Volume 6, Issue 6, June 2016 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Emprical Evaluation of Wavelet Transform Using Shrinkage Thresholding Techniques with Medical Images

M. Pitchammal *
Department of CS
Sadakathullah Appa College,
Tirunelveli, Tamilnadu, India

N. Rigana Fathima
Department of CS
Sadakathullah Appa College,
Tirunelveli, Tamilnadu, India

S. Shajun Nisha
Prof. & Head, PG Dept of CS
Sadakathullah Appa College,
Tirunelveli, Tamilnadu, India

Abstract— Noise Reduction in Medical Images is the challenging task in image Processing. It is the basic step for its further processing like image enhancement, segmentation, feature extraction and compression. The main objective is to remove the noises as well as to preserve the actual content of the image. Noise is an unwanted information in the data. In this paper, we have taken Computed Tomography(CT) and X-Ray images.CT and X-Ray images are exploited by Gaussian and Speckle Noise. To remove these noises in the medical images, Discrete Wavelet Transform(DWT) is used.DWT are advantageous due to its Multi-resolution, sparcity and Straightforward Technique and Various Threshold Shrinkage Techniques are used such as Visu Shrink, Sure Shrink, Neigh Shrink, Normal Shrink, Heursure Shrink, Block Shrink to remove the noises. To find the best Thresholding Technique based on the performance of PSNR value.

Keywords— Noise Reduction, CT and X-Ray Images, Gaussian Noise, Speckle Noise.

I. INTRODUCTION

Noise Removal in Medical Images is the present research area in image processing. Medical Images are corrupted by various types of noises such as Gaussian, Speckle, Rician, Salt and Pepper Noise, Poisson noises during its acquisition. When Medical Images gets Noises decreases its image quality besides it will affect its further processing such as image enhancement, segmentation, etc., In this paper, we have taken CT Knee image and hand X-ray image. CT Knee image on scan is a type of X-ray that shows cross-sectional images of a specific area on your body. CT scan diagnose disease or inspect injuries on your knee. Additionally, CT scan provides more accurate diagnosis for knee problems like arthritis, collection of pus(abscess), fractured bone, infection, torn ligaments or tendons, tumors. X-ray hand image is used to detect hand injuries. There are variety of hand injuries such as axial loading in catching a falling object or hitting a solid surface with fist, crushing, sharp injuries, thermal injuries, chemical injuries. A fracture of the hand include may present with pain,swelling, stiffness, weakness. CT knee and X-ray images are corrupted by Gaussian and speckle noises. To denoising these two images, Discrete Wavelet Transform(DWT) is used.

DWT is one of the methods to remove the noise. 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 this paper, Daubechies, Biorthogonal and Cioflet Wavelets are used. To denoise the image, various threshold shrinkage techniques are used such as VisuShrink, NeighShrink, SureShrink, BlockShrink,NormalShrink, HeurSureShrink for wavelet based denoising.

A. Related Work

Image De-noising is used to produce good estimates of the original image from noisy observations. The recovered image should contain less noise than the observations while still keep sharp transitions (i.e edges)[12]- Image de-noising techniquesvary from simple thresholding to complicate model based algorithm. However simple thresholding methods can remove most of the noise.

Denoising is nothing but the removing noise from image while retaining the original quality of the image. The great challenge of image denoising is how to preserve the edges and all fine details of an image while suppression of noise. It still remains challenge for researchers as noise removal introduces artifacts and causes blurring of the images [13]. So, it is necessary to develop an efficient denoising technique to avoid such knowledge corruption. To Removing noise from natural images, Discrete Wavelet Transform(DWT) is used. Recently, researchers have studied the dependency between wavelet coefficients and shrinking them has been shown to be a useful technique for image denoising especially for additive white noise. The Wavelet Denoising scheme thresholds the wavelet coefficients arising from the standard Discrete Wavelet Transform(DWT). Wavelet gives the excellent performance in field of image denoising because of sparcity and multiresolution structure[1]. 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 selecting proper thresholding value [2]. Wavelets are localized in time and frequency whereas the standard Fourier Transform is localized in frequency.

There are several types of wavelets are available such as Orthogonal Wavelets, Biorthogonal Wavelets, with scale function, without scale function and complex wavelets. Haar, Daubechies, Symlets, Coiflets are orthogonal wavelets and Biorthogonal, Reverse Biorthogonal, Meyer Wavelets, Mexican Wavelets are Biorthogonal Wavelets. In this paper, We have taken Daubechies, Biorthogonal, Reverse Biorthogonal Wavelets in Discrete Wavelet Transform.

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 [25,24]. 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 [3]. 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 [30]. The reverse biorthogonal family uses the synthesis functions for the analysis and vice versa.

Gaussian noise is statistical noise having a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution[14].This noise model is additive in nature [10].Additive white Gaussian noise (AWGN) can be caused by poor quality image acquisition, noisy environment or internal noise in communication channels.

Speckle-noise is a granular noise degrades the quality of the active radar, synthetic aperture radar (SAR), and medical ultrasound images. Speckle noise occurs in conventional radar due to random fluctuations in the return signal from an object [15].

Visu Shrink thresholding is done by applying universal threshold proposed in [26]. It uses the hard thresholding rule. Threshold value t is directly proportional to the noise's standard deviation. With additive Gaussian noise assumption Visu Shrink exhibits better denoising performance than the universal threshold but Visu Shrink does not deal with minimizing the mean squared error.

SURE Shrink threshold was developed by Donoho and Johnston[28],[29]. For each sub-band, the threshold is determined by minimizing Stein'sUnbiased Risk Estimate (SURE) for those coefficients.

NeighShrink[21], for each noisy wavelet coefficientto be shrinked, a square neighboringwindowcentered at it.In sub band thresholding,the threshold and neighboring window size keep unchanged in all sub bands.

Normal shrink method is computationally more efficient and adaptive because the parameters required for estimatingthe threshold depends on subband data. Performance of Normal shrink is similar to Bayes shrink. But normal shrink preserves edges better than Bayes shrink.[17]

Heursure Thresholding is a mixed rule. It is a mixture of the two previous rules: Rigrsure and universal threshold.[23].

Block Shrink is a completely data-driven block thresholding approach and is also easy to implement [20]. It can decide the optimal block size and threshold for every wavelet sub band by minimizing Stein's unbiased risk estimate (SURE).

B. Motivation and Justification

Discrete Cosine Transform(DCT) and Discrete Fourier Transform(DFT) could not find out line discontinuity. But Discrete Wavelet Transform could find out line discontinuity. Fourier Transform is used for non-stationary signals. But Wavelet Transform is used in both signals that are non-stationary signals as well as stationary signals. Wavelet Transform is well Performed for both time and frequency domain. But Fourier transform is performed only frequency domain. In fourier transform time information is lost. So Fourier Transform cannot be used where both time and frequency information is needed at the same time. Motivating by these facts, Discrete Wavelet Transform is performed well in image denoising.

C. Organization of the Work

The rest of the paper is organized as follows. The Methodologies are discussed in Chapter 2. This includes Discrete Wavelet Transform, Noises and Thresholding Techniques. Experimental results are shown in Chapter 3. Performance Evaluation is discussed in Chapter 4.Finally conclusion is presented in Chapter 5.

II. METHODOLOGY

A. Outline of the Work

In this work denoising is Performed by Wavelet Transform and Threshold Shrinkage Techniques. The system is expressed as Fig.1. The input image is taken and then the Gaussian and Speckle noise is added in the image. Dicrete Wavelet transform is applied to noisy image. And then apply the several thresholding methods on the transformed image.The applied thresholding methode are namely VisuShrink, SureShrink, NeighShrink, NormalShrink, HeursureShrink, BlockShrink.Finally, Inverse Wavelet Transform is applied and get the denoised image.

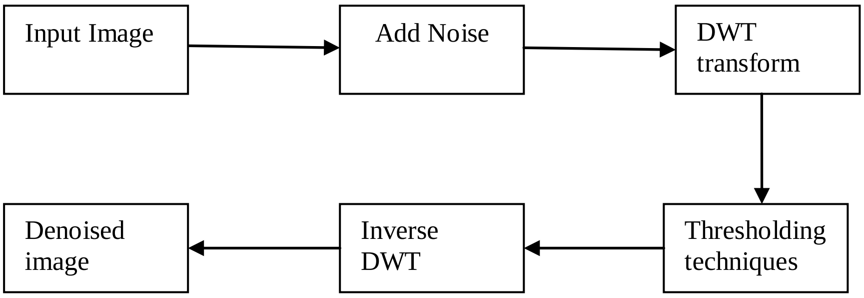


Fig.1. Block Diagram of Image Denoising Using Discrete Wavelet Transform

B. Discrete Wavelet Transform

Discrete Wavelet Transform can offer Multi-resolution analysis and can examine signals in time and frequency domain simultaneously. If any image is decomposed using Wavelet Function 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 while scaling function is used to low frequency component i.e., smooth part of an image.[8].

In DWT, the signal is passed through two complimentary filters and emerges 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. In case of a 2-D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely approximation coefficient LL(low frequency), Detailed coefficient LH(Vertical Details), HL(Horizontal details), HH(Diagonal details) as shown in Fig.2.[18]

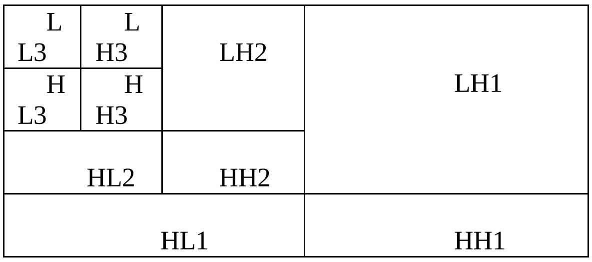


Fig.2. Three Level Decomposition in Discrete Wavelet Transform

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

i) 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[7]. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. This wavelet has finite vanishing moments. Daubechies wavelets have balanced frequency responses but nonlinear phase responses. Daubechies wavelets are useful in compression and denoising of audio signal processing because of its property of overlapping windows and high frequency coefficient spectrum reflect all high frequency changes. It is easily adapted to soft signals or images, in terms of low frequencies [16][8].

ii) Biorthogonal Wavelets:

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 [7].

C. Types of Noise

i) Gaussian Noise:

Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed. A special case is white Gaussian noise, in which the values at any pairs of times are statistically independent (and uncorrelated). In applications, Gaussian noise is most commonly used as additive white noise to yield additive white Gaussian noise. The probability density function of n-dimensional Gaussian noise is,

$$f(x) = \left((2\pi)^n \det K\right)^{-1/2} \exp\left(-(x-\mu)^T K^{-1}(x-\mu)\right)/2 \quad (1)$$

Where x is a length-n vector, K is the n-by-n covariance matrix, μ is the mean value vector, and the superscript T indicates matrix transpose.[9]

ii) Speckle Noise :

Speckle noise is multiplicative noise unlike the Gaussian and salt pepper noise. This noise can be modeled by random vale multiplications with pixel values of the image and can be expressed as

$$P = I + n * I \tag{2}$$

Where P is the speckle noise distribution image, I is the input image and n is the uniform noise image by mean o and variance v.[5].

D. Thresholding Techniques

i) Visu Shrink:

Visu shrink is a hard threshold method. The threshold value 't' here is in proportion with the standard deviation of the noise [19].Visu Shrink does not deal with minimizing the mean squared error. It can be viewed as general-purpose threshold selectors that exhibit near optimal min-max error properties and ensures with high probability that the estimates are as smooth as the true underlying functions. Visu Shrink follows the global thresholding scheme where there is a single value of threshold applied globally to all the wavelet coefficients. The formula for calculating the threshold value is: [28]

$$T = \sigma\sqrt{2\log M} \tag{3}$$

$\sigma = \text{Noise Variance}$

$M = \text{Image length}$

$$\sigma = \frac{\text{median}\{|W_k| : k = 1,2,....n\}}{0.6745}$$

Wk=Detail coefficients at the finest level

ii) Sure Shrink:

This Sure Shrink threshold was developed by Donoho and Johnston[28],[29]. For each sub-band, the threshold is determined by minimizing Stein's Unbiased Risk Estimat(SURE) for those coefficients. SURE is a method for estimating the loss $(\mu'-\mu)^2$ k in an unbiased fashion, where μ' is the estimated mean and μ is the realmean. The threshold is calculated as follows:

$$t^* = \min\left(t, \sigma\sqrt{2\log 2n}\right) \tag{4}$$

where,

σ =Standard deviation of noise

n= number of pixel elements in the image

Donoho and Johnsto[28]pointed out that SUREShrink is automatically smoothness adaptive. This implies that the reconstruction is smooth wherever the function is smooth and it jumps wherever there is a jump or discontinuity in the function[27]. This method can generate very sparse wavelet coefficients resulting in an inadequate threshold.

iii) Neigh Shrink:

The method Neigh Shrink thresholds the coefficients according to the magnitude of the squared sum of all the coefficients, i.e., the local energy, within the neighborhood window[6].The neighborhood window size may be 3×3, 5×5, 7×7, 9×9,etc. But, the authors have already demonstrated through the results that the 3×3 window is the best among all window sizes. The neighboring window of size 3* 3 centered at the coefficient to be shrinked. The shrinkage function for Neigh Shrink of any arbitrary 3×3 window centered at (i,j) is expressed as:

$$T_{ij} = 1 - \frac{T_u^2}{S_{ij}^2} \tag{5}$$

where, T_u^2 the universal threshold and S_{ij}^2 is the squared sum of all wavelet coefficients in the respective 3×3 window given by:

$$S_{ij}^2 = \sum_{n=j-1}^{j+1} \sum_{m=i-1}^{i+1} Y_{m,n}^2 \tag{6}$$

iv) Normal Shrink:

The optimum threshold value for Normal Shrink or Norm Shrink is given by [22], [11]:

$$T_{NORM} = \frac{\lambda \sigma_v^2}{\sigma_y} \tag{7}$$

Where, the parameter λ is given by the following equation:

$$\lambda = \sqrt{\log\left(\frac{L_k}{J}\right)} \tag{8}$$

Lk is the length of the sub-band at kth scale. And, J is the total number of decomposition. σv is the estimated noise variance, and σy is the standard deviation of the subband of noisy image. Normal Shrink also performs soft thresholding with the data driven subband dependent threshold TNORM, which is calculated by the equation (7).

v) Heursure Shrink :

Mixed rule is a mixture of the two previous rules: Rigrsure and universal threshold. First step calculates the variables A and B according to the system of Eq. (4)

$$\begin{cases} A = \dfrac{\sum_{i=1}^{n} |x|^2 - n}{n} \\ B = \sqrt{\dfrac{1}{n}} \left[\dfrac{\log n}{\log 2} \right]^3 \end{cases} \tag{9}$$

If A is less than B the universal form threshold is as Eq. (3) is used, else threshold selection rule based on Rigrsure is adopted. A and B are defined by [23].

vi) Block Shrink:

Block Shrink is a completely data-driven block thresholding approach and is also easy to implement[20]. It can decide the optimal block size and threshold for every wavelet subband by minimizing Stein's unbiased risk estimate (SURE). It also limits the block size search range by following[20] –

$$1 \le L \le \left\lceil \left(N/2^k \right)^{3/4} \right\rceil \tag{10}$$

III. EXPERIMENTAL RESULTS

Experiments were conducted to denoise a CT Knee image and X-Ray hand image which has a Original image shown in Fig.3(a) and Fig.3(b). Speckle and Gaussian noises were considered. To denoise the Medical images with different wavelet bases such as Daubechies, Biorthogonal 5.5, Coiflet 3 and different Thresholding techniques are shown in Fig 4.CT Knee image denoising using Daubechies wavelet bases, different Thresholding techniques and noises are presented in Fig.4(a). X-Ray hand image denoising using Daubechies wavelet bases, different Thresholding techniques and noises are presented in Fig.4(b).CT Knee image denoising using Biorthogonal 5.5 and Coiflet 3 wavelet bases, different Thresholding techniques and noises are presented in Fig.4(c). X-Ray hand image denoising using Biorthogonal 5.5 and Coiflet 3 wavelet bases, different Thresholding techniques and noises are presented in Fig.4(d).

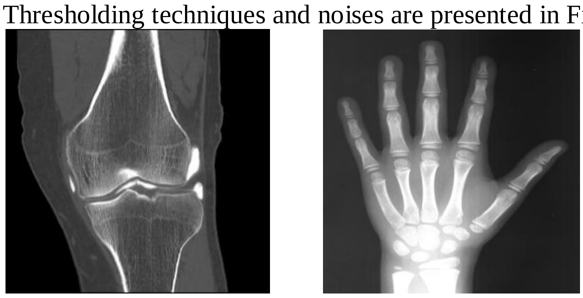


Fig-3: Original Images (a) CT Knee Image, (b) X-Ray Hand Image

Threshold	Wavelet Base	Gaussian Noise		Speckle Noise	
		Noisy Image	Denoised Image	Noisy Image	Denoised Image
Visu Shrink	DB-8				
	DB-16				
Sure Shrink	DB-8				
	DB-16				

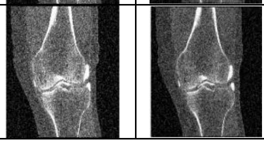
Neigh Shrink	DB-8				
	DB-16				

Fig.4(a). CT Knee image corrupted by Gaussian and Speckle noise reduction using Daubechies wavelet and different threshold shrinkage techniques

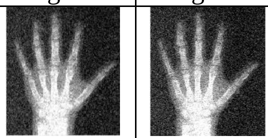
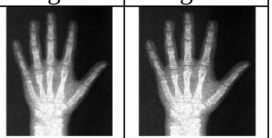
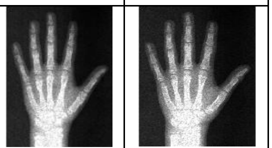
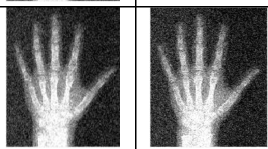
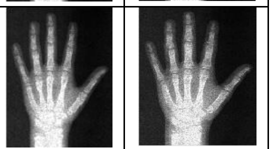
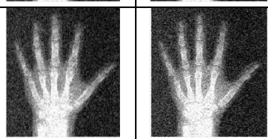
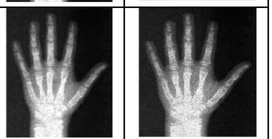
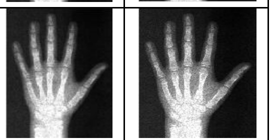
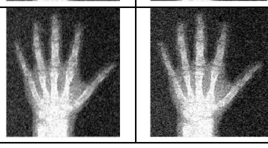
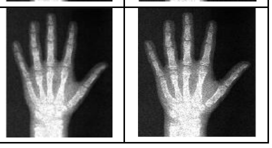
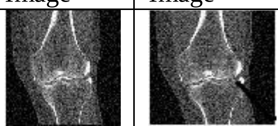
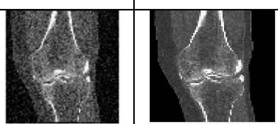
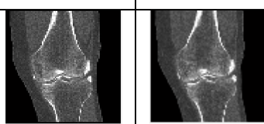
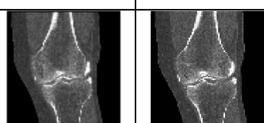
Threshold	Wavelet Base	Gaussian Noise		Speckle Noise	
		Noisy Image	Denoised Image	Noisy Image	Denoised Image
Visu Shrink	DB-8				
	DB-16				
Sure Shrink	DB-8				
	DB-16				
Neigh Shrink	DB-8				
	DB-16				

Fig.4(b).X-ray Hand image corrupted by Gaussian and Speckle noise reduction using Daubechies wavelet and different threshold shrinkage techniques

Threshold	Wavelet Base	Gaussian Noise		Speckle Noise	
		Noisy Image	Denoised Image	Noisy Image	Denoised Image
Normal Shrink	Bio 5.5				
	Coiflet 3				
Heursure Shrink	Bio 5.5				

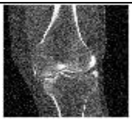
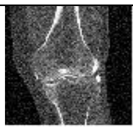
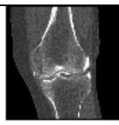
	Coiflet 3				
Block Shrink	Bio 5.5				
	Coiflet 3				

Fig.4(c). CT Knee image corrupted by Gaussian and Speckle noise reduction using biorthogonal, coiflet wavelet and different threshold shrinkage techniques

Threshold	Wavelet Base	Gaussian Noise		Speckle Noise	
		Noisy Image	Denoised Image	Noisy Image	Denoised Image
Normal Shrink	Bio 5.5				
	Coiflet 3				
Heursure Shrink	Bio 5.5				
	Coiflet 3				
Block Shrink	Bio 5.5				
	Coiflet 3				

Fig.4(d). X-ray Hand image corrupted by Gaussian and Speckle noise reduction using Biorthogonal, coiflet wavelet and different threshold shrinkage techniques

IV. PERFORMANCE ANALYSIS

A. Performance Metrics

i) 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[4].

$$\mathrm{PSNR} = 20\log10\left(255/\mathrm{RMSE}\right) \tag{11}$$

Higher the PSNR gives lower the noise in the image i.e.,higher the image quality.

B. Performance Evaluation

The performance of the Wavelet transform and different Threshold Shrinkage techniques were studied using the metrics PSNR value.The first experiment is conducted to estimate the performance of Daubechies wavelet bases with Gaussian and Speckle noise, different Thresholding techniques using CT knee and X-ray hand images. The Results are shown in Table 1 & 2. The second experiment is conducted to estimate the performance of Biorthogonal 5.5 and Coiflet 3 wavelet bases with Gaussian and Speckle Noise, different thresholding techniques using CT Knee and X-ray hand images.The Results are shown in Table 3 & 4. Finally, conclude the performance of best Shrinkage technique based on the performance of PSNR value.

Table 1 Daubechies Wavelet Bases with different Thresholding techniques & different noise in CT Knee Image

Threshold	Wavelet Base	Gaussian Noise PSNR	Speckle Noise PSNR
Visu Shrink	DB-8	20.6829	30.4673
	DB-16	20.6913	30.4974
Sure Shrink	DB-8	20.6824	30.5818
	DB-16	20.6624	30.5615
Neigh Shrink	DB-8	20.1431	30.525
	DB-16	20.2404	30.5359

Table 2 Daubechies Wavelet Bases with different Thresholding techniques & different noise in X-Ray hand Image

Threshold	Wavelet Base	Gaussian Noise PSNR	Speckle Noise PSNR
Visu Shrink	DB-8	22.0824	28.2588
	DB-16	22.0631	28.2681
Sure Shrink	DB-8	22.106	28.3347
	DB-16	22.099	28.3174
Neigh Shrink	DB-8	22.0786	28.0713
	DB-16	22.0614	28.2133

Table 3 Biorthogonal 5.5 and Coiflet 3 Wavelet Bases with different Thresholding techniques & different noise in CT Knee Image

Threshold	Wavelet Base	Gaussian Noise PSNR	Speckle Noise PSNR
Normal Shrink	Bio 5.5	20.5264	27.9982
	Coiflet 3	20.494	28.0003
Heursure Shrink	Bio 5.5	20.4889	28.0366
	Coiflet 3	20.4512	28.0631
Block Shrink	Bio 5.5	20.4965	28.0108
	Coiflet 3	20.4803	28.0282

Table 4 Biorthogonal 5.5 and Coiflet 3 Wavelet Bases with different Thresholding techniques & different noise in X-Ray hand Image

Threshold	Wavelet Base	Gaussian Noise PSNR	Speckle Noise PSNR
Normal Shrink	Bio 5.5	20.6188	30.4978
	Coiflet 3	23.8	30.5194
Heursure Shrink	Bio 5.5	20.6249	30.52
	Coiflet 3	20.698	30.5975
Block Shrink	Bio 5.5	20.6683	30.5228
	Coiflet 3	23.7639	30.5517

V. CONCLUSION

This paper presents CT Knee and X-Ray hand Image Denoising Using Different Wavelet bases with Thresholding Shrinkage Techniques. Experiments were performed to analyse the best wavelet bases such as Daubechies(Db-8,Db-16), BiOrthogonal,Coiflet. 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, BlockShrink, NormalShrink, HeurSureShrink have been applied.

Performance Metrics such as PSNR are used to evaluate the denoising effect. In CT Knee image it is observed from all wavelet bases, Coiflet performs well in association with NormalShrink for removing Gaussian noise and HeurSureShrink for removing Speckle Noise. In X-Ray image it is observed from all wavelet bases, Daubechies-8 performs well in association with SureShrink for removing Gaussian and Speckle Noise.

REFERENCES

[1] Neeraj Saini, Pramod Sethy, "Performance based Analysis of Wavelets Family forImage Compression-A Practical Approach" International Journal of ComputerApplications Volume 129 – No.9, November2015.

[2] Ms. Chipy Ashok , Ms. Anu V.S, "FPGA Implementation of Image Denoising usingAdaptive Wavelet Thresholding", International Journal of Advanced Research in Computer and Communication Engineering, Vol. 4, Issue 7, July 2015.

[3] 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.

[4] 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.

[5] Sukhjinder Kaur "Noise Types and Various Removal Techniques" International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)Volume 4, Issue 2, February 2015.

[6] M.Neelima1, Md. Mahaboob Pasha2" Wavelet Transform Based On Image DenoisinUsing Thresholding Techniques" International Journal of Advanced Research in Computer and Communication Engineering Vol. 3, Issue 9, September 2014.

[7] Sandeep kaur, Navdeep singh, "Image denoising Techniques: A Review" International Journal of innovative Research in Computer and communication engineering Vol2 Issue 6, June 2014.

[8] sezal Khera, Sheenam Malhotra, Survey on Medical Image Denoising Using various filter and Wavelet Transform, International Journal of Advanced Research in Computer Science and Software Engineering, vol4 issue 4 april 2014 www.ijarcsse.com].

[9] Sakthivel K."Contourlet Based Image Denoising Using New-Threshold Function" International Journal of Innovative Research in Computer and COmmunication Engineering, Vol.2, Special Issue 1, March 2014.

[10] R. Verma and J. Ali "A Comparative Study of Various Types of Image Noise and Efficient Noise Removal Techniques", International Journal of Advanced Research in Computer Science and Software Engineering, vol. 3, no. 10, (2013) October , ISSN: 2277 128X.

[11] Manjit Kaur. Kuldeep Sharma, Dr.Nveen Dhillon, "Image Denoising Using Wavelet Thresholding", International Journal Of EngineeringAnd Computer Science ISSN:2319-7242, Volume 2 Issue 10 October, 2013 Page No. 2932-2935.

[12] Miss Monika shukla1, Dr.Soni changlani, "A Comparative Study of Wavelet and Curvelet Transform for Image Denoising",IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) e-ISSN: 2278-2834,p-ISSN: 2278-8735. Volume 7, Issue 4 (Sep. -Oct. 2013), PP 63-68.

[13] Rupinderpal Kaur ,Rajneet Kaur "Image Denoising supported wavelet Techniques exploitation Threshold for for Medical photos"International Journal of computer Trends and Technology (IJCTT),voiume four issue eight aug2013.

[14] P. Kamboj and V. Rani, "A Brief Study Of Various Noise Model And Filtering Techniques", Journal of Global Research in Computer Science Review Article Available Online at www.jgrcs.info©, vol. 4, no. 4, (2013) April.

[15] Anutam and Rajni, "Comparative Analysis Of Filters And Wavelet Based Thresholding Methods For Image Denoising", International Journal of Computer Applications (0975 –8887) vol.86, no. 16, (2012) January.

[16] Chaudhari Anand, Chaudhari Piyush, Cheeran A.N., Aswani Yashant"Improving signal to noise ratio of low dose CT Image using Wavelet Transform" International Journal on Computer Science and Engineering(IJCSE),ISSN:0975-3397,Vol4,pp.:779-787,Issue 5 May 2012.

[17] S.Sulochana and R.Vidhya," Image Denoising using Adaptive Thresholding in Framelet Transform Domain", (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 3, No. 9, 2012.

[18] Rohit Sihag Rakesh Sharma, Varun Setia, "Wavelet Thresholding for Image-Denoising" International Journal of Computer Applications 2011.

[19] Iman Elyasi, and Sadegh Zarmehi,"Elimination Noise by Adaptive Wavelet Threshold" ,World Academy of Science, Engineering and Technology 56 2009, pp.462-466.

[20] Zhou Dengwen and Shen Xiaoliu,"Image Denoising Using Block Thresholding", IEEE Congress on Image and Signal Processing, pp. 335-338, 2008. doi:10.1109/CISP.2008.131.

[21] G. Y. Chen, T. D. Bui, A. Krzyzak, "Image denoising with neighbour dependency and customized wavelet and threshold",Pattern Recognition, 38, pp. 115–124, 2005. doi:10.1016/j.patcog.2004.05.009.

[22] Lakhwinder Kaur and Savita Gupta and R.C.Chauhan,"Image denoising using wavelet thresholding", ICVGIP, Proceeding of the Third Indian Conference On Computer Vision, Graphics & Image Processing, Ahmdabad, India Dec. 16-18, 2002.

[23] Guo D.-f., W.-H. Zhu, Z.-M. Gao, and J.-Q. Zhang, "A study of wavelet thresholding denoising", In Proc. of the 5th International Conference on Signal Processing WCCCICSP'2000, pp. 329-332, 2000.

[24] W. Sweldens, "The Lifting Scheme: A Construction of second generation wavelets", SIAM J. Math. Anal., 1997.

[25] W. Sweldens, "The Lifting Scheme: A Custom Design construction of Biorthogonal",Wavelets Appl. Comput. Harmon. Anal., Vol. 3, 1996.

[26] D. L. Donoho and I. M. Johnstone,"Adatpting to unknow smoothness via wavelet shrinkage",Journal of the American Statistical Association, vol. 90, no. 432, pp. 1200-1224, December 1995. doi:10.1.1.161.8697.

[27] D. L.Donoho and I. M. Johnstone, "Adapting to unknown smoothness via wavelet shrinkage" Journal American Statistical. Association. vol.90, no.432,pp. 1200–1224, 1995.

[28] D.L Donoho and I.M. Johnstone, "Denoising by Soft Thresholding", IEEE Transaction on Information Theor, vol.41, 1995, pp 613-627.

[29] D. L. Donoho and I. M. Johnstone, "Ideal Spatial Adaptation via Wavelet Shrinkage," Biometrika, Vol.81, No. 3, 1994, pp. 425-455.doi:10.1093/biomet/81.3.425.

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

AUTHOR DETAILS

M.Pitchammal, M.Phil., Research Scholar in Computer Science, Sadakathullah Appa College. I've completed M.Sc.,(CS) in Sadakathullah Appa College under Manonmaniam Sundaranar University. I've attended National and International Seminars.

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 Sundaranar University. 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.

