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Undecimated Wavelet Based New Threshold Method for Speckle Noise Removal in Ultrasound Images

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Abstract. This paper includes different approaches for adaptive wavelet threshold (Bayes Shrink and Normal Shrink) and a robust wavelet domain method for noise filtering in ultrasound images. The search for efficient image denoising methods is still a valid challenge at the crossing of functional analysis and statistics. The proposed work in this paper extends the existing technique by improving the threshold function and produces results which are based on different noise levels. The standard signal to noise ratio (SNR) is not adequate to evaluate the noise removal in speckled images therefore to calculate multiplicative noise suppression a signal-to-mse (S/MSE) ratio is used as a measure of the quality of denoising.

Keywords: Adaptive Threshold, Denoising, Ultrasound Image, Wavelet Transform.

Introduction

An image is often corrupted by noise in its acquisition and transmission. In recent years there has been a fair amount of research on wavelet thresholding and threshold selection for signal and image denoising [2] [3] [4] [5] [6] [7], because wavelet provides an appropriate basis for separating noisy signal from image signal. Many wavelet based thresholding techniques like VisuShrink [8], BayesShrink [9] have proved better efficiency in image denoising. We describe here an efficient thresholding technique for denoising by analysing the statistical parameters of the wavelet coefficients.

The paper is organized as follows. Section2. introduces the concept of wavelet. Section3. Explains different denoising techniques with proposed threshold. Section 4.describes the proposed denoising algorithm.Section5.contains the Experimental results & discussions. Section6 gives conclusion.

Wavelet Transform

Undecimated wavelet packet transform. Widely applied in image processing, the wavelet transform is a powerful approach to multiresolution analysis (MRA) which is concerned with the representation and analysis of images at more than one resolution. In MRA detection, the wavelet technique can well spot the nonstationary features of images such as edges, details and isolated points. Important edges and details could be separated and preserved during this type of processing. The wavelet transform of an image $I(x,y) \in L_2(R_2)$ is defined as a series of 4 subbands of different levels: LL_j, LH_j, HL_j and HH_j. The LL_j subband denotes the lowpass or coarse subband at level j, the remaining subbands are highpass or detail ones: the LH_j subband carries horizontal direction details, the HL_j subband carries vertical direction details, and the HH_j subband carries diagonal direction details. The wavelet transform has the property of representing an image sparsely. After the wavelet transform, the energy of the signal in the image has been focused on a few coefficients, while the coefficients representing noise of the image are always at low value. Moreover, in the same orientation detail subbands the coefficients of similar position and adjacent levels have highly correlated [10].

The wavelet packet transform (WPT)[23] is a generalization of the wavelet transform which offers a rich set of decomposition structures. The decomposition in WPT is possibly applied to all subbands. A best basis is selected which decides a decomposition structure among the library of possible bases. In our work, the WPT is used to decompose ultrasound images and separate the signal and noise in WPT domain. To avoid the down-sample step in WPT, we use the undecimated wavelet packet transform (UWPT) so that every subband has the same number of coefficients [11]. The decomposition level is chosen as 3, and the decomposition structure is shown as figure1 the decomposition structure of the proposed method.

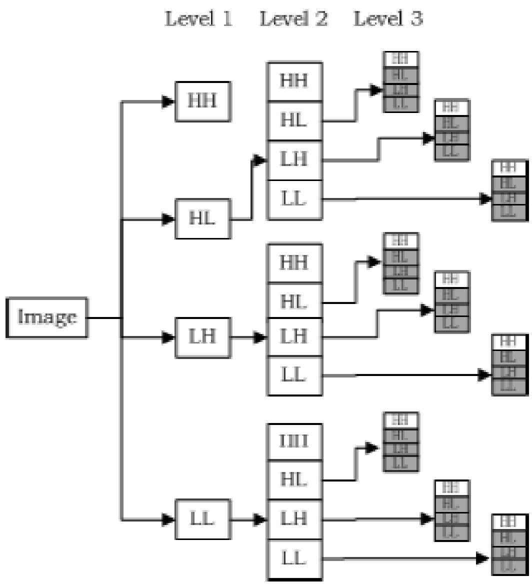

Fig. 1 The decomposition structure of the proposed method.

Denoising Techniques With Existing Threshold

Bayes Shrink. Wavelet shrinkage is a method of removing noise from images in wavelet shrinkage, an image is subjected to the wavelet transform, the wavelet coefficients are found, the components with coefficients below a threshold are replaced with zeros, and the image is then reconstructed[9]. In particular, the BS method has been attracting attention recently as an algorithm for setting different thresholds for every subband[21]. Here subbands are frequently bands that differ from each other in level and direction. The BS method is effective for images including noise. Bayes Shrink was proposed by Chang, Yu and Vetterli. The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink [9]. The Bayes threshold, is defined as

$$T_B = \frac{\sigma^2}{\sigma_x} \tag{1}$$

The observation model is expressed as follows:

$$Y = X + V \tag{2}$$

Here Y is the wavelet transform of the degraded image, X is the wavelet transform of the original image, and V denotes the wavelet transform of the noise components following the

$$Y(a,b) = X(a,b) + V(a,b)$$

$$\sigma_y^2 = \sigma_x^2 + \sigma_v^2 \qquad (3)$$

σ_y^2 is computed as below:

$$\sigma_y^2 = \frac{1}{n^2}\sum_{a,b-1}^{n} y^2(a,b) \qquad (4)$$

The variance of the signal, σ_x^2 is computed as

$$\hat{\sigma_x} = \sqrt{\max(\sigma_y - \sigma^2, 0)} \qquad (5)$$

With this we can compute the bayes threshold.

Normal Shrink. The method for computing the various parameters used to calculate the threshold value (T_N) [25] which is adaptive to different subband characteristics.

$$T_N = \frac{\beta\hat{\sigma}^2}{\sigma_y} \qquad (6)$$

Where scale parameter β is computed once for each scale using the following equation:

$$\beta = \sqrt{\log\left(\frac{L_k}{J}\right)} \qquad (7)$$

L_k is the length of the subband at *kth* scale.

$\hat{\sigma}^2$ is the noise variance, which is estimated from the subband HH1, using the formula [5][12]

$$\hat{\sigma}^2 = \left(\frac{\text{median}(|HH1|)}{0.6745}\right)^2 \qquad (8)$$

and σ_y is the standard deviation of the subband under consideration computed by using equation (4)

Pizurica. In a wavelet decomposition of an image a wavelet coefficient $w_{k,j}^D$ represents its bandpass content at resolution scale *2j* $(1 \leq j \leq J)$, spatial position k and orientation *D*. The lowpass image content is represented by scaling coefficients *uk,J*[1] . Typically, three orientation subbands are used:

D ∈ *{LH,HL,HH}*, leading to three detail images at each scale, characterized by horizontal, vertical and diagonal directions. We use a non-decimated wavelet transform, with an equal number of coefficients at each resolution scale. The algorithm is implemented using the quadratic spline wavelet [14] as in [15] [16]. Our wavelet domain estimation approach relies on the joint detection and estimation theory [20] and is related to the problem of the spectral amplitude estimation in [17][18][19].

Ultrasound images are corrupted by speckle noise [27], [28], which affects all coherent imaging systems. Figure 3, figure4 and figure 5 illustrates the examples of gradual speckle suppression using the proposed method and various denoising techniques for threshold. The results in this figure correspond to the window size 3x3.To investigate the quantitative performance of the method, we use images with artificial speckle noise. A speckled image d = *{d1...dN}* is commonly modelled as [29], [30] $d_k = f_k v_k$ where f = *{f1...fN}* is a reference noise-free image, and v = *{v1...vN}* is a unit mean random field. Realistic spatially correlated speckle noise vk in ultrasound images can be simulated by lowpass filtering a complex Gaussian random field and taking the magnitude of the filtered output [30].

We perform the lowpass filtering by averaging the complex values in a 3x3 sliding window. Such a short-term correlation was found sufficient [29] to model the realistic images well. We compare the performance of the proposed method to one conventional approach proposed by pizurica and one of the adaptive threshold techniques (NS,BS). The window size of the Shrinks was experimentally optimized to produce the maximum output S/MSE for each test image and for each amount of noise used in the simulations. The results clearly demonstrate that the proposed method outperforms the spatially adaptive thresholding methods both in terms of the visual quality (Fig. 3 and Fig. 4). Finally, Fig. 5 enables us to make a visual comparison of the results of the proposed method and rest of the techniques.

New Threshold function. There are different denoising scheme used to remove noise while preserving original information and basic parameter of the image. Contrast, brightness, edges and background of the image should be preserved while denoising in this technique. Performance measured in terms of signal to mean square error ratio. New threshold function is calculated as:

$$\text{newthresh} = \sqrt{J * \frac{\log(M)}{m}} \tag{9}$$

Where M is the total number of pixel, m is the mean of the image at particular level (J). This function preserves the contrast, edges, background of the images. This threshold function calculated at different scale level.

Speckle Noise Reduction Algorithm.

This section describes the image denoising algorithm, which achieves near optimal soft thresholding in the wavelet domain for recovering original signal from the noisy one. The algorithm is very simple to implement and computationally more efficient. It has following steps:

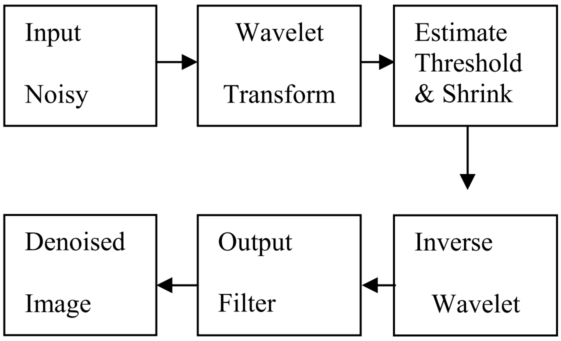

Fig. 2 Procedure to denoise an ultrasound image

A. Compute the non decimated wavelet transform with J resolution levels.
B. Initialize $\hat{y}_J^D = w_J^D, D \in \{HL, LH, HH\}$
C. For each orientation D and for each scale J for $J= 1...J-1$ apply new threshold using equation (9), which preserve edges & minimize the mean square error.
D. Invert the multiscale decomposition to reconstruct the denoised image.

Experimental Result

Our test consists of an image of ultrasound of baby, liver and bladder of size (256×256). The kind of noise is Speckle with variance 0.09, 0.1,…..0.3. In the test, Speckle noise is added to original image. In this test, we used from several methods for image denoising. Pizurica, Bayes shrink, Normal shrink. The result shows proposed method performs denoising that is consistent with the human visual system that is less sensitive to the presence of noise in vicinity of edges. However, the presence of noise in flat regions of the image is perceptually more noticeable by the human visual system. Bayes shrink performs little denoising in high activity sub-regions to preserve the sharpness of edges but completely denoised the flat sub-parts of the image.

Performance of normal shrink is similar to bayes shrink. But pizurica's code produces better noise removal In order to quantify the achieved performance improvement, three different measures were computed based on the original and the denoised data. For quantitative evaluation, an extensively used measure is the mse defined as

$$\mathrm{mse} = \frac{1}{K}\sum_{i=1}^{K}\left(\hat{S}_i - S_i\right)^2 \tag{10}$$

Where

S_i original image;
$\hat{S}_i$ denoised image;
K image size;

The standard signal to noise ratio (SNR) is not adequate to evaluate the noise suppression in case of multiplicative noise. Instead, a common way to achieve this in coherent imaging is to calculate the signal-to-mse (S/mse) ratio, defined as [24],[25]

$$\mathrm{S/mse} = 10\log_{10}\left(\sum_{i=1}^{K} S_i^2 \Big/ \sum_{i=1}^{K}\left(\hat{S}_i - S_i\right)^2\right) \tag{11}$$

This measure corresponds to the classical SNR in the case of multiplicative noise. Remember that in ultrasound imaging, we are interested in suppressing speckle noise while at the same time preserving the edges of the original image that often constitute features of interest for diagnosis.

Thus, in addition to the above quantitative performance measures, we also consider a qualitative measure for edge preservation. More specifically, we used a parameter originally defined in [22] and [23]

$$\beta = \frac{r\left(\Delta s - \overline{\Delta s}, \widehat{\Delta s} - \overline{\widehat{\Delta s}}\right)}{\sqrt{r\left(\Delta s - \overline{\Delta s}, \Delta s - \overline{\Delta s}\right) . r\left(\Delta s - \overline{\Delta s}, \widehat{\Delta s} - \overline{\widehat{\Delta s}}\right)}} \tag{12}$$

Where and are the high-pass filtered versions of and respectively, obtained with a 3×3 pixel standard approximation of the Laplacian operator

$$\rho = \frac{r\left(I - \hat{I}, S - \hat{S}\right)}{\sqrt{r\left(I - \hat{I}, I - \hat{I}\right) r\left(S - \hat{S}, S - \hat{S}\right)}} \tag{13}$$

The correlation measure, should be close to unity for an optimal effect of edge preservation. The obtained values of S/mse, and for all methods applied to the ultrasound images of baby, bladder and liver are given in Tables (1,2&3). It is evident from the table that the proposed threshold function is more successful in speckle noise suppression than normal shrink, bayes shrink and pizurica threshold. Observing the metric values, we see that the multiresolution techniques exhibit a clearly better performance in terms of edge preservation, as expected. Among them, our proposed threshold approach exhibits the best performance according to all three metrics. The simulated speckle noise is added to images shown in all figures. Noise suppression in ultrasound images using the proposed method, corresponds to a S/mse value in dB. For the various noise levels, all the methods that are tested achieved a good speckle suppression performance.

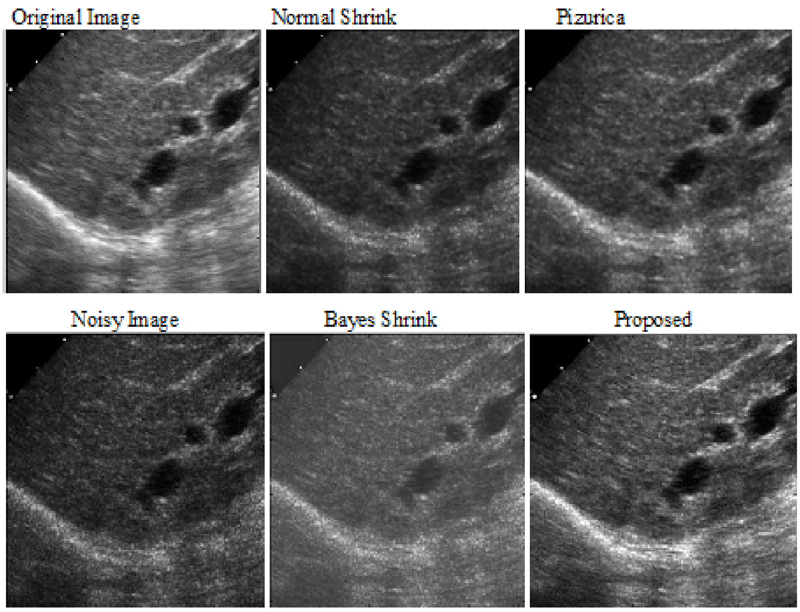

Fig. 3 Noise suppression for different ultrasound liver images using the proposed method, Pizurica,s code, Bayes Shrink and Normal Shrink

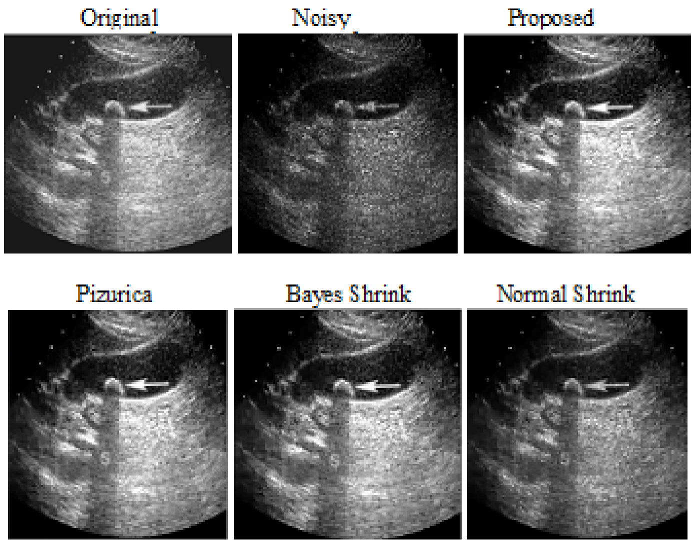

Fig. 4 Noise suppression for different ultrasound gall bladder images using the proposed method, Pizurica,s code, Bayes Shrink and Normal Shrink

Conclusion

The work in this paper is done on different methods that depend upon the noise variance for image denoising is proposed by adaptive threshold techniques and a very robust and efficient wavelet domain denoising technique applicable to various types of speckled ultrasound images in different formats. The proposed method, applied to medical image in order to remove speckle noise, produces better results that vary according to the level of noise

variance which is added to the image, the new threshold function is superior as compare to other threshold functions, gives better edge perseverance and improved signal to mean square error. It is further suggested that the proposed threshold may be extended further to improve the denoising performance of ultrasound images.

Table 1 Image Quality Measures Obtained by Four denoising methods tested on ultrasound baby with varience 0.09, 0.1 and 0.3

Method	S/MSE	B	ρ
Normal	16.0496	0.6539	0.9876
Bayes	14.4031	0.6528	0.9820
Pizurica	18.6884	0.7191	0.9932
Proposed	**21.6856**	**0.8905**	**0.9936**
Normal	16.0721	0.6494	0.9877
Bayes	14.3883	0.6442	0.9820
Pizurica	18.5468	0.7071	0.9930
Proposed	**21.5173**	**0.8282**	**0.9965**
Normal	15.5784	0.6356	0.9861
Bayes	14.2409	0.6389	0.9812
Pizurica	16.9554	0.6547	0.9899
Proposed	**18.1746**	**0.8227**	**0.9924**

Table 2 Image Quality Measures Obtained by Four denoising methods tested on ultrasound gall bladder with varience 0.09, 0.1 and 0.3.

Method	S/MSE	β	P
Normal	21.4383	0.7806	0.9965
Bayes	21.7917	0.8055	0.9967
Pizurica	22.5061	0.8078	0.9972
Proposed	**25.7315**	**0.9862**	**0.9987**
Normal	21.0135	0.7570	0.9961
Bayes	21.3673	0.7833	0.9964
Pizurica	22.4752	0.9023	0.9972
Proposed	**25.3918**	**0.9280**	**0.9986**
Normal	18.3661	0.7569	0.9926
Bayes	18.2619	0.7602	0.9925
Pizurica	18.6521	0.7973	0.9932
Proposed	**19.3412**	**0.8662**	**0.9940**

Table 3 Image Quality Measures Obtained by Four denoising methods tested on ultrasound liver with varience 0.09, 0.1 and 0.3

Method	S/MSE	β	ρ
Normal	8.5614	0.8511	0.9282
Bayes	7.2790	0.8715	0.9027
Pizurica	10.2828	0.8240	0.9525
Proposed	**12.0007**	**0.8856**	**0.9686**
Normal	8.5218	0.8387	0.9275
Bayes	7.2664	0.8492	0.9023
Pizurica	10.2750	0.8283	0.9524
Proposed	**11.9565**	**0.8537**	**0.9682**
Normal	8.5617	0.8480	0.9282
Bayes	7.3008	0.8508	0.9030
Pizurica	10.1837	0.8245	0.9513
Proposed	**11.7980**	**0.8556**	**0.9668**

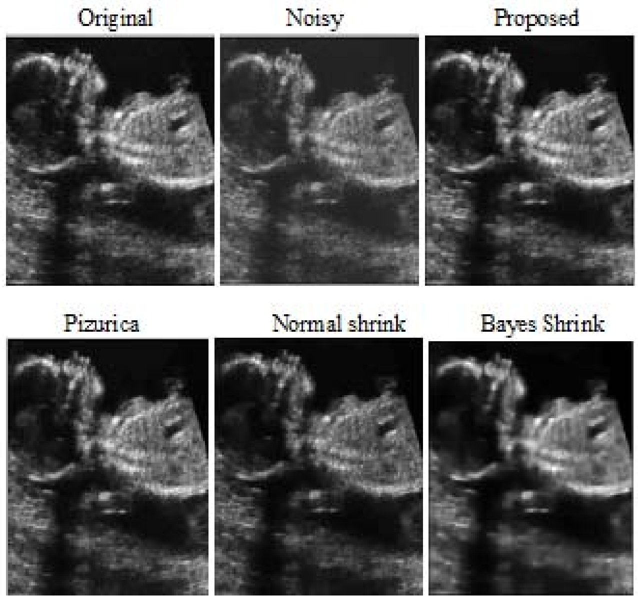

Fig. 5 Noise suppression for different ultrasound baby images using the proposed method, Pizurica,s code, Bayes Shrink and Normal Shrink

References

[1] A.Pizurica, W.Philips, I.Lemahieu, and arc Acheroy ,"A Versatile Wavelet Domain Noise Filtration Technique for Medical Imaging". IEEE Trans. on Medical Imaging Vol. 22, No. 3, March 2003, Pages 323–331.

[2] D.L. Donoho and I.M. Johnstone. (1995). Adapting to unknown smoothness via wavelet shrinkage. Journal of American Statistical Association., Vol. 90, no. 432, pp1200-1224.

[3] S. Grace Chang, Bin Yu and M. Vattereli. (2000). Wavelet Thresholding for Multiple Noisy Image Copies. IEEE Transaction. Image Processing, vol. 9, pp.1631- 1635.

[4] S. Grace Chang, Bin Yu and M. Vattereli. (2000). Spatially Adaptive Wavelet Thresholding with Context Modeling for Imaged noising. IEEE Transaction - Image Processing, volume 9, pp. 1522-1530.

[5] M. Vattereli and J. Kovacevic. (1995). Wavelets and Subband Coding. Englewood Cliffs. NJ, Prentice Hall.

[6] Maarten Janse. (2001). Noise Reduction by Wavelet Thresholding. Volume 161, Springer Verlag, United States of America, I edition.

[7] Carl Taswell. (2000). The what, how and why wavelet shrinkage denoising. Computing in science and Engineering, pp.12-19.

[8] D.L. Donoho. (1994). Ideal spatial adoption by wavelet shrinkage. Biometrika, volume 81, pp.425-455.

[9] S. Grace Chang, Bin Yu and M. Vattereli. (2000). Adaptive Wavelet Thresholding for Image denoising and Compression. IEEE Transaction, Image Processing, vol. 9, pp. 1532-15460.

[10] J. Portilla, V. Strela, M.J. Wainwright, E.P. Simoncelli, "Image Denoising Using Scale Mixtures of Gaussians in the Wavelet Domain," IEEE Trans. on Image Processing, vol. 12, no. 11, Nov. 2003

[11] S. Solbø, and T. Eltoft, "A Stationary Wavelet-Domain Wiener Filter for correlated Speckle," IEEE Trans. on Geosc. and Remote Sensing, , vol. 46, no.4, pp. 1219-1230, Apr. 2008.

[12] P.H. Westrink, J. Biemond and D.E. Boekee, An optimal bit allocation algorithm for subband coding, in Proc. IEEE Int. Conf. Acoustics, Speech, Signal Processing, Dallas, TX, April 1987, pp. 1378-1381.

[13] S. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," IEEE Trans. Pattern Anal. and Machine Intel., vol. 11, no. 7, pp. 674-693, July 1989.

[14] S. Mallat, A wavelet tour of signal processing, Academic Press, 1998.

[15] M. Malfait and D. Roose, "Wavelet-based image denoising using a Markov random field a priori model," IEEE Trans. Image Proc., vol. 6, no. 4, pp. 549–565, Apr 1997.

[16] Y. Xu, J. B. Weaver, D. M. Healy, J. Lu, "Wavelet transform domain filters: a spatially selective noise filtration technique," IEEE Trans. Image Proc., vol. 3, no. 6, pp. 747–758, Nov. 1994.

[17] T. Aach and D. Kunz, “Anisotropic spectral amplitude estimation for noise reduction and image enhancement,” Proc. IEEE Internat. Conf. on Image Proc., ICIP96, pp. 335–338, Lausanne, Switzerland, 1996.

[18] Y. Ephraim and D. Malah, “Speech enhancement using a minimum mean-square error short-time spectral amplitude estimation,” IEEE Trans. Acoust. Speech and Signal Proc., vol. 32, no. 6, pp. 1109–1121, Dec 1984.

[19] R. J. McAulay and M. L. Malpass, “Speech Enhancement Using a Soft-Decision Noise Suppression Filter,” IEEE Trans. Acoust. Speech and Signal Proc., vol. 28, pp. 137–144, Apr 1980.

[20] D. Middleton and R. Esposito, “Simultaneous optimum detection and estimation of signals in noise,” IEEE Trans. Inform. Theory, vol. 14, no. 3, pp. 434–443, May 1968.

[21] L. Gagnon and A. Jouan, “Speckle filtering of SAR images—A comparative study between complex-wavelet based and standard filters,” in SPIE Proc., vol. 3169, 1997, pp. 80–91.

[22] X. Hao, S. Gao, and X. Gao, “A novel multiscale nonlinear thresholding method for ultrasonic speckle suppressing,” IEEE Trans. Med. Imag., vol. 18, pp. 787–794, Sept. 1999.

[23] F. Sattar, L. Floreby, G. Salomonsson, and B. Lovstrom, “Image enhancement based on a nonlinear multiscale method,” IEEE Trans. Image Processing, vol. 6, pp. 888–895, June 1997.

[24] S.D. Ruikar and D.D. Doye, “Wavelet Based Image Denoising Technique.” (IJACSA) International Journal of Advanced Computer Science and Applications,Vol. 2, No.3, March 2011

[25] Lakhwinder Kaur , Savita Gupta and R.C. Chauhan, “Image Denoising using Wavelet Thresholding”.ICGVIP 2002

[26] Sheng Yan, Jianping Yuan, Minggang Liu, and Chaohuan Hou, “Speckle Noise Reduction of Ultrasound Images Based on an Undecimated Wavelet Packet Transform Domain Nonhomomorphic Filtering” IEEE 2009

[27] J. W. Goodman, “Some fundamental proprerties of speckle,” J.Opt. Soc. Am., vol. 66, pp. 1145–1150, 1976.

[28] R.F. Wagner, S.W. Smith, J.M. Sandrik, and H. Lopez, “Statistics of speckle in ultrasound B-scans,” IEEE Trans. on Sonics and Ultrasonics, vol. 30, no. 3, pp 156–163, May 1983.

[29] A. Achim, A. Bezerianos, and P. Tsakalides, “Novel Bayesian multiscale method for speckle removal in medical ultrasound images,” IEEE Trans. on Medical Imaging, vol. 20, no. 8, pp. 772- 783, Aug 2001.

[30] F. Sattar, L. Floreby, G. Salomonsson and B. L¨ovstr¨om, “Image enhancement based on a nonlinear multiscale method,” IEEE Trans. Image Proc., vol. 6, no. 6, pp. 888–895, June 1997.