Performance Evaluation of 2D Adaptive Bilateral Filter For Removal of Noise From Robust Images

B.Sridhar srib105@gmail..com
Faculty,Department of ECE
Lendi Enggneering college
Vizianagaram535220,India

Dr.K.V.V.S.Reddy kvvsreddy@gmail.com
Professor,Department ofECE
Andhra University
Visakhapatnam, 531003, India

Abstract

In this paper, we present the performance analysis of adaptive bilateral filter by pixel to noise ratio and mean square errors. It was evaluate changing the parameters of the adaptive filter half width values and standard deviations. In adaptive bilateral filter, the edge slope is enhanced by transforming the histogram via a range filter with adaptive offset and width. The variance of range filter can also be adaptive. The filter is applied to improve the sharpens of a gray level and color image by increasing the slope of the edges without producing overshoot or undershoots. The related graphs were plotted and the best filter parameters are obtained

Keywords: Image Restoration, Adaptive Filter, Laplacian, Gaussian, Pixel To Noise Ratio, Mean Square Error, Half Width Factor, Standard Deviation Factor

1. INTRODUCTION

Image restoration is the process to construct the image from a blurred and noise image. It used to perform the operation inverse convolution methods. In basic methods the noises are to be estimated. But in practical situations, we unable to get the information regarding blurring and other effect directly. As specially if the robustness increase of an image it is difficult to restored. So to improve the quality we may apply adaptive filtering methods. Bilateral filters shows the prominent results now days, In the first step to develop a sharpening method that is fundamentally different from the unsharp mask filter which sharpens an image by enhancing the high frequency components of the image [4]. In the spatial domain, the boosted high-frequency components lead to overshoot and undershoot around edges, which causes objectionable ringing or halo artefacts. The second aspect of the problem we wish to address is noise[14]. In terms of noise removal, conventional linear filters work well for removing additive Gaussian noise, but they also significantly blur the edge structures of an image. Therefore, a great deal of research has been done on edge-preserving noise reduction[5,6]. The bilateral filter is essentially a smoothing filter; it does not restore the sharpness of a degraded image. The idea of bilateral filtering has since found its way into many applications not only in the area of image de-noising, but also computer graphics, video processing, image interpolation, dynamic range compression, and several others.

This paper examines the performance of the bilateral filtering, a recent approach proposed in [3] that represents the optimum parameter to chosen to get restored image form the robust image. The quality parameters are PSNR and MSE. Applications of bilateral filtering is varied (see, for example, the mean shift filtering [2] applications, mean shift and bilateral filtering, are closely related the repaid advancements of computing technology, any use of the computer-based technologies.

2. INTRODUCTION TO BILATERAL FILTER

The Bilateral filtering was proposed by Tomasi and Manduchi in 1998 as a non-iterative method for edge-preserving, smoothing and noise reducing smoothing filter[3]. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight is based on a Gaussian distribution. Crucially the weights depend not only on Euclidean distance but also on the radiometric differences (differences in the range, e.g. color intensity). This preserves sharp edges by systematically looping through each pixel and according weights to the adjacent pixels accordingly.

$$\hat{f}(m.n) = \sum_{k}\sum_{l} h[m,n;k,l]\, g[k,l]$$

performs 2-D bilateral filtering for the grayscale or color image A. A should be a double precision matrix of size NxMx1 or NxMx3 (i.e., grayscale or color images, respectively) with normalized values in the closed interval [0, 1].

$$h[m,n;m_0,n_0] = I\left(\Omega_{m_0,n_0}\right) r_{m_0,n_0}^{-1}\, e^{\left(\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d{}^2}\right)} . e^{-\frac{1}{2}\left(\frac{g[m,n]-g[m_0,n_0]-\xi[m_0,n_0]}{\sigma_r[m_0,n_0]}\right)^2}$$

as shown in the fig.1 the response of bilateral filter. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight is based on a Gaussian distribution. Crucially the weights depend not only on Euclidean distance but also on the radiometric differences (differences in the range, e.g. color intensity). This preserves sharp edges by systematically looping through each pixel and according weights to the adjacent pixels accordingly

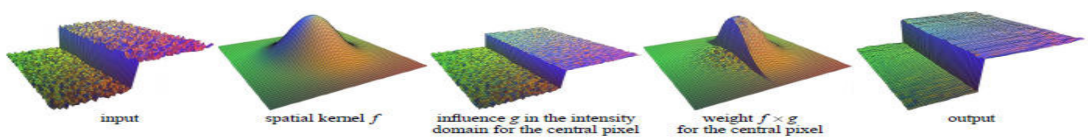

FIGURE 1: Response of Bilateral Filtering.

3. ADAPTIVE BILATERAL FILTERS

In adaptive filtering process here is using a combination of filtering process laplacian and Gaussian to improve the sharpness of edges of the image. the functional and graphical representation is shown in the figure 2,3.

The Laplacian is a 2-D isotropic measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection (see zero crossing edge detectors). The Laplacian is often applied to an image that has first been smoothed with something approximating a Gaussian smoothing filter in order to reduce its sensitivity to noise, and hence the two variants will be described together here. The operator normally takes a single graylevel image as input and produces another graylevel image as output.[3].In fact, since the convolution operation is associative, we can convolve the Gaussian smoothing filter with the Laplacian filter first of all, and then convolve this hybrid filter with the image to achieve the required result. Doing things this way has two advantages:[7,8]

- Since both the Gaussian and the Laplacian kernels are usually much smaller than the image, this method usually requires far fewer arithmetic operations.

- The LoG (`Laplacian of Gaussian') kernel can be precalculated in advance one convolution needs to be performed at run-time on the image. The 2-D LoG function centered on zero and with Gaussian standard deviation σ has the form:

$$\mathrm{LoG}(x,y) = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right] e^{-\frac{x^2+y^2}{2\sigma^2}}$$

as shown in the figure 2

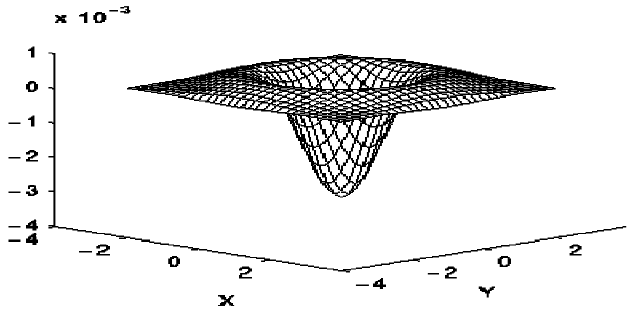

FIGURE 2: The 2-D Laplacian of Gaussian (LoG) Function.

The *x* and *y* axes are marked in standard deviations (σ).

A discrete kernel that approximates this function (for a Gaussian σ = 1.4) is shown in Fig.

0	1	1	2	2	2	1	1	0
1	2	4	5	5	5	4	2	1
1	4	5	3	0	3	5	4	1
2	5	3	-12	-24	-12	3	5	2
2	5	0	-12	-40	-24	0	5	2
2	5	3	-12	-24	-12	3	5	2
1	4	5	3	0	3	5	4	1
1	2	4	5	5	5	4	2	1
0	1	1	2	2	2	1	1	0

FIGURE 3: Discrete Approximation To LoG Function With Gaussian σ = 1.

Note that as the Gaussian is made increasingly narrow, the LoG kernel becomes the same as the simple Laplacian kernels shown in Figure 3. This is because smoothing with a very narrow Gaussian (σ < 0.5 pixels) on a discrete grid has no effect. Hence on a discrete grid, the simple Laplacian can be seen as a limiting case of the LoG for narrow Gaussians.[12,13]

4. EXPERIMENTAL DETAILS

In this section we analyze the performance of bilateral filters on gray level and color images. The proposed algorithm shows in the figure 4. The two most common forms of degradation an image suffers are loss of sharpness or blur and noise. The degradation model consists of a linear shift-invariant blur followed by additive noise . in this paper a common process can choose at time both gray and color images. It is simulated in MATLAB, the results and explanations as explained in the section –5.

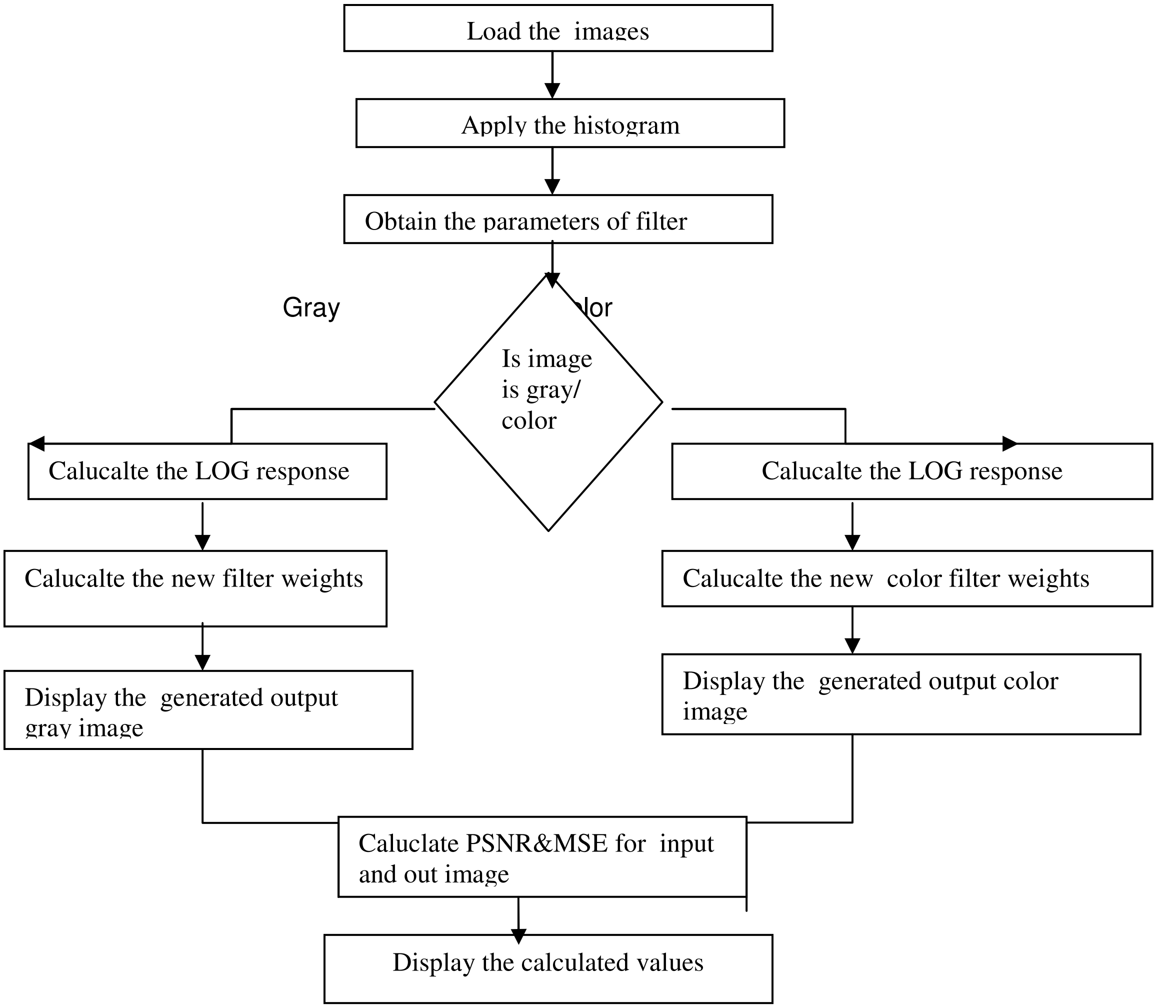

FIGURE 4: Flowchart For Proposed Method.

4.1 Mean Square Error

MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.[9].

The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated.

The MSE of an estimator $\hat{\theta}$ with respect to the estimated parameter θ is defined as

$$\mathrm{MSE}(\hat{\theta}) = \mathrm{E}\,[(\hat{\theta} - \theta)^2]$$

The MSE is equal to the sum of the variance and the squared bias of the estimator

$$\mathrm{MSE}(\hat{\theta}) = \mathrm{Var}(\hat{\theta}) + (\mathrm{Bias}(\hat{\theta}, \theta))^2$$

Thus assesses the quality of an estimator in terms of its variation and unbiasedness. Tthe MSE is not equivalent to the expected value of the absolute error. Since MSE is an expectation, it is not a random variable. It may be a function of the unknown parameter θ, but it does not depend on any random quantities. However, when MSE is computed for a particular estimator of θ the true value of which is not known, it will be subject to estimation error. In a Bayesian sense, there are cases in which it may be treated as a random variable.

4.2 Peak Signal to Noise Ratio

The peak signal-to-noise ratio (PSNR) is the ratio between a signal's maximum power and the power of the signal's noise. Signals can have a wide dynamic range, so PSNR is usually expressed in decibels, which is a logarithmic scale[10,11]. It is most easily defined via the mean squared error (MSE) which for two m×n monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$\mathrm{MSE} = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

The PSNR is defined as:

$$\mathrm{PSNR} = 10.\log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right)$$

$$= 20.\log_{10}\left(\frac{\mathrm{MAX}_I}{\sqrt{\mathrm{MSE}}}\right)$$

Here, MAX_I is the maximum possible pixel value of the image. Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, where higher is better. Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB.

5. RESULTS DISCUSSIONS

In this chapter we will discuss the results of gray and color images plotted for different values of bilateral filter width and MSEs and PSNRs and taken the best values of half width(w) and standard deviation.

5.1 Input Figures

The figures 5 and 6 are taken as the input images for the implementation of Adaptive Bilateral Filter i.e., these images are loaded into MATLAB environment. The adaptive bilateral filtering is applied to both gray scale image and color image.

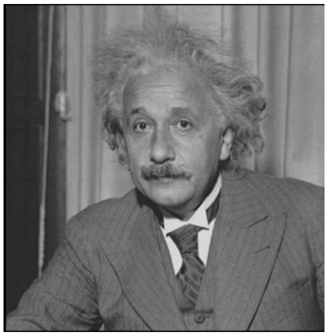

FIGURE 5: Input Gray Image.

FIGURE 6: Input Color Image.

The dimensions of the grayscale image are 256x256 and the dimension of the color image is 256x256x3.

5.2 Histogram

An image histogram is a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. The histogram for a specific image allows a viewer to judge the entire tonal distribution at a glance. The function "hist" displays the histogram of the images in Cartesian coordinate system.

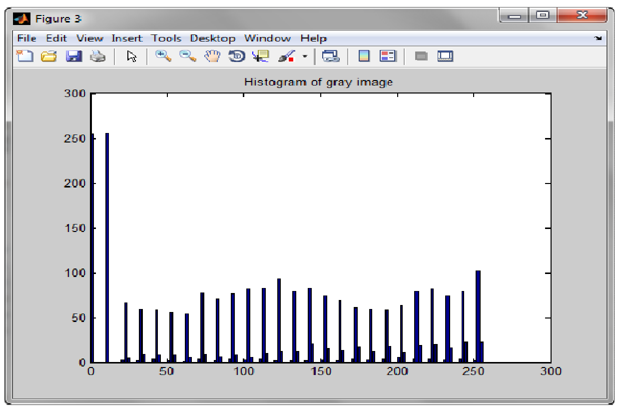

FIGURE 7: Histogram Function of Gray Image.

The Fig: 7 shows the histogram of the input gray image which represents the intensity distribution of different pixels in the image.

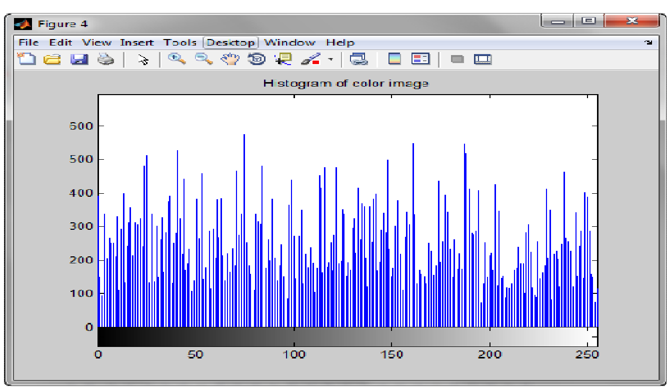

FIGURE 8: Histogram Function of Color Image.

The Figure 8 shows the histogram of the input colour image which represents the intensity distribution of different pixels in the image.

5.3 Output of Adaptive Bilateral Filter

After setting the bilateral parameters like bilateral filter width, domain and range filter standard deviations adaptive bilateral filtering is applied to both the images using the function

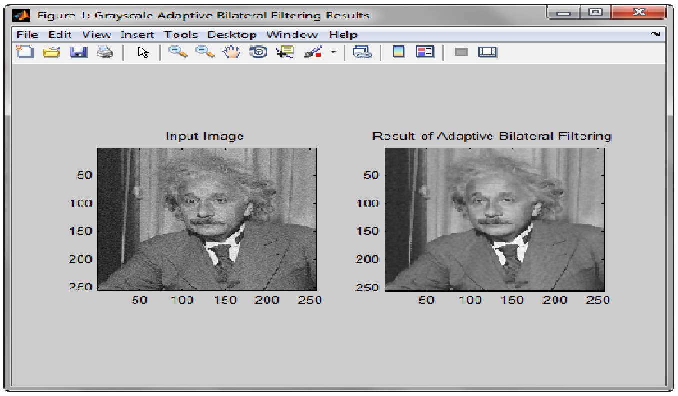

FIGURE 9: Adaptive Bilateral Filter Result for Gray Image.

The figure 9 shows the input gray image which is affected by some kind of noise and the output image after adaptive bilateral filtering. The input gray image appears blurred with unsharpened edges. As adaptive bilateral filter is the most effective one in removing the noise it enhances the slope without generating overshoot and undershoot around the edges. The output image is much clear compared to the input image because of the noise removal and edge preserving.

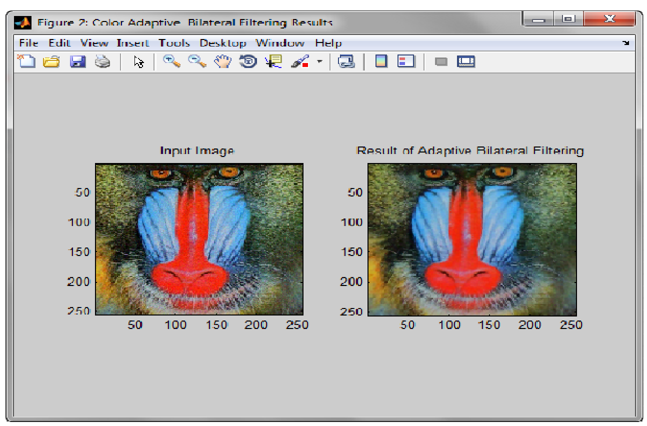

FIGURE 10: Adaptive Bilateral Filter Result for Color Image.

The figure 10 shows the input color image which is affected by some kind of noise and the output image after adaptive bilateral filtering. The input color image appears blurred with unsharpened edges. As adaptive bilateral filter is the most effective one in removing the noise it enhances the slope without generating overshoot and undershoot around the edges. The output image is much clear compared to the input image because of the noise removal and edge preserving.

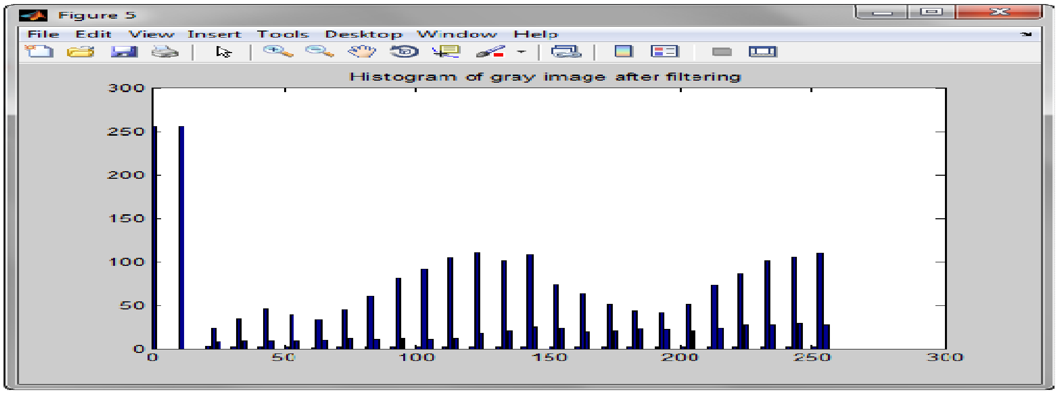

FIGURE 11: Histogram Function of Gray Image After Filtering.

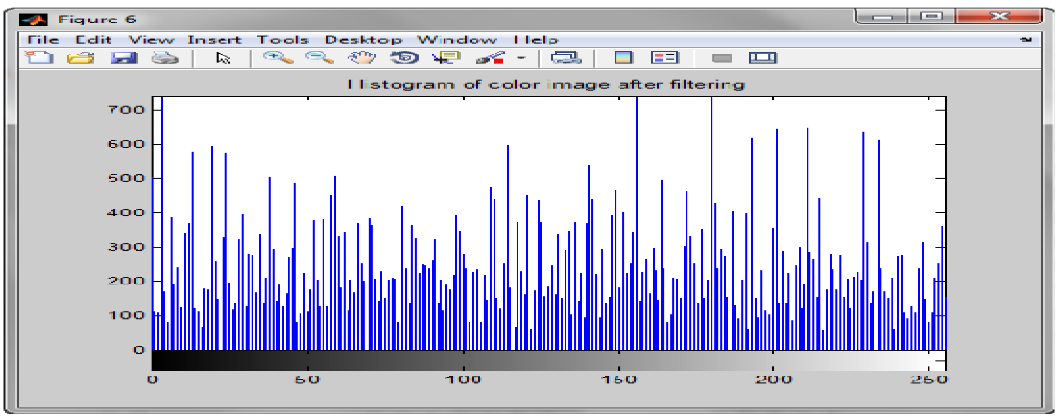

Figure: 12: Histogram Function of Color Image After Filtering.

Figures 11 and 12 represents the intensity levels of gray image and color image respectively after applying the adaptive bilateral filter.

5.5 Calculation of MSE And PSNR

By practically varying different values of the bilateral half width and by taking range filter standard deviation as σ_R = 0.1 the mean squared errors for gray image is measured and are tabulated as follows:

w	σ_R	Mean Squared Error		Peak signal to noise ratio	
		For Gray image	For Color image	For Gray image	For Color image
2	0.1	0.000501083	0.0016723	32.9944	27.7668
3	0.1	0.00050981	0.0019067	32.9259	27.1973
4	0.1	0.00050983	0.0020941	32.9257	26.7901
5	0.1	0.0005276	0.002253	32.7781	26.4724
2	0.2	0.00049998	0.0016711	33.0105	27.7701
3	0.2	0.00050168	0.0018949	32.9957	27.2241
4	0.2	0.00051173	0.002093	32.9096	26.7922
5	0.2	0.00052602	0.0022611	32.79	26.4569
2	0.3	0.00049903	0.0016618	33.0188	27.7942
3	0.3	0.00050871	0.0018971	32.9353	27.2193
4	0.3	0.00051518	0.0016618	32.8804	26.7983
5	0.3	0.00052855	0.0020901	32.7691	26.4465
2	0.4	0.00049568	0.001602	33.048	27.7828
3	0.4	0.00050479	0.0019082	32.9689	27.1938
4	0.4	0.00050963	0.0020929	32.9275	26.7925
5	0.4	0.00053133	0.0022544	32.7463	26.4697

TABLE 1: MSE And PSNR Values For Gray And Color Images For Fixed Values of $\sigma_{R.}$

The above Table .1 shows the vlaues for peak signal to noise ratio and mean squarred error for both gray and color images taken at fixed values of standard range deviation ($\sigma_{R)}$ against varying the values of half width (W)

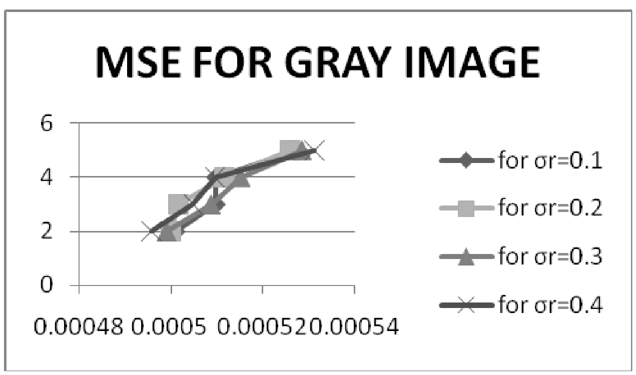

FIGURE 13: MSE Plot For Gray Image For Different Values of $\sigma_{R.}$

The above figure 13 shows the graph of a gray image plotted between MSE on x-axis and bilateral filter width on y-axis. For different values of bilateral filter standard range deviation σ_R, the values are taken between 0.1 to 0.4 and the respective graphs are being plotted.

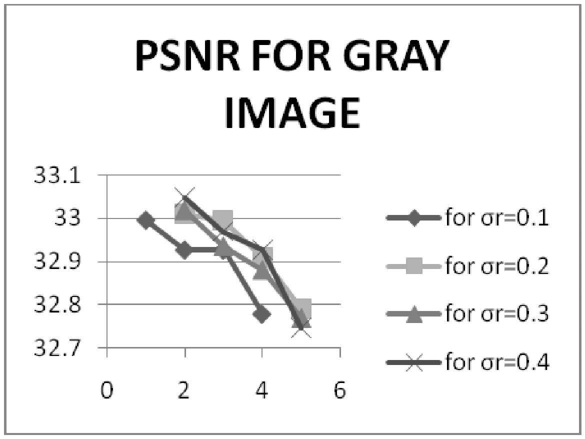

FIGURE 14: PSNR Plot for Gray Image For Different Values of $\sigma_{R.}$

The above figure 14 shows the graph of a gray image plotted between PSNR on y-axis and bilateral filter width on x-axis. For different values of bilateral filter standard range deviation σ_R, the values are taken between 0.1 to 0.4 and the respective graphs are being plotted.

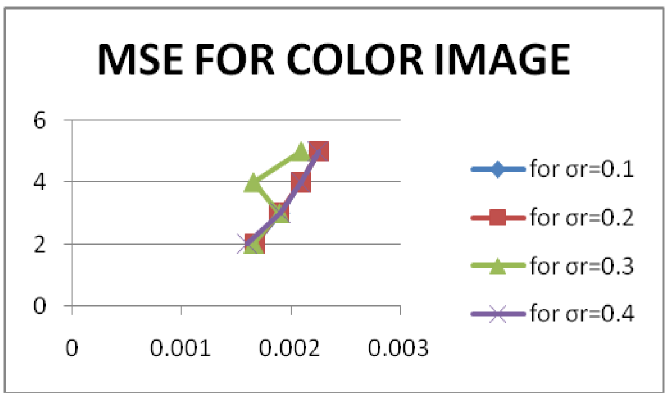

FIGURE 15: MSE Plot for Color Image For Different Values of $\sigma_{R.}$

The above figure 15 shows the graph of a color image plotted between MSE on x-axis and bilateral filter width on y-axis. For different values of bilateral filter standard range deviation σ_R, the values are taken between 0.1 to 0.4 and the respective graphs are being plotted.

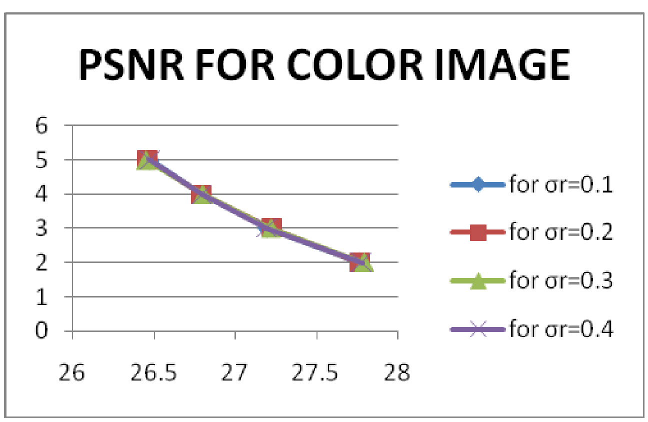

FIGURE 16: PSNR Plot for Color Image For Different Values of $\sigma_{R.}$

The above figure 16 shows the graph of a color image plotted between PSNR on y-axis and bilateral filter width on x-axis. For different values of bilateral filter standard range deviation σ_R, the values are taken between 0.1 to 0.4 and the respective graphs are being plotted.

w	σ_R	Mean Squared Error		Peak signal to noise ratio	
		For Gray image	For Color image	For Gray image	For Color image
2	0.1	0.00049729	0.0016573	33.0339	27.806
2	0.2	0.00050549	0.0016601	32.9629	27.7985
2	0.3	0.00049736	0.0016753	33.0333	27.759
2	0.4	0.00051037	0.0016589	32.9211	27.8019
3	0.1	0.00050324	0.0018911	33.001	27.2089
3	0.2	0.00050741	0.0019097	32.9464	27.1903
3	0.3	0.00050201	0.0018941	32.9929	27.226
3	0.4	0.00050843	0.0019041	32.9372	27.2036
4	0.1	0.00050887	0.0021106	32.934	26.756
4	0.2	0.00051846	0.002081	32.859	26.8173
4	0.3	0.00051271	0.002081	32.9013	26.8173
4	0.4	0.00050983	0.0020941	32.9257	26.7901
5	0.1	0.00053307	0.0022733	32.7322	26.4335
5	0.2	0.00052872	0.0022879	32.7677	24.4056
5	0.3	0.00052521	0.0022728	32.7967	26.4343
5	0.4	0.00052528	0.0022591	32.7961	26.4607

TALBE 2: MSE and PSNR Values For Gray And Color Images For Fixed Values of W.

The above table 5.2 shows the vlaues for peak signal to noise ratio and mean squarred error for both gray and color images taken at fixed values of half width (W) against varying the values of standard range deviation(σ_R)

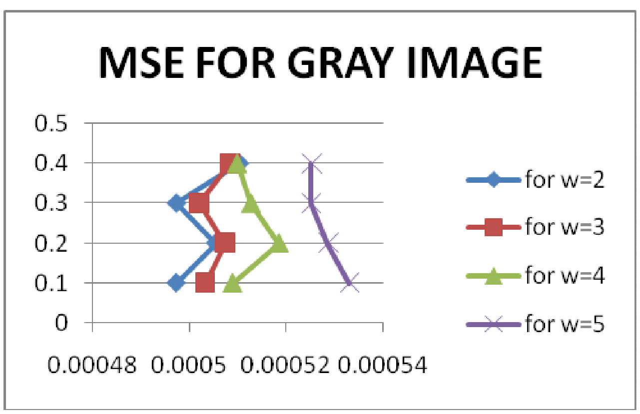

FIGURE 17: MSE Plot for Gray Image For Different Values of w.

The above figure 17 shows the graph of a gray image plotted between MSE on x-axis and bilateral filter standard range deviation σ_R on y-axis. For different values of bilateral filter half width(W), the values are taken between 2 to 5 and the respective graphs are being plotted.

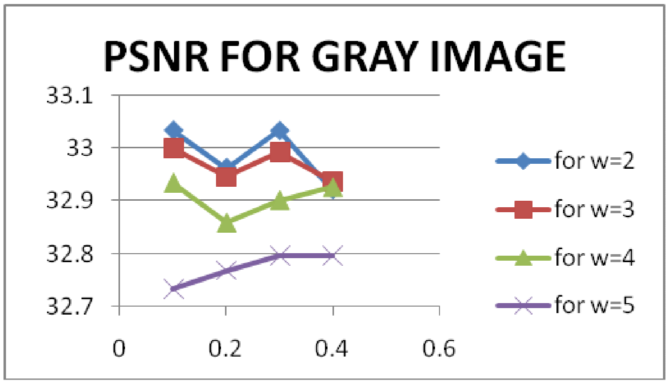

FIGURE 18: PSNR Plot for Gray Image For Different Values of w.

The above figure: 18 shows the graph of a gray image plotted between PSNR on x-axis and bilateral filter standard range deviation σ_R on y-axis. For different values of bilateral filter half width(W), the values are taken between 2 to 5 and the respective graphs are being plotted.

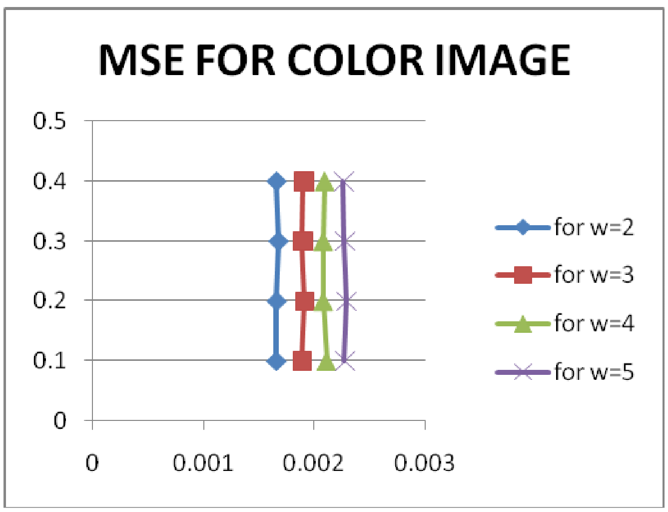

FIGURE 19: MSE Plot for Color Image For Different Values of w.

The above figure: 19. shows the graph of a color image plotted between MSE on x-axis and bilateral filter standard range deviation σ_R on y-axis. For different values of bilateral filter half width(W), the values are taken between 2 to 5 and the respective graphs are being plotted.

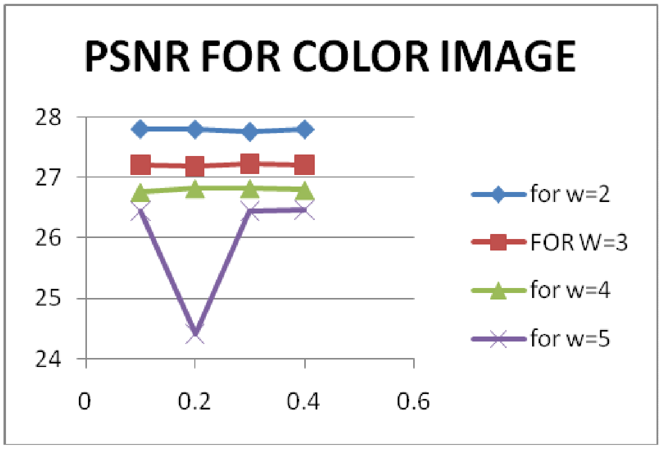

FIGURE 20: PSNR Plot for Color Image For Different Values of w.

The above figure: 20 shows the graph of a color image plotted between PSNR on x-axis and bilateral filter standard range deviation σ_R on y-axis. For different values of bilateral filter half width(W), the values are taken between 2 to 5 and the respective graphs are being plotted.

The proposed method was applied to gray level and color with different standard deviation noises. The PSNR of the restored image was measured for the proposed method as well as the original bilateral filtering method and the state-of-the-art image denoising method using Gaussian scale mixtures proposed by wang. [6] for comparison. A summary of the results is states that the average of PSNR is around 31. The proposed method achieves noticeable PSNR gains over 33 the original bilateral filtering method for all of the gray level. Also the color image signal filtering shows prominent results. It can be observed that the proposed method produced a restored image signal with noticeably improved perceptual quality compared to the Wang and the original bilateral filtering method.

6. CONCLUSIONS

In this paper, we present the adaptive bilateral filter for sharpness enhancement and noise removal. The adaptive bilateral filter sharpens an image by increasing the slope of the edges without producing overshoot or undershoots. In the adaptive bilateral filter, the edge slope is enhanced by transforming the histogram via a range filter with adaptive offset and width. The variance of range filter can also be adaptive. The adaptive bilateral filter is able to smooth the noise, while enhancing edges and textures in the image. Adaptive bilateral filter restored images are to be significantly sharper than those restored by the bilateral filter. The mean square error and peak signal to noise ratios are also calculated for different values of bilateral filter width and range filter standard deviation and corresponding graphs are plotted for both gray and color images. Adaptive bilateral filter works well for both gray images and color images. For future development of the adaptive bilateral filter, we would suggest that the following issues be addressed. First, the adaptive bilateral filter tends to resize the image, due to its fundamental mechanism of sharpening an image by pulling up or pushing down pixels along the edge slope. Second, the adaptive bilateral filter does not perform as well at corners as it does on lines and spatially slow-varying curves, since the adaptive bilateral filter is primarily based on transforming the histogram of the local data, which cannot effectively represent 2-D structures. Finally, in the current design of the adaptive bilateral filter, a fixed domain Gaussian filter is used. Future developments this proposed method does not work efficiently at corner edges, by choose a addition of transformation operation along with proposed method the problem will be solved.

7. REFERENCES

[1] C. Tomasi and R. Manduchi, ªBilateral Filtering for Gray and Color Images,º Proc. 1998 IEEE Int'l Conf. Computer Vision, 1998

[2] D. Comaniciu and P. Meer, ªMean Shift Analysis and Applications,º Proc.1999 IEEE Int'l Conf. Computer Vision, 1999.

[3] Buyue Zhang and Jan P. Allebach, Fellow Adaptive Bilateral Filter for Sharpness Enhancement and Noise Removal IEEE IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 17, NO. 5, MAY 2008

[4].Das and R. M. Rangayyan, “Enhancement of image edge sharpness and acutance,” in Proc. SPIE, 1997, vol. 3026, pp. 133 – 142.

[5]S. Kim and J. P. Allebach, “Optimal unsharp mask for image sharpening and noise removal,” J Electron Imaging, vol. 14, no. 2, pp. 023007–1 – 023007–13, 2005.

[6].Alexander Wong_”Adaptive bilateral filtering of image signals using local phase characteristics” Journal of Elsevier Signal Processing 88 1615–1619(2008)

[7].Rafael C. Gonzalez, Richard E. Woods and Steven L. Eddins (2004). Digital Image

[8].Processing using MATLAB. Pearson Education. ISBN 978-81-7758-898-9.
Gilat, Amos (2004). MATLAB: An Introduction with Applications 2nd Edition. John Wiley & Sons. ISBN 978-0-471-69420-5.

[9] http://www4.comp.polyu.edu.hk/~cslzhang/code.htm

[10] http://www4.comp.polyu.edu.hk/~cslzhang/

[11] http://sse.tongji.edu.cn/linzhang/

[12] http://sse.tongji.edu.cn/linzhang/UsefulLinks/links.htm

[13] http://www.csse.uwa.edu.au/~ajmal/code.html

[14]http://vlm1.uta.edu/~athitsos/vlm/

[15]http://users.soe.ucsc.edu/~milanfar/students/

[16].susan approach-----http://users.fmrib.ox.ac**.uk**/~**steve**/**susan**/**index**.html