International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 11, November-2014

Performance Evaluation of Spatial Domain Filtering with Brute Force Thresholding Algorithm for Image Denoising

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***Abstract*- For researchers the extraction of noise from the original image is still a problem. Several algorithms have been developed and they all have their own merits and demerits. This paper is focused on the denoising of image which is a pre processing step for an image before it can be used in image processing applications. In this work to achieve these de-noising, filtering approach and thresholding with wavelet based approach are used and their comparative performances are studied. Image filtering algorithms are applied on images to remove the different types of noise that are either present in the image during capturing or injected into the image during transmission. Here wavelet approach and special domain filter are used for the image reconstruction and denoising. In this paper, we propose an efficient algorithm for denoising of digital images.**

Keywords - Spatial Filters, Denoising, Brute Force, Thresholding, Wavelet Sub bands.

INTRODUCTION-

Image signals are often corrupted by acquisition channel or artificial editing. The main goal of image restoration techniques is to restore the original image from a noisy observation of it. Image noise problems arise when an image suffers with fluctuation or random variation in intensity level. Images may suffer with many of problems like additive multiplicative or impulse noise. It is undesirable because it degrades image quality and makes an image unpleasant to see. The several reasons due to which an image can reduce its quality or get corrupted are - motion between camera and object, improper opening of the shutter, atmospheric disturbances, misfocusing etc. Preprocessing can be done with image denoising and inpainting. Noise is the result of image acquisition system whereas image inpainting problems occur when some pixel values are missing. Denoising is a process of extracting useful information of image and to enhance the quality of image. Denoising is an enhancement technique to reconstruct a noiseless image which is better than the input image.

Generally in case of image denoising methods, the characteristics of the degrading system and the noises are assumed to be known beforehand. The image $i(x,y)$ is added with noise $n(x,y)$ to form the degraded image $d(x,y)$. This is convolved with the restoration procedure $g(x,y)$ to produce the restored image $o(x,y)$.

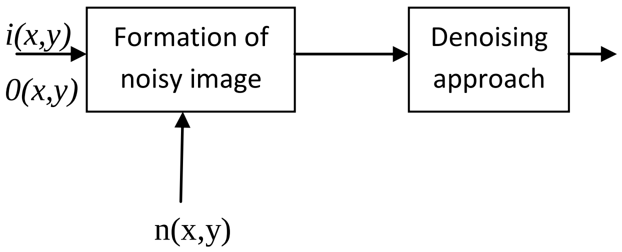


Fig. 1 Denoising Concept

Denoising is a necessary step to be taken before the image data is analyzed for further use. Because after introducing the noise in image, the important details and features of image are destroyed. It is necessary to apply efficient denoising technique to compensate for such data corruption So the main aim is to produce a noise free image from the noisy data. In this paper denoising of images which contain noise is defined by studying the actions of different special domain filters such as regular median filter, adaptive median filter, Gaussian filter and Bilateral filter. Also a thresholding technique called as brute force thresholding is used.

The organization of this paper is as follows: Section 2 is describes a noise models, Section 3 discusses about the filtering approach and thresholding technique, Section 4 describes simulation results on an image and Finally Section 5 gives conclusion.

NOISE MODELS-

Noise can affect an image by different ways upto different extent depending on type of disturbance. Generally our focus is to remove certain kind of noise. So we identify certain kind of noise and apply different algorithms to remove the noise. The common types of noise that arises in the image are: a) Impulse noise, b) Additive noise, c) Multiplicative noise. Different noises have their own characteristics which make them distinguishable from others.

(i). Impulse noise- This term is generally used for salt and pepper noise. They are also called as spike noise, random noise or independent noise. In image at random places black and white dots appears which makes image noisy. Over heated faulty component and dust particles on image

acquisition system is the main cause of such noise. Occurrence of such noise is independent of pixel values.
(ii) Additive noise- Gaussian noise comes under the category of additive noise. This noise model follows Gaussian distribution model. The resultant noisy pixel is a sum of original pixel value and randomly distributed Gaussian noise value. This can be expressed by following equation:

$$w(x, y) = i(x, y) + n(x, y) \qquad (1)$$

its probability distribution function can be given by:

$$f(g)= \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(g-m)^2}{2\sigma^2}} \qquad (2)$$

where σ is standard deviation, g is gray level of image and m is mean.
(iii). Multiplicative noise- This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR (Synthetic Aperture Radar) imagery. Speckle noise is a multiplicative noise. The source of this noise is attributed to random interference between the coherent backscattered signals. Fully developed speckle noise has the characteristic of multiplicative noise. Speckle noise follows a gamma distribution. It can be given as

$$w(x, y) = i(x, y)\times n(x, y) \qquad (3)$$

SPATIAL FILTERING AND THRESHOLDING APPROACH FOR IMAGE DENOISING-

(i). Spatial domain filters- Enhanced images can be reconstructed via filteration process. Image filters may be used to highlight parts or edges of image or boundaries. Filters provide an image better visualization. Image denoising is the process of obtaining original image from the degraded one. It helps to retain the edges and other major detail without modifying the visual information of image. Filtering in image processing is used to accomplish many things, including interpolation, noise reduction, and resampling. The choice of filter is often determined by the nature of the task and the type and behaviour of the data. Noise, dynamic range, color accuracy, optical artifacts, and many more details affect the outcome of filter functions in image processing.
A traditional way to remove noise is to employ spatial filters. Spatial filtering is commonly used to clean up the output of lasers, removing aberrations in the beam due to imperfect, dirty or damaged optics. The special filtering works directly on image plane and manipulates the pixel value of corrupted pixel by applying various algorithms of filters. The values of neighbourhood pixels decide the value of processed pixel therefore it is also known as neighbourhood process. Spatial filters can be further classified into non-linear and linear filters. In linear filters output values are linear function of the pixels in the original image. Linear methods are easy to analyse mathematically than the nonlinear filters. Non-linear filters have accurate results because they are able to reduce noise levels without blurring the edges. Some of the filtering techniques have been discussed below:

(A) Gaussian filter- Gaussian filters are linear low pass filters. It is basically a smoothing filter. Smoothness depends upon the deviation. To get intensive smoothness deviation must be larger.
(B) Regular median filter- Median filter is one of the most popular non-linear filters. It is very simple to implement and much efficient as well. In median filter a central pixel which appears to be noisy is replaced with the median values of neighbouring pixel values. Median filtering tends to remove image detail such as thin lines and corners while reducing noise. A limitation of median filter is that it acts as a low pass filter so it passes low frequencies while attenuates high frequency components of image like edges and noise. So it blurs the image.
(C) Adaptive median filter- Images affected by impulse noise can be denoised by the application of adaptive median filters. Its algorithm is simple and easy to implement. It is being used to remove high density of impulse noise as well as non-impulse noise while preserving fine details. Its algorithm works on two levels. In first level it the presence of residual impulse in a median filter output is tested. If there is an impulse then it will increase window size and repeat the test. If no impulse is present in median filter output then second level test is carried out to check whether central pixel is corrupted or not. If yes then the value of central pixel will be replaced with the median value.

Bilateral filter- Bilateral filter smooth the image as well as preserves edge information. It extends the concept of Gaussian smoothing by weighting the filter coefficients with their corresponding relative pixel intensities. Pixels that are very different in intensity from the central pixel are weighted less even though they may be in close proximity to the central pixel. This is effectively a convolution with a non-linear Gaussian filter, with weights based on pixel intensities. Its formulation is very simple.
(ii). Discrete Wavelet Transform
A 'wavelet' is a small wave which has its energy concentrated in time. It has an oscillating wavelike characteristic & it as time-scale and time-frequency analysis tools have been widely used in topographic reconstruction and still growing. Working in the wavelet domain is advantageous because the DWT tends to concentrate the energy of the desired signal in a small number of co-efficients, hence, the DWT of the noisy image consists of a small number of coefficients with high Signal Noise Ratio (SNR) and a large number of coefficients with low SNR. After discarding the coefficients with low SNR (i.e., noisy coefficients) the image is reconstructed using inverse DWT. As a result,

noise is removed or filtered from the observations[3]. The DWT is identical to a hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition. By applying DWT, the image is actually divided i.e., decomposed into four sub bands and critically sub sampled as shown in Figure.1(a). These four sub bands arise from separable applications of vertical and horizontal filters. The sub bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients, i.e., detail images while the sub band LL1 corresponds to coarse level coefficients, i.e., approximation image. To obtain the next coarse level of wavelet coefficients, the sub band LL1 alone is further decomposed and critically sampled. This results in two- level.

(iii) Brute force thresholding- brute force is

Finding an optimized value (λ) for threshold is a major problem. A small change in optimum threshold value destroys some important image details that may cause blur and artifacts. So, optimum threshold value should be found out, which is adaptive to different sub band characteristics. Here we proposed a Brute Force Thresholding technique which gives an efficient threshold value for noise to get high value of PSNR as compared to previously explained methods.
Threshold follows the same concept as in basic electronics, Brute force Threshold is given 5 times the maximum pixel intensity, which will be 127 in most of the images. Brute force thresholding always outclass other existing thresholding techniques in terms of better results. Algorithm for brute force thresholding is given

- Input wavelet sub band.
- Find maximum (max) and minimum (min) value of sub band coefficients.
- loop through (threshold=min to max) and execute desired algorithm
- save the results in array for each loop such that F= [threshold, result]
- When loop completed, select the (threshold) that gives best result.

(iv) Flow diagram for proposed algorithm-

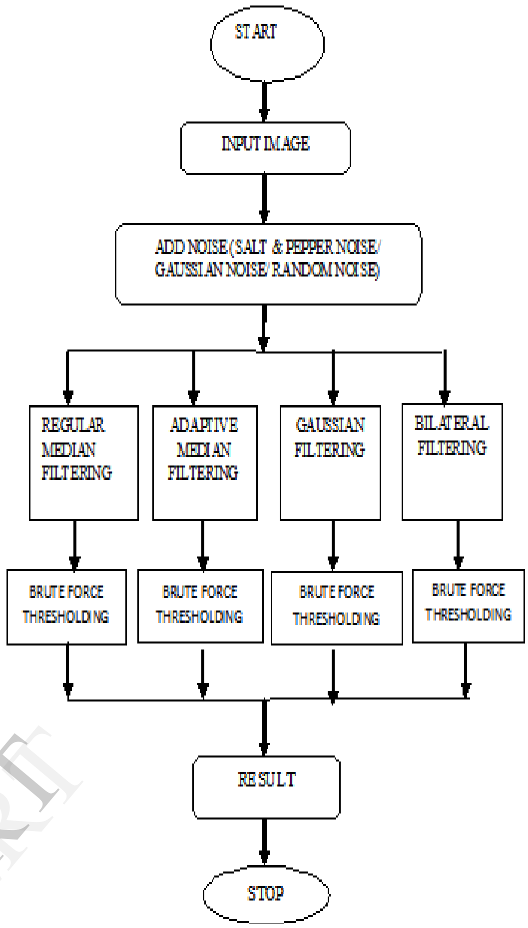


Fig 2 Flow diagram of proposed algorithem

PERFORMANCE EVALUATION AND SIMULATION RESULTS-

This work has been implemented using MATLAB as a simulation tool. The proposed method is tested on image 'SAR_Image.JPG' of size 1232 X 803. The image is corrupted by different type of noises like salt and pepper noise, random noise and Gaussian noise at various noise densities and the performance of algorithm is evaluated on the basis of peak signal to noise ratio, mean square error and root mean square error.

(i) Mean Square Error- Mean square error or MSE is the average square difference of pixels between orginal and denoised image throughout the image. Lower the MSE better will be the system response.

$$MSE=\frac{\Sigma[Is(r,c)-Id(r,c)]^2}{R \times c}$$

(ii) Peak Signal To Noise Ratio- the phrase peak signal to noise ratio abbreviated as PSNR represents the ratio between maximum possible power of signal and power of corrupting noise. Because of wide dynamic range

ISSN: 2278-0181
Vol. 3 Issue 11, November-2014

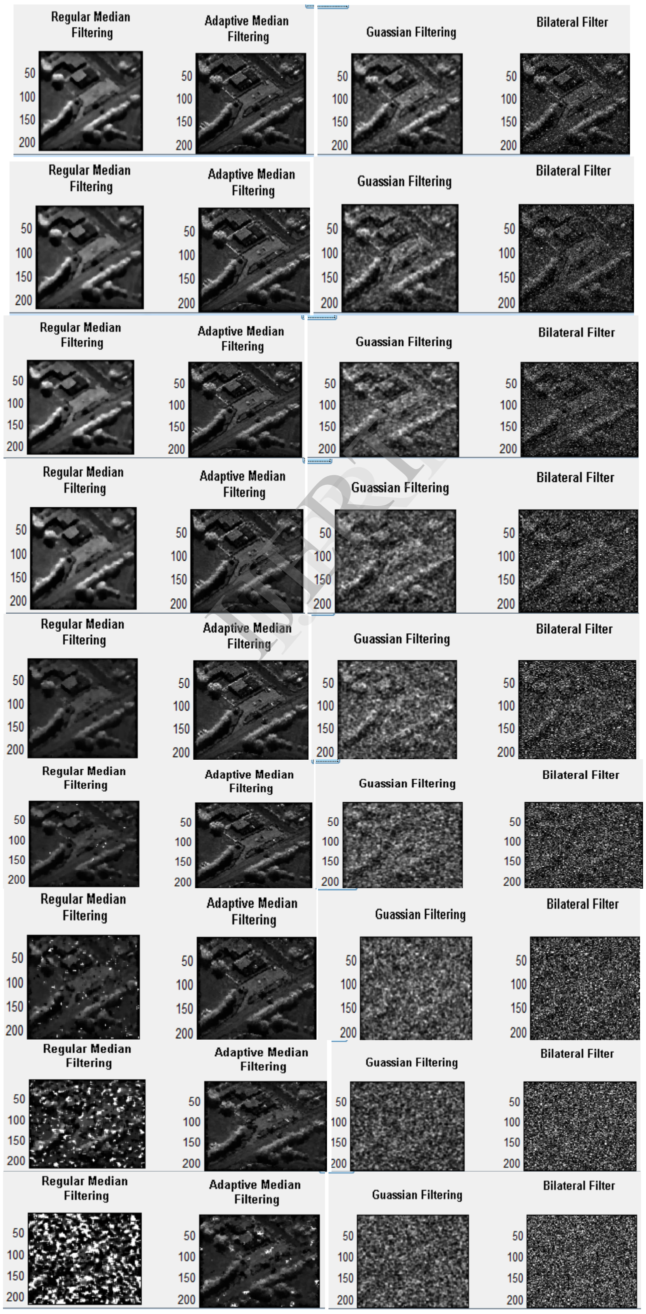
PSNR is usually expressed in logarithmic decibel scale. PSNR may be expressed as:

$$\text{PSNR}= 20\log_{10}\frac{\text{MAXi}^2}{\sqrt{\text{MSE}}}$$

(iii) Root Mean Square Error- The term root mean square error also known as root mean square deviation, also referred as standard deviation as it is the square value of variance. It represents the square root of the mean/average of the square of all of the error.The use of RMSE is very common and it makes an excellent general purpose error metric for numerical predictions.

$$\text{RMSE}= \frac{255}{10^{\frac{PSNR}{20}}}$$

Take an example of SAR image. The stimulation results and data are shown in below and Table respectively.



GAUSSIAN NOISE

Noise Value	Regular Median Filter			Adaptive Median Filter			Gaussian Filter			Bilateral Filter		
	PSNR	RMSE	MSE	PSNR	RMSE	MSE	PSNR	RMSE	MSE	PSNR	RMSE	MSE
0.1	21.3714	21.7756	276.4523	23.286	17.4678	474.1768	36.1425	3.9757	15.8063	30.1365	7.93807	63.013
0.2	20.4	25.5	593.035	19.1592	28.0918	789.15	33.5457	5.36148	28.74156	22.5818	18.9431	358.8395
0.3	18.7122	29.5754	874.7025	16.7906	36.898	1361.5	31.9569	6.4372	41.4372	17.6824	33.2982	1108.767
0.4	17.6329	33.4885	1121.477	15.4605	43.0046	1849.397	30.8811	7.2859	53.0848	14.6932	46.97645	2206.786
0.5	16.9449	36.2489	1313.985	14.7916	46.4473	2157.348	30.072	7.99724	63.95586	12.8509	58.07579	3372.798
0.6	16.1297	39.8157	1585.295	14.4675	48.21311	2324.504	29.4268	8.61391	74.1993	11.935	64.5342	4163.805
0.7	15.5911	39.8157	1794.6111	14.3926	48.6306	2364.94	29.3621	8.6783	75.31307	11.2258	70.0245	903.4343
0.8	15.2226	44.19876	1953.53	14.3449	48.8985	2391.0593	29.0507	8.9951	80.91152	10.5726	67.28374	5699.285

SALT AND PEPPER NOISE

Noise Value	Regular Median Filter			Adaptive Median Filter			Gaussian Filter			Bilateral Filter		
	PSNR	RMSE	MSE	PSNR	RMSE	MSE	PSNR	RMSE	MSE	PSNR	RMSE	MSE
0.1	36.0275	4.0287023	16.2304	27.5213	10.7269	115.067	33.8419	5.18137	26.8466	16.2096	39.4511	1556.3969
0.2	35.2163	4.423	19.5636	27.2825	11.0254	121.5711	32.247	6.22572	38.7596	13.565	53.49216	2861.4118
0.3	34.9112	4.58121	20.9874	27.036	11.3433	128.671	31.1325	7.0781	50.099	11.9158	64.67704	4183.1204
0.4	36.8114	3.681	13.55	26.8444	11.59632	134.4746	29.9744	8.0876	73.3905	10.8019	73.8267	5406.178
0.5	35.8235	4.12444	17.011	26.6975	11.7941	130.4789	29.9508	8.1096	65.765	9.9297	81.2934	6608.614
0.6	32.127	6.31233	39.8455	26.0661	12.6831	160.868	29.4495	8.5914	73.8125	9.153	88.8976	7902.789
0.7	26.2069	12.4794	155.736	25.9473	12.8581	165.3295	28.917	9.1346	83.4411	8.5801	94.95879	9017.172
0.8	20.2085	24.8951	619.7697	25.4429	13.6268	185.691	28.4272	9.6645	93.4029	8.0864	100.5125	10102.768
0.9	15.457	43.0219	1850.888	22.8269	18.41599	339.14885	28.5174	9.5647	91.4829	7.6896	105.21077	11069.305

RANDOM NOISE

Noise Value	Regular Median Filter			Adaptive Median Filter			Gaussian Filter			Bilateral Filter		
	PSNR	RMSE	MSE	PSNR	RMSE	MSE	PSNR	RMSE	MSE	PSNR	RMSE	MSE
0.1	21.0084	22.70493	515.5138	23.3076	17.424494	303.612	36.0585	4.01435	15.115	30.207	7.8734	61.9912
0.2	20.3529	24.48472	599.502	19.1113	28.24718	797.903	33.4539	5.4181	29.3555	22.726	18.630	347.089
0.3	18.8756	29.024195	842.404	16.7276	37.16723	1381.40	32.2994	6.18828	38.2948	17.794	32.871	1080.51
0.4	17.3755	34.49572	1189.955	15.4373	43.11965	1859.30	31.2187	7.00818	49.1145	14.687	47.007	2209.73
0.5	16.8269	36.74474	1350.1759	14.7832	46.49221	2161.52	29.9892	8.07384	65.1869	13.018	56.964	3244.96
0.6	16.3177	38.96325	1518.1348	14.4902	48.08728	2312.38	29.5818	8.46155	71.5979	11.915	66.187	4183.60
0.7	15.6572	42.04169	1767.5038	14.3893	48.64914	239.465	29.2333	8.80796	77.5801	11.167	70.493	4969.35
0.8	14.7754	46.83397	2165.411	14.2026	49.7062	2470.70	28.7082	9.35686	87.5508	10.586	75.738	5681.20
0.9	14.8013	46.39543	2152.536	14.2363	49.513677	2451.60	28.7894	9.26979	85.9291	10.181	78.975	6237.06

CONCLUSION-

In this work image denoising is achieved by various special filtering approach with a thresholding method named as brute force thresholding. Simulation is performed on image with various types of noises that are either present during acquisition or transmission of image. In this work three types of noises are added to image and special domain filtering is performed on each of them. The performances of the filters are compared using the Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE). The performance of brute force thresholding algorithm is very efficient in denoising.

REFERENCES-

[1]. Lopes A., Nezry E., Touzi R., Law H. ," Maximum A Posteriori Speckle Filtering And First Order Texture Models In Sar Images" 10th Annual International Geoscience and Remote Sensing Symposium, 1990.

[2]. H. Guo, J. E. Udegard, M. Lung, R. A. Gopinath, I. W. Selesnick and C. S. Burrui, "Wavelet Based Speckle Reduction With Application To SAR Based Atd/R" IEEE International Conference on Image Processing, 1994.

[3]. M. Lmg, Member, IEEE, H. GUO, Student Member, IEEE, J. E. Odegard, Student Member, IEEE, C. S. Burrus, Fellow, IEEE, and R. 0. Wells, Jr. "Noise Redction Using An Undecimated Discrete Wavelet Transform" IEEE Signal Processing Letters, Vol. 3, No. 1, January 1996

[4]. Sang-il Park, Mark J. T. Smith and Russell M. Mersereau, "A New Directional Filter Bank For Image Analysis And

Classification" IEEE International Conference on Acoustics, Speech, and Signal Processing, 1999. Proceedings., 1999

[5]. Vasily Strela, Peter Niels Heller, Member, IEEE, Gilbert Strang, Member, IEEE, Pankaj Topiwala, Member, IEEE, and Christopher Heil, "The Application of Multiwavelet Filterbanks to Image Processing" IEEE Transactions On Image Processing, Vol. 8, No. 4, April 1999

[6]. Fabrizio Argenti, Member, IEEE, and Luciano Alparone, "Speckle Removal From SAR Images in the Undecimated Wavelet Domain" IEEE Transactions On Geoscience And Remote Sensing, Vol. 40, No. 11, November 2002

[7]. Alin Achim, Student Member, IEEE, Panagiotis Tsakalides, Member, IEEE, and Anastasios Bezerianos, Member, IEEE, "SAR Image Denoising via Bayesian Wavelet Shrinkage Based on Heavy-Tailed Modeling" IEEE Transactions On Geoscience And Remote Sensing, Vol. 41, No. 8, August 2003

[8]. Stian Solbø and Torbjørn Eltoft, Member, IEEE, "Homomorphic Wavelet-Based Statistical Despeckling of SAR Images" IEEE Transactions On Geoscience And Remote Sensing, Vol. 42, No. 4, April 2004

[9]. Min Dai, Student Member, IEEE, Cheng Peng, Andrew K. Chan, Fellow, IEEE, and Dmitri Loguinov, Member, IEEE, "Bayesian Wavelet Shrinkage With Edge Detection for SAR Image Despeckling" IEEE Transactions On Geoscience And Remote Sensing, Vol. 42, No. 8, August 2004

[10]. Fabrizio Argenti, Member, IEEE, Tiziano Bianchi, Member, IEEE, and Luciano Alparone, "Multiresolution MAP Despeckling of SAR Images Based on Locally Adaptive Generalized Gaussian pdf Modeling" IEEE Transactions On Image Processing, Vol. 15, No. 11, November 2006

[11]. Michael Elad, Member, IEEE, "Why Simple Shrinkage Is Still Relevant for Redundant Representations?" IEEE Transactions On Information Theory, Vol. 52, No. 12, December 2006

[12]. Florian Luisier, Thierry Blu, Senior Member, IEEE, and Michael Unser, Fellow, IEEE, "A New SURE Approach to Image Denoising: Interscale Orthonormal Wavelet Thresholding" IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 16, NO. 3, MARCH 2007

[13]. Mario Mastriani, and Alberto E. Giraldez, "Kalman's Shrinkage for Wavelet-Based Despeckling of SAR Images", World Academy of Science, Engineering and Technology Vol:2 2008

[14]. Syed Musharaf Ali, Muhammad Younus Javed, Naveed Sarfraz Khattak, Athar Mohsin, and Umar Farooq, "Despeckling of Synthetic Aperture Radar Images Using Inner Product Spaces in Undecimated Wavelet Domain", World Academy of Science, Engineering and Technology. Vol:2 2008

[15]. Ruxin Wang and Qiang Li, "A Survey on SAR Image Despeckling", Huazhong University of Science and Technology. 2011

[16]. V.Radhika, Dr. G. Padmavathy, "Despeckling of Oil Spill SAR Images using Fusion Technique", International Journal of Computer Applications (0975 – 8887). Volume 21– No.1, 2011

[17]. Gitta Kutyniok and Demetrio Labate, "Introduction to Shearlets" Springer Science+Business Media, LLC, 2012

[18]. Wang-Q Lim, "Discrete Shearlet Transform: faithful digitization concept and its applications", *SPIE* 8138, Wavelets And Sparsity Xiv, 813810, 2011

[19]. S.Md.Mansoor Roomi, D.Kalaiyarasi, "Despeckling Of SAR Images By Optimizing Averaged Power Spectral Value In Curvelet Domain", International Journal of Information Sciences and Techniques (IJIST) Vol.2, No.2, March 2012