16}$$

F. NeighShrinkSURE

NeighShrinkSURE, an image denoising method proposed in [10] is an improved version of NeighShrink. The NeighShrink uses a suboptimal universal threshold and identical window size in all wavelet subbands, whereas the improved version of it determines an optimal threshold and neighboring window size for every subband by the Stein's unbiased risk estimate (SURE) as given in (17).

$$\left(T^{s}, k^{s}\right) = \arg\min_{T,k} SURE(w_{s}, T, k) \tag{17}$$

where T is the threshold, k is the window size and s denotes the subband.

III. Image Quality Assessment Measures

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

Peak Signal to Noise Ratio (PSNR) [12]:

$$\text{PSNR} = 10\log_{10}\left(\frac{255^{2}}{\text{MSE}}\right)[\text{dB}] \tag{18}$$

where MSE is the Mean Square Error, M x N is the size of the image and x, y represents the original and denoised images respectively. The PSNR is higher for a better transformed image.

The Edge Preservation Index (EPI) [13]:

$$\text{EPI} = \frac{\sum(\Delta\text{x} - \overline{\Delta\text{x}})(\Delta\text{y} - \overline{\Delta\text{y}})}{\sum(\Delta\text{x} - \overline{\Delta\text{x}})^{2}(\Delta\text{y} - \overline{\Delta\text{y}})^{2}} \tag{19}$$

where Δx and Δy are the high pass filtered versions of images x and y, obtained with a 3x3 pixel standard approximation of the Laplacian operator. The $\overline{\Delta\text{x}}$ and $\overline{\Delta\text{y}}$ are the mean values of the high pass filtered versions of Δx and Δy respectively.

Correlation Coefficient is computed using (CoC) [13]:

$$\text{CoC} = \frac{\sum(\text{x} - \bar{\text{x}})(\text{y} - \bar{\text{y}})}{\sqrt{\sum(\text{x} - \bar{\text{x}})^{2}(\text{y} - \bar{\text{y}})^{2}}} \tag{20}$$

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.

In addition to these quantitative measures, the original and denoised images are shown for visual comparison.

IV. Results and Discussion

To compare the performance of different wavelet thresholding techniques both synthetic and real ultrasound images are used. 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.All the techniques use db8 wavelet filters for one level of decomposition. The quality metrics obtained are presented in Table 1-6.

TABLE I
PSNR values obtained by various denoising methods tested on ultrasound image (Test image-1) at different noise levels.

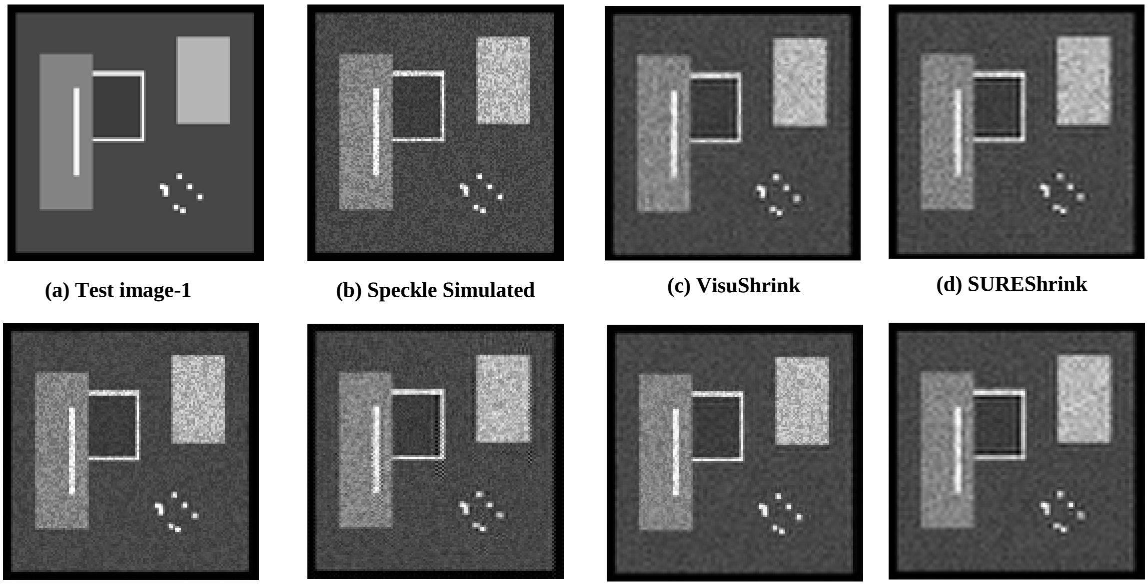
Peak Signal to Noise Ratio (PSNR)						
Wavelet thresholding Techniques	**Noise variance(σ^2)**					
	0.02	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**
VisuShrink	31.46	30.31	29.57	**28.96**	**28.40**	27.81
SUREShrink	30.63	30.04	29.39	28.67	28.22	27.77
BayesShrink	30.61	29.35	28.09	27.27	26.83	26.04
SmoothShrink	28.75	27.75	26.79	25.55	25.51	24.90
NeighShrink	**31.70**	**30.87**	**29.66**	28.87	28.17	**27.87**
NeighShrinkSURE	30.78	29.93	29.26	28.80	28.33	27.66

TABLE II
EPI values obtained by various denoising methods tested on ultrasound image (Test image-1) at different noise levels.

Edge Preservation Index (EPI)						
Wavelet thresholding Techniques	**Noise variance(σ^2)**					
	0.02	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**
VisuShrink	0.6949	0.6147	0.5739	0.5256	0.4997	0.4760
SUREShrink	0.5673	0.5406	0.5160	0.4836	0.4709	0.4465
BayesShrink	0.7101	0.6319	0.5629	0.5078	0.4863	0.4225
SmoothShrink	0.4854	0.4422	0.3830	0.3330	0.3316	0.3059
NeighShrink	**0.7624**	**0.7101**	**0.6367**	**0.5811**	**0.5330**	**0.5003**
NeighShrinkSURE	0.5709	0.5413	0.5094	0.4915	0.4769	0.4476

TABLE III
CoC values obtained by various denoising methods tested on ultrasound image (Test image-1) at different noise levels.

Correlation Coefficient (CoC)						
Wavelet thresholding Techniques	**Noise variance(σ^2)**					
	0.02	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**
VisuShrink	0.9801	0.9741	0.9692	**0.9647**	**0.9596**	0.9537
SUREShrink	0.9760	0.9724	0.9680	0.9623	0.9585	0.9542
BayesShrink	0.9762	0.9685	0.9575	0.9493	0.9438	0.9333
SmoothShrink	0.9632	0.9539	0.9430	0.9256	0.9157	0.9141
NeighShrink	**0.9814**	**0.9773**	**0.9700**	0.9640	0.9578	**0.9548**
NeighShrinkSURE	0.9768	0.9717	0.9671	0.9636	0.9594	0.9524



(a) Test image-1 **(b) Speckle Simulated** **(c) VisuShrink** **(d) SUREShrink**

(e) BayesShrink **(f) SmoothShrink** **(g) NeighShrink** **(g) NeighShrinkSURE**

Fig. 4. Denoising results of various wavelet thresholding methods on 128x128 artificial speckle simulated synthetic image (Test image1).

TABLE IV
PSNR values obtained by various denoising methods tested on ultrasound image (Test image-2) at different noise levels.

Peak Signal to Noise Ratio (PSNR)						
Wavelet thresholding Techniques	**Noise variance(σ^2)**					
	0.02	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**
VisuShrink	32.78	31.85	30.97	30.28	29.89	**29.41**
SUREShrink	32.24	31.51	30.75	30.14	29.69	29.27
BayesShrink	32.81	31.49	30.88	30.04	29.74	28.29
SmoothShrink	31.95	30.34	29.01	28.19	27.50	26.72
NeighShrink	**33.77**	**32.66**	**31.51**	**30.70**	**29.91**	29.34
NeighShrinkSURE	32.24	31.49	30.77	30.23	29.80	29.17

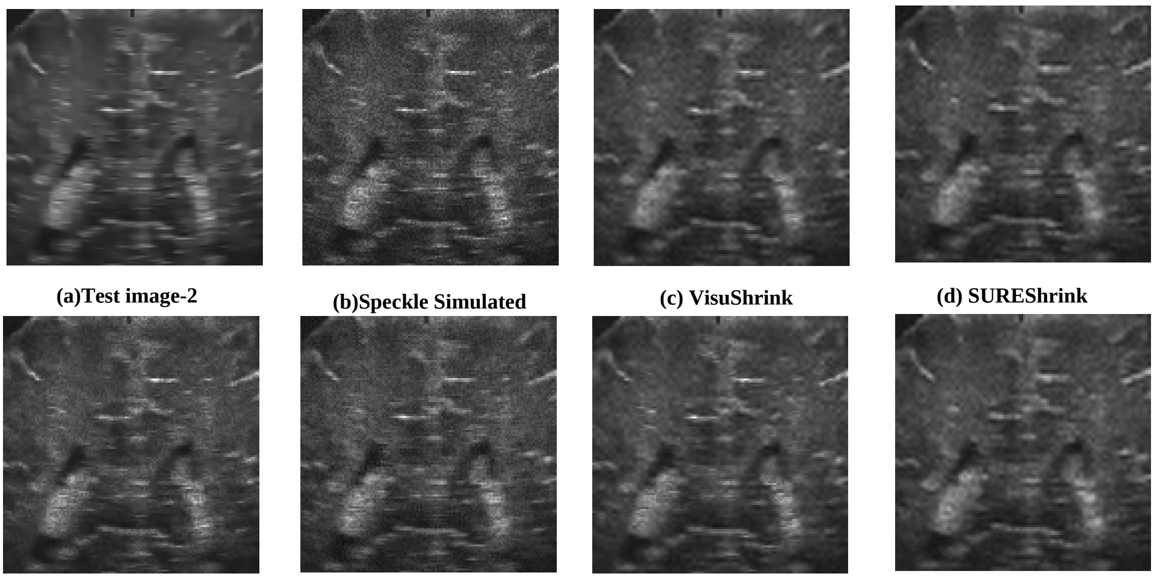
TABLE V
EPI values obtained by various denoising methods tested on ultrasound image (Test image-2) at different noise levels.

Edge Preservation Index (EPI)						
Wavelet thresholding Techniques	**Noise variance(σ^2)**					
	0.02	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**
VisuShrink	0.5131	0.4461	0.3997	0.3644	0.3493	0.2967
SUREShrink	0.3737	0.3506	0.3263	0.2946	0.2855	0.2735
BayesShrink	0.6655	0.5951	0.5313	0.4781	0.4611	0.4177
SmoothShrink	0.6197	0.5448	0.4963	0.4466	0.4350	0.3842
NeighShrink	**0.7032**	**0.6502**	**0.5772**	**0.5433**	**0.5004**	**0.4556**
NeighShrinkSURE	0.3773	0.3573	0.3250	0.3056	0.2994	0.2730

TABLE VI
CoC values obtained by various denoising methods tested on ultrasound image (Test image-2) at different noise levels.

Correlation Coefficient (CoC)						
Wavelet thresholding Techniques	**Noise variance(σ^2)**					
	0.02	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**
VisuShrink	0.9427	0.9267	0.9151	0.9023	0.8921	0.8799
SUREShrink	0.9333	0.9222	0.9086	0.8957	0.8859	0.8773
BayesShrink	0.9444	0.9256	0.9157	0.8982	0.8907	0.8616
SmoothShrink	0.9345	0.9090	0.8821	0.8610	0.8441	0.8157
NeighShrink	**0.9521**	**0.9324**	**0.9141**	**0.9019**	**0.8964**	**0.8813**
NeighShrinkSURE	0.9334	0.9219	0.9100	0.8970	0.8903	0.8769

The quantitative results in Tables I-VI show that the NeighShrink method outperforms the other wavelet thresholding techniques discussed. The higher values of PSNR indicate that the NeighShrink method reduces speckle noise effectively, and higher values of EPI and CoC indicate that the feature preservation ability is also good. From the Fig.4 and Fig. 5, it is observed that the visual quality is also improved by NeighShrink.



(a)Test image-2 **(b)Speckle Simulated** **(c) VisuShrink** **(d) SUREShrink**

(e)BayesShrink **(i)SmoothShrink** **(f) NeighShrink** **(g) NeighShrinkSURE**

Figure5: Denoising results of various wavelet thresholding methods on 128x128 ultrasound speckle simulated image (Test image-2).

V. CONCLUSION

The performance of different wavelet thresholding techniques is compared based on the image quality assessment parameters PSNR, EPI and CoC. These parameters helped in identifying a suitable thresholding technique for effective despeckling of medical ultrasound images. Results indicate that among the wavelet thresholding techniques discussed the performance of the NeighShrink is better in terms of denoising and edge preservation.

ACKNOWLEDGMENT

The authors thank Dr. S. Gupta for answering technical queries and for providing the ultrasound test images.

REFERENCES

[1] C.P.Loizou and C.P. Pattichis, *Speckle filtering algorithms and software and software for ultrasound imaging,* Morgan Claypool Publishers, 2008.

[2] N. Hiransakolwong, K.A. Hua, K. Vu and P.S. Windyga,"Segmentation of ultrasound liver images: An automatic approach.", Proceedings of the International Conference on Multimedia and Expo, Jul. 6-9, IEEE Xplore Press, I-573-576, 2003.

[3] A.A. Mahmoud, S. EL Rabaie, T. E. Taha, O. Zahran, F. E. and Abd El-Samie, "Comparative Study of Different Denoising Filters

for Speckle Noise Reduction in Ultrasonic B Mode Image", I.J. Image, Graphics and Signal Processing, vol. 2, pp.1-8, 2013.
[4] D.L. Donoho, "De-noising by soft-thresholding", IEEE Trans. Inform. Theory, vol. 41, pp. 613-627, 1995.
[5] W. Fourati, F. Kammoun and M.S. Bouhlel, "Medical image denoising using wavelet thresholding", Journal of Testing and Evaluation, vol.33, pp.364–369, 2005.
[6] A. Krishnakumar and J. Prabakar Rao , "Despeckling of medical ultrasound images by wavelet filters using soft thresholding", International Journal for Research and Development in Engineering (IJRDE),vol.1: Issue.1, pp-12-17, 2012.
[7] D.L Donoho, and I.M. Johnstone, "Adapting to unknown smoothness via wavelet shrinkage", J. Am. Statistical Assoc., vol. 90, pp. 1200-1224, 1995.
[8] Chang, S.G., B. Yu and M. Vetterli, "Adaptive wavelet thresholding for Image Denoising and Compression", IEEE Trans. Image Process.,vol. 9, pp.1532-1546, 2000.
[9] G.Y.Chen, T.D. Bui and A. Krzyzak, "Image denoising using neighbouring wavelet coefficients", Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, May, 17-21, IEEE Xplore Press, pp.917-920, 2004.
[10] Z. Dengwen and C.Wengang, "Denoising with an optimal threshold and neighboring window", Pattern Recognition Letters, pp.1694-1697, 2008.
[11] M.Mastriani and A.E. Giraldez, "Smoothing of coefficients in wavelet domain for speckle reduction in synthetic aperture radar images", J. Graphics Vision Image Process., pp: 1-8, , 2005.
[12] D. Sakrison, "On the role of observer and a distortion measure in image transmission", Proceedings of the IEEE Transactions on Communications, (ITC'97), IEEE Xplore Press, pp: 1251-1267, 1997.
[13] F. Sattar, L. Floreby, G. Salomonsson and B. Lovstrom, "Image enhancement based on a non linear multiscale method", IEEE Trans. Image Process., vol. 6, pp. 888-895, 1997.