ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

A New Innovative Approach for Natural Image Denoising Using Genetic Algorithm and Thresholding

S.Aaisha Nazleem, L.S.Subbulakshmi

Programmer, Dept. of I.T., Sadakathulla Appa College, Tirunelveli, Tamilnad, India

Assistant Professor, Dept. of I.T., Sadakathulla Appa College, Tirunelveli, Tamilnad, India

ABSTRACT: The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by Speckle noise, salt & pepper noise and Poisson using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values. Natural Image De-noising plays a cardinal role in the field of image pre-processing. Natural Image is recurrently debauched by noise in its acquisition and transmission. Natural Image De-noising is the process of undesirable noise in order to reinstate the original image. This thesis presents, image de-noising scheme based on Wavelet Transform. First the input natural image is taken and then the noise is applied in the image. Among different types of noises, this thesis focuses only the speckle noise, poisson noise and salt & pepper noise. And then apply Wavelet Transform on to the noisy natural image to produce the decomposed image representation. This thesis uses four different types of Wavelet Families such as COIF4, COIF5, RBio6.8 and Sym8. Finally threshold shrinkage methods are applied to de-noise the noisy coefficients and then apply the inverse transform to get the de-noised image. Among several shrinkage methods this thesis takes only four shrinkage methods such as Visu Shrink, Neigh Shrink, Sure Shrink and Modineighshrink. After the denoising process are completed the performance are analysed by using the performance metric 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).

KEYWORDS: Image Denoising,Natural Image, DFT,DWT

I. INTRODUCTION

Image noise means unwanted signal. It is random variation of color information and brightness in images, and is usually an aspect of electronic noise. It is an undesirable by-product of image capture that adds spurious and extraneous information. Speckle is a granular 'noise' that inherently exists in and degrades the quality of the active radar, synthetic aperture radar (SAR), natural ultrasound and optical coherence tomography images. Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean grey level of a local area. Speckle noise in SAR is generally serious, causing difficulties for image interpretation. Shot noise or Poisson noise is a type of electronic noise which can be modelled by a Poisson process. In electronics shot noise originates from the discrete nature of electric charge. Shot noise also occurs in photon counting in optical devices, where shot noise is associated with the particle nature of light .Salt-and-pepper noise–Fat-tail distributed or "impulsive" noise is sometimes called salt-and pepper noise. Any image having salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. In salt-and-pepper noise corresponding value for black pixels is 0 and for white pixels the corresponding value is 1.

II. RELATED WORK

Curvelet and Wavelet Image Denoising [1]this paper describes the image denoising of Curvelet and Wavelet Image Denoising by using 4 different additive noises like Gaussian noise, Speckle noise, Poisson noise and Salt & Pepper noise and also by using 4 different threshold estimators like heursure, rigrsure, mini-maxi and squawolog for wavelet

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

and curvelet transform both. It offer exact reconstruction, stability against perturbation, ease of implementation and low computational complexity. The curvelet reconstruction offering visual sharp image and in particular, higher quality recovery of edges and of faint linear and curvilinear features . Image Denoising Using Wavelet Thresholding [2] This paper proposes and explore different wavelets methods in digital image denoising. Using several wavelets threshold technique such as SURE Shrink, Visu Shrink, and Bayes Shrink in search for efficient image denoising method. This paper extend the existing technique and provide a comprehensive evaluation of the proposed method. Wiener filtering technique is the proposed method which was compared and analysed, while the performance of all the techniques were compared to ascertain the most efficient method. Image Denoising Techniques[3] This paper is to provide a review of some of those techniques that can be used in image processing (denoising). This paper outlines the brief description of noise, types of noise, image denoising and then the review of different techniques and their approaches to remove that noise . The aim of this paper is to provide some brief and useful knowledge of denoising techniques for applications using images to provide an ease of selecting the optimal technique according to their needs. Speckle Noise is a natural characteristic of medical ultrasound images. Speckle Noise reduces the ability of an observer to distinguish fine details in diagnostic testing. It also limits the effective implementation of image processing such as edge detection, segmentation and volume rendering in 3 D. Therefore; treatment methods of speckle noise were sought to improve the image quality and to increase the capacity of diagnostic medical ultrasound images. Such as median filters, Wiener and linear filters (Persona & Malik, SRAD ... ..).The method used in this work is 2-D translation invariant forward wavelet transform, it is used in image processing, including noise reduction applications in medical imaging[4]. Mohammad Ali says [5] A novel method for image denoising which relies on the DBNs' ability in feature representation. This work is based upon learning of the noise behavior. Generally, features which are extracted using DBNs are presented as the values of the last layer nodes. The nodes in the last layer of trained DBN are divided into two distinct groups of nodes. After detecting the nodes which are presenting the noise. A reduction of 65.9% in average mean square error (MSE) was achieved when the proposed method was used for the reconstruction of the noisy images. A novel self-learning based image decomposition framework. Based on the recent success of sparse representation, the proposed framework first learns an over-complete dictionary from the high spatial frequency parts of the input image for reconstruction purposes. This method perform unsupervised clustering on the observed dictionary atoms (and their corresponding reconstructed image versions) via affinity propagation, which allows us to identify image-dependent components with similar context information. The proposed and are able to automatically determine the undesirable patterns (e.g., rain streaks or Gaussian noise) from the derived image components directly from the input image, so that the task of single-image denoising can be addressed[6]. In Adaptive Multi-Column Deep Neural Networks with Application to Robust Image Denoising[7] Stacked sparse denoising autoencoders (SSDAs) have recently been shown to be successful at removing noise from corrupted images. However, like most denoising techniques, the SSDA is not robust to variation in noise types beyond what it has seen during training. This paper eliminate the need to determine the type of noise, let alone its statistics, at test time and even show that the system can be robust to noise not seen in the training set. It show that state-of-the-art denoising performance can be achieved with a single system on a variety of different noise types. Additionally, we demonstrate the efficacy of AMC-SSDA as a preprocessing (denoising) algorithm by achieving strong classification performance on corrupted MNIST digits. Contourlet Based Image Denoising[8] This paper proposed contour let based image denoising algorithm which can restore the original image corrupted by salt and pepper noise, Gaussian noise, Speckle noise and the poisson noise. The noisy image is decomposed into sub bands by applying contour let transform, and then a new thresholding function is used to identify and filter the noisy co efficient and take inverse transform to reconstruct the original image. This contourlet technique is computationally faster and gives better results compared to the existing wavelet technique. But this proposed method is not well suited for the removal of salt and pepper noise from the original image. Salt and Pepper Noise Removal[9] Images may be corrupted by salt and pepper impulse noise due to noisy sensors or channel transmission errors. A denoising method by detecting noise candidates and enforcing image sparsity with a patch-based sparse representation is proposed. Compared with traditional impulse denoising methods, including adaptive median filtering, total variation and Wavelet, the new method shows obvious advantages on preserving edges and achieving higher structural similarity to the noise-free images. Parallel Edge Preserving Algorithm for Salt and Pepper Image Denoising [10] this paper a two-phase filter for removing "salt and pepper" noise is proposed. In the first phase, an adaptive median filter is used to identify the set of the noisy pixels; in the second phase, these pixels are restored according to a regularization method, which contains a data-fidelity term reflecting the impulse noise characteristics.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

III.METHODOLOGY

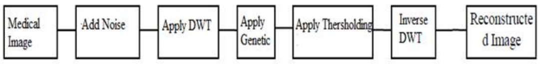


Fig.1 Image denoising block diagram for DWT & Contourlet transform

The overall block diagram of the proposed method is shown in Fig.1.1. In this paper decompose the image using discrete wavelet and then applied genetic algorithm for feature selection and threshold for noise removal. The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Additive random noise can easily be removed using simple threshold methods. In this paper Visu Shrink, Neigh Shrink, Sure Shrink and Modineighshrink.Min-Max Shrink are used. De-noising of natural images corrupted by Speckle noise and Poisson using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values. The further details of these modules are discussed below:

Step 1: Input Image Choosing

This is the first step of the proposed method. In this step the input image is get from the user via open dialog box control.

Step 2: Apply Noise

This is the second step of the proposed method. In this step the input is corrupted by noise. Image noise is random (not present in the object imaged) variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information.In this paper two types of noises are used. They are Speckle Noise and Poisson Noise.

Speckle is a granular 'noise' that inherently exists in and degrades the quality of the active radar, synthetic aperture radar (SAR), natural ultrasound and optical coherence tomography images. The vast majority of surfaces, synthetic or natural, are extremely rough on the scale of the wavelength. Poisson noise is a type of electronic noise which can be modelled by a Poisson process. In electronics shot noise originates from the discrete nature of electric charge. Shot noise also occurs in photon counting in optical devices, where shot noise is associated with the particle nature of light.In this paper, we have used three types of noises. There are speckle noise, Poisson noise, salt and pepper noise.

Step 3:Apply Discrete Wavelet Transform

This is the third step of the proposed method. In this step the noisy image is decomposed using 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 as 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. An image can be decomposed into a sequence of different spatial resolution images using DWT. These are also known by other names, the sub-bands may be respectively called a1 or the first average image, h1 called horizontal fluctuation, v1 called vertical fluctuation and d1 called the first diagonal fluctuation.

The wavelet transform has gained widespread acceptance in signal processing and image compression. Recently the JPEG committee has released its new image coding standard, JPEG-2000, which has been based upon DWT. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet called mother wavelet by dilations and shifting. The DWT has been introduced as a highly efficient and flexible method for sub band decomposition of signals. The 2D-DWT is nowadays established as a key operation in image processing .It is multi-resolution analysis and it decomposes images into wavelet coefficients and scaling function. In Discrete Wavelet Transform, signal energy concentrates to specific wavelet coefficients. This characteristic is useful for compressing images.

The sub-image a1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

trends along columns. The next level of wavelet transform is applied to the low frequency sub band image LL only. The Speckle noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be thresholded. Several families are available in DWT. Among those this paper consider four families such as coif4, coif5, rbio6.8 and sym8.

Step 4: Feature Selection using Genetic Algorithm

This is the fourth step of the proposed method. In this step the noisy wavelet coefficient feature are selected using genetic algorithm. In a genetic algorithm, a population of strings (called chromosomes or the genotype of the genome), which encode candidate solutions (called phenotypes) to an optimization problem, evolves toward better solutions. Solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. The algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

A typical genetic algorithm requires: A genetic representation of the solution domain

Step 5: Apply Thersholding

This is the fifth step of the proposed method. In this step the image denoised by using thresholding approach. Here, the threshold plays an important role in the denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details. Normally, hard thresholding and soft thresholding techniques are used for such de-noising process. Hard thresholding is a keep or kill rule whereas soft thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule. The following are the methods of threshold selection for image de-noising based on wavelet transform.

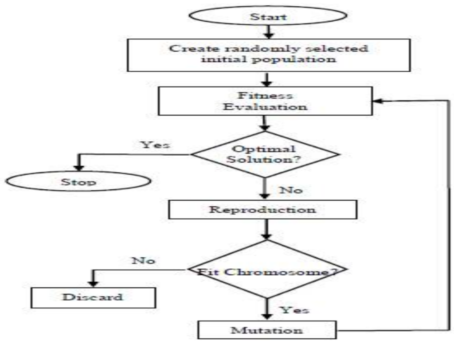


Fig.1.2. Flow Chart of the Genetic Algorithm

Method1: SureShrink

SureShrink is a thresholding technique in which adaptive threshold is applied to sub band, but a separate threshold is computed for each detail sub band based upon SURE (Stein.s Unbiased Estimator for Risk), a method for estimating the loss in an unbiased fashion. The optimal λ and L of every sub band should be data-driven and should minimize the Mean Squared Error (MSE) or risk of the corresponding sub band. Fortunately, Stein has stated that the MSE can be estimated unbiased from the observed data. Neighshrink can be improved by determining an optimal threshold and neighbouring window size for every wavelet sub band using the Stein‟s Unbiased Risk Estimate (SURE). For ease of notation, the Ns noisy wavelet coefficients from sub band s can be arranged into the 1-D vector. Similarly, the unknown noiseless coefficients from subband „s‟ is combined with the corresponding 1-D vector. Stein shows that, for almost any fixed estimator based on the data , the expected loss (i.e risk) $E\{\|\underline{\theta}^{s}-\theta^{s}\|_{s}^{s}\}$ can be estimated unbiasedly. Usually, the noise standard deviation σ is set at 1, and then

$$E\{\|\overline{O}_s - O_s\|_2^2\} - N_s + E\{\|g(w_s)\|_2^2 + 2\nabla . g(w_s)\}$$

$$g(w_s) = \{g_n\}_{n=1}^{N_s} = \overline{\theta}_s - w_s, \nabla . g = \sum_n \partial g_n / \partial w_n$$

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

Method 2: Visushrink

Heshol can be calculated using formula T= σ√2logn2. This method performs well under a number of applications because wavelet transform has the compaction property of having only a small number of large coefficients. All the rest wavelet coefficients are very small. This algorithm offers the advantages of smoothness and adaption.

Method 3: Neighshrink

Let d(i,j) denote the wavelet coefficients of interest and B(i,j) is a neighborhood window around d(i,j). Also let S2=Σd2(i,j) over the window B(i,j). Then the wavelet coefficient to be thresholded is shrinked according to the formulae, d(i,j)= d(i,j)* B(i,j) where the shrinkage factor can be defined as B(i,j) = (1- T2/ S2(i,j))+, and the sign + at the end of the formulae means to keep the positive value while set it to zero when it is negative.

Method 4: Mod neighshrink

During experimentation, it was seen that when the noise content was high, the reconstructed image using Neighshrink contained mat like aberrations. These aberrations could be removed by wiener filtering the reconstructed image at the last stage of IDWT. The cost of additional filtering was slight reduction in sharpness of the reconstructed image. However, there was a slight improvement in the PSNR of the reconstructed image using wiener filtering. The de-noised image using Neighshrink sometimes unacceptably blurred and lost some details. This problem will be avoided by reducing the value of threshold itself. So, the shrinkage factor is given by B(i,j) = (1- (3/4)*T2/ S2(i,j))

Step 6: Apply Inverse Wavelet Transform

This is the final step of the proposed method. In this step the inverse wavelet transform is applied and get the denoised image.

IV.EXPERIMENTAL RESULTS

Genetic Algorithm and Thresholding to verify its effectiveness. One is use objective data such as RMS,PSNR,MSSIM to objective analyzed its performance. Experimental results were conducted to denoise a normal image such as cameraman shown in Fig.1 and Fig 2. Speckle, Poisson noise and Salt & Pepper noise were considered. Genetic Algorithm and Thresholding used and their various denoised images is shown in Fig.3 and Fig.4.

Thresholding Shrinkage techniques		Speckle Noise	Poisson Noise	Salt and pepper Noise
Noisy Image				
Denoised image using Different Wavelet Families	Coiflets 4			
	Coiflets 5			
	Reverse Biorthog onal			
	Symlet 8			

Fig 1 De-noising using wavelet bases with thresholding techniques

Noisy Type		Speckle Noise	Poisson Noise	Salt and pepper Noise
Noisy Image				
Denoised image using Decomposing levels	1			
	2			
	3			

Fig 2Denoising image using Decomposing levels with threshold techniques

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

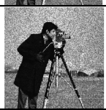
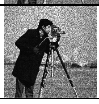
Noise Variance	Noisy Image	
	Speckle Noise	Salt and pepper noise
0.01		
0.02		
0.04		
0.06		

Fig 3 Noisy image with noise variance for speckle and salt and pepper noise

Noise Variance	Noisy Image	
	Speckle Noise	Salt and pepper noise
0.01		
0.02		
0.04		
0.06		

Fig 4 Denoised image with noise variance for speckle and salt and pepper noise

V. PERFORMANCE EVALUATION

PERFORMANCE METRICS

i. Peak Signal-to-Noise-Ratio

The peak signal-to-noise ratio (PSNR) is used to evaluate the quality between the denoised image and the original image. The PSNR formula is defined as follows:

$$\mathbf{PSNR} = 10 \times \log 10 \frac{255 \times 255}{\frac{1}{H \times W} \sum_{x=0}^{H-1} \sum_{y=0}^{W-1} [f(x,y) - g(x,y)]^2} \mathbf{dB}$$

where H and W are the height and width of the image, respectively; and f(x,y) and g(x,y) are the grey levels located at coordinate (x,y) of the original image and denoised image, respectively.

To analysis the performance of the three methods by using the performance metrics which are mentioned above. This is shown in the below tables and graphs.

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

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

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

ii. Root Mean Square Error(RMSE)

Mean square error (MSE) is given by

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

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

$$RMSE = \sqrt{MSE}$$

iii. Mean Structural Similarity Index Measure(MSSIM)

The Structural Similarity Index between two images is computed as :

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

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

$$\sigma_x = \left(\sum_{i=1}^{N} w_i (x_i - \mu_x)^2\right)^{1/2}, \qquad \sigma_{xy} = \sum_{i=1}^{N} (x_i - \mu_x)(y_i - \mu_y), \qquad C_1 = (K_1 L)^2, and C_2 = (K_2 L)^2$$

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

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

$$MSSIM = \sqrt{SSIM}$$

To analysing the performance by using performance metrics which are shown in the above. The result is shown in below tables.

Table.1.Decomposition levels with poisson Noise

Metrics	Wavelet Decomposition Level	Poisson Noise			
		Visu Shrink	**Neigh Shrink**	**Sure Shrink**	**Modneigh Shrink**
PSN	1	27.4216	27.4337	27.4173	27.3855
	2	22.0409	22.0656	22.0747	22.0615
	3	18.6575	18.6569	18.6484	18.6621
MSS	1	0.64586	0.64767	0.6464	0.64336
	2	0.52498	0.52782	0.52894	0.52467
	3	0.42249	0.42463	0.42552	0.42316
NAE	1	0.068464	0.06852	0.068696	0.06893
	2	0.11241	0.11193	0.11158	0.11237
	3	0.15545	0.15525	0.15534	0.15522
NCC	1	1.0002	1.0002	0.99985	0.99994
	2	0.98849	0.98726	0.98812	0.9878
	3	0.96832	0.96889	0.96853	0.9685

Table.2.Noise variance with speckle noise

Metircs	**Speckle noise**			
Noice Variance	**0.01**	**0.02**	**0.04**	**0.06**
PSNR	25.6569	22.6331	19.6118	17.8568
MSSIM	0.61287	0.53271	0.45561	0.41565
NAE	0.08546	0.12135	0.17191	0.21066
NCC	0.99865	0.99945	0.99898	0.99805

Table.3. Noise variance with salt & pepper noise

Metircs	**Salt & pepper noise**			
Noice Variance	0.01	0.02	0.04	0.06
PSNR	25.4053	22.1805	19.1857	17.1537
MSSIM	0.79437	0.63342	0.46082	0.33628
NAE	0.01005	0.02181	0.04226	0.06653
NCC	0.99806	0.99673	0.99433	0.99045

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

VI. CONCLUSION AND FUTURE WORK

In this thesis, Wavelet based different thresholding techniques are used to enhance the quality of the input natural Image. Mainly in the case of existence of Speckle noise, Salt & Pepper and Poisson Noise, the shrinkage approaches are very much needed with the intention of improving the natural image diagnostic examination. The Wavelet based Thershlding techniques for noise removal gives superior quality of denoising effect with enhanced effect of denoised images. The thersholding technique is applied on every subband of the Wavelet coefficient images for enhancing the denoising performance. Among several shrinkage methods this thesis considers only Visu Shrink, Neigh Shrink, Sure Shrink and Modineighshrink. Experiments were performed to analyse the best suitable shrinkage methods for Wavelet against different noises(Speckle noise, Poisson noise and Salt & Pepper noise). And also this thesis use four different types of Wavelet Families such as COIF4, COIF5, RBio6.8 and Sym8The shrinkage approaches take account of the use of nearest coefficients. So it supply the better worth of denoising images. Performance Metrics such as Peak Signal to Noise Ratio(PSNR), Mean Structural Similarity Index Measure(MSSIM), Normalized Cross Correlation(NCC) , Normalized Absolute Error(NAE) are used to evaluate the denoising effect of output images. It is observed from Wavelet decomposed subband with the help of thersholding approached. From the conducted experimental research one thing is clearly proved that the wavelet shrinkage approach performs well and enhance the denoising performance. In speckle noice wavelet coif4 and threshold neigh shrink gives the best result. In salt and pepper noice wavelet sym8 and threshold visu shrink gives the best result. In poisson noice wavelet sym8 and threshold neigh shrink gives the best result.

REFERENCES

[1]Monika Shukla, Dr. Soni Changlani, Mr. Ayoush Johari " Study of Curvelet and Wavelet Image Denoising by Using Different Threshold Estimators" International Journal of Electrical, Electronics ISSN No. (Online): 2277-2626 and Computer Engineering 3(1): 48-54(2014).

[2] Okuwobi Idowu Paul Yonghua Lu "Image Denoising Using Wavelet Thresholding Techniques" International Journal of Education and Research Vol. 2 No. 2 February 2014.

[3] Monika Raghav, Sahil Raheja "Image Denoising Techniques" International Journal Of Engineering And Computer Science ISSN:2319-724Volume 3 Issue 5 May, 2014 Page No. 5637-5641.

[4] R. Bouchouareb, N. Hedjazi, and D.Benatia "Denoising Medical Ultrasound Images and Error Estimate by Translation-Invariant Wavelets" International Journal of Signal Processing, Image Processing and Pattern Recognition Vol.7, No.1 (2014), pp.193-202 http://dx.doi.org/10.14257/ijsip.2014.7.1.18 .

[5] Mohammad Ali ,Keyvanrad,Mohammad Mehdi Homayounpour"Deep Belief Networks for Image Denoising" arXiv:1312.6158v2 [cs.LG] 2 Jan 2014.

[6] De-An Huang, Li-Wei Kang, Yu-Chiang Frank Wang, Chia-Wen Lin, "Self-Learning Based Image Decomposition With Applications to Single Image Denoising" IEEE TRANSACTIONS ON MULTIMEDIA, VOL. 16, NO. 1, JANUARY 2014 83.

[7] Forest Agostinelli Michael R. Anderson Honglak Lee "Adaptive Multi-Column Deep Neural Networks with Application to Robust Image Denoising"

[8] Sakthivel K."Contourlet Based Image Denoising Using New-Threshold Function" International Journal of Innovative Research in Computer and Communication Engineering (An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014.

[9] Di Guo, Xiaobo Qu, Xiaofeng Du, Keshou Wu, and Xuhui Chen "Salt and Pepper Noise Removal with Noise Detection and a Patch-Based Sparse Representation" Hindawi Publishing Corporation Advances in Multimedia Volume 2014, Article ID 682747, 14 pages.

[10] M. Aldinucci, C. Spampinato, M. Drocco, M. Torquati, S. Palazzo "A Parallel Edge Preserving Algorithm for Salt and Pepper Image Denoising"

[11] Hari Om, Mantosh Biswas "An Improved Image Denoising Method Based on Wavelet Thresholding" Journal of Signal and Information Processing, 2012, 3, 109-116 .

[12] Kamlesh Dixit, Mohit Khandelwal "Digital Image Denoising Using Histogram and Dynamic Filters" InternationalJournal of Computer & Organization Trends – Volume 5 – February 2014