CT Image Denoising in Wavelet Transform using Threshold Shrinkage Techniques

N. Rigana Fathima, S. Shajun Nisha, Dr. M. Mohammed Sathik

Abstract— **Medical Image Denoising plays a cardinal role in the field of image preprocessing. Medical Image is recurrently debauched by noise in its acquisition and transmission. Medical Images are corrupted by various types of noises. In this paper, We have taken Computed Tomography(CT) image. CT images are exploited by speckle Noise and Gaussian Noise. To denoising in medical images using Discrete Wavelet Transform are very efficacious because of its excellent localization property. Discrete Wavelet Transform can furnish sparcity, multiresolution structure and it is straightforward technique . Various Thresholding Shrinkage Techniques such as Visushrink, Neighshrink, Sureshrink, Bayeshrink are applied to eradicate noise. The performance of denoising is evaluated using the performance metrics such as Peak Signal to Noise Ratio(PSNR), Root Mean Square Error(RMSE), Mean Structural Similarity Index Measure(MSSIM), Mean Absolute Error(MAE),Normalized Cross Correlation(NCC) , Normalized Absolute Error(NAE).**

Index Terms—**Discrete Wavelet Transform(DWT), Gaussian Noise, Image Denoising, Thresholding Techniques.**

I. INTRODUCTION

Medical Image Denoising plays substantial role in the field of image preprocessing. Image Denoising is preprocessing task in image processing. An image is often distorted by noise in its acquisition and transmission. Image Denoising is the process of undesirable noise in order to reinstate the original image. The most important image processing tasks such as image enhancement, image segmentation, feature extraction has significant scope depends on image denoising. So Denoising from an image has great consequence in image processing. In this paper, We have taken Computed Tomography(CT) image. CT image is degraded by speckle noise and Gaussian Noise.

Discrete Wavelet transform is the one of the best methods used for image denoising. Wavelet Transform, due to its excellent localization property, has rapidly become an indispensable signal and image processing tool for image denoising. So Discrete Wavelet Transform(DWT) are used to remove noises. Discrete Wavelet Transform is a straightforward computation technique. If any image is fragmented to employ wavelet then it has two functions one is wavelet function and another one is scaling function. Wavelet function is used to represent the high frequency component i.e. detail part of an image and scaling function is used to represent the low frequency component i.e. smooth part of an image. DWT can be implemented by high pass filters and low pass filters. The High Pass Filter represent data set in the form of differences called detailed coefficient. Low pass filter represent data set in the form of average values called approximation coefficient. There are several types of wavelet families are availabe such as Daubechies, Haar, Shannon, Meyer, Biorthogonal, Reverse Biorthogonal wavelets. In our proposed work Daubechies, Biorthogonal and Reverse Biorthogonal Wavelets are used. To denoise the image, various threshold shrinkage techniques are used such as VisuShrink (Donoho,1995), NeighShrink, SureShrink (Donoho and Johnstone,1995), BayesShrink(Chang et al., 2000) for wavelet based denoising.

A. Related Work

Medical Images are used to detect various diseases like lymphoma, neuroblasma, kidney tumors, breast cancer, etc.,Computed Tomography(CT) images gives detailed images of several types of tissues coupled with lungs, bones, blood vessels. CT images are affected by various noises like speckle noise and Gaussian Noise. CT image quality is influenced by the radiation dose since it increases with the significant amount of radiation dose. This increases the amount of rays being absorbed by the human body and increases the chances of cancer. So we need to reduce the radiation dose and this leads to noisy CT Images[19].So we conclude that CT image is essential for Medical Image Denoising.

To denoising medical images, we have used Discrete Wavelet Transform. Discrete Wavelet Transorm is used to Decomposing the original image into wavelet coefficients. The main advantages of the discrete wavelet transform over conventional transforms, such as the Fourier transform, are well recognized. Because of its excellent locality in time and frequency domain, wavelet transform is extensively and remarkable used for image processing like compression and denoising. Wavelet transforms have advantages over traditional Fourier Transforms for representing functions that discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic or non-stationary signals. DWT makes the energy of signal concentrate in a small number of coefficients hence the DWT of a noisy image consist of large number of coefficients with low signal to noise ratio (SNR), Removing this low SNR by

N. Rigana Fathima, *M.Phil Computer Science,Sadakathullah Appa College, Tirunelveli, India, 9486243197*

S. Shajun Nisha, *Professor & Head, P.G Dept of Computer Science, Sadakathullah Appa College, Tirunelveli, India*

Dr. M. Mohammed Sathik, *Principal and Research Co-ordinator, Research Department of Computer Science, Sadakathullah Appa College,Tirunelveli,India.*

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selecting proper thresholding value [15]. Wavelet denoising using thresholding involves three basic steps- first step involves computation the wavelet transform of noisy image, second step is used to apply thresholding on noisy wavelet coefficient according to some rule and finally computing inverse wavelet transform of modified wavelet coefficients. Wavelet denoising using thresholding algorithm is also known as wavelet shrinkage in which wavelet coefficient of noisy image are grouped based on certain threshold value and threshold function[12]. A signal is decomposed into component wavelets in wavelet transform.

Wavelet Transforms are classified into Discrete Wavelet Transform(DWT) and Continuous Wavelet Transform(CWT). CWT operate over every possible scale and translation whereas DWT use a specific subset of scale and translation values. Based on these basis function wavelets are classified as Haar, Coiflet, Daubechies, Symlet, Biorthogonal etc[22].

There are several wavelet families Daubechies, Haar, symlet, Shannon, coiflet have been performed for noise removing. There are two categories of wavelet bases: Orthogonal and BiOrthogonal. Orthogonal wavelets are daubechies, Coiflet, Symlet.

Biorthogonal wavelet system can be designed to achieve symmetry property and exact reconstruction by using two wavelet filters and two scaling filters instead of one [4,5]. Biorthogonal family contains biorthogonal compactly supported spline wavelets. With these wavelets symmetry and perfect reconstruction is possible using FIR (Finite Impulse Response) filters, which is impossible for the orthogonal filters (except for the Haar filters). The biorthogonal bases uses separate wavelet and scaling functions for the analysis and synthesis of image. Biorthogonal Wavelet Transform:- This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition and the other for reconstruction instead of the same single one, interesting properties are derived.We have following biorthogonal wavelet :-
bior1.1 bior1.3 bior1.5 bior2.2 bior2.4 bior2.6 bior2.8 bior3.1 bior3.3 bior3.5 bior3.7 bior3.9 bior4.4 bior5.5 bior6.8. In our proposed work we have used bior6.8 [13]. Daubechies Wavelet transform have the following advantages:-1) It is approximate shift invariant 2) It has perfect reconstruction property. 3) It provides true phase information and no redundancy [24]. The reverse biorthogonal family uses the synthesis functions for the analysis and vice versa.

The scale of decomposition depends on the maximum noise in details of first level and lower noise at higher decomposition levels. Analysis of noise in an image can be done by using the concept that large scale of low magnitude coefficient is the noise while small scale of high magnitude coefficient will be the image. In DWT, an image can be decomposed into a series of different spatial resolution images. For a 2D image, an N level decomposition may result in providing 3N+1 sub bands LL, HL, LH and HH. Then the wavelet transform is applied to the low frequency sub band image [23].

To Denoising an image using Wavelet Transform, there are various important thresholding Shrinkage techniques to be used. The techniques are VisuShrink, SureShrink, NeighShrink, BayesShrink. To evaluate the performance of denoised image in this paper, the performance metrics such as PSNR, MSSIM, RMSE, MAE, NCC are used.

B. Motivation and Justifications

In the recent years, there has been a fair amount of research on image denoising. An image is often corrupted by noise in its acquition and transmission. Denoising plays a vital role in the field of the image preprocessing. It is often a necessary to be taken, before the image data is analyzed. The main of an image denoising algorithm is to reduce the noise level, while preserving the image features. So it is still a challenging problem for researchers. To remove noises from image, there are lot of imaging modalities are present in medical images. CT image quality is influenced by the radiation dose since it increases with the significant amount of radiation dose. This increases the amount of rays being absorbed by the human body and increases the chances of cancer. So we need to reduce the radiation dose and this leads to noisy CT Images[19].So we conclude that CT image is essential for Medical Image Denoising.

In this paper, we are proposed Medical Image Denoising in Different types of Wavelets cooperative with Thresholding Shrinkage Techniques. The Main Advantages of Discrete Wavelet Transform provides higher flexibility other than Discrete Cosine Transform and Discrete Fourier Transform. Only spatial correlation of the pixels inside the single 2-D block is considered and the correlation from the pixels of the neighboring blocks is neglected Impossible to completely decorrelate the blocks at their boundaries using DCT Undesirable blocking artifacts affect the reconstructed images or video frames. (high compression ratios or very low bit rates) .Discrete Cosine Transform and Discrete Fourier Transform could not find out line discontinuity. To overcome this drawback, Discrete Wavelet Transform is used. M. Sifuzzaman1, M.R. Islam et.al resolved Application of Wavelet Transform and its advantages compared to fourier transform. The Fourier transform is less useful in analyzing non-stationary signal (a non-stationary signal is a signal where there is change in the properties of signal). Wavelet transforms allow the components of a non-stationary signal to be analyzed. Wavelets also allow filters to be constructed for stationary and non-stationary signals. The main difference is that wavelets are well localized in both time and frequency domain whereas the standard Fourier transform is only localized in frequency domain.

Discrete Wavelet Transform is advantageous because there is no need to divide the input coding into non-overlapping 2-D Blocks, it has higher Compression Ratio. It allows good localization both in time and spatial domain. The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression. Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where scalability and tolerable

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degradation are important. Transformation of the whole image introduces inherent scaling. Better identification of which data is relevant to human perception higher compression ratio. Motivated by all these facts, we are inspired to denoising a medical image in Discrete Wavelet Transform. Therefore I justified that the Discrete Wavelet Transform is well suited in medical image Denoising. In this paper, a comparative analysis of wavelet transform with thresholding shrinkage techniques in medical image denoising.

C. Organisation of the paper

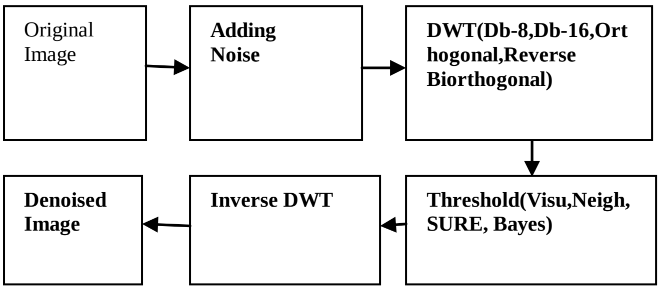
Section 2 includes Methodology which includes Outline of the Proposed Work, Section 3 concludes Experimental Results. Section 4 concludes Performance Evaluation Metrics. Ultimately Section 5 concludes Conclusion of the paper.

II.METHODOLOGY

A. Outline of the Proposed Method

In this paper, image denoising that apply Discrete Wavelet Transform resides five steps: There are

1. Get the noisy image to give as input.
2. Apply Discrete Wavelet Transform(Db-8,Db-16,Bio 6.8,Rbio 5.5) on noisy image and to acquire Wavelet Coefficients.
3. Apply Thresholded Shrinkage Techniques (VisuShrink, SUREShrink, NeighShrink, BayesShrink) on the modified wavelet coefficients.
4. Apply Inverse DWT on the coefficients to attain denoised image.
5. In our proposed work, To find the best wavelet bases is suitable for best thresholding shrinkage techniques.



B. Types of Noises

In this paper,we have used two types of noises. They are:- Gaussian Noise,Speckle Noise.

1. Gaussian Noise

Gaussian noise is the statistical noise which has its probability density function equal to that of a normal distribution, which is called as the Gaussian distribution. In the different words, the noise values can take on being Gaussian-distributed. It can influence the values of all the pixels[21]. A different case is white Gaussian noise, values at any pair of the times are identically distributed and also statistically independent [16].

$$g(x,y) = f(x,y) + n(x,y) \tag{1}$$

Where is output $g(x,y)$ of original image function $f(x,y)$corrupted by the additive Gaussian Noise Probability density function for Gaussian noise given below.

$$p(g) = \sqrt{\frac{1}{2\pi\sigma^2} e^{\frac{-(g-\mu)^2}{2\sigma^2}}} \tag{2}$$

Where g represents the grey level, μ the mean value and σ the standard deviation[14].

2. Speckle Noise

Speckle noise is a multiplicatie noise. Speckle is a complex phenomenon, which degrades image quality with a backscattered wave appearance which originates from many microscopic diffused reflections that passing through internal organs and makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations [3].

$$g(x,y = f(x,y) * n(x,y) \tag{3}$$

Where $g(x,y)$ is the result of the original image function $f(x,y)$
corrupted by the multiplicative noise $n(x,y)$.

C. Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Discrete Wavelet Transform has attracted more and more interest in image de-noising. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges a two signals, approximation and details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform . Another consideration of the wavelets is the sub-band coding theory or multi resolution analysis. The signal passes successively through pairs of low pass and high pass filters, the analysis filters, which produce the transform coefficients. These coefficients, if passes successively through the synthesis filters, may reproduce the initial signal at the decoder's side. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL (low frequency or approximation coefficients), LH (vertical details), HL (horizontal details) and HH (diagonal details) as shown in Fig 2, the number written next to sub-band name shows the level. The next level of wavelet transform is applied to the low frequency sub-band image LL only.

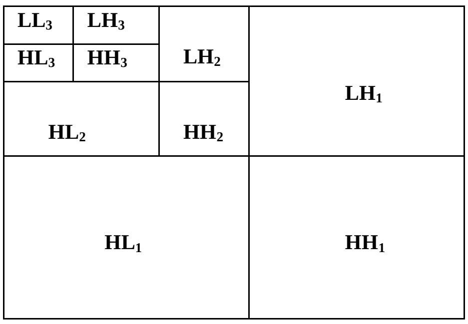


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Fig.2 Three Level Decomposition in Discrete Wavelet Transform

1,2,3 – Decomposition Level
H----High Frequency Bands
L-----Low Frequency Bands

1. Daubechies wavelets

This family is based on orthogonal, and categorized by supported scaling wavelet functions, which generates an orthogonal multi-resolution analysis. This wavelet function is denoted as db1. It is difficult to get an orthogonal supported wavelet that is either symmetric or asymmetric except for Haar wavelets[17]. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet.

2. Biorthogonal

They are denoted as bior wavelet, biorthogonal if often used instead of orthogonal i.e. rather than having one scaling and wavelet function, there are two scaling functions that may generate different multi-resolution analysis, and accordingly two different wavelet functions used in the analysis and combination [17].

3. Reverse Biorthogonal

It is based on reconstruction and decomposition of scaling filters. This wavelet has vanishing moments on decomposition for analysis and vanishing moment for the reconstruction of synthesis. It is denoted as rbio [17].

D. Wavelet Shrinkage Thresholding Techniques

To denoise an image,the following threshold shrinkage techniques to be used.

The techniques are:- Visu Shrink,SURE Shrink,Neigh Shrink,Bayes Shrink.

1. Visu Shrink

Visu Shrink was introduced by Donoho [2]. It follows the hard threshold rule. The drawback of this shrinkage is that neither speckle noise can be removed nor MSE can be minimized deal with additive noise [6]. Threshold T can be calculated using this formula [10].

$$T_v = \hat{\sigma}\sqrt{2logN}$$

$$\hat{\sigma}^2 = \left[\frac{median(|x_{ij}|)}{0.675}\right]^2 , X_{ij} \in HH1 \quad (4)$$

Where σ is calculated as mean of absolute difference (MAD) which is a robust estimator and N represents the size of original image.

2. Bayes Shrink

The Bayes Shrink method has been attracting attention recently as an algorithm for setting different thresholds for every sub band. Here sub-bands refer to frequency bands that are different from each other in level and direction [8]. The Bayes shrink[11] method is for images including Gaussian noise. The observation model is expressed as follows:

$$Y = X + V \quad (5)$$

Here Y is the wavelet transform of the degraded image, X is wavelet transform of the original image,and V denotes the wavelet transform of the noise components following the Gaussian distribution $N(0,\sigma_v^2)$. Here, since X and V are mutually independent, the variances $\sigma_y^2, \sigma_x^2, \sigma_v^2$ of y, x and v are given by:

$$\sigma_y^2 = \sigma_x^2 + \sigma_v^2 \quad (6)$$

$$\sigma_v^2 = \left[\frac{median(|HH_1|)}{0.6745}\right]^2 \quad (7)$$

The variance of the sub-band of degraded image can be estimated as:

$$\sigma_y^2 = \frac{1}{M}\sum_{m=1}^{M} A_m^2 \quad (8)$$

Where A_m are the wavelet coefficients of sub-band under consideration, M is the total number of wavelet coefficient in that sub-band. The bayes shrink thresholding technique performs soft thresholding, with adaptive data driven, sub-band and level dependent near optimal threshold given by

$$T_{BS} = \begin{cases} \frac{\sigma_v^2}{\sigma_x} & if\ \sigma_v^2 < \sigma_y^2 \\ max\{|A_m|\} & otherwise \end{cases} \quad (9)$$

Where $\sigma_x = \sqrt{max(\sigma_y^2 - \sigma_v^2, 0)}$

In the case, where $\sigma_v^2 > \sigma_y^2$, σ_x is taken to be zero, i.e. $T_{BS} \to \infty$. or, in practice,

$T_{BS} = max(|Am|)$ and all coefficients are set to zero.

3. NeighShrink

Let **g**= $\{g_{ij}\}$ will denote the matrix representation of the noisy signal. Then, $w\,W_g$ denotes the matrix of wavelet coefficients of the signal under consideration. For every value of w_{ij}, let B_{ij} is a neighbouring window around w_{ij} , w_{ij} denotes the wavelet coefficient to be shrinked. The neighbouring window size can be represented as *L*, where L is a positive odd number. A3×3 neighbouring window centered at the wavelet coefficient to be shrinked is shown in Fig 4.

Let

$$S_{ij} = \sum_{(k,l)\in B_{ij}} w_{kl}^2 \quad (10)$$

We omit the corresponding terms in the summation when the above summation has pixel indexes out of the wavelet sub-band range. The shrinked wavelet coefficient according to the neighshrink is given by this formula [7]

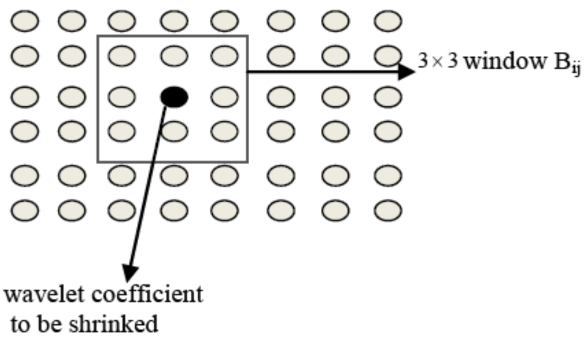

Fig.3 An illustration of the neighbouring window of size 3*3 centred at the wavelet coefficient to be shrinked

$$w'_{ij} = w_{ij}\beta_{ij} \quad (11)$$

The shrinkage factor β_{ij} can be defined as:

$$\beta_{ij} = \left(1 - T_{UNI}^2 / S_{ij}^2\right)_+ \quad (12)$$

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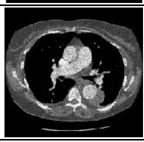
Thresholding Shrinkage Techniques		Speckle Noise	Gaussian Noise
Noisy Image			
Denoised Images Using Different Wavelet Families	**DB-8**		
	DB-16		
	Biorthogonal		
	Reverse Biorthogonal		

here, the + sign at the end of the formula means to keep the positive value while set it to zero when it is negative and T_{UNI} is the universal threshold, which is defined as [1]:

$$T_{UNI} = \sqrt{2\sigma^2 \ln(n)} \quad (13)$$

where n is the length of the signal.

Different wavelet coefficient sub-bands are shrinked independently, but the universal threshold T_{UNI} and neighbouring window size L kept unchanged in all sub-bands. The estimated denoised signal $\acute{f} = \acute{f}_{ij}$ is calculated by taking the inverse wavelet transform of the shrinked wavelet coefficients $\acute{w}_{ij}$ i.e. $\acute{f} = W\hat{w}$.

4. SureShrink

SureShrink works on the principle of Stein's Unbiased Risk Estimator(SURE) proposed by [3]. Threshold value t_j for each resolution level j in the wavelet transform is used, which is referred to level dependent thresholding. The SureShrink threshold t^* is defined as follows[3]:--

$$t^* = min\left(t, \hat{\sigma}_n\sqrt{2 \times \log(n)}\right) \quad (14)$$

Where t denotes the value that minimizes Stein's Unbiased Risk Estimator. Sure Shrink minimizes the mean squared error and also it is smoothness adaptive,which means that if any unknown function includes abrupt changes or boundaries in the image, the reconstructed image also has the same. But in situations of extreme sparsity of the wavelet coefficients the noise contributed to the SURE profile by many coordinates at which the signal is zero, swamps the information contributed to the SURE profile by the few coordinates where the signal is nonzero[12].

III. EXPERIMENTAL RESULTS

Experiments were performed to denoising a CT chest image is shown in Fig.4. Speckle and Gaussian Noise are examined. The denoised output images for types of wavelet families such as Daubechies, Biorthogonal and reverse biorthogonal for various thresholding techniques are illustrated in Fig.5. Reverse BiOrthogonal gives better results . Therefore it is decomposed in to three levels and the output is presented in Fig.6. Reverse Biorthogonal Level 1with sureShrink gives better results for Speckle and Gaussian NoiseThen Different Noise variance is applied for noisy image is presented in Fig.7.Denoised image is illustrated in Fig.8.

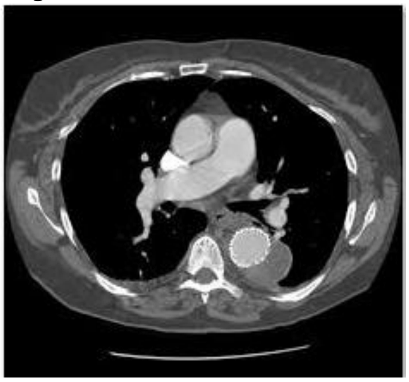


Fig. 4. Original Image

Fig. 5. Denoising using Wavelet bases with thresholding techniques

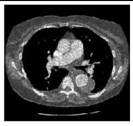
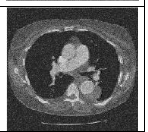
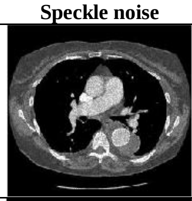
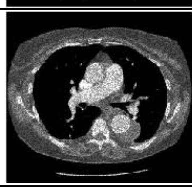
Noise Type		Speckle Noise	Gaussian Noise
Noisy Image			
Denoised image using decomposition levels	1		
	2		
	3		

Fig. 6. Denoising using decomposition level with threshold techniques

Noise Variance	Noisy Image	
	Speckle noise	Gaussian noise
0.01		
0.02		
0.04		

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0.06		
0.08		

Fig. 7. Noisy Image with noise variance for speckle and Gaussian noise

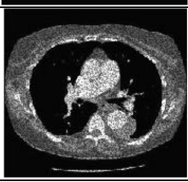
Noise Variance	**Denoised Image**	
	Speckle Noise	**Gaussian noise**
0.01		
0.02		
0.04		
0.06		
0.08		

Fig. 8. Denoised Image with noise variance for speckle and Gaussian noise

IV. PERFORMANCE EVALUATION

A. Performance Metrics

1. Peak-signal to Noise-Ratio(PSNR)

It gives the ratio between possible power of a signal and the power of corrupting noise present in the image[20].

$$PSNR = 20 \log 10(255/RMSE) \qquad (15)$$

Higher the PSNR gives lower the noise in the image i.e.,higher the image quality[9,25].

2. Root Mean Square Error(RMSE)

Mean square error (MSE) is given by[20]

$$MSE = \sum_{i=j=1}^{N} [(i,) - F(i,j)]^2/N^2 \qquad (16)$$

Where, f is the original image F is the image denoised with some filter and N is the size of image. [9,25].

$$RMSE = \sqrt{MSE} \qquad (17)$$

3. Mean Structural Similarity Index Measure(MSSIM)

The Structural Similarity Index between two images is computed as[9,25] :

$$SSIM(x,y) = (2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)/(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2) \qquad (18)$$

Where $\mu_x = \sum_{i=1}^{N} w_i x_i$

$\sigma_x = (\sum_{i=1}^{N} w_i(x_i - \mu_x)^2)^{1/2}$, $\sigma_{xy} = \sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y)$,

$C_1 = (K_1 L)^2$, and $C_2 = (K_2 L)^2$

Where L is the range of pixel values(255 for 8-bit grayscale images). And K1<<1 is a small constant and also K2<<1 [20]

$$\mathbf{MSSIM} = \sqrt{\mathbf{SSIM}} \qquad (19)$$

4. Normalized Cross Correlation (NK/NCC)

It is a measure of similarity of two images as a function of a time-lag applied to any one of them. It is co relational based quality measure which normally looks at correlation features between the pixels of original and reconstructed image[18]. Normally NK is in the range of 0 to1, very near to or one is the best. This is also known as a sliding dot product or sliding inner-product. It is expressed as

$$NK = \sum_{j=1}^{M}\sum_{k=1}^{N} x_{j,k} \cdot x'_{j,k} / \sum_{j=1}^{M}\sum_{k=1}^{N} x_{j,k}^2 \qquad (20)$$

Where x is the original image and x' is the denoised image, Where M, N are number of rows and columns of an image.

5. Mean Absolute Error(MAE)

It is a quantity used to measure closeness of predictions to the true value[16].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i| \qquad (21)$$

It is an average of absolute errors $'e^{i}'$. $'f^{i}'$ is the prediction and $'y^{i}'$ is the true value.

4.2. Performance Evaluation

The performance of the Wavelet Families and Thresholding Techniques were examined using the metrics PSNR, MSSIM, RMSE, MAE, NCC/NK. The first experiment is performed to estimate the performance of different wavelet families such as Daubechies,Biorthogonal, Reverse Biorthogonal. Results are shown in Table I& II. Taking into considertation of all the metrics, it is surveyed that the Reverse Biorthogonal base performances is better than than other bases. It is anticipated that the best level of decomposition plays a key role in denoised image quality. So the Second Experiment is conducted to identify the best level of decomposition for Speckle and

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Gaussian noice and its metrics are shown in Table III & IV. Then the results are applied to Threshold shrinkage techniques and also VisuShrink, NeighShrink, SureShrink, BayesShrink are examined and the performance metrics is illustrated in Table III&IV. Noise Variance is used to find how much each pixel varies from the neighbouring pixel and also used to classify different regions. So , by varying the noise variance for speckle & Gaussian noise is tested and the results is shown in Table V& VI.

I. Wavelet Bases with Speckle Noise

Metrics	Wavelet Bases	Speckle Noise			
		Visu Shrink	Neigh Shrink	Sure Shrink	Bayes Shrink
PSNR	DB-8	23.2402	23.247	23.2556	23.2666
	Db-16	23.2825	23.219	23.265	23.2905
	Biortho-gonal	23.2062	23.1864	23.2305	23.2559
	Reverse BiOrtho-gonal	23.3109	23.2769	23.4040	23.3001
MSSIM	DB-8	0.84946	0.85034	0.84776	0.84996
	Db-16	0.84988	0.85054	0.85008	0.85057
	Biortho-gonal	0.84914	0.84952	0.85046	0.84964
	Reverse BiOrtho-gonal	0.85023	0.84983	0.85189	0.84989
RMSE	DB-8	17.5567	17.5464	17.5292	17.5069
	Db-16	17.4749	17.6032	17.5102	17.4588
	Biortho-gonal	17.6291	17.6693	17.5798	17.5285
	Reverse BiOrtho-gonal	17.4178	17.4861	17.3915	17.5391
MAE	DB-8	49.6471	49.7425	49.6991	49.635
	Db-16	49.7513	49.6604	49.7704	49.6358
	Biortho-gonal	49.6532	49.7715	49.7268	49.7421
	Reverse BiOrtho-gonal	49.6423	49.7396	49.6168	49.6747
NCC	DB-8	0.9786	0.97852	0.97849	0.97863
	Db-16	0.97899	0.97819	0.97862	0.9787
	Biortho-gonal	0.97833	0.97826	0.97842	0.97869
	Reverse BiOrtho-gonal	0.979	0.97868	0.97888	0.97897

II. Wavelet Bases with Gaussian Noise

Metrics	Wavelet Bases	Gaussian Noise			
		Visu Shrink	Neigh Shrink	Sure Shrink	Bayes Shrink
PSNR	DB-8	20.9499	20.9524	20.7181	20.9251
	Db-16	20.9579	20.9926	20.9122	20.9201
	Biortho-gonal	20.8943	20.9092	20.884	20.9626
	Reverse BiOrtho-gonal	20.9886	20.9513	20.9968	20.9846
MSSIM	DB-8	0.68954	0.68577	0.68768	0.6913
	Db-16	0.69139	0.69023	0.69058	0.6888
	Biortho-gonal	0.68001	0.68424	0.68557	0.69117
	Reverse BiOrtho-gonal	0.69821	0.69153	0.69859	0.69197
RMSE	DB-8	22.8584	22.8517	23.4762	22.9238
	Db-16	22.8374	22.7462	22.9578	22.9368
	Biortho-gonal	23.005	22.9656	23.0325	22.825
	Reverse BiOrtho-gonal	22.6145	22.8547	22.4878	22.7673
MAE	DB-8	59.0424	58.8876	58.6399	58.7645
	Db-16	58.8444	58.8478	58.9139	58.856
	Biortho-gonal	58.9282	58.8397	58.8653	58.832
	Reverse BiOrtho-gonal	58.7759	58.8594	58.7739	58.8578
NCC	DB-8	0.9705	0.9708	0.9671	0.9703
	Db-16	0.97056	0.9768	0.96943	0.97035
	Biortho-gonal	0.97029	0.97013	0.97012	0.97051
	Reverse BiOrtho-gonal	0.97041	0.97048	0.9799	0.97071

III. Decomposition Levels with Speckle Noise

Metrics	Wavelet Decomposition level	Speckle Noise			
		Visu Shrink	Neigh Shrink	Sure Shrink	Bayes Shrink
PSNR	1	22.7901	22.7691	22.7964	22.7858
	2	20.4254	20.4932	20.4714	20.4556
	3	20.4856	20.4201	20.4405	20.4477
MSSIM	1	0.84073	0.83874	0.84088	0.84011
	2	0.74048	0.73915	0.73956	0.73945
	3	0.73862	0.73902	0.74098	0.74097
RMSE	1	18.4795	18.539	18.4708	18.4819
	2	24.2818	24.0925	24.1531	24.197
	3	24.1136	24.2959	24.239	24.2189
MAE	1	49.6035	49.6985	49.5899	49.6927
	2	49.8512	49.8653	49.9671	49.8126
	3	49.963	50.0138	50.0136	49.9483
NCC	1	0.97711	0.97702	0.97712	0.9776
	2	0.95154	0.9521	0.95231	0.95203
	3	0.95254	0.9518	0.95223	0.95243

IV. Decomposition Levels with Gaussian Noise

Metrics	Wavelet Decomposition level	Gaussian Noise			
		Visu Shrink	Neigh Shrink	Sure Shrink	Bayes Shrink
PSNR	1	20.8461	20.8366	20.8645	20.8487
	2	19.0327	19.0016	18.9623	19.0045
	3	18.9648	19.0024	18.9378	19.0109
MSSIM	1	0.69076	0.68923	0.69125	0.68994
	2	0.58532	0.57837	0.57991	0.58172
	3	0.5774	0.58191	0.58091	0.58004
RMSE	1	23.1232	23.1585	23.0709	23.1263
	2	28.504	28.6062	28.7359	28.5968
	3	28.7277	28.6036	28.8169	28.5756
MAE	1	60.6198	60.7069	60.5068	60.7037
	2	61.6218	61.5219	61.6467	61.5493
	3	61.4572	61.3741	61.4478	61.5073
NCC	1	0.97075	0.9705	0.97083	0.97068
	2	0.94664	0.94663	0.94603	0.94623
	3	0.9456	0.94601	0.94532	0.9462

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V. Noise Variance with Speckle Noise

Metrics	Speckle Noise				
Noise Variance	**0.01**	**0.02**	**0.04**	**0.06**	**0.08**
PSNR	23.8237	23.2726	22.3799	21.6396	21.0987
MSSIM	0.86452	0.85013	0.83276	0.823	0.81473
RMSE	16.4193	17.4949	19.3885	21.1135	22.4869
MAE	49.7639	49.6694	49.6628	49.4622	49.1820
NCC	0.98006	0.97857	0.9762	0.97317	0.97079

VI. Noise Variance with Gaussian Noise

Metrics	Gaussian Noise				
Noise Variance	**0.01**	**0.02**	**0.04**	**0.06**	**0.08**
PSNR	21.0353	20.9089	20.758	20.6495	20.4557
MSSIM	0.69097	0.68942	0.68658	0.68649	0.68216
RMSE	22.6348	22.9665	23.3689	23.6626	23.9465
MAE	56.8758	58.9181	62.8709	67.1491	71.3869
NCC	0.96989	0.96008	0.97169	0.97278	0.97286

From Table I &II, it is noted that the wavelet families are best fit for speckle noise removal than Gaussian Noise. All type of wavelet family are equally perform well in removing speckle and Gaussian Noise. It is observed that the performance of Reverse Biorthogonal wavelet base is somewhat better than other bases. From Table III&IV, It is identified that all performance metrics of speckle and Gaussian Noise are higher when the decomposition Level is 1. So, it is suggested that further level decomposition will only increase the computational difficulties without best performance,also it is Observed that, Sure Shrink performs well than other thresholding Techniques for Speckle and Gaussian Noise. From Table V&VI, Reverse BiOrthogonal Wavelet Bases with 1st level Decomposition Performs well in Sure Shrink Thresholding Techniques. Noise Variance is applied to evaluate the performance of CT image. Noise variance= 0.01 is best fit for speckle and Gaussian Noise.

V. CONCLUSION

This paper presents a comparative analysis of Medical Image Denoising Using Different Wavelet bases with Thresholding Shrinkage Techniques. Experiments were performed to analyse the best suitable different wavelet bases such as Daubechies(Db-8,Db-16), BiOrthogonal, Reverse BiOrthogonal. When using wavelet transform, the choices of choosing a wavelet bases have a great impact on the success of thresholding shrinkages techniques. Thresholding Shrinkage techniques like VisuShrink, NeighShrink, SureShrink, BayesShrink have been applied.

Performance Metrics such as PSNR, MSSIM, RMSE, MAE, NCC are used to evaluate the denoising effect. It is observed from all wavelet bases, Reverse Biorthogonal performs well in federation with SureShrink at first level of decomposition for Speckle and also Gaussian Noise.

VI. REFERENCES

[1] D. L. Donoho and I. M. Johnstone, "Ideal spatial adaptation via wavelet shrinkage," *Biomefrika*, vol. 81, pp. 425455, 1994.
[2] D.L. Donoho and I.M. Johnstone, "Denoising by soft thresholding," IEEE Trans. on Information Theory, Vo.41, 1995
[3] Iain M.Johnstone David L Donoho. "Adapting to smoothness via wavelet shrinkage" Journal of the Statistical Association, 90(432):1200–1224, Dec 1995
[4] W. Sweldens, "The Lifting Scheme: A Custom Design construction of Biorthogonal", Wavelets Appl. Comput Harmon.Anal., Vol. 3, 1996.
[5] W. Sweldens, "The Lifting Scheme: A Construction of second generation wavelets", SIAM J. Math. Anal., 1997.
[6] Raghuveer M. Rao, A.S. Bopardikar" Wavelet Transforms: Introduction to Theory and Application published by Addison-Wesley, 2001
[7] G. Y. Chen and T. D. Bui, "Multi-wavelet De-noising using Neighboring Coefficients," IEEE Signal Processing Letters, vol.10,no.7, pp.211-214, 2003.
[8] E.Jebamalar Leavline, S.Sutha, D.Asir Antony Gnana Singh, "Wavelet Domain Shrinkage Methods for Noise Removal in Images: A Compendium," International Journal of Computer Applications,Vol.33, No.10, November 2011
[9] BalaPrakash.K., VenuBabu.R, VenuGopal.B "Image Independent Filter for Removal of Speckle noise" International Journal of Computer science Issues, 8(5),1694-0814. 2011
[10] S.Sutha, E. Jebamalar Leavline, D. ASR Antony Gnana Singh, " A Comprehensive Study on Wavelet based Shrinkage Methods for Denoising Natural Images," WSEAS Transactions on Signal Processing, Vol. 9, Issue 4, October 2013
[11] V. Mahesh, M. Someswara Rao, Ch. Sravani , P. Durgarao, S. Venkatesh," An Effective Image Denoising Using Adaptive Thresholding In Wavelet Domain" Int. Journal of Engineerin Research and Applications ISSN : 2248-9622, Vol. 4, Issue 4(Version 1), April 2014, pp.365-368\
[12] Arun Dixit, Poonam Sharma, "A Comparative Study of Wavelet Thresholding for Image Denoising", I.J. Image, Graphics and Signal Processing, Nov 2014, 39-46
[13] Arpit Sharma, "Efficient Use of Biorthogonal Wavelet Transform for Caridac Signals", IJCSNS International Journal of Computer Science and Network Security, VOL.15 No.2, February 2015
[14] Ajay Kumar Boyat1 and Brijendra Kumar Joshi," A REVIEW PAPER: NOISE MODELS IN DIGITAL IMAGE PROCESSING", Signal & Image Processing : An International Journal (SIPIJ) Vol.6, No.2, April 2015 DOI : 10.5
[15] Ms. Chipy Ashok , Ms. Anu V.S, "FPGA Implementation of Image Denoising using Adaptive Wavelet Thresholding", International Journal of Advanced Research in Computer and Communication Engineering, Vol. 4, Issue 7, July 2015
[16] Satendra singh bhadoriya, Rajeev kumar singh," A Comparative Study on Image Denoising with its classifications and application", International Journal of Advanced Technology & Engineering Research, Volume 5,Issue 6,Nov 2015
[17] Neeraj Saini, Pramod Sethy, "Performance based Analysis of Wavelets Family for Image Compression-A Practical Approach" International Journal of Computer Applications Volume 129 – No.9, November2015
[18] Prateek Kumar and Sandeep Kumar Agarwal," Analysis of Wavelet Denoising of a Colour ImageWith Different Types of Noises", International Journal of Signal Processing, Image Processing and Pattern Recognition", kumarprateek34@gmail.com,rjitsandeep@gmail.com, Vol.8, No.6 (2015), pp.125-134
[19] Lubna Gabralla, Marwan Zaroug, Hela Mahersia, "Denoising CT Images using Wavelet Transform", International Journal of Advanced Computer Science and Applications, Vol.6.No.5,2015.
[20] Gopinathan S, Poornima S, "Enhancement of images with speckle

Noise reduction using different filters" International Journal of Applied Sciences and Engineering Research,Vol 4,Issue 3 2015.
DOI:10.6088.ijaser.04033

[21] Chhavi Sharma, Neha Sahu, "Efficient Removal of Impulse Noise from Digital Images" Communications on applied Electronics(CAE)-ISSN: 2394-4714, Volume-1-No.4,2015 www.caeaccess.org

[22] Renjini L, Jyothi R L, "Wavelet Based Image Analysis: A Comprehensive Survey" International Journal of Computer Trends and Technology (IJCTT) – Volume 21 Number 3 – Mar 2015 ISSN: 2231-2803 http://www.ijcttjournal.org

[23] M.S.anjaly chauhan, "Comparative Analysis of Wavelet Thresholding for Image Denoising Using Discrete Wavelet Transform", Mathematical and Computational Methods in Electrical Engineering ISBN: 978-1-61804-329-0

[24] Manish Khare, Rajneesh Kumar Srivastava and Ashish Khare **"**Daubechies Complex Wavelet based Computer Vision Applications"

[25] Thangavel.P, Gopinathan.S, "A Novel Method for Image Enhancement System Using Wavelet Transform and a Non-linear piecewise filter", http://www.foxitsoftware.com

N.Rigana Fathima, M.Phil., Research Scholar in Computer Science, Sadakathullah Appa College. I've completed M.Sc.,(CS) in Sadakathullah Appa College under Manonmaniam SundaranarUniversity. I've attended National and International Seminars, Workshops.

S.Shajun Nisha Prof. & Head, PG Dept of CS Sadakathullah Appa College. She has completed M.Phil.(Computer Science) and M.Tech (Computer and Information Technology) in Manonmaniam Sundaranar University, Tirunelveli. She has involved in various academic activities. She has attended so many national and international seminars, conferences and presented numerous research papers. She is a member of ISTE and IEANG and her specialization is Image Processing and Pattern recognition.

Dr.M.Mohamed Sathik M.Tech., M.Phil., M.Sc., M.B.A., M.S., Ph.D has so far guided more than 35 research scholars. He has published more than 100 papers in International Journals and also two books. He is a member of curriculum development committee of various universities and autonomous colleges of Tamil Nadu. His specializations are VRML, Image Processing and Sensor Networks

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