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An Efficient Gaussian Noise Removal Image Enhancement Technique for Gray Scale Images

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***Abstract*—**Image enhancement is a challenging issue in many applications. In the last two decades, there are various filters developed. This paper proposes a novel method which removes Gaussian noise from the gray scale images. The proposed technique is compared with Enhanced Fuzzy Peer Group Filter (EFPGF) for various noise levels. Experimental results proved that the proposed filter achieves better Peak-Signal-to-Noise-Ratio PSNR than the existing techniques. The proposed technique achieves 1.736dB gain in PSNR than the EFPGF technique.

***Keywords*—**Gaussian noise, adaptive bilateral filter, fuzzy peer group filter, switching bilateral filter, PSNR.

I. Introduction

DIGITAL images are often corrupted by noise during their acquisition and transmission. A fundamental challenge in image enhancement is to reduce noise while maintaining the desired image features such as edges, textures, and fine details. In particular, there are two common types of noise namely Gaussian noise and Impulse noise, which are introduced during the acquisition and transmission processes [1]–[3]. Noisy images can be found in many applications. Noise is also introduced in digital images, when a damaged image is scanned. Digital cameras may introduce noise because of CCD sensor malfunction, electronic interference or flaws in data transmission. In the last two decades, many methods have been introduced in the literature to remove either Gaussian or Impulse noise. This paper proposed an efficient technique to remove Gaussian noise. Some of the recent methods for removing Gaussian noise are discussed in this section.

Adaptive Bilateral filter (ABF) is proposed by Buyue Zhang for sharpness enhancement and noise removal [4]. The ABF sharpens an image by increasing the slope of the edges without producing overshoot or undershoot. The ABF is efficient to implement, and provides a more reliable and more robust solution to slope restoration. The ABF works well for both natural images and text images.

Samuel Morillas et al. introduced Fuzzy Peer Group Filter (FPGF) concept [5], which extends the peer group concept in the fuzzy setting.

A fuzzy peer group will be defined as a fuzzy set that takes a peer group as support set and where the membership degree of each peer group member will be given by its fuzzy similarity with respect to the pixel under processing. The FPGF is able to efficiently suppress Gaussian noise and impulse noise, as well as mixed Gaussian-impulse noise.

Chih-Hsing Lin et al. proposed switching bilateral filter (SBF) [6] with a texture and noise detector for universal noise removal. This filter can remove both the additive Gaussian noise and the impulse noise. In most of the noise model cases, the SBF outperforms other filters, both in PSNR and visually. Moreover, it shows excellent performance in the simultaneous removal of both impulse and Gaussian noise

In 2012, a noise detection and reduction method using fuzzy logic has been proposed [7]. This method designed a fuzzy based adaptive mean filter to remove impulse, Gaussian and speckle noise. It removes all types of noise efficiently.

In 2012, a switching scheme for noise detection and genetic algorithm for reduction [8] has been proposed. This method uses a supervised learning algorithm using non-linear filters. It removes impulse and Gaussian noise for gray scale image. It needs more computational time.

In October 2013, a noise detection method named fuzzy filter and vector median filter has been proposed to remove Gaussian, impulse and mixed noises [9]. This method performs better than other methods but the computational time is high.

To further improve the quality of the image, we proposed an Enhanced Fuzzy Peer Group filter (EFPGF) [10]. In [10], EFPGF is compared with ABF, SBF and FPGF for various noise levels. It performs better than those methods for both Gaussian and mixed noise.

This paper proposes an efficient technique for removing Gaussian noise in gray scale images. The key point of the proposed technique is to use the probability concept in the images. The least probable pixel in the image may be identified as noisy pixel and it is replaced with most probable gray level value. It uses the histogram concept to check the least and most probable gray level values. The proposed technique uses Wiener filter as pre-processing step to remove Gaussian noise to some extent.

This paper is organized as follows: Section II describes the overall system architecture for noise removal. Section III elaborates the proposed technique for removing the Gaussian noise. Section IV demonstrates the experimental results followed by conclusion in Section V.

II. System Architecture

The overall system architecture is shown in Fig. 1. The noisy image (I) is initially filtered using Wiener filter. This filter is used to remove Gaussian noise to some extent. The

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Wiener Filtered Image (WFI) obtained in this step is analyzed in Section IV. The most probable gray level of the entire filtered image is calculated and it is set as Global Probable Histogram Count (G). Each pixel (i) in the WFI is restored by using neighboring pixels which is formed as a window of size 3 x 3. The most probable gray level value within the window is calculated and it is termed as Local Probable Histogram Count (L). Each pixel can be replaced by the most probable gray value (S) depends on a threshold (T). S is calculated as minimum of L and G. If only L is used, then every pixel will be replaced with the local most probable histogram count value. Hence, G is also used to normalize the image. If every pixel in the image is replaced, then the restored image will have the same value in each coordinate. In order to avoid this, T is calculated to know the noisy pixel only. The optimum threshold value is obtained through various experiments which is shown in Section IV. Absolute difference of the current pixel and S is calculated to know if the pixel has more variance than the neighbouring pixels. If the absolute difference is greater than the threshold, then the pixel is considered as noisy image and it is replaced with S.

III. Proposed Noise Removal Algorithm

The proposed technique is based on the most probable gray value in the image. Before applying the proposed technique, the noisy image is given to Wiener filter as it removes Gaussian noise more efficiently to some extent. Next level is based on Global and Local histogram count for filtering. Global histogram count is used to avoid pixel replication locally.

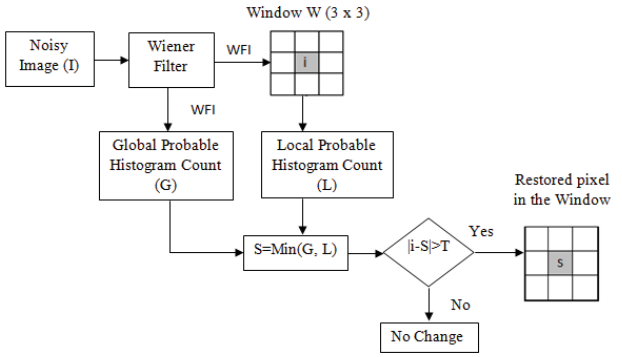


Fig. 1 System Architecture

(-1,-1)	(-1,0)	(-1,1)
(0,-1)	(0,0)	(0,1)
(1,-1)	(1,0)	(1,1)

Fig. 2 Pixel positions in a window

The following are steps in the proposed technique:

Step1. The noisy image (I) is filtered using Wiener filter [11] to obtain WFI. For each pixel n_1,n_2 in the window (α), Wiener filter estimates the local mean (μ) and variance (σ^2) around each pixel.

$$\mu = \frac{1}{NM}\sum_{n_1,n_2\epsilon\eta}\alpha(n_1,n_2) \quad (1)$$

$$\sigma^2 = \frac{1}{NM}\sum_{n_1,n_2\epsilon\eta}\alpha^2(n_1,n_2) - \mu^2 \quad (2)$$

where η is the N-by-M local neighborhood of each pixel in the image. Then, it creates a pixel-wise Wiener filter using these estimates,

$$b(n_1,n_2\ )=\mu+(\sigma\text{^}2-v\text{^}2)/\sigma\text{^}2\ (\alpha(n_1,n_2\ )-\mu) \quad (3)$$

where ν2 is the noise variance. If the noise variance is not given, then it uses the average of all the local estimated variances. This step yields WFI, which is used for further processes.

Step2. Calculate histogram count of WFI. The maximum value in the histogram count is set as G.

Step3. Each pixel in WFI undergoes the following condition

$$i = \begin{cases} \text{i} & \text{abs (i} - \text{S)} < T \\ \min\{\text{G, L}\} \text{ or S} & \text{abs (i} - \text{S)} > T \end{cases} \quad (4)$$

The position of the window in the WFI for a center pixel (0,0) is given in Fig. 2. G, L are Global Probable Histogram Count and Local Probable Histogram Count respectively. S= min {G, L} and T is Threshold

In (4), the first condition indicates that if the pixel is not affected by noise then the pixel is retained. Otherwise replace the pixel with S. The threshold (T) value selection is based on various manual testing explained in the next section.

IV. Experimental Results

Experiments are conducted for images such as MRI brain image, Lena and many gray scale images. Images are tested with noise levels ranges from 0.01 to 0.1. The quality of the filtered image should be estimated by subjective tests. One of the subjective metrics is Mean Square Error (MSE), which is evaluated between original frame and reconstructed frame. The lesser the MSE value, the better is the prediction quality.

Mean Square Error is given by

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left(f(M,N) - f^{'}(M,N)\right)^2 \quad (5)$$

where f(M,N) represents the original image and f^' (M,N) is the restored image with size M x N. Another widely used metric for comparing various image enhancement techniques is the PSNR. The mathematical formula for PSNR is

$$PSNR = 10\ log_{10}\left[\frac{(2^b-1)^2}{MSE}\right] \quad (6)$$

where b in the equation is the number of bits to represent a pixel. For 8-bit uniformly quantized image, b = 8. The higher the PSNR value, the better is the quality of the restored image. Another important performance metrics used is Structural Similarity Index Measure (SSIM).

The SSIM is given by

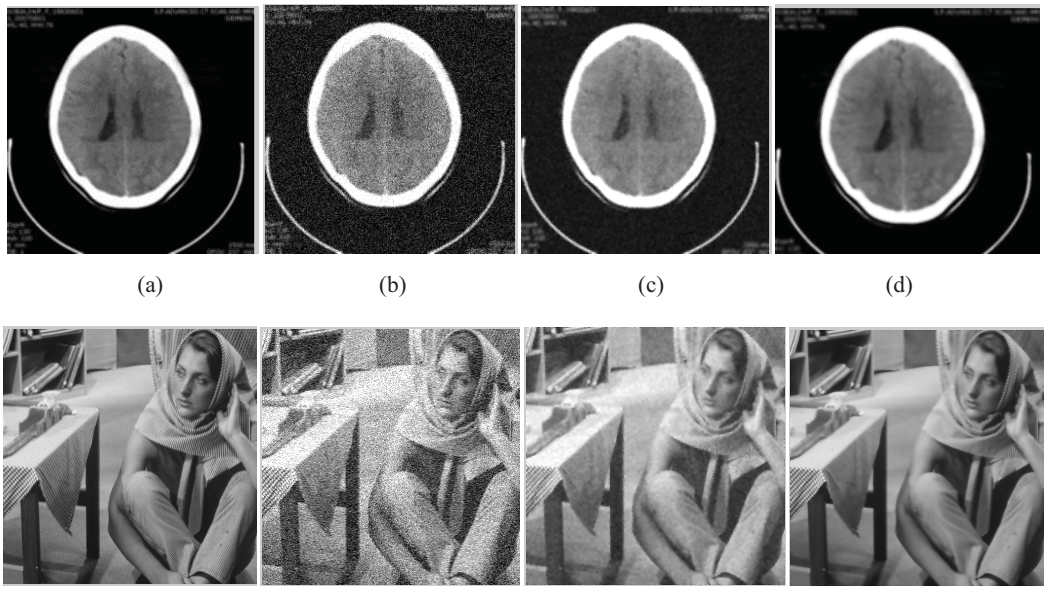
$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (7)$$

where μ_x and μ_y are mean in x and y coordinates respectively. σ_x^2 and σ_y^2 are variance of the image in x and y coordinates respectively. c_1 and c_2 are included to avoid instability when μ_x^2 and μ_y^2 are very close to zero, respectively.

Experiments are performed for various threshold values for noise level 0.1. Table I shows PSNR obtained by the proposed technique for various threshold levels.

TABLE I
PSNR ACHIEVED BY THE PROPOSED TECHNIQUE FOR VARIOUS THRESHOLD VALUES

Threshold/Image	PSNR (dB)								
	1	2	3	4	5	6	7	8	9
MRI Brain Image	32.7235	32.956	33.0152	33.2145	**33.366**	33.181	32.658	31.875	30.593
Lena	32.4486	32.9856	33.1524	33.854	**34.476**	33.675	32.1896	31.124	30.852
Barbara	28.248	29.6741	30.254	31.1472	**31.685**	30.654	29.975	28.458	27.124
Cameraman	31.524	31.971	32.284	33.018	**33.8024**	32.952	31.856	30.235	29.657



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

(e) (f) (g) (h)

Fig. 3 (a), (e) Original Image (b), (f) Noisy Image (c), (g) Wiener Filtered Image (d), (h) Noise Removal Image of the Proposed Technique of MRI brain image and Barbara image respectively

Some of the experimental images and their results are shown in Fig. 3. It shows the original image, noisy image of noise level 0.1 and the filtered image. From Fig. 3, it is clear that the quality of the filtered image in the proposed technique is visually better. The PSNR value obtained by the Wiener Filter is shown in Table II. Table III shows the results for MRI brain image, Lena and cameraman images for various noise levels.

From Tables II and III, it is clear that the PSNR obtained by the proposed technique is better than the PSNR obtained by Wiener filter. It is also observed that obtained PSNR for all images decreases as noise level increases. The maximum PSNR is obtained in Lena image for noise level 0.01 which is 35.92dB.

The average time taken for the proposed technique to remove noise is 12.65 seconds. The PSNR achieved by the proposed technique with and without Wiener filter for noise level 0.1 is shown in Fig. 4. It is observed that Wiener filter plays a small role in the proposed technique.

TABLE II
PSNR OBTAINED BY WIENER FILTER FOR NOISE LEVEL 0.1

Image	PSNR (dB)
MRI Brain	32.201
Lena (512x512)	32.4321
Barbara (512x512)	30.1858
Cameraman (512x512)	32.1412

From the results [10], it is observed that EFPGF technique is better than the conventional ABF, SBF and FPGF techniques. Hence the results obtained by the proposed technique are compared with the results obtained by the EFPGF technique. Fig. 5 shows the PSNR comparison of the proposed technique with EFPGF technique for all noise levels of MRI brain image. Table IV shows the PSNR obtained by the proposed technique and the EFPGF technique of MRI brain image for various noise levels. Table IV also shows the PSNR gain of the proposed technique over EFPGF technique. It is calculated as

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$$PSNR\ Gain = P_1 - P_2 \quad (8)$$

where P_1 is the PSNR achieved by the proposed technique and P_2 is PSNR achieved by the EFPGF technique.

From the Table IV, it is observed that the proposed technique achieves better PSNR than the EFPGF technique for all noise levels.

V. Conclusion

This paper presents an efficient image enhancement technique for removing Gaussian noise of gray scale images. The proposed technique identifies the noisy pixel in the image and restores that pixel. The least probable pixel is identified as noisy pixel and it is replaced by the most probable pixel. The proposed technique is compared with Wiener Filter and EFPGF techniques for various noise levels. Experimental results found that the proposed technique is better than the Wiener Filter EFPGF techniques. The PSNR gain obtained by the proposed technique is 1.7358dB higher than the EFGPF technique.

TABLE III
Results Obtained for Various Noise Levels

Images		Noise Level									
	Metrics	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
MRI Brain	PSNR	34.4406	34.4445	34.3723	34.3194	34.2126	34.0834	33.9409	33.758	33.5914	33.366
	MSE	4.8362	4.8431	4.8744	4.9042	4.9649	5.0393	5.1227	5.2317	5.333	5.4732
	SSIM	0.9821	0.9365	0.8774	0.8187	0.7661	0.721	0.6832	0.6528	0.6274	0.6047
	Time	12.2839	18.7979	12.9047	12.9452	13.8962	15.1071	12.0742	11.1263	11.8475	11.235
Lena	PSNR	35.9164	35.8566	35.7762	35.6571	35.5134	35.3243	35.1485	34.938	34.6851	34.476
	MSE	4.0806	4.1088	4.147	4.2042	4.2743	4.3684	4.4577	4.5671	4.702	4.8196
	SSIM	0.9994	0.9978	0.995	0.9911	0.9863	0.9804	0.9736	0.9661	0.9575	0.9486
	Time	13.2355	11.7828	16.5495	10.9163	13.6959	10.8435	11.0017	11.3171	11.5812	11.689
barbara	PSNR	32.3752	32.3512	32.3101	32.2602	32.1976	32.0959	32.0176	31.9071	31.7986	31.685
	MSE	6.1345	6.1515	6.1807	6.2163	6.2612	6.3349	6.3923	6.4742	6.5555	6.6422
	SSI	0.9996	0.9984	0.9964	0.9935	0.99	0.9858	0.9808	0.9752	0.9689	0.9621
	Time	22.1398	12.7815	14.5502	14.0396	11.8763	12.1222	11.4959	11.3224	13.4105	12.8919
Camera man	PSNR	35.0264	34.9818	34.9127	34.8134	34.6931	34.5506	34.3994	34.2223	34.0093	33.8024
	MSE	4.5208	4.5441	4.5804	4.6331	4.6977	4.7754	4.8593	4.9594	5.0825	5.205
	SSIM	0.9991	0.9965	0.9923	0.9864	0.9791	0.9705	0.9605	0.9497	0.9376	0.9249
	Time	10.9047	11.4191	11.8439	12.356	11.4238	11.5394	11.8304	10.8488	11.1778	10.9875

TABLE IV
PSNR Obtained by the Proposed Technique and the EFPGF Technique of MRI Brain Image

	PSNR (dB)									
Noise Level/ Technique	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**	**0.08**	**0.09**	**0.1**
EFPGF Technique	34.11	33.729	33.028	32.921	32.569	32.007	31.77	31.337	30.457	29.899
Proposed technique	34.4406	34.4445	34.3723	34.3194	34.2126	34.0834	33.9409	33.758	33.5914	33.366
PSNR Gain	0.3306	0.7155	1.3443	1.3984	1.6436	2.0764	2.1709	2.421	3.1344	3.467
Average Gain	1.7358									

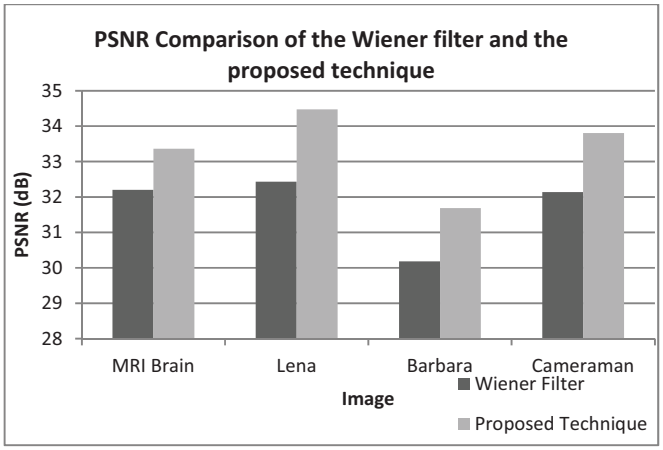


Fig. 4 PSNR comparison of the proposed technique with and without Wiener Filter for noise level 0.1

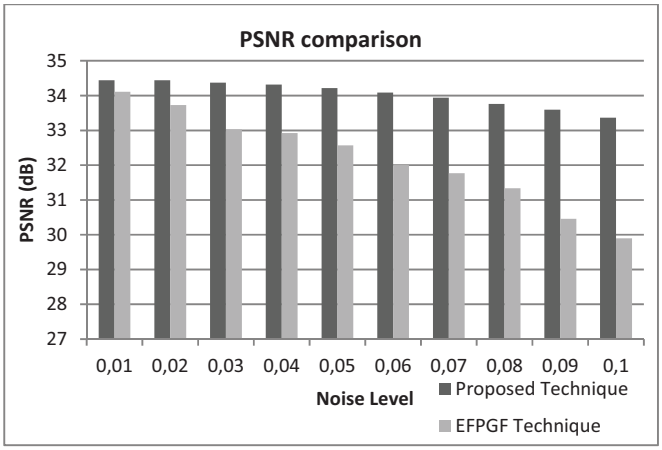


Fig. 5 PSNR comparison of the Proposed Technique with EFPGF Technique

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REFERENCES

[1] K, N. Plataniotis and A. N. Venetsanopoulos, Color Image Processing and Applications. Berlin, Germany: Springer, 2000.

[2] R. Lukac, B. Smolka, K. Martin, K. N. Plataniotis, and A. N. Venetsanopoulos, "Vector filtering for color imaging," IEEE Signal Process. Mag., vol. 22, no. 1, pp. 74–86, Jan. 2005.

[3] R. Lukac, and K. N. Plataniotis, "A taxonomy of color image filtering and enhancement solutions," in Advances in Imaging and Electron Physics, P. W. Hawkes, Ed. New York: Elsevier, 2006, vol. 140, pp.187–264.

[4] Buyue, Zhang, Member, IEEE, and Jan P. Allebach, Fellow, IEEE "Adaptive Bilateral Filter for Sharpness Enhancement and Noise Removal" IEEE Transactions on Image Processing, Vol. 17, No. 5, May 2008

[5] Samuel Morillas, Valentín Gregori, and Antonio Hervás "Fuzzy Peer Groups for Reducing Mixed Gaussian-Impulse Noise From Color Images" IEEE Transactions on Image Processing, Vol. 18, No. 7, July 2009

[6] Chih-Hsing Lin, Jia-Shiuan Tsai, and Ching-Te Chiu "Switching Bilateral Filter With a Texture/Noise Detector for Universal Noise Removal" IEEE Transactions on Image Processing, Vol. 19, No. 9, September 2010 2307

[7] Punyaban Patel, Bibekananda Jena, Banshidhar Maji, "Fuzzy based Adaptive mean filtering techniques for removal of impulse noise from images", International journal of Computer Vision and Signal Processing",Vol(1),15-21,2012.

[8] Aher, Jodhanle "Removal of Mixed Impulse Noise and Gaussian Noise Using Genetic Programming", IEEE con. Image processing 978-1-4673-1714-6-2012.

[9] Joan-Gerard Camarena, Valent´ın Gregori, Samuel Morillas, and Almanzor Sapena "A Simple Fuzzy Method to Remove Mixed Gaussian-Impulsive Noise from Color Images" IEEE Transactions on Fuzzy Systems, Vol. 21, no. 5, October 2013.

[10] V.Murugan, T. Avudaiappan and R. Balasubramanian, "Implementation of MRI Brain Image Enhancement Techniques Using Parallel Processing On Clustering Environment", Australian Journal of Basic and Applied Sciences, 8(13), Pages: 390-402, August 2014.

[11] S.Lim, Jae, Two-Dimensional Signal and Image Processing, Englewood Cliffs, NJ, Prentice Hall, 1990, p. 548, equations 9.44 -- 9.46.