Image Denoising Based on Wavelet Techniques Using Thresholding for Medical Images

Rupinderpal Kaur[#1], Rajneet Kaur[*2]
[#]Research Fellow,CSE Department, SGGSW University,Fatehgarh Sahib, Punjab, India
[*]Asst. Professor, CSE Department, SGGSW University, Fatehgarh Sahib, Punjab, India.

***Abstract* —** In medical image processing, image denoising has become a very essential exercise all through the diagnose. Arbitration between the perpetuation of useful diagnostic information and noise suppression must be treasured in medical images. In general we rely on the intervention of a proficient to control the quality of processed images. In certain cases, for instance in MRI images, the noise can restrain information which is valuable for the general practitioner. Consequently medical images are very inconsistent, and it is crucial to operate case to case. The objective of image denoising is to reduce the noise while retaining the fine details of an image. This paper presents a Wavelet -based scheme for noise detection & removal in MRI images. The motivation to use wavelet as a possible alternative is to explore new ways to reduce computational complexity and to achieve better noise reduction performance. The entire set of wavelet share some common properties but each wavelet has certain unique properties of image decomposition, denoising and reconstruction which provides difference in PSNR and MSE. In this paper, Quantitative and qualitative comparisons of the results obtained by the daubechies wavelet transform and mallat wavelet transform for the salt & pepper noise and Gaussian noise. It shows that mallat transform using soft thresholding demonstrate its higher performance for salt and paper reduction & Gaussian noise reduction.

***Keywords*— Medical Images, Denoising, Wavelet, Salt & Pepper noise, Gaussian Noise.**

I. INTRODUCTION

It is well known to any scientist and engineer who work with a real world data that signals do not exist without noise, which may be negligible (i.e. high PSNR) under certain conditions. However, there are many cases in which the noise corrupts the signals or images in a significant manner, and it must be removed from the data in order to proceed with further data analysis. The process of noise removal is generally referred to as denoising. Noise is any undesired information that contaminates an image. Generally the term Image Denoising is usually devoted to the recovery of a digital image that has been corrupted by Gaussian noise and Salt & Pepper noise, rather than other types of noise (e.g. Speckle noise, Poisson noise/ Laplace noise, etc.). This paper will concentrate on the case of Gaussian noise and Salt & Pepper noise. The Salt and Pepper type noise is typically caused by malfunctioning of the pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. For the images corrupted by Salt and Pepper noise, the noisy pixels can take only the maximum or the minimum values in the dynamic range. Where as in the Gaussian noise, every value of each pixel changes from its original value.

MRI images are typically corrupted with noise since its acquisition or transmission, which hinder the medical diagnosis based on these images. The noise in the image has two disadvantages, the first being the degradation of the image quality and the second, more important, obscures important information required for accurate diagnosis. The great challenge of image denoising is how to preserve the edges and all fine details of an image when reducing the noise. Denoising is often a necessary and the first step to be taken before the images data is analyzed. Several denoising methods Spatial filtering, Anisotropic diffusion, Contoulet transform, Curvelet transform and wavelet transform have been implemented. But image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. It is necessary to apply an efficient denoising technique to compensate for such data corruption.This paper presents the wavelet techniques for noise reduction. One is daubechies wavelet transform and other is fast wavelet transform.

II. DENOISING USING WAVELET

Wavelet gaining popularity in the area of biomedical image denoising due to its sparsity and multiresolution properties. The important property of wavelet analysis is perfect reconstruction,which is the process of reassembling a decomposed image into its original form without loss of information. To achieve a high PSNR, it is necessary to choose the best wavelet filter bank and decomposition level, which will play a crucial role in denoising the images.

A. The Discrete Wavelet Transform

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. What if we choose only a subset of scales and positions at which to make our calculations? It turns out, rather remarkably, that if we choose scales and positions based on powers of two — so-called dyadic scales and positions — then our analysis will be much more efficient and just as accurate. We obtain such an analysis from the discrete wavelet transform (DWT). An efficient way to implement this scheme using filters was developed in 1988 by Mallat

.The Mallat algorithm is in fact a classical scheme known in the signal processing community as a two-channel subband coder .This very practical filtering algorithm yields a fast wavelet transform — a box into which a signal passes, and out of which wavelet coefficients quickly emerge.

B. Daubechies Wavelet Transform

The Daubechies wavelet transforms are defined in the same way as the Haar wavelet transform by computing the running averages and differences via scalar products with scaling signals and wavelets the only difference between them consists in how these scaling signals and wavelets are defined[26]. This wavelet type has balanced frequency responses but non-linear phase responses. Daubechies wavelets use overlapping windows, so the high frequency coefficient spectrum reflects all high frequency changes. Therefore Daubechies wavelets are useful in compression and noise removal of audio signal processing .

C. Fast wavelet transform

Mallat's algorithm [Ma68] is a computationally efficient method of implementing the wavelet transform. It calculates DWT wavelet coefficients for a finite set of input data, which is a power of 2. This input data is passed through two convolution functions, each of which creates an output stream that is half the length of the original input. This procedure is referred to as down sampling [Wi92]. The convolution functions are filters. One half of the output is produced by the low pass filter function and the other half is produced by the high pass filter function. The low pass outputs contain most of the information of the input signal and are known as "coarse" coefficients. The outputs from the high pass filter are known as "detail" coefficients. The coefficients obtained from the low pass filter are used as the original signal for the next set of coefficients. This procedure is carried out recursively until a trivial number of low pass filter coefficients are left. The final output contains the remaining low pass filter outputs and the accumulated high pass filter outputs. This procedure is termed as decomposition.
In certain applications, some form of processing is done to the wavelet coefficients obtained after the DWT. Once the processing is done, the data vector is built back from the coefficients. This processes of reconstruction is referred to as the inverse Mallat's algorithm.

In the reconstruction procedure, quadrature mirror filters Equation are supplied with the coarse coefficients and the accumulated detail coefficients. The so obtained outputs of the two filters are summed and are treated as the coarse coefficients for the next stage of reconstruction. This procedure is continued until the data vector is obtained.

III. Proposed Scheme For Denoising

The effectiveness of traditional linear filtering techniques is limited since this leads to blurred results in high frequencies. Contourlet transform provides high PSNR values and can remove the Gaussian noise from medical images very effectively, but it does not effectively remove the Salt and Pepper noise from medical images. Daubechies wavelet transform are excellent tools for denoising. Bayes shrinkage is also a good technique for denoising. Whereas anisotropic technique can be time consuming. Fast wavelet transform has an advantage that it deals with low memory requirement and reduced execution time.

A. Proposed Model

The proposed modal focuses on following objectives which are helpful to remove noise using wavelets from the image & also increases image quality.

1. Understanding of denoising methods.
2. Understanding of wavelets.
3. Implementation of Daubechies wavelet transform on Medical Images.
4. Implementation of Mallat wavelet transform Medical Images.
5. Removal of Salt and pepper noise and Gaussian noise and Calculation of MSE (Mean Square Error) and PSNR (peak to signal noise ratio) of both Daubechies and Mallat using soft thresholding and hard thresholding.
6. Performance Comparison of MSE and PSNR on Medical image for mallat and daubechies.

The algorithm used in this paper is summarized below and it consists of the following steps:

B. Algorithm : Image Denoising using Wavelet
Input: Medical MRI image.
Output: Denoised image
Start

- Input Medical MRI image.
- Add noise to the medical image.
- Apply Wavelet transform to the image.
- Perform thresholding of wavelet transformed image.
- By performing the inverse wavelet transform on the thresholded image, the denoised image is obtained (output image).
- Compute the performance parameters, namely, MSE and PSNR for the denoised image.
  Stop.

In this proposed work, Wavelet based denoising is done using medical images to improve the quality of image. Then we add Salt & pepper noise and Gaussian noise then apply Daubechies wavelet transform & mallat wavelet transform to remove noise. It results as noise free image with high quality & provides better results which are helpful in the medical field to detect the symptoms of any disease.

C) Daubechies Wavelet Transform

Daubechies wavelet is the first wavelet family which has set of scaling function which are orthogonal. This wavelet has finite vanishing moments. Daubechies wavelets have balanced frequency responses but non-linear phase responses. Daubechies wavelets are useful in noise removal of image processing because of its property of overlapping windows and high frequency coefficient spectrum reflect all high frequency changes.

D) Fast Wavelet Transform

In 1988, Mallat produced a fast wavelet decomposition and reconstruction algorithm [Mal89]. The Mallat algorithm for discrete wavelet transform (DWT) is, in fact, a classical scheme in the signal processing community, known as a two-channel subband coder using conjugate quadrature filters or quadrature mirror filters (QMF's).

- The decomposition algorithm starts with signal s, next calculates the coordinates of *A1* and *D1*, and then those of *A2* and *D2*, and so on.
- The reconstruction algorithm called the inverse discrete wavelet transform (IDWT) starts from the coordinates of *AJ* and *DJ* , next calculates the coordinates of *AJ-1*, and then using the coordinates of *AJ-1* and *DJ-1*

  Calculates those of *AJ-2* , and so on. In order to understand the multiresolution analysis concept based on Mallat's algorithm it is very useful to represent the wavelet transform as a pyramid as shown in figure. The basis of the pyramid is the original image, with C columns and R rows.

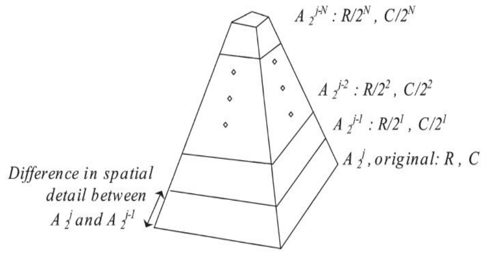
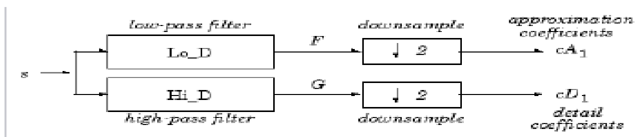


Fig 1 : Pyramidal representation of Mallat's wavelet decomposition algorithm.

Given a signal s of length N, the DWT consists of $\log_2 N$ stages at most. Starting from *s*, the first step produces two sets of coefficients: approximation coefficients cA_1, and detail coefficients cD_1. These vectors are obtained by convolving s with the low-pass filter Lo_D for approximation, and with the high-pass filter Hi_D for detail, followed by dyadic decimation.



The length of each filter is equal to $2n$. If N = length (s), the signals F and G are of length $N + 2n - 1$, and then the coefficients $cA1$ and $cD1$ are of length

$$\text{floor}\left(\frac{(N-1)}{2} + n\right)$$

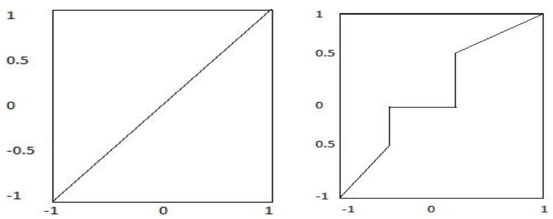
The next step splits the approximation coefficients $cA1$ in two parts using the same scheme, replacing s by cA1 and producing cA2 and cD2, and so on.

Classically , the DWT is defined for sequences with length of some power of 2, and different ways of extending samples of other sizes are needed. Methods for extending the signal include zero-padding, smooth padding, periodic extension, and boundary valuereplication (symmetrisation). The basic algorithm for the DWT is not limited to dyadic length and is based on a simple scheme: convolution and downsampling [13]. As usual, when a convolution is performed on finite-length signals, border distortions arise. To Remove these border effects, Fast Wavelet Transform was introduced. This algorithm is a method for the extension of a given finite-length signal [12].

E) Thresholding Techniques

Threshold plays an important role in the denoising process. Here the main focus is on to find an optimum threshold value. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image details. There are mainly two types of thresholding techniques that are used for denoising:

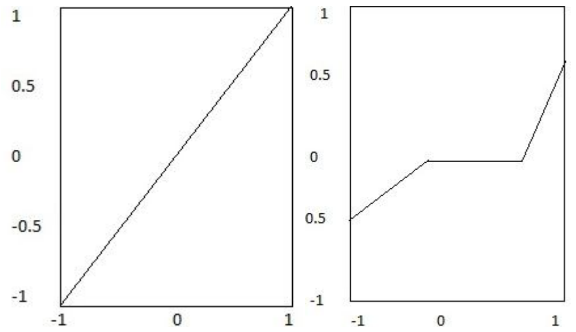
1)Hard Thresholding: Hard threshold is a "kill or keep" procedure and is more intuitively appealing. Hard thresholding may seem to be natural. Sometimes pure noise coeffiecients may pass the hard threshold and this thresholding method is mainly used in medical image processing.



Original signal Hard thresholded signal

Fig 2 : Original and Hard thresholded signal

2)Soft Thresholding: Soft threshold shrinks coefficients above the threshold in absolute value. The false structure in hard thresholding can be overcome by soft thresholding. Now a days, wavelet based denoising methods have received a greater attention. Important features are characterized by large wavelet coefficient across scales in most of the timer scales.



Original Signal Soft thresholded signal

Fig 3: Original and Soft thresholded signal

IV. PERFORMANCE EVALUATION DENOISING TECHNIQUE

To get the measure of the wavelet filter performance, the experimental results are evaluated according to two error criteria namely, the mean square error (MSE), the peak signal to noise ratio (PSNR). These two parameter decides that which wavelet & thresholding technique gives best result.

A) Peak Signal-to-Noise Ratio (PSNR)

PSNR values can be calculated by comparing two images one is original image and other is distorted image. The PSNR has been calculated using the following formula:

$$PSNR = 10 \log_{10} \left(\frac{S^2}{MSE}\right)$$

Where S is the maximum intensity in the original image. For the better-transformed image, the PSNR is higher and lower for poorly transformed image. It measures how closely the transformed image resembles the original image.

Noise	Db using HT	Db using ST	Mallat using HT	Mallat using ST
0.01	70.9206	72.9183	74.2653	76.3773
0.02	67.917	69.9078	72.0326	75.4101
0.03	66.1492	68.1214	72.3325	74.682

B) Mean Square Error (MSE)

It is defined as to compute an error signal by subtracting the test signal from the reference, and then computing the average energy of the error signal.

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - y(i,j))^2$$

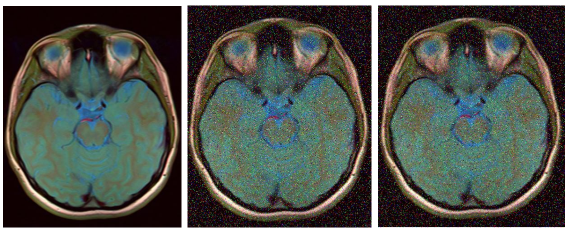
Where x(i, j) represents the original image and y(i, j) represents the denoised image and i and j are the pixel position of the M×N image. MSE is zero when x(i, j) = y(i, j).

V. RESULTS

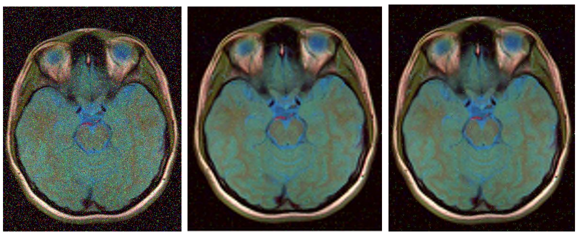
For our test experiments we have considered salt & pepper noise and Gaussian noise which have been used to corrupt our real MR test image objects. Artificially adding noise to an image allows us to test and assess the performance of various wavelet functions.

A. Algorithm Implementation:

We used MATLAB to implement the denoising algorithm. MATLAB has a wavelet toolbox and functions which are very convenient to do the DWT and FWT. A usual way to de noise is to find a processed image such that it minimizes mean square error MSE and increases the value of the PSNR.



(a) (b) (c)



(d) (e) (f)

Fig 4: (a) Original Image, (b) Image with Salt & pepper noise, (c) denoising using db soft thresholding, (d) using db hard thresholding, (e) using FWT soft thresholding, (f) using FWT hard thresholding.

TABLE I

Comparison Table of PSNR at different Noise levels

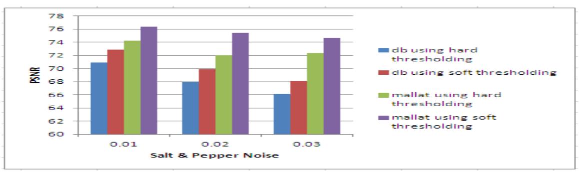
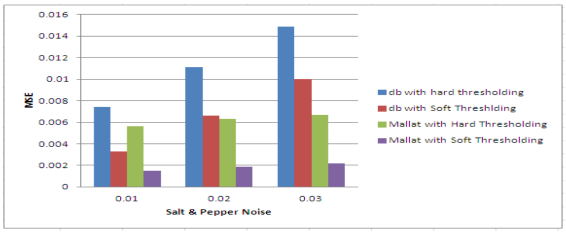


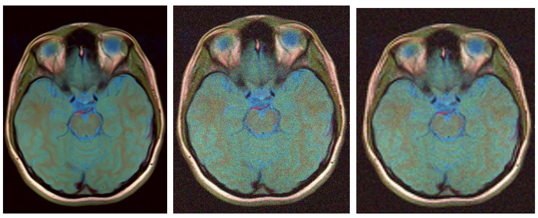
Fig 5:Comparison Graph of PSNR at different noise levels

TABLE II

Comparison Table of MSE at different Noise levels

Noise	Db using HT	Db using ST	Mallat using HT	Mallat using ST
0.01	0.0074	0.0033	0.0056	0.0015
0.02	0.0111	0.0066	0.0063	0.0019
0.03	0.0149	0.0100	0.0067	0.0022

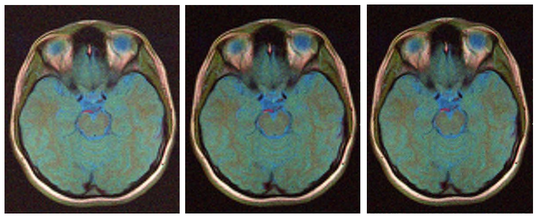




(a) (b) (c)

Noise	Db using HT	Db using ST	Mallat using HT	Mallat using ST
0.01	0.0054	0.0023	0.0054	0.0021
0.02	0.0059	0.0027	0.0058	0.0026
0.03	0.0064	0.0033	0.0063	0.0031

Fig 6:Comparison Graph of MSE at different noise levels



(d) (e) (f)

Fig 7: (a) Original Image, (b) Image with Gaussian noise, (c) denoising using db soft thresholding, (d) using db hard thresholding, (e) using FWT soft thresholding, (f) using FWT hard thresholding.

TABLE III

Comparison Table of PSNR at different Noise levels

Noise	Db using HT	Db using ST	Mallat using HT	Mallat using ST
0.01	74.2229	74.4422	74.8082	74.9448
0.02	73.2984	73.7463	73.9847	74.0587
0.03	72.2757	72.9192	72.9485	73.2295

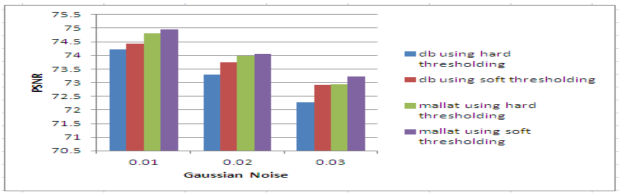


Fig 8:Comparison Chart of PSNR at different noise levels

TABLE IV

Comparison Table of MSE at different Noise levels

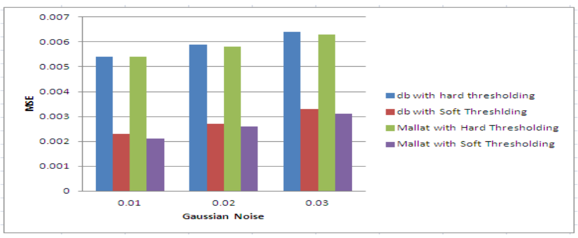


Fig 9:Comparison Chart of MSE at different noise levels

TABLE V

Comparison Table of PSNR for Salt & Pepper Noise

MRI Images	Salt & Pepper Noise	Db using hard thresholding	Db using soft thresholding	Mallat using hard thresholding	Mallat using soft thresholding
1.	0.01	70.5335	72.4513	72.8587	74.7532
	0.02	67.6472	69.5732	71.8779	74.0343
	0.03	65.9145	67.9561	71.152	73.3879
2. Mri2	0.01	71.2009	73.4604	74.5398	78.3768
	0.02	68.2902	70.7177	73.2808	77.2240
	0.03	66.5734	68.9867	72.4238	76.2389
3. Brain	0.01	70.8999	72.9017	74.3480	76.3820
	0.02	67.8926	69.8817	72.9797	75.3952
	0.03	66.2614	68.2356	72.3257	74.7102
4.legs/feet	0.01	70.1833	71.6833	72.7527	75.5326
	0.02	67.2064	68.7064	72.1061	74.6045
	0.03	65.3470	66.8470	70.8679	73.7475
5. Spine	0.01	70.0471	71.5471	72.7512	75.7439
	0.02	66.9929	68.4929	72.0239	74.7258
	0.03	65.2777	66.7777	70.9040	73.9305
6. ULimb	0.01	70.0300	71.5300	72.6837	75.7256
	0.02	67.1452	68.6452	72.0964	74.7742
	0.03	65.3783	66.8783	70.8904	73.9533
7. lungs	0.01	70.9965	72.9787	73.7142	75.5638
	0.02	68.0560	70.0389	72.7566	74.8113
	0.03	66.2709	68.2421	72.0464	74.1595
8. liver	0.01	71.5792	73.0792	75.8032	82.1634
	0.02	68.4865	69.9865	74.1295	80.1702
	0.03	66.7299	68.7753	73.1104	78.7005

TABLE VI

Comparison Table of PSNR for Gaussian Noise

MRI Images	Gaussian Noise	Db using hard thresholding	Db using soft thresholding	Mallat using hard thresholding	Mallat using soft thresholding
1.Mri1	0.01	72.3913	72.9746	73.0532	73.5245
	0.02	71.8294	72.5158	72.4957	73.0219
	0.03	71.1082	71.9211	718066	72.4112
2. Mri2	0.01	74.6910	75.9349	74.5840	76.5093
	0.02	73.8688	75.1529	73.8103	75.6186
	0.03	72.8565	74.2023	72.9242	74.5645
3. Brain	0.01	74.2244	74.4545	74.9036	74.7916
	0.02	73.2945	73.7359	73.9939	74.0742
	0.03	72.2729	72.9069	72.9514	73.2099
4.legs/feet	0.01	72.4913	73.2232	72.9349	73.5314

	0.02	71.7179	72.5587	72.2233	72.8809
	0.03	70.8762	71.8167	71.4214	72.1315
5. Spine	0.01	72.5714	73.3425	72.9797	73.6148
	0.02	71.7515	72.6150	72.2005	72.8994
	0.03	70.8969	71.8631	71.3974	72.1483
6. ULimb	0.01	72.5221	73.3156	72.9784	73.6391
	0.02	71.6925	72.6067	72.2036	72.9308
	0.03	70.8821	71.8799	71.4212	72.1948
7. lungs	0.01	73.8988	74.1811	74.7238	74.5747
	0.02	73.0884	73.5677	73.8722	73.9321
	0.03	72.1394	72.7952	72.8871	73.1172
8. liver	0.01	76.6579	78.1607	74.9801	78.1059
	0.02	75.3397	76.8403	74.1310	76.8022
	0.03	73.9256	75.4253	73.1298	75.3972

VI. CONCLUSION & FUTURE SCOPE

In this paper, denoising of medical MRI images is performed using daubechies and fast wavelet transform at both soft and hard threshold levels and PSNR and MSE are calculated for both techniques. From the results, it has been concluded that image denoising using fast wavelet transform shows better results as compared to daubechies wavelet transform with lesser processing time. It enhances the visual quality of the medical images by achieving high PSNR value and minimum MSE. One of the key advantage of fast wavelet transform is that it reduces both memory requirements and complexity. It also increases the flexibility. The above calculations are being performed on medical MRI images to remove salt & pepper and gaussian noise of the images, future plan is to make this valuable for other medical images like Xrays, ultrasound images and for different noise like speckle noise.

REFERENCES

[1] Bhausaheb Shinde, Dnyandeo Mhaske, Machindra Patare, A.R. Dani," Apply Different Filtering Techniques To Remove The Speckle Noise Using Medical Images", *International Journal Of Engineering Research And Applications (IJERA)* ISSN: 2248-9622, Vol. 2, Issue 1,Jan-Feb 2012.

[2] Ashraf Aboshosha, M. Hassan, M. Ashour, M. El Mashade," Image Denoising based on Spatial Filters,an Analytical Study".

[3] Ms. Alka Vishwa,Ms. Shilpa Sharma,"Speckle Noise Reduction In Ultrasound Images By Wavelet Thresholding",*International Journal Of Advanced Research In Computer Science And Software Engineering*, ISSN: 2277 128x,Volume 2, Issue 2, February 2012.

[4] Jappreet Kaur, Manpreet Kaur, Poonamdeep Kaur, Manpreet Kaur,"Comparative Analysis of Image Denoising Techniques",*International Journal of Emerging Technology and Advanced Engineering*,ISSN 2250-2459, Volume 2, Issue 6, June 2012 .

[5] Dikendra Verma , Sanjay Mathur," Image Denoising Based On Averaging Of Two Wavelet Transformed Images", *International Journal of Engineering Research and Applications (IJERA)* ISSN: 2248-9622, Vol. 2, Issue 5, September- October 2012, pp.2112-2119.

[6] K.karthikeyan, and Dr. C. Chandrasekar,"Speckle Noise Reduction of Medical Ultrasound Images using Bayesshrink Wavelet Threshold," *International journal of computer applications*(0975-8887),vol. 22-No.9,May 2011.

[7]P.S. Hiremath, Prema T. Akkasaligar, Sharan Badiger," Performance Comparison of Wavelet Transform and Contourlet Transform based methods for Despeckling Medical Ultrasound Images", *International Journal of Computer Applications (0975 – 8887)*, Volume 26– No.9, July 2011.

[8]Amandeep Kaur, Karamjeet Singh,"Speckle Noise Reduction By Using Wavelets", *NCCI 2010 -National Conference On Computational Instrumentation*, Csio Chandigarh, India, 19-20 March 2010.

[9]P.S. Hiremath, Prema T. Akkasaligar, and Sharan Badiger," Speckle Reducing Contourlet Transform for Medical Ultrasound Images", *International Journal of Computer and Information Engineering* 4:4 2010.

[10]Er. Neha Goyal, Er. Monika Aggarwal," Implementation of Image Compression using fast Wavelet Transform using HAAR and Daubechies Wavelets", *IOSR Journal of Engineering (IOSRJEN)* e-ISSN: 2250-3021, p-ISSN: 2278-8719, Volume 2, Issue 11 (November2012).

[11]Mahesh S. Chavan, Nikos Mastorakis,"Studies on Implementation of Harr and daubechies Wavelet for Denoising of Speech Signal" ,*International Journal Of Circuits, Systems And Signal Processing*.

[12]Mohamed I. Mahmoud, Moawad I. M. Dessouky, Salah Deyab, And Fatma H. Elfouly," Comparison Between Haar And Daubechies Wavelet Transformions On Fpga Technology", *Proceedings Of World Academy Of Science, Engineering And Technology* ,Volume 20 April 2007 Issn 1307-6884.

[13]Ami Vibhakar,Mukesh Tiwari,Jaikaran Singh,"Performance Analysis for MRI Denoising using Intensity Averaging Gaussian Blur Concept and its Comparison with Wavelet Transform Method", *International Journal of Computer Applications (0975 – 8887)*, Volume 58– No.15, November 2012.

[14] Bhausaheb Shinde, Dnyandeo Mhaske,A.R. Dani," Study of Noise Detection and Noise Removal Techniques in Medical Images", I.J. Image, Graphics and Signal Processing, 2012, 2, 51-60 Published Online March 2012 in MECS,DOI: 10.5815/ijigsp.2012.02.08.

[15]Mariana Carmen Nicolae, Luminiţa Moraru, Laura Onose," Comparative Approach For Speckle Reduction In Medical Ultrasound Images".

[16]S.Sudha,G.R.Suresh,R.Sukanesh," Wavelet Based Image Denoising using Adaptive Thresholding", *International*

Conference on Computational Intelligence and Multimedia Applications 2007.

[17] R. Sivakumar, and D. Nedumaran," Performance study of Wavelet denoising techniques in Ultrasound images", Jl. of Instrum. Soc. of India Vol.39 No.3 September 2009.

[18]Vikas D Patil, Sachin D Ruikar, "Wavelet-based Image Enhancement using Nonlinear Anisotropic Diffusion," *International Journal Of Advanced Research In Computer Science And Software Engineering*, vol.2, issue 3, March 2012.

[19]Jose Oliver and Manuel Perez Malumbres," On The Design Of Fast Wavelet Transform Algorithms With Low Memory Requirements", *IEEE Transactions On Circuits And Systems For Video Technology*, Vol. 18, No. 2, February 2008.

[20]Namrata Dewangan, Agam Das Goswami," Image Denoising Using Wavelet Thresholding Methods", *International Journal Of Engineering Sciences & Management*, ISSN: 2277-5528, April-June, 2012.

[21]Yogesh Bahendwar, Dr.G.R.Sinha," A Modified Algorithm For Denoising Mri Images Of Lungs Using Discrete Wavelet Transform", *National Conference on Innovative Paradigms in Engineering & Technology (NCIPET-2012)* Proceedings published by International Journal of Computer Applications® (IJCA).

[22]Shashikant Agrawal, Yogesh Bahendwar," Denoising of MRI Images Using Thresholding Techniques through Wavelet", *International Journal of Computer Applications in Engineering Sciences,* ISSN: 2231-4946, Vol I, Issue III, September 2011.

[23]Sabine Dippel, Martin Stahl, Rafael Wiemker, and Thomas Blaffert," Multiscale Contrast Enhancement for Radiographies: Laplacian Pyramid Versus Fast Wavelet Transform", *IEEE Transactions On Medical Imaging*, Vol. 21, No. 4, April 2002.

[24]Mukesh C. Motwani, Mukesh C. Gadiya, Rakhi C. Motwani, Frederick C. Harris," Survey of Image Denoising Techniques".

[25]Mahdi Nakhaie Kohan, Hamid Behnam," Denoising Medical Images using Calculus of Variations".

[26]James S. Walker. 1999. A Primer on Wavelets and Scientific Applications.