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A Novel Threshold Technique for Eliminating Speckle Noise In Ultrasound Images

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Abstract. Ultrasound images are degraded as they contain speckle noise. Recently image denoising using the wavelet transform has been attracting much attention. The work in this paper includes different filtration techniques (Wiener and Median) and a proposed novel technique that extends the existing technique by improving the threshold function parameter K which produces results that are based on different noise levels. A signal to mean square error as a measure of the quality of denoising was preferred.

Keywords: Adaptive Threshold, Bayes Shrink, Denoising, Wavelet Transform, Ultrasound Images.

Introduction

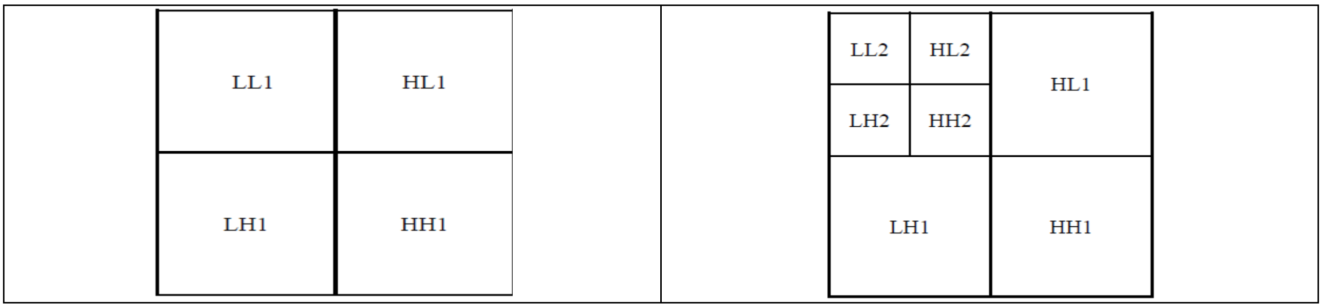
Ultrasound is a powerful technique for imaging the internal anatomy (e.g., abdomen, breast, liver, kidney, and musculoskeletal). It is relatively inexpensive, noninvasive, harmless for the human body, and portable, but it suffers from a main disadvantage, i.e., contamination by speckle noise. Speckle noise significantly degrades the image quality and complicates diagnostic decisions for discriminating fine details in ultrasound images. Many techniques have been proposed to reduce this noise [2]–[10]. Early methods use various spatial filters such as average, median, and Wiener filter [2]–[6]; however, they usually do not accurately preserve all the useful information such as anatomical boundaries in the image. Recently, wavelet-based despeckling has been considered [7]–[11]. These methods usually include: 1) noisy image ; 2) wavelet transformation; 3) modification of noisy coefficients using shrinkage function; and 4) inverse wavelet transformation; The first step is exerted to convert the multiplicative speckle noise into an additive noise [6], [7], and, after that, a wavelet-shrinkage technique s [12]–[20] is employed for noise reduction. Wavelet-based image denoising methods are formulated as a Bayesian estimation problem. Thus, the employed probability density function (pdf) for noise-free data and noise (for wavelet coefficients of log-transformed data), and the type of estimator have significant impact on the performance of the noise reduction process. The preliminary classification step in the proposed method relies on the persistence of useful wavelet coefficients across the scales [23], and is related to the one in [24], but avoids its iterative procedure. In contrast to [24], and related methods like [21], [22], where the inter-scale correlations between wavelet coefficients are used for a “hard” selection of the coefficients from which the denoised image is reconstructed, our algorithm performs a soft modification of the coefficients adapted to the spatial image context. The classification step of the proposed method involves an adjustable parameter that is related to the notion of the expert-defined “relevant image features”. In certain applications the optimal value of this parameter can be selected as the one that maximizes the signal-to-noise ratio (SNR) and the algorithm can operate as fully automatic. However, we believe that in most medical applications the tuning of this parameter leading to a gradual noise suppression may be advantageous. The proposed algorithm is simple to implement and fast. We demonstrate its usefulness for denoising and enhancement of the ultrasound images.

Most of the wavelet thresholding methods suffer from a drawback that the chosen threshold may not match the specific distribution of signal and noise components in different scales. To address this issue, Simoncelli et al. [10] developed nonlinear estimators, based on formal Bayesian theory.

The rest of the paper is organized as follows. Section 2 explains the Wavelet Transform. The Adaptive wavelet threshold (bayes shrink) and estimation of proposed threshold by minimizing a Bayesian risk with squared error is explained in section 3. The speckle reduction algorithm is presented in section 4. Experimental results are shown in section 5 and compared with Median filter and Wiener filter.

Wavelet Transform

The DWT is identical to a hierarchical subband system where the subbands are logarithmically spaced in frequency and represent octave-band decomposition. Due to the decomposition of an image using the DWT [25] the original image is transformed into four pieces which is normally labeled as LL, LH, HL and HH as in the schematic depicted in Fig. 1 a. The LL subband can be further decomposed into four subbands labeled as LL2, LH2, HL2 and HH2 as shown in Fig.1 b.



(a)One-Level (b) Two-Level

Fig. 1 Image decomposition by using DWT

As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides a non redundant and unique representation of the signal. Several properties of the wavelet transform, which make this representation attractive for denoising, are

- Multiresolution - image details of different sizes are analyzed at the appropriate resolution scales
- Sparsity - the majority of the wavelet coefficients are small in magnitude.
- Edge detection - large wavelet coefficients coincide with image edges.
- Edge clustering - the edge coefficients within each sub band tend to form spatially connected clusters

The procedure for wavelet decomposition consists of consecutive operations on rows and columns of the two-dimensional data. The wavelet transform first performs one step of the transform on all rows. This process yields a matrix where the left side contains down sampled low pass coefficients of each row, and the right side contains the high pass coefficients. Next, one step of decomposition is applied to all columns; this results in four types of coefficients, HH, HL, LH and LL.

Adaptive Wavelet 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[26]. In particular, the bayes shrink method has been attracting attention recently as an algorithm for setting different thresholds for every subband[27]. 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 [28]. The Bayes threshold, is defined as

$T_B=\sigma^2/\sigma^s$. (1)

The observation model is expressed as follows:

$$W=S+N \tag{2}$$

Here W is the wavelet transform of the degraded image, S is the wavelet transform of the original image, and N denotes the wavelet transform of the noise components following the

$$W(x,y)=S(x,y)+N(x,y) \tag{3}$$

$$\sigma_w^2 = \sigma_s^2 + \sigma^2 \tag{4}$$

$\sigma_w^2$is computed as below:

$$\sigma_w^2 = \frac{1}{n^2}\sum_{x,y-1}^{n} w^2(x,y) \tag{5}$$

The varience of the signal, $\hat{\sigma_s}$ is computed as

$$\hat{\sigma_s} = \sqrt{\max(\sigma_y - \sigma^2, 0)} \tag{6}$$

With this we can compute the bayes threshold.

Proposed Bayes Shrink. There is the problem of noise not being sufficiently removed in an image processed using bayes shrink method[1].But proposed bayes shrink can remove noise better than bayes shrink. It performs its processing using threshold values that are different for each subband coefficient the threshold T can be determined as follows:

$$K = J * \sqrt{\log(L_k)}/m \tag{7}$$

Where L_k is the length of band with total number of decomposition *J* and *m* is mean.

$$T_B = K\frac{\sigma^2}{\sigma_x} \tag{8}$$

Where the noise variance σ^2 is estimated from subband HHI, using the formula [28][27]

$$\hat{\sigma^2} = \left(\frac{\text{median}(|Y_{ij}|)}{0.6745}\right)^2 \; Y_{ij} \; \epsilon \text{ Subband HH1} \tag{9}$$

and the standard deviation $\hat{\sigma_x}$, of thc subband is computed by

$$\hat{\sigma_x} = \sqrt{\max(\sigma_y = \sigma^2, 0)} \tag{10}$$

when $\sigma_x^2 \geq \sigma_y$ & σ, is taken to be zero i.e. threshold is infinity or in practice it is taken as maximal value f subband, setting all the coefficients to zero. Since Y is modeled as zcro mean σy is computed as

$$\hat{\sigma_y} = \sqrt{\frac{1}{n^2}\sum_{i,j=1}^{n} Y_{ij}^2} \qquad (11)$$

where n×n is size of subband.

Algorithm For Denoising bases on new threshold.

We can summarize the process Bayes Shrink, proposed bayes shrink as follows:

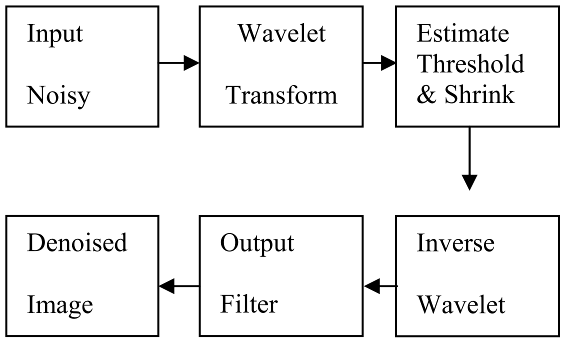


Fig. 2 Procedure for denoising ultrasound image

A. Input Noisy ultrasound image.
B. Perform Multiscale decomposition of the image corrupted by Speckle noise using wavelet transform.
C. Estimate the noise variance σ^2 using eqution (9)
D. For each scale compute the scale parameter K.
E. from equation (7)
F. For each subband (except the lowpass residual).
    - Compute the standard deviation σ_x using equation (10).
    - Compute threshold T using equation (8) if subband variance σ_x^2 is greater than noise variance, otherwise set T to maximum coefficient of the subband.
G. Invert the multiscale decomposition to reconstruct the denoised image.

Experimental Result

Our test consists of an ultrasound image baby, kidney, liver 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. Median filter and other nonlinear filters, as well as wiener filters and other optimization filters have been used as denoising methods for images with noise, as shown in figure 3, figure4, figure5. As well as, the wiener filter is more effective than the conventional linear filter high frequency components in images and it works efficiently when the noise is Speckle noise. The results show both of filter, denoise weakly as well as new blurriness occurs in the processed image. Therefore they remove a lot of details of original image during denoising.

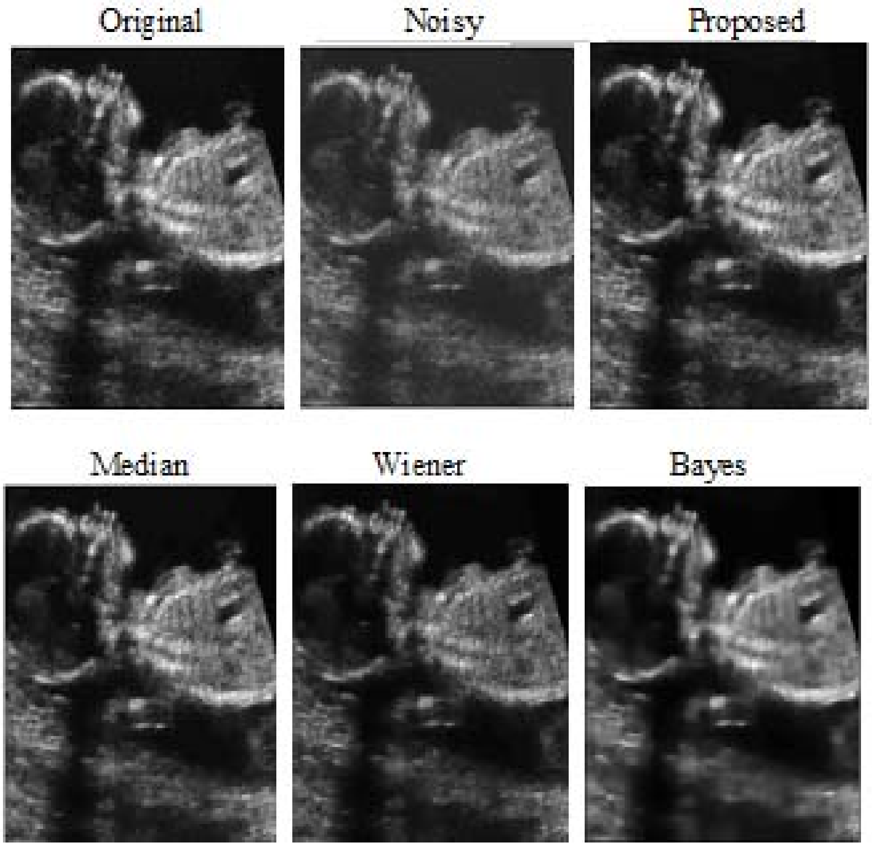


Fig. 3 Noise suppression in ultrasound baby using the proposed method, Bayes shrink, Wiener filter, Median filter

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 shown in eq (12).

$$\mathrm{mse} = \frac{1}{K}\sum_{i=1}^{K}\left(\hat{S}_i - S_i\right)^2 \tag{12}$$

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]

$$\mathrm{S/mse} = 10\log_{10}\left(\sum_{i=1}^{K} S_i^2 \Big/ \sum_{i=1}^{K}\left(\hat{S}_i - S_i\right)^2\right) \tag{13}$$

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 we used a parameter originally defined in [29] and [30].In soft threshold, we used from one threshold value. In the wavelet decomposition, the magnitude of the coefficients varies depending on the decomposition level. Hence, if all levels are processed with one threshold value the processed image may be overly smoothed so that sufficient information preservation is not possible and the image get blurry. Therefore the method is not suitable. The result shows Proposed Bayes shrink 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.

The coefficient of correlation (ρ) is given by:

$$\rho = \frac{r(I-\hat{I}, S-\hat{S})}{\sqrt{r(I-\hat{I}, I-\hat{I})\, r(S-\hat{S}, S-\hat{S})}} \tag{14}$$

The ρ is the key measure of similarity between the original and the denoised image. The closer the ρ is o 1, the stronger the correlation between the original and the denoised image.

Table 1. Image Performance Measure on Ultrasound baby

σ =0.09	**Median**	**Wiener**	**Bayes**	**Proposed**
S/MSE	15.7588	17.0436	18.9654	**21.7787**
CoC	0.9967	0.9101	0.9937	**0.9983**
σ =0.1	**Median**	**Wiener**	**Bayes**	**Proposed**
S/MSE	15.7377	17.0086	18.9598	**21.7589**
CoC	0.9866	0.9900	0.9937	**0.9967**
σ =0.3	**Median**	**Wiener**	**Bayes**	**Proposed**
S/MSE	15.1724	16.1086	17.8363	**18.3798**
CoC	0.9847	0.9877	0.9904	**0.9927**

Table 2. Image Performance Measure on Ultrasound kidney

σ =0.09	**Median**	**Wiener**	**Bayes**	**Proposed**
S/MSE	12.1007	13.6522	15.1059	**19.2299**
CoC	0.9689	0.9783	0.9846	**0.9941**
σ =0.1	**Median**	**Wiener**	**Bayes**	**Proposed**
S/MSE	12.1001	13.6382	15.0104	**18.9206**
CoC	0.9687	0.9782	0.9242	**0.9936**
σ =0.3	**Median**	**Wiener**	**Bayes**	**Proposed**
S/MSE	11.6546	12.8754	13.8761	**15.3913**
CoC	0.9653	0.9938	0.9793	**0.9856**

Table 3. Image Performance Measure on Ultrasound liver

σ =0.09	**Median**	**Wiener**	**Bayes**	**Proposed**
S/MSE	16.1193	17.1058	22.2087	**22.5893**
CoC	0.9904	0.9904	0.9970	**0.9973**
σ =0.1	**Median**	**Wiener**	**Bayes**	**Proposed**
S/MSE	17.0599	16.5109	22.9181	**22.3069**
CoC	0.9903	0.9880	0.9968	**0.9971**

σ =0.3	Median	Wiener	Bayes	Proposed
S/MSE	15.7967	14.9151	16.0568	**16.4367**
CoC	0.9868	0.9841	0.9897	**0.9888**

The result shows all of the adaptive wavelet threshold (bayes shrink, modified bayes shrink and proposed bayes shrink) remove noise better than others as shown in table1, table2, table 3.

But, it depends on noise, one of the adaptive wavelet threshold is better. Proposed bayes shrink is the best because it has maximum SNR (signal to noise ratio) and coefficient of correlation.

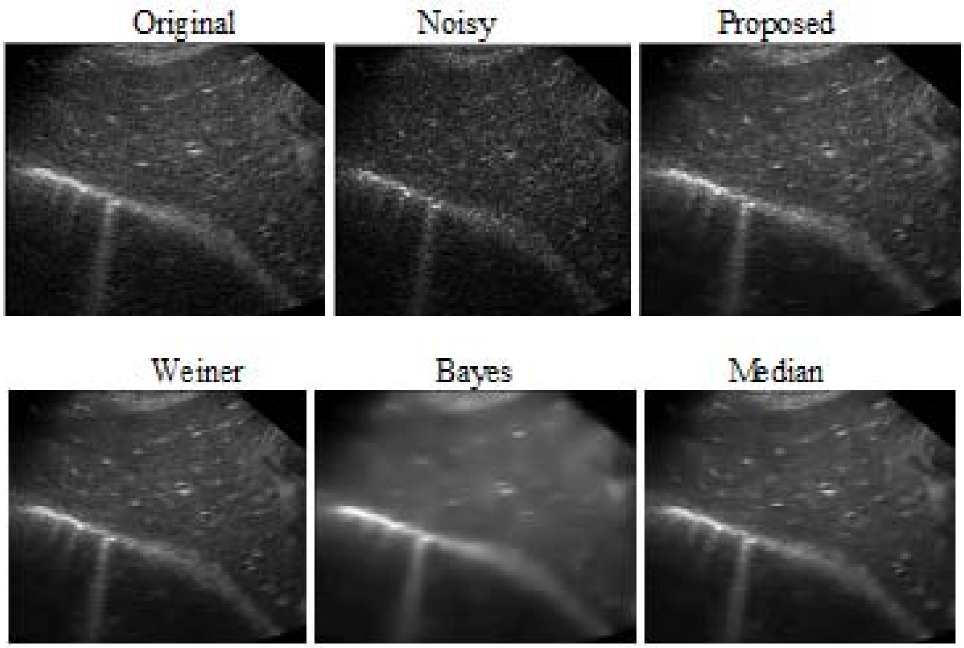


Fig. 4 Noise suppression in ultrasound kidney using the proposed method, Bayes shrink, Wiener filter, Median filter

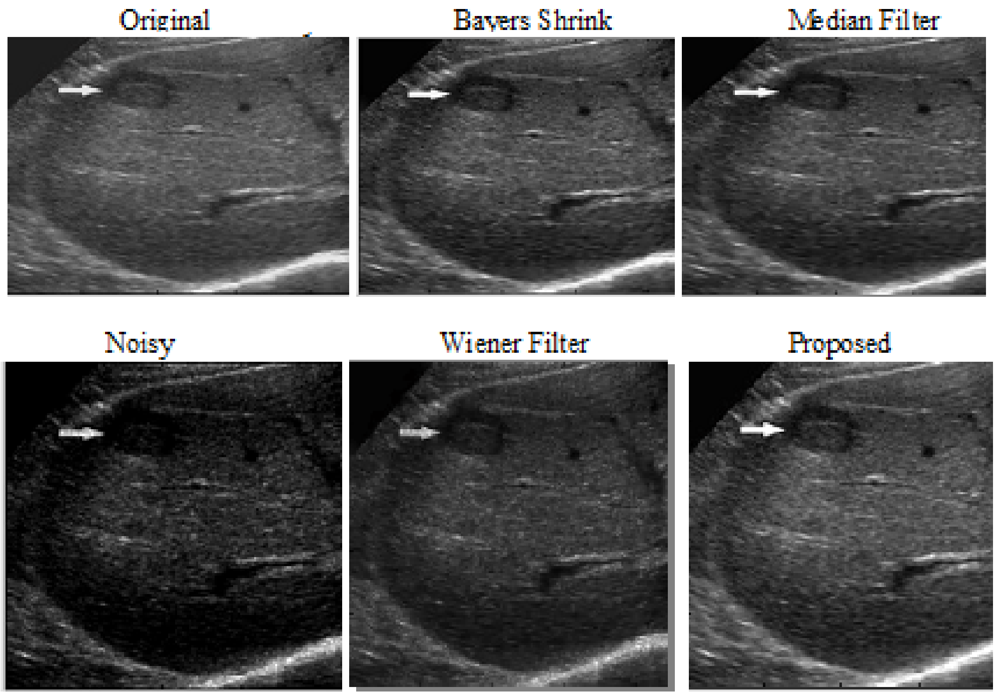


Fig. 5 Noise suppression in ultrasound liver using the proposed method, Bayes shrink, Wiener filter, Median filter

Conclusion

The technique gives better results which vary as the noise variance increases. Our new threshold function is better as compare to other threshold function, gives a greater amount of signal to mean square error and preserves background information. In future we can use same threshold function for medical images as well as texture images to get denoised image with improved performance parameter.

References

[1] Savita Gupta', L. Kaur', R.C. Chauhan'; and S. C. Saxena' “A Wavelet Based Statistical Approach for, Speckle Reduction in Medical Ultrasound Images”.

[2] J. U. Quistgaard, “Signal acquisition and processing in medical diagnostic ultrasound,” IEEE Signal Process. Mag., vol. 14, no. 1, pp. 67–74, Jan. 1997.

[3] M. Karaman,M. A. Kutay, and G. Bozdagi, “An adaptive speckle suppression filter for medical ultrasonic imaging,” IEEE Trans. Med. Imaging, vol. 14, no. 2, pp. 283–292, Jun. 1995.

[4] J. W. Goodman, “Some fundamental properties of speckle,” J. Opt. Soc. Amer., vol. 66, pp. 1145–1150, Nov. 1976.

[5] T.Loupas,W. N. Mcdicken, and P. L. Allan, “Anadaptive weighted median filter for speckle suppression in medical ultrasonic images,” IEEE Trans. Circuits Syst., vol. 36, no. 1, pp. 129–135, Jan. 1989.

[6] A. K. Jain, Fundamental of Digital Image Processing. Englewood Cliffs, NJ: Prentice-Hall, 1989.

[7] X. Zong, A. F. Laine, and E. A. Geiser, “Speckle reduction and contrast enhancement of echocardiograms via multi-scale nonlinear processing,” IEEE Trans. Med. Imaging, vol. 17, no. 4, pp. 532–540, Aug. 1998.

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

[9] A. Pizurica,W. Philips, I. Lemahieu, and M. Acheroy, “A versatilewavelet domain noise filtration technique formedical imaging,” IEEE Trans.Med. Imaging, vol. 22, no. 3, pp. 323–331, Mar. 2003.

[10] S. Gupta, R. C. Chauhan, and S. C. Saxena, “Locally adaptive wavelet domain Bayesian processor for denoising medical ultrasound images using speckle modelling based on Rayleigh distribution,” IEE Proc. Vision, Signal Image Process., vol. 152, pp. 129–135, 2005.

[11] M. I. H. Bhuiyan, M. O. Ahmad, and M. N. S. Swamy, “Wavelet-based despeckling of medical ultrasound images with the symmetric normal inverse Gaussian Prior,” in Proc. ICASSP, Apr. 2007, vol. 1, pp. 721–724.

[12] D. L. Donoho and I. M. Johnstone, “Ideal spatial adaptation by wavelet shrinkage,” Biometrika, vol. 81, no. 3, pp. 425–455, 1994.

[13] D. L. Donoho and I.M. Johnstone, “Adapting to unknown smoothness via wavelet shrinkage,” J. Amer. Stat. Assoc., vol. 90, no. 432, pp. 1200–1224, 1995.

[14] D. L. Donoho, “De-noising by soft-thresholding,” IEEE Trans. Inform. Theory, vol. 41, no. 3, pp. 613–627, May 1995.

[15] M. S. Crouse, R. D. Nowak, and R.G. Baraniuk,“Wavelet-based statistical signal processing using hidden Markov models,” IEEE Trans. Signal Process., vol. 46, no. 4, pp. 886–902, Apr. 1998.

[16] S. G. Chang, B. Yu, and M. Vetterli, “Adaptive wavelet thresholding for image denoising and compression,” IEEE Trans. Image Process., vol. 9, no. 9, pp. 1532–1546, Sep. 2000.

[17] J. Portilla, V. Strela, M. J. Wainwright, and E. P. Simoncelli, “Image denoising using gaussian scale mixtures in the wavelet domain,” IEEE Trans. Image Process., vol. 12, no. 11, pp. 1338–1351, Nov. 2003.

[18] M. K. Mihcak, I. Kozintsev, K. Ramchandran, and P. Moulin, “Lows complexity image denoising based on statistical modeling of wavelet coefficients,” IEEE Signal Process. Lett., vol. 6, no. 12, pp. 300–303, Dec. 1999.

[19] L. Sendur and I. W. Selesnick, “Bivariate shrinkage with local variance estimation,” IEEE Signal Process. Lett., vol. 9, no. 12, pp. 438–441, Dec. 2002.

[20] H. Rabbani, S. Gazor, andM. Vafadoost, “Sparse domain image denoising employing local mixture models,” submitted for publication.

[21] S. Foucher, G. B. Benie, and J. M. Boucher, “Unsupervised multiscale speckle filtering,” Proc. IEEE Internat. Conf. on Image Proc ICIP96, pp. 391–394, Lausanne, Switzerland, 1996.

[22] T.-C. Hsung, D.P.-K. Lun, and W.-C. Siu, “Denoising by singularity detection,” IEEE Trans. Signal Proc., vol. 47, pp. 3139– 3144, 1999.

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

[24] 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.

[25] Raghuveer M. Rao and Ajit. S. Bopardikar. (1998). Wavelet Transforms: Introduction to theory and applications”. Addison Wesley Longman Inc, pp 151-166.

[26] S. Grace Chang, “adaptive Wavelet Thresholding for Image denoising and compression,” IEEE transactions on Image processing, Vol.9, No.9 september.2000.

[27]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

[28] Chang, S. G., Yu, B., and Vetterli, M. (2000). Adaptive wavelet thresholding for image denoising and compression. IEEE Trans. On Image Proc., 9, 1532–1546.

[29] 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.

[30] 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.