Fast and Efficient Algorithm to Remove Gaussian Noise in Digital Images

V.R.Vijaykumar, P.T.Vanathi, P.Kanagasabapathy

Abstract— **In this paper, a new fast and efficient algorithm capable in removing Gaussian noise with less computational complexity is presented. The algorithm initially estimates the amount of noise corruption from the noise corrupted image. In the second stage, the center pixel is replaced by the mean value of the some of the surrounding pixels based on a threshold value. Noise removing with edge preservation and computational complexity are two conflicting parameters. The proposed method is an optimum solution for these requirements. The performance of the algorithm is tested and compared with standard mean filter, wiener filter, alpha trimmed mean filter K- means filter, bilateral filter and recently proposed trilateral filter. Experimental results show the superior performance of the proposed filtering algorithm compared to the other standard algorithms in terms of both subjective and objective evaluations. The proposed method removes Gaussian noise and the edges are better preserved with less computational complexity and this aspect makes it easy to implement in hardware.**

Index Terms— **Additive Gaussian noise, Image Denoising, Nonlinear Filter, Noise Variance, Standard Deviation and Smoothing Factor**

I. INTRODUCTION

Noise having Gaussian-like distribution is very often encountered in acquired data. Gaussian noise is characterized by adding to each image pixel a value from a zero-mean Gaussian distribution. The zero-mean property of the distribution allows such noise to be removed by locally averaging pixel values [1]. Conventional linear filters such as arithmetic mean filter and Gaussian filter smooth noises effectively but blur edges. Since the goal of the filtering action is to cancel noise while preserving the integrity of edge and detail information, nonlinear approaches generally provide more satisfactory results than linear techniques. The Wiener filter is the mean square error-optimal stationary linear filter for images degraded by additive noise and blurring. However a common drawback of the practical use of this method is the fact that they usually require some 'a priori' knowledge about the spectra of noise and the original signal. This information is necessary to perform the optimal choice of parameter values and/or threshold selections. Unfortunately, such information is very often not available

in real time applications. Also Wiener filter experiences uniform filtering throughout the image, with no allowance for changes between busy and flat regions, resulting in unacceptable blurring of fine detail across edges and inadequate filtering of noise in relatively flat areas [2].

In the field of image processing, there have been many attempts to construct digital filters which have the qualities of noise attenuation and detail preservation. For impulsive noise, the median filter is one of the best [3]-[5]. But for Gaussian noise, it is less successful. Several researchers have attempted to generalize the standard median filter but such filters are seldom suitable for removing Gaussian noise. In [6]-[8] nonlinear diffusion equations called as an anisotropic diffusion algorithm have been proposed for Gaussian noise removal. In [9] Tomasi and Manducci have proposed a bilateral filter to remove Gaussian noise. In [10] a Tamer Rabie has proposed a robust estimation based filter to remove Gaussian noise with detail preservation. The main draw backs of the above algorithms are, it takes much computation time and complex circuit to implement. In [11] Garnett et.al have proposed a trilateral filter to remove different type of noises in an image In this paper we proposed a simple and efficient method to remove low to high density Gaussian noise. Compare to other existing non linear based methods the proposed method performs well with very less computational time.

This paper is organized as follows: Section II describes the Gaussian noise model and estimation, Section III describes the proposed algorithm, and in section IV describes the results and discussion. Finally Section V reports conclusion.

II. NOISE MODEL AND ESTIMATION

Noise is modeled as additive white Gaussian noise (AWGN), where all the image pixels deviate from their original values following the Gaussian curve. That is, for each image pixel with intensity value O_{ij} ($1 \le i \le M, 1 \le j \le N$ for an M x N image), the corresponding pixel of the noisy image X_{ij} is given by,

$$X_{ij} = O_{ij} + G_{ij} \qquad (1)$$

Where, each noise value G is drawn from a zero-mean Gaussian distribution. Many Gaussian noise removal techniques require the knowledge of the standard deviation as a measure of the extent of corruption for the purpose of setting thresholds, filtering window size etc. One effective way to achieve this objective is to use Immerkaer's fast method [11] in which the noisy image X of size M x N is convolved with

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the mask defined as $\text{MASK} = \begin{pmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{pmatrix}$

The formula for the estimation of Gaussian noise standard deviation (σ_{GN}) is given by the equation

$$\sigma_{GN} = \sqrt{\frac{\pi}{2}} \frac{1}{6MN} \sum_{i,j=1}^{M,N} \left| (X * MASK)_{i,j} \right| \tag{2}$$

where, '*' denotes convolution operation.

III. PROPOSED ALGORITHM

The noise standard deviation of the image is estimated using the Immerkaer's fast method. The absolute difference between the center pixel and surrounding pixels in the filtering window is obtained by subtracting each element in the filtering window with the center pixel. The difference will be large when the image is highly corrupted.. This difference is compared with a threshold. The threshold can be defined as the product of smoothing factor and noise standard deviation. The value of smoothing factor is chosen as two for optimal performance. If the smoothing factor is chosen to be a high value, the noise removal is better at the cost of loss of image details. If this absolute difference is within the threshold, the corresponding pixel values are alone taken for further processing. The number of pixels taken into consideration in a filtering window should be at least 5. If it fails to satisfy the above condition, the window size is get increased and repeat the above procedures till the number of pixels under consideration in a filtering window is at least five. Then the center pixel is then replaced by the mean of those pixels that are considered. The above procedure is repeated for the entire image. The algorithm can be summarized as follows:

Let $X(i,j)$ be the current pixel to be processed; $S_{i,j}$ is the sliding or filtering window of size $(2L+1) \times (2L+1)$ centered at $X(i,j)$. The elements of this window are $S_{i,j} = \{X_{i-u, j-v}, -L \leq u,v \leq L\}$ (where L is depends on the window size).

1. The noisy image is taken as X.
2. The noise standard deviation (SD) is found out using Immerkaer's fast method.
3. A 2-D filtering window S_{ij} of size 3x3 is selected from the noisy image and let the center pixel be $X(i,j)$. In the window, subtract each element with the center pixel and the absolute value of the difference is calculated as $AD = |S_{ij} - X(i,j)|$.
4. If the absolute difference $AD < (SF*SD)$ (where SF is the smoothing factor and SD is the standard deviation), store the corresponding pixels in a one dimensional array as DA(x).
5. If the number of elements in the DA(x) is at least $(2*W) -1$ (where W is chosen to be 3 for a 3 x 3 window) then the mean of DA(x) is calculated and replaced it at the center pixel $X(i,j)$ of the window.
6. Else the window size is increased and the same process is repeated.
7. Steps 3-6 are repeated until the processing is completed for the entire image.

A. Illustration of the algorithm

Demonstration for Gaussian noise of standard deviation (SD) is 20 and window size is 3.

Original Image Segment

$\begin{pmatrix} 78 & 99 & 112 \\ 88 & 107 & 116 \\ 93 & 110 & 117 \end{pmatrix}$

Noisy Image Segment

$\begin{pmatrix} 65 & 91 & 114 \\ 103 & 121 & 128 \\ 88 & 84 & 116 \end{pmatrix}$

The absolute difference between the center pixel and surrounding pixels are [65 30 7 18 7 33 37 5]. Compare the absolute difference AD < SF * SD where SF=2 and SD = 20. Therefore SF*SD=40. Therefore, the DA = [91, 114, 103, 128, 88, 84, 116]. Total number of elements in the array is 7

For a 3 X 3 window, W=3 and (2*W) -1=5. The number of elements in DA is greater than the threshold 5. Therefore, the center pixel is replaced by the mean of the DA , that is 91+114+103+128+88+84+116)/7=103. This value is very close to the original value of 107. But the mean filter value is (65+91+114+103+121+128+88+84+116)/9=101.

IV. RESULTS AND DISCUSSIONS

A. Configuration

The proposed algorithm is tested using 512X512, 8-bits/pixel standard images such as Lena (Gray), Elaine (Gray), Pepper (Gray) and Barbara (color). The performance of the proposed algorithm is tested for various levels of noise corruption and compared with standard filters namely mean filter, wiener filter, alpha trimmed mean filter, K-Means filter, bilateral filter and recently proposed trilateral filter. Each time the test image is corrupted by different Gaussian noise standard deviation ranging from 10 to 50 with an increment of 10 will be applied to the various filters. In addition to the visual quality, the performance of the proposed algorithm and other standard algorithms are quantitatively measured by the following parameters such as peak signal-to-noise ratio (PSNR) and the mean absolute error (MAE).

$$PSNR = 10\log_{10}\left[\frac{255^2}{\frac{1}{MN}\sum_i \sum_j (r_{ij} - o_{ij})^2}\right] \tag{3}$$

$$MAE = \frac{1}{MN}\sum_i \sum_j \left| r_{ij} - o_{ij} \right| \tag{4}$$

Where $r_{i,j}$ and $o_{i,j}$ denote the pixel values of the restored image and the original image respectively and M x N is the size of the image. All the filters are implemented in MATLAB 7.1 and filtering window used for mean filter, wiener filter, alpha-trimmed mean filter, K-means filter, bilateral filter and trilateral filter is of size 3x3. The standard deviation values in the bilateral and trilateral filters are tuned to give better performance in terms of PSNR and MAE.
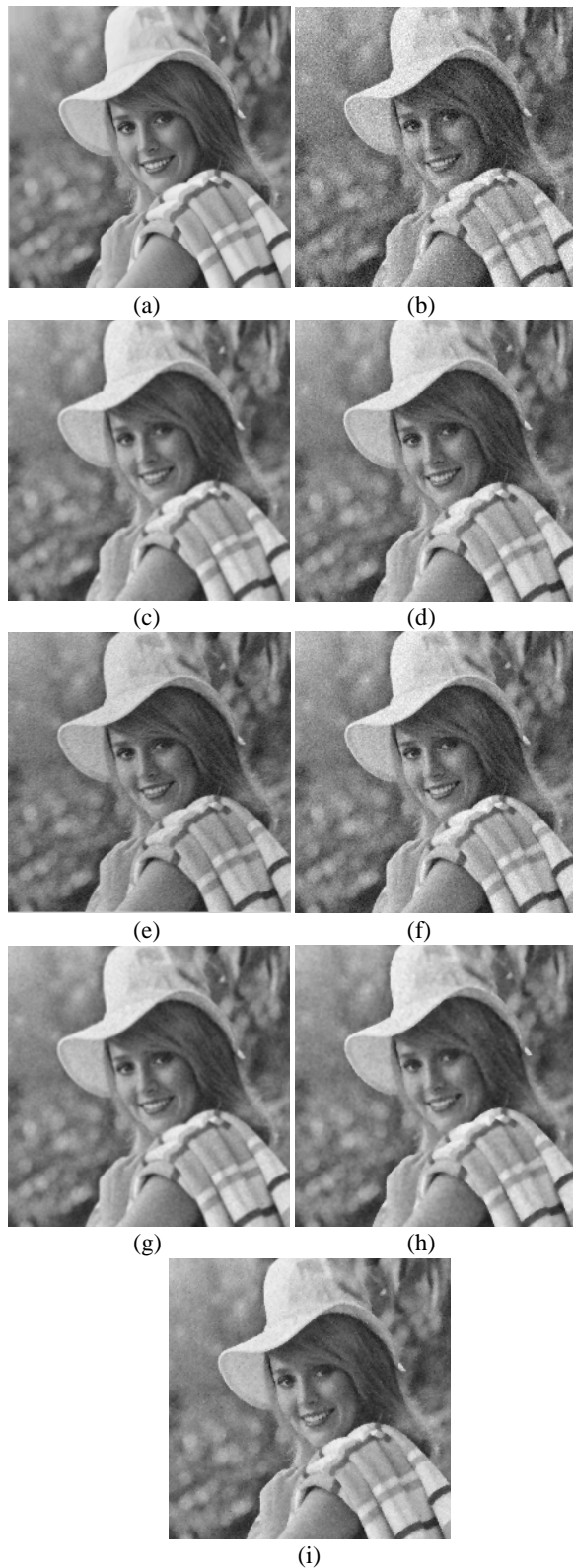
Figure2 (a) Original Elaine image (b) Noisy Image (σ =20)
(c) Mean Filter (d) Wiener filter (e) Alpha trimmed mean
filter (f) K-Means filter (g) Bilateral filter (h) Trilateral filter
(i) Proposed Method

Figure3 (a) Original Elaine image (b) Noisy Image (σ = 30)
(c) Mean Filter (d) Wiener filter (e) Alpha trimmed mean
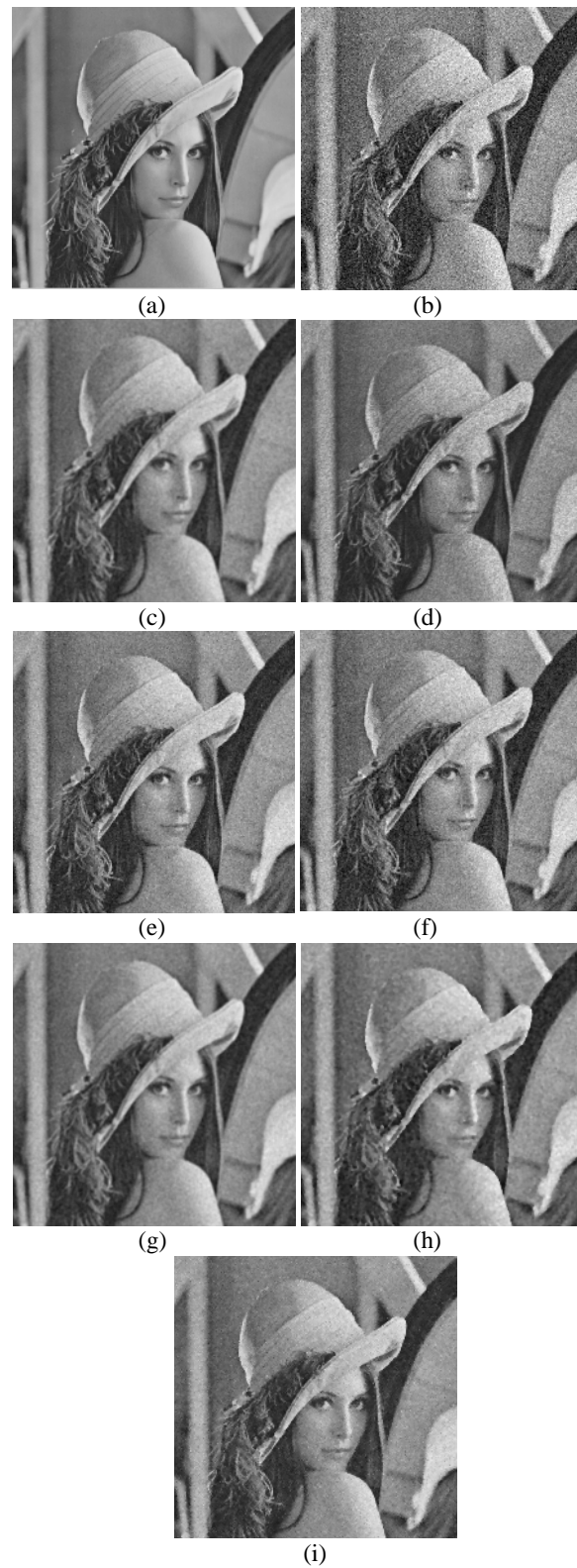filter (f) K-Means filter (g) Bilateral filter (h) Trilateral filter
(i) Proposed Method

Figure.4 (a) Original Elaine image (b) Noisy Image (=40) (c) Mean Filter (d) Wiener filter
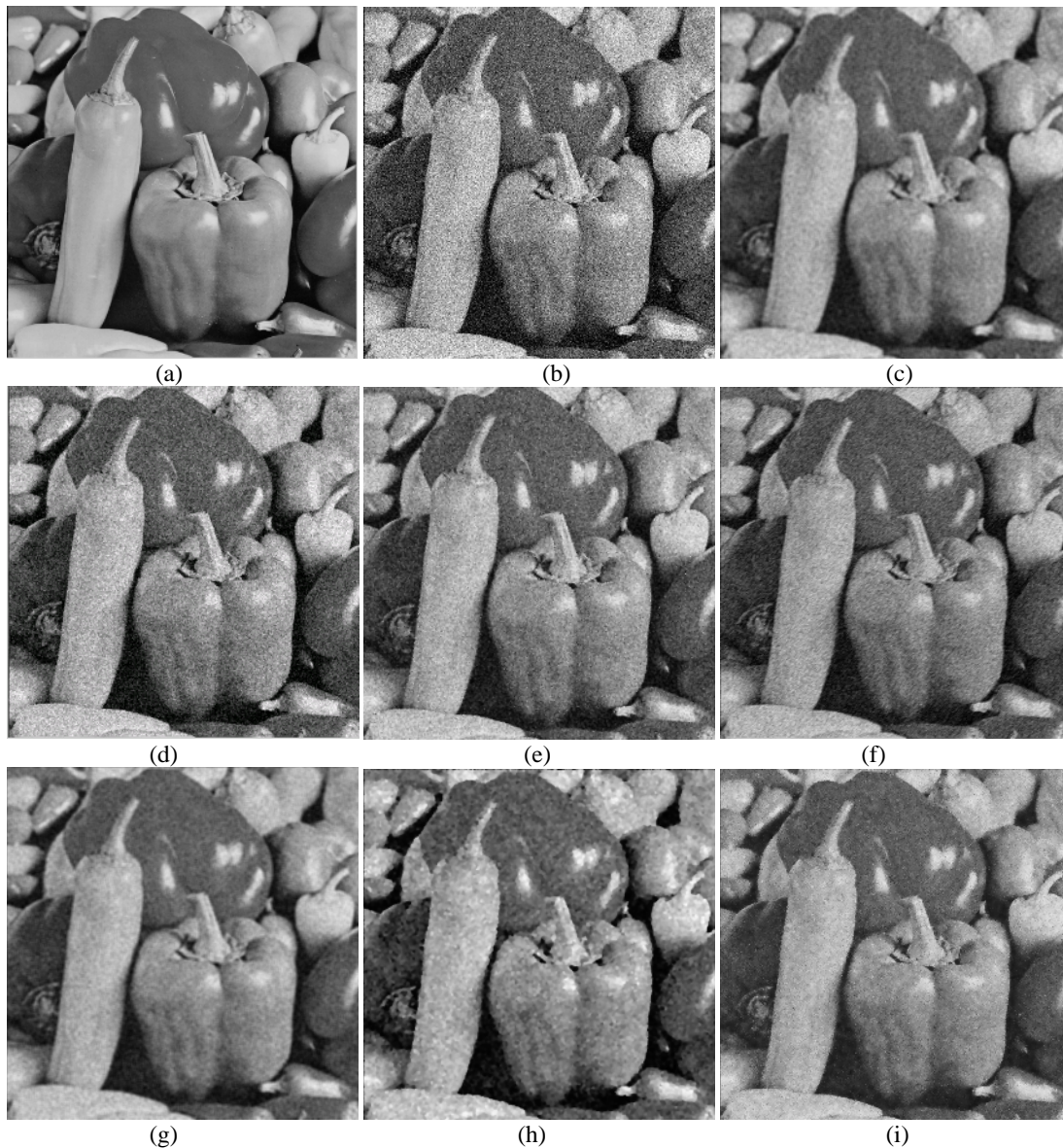(e) Alpha trimmed mean filter (f) K-Means filter (g) Bilateral filter (h) Trilateral filter (i) Proposed Method

TABLE I

PSNR FOR VARIOUS FILTERS FOR ELAINE.TIFF (GRAY) IMAGE AT DIFFERENT NOISE DENSITIES

SD	Mean filter	Wiener	Alpha trimmed	K-Means	Bilateral filter	Trilateral filter	PA
10	26.25	30.94	29.19	30.5	30.4355	29.4542	32.53
20	25.6	28.5	28.89	26.66	29.0547	28.0619	30.56
30	24.45	25.58	26.42	23.47	27.9844	26.1225	28.07
40	23.19	23.39	23.64	22.27	24.34	23.8076	26.85
50	20.65	21.78	20.7	19.35	22.43	21.6682	25.83

TABLE II

MAE FOR VARIOUS FILTERS FOR ELAINE.TIFF (GRAY) IMAGE AT DIFFERENT NOISE DENSITIES

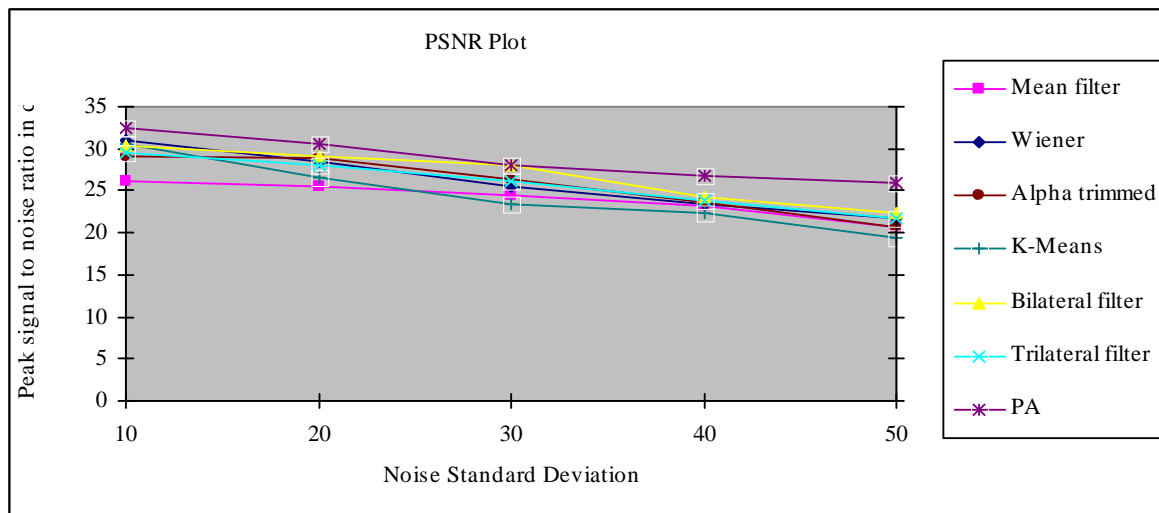| SD	Mean filter	Alpha trimmed	Wiener	K-Means	Bilateral filter	Trilateral filter	PA
10	10.36	10.82	5.02	5.34	4.9135	4.9515	4.54
20	11.13	11.97	7.45	9.52	7.01	6.4729	6.08
30	11.87	13.88	10.31	13.84	8.84	8.8444	7.27
40	14.21	16.29	13.26	18.15	10.24	12.0853	8.6
50	16.08	18.77	15.97	22.46	15.44	16.0976	9.93

Figure 5. PSNR of Various Filters for Lena Image at Different Noise Standard Deviations (in dB)
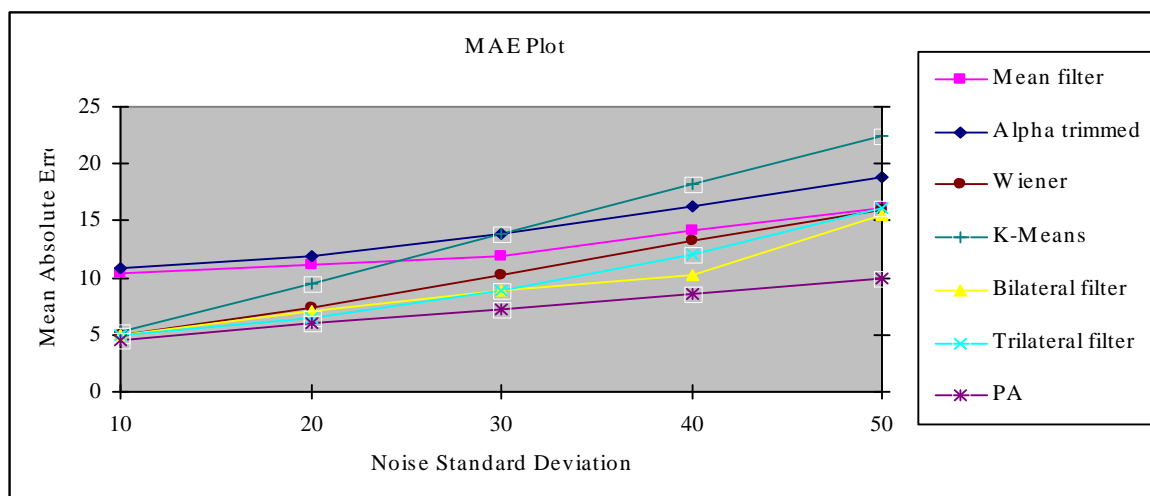

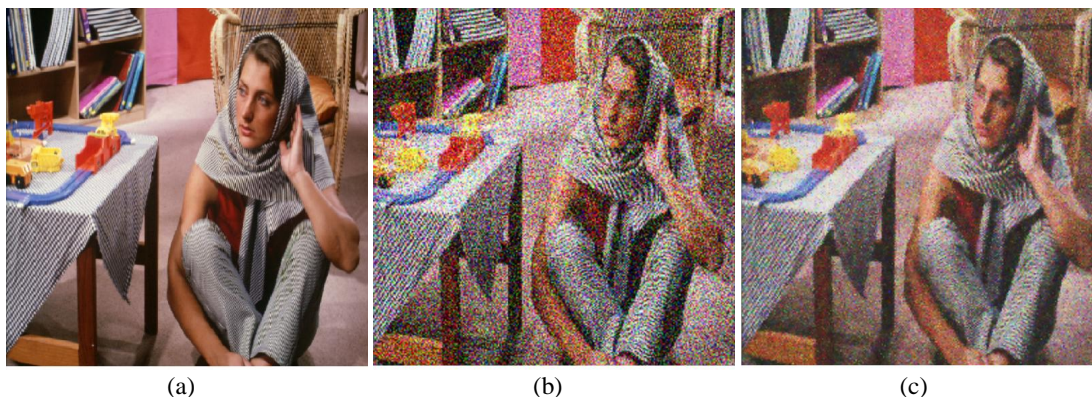Figure 6. MAE of Various Filters for Lena Image at Different Noise Standard Deviations

Figure 7 (a) Original image (b) Noisy image (SD=50)   Restoration result of (c) Proposed algorithm

B. Denoising performance

The denoising performance of the proposed algorithm and other standard methods are tested for gray scale image and color image. The visual quality results are presented in figure 2, 3 and 4. Figure 2(a),3(a) and 4(a) shows the original Elaine, Lena and Pepper image. Figure 2(b),3(b) and 4(b) shows the noisy image of noise standard deviation of (σ) 20,30 and 40 respectively. Figure 2(c), 3(c), 4(c) -2(h),3(h),4(h) shows the restoration results of standard algorithms such as mean filter, wiener filter, alpha trimmed mean filter, K-means filter, bilateral filter and recently proposed trilateral filter. Figure 2(i),3(i) and 4(i) shows the restoration results of proposed filter.   The quantitative performances in terms of PSNR and MAE for all the algorithms are given in Table I and Table II. The same are plotted in figure 5 and figure 6. For lower noise variance upto 400 (σ=20) all the algorithms are perform equally good in smoothening the noise and edge preservation,

In the case of high noise variance, the performance of the standard methods is poor in terms of noise smoothening and detail preservation. The output of the proposed algorithm is shown in figure 2 (i), 3(i) and 4(i) clearly shows less blurring and so the edges are better preserved. For high noise variance, the visual quality and quantitative results clearly show the proposed algorithm perform much better than the existing methods in terms of noise cleaning and detail preservation. The recently proposed trilateral filter performs poorly when the image is highly corrupted and the bilateral filter shows more blurring than the proposed method at high noise variance.

TABLE III

Comparison of computation time in seconds between recently proposed trilateral filter and proposed filter

Standard Deviation	Trilateral filter	Proposed Algorithm
10	64.42	26.86
20	66.72	27.00
30	69.21	27.10
40	71.35	27.24
50	73.65	27.48

C. Computation Time

The CPU time of the proposed algorithm is compared to the recently proposed trilateral filter is given in the Table III. For comparison 'Lena.png' image is corrupted with Gaussian noise of standard deviation varying from 10 to 50 with an increment of 10 and applied to the trilateral filter and the proposed filter. Both the algorithms are implemented in MATLAB 7.1 on a PC equipped with INTEL Pentium IV, 2.4-GHz CPU and 256 MB RAM memory. In all the cases, the proposed algorithm takes as an average of 27 seconds that is less than half of the time required for trilateral filter to restore the original image.

D. Colour Image Denoising

The performance of the proposed filter is also tested for colour images. Generally, there are two approaches for colour image denoising, scalar median filtering approach and Vector Median (VM) filtering (Astola et al 1990) approach. The scalar median filtering approach has been used in this paper.

The RGB colour space is used in this paper to represent the colour images. In the RGB colour space, each pixel at the location (i,j) can be represented as colour vector $O_{i,j} = \left[O_{i,j}^R, O_{i,j}^G, O_{i,j}^B \right]$, where $O_{i,j}^R$, $O_{i,j}^G$, and $O_{i,j}^B$ are the red (R), green (G), and blue (B) components, respectively. The noisy colour images are modeled by injecting the Gaussian noise to each of these colour components. That is, when a colour image is being corrupted by the noise standard deviation σ, it means that each colour component is being corrupted by σ. Thus, for each pixel $O_{i,j}$, the corresponding pixel of the noisy image will be denoted as $X_{i,j} = \left[X_{i,j}^R, X_{i,j}^G, X_{i,j}^B \right]$, in which the probability density functions of each colour components is the same as the noise model described earlier. The proposed filter is applied to the corrupted colour image, using the scalar median filtering approach. In the scalar median filtering approach, each colour component can be treated as an independent entity; that is, the same filtering scheme will be applied to R, G, and B planes independently. It considers each plane as a separate monochrome image. The filtered R, G, and B planes are to be then combined to form the recovered colour image. The performance of the proposed filter is tested for Barbara (colour) image of size 512 X 512. . Figure 7(a), 7(b) and 7(c) shows the original, noisy image of standard deviation (σ) 50 and restored image using the proposed filter. The restored image clearly shows the proposed filter smoothen the Gaussian noise with better edge preservation.

V. CONCLUSION

In this paper, a new fast algorithm is presented to restore high Gaussian noise corrupted digital images. The proposed algorithm is a simple and fast nonlinear method to remove the Gaussian noise in digital images. The performance of the new filter is tested for various noise corrupted gray scale and colour images. The restoration results of the proposed filter is compared with standard methods and recently proposed methods. The proposed algorithm removes Gaussian noise with edge preservation for low to high Gaussian noise corrupted images. Experimental results show that the proposed algorithm has less MAE and higher PSNR than mean filter, wiener filter, alpha trimmed filter, K means algorithm, bilateral filter and recently proposed trilateral filter. The computational time and complexity of the proposed algorithm is such less and hence the proposed algorithm can also be implemented in hardware.

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