A PROPOSED APPROACH FOR IMAGE DE-NOISING

Tajinder Singh[1] , Mandeep Kaur Sandhu[2]

[1] Department of Information Technology BCET Gurdaspur, Punjab, India

[2] Department of Information Technology GIMET Amritsar, Punjab, India

Abstract: *One of the main challenges facing in the image de-noising is to identify the type of noise and to implement the technique for removing the noise from images. Fewer knowledge about the noise means lesser the performance. This situation in image de-noising is critical and can be handled by implementing various techniques for de-noising the image. This paper describes the proposed approach for image de-noising using wavelets. The various algorithms are implemented and critically analyzed. Relevant issues such as Noise Removal, the influence of Noise, and system evaluation are discussed, and several parameters are described for the performance metrics with the comparison of existing techniques. Finally the proposed technique is implemented and comprehensively analyzes to test its efficiency considering PSNR, Time Complexity, MAE and MSE.*

Keywords: Image De-Noising, Wavelet, DWT, CWT, Noise.

I. Introduction

An image may be defined as a two-dimensional function, $f(x, y)$, where x and y are spatial (plane) coordinates, and the amplitude of f at any pair coordinates (x, y) is called the intensity or gray level of the image at that point [2][4]. When (x, y) and the amplitude values of f are all finite, discrete quantities, we call the image a digital image as shown in figure 1.Therefore, a digital image is a two-dimensional array of small square regions known as pixels.

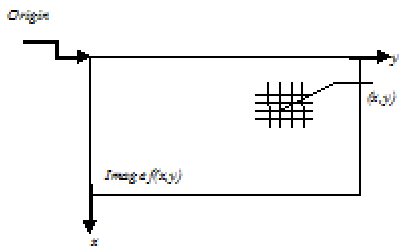


Figure 1.1 “Representation of an Image in 2D-Plane”

Ii. Image De-Noising

There are two basic approaches to image de-noising, spatial filtering methods and transform domain filtering methods.

A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters.

A. Non-Linear Filters

With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum.

B. Linear Filters

A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise.

Iii. Image Metrics

The quality of an image is examined by objective evaluation as well as subjective evaluation. For subjective evaluation, the image has to be observed by a human expert. The human visual system (HVS) is so complicated that it is not yet modelled properly. Therefore, in addition to objective evaluation, the image must be observed by a human expert to judge its quality. There are various metrics used for objective evaluation of an image. Some of them are mean squared error (MSE), mean absolute error (MAE) and peak signal to noise ratio (PSNR) [7] [10].

Then, MSE and RMSE are defined as:

$$\mathrm{MSE} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[\hat{f}(x,y) - f(x,y)]^2}{\mathrm{MxN}}$$

The MAE is defined as:

$$\mathrm{MAE} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[\hat{f}(x,y) - f(x,y)]}{\mathrm{MxN}}$$

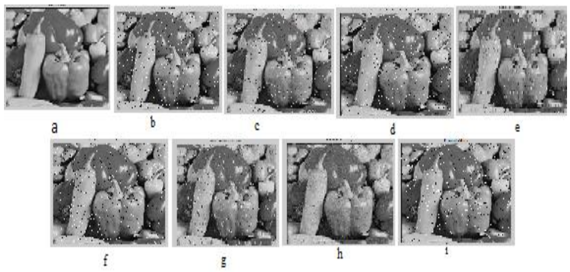
Since the Mean square error (MSE) represents the noise power and the peak signal power is unity in case of normalized image signal, the image metric peak signal to noise ratio (PSNR) is defined as:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{1}{\mathrm{MSE}}\right)\mathrm{dB}$$

The PSNR is defined in logarithmic scale, in dB. It is a ratio of peak signal power of corrupting noise that affects the fidelity of its representation.

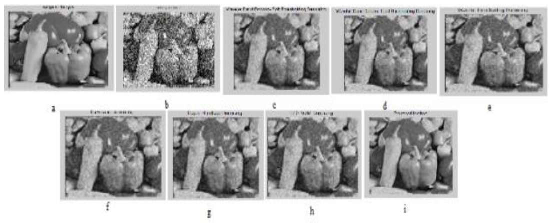
Iv. Implementation Of Proposed Approach

(a) Results for Salt& peppers noise with standard deviation σ= 0.4 for Peppers Image



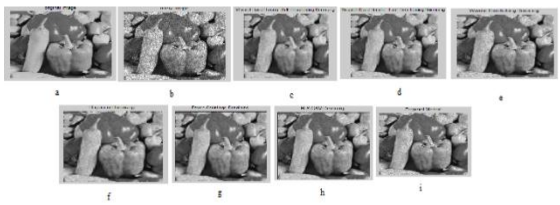
Results for image “Peppers” Noise type= Salt & Peppers and standard deviation (σ) =0.4 (a) Original image of Peppers(256*256) (b) Noisy Image of Peppers(256*256) (c) De-noised of “Peppers” by Donoho Soft Thresholding (d) De-noised of “Peppers” by Donoho Hard Thresholding (e) De-noised of “Peppers” by Wavelet Thresholding (f) De-noised of “Peppers” by Bayesian De-Noising (g) De-noised of “Peppers” by Bayes Shrinkage De-Noising (h) De-noised of “Peppers” by BLS-GSM De-Noising (i) De-noised of “Peppers” by Proposed Method.

(b) Results for Zero Mean Gaussian white Noise with standard deviation σ= 0.4 for Peppers image



Results for image “Peppers” Noise type= Zero Mean Gaussian Noise and standard deviation (σ) =0.4 (a) Original image of Peppers (256*256) (b) Noisy Image of Peppers(256*256) (c) De-noised of “Peppers” by Donoho Soft Thresholding (d) De-noised of “Peppers” by Donoho Hard Thresholding (e) De-noised of “Peppers” by Wavelet Thresholding (f) De-noised of “Peppers” by Bayesian De-Noising (g) De-noised of “Peppers” by Bayes Shrinkage De-Noising (h) De-noised of “Peppers” by BLS-GSM De-Noising (i) De-noised of “Peppers” by Proposed Method.

(c) Results for Speckle Noise with standard deviation σ= 0.4 for Peppers image



Results for image “Peppers” Noise type= Speckle Noise and standard deviation (σ) =0.4 (a) Original image of Peppers (256*256) (b) Noisey Image of Peppers(256*256) (c) De-noised of “Peppers” by Donoho Soft Thresholding (d) De-noised of “Peppers” by Donoho Hard

Thresholding (e) De-noised of “Peppers” by Wavelet Thresholding (f) De-noised of “Peppers” by Bayesian De-Noising (g) De-noised of “Peppers” by Bayes Shrinkage De-Noising (h) De-noised of “Peppers” by BLS-GSM De-Noising (i) De-noised of “Peppers” by Proposed Method.

V. Proposed Approach

The detailed algorithm for the proposed approach is given as follows.

1. Assume *D*(*i*, *j*) is a window centred at pixel *d*(*i*, *j*) with a window size of 2*k* + 1 (where *k* is an integer). In this case, the window size is equal in both dimensions and has to be an odd number, such as 3, 5, 7, etc.
2. Calculate the median value of pixel by using:

$$Y(m,n) = \text{median}\ \{x\ (i, j), i, j\ ) \in w\}$$

3. To calculate the local mean and local standard deviation, it is necessary to first obtain the sum *S* (*i*, *j*) of the entire *N (i,j)* pixel values in the moving window.

$$S(i,j) = \sum_{m=i-k}^{i+k} \sum_{n=j-k}^{j+k} d(m,n) \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

$$N(i,j) = (2k+1)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

4. The local mean μ(*i*, *j*) of the moving window *D* is then computed as

$$\mu(i,j) = \frac{S(i,j)}{N(i,j)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{'}(3)$$

5. The local standard deviation σ(*i*, *j*) is calculated as

$$\sigma(i,j) = \frac{\sqrt{\sum_{m=i-k}^{i+k} \sum_{n=i-k}^{i+k} (d(i,j)-\mu(i,j))^2}}{N(i,j)} \ldots\ldots\ldots\ldots.(4)$$

6. Valid pixels are then identified and labelled in a separate mask with moving window *L* cantered at *l*(*i*, *j*). For every pixel *l*(*m*, *n*)

$$l(m,n) = 0 \text{ if } d(m,n) < LB(i,j) \text{ or } d(m,n) > UB(i,j) \ldots \quad (5)$$

$$l(m,n) = 1 \quad \text{if } LB(i,j) \ \leq\ d(m,n) \leq UB(i,j) \ldots\ldots\ldots \quad (6)$$

Where $i - k \leq m, n \leq i + k$,

0 indicates noise and 1 a valid pixel. It is important to note that a non-central pixel outside the range in the current moving window may not be a speckle in another moving window centred on it.

7. Reconstruction of wavelet decomposition is done.

8. End.

Vi. Mse Vs Noise Variance (Sigma) Of Salt & Peepers Noise For Peppers (256 X 256) Image

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	Basian Thresholding	Bayes Shrinkage Denoising	BLS De-noising	Proposed
1	0.1	0.0054	0.0098	0.0099	0.0093	0.0094	0.0034	0.0025
2	0.2	0.003	0.0037	0.006	0.0034	0.0031	0.0034	0.0023
3	0.3	0.0042	0.0042	0.005	0.0042	0.0042	0.0043	0.0038
4	0.4	0.0057	0.0057	0.0062	0.0057	0.0057	0.0058	0.0052
5	0.5	0.0075	0.0075	0.0077	0.0075	0.0075	0.0075	0.0069

MSE for Peppers with Salt & Peppers Noise

Vii. Mae Vs Noise Variance (Sigma) Of Salt & Peepers Noise For Peppers (256x256) Image

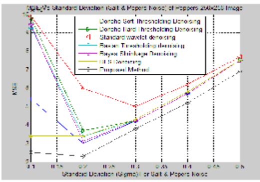
Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.1	0.0629	0.072	0.0638	0.0729	0.0729	0.0725	0.0513
2	0.2	0.0694	0.0725	0.89	0.0713	0.0697	0.0735	0.0527
3	0.3	0.0853	0.0853	0.0893	0.0853	0.0853	0.086	0.0751
4	0.4	0.1013	0.1013	0.1037	0.1013	0.1013	0.1018	0.1013
5	0.5	0.1184	0.1184	0.1191	0.1184	0.1184	0.1186	0.1184

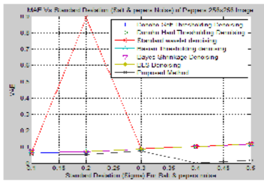
MAE for Peppers with Salt & Peppers Noise

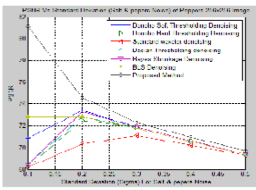
Viii. Psnr (In Db) Vs Noise Variance (Sigma) Of Salt & Peepers Noise For Peppers (256x256) Image

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.1	70.832	68.2196	68.1709	68.4335	68.4105	72.7984	81.1023
2	0.2	73.3971	72.4829	70.322	72.8098	73.2786	72.7917	74.5589
3	0.3	71.8554	71.8484	71.1015	71.8514	71.8554	71.7521	72.2771
4	0.4	70.5804	70.5804	70.1934	70.5804	70.5804	70.5031	70.9309
5	0.5	69.3889	69.3889	69.2887	69.3889	69.3889	69.3633	69.7169

PSNR for Peppers with Salt & Peppers Noise


a


b


c

The above figure shows the relationship between MSE and standard deviation(σ) of Peppers image using Donoho Soft Thresholding (Blue Colour), De-Noised by Donoho Hard Thresholding (Green Colour), De-noised by Wavelet Thresholding (Red Colour), De-Noised by Basian Thresholding (Light Blue Colour), De-noised by Bayes Shrinkage (Magenta Colour), De-noised by BLS (Yellow Colour), De-noised by Proposed Approach (Gray Colour).

It is very clear from the plot that there is decrease in MSE value of image with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image.

Ix. Mse Vs Noise Variance (Sigma) Of Zero-Mean Gaussian White Noise for Peppers (256x256) Image

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.01	0.0012	0.0015	0.0017	0.0016	0.0015	0.0016	0.0009
2	0.02	0.0015	0.0014	0.0012	0.0014	0.0014	0.0013	0.0010
3	0.03	0.0018	0.0017	0.0015	0.0017	0.0017	0.0015	0.0013
4	0.04	0.002	0.0019	0.0018	0.0019	0.0019	0.0018	0.0015
5	0.05	0.0022	0.0022	0.0021	0.0022	0.0022	0.002	0.0013

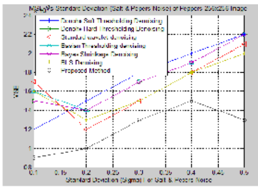
MSE for Peppers with Gaussian Noise

X. Mae Vs Noise Variance (Sigma) Of Zero-Mean Gaussian White Noise for Peppers (256x256) Image

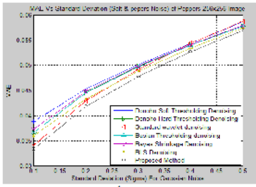
Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.01	0.0388	0.0366	0.0341	0.0366	0.0373	0.036	0.0334
2	0.02	0.0453	0.0446	0.0429	0.0445	0.0448	0.0433	0.0418
3	0.03	0.0501	0.0498	0.0492	0.0497	0.0499	0.0488	0.0478
4	0.04	0.0543	0.0541	0.0543	0.054	0.0541	0.0534	0.0527
5	0.05	0.0586	0.0578	0.0587	0.0578	0.0579	0.0574	0.0569

Xi. Psnr (In Db) Vs Noise Variance (Sigma) Of Gaussian White Noise for Peppers (256x256) Image

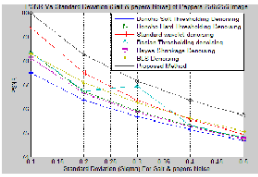
Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.01	77.4944	78.3433	79.3841	78.3506	78.1186	78.2808	79.973
2	0.02	76.3659	76.7173	77.4944	76.7471	76.6467	77.1048	78.2464
3	0.03	75.6698	75.9229	76.3643	76.9409	75.8712	76.2622	77.1591
4	0.04	75.1268	75.294	75.5615	75.3073	75.2486	75.6031	76.3528
5	0.05	74.679	74.7888	74.9384	74.7975	74.741	75.0587	75.7257



a



b



c

The above figure shows the relationship between MSE and standard deviation(σ) of Peppers image using Donoho Soft Thresholding (Blue Colour), De-Noised by Donoho Hard Thresholding (Green Colour), De-noised by Wavelet Thresholding (Red Colour), De-Noised by Basian Thresholding (Light Blue Colour), De-noised by Bayes Shrinkage (Magenta Colour), De-noised by BLS (Yellow Colour), De-noised by Proposed Approach (Gray Colour).

It is very clear from the plot that there is decrease in MSE value of image with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image.

Xii. Mse Vs Noise Variance (Sigma) Of Speckle Noise For Peppers (256x256) Image

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.01	0.0012	0.0013	0.0015	0.0016	0.0015	0.0016	0.0008
2	0.02	0.0014	0.0013	0.0012	0.0014	0.0014	0.0013	0.0009
3	0.03	0.0010	0.0016	0.0015	0.0017	0.0017	0.0009	0.0010
4	0.04	0.0011	0.0015	0.0018	0.0019	0.0019	0.0018	0.0011
5	0.05	0.0012	0.0011	0.0011	0.0011	0.0011	0.0011	0.0007

MSE for Peppers with Speckle Noise

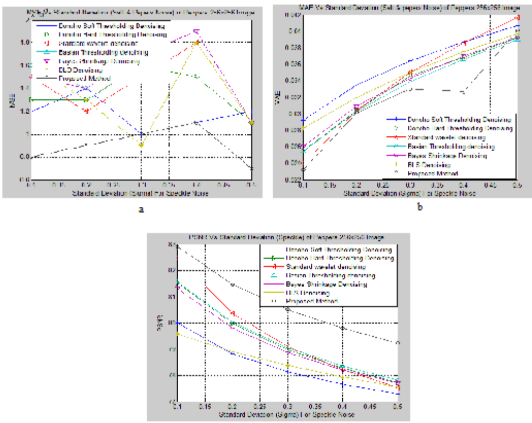
Xiii. Mae Vs Noise Variance (Sigma) Of Speckle Noise for Peppers (256x256) Image

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.01	0.0292	0.0255	0.024	0.0254	0.026	0.0282	0.0232
2	0.02	0.0335	0.0304	0.0304	0.0303	0.0309	0.032	0.0301
3	0.03	0.0364	0.0346	0.035	0.0339	0.0343	0.035	0.033
4	0.04	0.0387	0.0368	0.0386	0.0366	0.037	0.0375	0.0327
5	0.05	0.0407	0.0392	0.0417	0.039	0.0393	0.0397	0.0401

MAE for Peppers with Speckle Noise

Xiv. Psnr (In Db) Vs Noise Variance (Sigma) Of Speckle Noise for Lena (256x256) Image

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.01	79.9874	81.5247	82.4758	81.5501	81.3111	79.573	82.9118
2	0.02	78.8182	79.9771	80.3652	80.0239	79.7932	78.9005	81.4702
3	0.03	78.1365	78.9778	79.1034	79.0471	78.8635	78.3713	80.5086
4	0.04	77.6531	78.2754	78.2151	78.3605	78.2069	77.9302	79.7956
5	0.05	77.2808	77.7306	77.5436	77.8162	77.7159	77.5597	79.228



a b c

The above figure shows the relationship between MSE and standard deviation(σ) of Peppers image using Donoho Soft Thresholding (Blue Colour), De-Noised by Donoho Hard Thresholding (Green Colour), De-noised by Wavelet Thresholding (Red Colour), De-Noised by Basian Thresholding (Light Blue Colour), De-noised by Bayes Shrinkage (Magenta Colour), De-noised by BLS (Yellow Colour), De-noised by Proposed Approach (Gray Colour).

It is very clear from the plot that there is decrease in MSE value of image with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image.

Xv. Execution Time (Sec.) Vs. Noise Variance (Sigma) For Peppers Image With Salt & Peppers Noise

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.1	0.022884	0.020804	0.019375	0.016347	0.017927	0.017093	0.01601
2	0.2	0.028031	0.05	0.034593	0.016641	0.016402	0.016042	0.015047
3	0.3	0.022965	0.050182	0.027666	0.016264	0.017836	0.015998	0.015257
4	0.4	0.02386	0.018694	0.022852	0.016751	0.023427	0.020069	0.015362
5	0.5	0.023209	0.016611	0.017284	0.015657	0.01666	0.018819	0.014353

Execution Time for Peppers with Salt & Peppers Noise

Execution time (sec.) Vs. Noise variance (Sigma) for Peppers image with Gaussian Noise

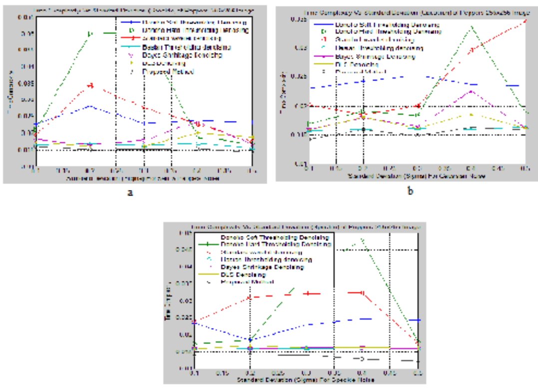
Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.01	0.022951	0.016864	0.02018	0.015768	0.015889	0.015811	0.014286
2	0.02	0.024167	0.019164	0.018603	0.015868	0.017878	0.017951	0.015892
3	0.03	0.025176	0.01841	0.020054	0.016116	0.016469	0.016087	0.014877
4	0.04	0.023621	0.033491	0.029571	0.015894	0.022625	0.018594	0.016259
5	0.05	0.023326	0.018874	0.034531	0.01632	0.016084	0.016083	0.015779

Execution Time for Peppers with Gaussian Noise

Execution time (sec.) Vs. Noise variance (Sigma) for Peppers image with Speckle Noise

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.01	0.023356	0.017316	0.023719	0.015828	0.01595	0.015885	0.014163
2	0.02	0.018322	0.018322	0.031009	0.016003	0.015868	0.016679	0.015986
3	0.03	0.022975	0.038403	0.032027	0.015971	0.016227	0.016092	0.015971
4	0.04	0.024563	0.047679	0.032245	0.015899	0.016084	0.016233	0.015845
5	0.05	0.024166	0.017895	0.017508	0.015855	0.016	0.016103	0.014246

Execution Time for Speckle Noise



From the above graph it is very clear that the proposed approach take less time over the existing techniques. The proposed approach is tested using Donoho Soft Thresholding (Blue Colour), de-Noised by Donoho Hard Thresholding (Green Colour), de-noised by Wavelet Thresholding (Red Colour), de-Noised by Basian Thresholding (Light Blue Colour), de-noised by Bayes Shrinkage (Magenta Colour), de-noised by BLS (Yellow Colour), de-noised by Proposed Approach (Gray Colour).

So It is very clear from the below given plots that there is very less time complexity with the use of proposed method over existing methods. This decrease represents improvement in the objective quality of the image.

Xvi. Conclusion And Future Scope

From the experimental and mathematical results it can be concluded that for salt and pepper noise, the median filter is optimal compared to mean filter and LMS adaptive filter. It produces the maximum SNR for the output image compared to the linear filters considered. The LMS adaptive filter proves to be better than the mean filter but has more time complexity. It has been observed that BayesShrink is not effective for noise variance higher than 0.05. De-noising salt and pepper noise using proposed method has proved to be efficient due to adaptive median filter used in it. When the noise characteristics of the image are unknown, de-noising by multi fractal analysis has proved to be the best method. Since selection of the right de-noising procedure plays a major role, it is important to experiment and compare the methods. Various techniques such as Fuzzy logic and neural network can be used for the rate of successful classification & for determine the ultimate measure by which to compare various de-noising procedures for the future part.

References

[1] Aliaa A.A.Youssif **"Adaptive Algorithm for Image Denoising Based on Curvelet Threshold"** IJCSNS International Journal of Computer Science and Network Security, VOL.10 No.1, January 2010.

[2] A. Buades, B. Coll, and J. Morel, "**Neighborhood Filters and PDE's,"** *Numerische Mathematik*, 105, No. 1,pp. 1-34,2006.

[3] F. Russo **"Evolutionary neural fuzzy system for noise cancellation in image processing",** IEEE Trans. Inst & Meas., vol. 48, no. 5, pp. 915-920, Oct. 1999.

[4] H-L Eng, K-K Ma **"Noise adaptive soft switching median filter"**, IEEETrans. on Image Processing, vol.10, no.2, pp. 242-251, Feb 2001.

[5] J.L.Starck, E.J.Candes, and D.L.Donoho, "**The curvelet transform for image denoising,"** *IEEE Trans. on Image Proc.*, vol. 11, no. 6, pp. 670- 684, 2002.

[6] J.Portilla, V.Strela, M.Wainwright, and E.Simoncelli, **"Image denoising using scale mixtures of gaussians in the wavelet domain,"** *IEEE Trans. Image Proc.*, vol. 12, no. 11, pp. 1338-1351, 2003.

[7] Kashif Rajpoot, Nasir Rajpoot and J. Alison Noble, **" Discrete Wavelet Diffusion for Image De-noising "** IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12 2006.

[8] Mukesh C. Motwani, Mukesh C. Gadiya, Rakhi C. Motwani, Frederick C. Harris, Jr, (2004) **"Survey of Image Denoising Techniques,"** *Proc. of GSPx 2004*, Santa Clara Convention Center, Santa Clara, CA, pp. 27-30.

[9] Pankaj Hedaoo and Swati S Godbole, **"Wavelet Thresholding Approach For Image Denoising,** "International Journal of Network Security & Its Applications (IJNSA), Vol.3, No.4, pp. 16-21, 2011

[10] Prashant Bhati and Prof. Mukesh Tiwari, "**A Novel Image Denoising using Matched Partial Biorthogonal Wavelets and Adaptive Thresholding"** International Journal of Computer Applications, Volume 12– No.7, pp. 41-45, December 2010.

[11] Raghuram Rangarajan, Ramji Venkataramanan and Siddharth Shah **"Image Denoising Using Wavelets"** pp. 1- 16, December 16, 2002.

[12] Rong Bai, **"Wavelet Shrinkage Based Image Denoising Using Soft Computing",** *Thesis for Master of Applied Science* in University of Waterloo, Waterloo, Ontario, Canada.2008.

[13] Rudra Pratap Singh Chauhan, "**A Novel Approach To Overcome The Intertwined Shortcomings Of DWT for Image Processing and De-Noising"** *International Journal of Engineering Research and Applications (IJERA)* ISSN: 2248-9622 ,Vol. 2, Issue 1, pp. 464-470, Jan-Feb 2012.