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Gaussian Noise Removal Image Reconstruction Algorithm using Gaussian Filtering

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***Abstract* – In this paper we proposed image reconstruction algorithm by using Gaussian filtering in gray scale and color images. Noise detection and noise removal are two important stages of the proposed algorithm. The algorithm is working on the principle of local weighted mean, local weighted variance and local weighted maxima. Proposed algorithm is very simple & PSNR performance demonstrates that, proposed algorithm is better and effective where image are highly corrupted by Gaussian noise. The output results are justified that reconstructed image quality is high**.

***Keywords* – Gaussian Noise Removal, Gaussian Filter, Local Statistics, PSNR.**

I. Introduction

Image captured by any system is the degraded version of an original image. The degradation is due to sensing environment when it acquire through optical, electro optical and electronics medium. The degradation is in the form of sensor noise, communication channel, and atmospheric turbulence. The intensity of noise has the tendency of being either relatively high or relatively low. Thus, it could severely degrade the image quality and cause great loss of information details. So it is important to eliminate noise in the images before some subsequent processing, such as edge detection, image segmentation and object recognition detection, image segmentation and object recognition.

Noise introduced in an image is usually classified as impulsive noise and additive white Gaussian noise. In Fixed valued impulse noise, noisy pixels can take either zero or 255 and in Random valued impulse noise, noisy pixels can take any value between zeros to 255.

Pixels in a 'Gaussian noise corrupted' image are constructed by the addition of a numerical value from a zero mean Gaussian distribution. AWGN is additive white Gaussian noise observed in an image, when all pixels from images are deviate from their original values. Noise in digital images is additive white Gaussian noise (AWGN) with Gaussian probability distribution. AWGN is suppressed using linear filters like Mean filter, Wiener filter, etc [1]. Linear techniques are simple but it gives blurred edges. Nonlinear filters [3] provide great noise reduction capability with less blurring.

Adaptive window based efficient algorithm [4] is used to remove Gaussian noise. In this algorithm each corrupted pixel is replaced by its mean value inside the adaptive window. To remove Gaussian noise Weiner filter [5] is used. But it gives huge blurring near the regions having edges. The noise detection stage is very important to differentiate noisy and noise-free pixel, so it is better to apply a noise removal filter. A progressive switching median (PSM) filter [6] was presented, where switching and progressive methods were applied through several iterations.

To remove the detected noise pixels adaptive weighted mean filter is used [7]. Over smoothness is occurring in the reconstructed image around important edge information. To minimize over smoothness in the noise removal process adaptive bilateral filtered was used. Tomasi and Manducci have proposed bilateral filter to eliminate Gaussian noise [8]. Robust estimation based filter has proposed in Tamer Rabie to remove Gaussian noise [9].

By taking into account local statistics [10] it is very important to define local constraints so that over smoothness of recovered image can be avoided. Noise detection and removal algorithm which uses local statistics is proposed in this paper.

This paper proposed simple and efficient algorithm to remove noisy components by assuming that an image is Gaussian distributed. This paper is organized as follows: Section II describes propose algorithm. Section III describes Experimental results & analysis. Sections IV address the conclusion.

II. Proposed Algorithm

Digital image is degraded by additive noise. It is assume that noise is statistically independent of the signal. Mathematically degraded image $y_{i,j}$ is represented as,

$$y_{i,j} = x_{i,j} + n_{i,j} \qquad (1)$$

Where $x_{i,j.}$ denote true image and $n_{i,j}$ represents additive noise.

To remove Gaussian noise from the images, it is very important to remove noisy component. Instead of keeping fixed threshold to remove noisy components from the images, proposed algorithm discriminate the noisy and noise free pixels to applying noise removal filter. This can be done by using local statistics.

To reduced noise, window function is used in which assume window size (2U+1) × (2V+1) where U & V =1. To preserve smaller details in the images small window size is used but it give less noise reduction. R1 and R2 are two regions of the analysis window where R1 has dark region & R2 has White region. Intersection region between R1 and R2 is null. Window has weighted coefficient as w (m, n) at point m, n. Filtered pixels arrived in the dark region and observed pixels are arrived in the white region. Noise is detected by using the local statistics such as the local weighted mean ($\mu_{i,j}$), the local weighted variance ($\sigma_{i,j}$) and the local maxima (Y_{max} i,j). The Local weighted mean & local weighted variance and local maxima for pixel $y_{i,j}$ are shown in Eq. (2), Eq. (3) & Eq. (4) respectively.

$$\mu_{i,j} = \frac{\sum_m \sum_{n(m,n)} w_{m,n}\, \hat{x}_{i+m,j+n} + \sum_m \sum_{n(m,n)} w_{m,n} y_{i+m,j+n}}{\sum_{m=-U}^{u} \sum_{n=-v}^{v} w_{m,n}} \quad (2)$$

$$\sigma_{i,j} = \frac{\sum_{n(m,n)} w_{m,n} \left|\hat{x}_{i+m,j+n} - \mu_{i,j}\right| + \sum_m \sum_{n(m,n)} w_{m,n} \left|y_{i+m,j+n} - \mu_{i,j}\right|}{\sum_{m=-U}^{u} \sum_{n=-v}^{v} w_{m,n}} \quad (3)$$

$$Y_{max\ i,j} = max\ y_{p,q} \quad (4)$$

It's really important to find pixels is highly corrupted or not .This can be done by assuming Gaussian distributed model. To find noisy pixel, local statistics parameter are consider with the help of flag. Flag can be define as

$$flag_{i,j} \begin{cases} 1 & if\ \ y_{i,j} > \mu_{i,j} + B_{i,j} \\ & or\ \ y_{i,j} < \mu_{i,j} - B_{i,j} \\ 0 & other\ wise \end{cases} \quad (5)$$

$$B_{i,j} = k \times \frac{\sigma_{i,j}}{y_{max\ ,i,j}} \quad (6)$$

In Eq. (6) k is constant. From Eq. (5), we can say that if flag is 1 then pixel is corrupted & if flag is 0 pixels is uncorrupted. If $B_{i,j}$ is small, tighter bound will produced. In highly active region looser bounds will produced. Algorithm eliminates Gaussian noise from the corrupted image with the help of local statistics. Flow of the algorithm is as follows:

1. Take input image.
2. Add Gaussian noise in the input image.
3. Calculate the local weighted mean, local weighed variance & local maxima. (use Eq.2,3 & 4)
4. If flag=1; use Gaussian filtering,
   Else; No filtering (use Eq.5, 6 &7)
5. reconstructed image(use Eq.8)

With the help of local statistics Gaussian filtering is use to control smoothness of the reconstructed image. Modified Gaussian filter is as follows:

$$h_{i,j} = \frac{1}{Z} \exp\left(-T \frac{\sigma_{i,j}^2 \ \ (i^2+j^2)}{\sqrt{\mu_{i,j}+1}}\right) \quad (7)$$

In Eq. (7) Z is the normalizing constant and T is tuning parameter. When T is high, weaker filtering is used to remove noisy component which is not acceptable in the noise removal process. Smaller T needs strong filtering but it gives loss of edges of the image so specific range of T is used. The regenerated pixel can be written as

$$\hat{x}_{i,j} = \begin{cases} \dfrac{\sum_m \sum_{n(m,n)} h_{m,n}\, \hat{x}_{i+m,j+n} + \sum_m \sum_{n(m,n)} h_{m,n} y_{i+m,j+n}}{\sum_{m=-U}^{u} \sum_{n=-V}^{v} h_{m,n}} \\ \quad ; if\ flag_{i,j} = 1 \\ y_{i,j} \quad ;\ otherwise \end{cases}$$

(8)

III. Experimental Result

The proposed noise removal algorithm is tested with different gray or color image like Lena, Pepper, Elaina, and Mandrill of size 512×512. The image is corrupted by Gaussian noise. To evaluate performance of the proposed algorithm PSNR (peak signal to noise ratio) is compare with different sigma.

Consider U=1, V=1, that window size 3×3 to avoid high cost and to reduced effect of blurring. In this paper, the weighting coefficient use is 3.To avoid over-smoothness, uniform value is taken. If k from the flag is higher, looser bound will appear which gives to higher missing detection error else tighter bounds gives higher fault detection error. As size of the window increases, reconstructed blurred image is obtained. It is required to select good range of k and T, to get better result. It is observed that 0.03≤ k ≤0.09 is the good range to reduce the level of the noise.

Tunings parameter T from the modified Gaussian filter gives idea about the smoothness of the reconstructed image. Smaller T needs, strong low pass filtering to suppress the noise but smaller T gives the over smoothness. Large value of the T required the weak low pass filtering. On the basic of this experiment 0.01≤T≤0.09 is the selected range. It is observed that value of PSNR is changed for different combinations of k & T. Z is the constant which used to determine filter coefficient. In this paper z is taken as 1because proposed algorithm is not depending on Z.

Table I: PSNR Performance of Lena gray image with=5

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	39.64	39.87	40.28	39.05	38.97
0.05	38.55	40.09	39.88	39.06	38.99
0.07	39.39	40.23	39.4	39.03	38.97
0.09	39.19	38.97	39.07	39.04	38.96

Table II: PSNR Performance of Lena gray image with σ=10

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	38.02	37.09	36.4	35.93	35.64
0.05	37.94	37.15	36.41	35.91	35.61
0.07	38.1	37.16	36.4	35.91	35.64
0.09	37.93	37.14	36.42	35.89	35.6

Table III: PSNR Performance of Lena gray image with σ=15

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	36.36	34.56	33.91	33.61	33.64
0.05	36.49	34.59	33.91	33.63	33.52
0.07	36.38	34.55	33.9	33.61	33.51
0.09	36.45	34.57	33.93	33.62	33.5

From Table I-III, it is observed that as sigma increases, PSNR decreases. Better PSNR is achieved at sigma=5. At k=0.03 & T=0.05 better PSNR value 40.28 is obtained for Lena (Gray) image.

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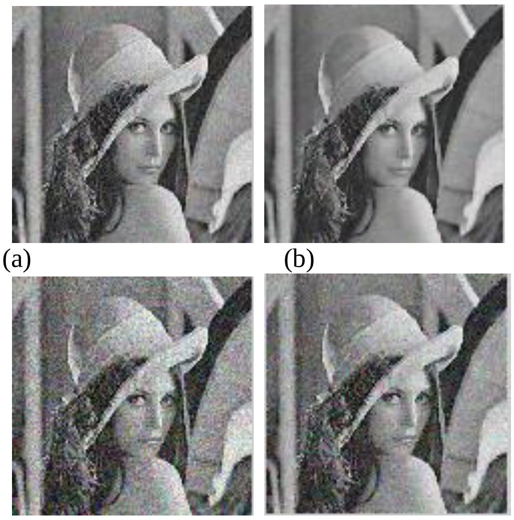


(a) (b) (c) (d)

Fig.1. Experimental results with Lena Gray image: (a) degraded image with σ=5 (b) corresponding reconstructed image with σ=5 (c) degraded image with σ=10 (d) corresponding reconstructed image with σ=10

Fig.(1) shows PSNR comparison of degraded “Lena” Gray image & corresponding reconstructing “Lena” Gray image with sigma 5& 10.It is observed that at sigma=5 quality of the reconstructing image is better than other & PSNR improved. It is observed that if the quantity of the Gaussian noise is less, degree of smoothness is more.

Table IV: PSNR Performance of Pepper image with σ=5

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	41.7	41.76	41.55	41.2	40.85
0.05	41.72	41.79	41.56	41.22	40.85
0.07	41.67	40.77	40.55	41.22	40.86
0.09	41.67	41.76	41.55	41.23	40.86

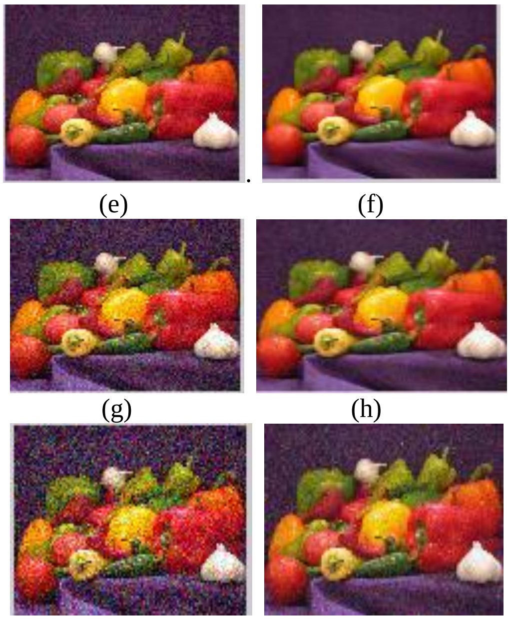
Table V: PSNR Performance of Pepper image with σ=10

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	39.27	37.91	36.84	36.25	35.95
0.05	39.28	37.92	36.83	36.26	35.94
0.07	39.28	37.91	36.83	36.25	35.58
0.09	39.27	37.93	36.83	36.25	35.87

Table VI: PSNR Performance of Pepper image with σ=15

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	37.17	34.9	34.21	33.97	33.86
0.05	37.14	34.9	34.21	33.98	33.86
0.07	37.17	34.89	34.2	33.96	33.87
0.09	37.16	34.89	34.21	33.98	33.87

From Table IV-VI, it is observed that as sigma increases, PSNR decreases. Better PSNR is achieved at sigma=5. At k=0.03 & T=0.05 better PSNR value 41.79 is obtained for Lena (Gray) image.



(e) (f) (g) (h) (i) (j)

Fig.2. Experimental results with Pepper image: (e) degraded image with σ=5 (f) corresponding reconstructed image with σ=5 (g) degraded image with σ=10 (h) corresponding reconstructed image with σ=10 (i) degraded image with σ=15 (j) corresponding reconstructed image with σ=15

Fig.(2) shows PSNR comparison of degraded “Pepper” color image & corresponding reconstructing “Pepper” color image with sigma 5,10 & 15.It is observed that at sigma=5 quality of the reconstructing image is better than other & PSNR improved. It is observed that if the quantity of the Gaussian noise is less, degree of smoothness is more.

Table VII: PSNR Performance of Lena image with σ=5

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	40.78	40.86	40.84	40.72	40.52
0.05	40.69	40.86	40.85	40.72	40.52
0.07	40.68	40.87	40.85	40.71	40.53
0.09	40.77	40.85	40.83	40.72	40.51

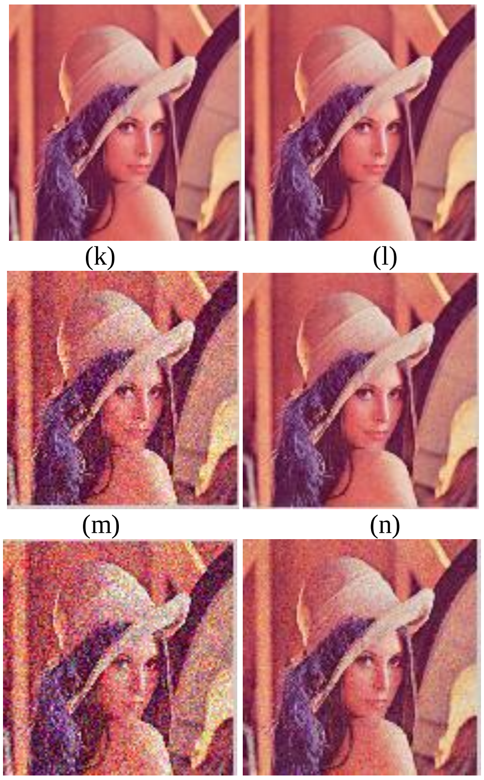
Table VIII: PSNR Performance of Lena image with σ=10

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	38.94	38.01	37.05	36.42	36.04
0.05	38.96	38.01	37.04	36.41	36.04
0.07	38.89	38.03	38.03	36.43	36.03
0.09	38.97	38.02	37.04	36.42	36.03

Table IX: PSNR Performance of Lena image with σ=15

K\T	**0.01**	**0.03**	**0.05**	**0.07**	**0.09**
0.03	37.09	35.03	34.21	33.91	33.73
0.05	37.08	35.02	34.22	33.9	33.75
0.07	37.1	35.01	35.02	33.89	33.73
0.09	37.12	35	34.21	33.88	33.74

From Table VII-IX, it is observed that as sigma increases, PSNR decreases. Better PSNR is achieved at sigma=5. At k=0.03 & T=0.07 better PSNR value 40.87 is obtained for Lena (Gray) image.



(k) (l) (m) (n) (o) (p)

Fig.3. Experimental results with Lena image: (k) degraded image with σ=5 (l) corresponding reconstructed image with σ=5 (m) degraded image with σ=10 (n) corresponding reconstructed image with σ=10(o) degraded image with σ=15 (p) corresponding reconstructed image with σ=15

Fig.(3) shows PSNR comparison of degraded "Lena" color image & corresponding reconstructing "Lena" color image with sigma 5,10 & 15.It is observed that at sigma=5 quality of the reconstructing image is better than other & PSNR improved. It is observed that if the quantity of the Gaussian noise is less, degree of smoothness is more.

IV. Conclusion

The Proposed algorithm is very simple & works effectively to remove Gaussian noise from the images. The Proposed algorithm is less complex as compare with other methods. It gives the better performance while preserving edges of the image. Due to use of local statistics in algorithm, complexity decreases. Without any training, algorithm provides better results with minimum time. The proposed algorithm is better and effective at k=0.03 &T=0.05 where images are highly corrupted by Gaussian noise.

References

[1] G. R. Arce, Nonlinear Signal Processing: A Statistical Approach, John Wiley and Sons Inc., 2004.

[2] A.K. Jain, Fundamentals of Digital Image Processing. Englewood Cliffs, NJ: Prentice-Hall; 1989

[3] I. Pitas and A.N. Venetsanopoulos, Nonlinear Digital Filters: Principles and Applications. Norwell, MA: Kluwer, 1990.

[4] V.R.Vijaykumar,P.T.Vanathi,"Adaptive window based efficient algorithm for removing Gaussian noise in gray scale and color images. IEEE *2007*

[5] B. Zhang and J. P. Allebach, "Adaptive bilateral filter for sharpness enhancement and noise removal," *IEEE Trans. Image Processing*, vol. 17, no. 5, pp. 664-668, May 2008

[6] Z. Wang and D. Zang, "Progressive switching median filter for removal of impulse noise from highly corrupted images," *IEEE Trans. Circuits System II*, vol. 46, pp. 78-80, Jan. 1999.

[7] X. Zhang and Y. Xiong, "Impulse noise removal using directional differences based noise detector and adaptive weighted mean filter," *IEEE Signal Processing Letters*, vol. 16, no. 4, pp. 295-298, Apr. 2009.

[8] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," Proc. IEEE Int. Conf. Computer Vision, pp. 839–846., 1998.

[9] Tamer Rabie, 'Robust Estimation Approach for Blind Denoising', IEEE Trans. on Image Processing, Vol. 14, No. 11, pp.1755-1765, 2005

[10] Tuan-Anh Nguyen, Myoung-Jin Kim, Min Cheol Hong, "Fast and efficient noise removal algorithm by spatially adaptive filtering" IEEE PCS2010, December 8-10

[11] Z. Wang and A. C. Bovik, "A universal image quality index," *IEEE Signal Process. Lett.*, vol. 9, pp. 81-84, M

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