

SPECKLE NOISE FILTERING FOR ULTRASOUND IMAGES OF COMMON CAROTID ARTERY: A REVIEW

D. Sasikala¹ and M. Madheswaran²

¹Department of Electronics and Communication Engineering, Vivekanandha College of Engineering for Women, India
E-mail: sasivas@rediffmail.com

²Mahendra Engineering College, India
E-mail: madheswaran.dr@gmail.com

Abstract

Speckle is modeled as a signal dependent noise, which tends to reduce the image resolution and contrast, thereby reducing the diagnostic values of the ultrasound imaging modality. Reduction of speckle noise is one of the most important processes to increase the quality of biomedical images. Filters are used to improve the quality of ultrasound images by removing the noise. This paper compares the performance of the thresholding technique Bayes Shrink in despeckling the medical ultrasound images with other classical speckle reduction filters like Lee, Frost, Median, Kaun, Wavelet Bayes, Anisotropic diffusion and Wavelet. The performance of these filters is analyzed by the statistical measures such as Peak Signal-to-Noise Ratio, Mean Square Error and Equivalent Number of Looks. To produce a better quality resolution picture, the filter should have high Peak Signal to Noise Ratio, low Mean Square Error, high Equivalent Number of Looks. The results obtained are presented in the form of filtered images, statistical tables and graphs. Finally, the best filter has been recommended based on the statistical and experimental results. From the results obtained Lee and Frost filter outperforms the other mentioned filters in terms of high PSNR and low MSE for high variance of noise where as anisotropic diffusion filter outperforms with high PSNR and low MSE with maximum ENL for low variance values of noise.

Keywords:

Speckle Noise, Image Denoising, Wavelet Thresholding, Filters

1. INTRODUCTION

In medical field for the diagnosis of diseases, the ultrasound B-Scan images play an important role. These images are obtained with a simple linear or sector scan ultrasound probe, which show a granular appearance called speckle. The biomedical images obtained by ultrasound (US) systems are significantly poorer compared to other medical imaging systems [1]. But, US images are considered to be non-invasive, portable, accurate, practically harmless to the human beings, and relatively low-cost imaging modality. These features make the ultrasound B-Scan imaging be the most common medical diagnostic tool in hospitals around the world. The medical imaging devices namely X-ray, CT/MRI and ultrasound are producing abundant images which are used by medical practitioners in the process of diagnosis. The main problem faced by them is the noise introduced due to the consequence of the coherent nature of the wave transmitted. (i.e., different phases of reflected signals). These noises corrupt the image and often lead to incorrect diagnosis. Each of these medical imaging devices is affected by different types of noise. For example, the x-ray images are often corrupted by Poisson noise, while the ultrasound images are affected by speckle noise. Speckle is a complex phenomenon, which degrades image quality with a

backscattered wave appearance which originates from many microscopic diffused reflections that pass through internal organs and makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations. Thus, denoising or reducing these speckle noise from a noisy image has become the predominant step in medical image processing. In recent years there has been a fair amount of research on wavelet thresholding and threshold selection for signal and image denoising [2],[3],[12] because wavelet provides an appropriate basis for separating noisy signal from image signal. Two threshold operators used during denoising are soft thresholding and hard thresholding. Soft thresholding is more frequently used because it reduces the abrupt sharp changes and provides an image whose quality is not affected. Statistical filters like Frost filter, Kuan filter, Lee Filter and wavelet filters are chosen for this study due to their efficient speckle reduction property [7],[9],[11]. In addition, a combination of wavelet filter with soft thresholding techniques have been attempted which exhibits better results than the standard filters.

2. SPECKLE NOISE MODELLING

The mathematical expression for a signal [10] observed at point p whose coordinates (x, y) in the image is as follows:

$$O(x, y) = \sum \sum e(x, y)h(x - x_i, y - y_i) \quad (1)$$

where, $e(x, y)$ is signal received by the sensor, h is the impulse response of the acquisition system. The intensity $I(x, y)$ at this point can be stated in a multiplicative form as:

$$I(x, y) = |O(x, y)|^2 = e(x, y)^2 \times u(x, y) \quad (2)$$

where, $u(x, y)$ is noise independent from the useful signal. The model used for the ultrasound image is:

$$g(x, y) = f(x, y) \times u(x, y) \quad (3)$$

where, g is the observed intensity of the image and f is the free noise intensity. Within homogenous regions this model offers a good approximation. To address the multiplicative nature of speckle noise, Jain [10] developed a homomorphic approach. An appropriate method for speckle reduction is one which enhances the signal to noise ratio while preserving the edges and lines in the image. So the multiplicative noise model is transformed into additive noise model by taking logarithms.

$$\log(g) = \log(f \times u) = \log(f) + \log(u) \quad (4)$$

Also the additive model is transformed into the multiplicative one by taking the exponentiation. By considering the additive model of a noise as,

$$g = f + u \quad (5)$$

The exponentiation of Eq.(5) is given by,

$$e^g = e^{f+u} = e^f \cdot e^u \quad (6)$$

The presence of multiplicative speckle noise in carotid ultrasound images tends to reduce the image resolution and contrast thereby degrading the image quality. There are many methods based on different thresholding techniques available for speckle noise reduction. The goal of an image denoising algorithm is to recover the clean image from its noisy version by removing noise and retaining as much as possible the image information.

3. MATERIALS AND METHODS

The cross sectional images of carotid artery recorded with an ATL (Advanced Technology Laboratory) Ultramark 4 Duplex scanner and a high resolution 7.5 MHz linear scan head were used for the analysis. The images were standardized manually by adjusting the image so that the median gray level value of the blood and adventitia (artery wall) were 0 and 190 respectively. This standardization of blood and adventitia as reference points becomes necessary to extract the comparable measurements in case of processing images obtained by different operators or different equipment [14]. In this paper the comparison is carried out between the Bayes shrink thresholding technique with the standard filters viz. Kaun filter, Lee filter, Frost filter, median filter, anisotropic diffusion filter, wavelet filter and wavelet Bayes filter.

3.1 WAVELET BASED SPECKLE REDUCTION

Wavelets are an oscillating function of time or space and are suitable for the analysis of transient signals. In wavelet analysis the signal to be analyzed is multiplied with a wavelet function and then the transform is computed for each segment generated. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content [4],[5],[6],[8]. As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides a non redundant and unique representation of the signal. During the first level of decomposition of an image using a scalar wavelet, the two-dimensional data is replaced with four blocks. The wavelet transform performs the first 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; that results in four types of coefficients, HH, HL, LH and LL. The LL sub-band is the result of low-pass filtering both the rows and columns and it contains a rough description of the image as such shown in Fig.1.

Hence, the LL sub-band is also called the approximation sub-band. The HH sub-band is high-pass filtered coefficients in both directions and contains the high frequency components along the diagonals as well. The HL and LH images are the result of low-pass filtering in one direction and high-pass filtering in another direction. LH contains mostly the vertical detail information that corresponds to horizontal edges and HL represents the horizontal detail information from the vertical edges. All three sub-bands HL, LH and HH are called the detail sub bands because they add the high-frequency detail to the approximation image.

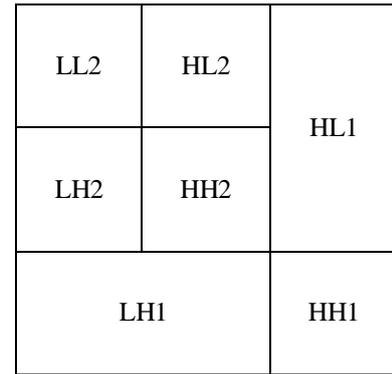


Fig.1. Two-Level Image decomposition by using DWT

3.2 BAYES SHRINK METHOD

Bayes shrink method of denoising uses soft thresholding that is sub-band dependent. This means that thresholding is done at each band of resolution in the wavelet decomposition [3],[11],[13]. Like the Sure Shrink procedure, it is smoothness adaptive. The Bayes threshold t_B is defined as,

$$t_B = \sigma^2 / \sigma_s^2 \quad (7)$$

where, σ^2 is the noise variance and σ_s^2 is the signal variance without noise. The noise variance σ^2 is estimated from the sub band HH1 by the median estimator. From the definition of additive noise, $w(x, y) = s(x, y) + n(x, y)$ the noise and the signal are independent of each other. It can be stated that,

$$\sigma_w^2 = \sigma_s^2 + \sigma^2 \quad (8)$$

σ_w^2 can be computed using the equation

$$\sigma_w^2 = \frac{1}{n^2} \sum_{x,y=1}^n w^2(x, y) \quad (9)$$

The variance of the signal σ_s^2 can be computed using the equation

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma^2, 0)} \quad (10)$$

With σ^2 and σ_s^2 , the Bayes threshold is computed from Eq.(7).

3.3 ANISOTROPIC DIFFUSION FILTER

Anisotropic diffusion is a nonlinear smoothing filter which uses a variable conductance term that controls the contrast of the edges that in turn influence the diffusion [1]. This filter has the ability to preserve edges, while smoothing the rest of the image to reduce noise. The anisotropic diffusion has been used by several researchers in image restoration and image recovery. In anisotropic diffusion the main motto is to encourage smoothing within the region in preference to the smoothing across the edges. This is achieved by setting the conduction coefficient as 1 within the region and as 0 near edges, however the main problem involved in this is the detection of the presence and absence of edges. As a solution for this problem it is identified that conduction coefficient if chosen locally as a function of magnitude of the gradient of the brightness function

of the image the edges can be determined. A general expression for anisotropic diffusion can be written as,

$$I(x, o) = I_0 \tag{11}$$

$$\frac{\partial I}{\partial t} = \text{div}(F) + \beta(I_0 - I) \tag{12}$$

where, I is the input image, I_0 is the initial image, F is the diffusion flux and β is a data attachment coefficient. If $\beta = 0$, particular cases of equation are: The heat diffusion equation $F = \tilde{N}I$ which is equivalent to Gaussian convolution. The non linear probability density function (PDF) with $F = c(|\nabla I|)$. ∇I where, ∇ is the gradient operator, div is the divergence operator, $\|\cdot\|$ denotes the magnitude diffusion coefficient $c(x)$ given by,

$$c(x) = \frac{1}{1 + \left(\frac{x}{k^2}\right)} \tag{13}$$

$$c(x) = \exp\left[-\left(\frac{x}{k^2}\right)\right] \tag{14}$$

3.4 LEE FILTER

The Lee filter is based on the assumption that the mean and variance of the pixel of the interest is equal to the local mean and variance of all pixels within the moving kernel. The formula for the Lee filter for speckle noise reduction is given as,

$$\hat{R}(t) = I(t)W(t) + \bar{I}(t)(1 - W(t)) \tag{15}$$

where, $W(t) = 1 - \frac{c_u^2}{c_1^2(t)}$ is the weighted function and $c_u = \frac{\sigma_u}{u}$; $c_1(t) = \sigma^2(t)/I(t)$ are the various coefficients of the speckle $u(t)$ and the image $I(t)$ respectively.

3.5 KUAN FILTER

In this filter, the multiplicative noise model is first transformed into signal-dependent additive noise model. Then the MMSE criterion was applied to this model. The resulting filter has the same form as the Lee filter but with the different weighting function which is given as,

$$W(t) = \frac{1 - \frac{c_u^2}{c_i^2}}{1 + c_u^2} \tag{16}$$

The Lee and Kaun filters have the same formation although the signal model assumptions and the derivations are different. Essentially both the Lee and Kaun filters form an output image by computing a linear combination of the center pixel intensity in a filter window with the average intensity of the window. So the filter achieves a balance between straightforward averaging in homogeneous regions and the identity filter where edges and point features exist. This balance depends on the coefficient of variation inside the moving window.

3.6 FROST FILTER

The Frost filter also strikes a balance between averaging and the all-pass filter. In this case, the balance is achieved by forming an exponentially shaped filter kernel that can vary from a basic

average filter to an identity filter on a point wise adaptive basis. Also the response of the filter varies locally with the coefficient of variation. In case of low coefficient of variation, the filter is more average-like and in cases of high coefficient of variation, the filter attempts to preserve sharp features by not averaging.

3.7 MEDIAN FILTER

Median filtering is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges [1],[10]. Median filtering is similar to using an averaging filter in that each output pixel is set to an average of the pixel values in the neighborhood of the corresponding input pixel. However, with median filtering, the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values called outliers. Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The US medical image speckle reduction algorithm has been implemented in the MATLAB environment. The US carotid artery image with plaque is used for the analysis. The above mentioned filters have been applied on the ultrasound images of common carotid artery of size 256×256 , tested for different variance values of $\sigma^2 = 0.02, 0.06, 0.1, 0.4, 0.8$ and 1 and the results of the filters were shown in Fig.2. The results are analyzed both qualitatively and quantitatively. For qualitative analysis three parameters used are PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error) and ENL (Efficient Number of Looks).

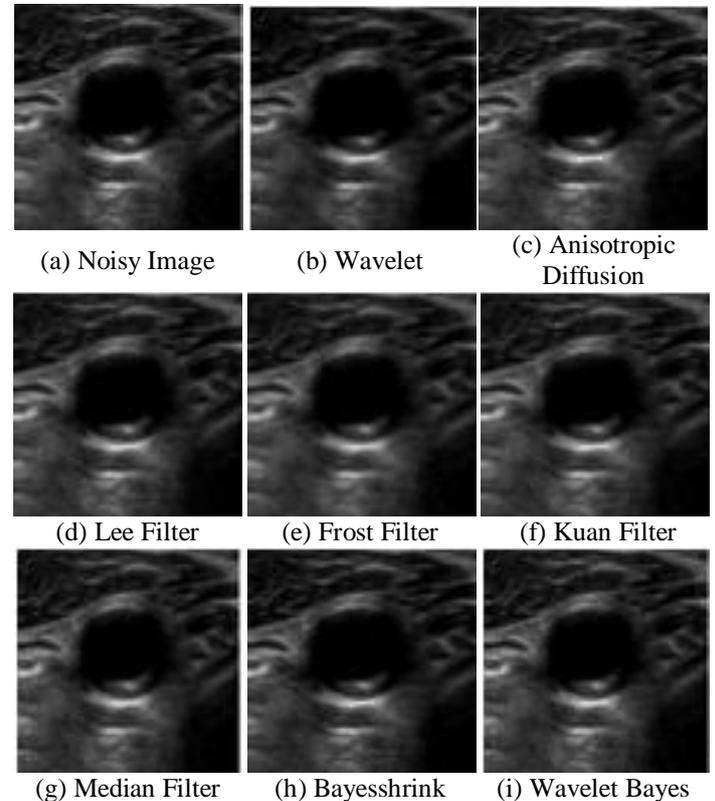


Fig.2. Filtered images of carotid artery for various filters

The parameters are calculated for all the resultant images of the above mentioned filters with their noisy and denoised counterparts, respectively. MSE is an estimator in many ways to quantify the amount by which a filtered/noisy image differs from noiseless image. It is calculated as,

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N [X(i, j) - Y(i, j)]^2 \quad (17)$$

where, X and Y are the original (the noisy) and denoised image respectively. M and N represent the width and height of image. PSNR stands for the peak signal to noise ratio. It is an engineering term used to calculate the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. It is calculated using,

$$PSNR = 10 \log_{10} \frac{255 \times 255}{MSE} \quad (18)$$

ENL is the square of the ratio of Mean of the image to the standard deviation of the image.

$$ENL = \left(\frac{\text{Mean of the image}}{\text{Standard deviation of the image}} \right)^2 \quad (19)$$

Higher the ENL, the performance of the filter is good. Table.1 shows the variation of PSNR for various noise variances.

Table.1. PSNR values for the carotid artery image

FILTERS	VARIANCE					
	0.02	0.06	0.1	0.4	0.8	1.0
Wavelet	25.73	25.33	25.13	21.29	19.61	19.39
Anisotropic diffusion	30.56	25.88	23.71	17.90	15.70	15.16
Lee	29.81	28.84	28.10	25.02	23.22	22.94
Frost	27.80	27.55	27.27	25.76	24.21	23.95
Kuan	29.81	28.84	28.10	25.02	23.22	22.94
Median	24.64	24.04	23.59	21.00	18.99	18.52
Bayeshrink	29.64	25.60	23.55	17.92	15.75	15.22
Wavelet Bayes	30.55	25.87	23.70	17.91	15.76	15.23

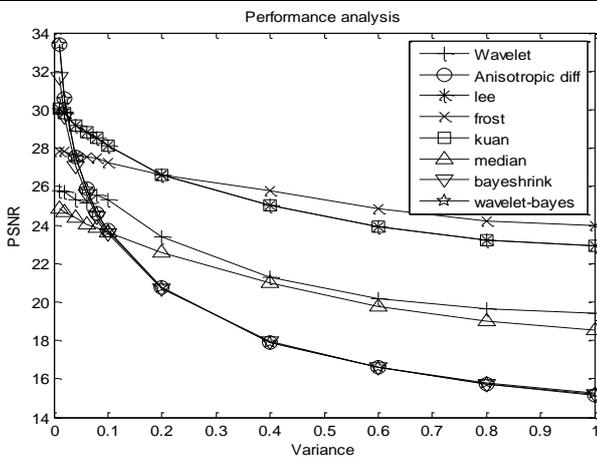


Fig.3. Plot of PSNR values vs variance for the carotid artery image

It is observed that the PSNR of the Lee, Frost and Kuan filters is maintained high over the range of higher values of noise variance in the image and is shown in Fig.3.

Table.2. MSE values for the carotid artery image

FILTERS	VARIANCE					
	0.02	0.06	0.1	0.4	0.8	1.0
Wavelet	192	210	221	534	786	827
Anisotropic diffusion	63	186	306	1166	1936	2193
Lee	75	94	111	226	342	365
Frost	119	126	134	191	273	289
Kuan	75	94	111	226	342	365
Median	246	283	314	572	907	1010
Bayeshrink	78	198	318	1161	1912	2164
Wavelet Bayes	63	186	307	1163	1910	2156

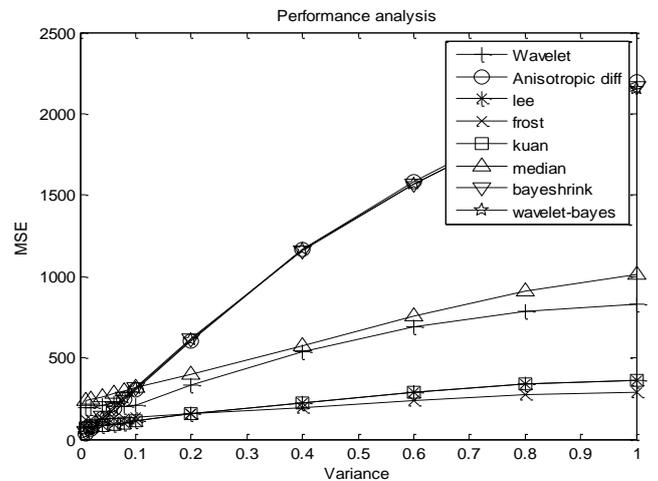


Fig.4. Plot of MSE values vs variance for the carotid artery image

The variation of MSE and ENL for the filters is given in Table.2 and Table.3. The Fig.4 and Fig.5 shows that the MSE for Lee and Frost filters are at the minimum and the ENL for these filters are obtained at the maximum and consistent with noise variation compared to the other filters.

Table.3. ENL values for the carotid artery image

FILTERS	VARIANCE					
	0.02	0.06	0.1	0.4	0.8	1.0
Wavelet	1.273	1.252	1.222	1.012	0.938	0.923
Anisotropic diffusion	1.484	1.384	1.308	0.863	0.699	0.658
Lee	1.704	1.689	1.705	1.640	1.647	1.602
Frost	1.824	1.813	1.836	1.797	1.814	1.760
Kuan	1.704	1.689	1.705	1.640	1.647	1.602
Median	1.713	1.648	1.614	1.329	1.139	1.018
Bayeshrink	1.302	1.229	1.172	0.811	0.675	0.640
Wavelet Bayes	1	1.358	1.276	0.828	0.673	0.634

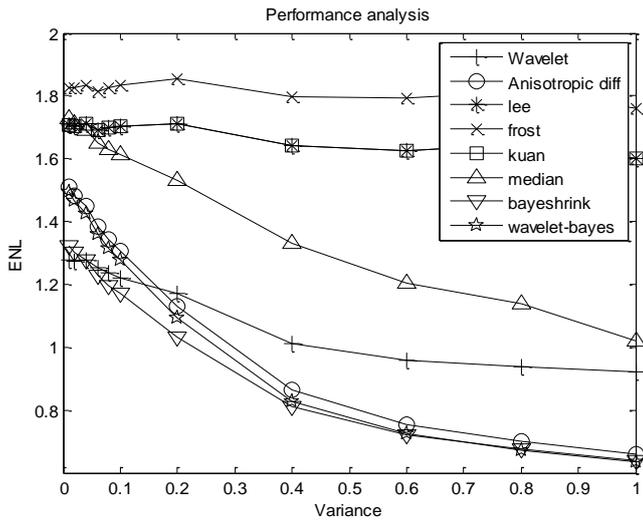


Fig.5. Plot of ENL values vs variance for the carotid artery image

For low values of variance of noise, performance of anisotropic diffusion is good with high PSNR and less MSE, but greater the variance value Frost filters outperform all other filter in terms of having high PSNR and ENL values.

5. CONCLUSION

The presence of random speckle noises caused by the interference of reflected ultrasound wave makes computer aided diagnosis of carotid artery images and interpretation a difficult task. Thus speckle noise reduction is very much important for improving suitable conditions of post processing the images. Images are filtered by using various filters like Wavelet, Lee, Kuan, Frost, Median, Bayes Shrink, Wavelet Bayes and their results are formulated in terms of statistical parameters like PSNR, MSE and ENL. From the results obtained it is concluded that for lower values of variance of noise, performance of anisotropic diffusion is good with high PSNR and less MSE but as the noise variance increases, Lee and Frost filters outperform all other filters in terms of having high PSNR. Hence under low variance values anisotropic diffusion filter outperforms with high PSNR and low MSE with maximum ENL.

REFERENCES

- [1] O. V. Michailovich and A. Tannenbaum, "Despeckling of Medical Ultrasound Images", *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control* Vol. 53, No. 1, pp. 64-78, 2006.
- [2] R. Sivakumar and D. Nedumaran, "Comparative study of Speckle Noise Reduction of Ultrasound B-scan Images in Matrix Laboratory Environment", *International Journal of Computer Applications*, Vol. 10, No. 9, pp. 46-50, 2010.
- [3] K. Karthikeyan and C. Chandrasekar, "Speckle Noise Reduction of Medical Ultrasound Images using Bayesshrink Wavelet Threshold", *International Journal of Computer Applications*, Vol. 22, No. 9, pp. 8-14, 2011.
- [4] Grace. S. Chang, Bin Yu and M. Vattereli, "Adaptive Wavelet Thresholding for Image de-noising and Compression", *IEEE Transaction on Image Processing*, Vol. 9, No. 9, pp. 1522-1530, 2000.
- [5] C.S. Burrus, R.A. Gopinath and H. Guo, "Introduction to Wavelets and Wavelet Transform", Prentice-Hall, Englewood Cliffs, 1997.
- [6] David L. Donoho and Iain M. Johnstone, "Ideal Spatial Adaptation via Wavelet Shrinkage", *Biometrika*, Vol. 81, No. 3, pp. 425-455, 1994.
- [7] S.C. Kang and S.H. Hong, "Experimental and Theoretical Analysis of Wavelet based denoising filter for Echocardiographic images", *Studies in Health Technology and Informatics*, Vol. 84, No. Part 2, pp. 906-909, 2001.
- [8] R. Maini and H. Aggarwal, "A Novel Technique for Speckle Noise Reduction on Medical Images", *International Journal of Applied Engineering Research*, Vol. 5, No. 1, pp. 1-8, 2010.
- [9] S. Sudha, G.R. Suresh and R. Sukanesh, "Speckle noise reduction in ultrasound images using context – based adaptive wavelet Thresholding", *IETE Journal of Research*, Vol. 55, No. 3, pp. 135, 2009.
- [10] Anil K. Jain, "Fundamentals of Digital Image Processing", Englewood Cliffs, Prentice-Hall, University of Michigan, 1989.
- [11] Manish Goyal and Gianetan Singh Sekhon, "Hybrid Threshold Technique for Speckle Noise Reduction using wavelets for Grey scale images", *International Journal of Computer Science and Technology*, Vol. 2, No. 2, pp. 620-625, 2011.
- [12] David L. Donoho, "De-Noising by Soft-Thresholding", *IEEE Transactions on Information Theory*, Vol. 41, No. 3, pp. 613- 627, 1995.
- [13] R. Sivakumar and D. Nedumaran, "Performance Study of Wavelet denoising techniques in Ultrasound images", *Journal of Instrument Society of India*, Vol. 39, No. 3, pp. 194-197, 2009.
- [14] T. Elatrozy, A. Nicolaidis, T. Tegos, A. Zarka, M. Griffin and M. Sabetai, "The effect of B-mode ultrasonic image standardisation on the echogenicity of symptomatic and asymptomatic carotid bifurcation plaques", *International Angiology*, Vol. 17, No. 3, pp. 179-186, 1998.