Reduction of Speckle noise from Medical Images using Principal Component Analysis Image Fusion

Indrajeet Kumar[1] H.S Bhadauria[2], PhD Jitendra virmani[3], PhD Jyoti Rawat[4]

[1,4]*Research Scholar, GB Pant Engineering College, Uttrakhand, India*

[1]*erindrajeet@gmail.com*, [4]*jyotirawat19@outlook.com*

[2] *Assistant professor, GB Pant Engineering College, Uttrakhand, India. E-mail: hsb76iitr@gmail.com*

[3]*Assistant Professor, Jaypee University of Information Technology, Waknaghat, Solan, India. E-mail: jitendra.virmani@gmail.com*

Abstract- **Images captured by different medical devices contain intrinsic artefacts, like ultrasound, CT, MRI images often contain speckle noise, which is the result of the destructive and constructive coherent summation of echoes. In these images, the speckle noise must be reduced cautiously as it also contains diagnostic information. Thus the despeckling algorithms should reduce speckle in homogeneous areas of the image and edges in the image should be preserved. In this paper a method to reduce the speckle noise is proposed which uses the concept of fusion. The performance of the proposed algorithm is quantified by calculating measures like MSE, SNR, PSNR and MSSI, which gives information about the extent of feature preservation and denoising.**

***Keywords*: Ultrasound, Medical images, Despeckling, PCA, Image fusion.**

I. INTRODUCTION

With the advancement of technology, the images obtained by the medical imaging modalities these days are high quality images and these images are increasingly being used by medical fraternity for diagnosis. Out of all the imaging modalities the use of ultrasound (US) imaging modality is gaining importance because of its non-invasive, no-ionizing and real time imaging capabilities [1-6]. However, the ultrasound images are often degraded by speckle which also contains diagnostic information. Therefore despeckling in these images must be carried out in a way, such that edges are preserved and speckle is removed from the homogeneous areas of the image.

There has been a significant interest amongst the research community to develop robust despeckling algorithms capable of edge preservation, feature preservation and removal of speckle from the homogeneous areas. There are many existing techniques for reducing speckle noise like lee filter [7], frost filter, median filter, Butterworth filter, Baye's algorithm wavelet's filtering techniques, Kaun [8] filter, anisotropic diffusion, Butterworth filter and adaptive weighted median filter etc. In the present work, a method of despeckling based on image fusion using PCA is proposed. In fusion techniques multiple images of similar type are combined to produce a resultant image which is combination of all the input images. Some well-known image fusion methods are principal component analysis (PCA) based fusion, Intensity-hue-saturation (IHS) transform based fusion, ratio enhancement technique, high-pass filtering method, discrete wavelet transform (DWT), stationary wavelet transform (SWT), dual tree discrete wavelet transform, Lifting wavelet transform, Multi-wavelet transform, Biologically inspired information fusion [9-11].

The diagnostic quality of the ultrasound images is often affected by the presence of inherent multiplicative noise known as speckle noise [12]. Images having speckle noise display a granular pattern and the waves reflected from the resulting rough texture create an interference which causes the noise in registered image. In low contrast images it limits the detection of region of interests. The following model is considered to express with speckle noise:

$$f(x,y) = g(x,y).\eta_m(x,y) + \eta_a(x,y) \tag{1}$$

here *f(x,y)* is noisy image, g*(x,y)* noise free image, $\eta_a(x,y)$ and $\eta_m(x,y)$ are additive and multiplicative noise. Since, additive noise is lower than multiplicative noise ignoring the additive noise, the image with the speckle noise is expressed as:

$$f(x,y) = g(x,y).\eta_m(x,y) \tag{2}$$

The rest of the paper is organized as: section II presents a brief summary of the literature survey, in section III, proposed methodology is presented, in section IV the results are discussed and finally conclusion is drawn in section V.

II. LITERATURE SURVEY

In last few years, much research has been focused on the filtering methods applied directly to the original image, i.e. post formation filtering methods. Under this class, many adaptive and fixed filters, such as L2-mean filter [13], nonlinear diffusion [14], adaptive weighted median filter (AWMF)[15], adaptive filter reduction (ASR) [12,16,18], and MAP [20] etc are developed.

The study in [20] proposed a filtering technique to select a region using an estimated homogeneity value for growing the region. In their algorithm the edge pixels are processed using a non-linear median filter and same intensity valued pixels (i.e., homogeneous regions are processed with mean filter. The study reported in [21], proposed an improved method of conventional distance-weighted interpolation, which uses the square of the inverse distance as the intensity for each pixel. The technique as further modified and reported in [22], and was used for volume reconstruction of 3D freehand ultrasound. The work reported in [23] proposes a diffusion stick for suppression of speckle noises in US images. Kernel in asymmetric stick filter is calculated by decomposition of the neighbourhood into line segments of variable orientations, and then average of weighted sum is helpful in generating the filtered images.

The related study in [18] reports the analysis of different kind of wavelet filter based de-noising methods according to various threshold values applied to US images. Related work on wavelet domain thresholding techniques is also given [24,22], Marche et al. A soft-threshold denoising method based on signal decomposition in wavelet domain is presented by Donoho, in [25]. The study in [26] used image quality metrics like peak signal-to-noise (PSNR) and normalized mean square error (NMSE) as performance measures for despeckling in US images.

Speckle noise degrades the already limited resolution of US images i.e. the edge details and fine details are suppressed by speckle and therefore it becomes difficult to detect small and low contrast lesions in patients. Thus edge and feature preserving denoising is must for US images. However, the developing a denoising method which can reduce the noise without losing significant features, information and edges is challenging issue faced by the research community. Accordingly there has been a significant attempt to propose various despeckling methods based on Wiener filtering [26]. Median filtering [27], temporal averaging [12], wavelet thresholding [28] and adaptive speckle reduction [15]. Among these filters few are based on local statistics of the image, in these filters speckle noise is reduced but small information is lost [29].

The performance of the despeckling algorithms can be measured by image quality parameters as discussed in [16], [30], [31].

III. PROPOSED METHOD

The steps of the proposed method are summarized in flow chart as shown in Fig 1. The first step is image loading and then pre-processing the input image by histogram equalization, as it does the necessary contrast adjustment transformation which transforms the areas of lower contrast to gain a higher contrast.

Speckle noise being multiplicative in nature, contains some information's itself, so it is feasible to convert it to an additive one by using logarithmic transformation. If neglecting the additive Gaussian's noise, then we have:

$$f(x, y) = \eta_s f_0(x, y) \tag{3}$$

here: $f(x,y)$ is noisy image $f_0(x, y)$: noiseless original image, η_s : Multiplicative noise.

Now applying log transformation then we get

$$g(x, y) = \log(f(x, y)) = \log(\eta_s f_0(x, y))$$
$$g(x, y) = \log(f(x, y)) = \log(\eta_s) + \log(f_0(x, y) \tag{4}$$

The Proposed work follows the following steps:

1) Load the US image and convert it to the gray scale notation
2) Image pre-processing
3) log transformation
4) Applying the different filter
5) Image fusion

In the first step load the input image of different abdominal after that loaded image would be converted to gray scale format if required for the further processing.

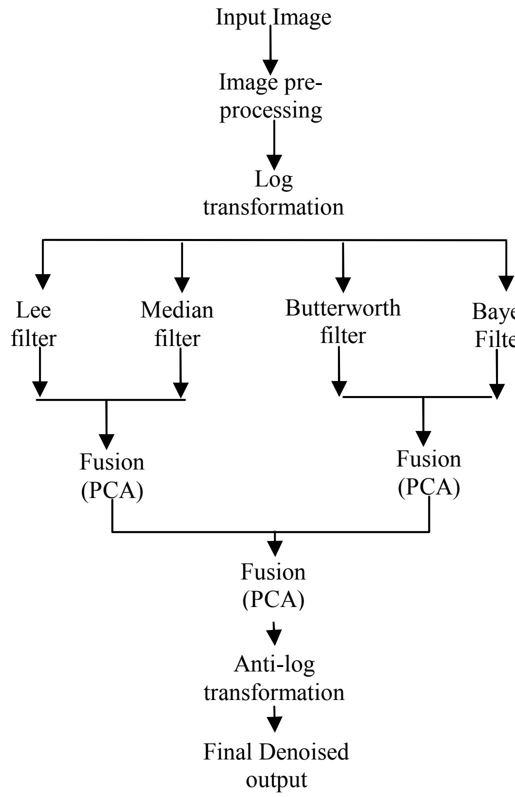

Fig. 1 Proposed model

The next step is image pre-processing, in this step enhancing the contrast level of image because the input image has low contrast. After that the enhanced contrast image is passing through the log transform co convert multiplicative noise to additive noise. After this step we have the additive noise image like Gaussian noise so we can easily apply the different filter for de-noising the image. When images are de-noised by different filtering techniques are fused by the principle component analysis algorithm then applying anti-log operation to reconvert the image into original form.

After the fusion of images we are calculating the some parameter like MSE, PSNR, MSSI, and SNR for assurance the image quality.

A. *Signal to Noise ratio (SNR)*: The signal to noise ratio is often used for the characterization of signals. A higher value of SNR indicates that the fused image is good in quality and has more information than individual denoised images. Mathematically expressed as:

$$SNR\ in\ dB = 10 \times \log_{10} \frac{\sigma_f^2}{\sigma_n^2} \tag{5}$$

Where σ_f^2 *and* σ_n^2 are the values of variance in the image and noise respectively.

B. *Mean square error (MSE)*: The lesser the value of MSE between the original image and restored image better the result. If it is larger, than the filter is not smoothing or reducing noise from the image, and also mathematically expressed as

$$MSE = \frac{1}{M \times N} \sum (g(x,y) - f(x,y))^2 \tag{6}$$

C. *Structure similarity index measure (SSIM) [32]:* The *MSSI* is used for measuring the structural similarity by comparing the local patterns of pixel intensities, normalized for contrast and luminance. The *MSSI* is expressed in a multiplication of the three terms.

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma} \tag{7}$$

Where

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1},$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2},$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

Here: μ_x, μ_y, σ_x,σ_y, and σ_{xy} are the local means, standard deviations, and cross-covariance for images *x, y*. Also, $\alpha = \beta = \gamma = 1$ and $C_3 = C_2/2$.

D. *Peak signal to noise ratio (PSNR):* The *PSNR* is the ratio between the maximum possible power of a signal to the power of corrupting noise It is calculated by

$$PSNR = 10\log_{10}\left(\frac{256 \times 256}{MSE}\right) \tag{8}$$

Image Fusion using PCA (Principal Component Analysis)

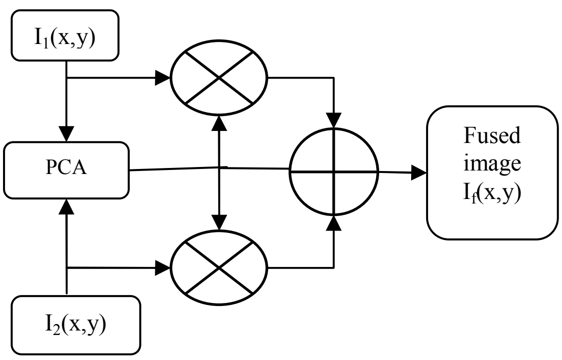

Fig. 2 Illustration of Image fusion using PCA

The Step wise explanation of the algorithm (Fig. 2)

1) Source images and data are organized as two-column vector and column vector, respectively. Let S : resulting column vector of dimension 2xN
2) Compute the empirical mean along each column of S. The empirical mean vector M_e has a dimension 1x2. Then, Subtract M_e from each column of S. The resulting matrix X has the dimension of 2 x N. Then, find the covariance matrix C of matrix X. mean expectation will be equal to the covariance of X.
3) Compute Eigen vectors and Eigen values and sort them in the decreasing order.
4) To compute normalized component P_1 and P_2, taking 1st column of Eigen vector with largest Eigen value. P1 and P2 are calculated by using

$$P_1 = \frac{V(1)}{\sum (V)} \quad \text{and} \quad P_2 = \frac{V(2)}{\sum V}$$

Where V is eigen vector with respect to largest value.

The I_1(x, y) and I_2(x, y) i.e. the input images are arranged as two column vectors and their means are subtracted. The resulting vector has N x2 dimension, here N is length of the each image vector. The fused image for input images I_1(x, y) and I_2(x, y) is given by the formula below:

$$I_f(x,y) = P_1 I_1(x,y) + P_2 I_2(x,y) \tag{9}$$

Finally conserving the quality of images and preserving the information calculating some deciding parameters like MSE, SNR, MSSI and PSNR.

IV. IMPLEMENTATION & RESULT ANALYSIS

This section discusses the implementation and performance of the proposed algorithm "Reduction of Speckle noise from medical Images using PCA image fusion" all the implementation and performance evolution done in MATLAB@2013. The proposed algorithm implemented on US, CT, and MRI images. All medical images are taken from the GOURDIX database for US images, for CT UCLA S.M.O.C and MRI from Toronto TRI hospital MRI centre.

As mention earlier, the process involves few image pre-processing steps like converting an image in to gray scale, unit conversion. After that logarithmic transformation is applied for behaviour of speckle noise conversion multiplicative to additive by nature. On converted image applying some existing filtering techniques and output of the each filters works as a input image for PCA for fusion of images. Finally we get the fused image with better quality for visualizing the defects. For performance measurements of the algorithm we are calculating the some parameter like MSE, SNR, PSNR and the most important for medical images is structure preserving features known as structure similarity index. Details of each case are provided below in the table and pictorial form.

US Images: US is very important medical imaging modalities to suspected liver disease. It is the simply best tool in the evaluation of FLL with respect to other modality, due to dynamic nature, high resolution, real time and safety. It is invaluable in the diagnosis of jaundice, liver cirrhosis complications, and in any form of US guided intervention.

Input image and patient details are given below:

Patient ID: 2001302

Patient Sex: F

Patient Weight (kg): 43.112000

Study Date: 8-January-2001

Study ID: 5801, Study Modality: US

TABLE. 1 US Image Details after Result

Operation	MSE	SNR (db)	SSIM (%)	PSNR (db)
Noisy image	0.020	3.893	96.93	16.827
Median filter	0.023	6.043	99.95	16.193
Butterworth	0.022	5.426	99.96	16.376
Bayes filter	0.021	5.995	99.96	16.733
Lee filter	0.020	6.161	99.96	16.846
Proposed algo	0.016	7.103	99.96	16.831

Input image

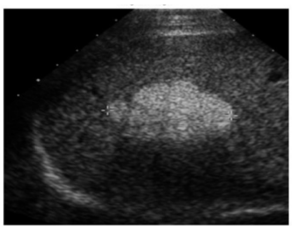

Fig. 3 Input image in gray scale

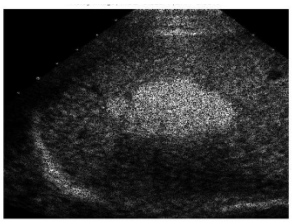

Fig. 4 Image after adding speckle noise

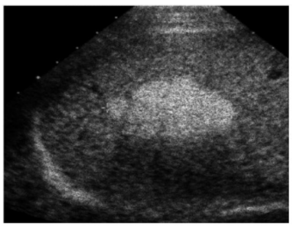

Fig. 5 Final resultant de-noised image

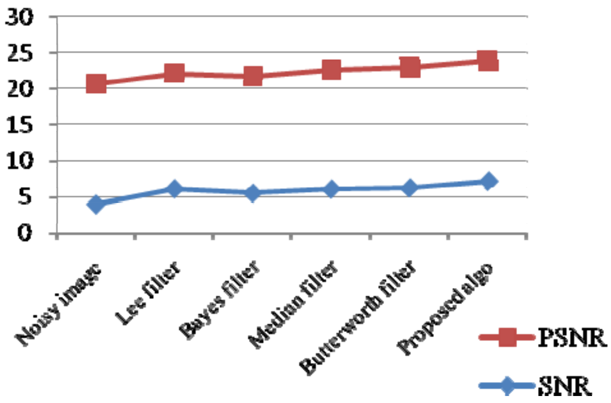

Fig. 6 Comparison between filters for US image.

MRI image: For radiologist to diagnosing the function of the human body and anatomy for two cases like in normal (healthy) and disease, there is a imaging technique known as Magnetic resonance imaging (MRI) which is mostly used in health centres for diagnosis, disease levelling and for follow-up without exposure to ionizing radiation, it is based on radio waves and strong magnetic fields for forming images of the body tissues.

Input image details:

Patient ID: 02, Patient Sex: M, Patient Weight: 33.112000,

Study Date: 8-January-2001

Study ID: 5801, Study Modality: MRI, Study Description:

BRAIN SELLA

TABLE. 2 MRI Image details after result

Operation	MSE	SNR (db)	SSIM (%)	PSNR (db)
Noisy image	0.0096	6.516	96.97	20.141
Lee filter	0.0116	7.286	99.97	19.681
Bayes filter	0.0126	7.018	99.97	19.321
Median filter	0.0125	7.591	99.97	19.367
Butterworth filter	0.011	7.305	99.97	19.802
Proposed algo	0.011	7.399	99.97	19.726

Input image

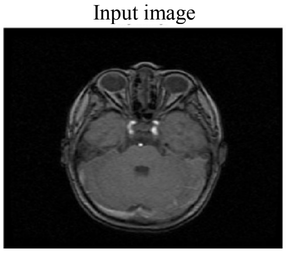

Fig. 7 Input image in gray scale

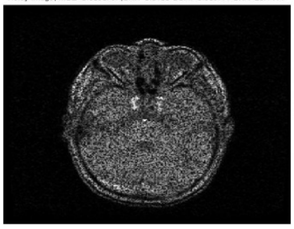

Fig. 8 Image after adding speckle noise

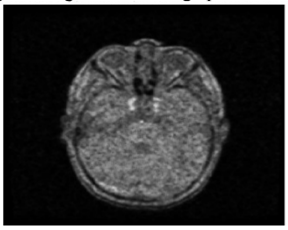

Fig. 9 Final resultant de-noised image

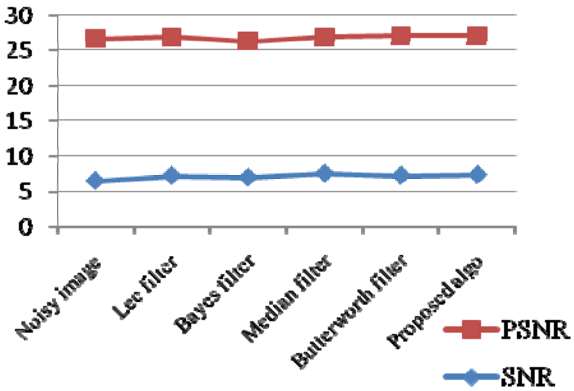

Fig. 10 Comparison between filters for MRI

CT imaging system: As we know that computed tomography (CT) imaging also known as Computerized Axial Tomography,
"CAT scanning" is able to provide a variable form of imaging known as cross-sectional imaging based on the different tissues ability of absorbing x-rays.

The Patient details given below:

Patient ID: 001, Patient Sex: M, Patient

Weight: 48.035, Study Date: 8-apr-2004

Study ID: 01, Study Modality: CT, Study Description:

SPECIALS CORONARY CT COMBI.

TABLE. 3: CT Image details after result

Operation	**MSE**	**SNR (db)**	**SSIM (%)**	**PSNR (db)**
Noisy image	0.029	8.279	96.96	15.229
Lee filter	0.023	9.019	99.95	16.546
Bayes filter	0.025	8.638	99.96	16.300
Median filter	0.027	10.265	99.97	15.933
Butterworth filter	0.027	7.820	99.98	15.890
Proposed algo	0.024	9.73.	99.99	16.467

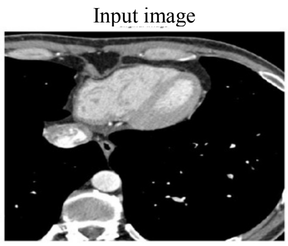

Fig. 11 Input image in gray scale

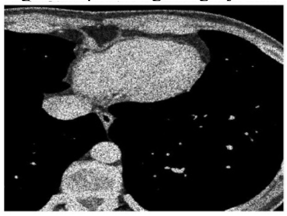

Fig. 12 Image after adding speckle noise

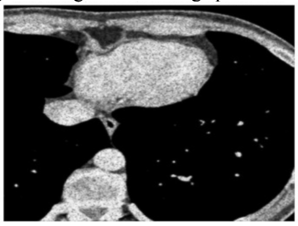

Fig. 13 Final resultant de-noised image.

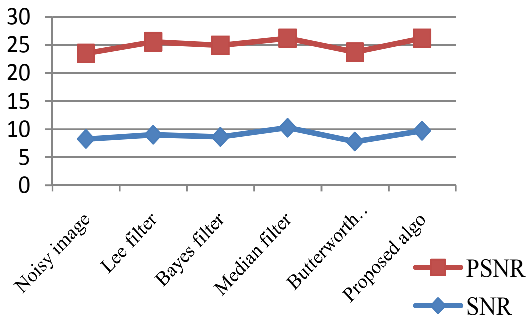

Fig. 14 Comparison between filters for CT image.

V. CONCLUSION

Speckle noise is multiplicative and inherited by the imaging devices. In this paper an algorithm for reducing the speckle noise is proposed. The performance of the proposed algorithm is compared with other filtering techniques. It is concluded that the proposed algorithm is capable of reducing noise without losing any diagnostic information.

REFERENCES

[1] Virmani, J., Kumar, V., Kalra, N. and Khandelwal, N., "SVM Based characterization of liver ultrasound images using wavelet packet texture descriptors", Journal of Digital Imaging, Vol. 26,No.3, pp.530-543, 2013, DOI: 10.1007/s10278-012-9537-8.

[2] Virmani, J., Kumar, V., Kalra, N. and Khandelwal, N., "Characterization of primary and secondary malignant liver lesions from B-mode ultrasound", Journal of Digital Imaging,

2013, Vol. 26, No.6, pp.1058-1070, 2013, DOI: 10.1007/s10278-013-9578-7.

[3] Virmani, J., Kumar, V., Kalra, N. and Khandelwal, N., “A comparative study of computer-aided classification systems for focal hepatic lesions from B-mode ultrasound”, Journal of Medical Engineering and Technology, Vol. 37, No. 4, pp. 292-306, 2013, DOI:10.3109/030919 02.2013.794869.

[4] Virmani, J., Kumar, V., Kalra, N. and Khandelwal, N., “Prediction of cirrhosis based on singular value decomposition of gray level co-occurence matrix and a neural network classifier”, In Proceedings of the IEEE International Conference on Development in E-Systems Engineering, DeSe-2011, Dubai, pp. 146-151, 2011, DOI:10.1109/DeSE.2011.56.

[5] Virmani, J., Kumar, V., Kalra, N. and Khandelwal, N., “Prediction of liver cirrhosis based on multiresolution texture descriptors from B-mode ultrasound”, International Journal of Convergence Computing, Vol. 1, No.1, pp. 19-37, 2013, DOI:0.1504/IJCONVC.2013. 054658.

[6] Virmani, J., Kumar, V., Kalra, N. and Khandelwal, N., ‘Neural network ensemble based CAD system for focal liver lesions using B-mode ultrasound’, Journal of Digital Imaging, Vol. 27 No. 4, pp. 520-537, 2014.

[7] Lee J.S : Digital image enhancement and noise filtering by using local statistics, IEEE Trans. Pattern Anal. Machine Intelligence 1980.

[8] Kaun. D.T, Sowchauk T., Strand C., Chavel P.: Adaptive noise smoothing filters for signal dependent Noise”, IEEE Transaction on pattern analysis and machine intelligence, 1985, Vol 7, pp 165-177 .

[9] http://staff.utia.cas.cz/sroubekf/papers/EUSIPCO_ 07_fusion _ tut.pdf.

[10] Sroubek F. and Flusser J., “Fusion of Blurred Images”, in Multi-Sensor Image Fusion and Its Applications, Blum R. and Liu Z. eds., CRC Press, Signal Processing and Communications Series, vol. 25, pp. 423-449, 2005.

[11] S.S.Bedi, Agarwal J., Agarwal P, “Image Fusion Techniques and Quality Assessment Parameters for Clinical Diagnosis: A Review”, International Journal of Advanced Research in Computer and Communication Engineering Vol. 2, Issue 2, February 2013, ISSN : 2278-1021, pp. 1153-1157.

[12] Bamber, J. C., & Daft, C. (1986). Adaptive filtering for reduction of speckle in ultrasonic pulse-echo images. Ultrasonics, 24(1), 41–44.

[13] Kotropoulos, C., & Pitas, I. (1992). Optimum non-linear signal detection and estimation in the presence of ultrasonic speckle. Ultrasonic Imaging, 14(3), 249–275.

[14] Abd-Elmoniem, K. Z. Youssef, A. B., & Kadah, Y. M. (2002). Real-time speckle reduction and coherence enhancement in ultrasound imaging via nonlinear anisotropic diffusion. IEEE Transactions on Biomedical Engineering, 49(9), 997–1014.

[15] Loupas, T., McDicken, W., & Allan, P. (1989). An adaptive weighted median filter for speckle suppression in medical ultrasound images. IEEE Transactions on Circuits and Systems, 36(1), 129–135.

[16] Chen, Y., Broschat, S., & Flynn, P. (1996). Phase insensitive homomorphic image processing for speckle reduction. Ultrasonic Imaging, 18(2), 122–139.

[17] Thakur, A., & Anand, R. S. (2005). Image quality based comparative evaluation of wavelet filters in ultrasound speckle reduction. Digital Signal Processing, 15(5), 455–465.

[18] Thakur, A., & Anand, R. S. (2005). Image quality based comparative evaluation of wavelet filters in ultrasound speckle reduction. Digital Signal Processing, 15(5), 455–465.

[19] Sanches, J. M., & Marques, J. S. (2003).A MAP estimation algorithm with Gibbs prior using an IIR filter. Energy Minimization Methods in Computer Vision and Pattern Recognition, Lecture Notes in Computer Science, 2683, 436–449.

[20] Chen, Y., Yin, R., Flynn, P., & Broschat, S. (2003). Aggressive region growing for speckle reduction in ultrasound images. Pattern Recognition Letters, 24(4-5), 677–691.

[21] Huang, Q. H., Zheng, Y. P., Lu, M. H., & Chi, Z. R. (2005).Development of a portable 3D ultrasound imaging system for musculo skeletal tissues. Ultrasonics, 43(3), 153–163.

[22] Huang, Q. H., & Zheng, Y. P. (2006). An adaptive squared-distance-weighted interpolation for volume reconstruction in 3D freehand ultrasound. In Proceedings of Ultrasonics International (UI’05) and World Congress on Ultrasonics (WCU).Ultrasonics, 44(Supplement 1), e73–e77.

[23] Chen, G. Y., Bui, T. D., & Krzyz` (2005). Image denoising with neighbour dependency and customized wavelet and threshold. Pattern Recognition, 38(1), 115–124.

[24] Hao, X., Gao, S., & Gao, X. (1999). A novel multiscale nonlinear thresholding method for ultrasonic speckle reduction. IEEE Transactions on Medical Imaging, 18(9), 787–794.

[25] Donoho, D. L. (1995). De-noising by soft-thesholding. IEEE Transactions on Information Theory, 41(3), 613–627.

[26] Garg. A, Goal J., Malik S., Choudhary K., Deepika: Despeckling of Medical Ultrasound Images using Wiener Filter and Wavelet Transform” IJECT, 2011.

[27] Sudha S., Suresh G.R, Sukanesh R: Speckle Noise Reduction in Ultrasound Images by Wavelet Thresholding based on Weighted Variance “International Journal of Computer Theory and Engineering, 2009, Vol 1,pp 1793-8201.

[28] Taya P.C., Acton S. T., Hossack J. A.: A wavelet thresholding method to reduce ultrasound artifacts” Computerized Medical Imaging and Graphics 35, 42–50 (2011).

[29] F. Benzarti, H. Amiri, "Speckle Noise Reduction in Medical Ultrasound Images" IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 2, No 3, March 2012,ISSN:1694-0814. pp. 187-194 .

[30] Adam, D., Beilin-Nissan, S., Friedman, Z., & Behar, V. (2006). The combined effect of spatial compounding and nonlinear filtering on the speckle reduction in ultrasound images. Ultrasonics, 44(2), 166–181.

[31] Tolba, T. S. (2002). Wavelet packet compression of medical images. Digital Signal Processing, 12(4), 441–470.

[32] http://www.mathworks.com/help/images/ image-quality metrics.html.