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An Improved Adaptive Bilateral Filter to Remove Gaussian Noise from Color Images

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Abstract

Introduction of noise in image causes variation in brightness or colour information. Various noises such as Gaussian, Impulse, Speckle, Periodic andPoisson noise deteriorates the picture quality. Gaussian noise is the most popular one that incurs during acquisition process caused by poor illumination and/or high temperature. This paper proposes an improved modified adaptive Bilateral Filter to remove Gaussian noise from colour images. This technique is implemented in MATLAB-9 and various performance metrics taken into consideration are: Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Mean Absolute Error (MAE), and Normalized Colour Difference (NCD). The result shows that the proposed technique gives the best results than all other techniques in terms of all comparison parameters.

Keywords: *Bilateral filter, Gaussian noise, NCD value, noise removal, range filter, sharpness enhancement*

1. Introduction

Any degradation in the image due to external disturbance can be called as noise[15]. There are various reasons for introduction of noise in the image. The main types of noises are discussed below:

1. *Salt and Pepper Noise:* This noise is introduced due to sharp and sudden disturbance in the image signal. It appears as white or black (or both) pixels scattered randomly over the image. It is also called impulse noise or binary noise.
2. *Gaussian Noise:* Gaussian noise is an idealized form of white noise. White noise is a random signal with flat power spectral density. Gaussian noise is caused due to random fluctuations in the signal. It is also called additive noise as it can be modeled by random values added to an image.
3. *Poisson Noise:* Poisson noise is also called photo shot noise, as it is caused by random variations of photons, which cause photons to enter one sensor than the other.
4. Speckle Noise: This noise can be modeled by random values multiplied by pixel values, hence it is called multiplicative noise. It causes major problem in some radar applications.
5. *Periodic Noise:* This noiseis introduced due to periodic disturbance in the image signal. It is created by cyclic processes such as machines, engines etc. It is commonly caused by interference between electronic components.

These noises affect the image quality differently. The effect of the introduction of above mentioned noises on images is shown in Table 1.

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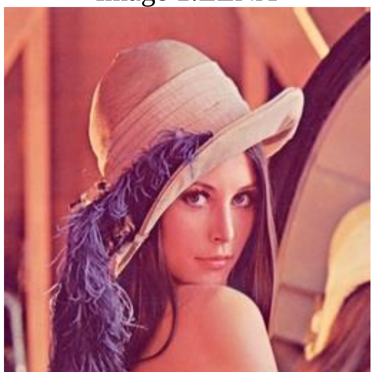
Table 1. Effect of Addition of Noises on Picture Quality

Original Image	Image 1:LENA 	Image 2:GOLDHILL 
Salt and pepper noise		
Gaussian noise		
Poisson noise		

Speckle noise		
Periodic noise		

This paper deals with the removal of Gaussian noise, the most common form of noise which degrades the image quality. To remove Gaussian noise various filtering techniques are proposed in literature. In this paper we implemented Bilateral Filter, Modified Bilateral Filter (MBF), Joint Bilateral Filter (JBF), Fuzzy Bilateral Filter (FBF), and Switching Bilateral Filter (SBF) for the comparison with the proposed Modified Adaptive Bilateral Filter (MABF). The rest of the paper is organised as follows. In section II, literature survey and problem identification is given. Section III presents the proposed technique and the simulation setup parameters used in implementation of filtering techniques. Section IV presents the performance metrics taken into consideration for comparison. In Section V , results of comparison of performance and visual quality is given. Finally the conclusion is given in Section VI.

2. Literature Survey and Problem Formulation

1. Bilateral Filter: The bilateral filter proposed by Tomasi and Manduchi[1] is the combination of range and domain filtering. It adopts a low pass Gaussian filter for both range and domain filtering. As presented in [12] if $[m_0,n_0]$ is the center pixel of window defined, σ_d and σ_r are the standard deviations of the domain and range Gaussian filters, respectively, and

$$r_{m_0,n_0} = \sum_{m=m_0-N}^{m_0+N} \sum_{n=n_0-N}^{n_0+N} e^{\left(-\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^2}\right)} \times e^{\left(-\frac{(g[m,n]-g[m_0,n_0])^2}{2\sigma_r^2}\right)}$$

is the kernel weight function or normalisation factor. The domain low pass Gaussian filter compares the other pixels with the centre pixel in window and assigns higher weights to pixels that are especially close to centre pixel. Similarly, range low pass Gaussian filter assigns higher weights to pixels which are similar to centre pixel in grey value.

The results of bilateral filter show that it reduces the noise significantly but does not sharpen the edges. Hence in order to enhance the sharpness we need to modify the bilateral filter and therefore an attempt is made in this paper to improve the results of bilateral filter. In addition to the standard bilateral filter we also implemented other bilateral filtering techniques proposed in literature to remove Gaussian noise and then compared the results in terms of PSNR, MSE, MAE and NCD values.

2. Fuzzy Bilateral Filter: In FBF [5-6] a particular class of fuzzy metrics is used to represent the spatial and photometric relations between the colour pixels adapting the classical bilateral filtering [1]. In the first step, two fuzzy metrics are used; the first one to measure the photometric fuzzy distance between colour vectors and the second one to measure the spatial fuzzy distance between the pixels under comparison. In this filter the weight vector is calculated as follow:

$$w(i,j,t) = \prod_{s=1}^{3} \frac{\min\{F_i^s, F_j^s\} + K}{\max\{F_i^s, F_j^s\} + K} \times \frac{t}{t + \|i-j\|_2}$$

By using this weight vector the FBF output is calculated as

$$\widetilde{F_i} = \frac{\sum_{j \in W} w(i,j,t) F_j}{\sum_{j \in W} w(i,j,t)}$$

Where F_i and F_j are the pixels under the window at i^{th} and j^{th} locations and t is the parameter to adjust the output. The value of K is 1024 for RGB image. It is a very fast and simple method for removing Gaussian noise from images but it blurs the image.

3. Joint Bilateral Filter: The joint bilateral filter [4, 14] is basically an extension of bilateral filter in which two correlated images, one taken with flash and other without flash are used for filtering process. The non-flash image is sometimes referred as the ambient image. In joint bilateral filter the flash image is used to compute range filter kernel rather than the ambient image. The illumination from a flash may change appearance of the scene due to brightness, it also increases the signal-to-noise ratio and provides much better estimate of true high-frequency information than the ambient image, hence the flash image is called an estimator. In [4] after detecting flash shadows, the basic bilateral filter is applied within those regions. The results of joint bilateral filter show that it preserves the detail while reducing noise.

4. Modified Bilateral Filter: In modified bilateral filter [12], each pixel from the filtering window W_x is assigned a minimum connection cost of a path that joins them with the central pixel x. The connection cost is a function of absolute differences of pixel intensities. For finding the minimum cost paths we apply the Dijkstra algorithm. The cost of a path is the sum of connection costs of adjacent pixels forming a path. The connection cost is used to calculate a weight assigned to each pixel from W_x and the filter output is the weighted average of the surrounding pixels of x. The weights are defined as:

$$w(x,y) = exp\left(-\frac{C(x,y)^2}{h^2}\right)$$

Where h is a tuning parameter. The range of h is [150,250]. The default value of h is taken as 200. C(x,y) is a cost function of the minimum path connecting x and y. For color images the connection costs are calculated using the Euclidean distance in RGB color space between neighboring pixels.

5. Switching Bilateral Filter: The SBF removes noise without adding another weighting function [7, 10]. The operation is performed in two stages: detection followed by filtering. For detection the sorted quadrant median vector (SQMV) scheme is used, which includes important features such as edge or texture information. During detection process a status is assigned to each pixel such that, whether it is noise-free or noisy. If pixel is found noisy it is replaced by a proper median value obtained by edge detector in the range filter function according to the following weight function as in bilateral filter:

$$w(x,y) = w_d(x,y)w_{sr}(x,y)$$

Except that here $w_{sr}(x,y)$ is calculated as:

$$W_{SR}(x,y) = e^{-\frac{1}{2}\left(\frac{I_x - F_y}{\sigma_d}\right)^2}$$

Where I_x is F_x if it is found Gaussian noise otherwise it is replaced by a reference median which is calculated in detection process. This technique performs well for removal of gaussian noise from images.

3. The Proposed Technique

Bilateral filter [1] is a smoothing filter, it does not restore the sharpness of a degraded image. To enhance the results of bilateral filter, we proposed a modified adaptive bilateral filter. The adaptive bilateral filter [8] is the general form of bilateral filter. The important modifications done in bilateral filter to increase the picture quality of de-noised image are:

1. An offset ζ is introduced to the range filter.
2. Both ζ and σ_r i.e. the width of the range filter are made locally adaptive.
3. The CIE-Lab color space is used.

If $[m_0,n_0]$ is the center pixel of window defined, σ_d and σ_r are the standard deviations of the domain and range Gaussian filters, respectively, then the kernel weight function or normalisation factor used in the proposed technique can be defined as:

$$r_{m_0,n_0} = \sum_{m=m_0-N}^{m_0+N} \sum_{n=n_0-N}^{n_0+N} e^{\left(-\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^2}\right)} \times e^{\left(-\frac{\|(g[m,n]-g[m_0,n_0]-\zeta[m_0,n_0])\|^2}{2\sigma_r^2[m_0,n_0]}\right)}$$

By making ζ and σ_r adaptive and jointly optimizing both the bilateral filter is transformed into much more powerful and versatile filter. To find the pair of parameters which minimizes the MSE, an exhaustive search is performed in the parameter space $\phi=\{(\zeta,\sigma_r): \zeta \in \phi_\zeta \,\&\sigma_r \in \phi_{\sigma_r}\}$,

Where ϕ_ζ = [-60,60] and ϕ_{σ_r}= [5,45]. The range and step size of the parameters are chosen empirically such that they can yield adequate sharpening and smoothing for all types of images.

The feature we have chosen for pixel classification is the strength of edges measured by a Laplacian of Gaussian (LoG) operator which can be defined as:

$$\text{LoG}[m,n] = \begin{cases} -\frac{1}{\pi\sigma_{LoG}^4}\left(1-\frac{m^2+n^2}{2\sigma_{LoG}^2}\right)\exp\left(-\frac{m^2+n^2}{2\sigma_{LoG}^2}\right) - C, & |m|,|n| \le N \\ 0, & else \end{cases}$$

and $C = \frac{1}{(2N+1)^2}\sum_{m=m_0-N}^{m_0+N}\sum_{n=n_0-N}^{n_0+N} - \frac{1}{\pi\sigma_{LoG}^4} \times \left(1 - \frac{m^2+n^2}{2\sigma_{LoG}^2}\right)\exp\left(-\frac{m^2+n^2}{2\sigma_{LoG}^2}\right)$

Where σ_{LoG}=1.5 and N=4.

The LoG operator [15] has following characteristic properties:

1. It is a high pass filter.
2. It computes the second derivative of input image.
3. Response: Near edges: magnitude of its response is high
   In smooth regions: magnitude of its response is low
   On the center of an edge: magnitude of its response is 0.

The pixel class index is computed according to

$$L[m,n] = \begin{cases} \lfloor g_{LoG}[m,n] \rceil, & |g_{LoG}[m,n]| \leq L_{max} \\ L_{max}, & g_{LoG}[m,n] > L_{max} \\ -L_{max}, & g_{LoG}[m,n] < -L_{max} \end{cases}$$

where $g_{LoG}[m,n] = LoG[m,n] ** g[m,n], L_{max}$=60 and $\lfloor x \rceil$ denotes rounding x to the nearest integer. ζ is approximately equal to the LoG class. The desired amount of offset is proportional to the magnitude of the LoG response. In additional, the sign of ζ is the same as that of the LoG class. The flow chart of bilateral filtering technique and the proposed filtering technique is given in Figure 1 and Figure 2 respectively.

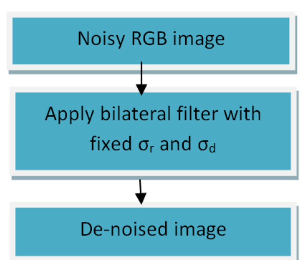


Figure 1. Flow Chart of Bilateral Filtering Technique

In basic bilateral filter the width of range filter *i.e.* σ_r is fixed. To make the bilateral filter more powerful and versatile we introduced offset ζ, and both ζ and σ_r are made locally adaptive as shown in Figure 2 below.

FLOW CHART OF PROPOSED FILTERING TECHNIQUE:

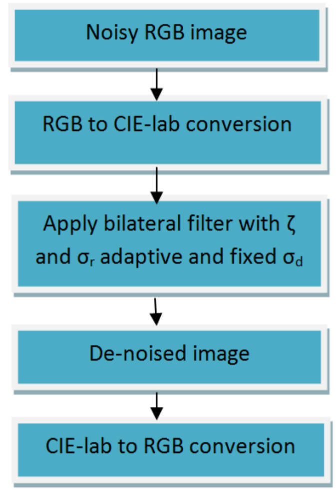


Figure 2. Flow Chart of Improved Adaptive BF

MATLAB is used as simulator to implement various filtering techniques. Various setup parameters used in simulation which are common to all techniques are as shown in Table 2.

Table 2. Setup Parameters

Image size(pixels)	LENA: 256*256*3 (color) GOLDHILL: 275*183*3 (color)
Image type	Jpg
Gaussian Noise	Standard deviation (sigma)= 5,10,15,20,25,30
Simulation Tool	MATLAB R2009a
Processor	Intel(R) Core(TM) i3-3110M CPU 2.40 GHz
RAM	2.00 GB

In the next section various performance metrics used in the simulation are defined.

4. Performance Metrics for Comparison

Peak Signal to Noise Ratio (PSNR): It is the measure of quality of the image by comparing denoised image with original image. It is an expression used to depict the ratio of maximum possible power of image (signal) and the power of the corrupting noise that affects the quality of its representation.
Mean Square Error (MSE): It is the cumulative squared error between the final de-noised image and the original image. This enables us to compare mathematically as to which method provides better results.
Mean Absolute Error (MAE): It is the absolute error between the original image and the de-noised image. It represents the average value of introduced deviation per pixel with respect to original image.

Normalized color difference (NCD): It is used to measure the degradation in color quality in color images since it approaches the human perception.
Perceptual Quality: Picture quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Instead of de-noised image should possess high PSNR and Low MSE, MAE; the de-noised image should be smooth, clean and clear also. De-noised image should be so fine for human observer as if it seems natural image. It should not have color blurriness or any odd looking structure.

5. Results

In this section the simulation results of filtering techniques as discussed above, are compared. Figures 3-6 show the results of PSNR, MSE, MAE, and NCD respectively.

Results of PSNR:

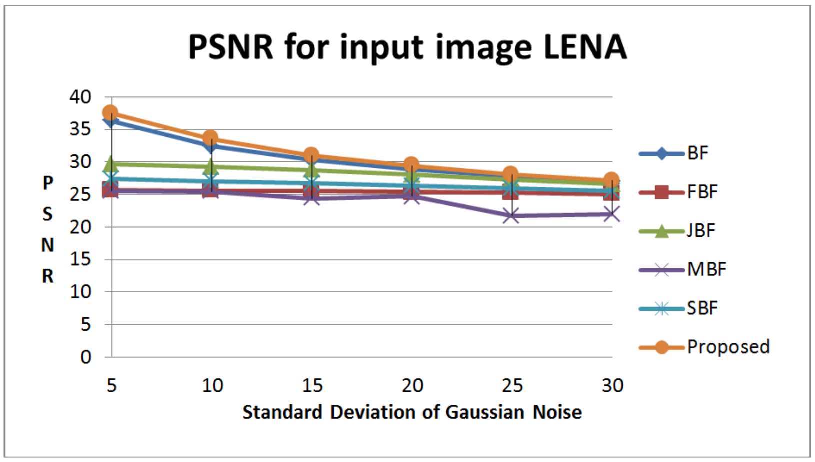


Figure 3(a). Comparison of PSNR Results for Input Image LENA

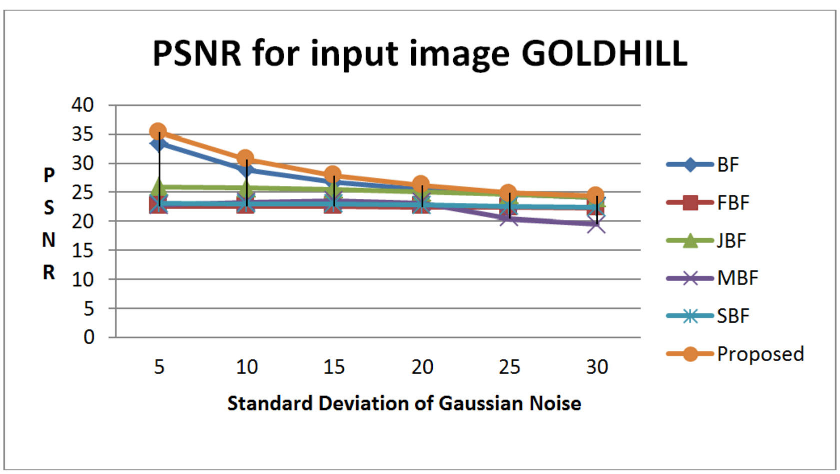


Figure 3(b). Comparison of PSNR Results for Input Image GOLDHILL

Figure 3. Comparison in Terms of PSNR

In Figure 3 the results of PSNR for all variants of BF and proposed technique are shown for standard deviation from 5 to 30. From the results following inferences can be made:

- The proposed filtering technique gives the highest PSNR value when the image is corrupted with Gaussian noise.
- The MBF gives the lowest value of PSNR for large values of standard deviation whereas FBF gives lowest PSNR for small values of standard deviation of Gaussian noise.

Results of MSE:

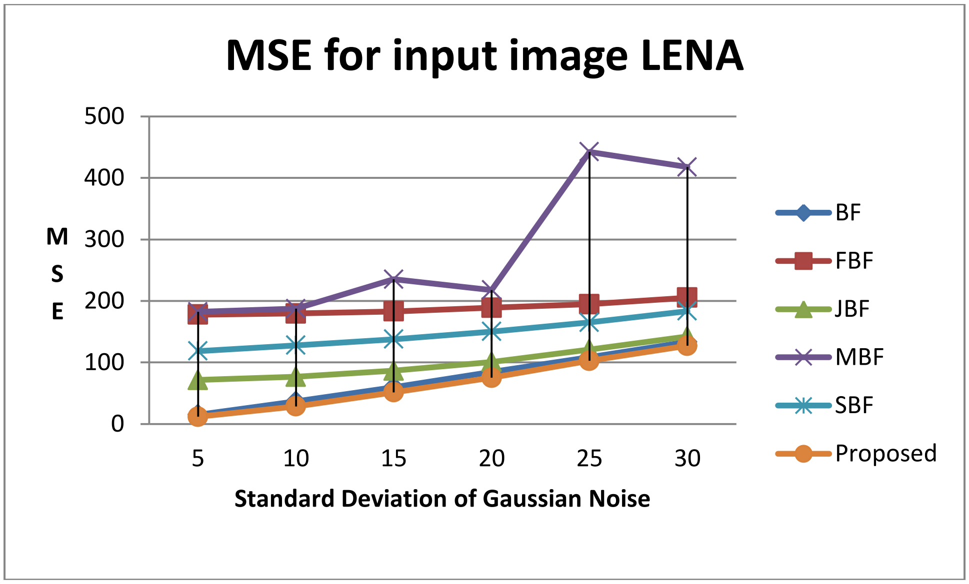


Figure 4(a). Comparison of MSE Results for Input Image LENA

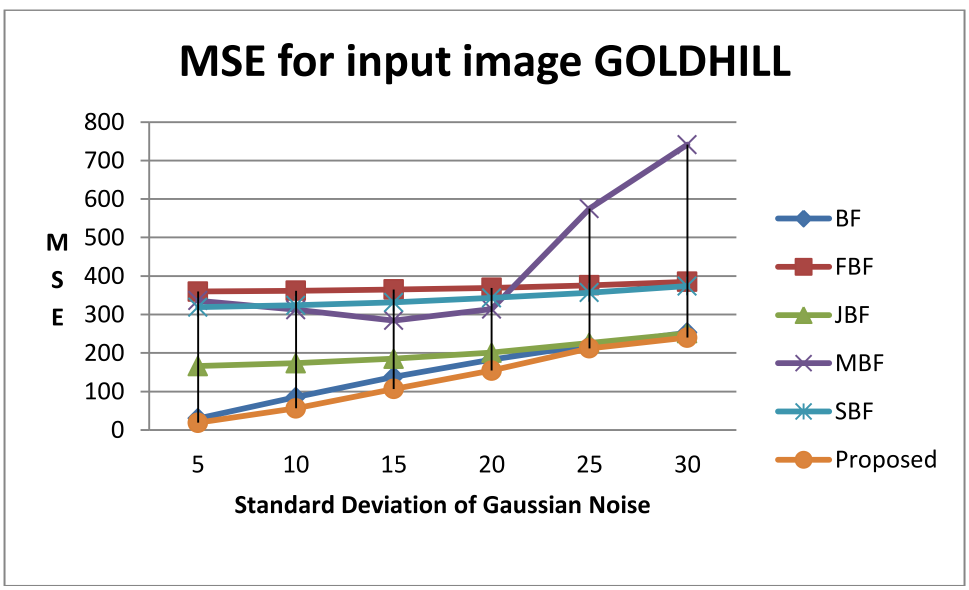


Figure 4(b). Comparison of MSE Results for Input Image GOLDHILL

Figure 4. Comparison in Terms of MSE

In Figure 4 the results of MSE for all variants of BF and proposed technique are shown for standard deviation from 5 to 30. From the results following inferences can be made:

- The proposed filtering technique gives the lowest MSE value when the image is corrupted with Gaussian noise.
- The MBF gives the highest value of MSE for large values of standard deviation whereas FBF gives large MSE for small values of standard deviation of Gaussian noise.

Results of MAE:

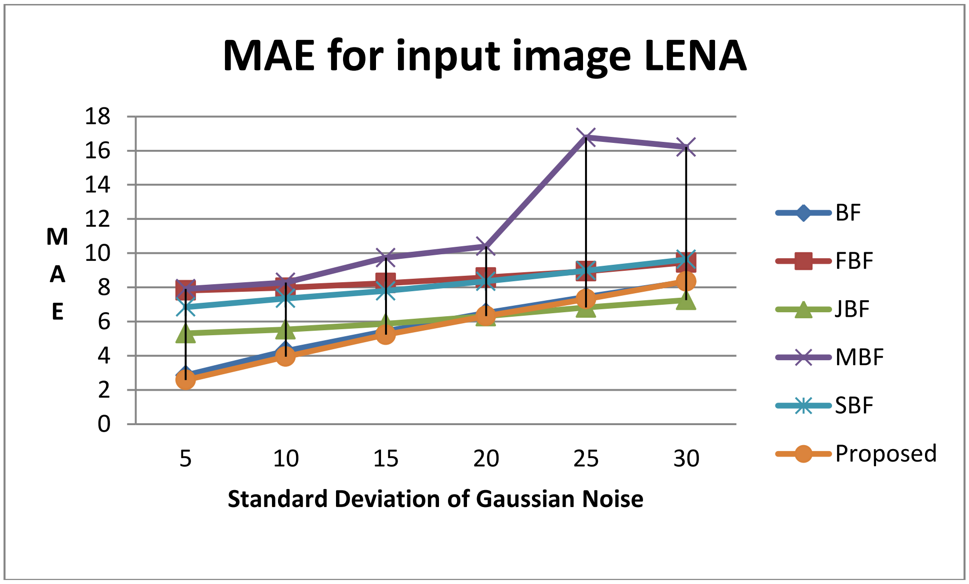


Figure 5(a). Comparison of MAE Results for Input Image LENA

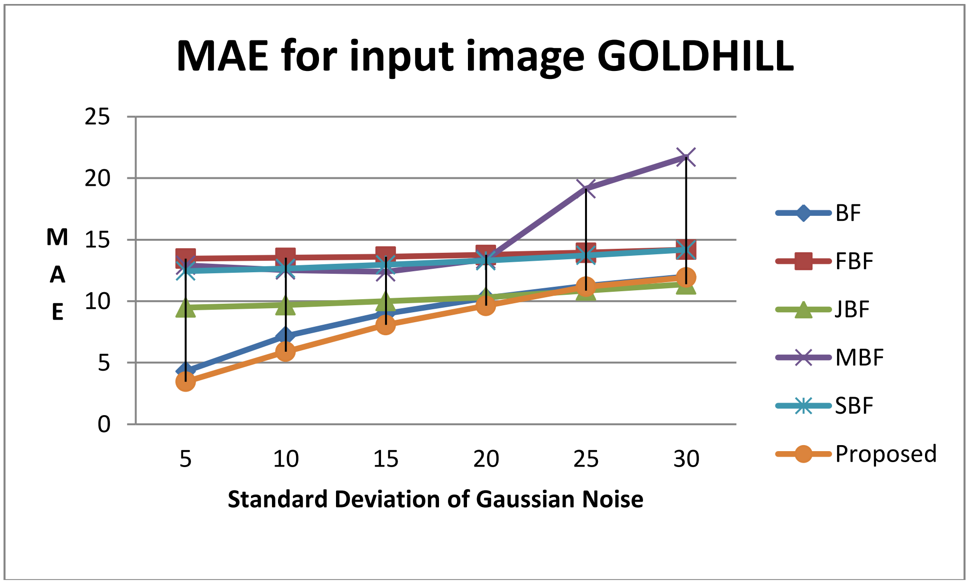


Figure 5(b). Comparison of MAE Results for Input Image GOLDHILL

Figure 5. Comparison in Terms of MAE

In Figure 5 the results of MAE for all variants of BF and proposed technique are shown for standard deviation from 5 to 30. From the results following inferences can be made:

- The proposed filtering technique gives the lowest MAE value when the image is corrupted with Gaussian noise.
- The MBF gives the highest value of MAE for large values of standard deviation while FBF gives large MAE for small values of standard deviation of Gaussian noise.

Results of NCD:

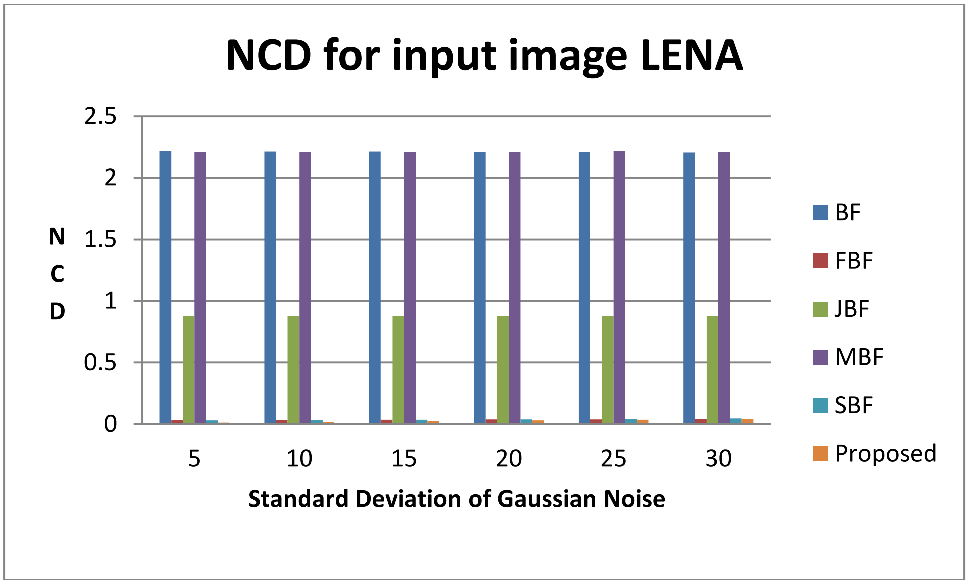


Figure 6(a). Comparison of NCD Results for Input Image LENA

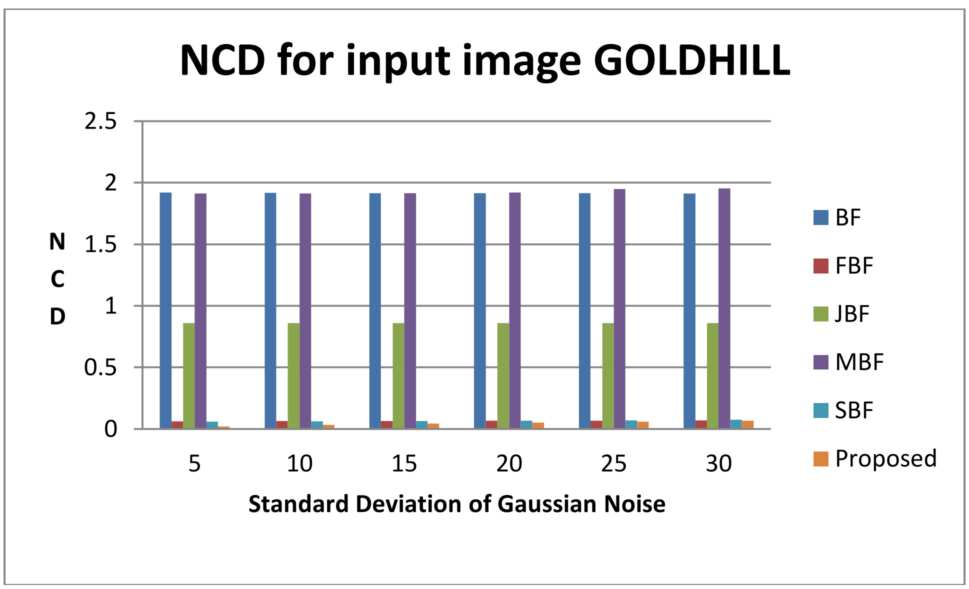


Figure 6(b). Comparison of NCD Results for Input Image GOLDHILL

Figure 6. Comparison in Terms of NCD

In Figure 6 the results of NCD for all variants of BF and proposed technique are shown for standard deviation from 5 to 30. From the results following inferences can be made:

- The proposed filtering technique gives the lowest NCD value when the image is corrupted with Gaussian noise.
- The MBF gives the highest value of NCD for large values of standard deviation whereas BF gives large NCD for small values of standard deviation.

Also the overall results of all filtering techniques are given in Table 2 and Table 3 for σ=5 to 30 for LENA and GOLDHILL images respectively.

Table 2. PSNR, MSE, MAE and NCD for Gaussian Noise Removing Techniques (LENA)

Standard Deviation	Parameter	BF	FBF	JBF	MBF	SBF	PROPOSED
5	PSNR	36.3371	25.6333	29.5887	25.5266	27.394	37.4039
	MSE	15.1138	177.7274	71.4837	182.1883	118.4899	11.8221
	MAE	2.85	7.8168	5.3101	7.9141	6.852	2.5807
	NCD	2.2163	0.0331	0.8783	2.2081	0.0308	0.0122
10	PSNR	32.4866	25.5913	29.2849	25.4056	27.0632	33.5518
	MSE	36.6796	179.4527	76.6646	187.2946	127.8665	28.701
	MAE	4.2851	7.982	5.5431	8.2913	7.3571	3.944
	NCD	2.2142	0.0341	0.8783	2.2076	0.0336	0.0188
15	PSNR	30.3594	25.5059	28.7534	24.417	26.7406	31.0234
	MSE	59.8607	183.0155	86.6442	235.1668	137.7281	51.3734
	MAE	5.4402	8.2502	5.8789	9.7373	7.793	5.2301
	NCD	2.2123	0.0355	0.8783	2.2072	0.0357	0.0248
20	PSNR	28.8499	25.3701	28.0905	24.749	26.3646	29.3733
	MSE	84.7404	188.8287	100.9319	217.8617	150.1831	75.1183
	MAE	6.4993	8.5744	6.3173	10.407	8.3551	6.3212
	NCD	2.2101	0.0374	0.8781	2.2082	0.0387	0.0303
25	PSNR	27.7673	25.2373	27.2983	21.6747	25.954	28.0171

	MSE	108.7306	194.6952	121.13	442.1911	165.0751	102.6538
	MAE	7.4394	8.9456	6.8179	16.7701	8.9783	7.3148
	NCD	2.2088	0.0394	0.8779	2.2157	0.042	0.0347
30	PSNR	26.8812	25.0059	26.6069	21.9231	25.4966	27.0893
	MSE	133.3388	205.3491	142.033	417.609	183.4098	127.1014
	MAE	8.3239	9.459	7.2617	16.2088	9.6404	8.3574
	NCD	2.2052	0.0421	0.8779	2.2083	0.0455	0.0409

Table 3. PSNR, MSE, MAE and NCD for Gaussian Noise Removing Techniques (GOLDHILL)

Standard Deviation	Parameter	BF	FBF	JBF	MBF	SBF	PROPOSED
5	PSNR	33.3898	22.5698	25.9263	22.8689	23.0955	35.35
	MSE	29.7923	359.8319	166.1322	335.8877	318.8059	18.9705
	MAE	4.302	13.4631	9.4861	12.9103	12.4479	3.4527
	NCD	1.9206	0.0629	0.8605	1.9117	0.0605	0.0191
10	PSNR	28.8174	22.5458	25.7403	23.1861	23.028	30.6419
	MSE	85.376	361.8298	173.4	312.2267	323.8058	56.09
	MAE	7.1589	13.5272	9.6806	12.5304	12.6609	5.9018
	NCD	1.9168	0.0636	0.8605	1.9116	0.0626	0.0323
15	PSNR	26.7264	22.5073	25.4567	23.5884	22.9254	27.8502
	MSE	138.1791	365.0474	185.1032	284.6039	331.5452	106.6756
	MAE	8.9785	13.6126	10.0021	12.3838	12.9517	8.0718
	NCD	1.9151	0.0646	0.8605	1.9145	0.0649	0.0427
20	PSNR	25.521	22.4556	25.106	23.1649	22.7787	26.2477
	MSE	182.3796	369.4194	200.669	313.757	342.9358	154.2791
	MAE	10.2505	13.7579	10.3147	13.4039	13.2932	9.6248
	NCD	1.9145	0.066	0.8606	1.9188	0.0677	0.0514
25	PSNR	24.6924	22.3792	24.5869	20.5355	22.6064	24.8669
	MSE	220.7213	375.9745	226.1458	574.8226	356.8122	212.0269
	MAE	11.2366	13.9374	10.8574	19.1364	13.7181	11.1727
	NCD	1.914	0.0675	0.8606	1.9486	0.0708	0.0588
30	PSNR	24.0995	22.2744	24.1278	19.4299	22.4058	24.3301
	MSE	253.0044	385.1557	251.3623	741.4695	373.6783	239.9205
	MAE	11.9986	14.186	11.3701	21.7147	14.1787	11.9287
	NCD	1.9125	0.0696	0.8607	1.9547	0.0742	0.0661

The results of perceptual quality are given in Table 4 and 5. From the results it is seen that the proposed technique gives best perceptual quality results.

Table 4. Comparison of Perceptual Quality of De-noised Image (LENA)

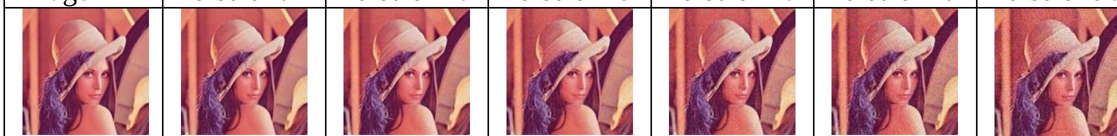
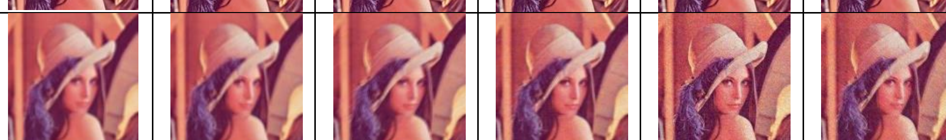
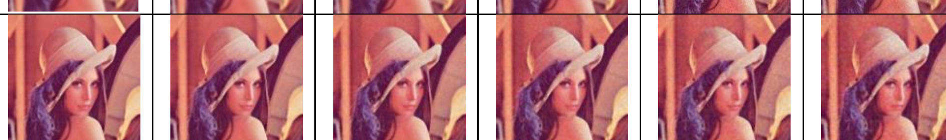
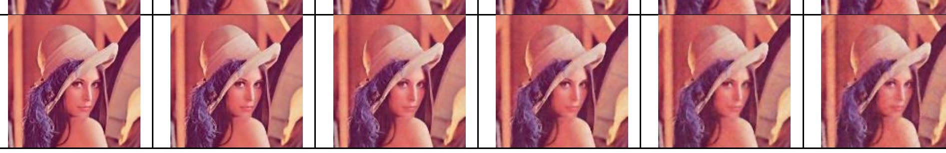
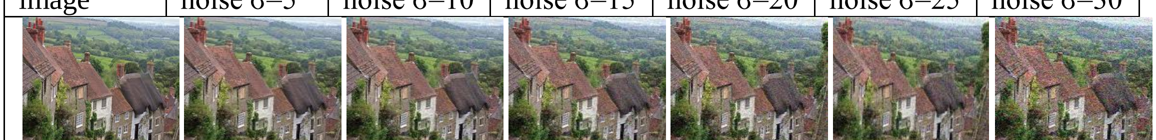
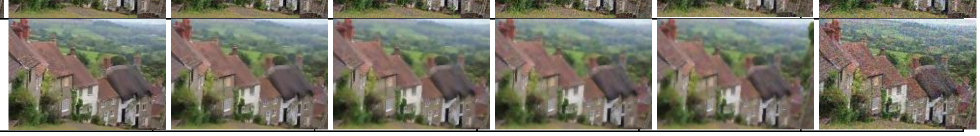
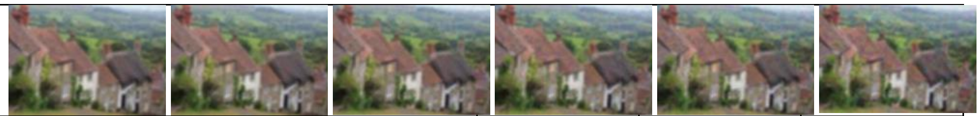
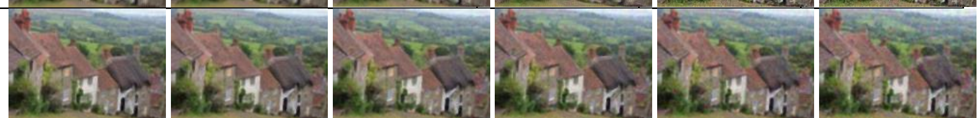
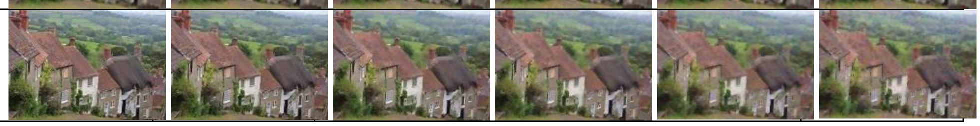
Original image	Gaussian noise σ=5	Gaussian noise σ=10	Gaussian noise σ=15	Gaussian noise σ=20	Gaussian noise σ=25	Gaussian noise σ=30
						
Filtered by BF						
Filtered by FBF						
Filtered by JBF						
Filtered by MBF						
Filtered by SBF						
Filtered by proposed method						

Table 5. Comparison of Perceptual Quality of De-noised Image (GOLDHILL)

Original image	Gaussian noise σ=5	Gaussian noise σ=10	Gaussian noise σ=15	Gaussian noise σ=20	Gaussian noise σ=25	Gaussian noise σ=30
						
Filtered by BF						

Filtered by FBF	
Filtered by JBF	
Filtered by MBF	
Filtered by SBF	
Filtered by proposed method	

6. Conclusion

The following important inferences can be drawn from the above results as follows:

- The proposed technique gives best results in terms of PSNR, MSE, MAE and NCD values than all other filtering techniques implemented to remove Gaussian noise.
- Proposed technique provide best perceptual quality by edge sharpening and reducing the color blurriness.
- The use of CIE-Lab color space smoothens the image and preserves the edges in a way that is tuned to human performance .
- The proposed filtering technique works very well for dense noise and does not introduces blurriness as in case of other filtering techniques.

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