International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.9, No.2 (2016), pp.433-444
http://dx.doi.org/10.14257/ijsip.2016.9.2.37

Comparison of Noise Removal Techniques Using Bilateral Filter

Manjeet Kaur[1] and Shailender Gupta[2]

Electronics and Communication Engineering Department, YMCA University of Science and Technology, Faridabad, India
mkgrewal31@gmail.com[1], shailender81@gmail.com[2]

Abstract

This paper compares the standard Bilateral Filter and its variants such as Modified Bilateral Filter(MBF), Joint Bilateral Filter(JBF), Fuzzy Bilateral Filter(FBF) and Switching Bilateral Filter(SBF). For comparison purpose various performance matrices such as: Peak Signal to Noise Ratio(PSNR), Mean Square Error(MSE), Mean Absolute Error(MAE), Normalized Color Difference(NCD), Perceptual Quality and Time complexity are used . All the techniques are implemented using simulation in MATLAB-9. It is found that the standard BF is the best technique to remove Gaussian noise from images with high PSNR value. However when the image is corrupted with mixed Gaussian and impulse noise, SBF gives the best results of PSNR value, MSE value, MAE value , NCD value and a good picture quality of de-noised image.

Index Terms: *Bilateral Filter, domain filtering, Gaussian noise, MAE, MSE, noise removal, PSNR, range filtering, sharpening, time complexity*

1. Introduction

The addition of noise and loss of sharpness are the two most common degradations suffered by an image. Noise can be defined as random variation of brightness or color information, caused by external disturbance in the image signal. There are various sources of noise in digital images some of which are: heat in the sensor, slow shutter speed and noise introduced via communication channel during the acquisition[26], signal amplification and transmission[8, 26]. The acquisition process[26] for digital images converts optical signal into electrical signal and subsequently into digital signal, and is one process by which the noise is introduced in digital images. Various factors like Dark Current, Pixel Non-Uniformity, Shot Noise, CCD Read Noise[25], Electronic Interference etc. affect the acquisition process of image. Moreover each step in the conversion process may experience fluctuations caused by natural phenomena, and each of these steps adds a random value to the resulting intensity of a given pixel. These noises can be modeled as Gaussian noise.

Another type of noise is introduced due to transmission errors or storage faults. If an image is being sent electronically from one place to another *i.e.,* via satellite, through wireless transmission or through networked cable, we may expect errors to creep in the image. These errors will appear on the image output in different ways depending on the type of disturbance in the signal. These noises can be modeled as impulse noise. Impulse noise is characterized by appearance of light pixels on dark background and dark pixels on light background[24].

Both noises are independent of each other and may randomly be introduced in image. When a noisy image is further transmitted over faulty transmission line, the image will be corrupted by mixed[26,16] Gaussian and impulse noise. The removal of mixed noise from images becomes more difficult because in mixed noise, parameters of individual noise may change. For example zero mean property of Gaussian noise[8, 26] no longer exists if image is corrupted by other noise also. Therefore noise specific filters cannot remove mixed noise sufficiently[16]. Hence there is a need for techniques to remove both the noises from image simultaneously.

The impact of introduction of these noises in the image is shown in the Figure 1 below:

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

Figure 1: Impact of introduction of various noises:

(a) original image, (b) gaussian noise

(c) impulse noise, (d) mixed noise

Filtering is one of the most fundamental operations used in image processing. Image smoothing is a technique based on filtering which is utilized by noise reduction methods. In the recent past BF and its variants have been proposed in literature to remove single and mixed noise. This paper is an effort to compare BF and its variants, and to analyze the efficiency of a specific filter to remove noise from the images.

The rest of the paper is organised as follows. In Section 2, BF technique and its variants are discussed. Section 3 presents the simulation setup parameters used in implementation of filtering techniques. Section 4 presents the performance metrics taken into consideration for comparison. In Section 5, results of comparison of performance and visual quality is given. Finally a brief conclusion is given in last section.

2. Filtering Techniques

A. Bilateral Filter (BF)

Bilateral filter[3,6] is a non-iterative, local and simple method for removing Gaussian noise while preserving edges. As the name implies Bilateral filter is combination of range and domain filtering. Traditional filtering is domain filtering, and enforces closeness by weighing pixel value with coefficients that fall off with distance. Similarly, range filtering can be defined as which averages image values with weights that decay with dissimilarity. Range filters are nonlinear because their weights depend on image intensity or color. Computationally, they are no more complex than standard non-separable filters. Most importantly, they preserve edges also.

A low-pass domain filter on image f(x) can be defined as:

$$h(x)=k_d^{-1}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x) * c(x,y)\, d(y)$$

Where c(x,y) measures the geometric closeness between the neighborhood center x and a nearby point y.kd(x) is the normalized constant and is calculated as

$$k_d(x) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} c(x,y)d(y)$$

Similarly range filter is defined as:

$$h(x)=k_r^{-1}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(y) * s(f(x),f(y))dy$$

except that now s(f (x),f(y)) measures the photometric similarity between the pixel at the neighborhood center x and that of a nearby point y. The normalized constant is replaced by

$$k_r(x)= \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} s(f(x),f(y))dy$$

Both geometric and photometric similarity Combined as follows:

$$h(x)=k_r^{-1}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(y) * c(x,y) * s(f(x),f(y))dy$$

With the normalized parameter as:

$$k_r(x)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} s(f(x),f(y)) * c(x,y)dy$$

This combined domain and range filtering is denoted as bilateral filtering. The Gaussian function is popular for calculation of geometric and photometric similarity as below:

$$s(f(x),f(y))=e^{-\frac{1}{2}}\left(\frac{\|f(x)-f(y)\|}{\sigma r}\right)^2$$

$$c(x,y)=e^{-\frac{1}{2}}\left(\frac{\|x-y\|}{\sigma d}\right)^2$$

Where ‖x-y‖ is the euclidean distance between x and y. The parameters σd and σr are geometric spread and photometric spread respectively and control the behaviour of the weights. They are the values at which the respective Gaussian weighting functions take their maximum derivatives, so they serve as rough thresholds for identifying pixels sufficiently close spatially or geometrically. Note, in particular when σr→∞, that as and photometric differences are rendered irrelevant by this high threshold, the bilateral filter approaches a Gaussian filter of standard deviation σd and when σd→∞ the filter approaches a range filter with no spatial notion. When both σr, σd→∞ so that all neighboring pixels easily meet both thresholds, the bilateral filter approaches the Arithmetic mean filter (AMF).

B. Modified Bilateral Filter (MBF)

The standard BF is highly efficient noise reducing scheme, but it cannot remove the pixels that appear due to addition of impulse noise. Therefore a modification of BF which takes into account the similarity between color pixels and their spatial distance is proposed by [24]Malik *et. al.*, which can remove the impulse noise from images. In this technique instead of direct calculation of the dissimilarity measure, the cost of a connection through a digital path joining the central pixel of the filtering window with the remaining pixels is determined. The cost of a path is the sum of connection costs of adjacent pixels forming a path. The connection cost in this case is a function of absolute differences of pixel intensities. The minimum cost paths of each pixel are calculated by applying Dijkstra algorithm. This means that every pixel from the filtering window is connected to center pixel x through a minimum cost path. The connection costs are then used to calculate the weight of each pixel within the filtering window, and the filter output is calculated as a weight average of surrounding pixels of x. For color images the connection costs are calculated using the Euclidean distance in RGB color space between neighboring pixels. Thus, the structure of filter output is the same as in the case of the bilateral filter.

C. Joint Bilateral Filter (JBF)

The joint bilateral filter[12] is an extension of the bilateral filter. In this filter two correlated images are used for filtering process. The method filters an image by weight-average under guidance by another image. The filter produces high quality pictures by combining two images, one taken with flash to capture details and one without-flash to capture ambient illumination. Thereby the flash image is used as an estimator. This guidance image is explicitly built into filter kernels. Computational cost of brute force implementation of joint bilateral filter is in the same range as brute force implementations of standard bilateral filter. It contains the global information about the two images. One limitation of both BF and JBF is that they are non-linear and therefore the implementation requires convolution in the spatial domain.

D. Fuzzy Bilateral Filter (FBF)

S. Morillas *et. al.*, proposed Fuzzy bilateral filter [14] by adapting the classical bilateral filtering using fuzzy metrics. In this filter the weight vector is calculated as follow:

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

Where Fi and Fj are the pixels under the window at ith and jth locations and t is the parameter to adjust the output. The value of K is 1024 for RGB image. It is fast and simple method for Gaussian noise and it remove impulse noise also upto some extent but not so effective for removing mixed noise.

E. Switching Bilateral Filter (SBF)

The SBF removes both Gaussian and impulse noise without adding another weighting function[15]. Operation in this method is performed in two stages: detection followed by filtering. For detection the sorted quadrant median vector (SQMV) scheme is proposed, which includes important features such as edge or texture information. In detection process a status is assigned to each pixel that whether it is noise-free or impulse noise or Gaussian noise. Then if pixel is found noisy it is replaced by filtered value 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 mixed noise from gray-scale images.

3. Simulation Setup Parameters

MATLAB is used as simulator to implement various techniques of filtering. Various setup parameters used in simulation which are common to all techniques are as shown in Table 1.

Table.1 Setup Parameters

Image size (pixels)	256*256*3 (color)
Image type	Jpg
Impulse Noise	10%
Gaussian Noise	Standard deviation (sigma)= 10
Mixed Noise	Impulse + Gaussian
Simulation Tool	MATLAB R2009a.lnk
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 Simulation

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 distance (NCD): It is used to measure the degradation in color quality in color images since it approaches the human perception.

Time Complexity: It is used to define the time taken by each method under varying parametric conditions like image size, noise density, *etc*. Time complexity defines the complexity of each algorithm and is hence used to define the algorithm with least and maximum computational cost.

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. Result Analysis

In this section the simulation results of BF and its variant techniques are compared. The various results are as follows:

Comparison of PSNR: The results of PSNR value for various BF techniques are shown in Figure 2 for Gaussian, Impulse and mixed noise. From the results the following inferences can be drawn:

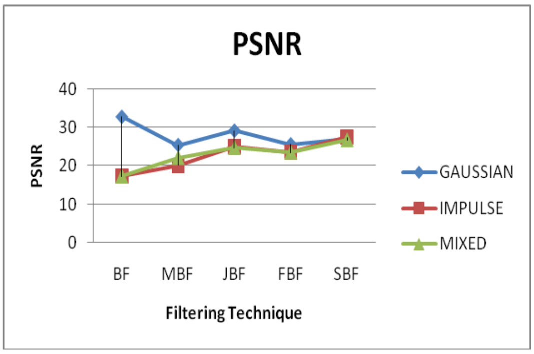


Figure 2. Comparison of PSNR Results

Inference:

1) The standard BF gives the highest PSNR value and MBF gives lowest when the image is corrupted with Gaussian noise only. It shows that the BF technique is the best on the basis of PSNR value for removal of Gaussian noise.

2) When image is corrupted with impulse noise or mixed noise, SBF gives the highest and standard BF gives the least PSNR value. It shows that the SBF technique is the best on the basis of PSNR value for removal of impulse and mixed noise.

Comparison of MSE: The results of MSE value for various BF techniques are shown in Figure.3 for Gaussian, Impulse and mixed noise. From the results the following inferences can be drawn:

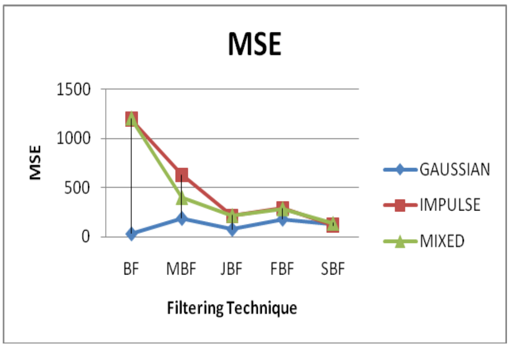


Figure 3. Comparison of MSE Results

Inference:

1) The standard BF gives the lowest and MBF gives the highest MSE value when the image is corrupted with Gaussian noise only. It shows that the standard BF technique is the best on the basis of MSE value for removal of Gaussian noise.

2) When image is corrupted with impulse noise or mixed noise SBF gives the least and standard BF gives highest MSE value. It shows that the SBF technique is the best on the basis of MSE value for removal of impulse and mixed noise.

Comparison of MAE: The results of MAE value for various BF techniques are shown in Figure 4 for Gaussian, Impulse and mixed noise. From the results the following inferences can be drawn:

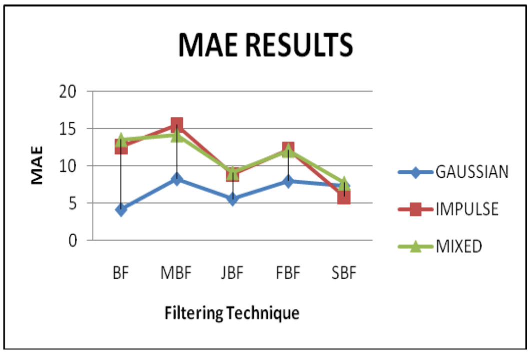


Figure 4. Comparison of MAE results

Inference:

1) The BF gives the least MAE value and MBF gives highest, when the image is corrupted with Gaussian noise only. It shows that the BF technique is the best on the basis of MAE value for removal of Gaussian noise.

2) When image is corrupted with impulse noise or mixed noise SBF gives the lowest and MBF gives highest MAE value. It shows that the SBF technique is the best on the basis of MAE value for removal of impulse and mixed noise.

Comparison of NCD: The results of NCD value for various BF techniques are shown in Figure 5 for Gaussian, Impulse and mixed noise. From the results the following inferences can be drawn:

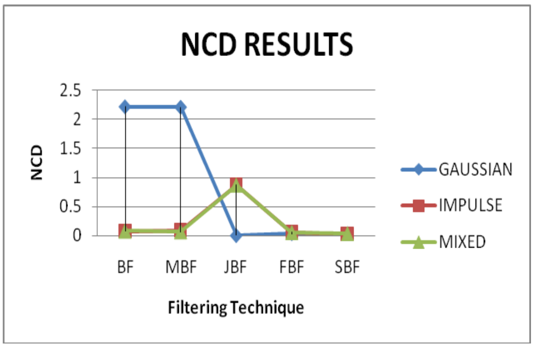


Figure 5. Comparison of NCD Results

Inference:

1) The BF gives the highest and JBF gives the lowest NCD value when the image is corrupted with Gaussian noise only. It shows that the JBF technique is the best on the basis of NCD value for removal of Gaussian noise.

2) When image is corrupted with impulse noise or mixed noise SBF gives the lowest NCD value and JBF gives the highest. It shows that the SBF technique is the best on the basis of NCD value for removal of impulse and mixed noise.

Comparison of TIME COMPLEXITY: The results of Time complexity taken by various BF techniques are shown in Figure 6 for Gaussian, Impulse and mixed noise. From the results the following inferences can be drawn:

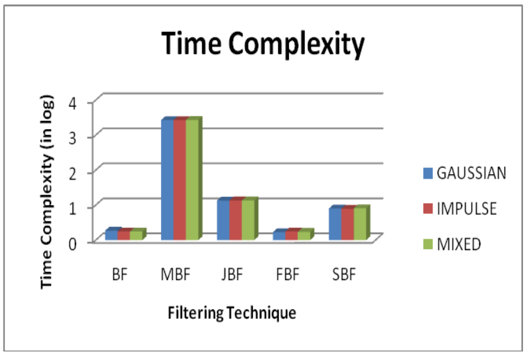


Figure 6. Comparison of Time Complexity Results

Inference:

1) The time complexity taken by FBF is least while the time complexity of MBF is highest for removing all three types of noises taken into consideration.

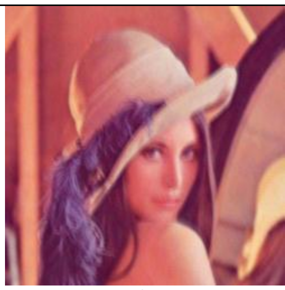
Table 2. Quantitative Results

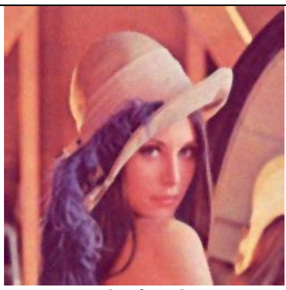
GAUSSIAN NOISE					
Parameter	BF	MBF	JBF	FBF	SBF
PSNR	32.85	25.41	29.20	25.59	27.06
MSE	33.73	187.29	78.12	179.65	127.85
MAE	4.15	8.29	5.57	7.98	7.36
NCD	2.21	2.21	0.001	0.03	0.03
TIME COMPLEXITY (in seconds)	1.85	2673.70	13.41	1.68	7.95
IMPULSE NOISE					
Parameter	BF	MBF	JBF	FBF	SBF
PSNR	17.35	20.15	24.92	23.53	27.46
MSE	1197.90	628.72	209.33	288.62	116.65
MAE	12.60	15.48	8.85	12.17	5.87
NCD	0.07	0.09	0.87	0.06	0.03
TIME COMPLEXITY (in seconds)	1.65	2688.02	13.56	1.76	7.82
MIXED NOISE					
Parameter	BF	MBF	JBF	FBF	SBF
PSNR	17.32	22.11	24.72	23.54	26.73

MSE	1205.30	399.90	219.35	287.61	138.22
MAE	13.58	14.22	9.15	12.16	7.73
NCD	0.08	0.07	0.87	0.06	0.04
TIME COMPLEXITY (in seconds)	1.76	2701.39	13.57	1.72	8.14

Comparison of PERCEPTUAL QUALITY: In Table 3, the results of perceptual quality of filtering techniques are shown. It is observed that the results of standard BF technique are best for Gaussian noise whereas results of SBF technique are best for impulse noise and mixed noise.

Table 3. Qualitative Results

 Original image (256×256)	 Image corrupted with Gaussian noise
 Result of applying BF on image corrupted with Gaussian noise	 Result of applying MBF on image corrupted with Gaussian noise
 Result of applying JBF on image corrupted with Gaussian noise	 Result of applying FBF on image corrupted with Gaussian noise

 Result of applying SBF on image corrupted with Gaussian noise	 Image corrupted with Impulse noise
 Result of applying BF on image corrupted with Impulse noise	 Result of applying MBF on image corrupted with Impulse noise
 Result of applying JBF on image corrupted with Impulse noise	 Result of applying FBF on image corrupted with Impulse noise
 Result of applying SBF on image corrupted with Impulse noise	 Image corrupted with Mixed noise
 Result of applying BF on image corrupted with Mixed noise	 Result of applying MBF on image corrupted with Mixed noise

Result of applying
JBF on image corrupted with Mixed noise

Result of applying
FBF on image corrupted with Mixed noise

Result of applying
SBF on image corrupted with Mixed noise

5. Conclusion

1) When the image is corrupted with Gaussian noise only, the standard BF gives us the best PSNR with less time complexity.

2) If impulse noise is introduced in the image then SBF performs efficiently but as this is applied on all planes separately it blurs the image.

3) The time complexity of MBF is very high due to use of Dijkstra algorithm during the implementation, to find shortest path distance.

4) JBF performs well for all three types of noises and produce detail-transferred image with denoising.

5) FBF is the fastest *i.e.*, having less time complexity among all techniques but in this technique blurriness in color is large.

References

[1] E. Abreu, M. Lighstone, S. K. Mitra and K. Arakawa, “A new efficient approach for the removal of impulse noise from highly corrupted images”, IEEE Transactions on Image Processing, vol. 5, no. 6, **(1996)** Jun, pp. 1012–1025.

[2] D. Karakos and P. Trahanias, “Generalized multichannel image-filtering structure”, IEEE Transactions on Image Processing, vol. 6, no. 7, **(1997)** July, pp. 1038–1045.

[3] C. Tomasi and R. Manduchi, “Bilateral filter for gray and color images”, in Proceeding of IEEE International Conference on Computer Vision, **(1998)**, pp. 839-846.

[4] K. N. Plataniotis, D. Androutsos and A.N. Venetsanopoulos, “Adaptive fuzzy systems for multichannel signal processing”, in Proceedings of the IEEE, vol. 87 no. 9, **(2002)** Aug, pp. 1601-1622.

[5] H. L. Eng and K. K. Ma, “Noise adaptive soft-switching median filter”, IEEE Transactions on Image Processing, vol. 10, no. 2, **(2001)** Feb., pp. 242–251.

[6] Michael Elad,"On the Origin of the Bilateral Filter and Ways to Improve It", IEEE transactions on image processing, vol. 11, no. 10, pp. 1141-1151, October 2002.

[7] Y. Shen, K.E. Barner, “Fuzzy Vector Median Based Surface Smoothing”, IEEE Transactions on Visualization and Computer Graphics, vol. 10, no.3, pp. 252-265, May-June 2004.

[8] Roman Garnett, Timothy Huegerich, Charles Chui, “A Universal Noise Removal Algorithm With an Impulse Detector”, IEEE transactions on image processing, vol. 14, no. 11, pp. 1747-1754, November 2005.

[9] M. E. Yüksel, “A simple neuro-fuzzy method for improving the performances of impulse noise filters for digital images,” International journal of Electronics Communication, vol. 59, no.8, pp. 463-472, 2005.

[10] S. Schulte, B. Huysmans, A. Pizurica, E. E. Kerre, and W. Philips, “A new fuzzy-based wavelet shrinkage image denoising technique,” in Proceeding of Advanced Concepts for Intelligent Vision Systems, vol. 1, pp. 12–23, 2006.
[11] S. Morillas, V. Gregori, and A. Sapena, “Fuzzy bilateral filtering for color images,” in Proceeding of International Conference on Image Analysis and Recognition, vol. 4141, pp. 138–145, 2006.
[12] Petschnigg, G., Szeliski, R., Agrawala, M., Cohen, M., Hoppe, H. and Toyama K., “Digital photography with flash and no-flash image pairs”, In ACM Trans. Graph., Volume: 23, Issue: 3, Page(s): 664-672, 2004.
[13] S. Schulte, V. De Witte, and E. E. Kerre, “A fuzzy noise reduction method for color images,” IEEE Transactions on Image Processing, vol. 16, no. 5, pp. 1425–1436, May 2007.
[14] S. Morillas, S. Schulte, T. Mélange, E. E. Kerre, and V. Gregori, “A soft-switching approach to improve visual quality of color image smoothing filters,” in Proceeding of Advanced Concepts for Intelligent Vision Systems, vol. 4678, pp. 254–261, 2007.
[15] C.H. Lin, J.S. Tsai, C.T. Chiu, “Switching bilateral filter with texture/noise detector for universal noise removal,” IEEE Transactions on Image Processing, vol. 19, no. 8, pp. 2307-2320, Sep. 2010.
[16] X. Zeng, L. Yang, “Mixed impulse and Gaussian noise removal using detail-preserving regularization”, Optical Engineering vol. 49, no. 9, pp. 097002-1-097002-9, Sep. 2010.
[17] Florian Luisier, Thierry Blu, Michael Unser, “Image Denoising in Mixed Poisson–Gaussian Noise”, IEEE transactions on image processing, vol. 20, no. 3, pp. 696-708, march 2011.
[18] Y. Xiao, T. Zeng, J. Yu, M.K. Ng, “Restoration of images corrupted by mixed Gaussian-impulse noise via l0-l1 minimization”, Pattern Recognition, vol. 44, no. 8, pp. 1708-1720, Aug. 2011.
[19] Zhang, K., Lafruit, G., Lauwereins, R. And Van Gool, L., “Constant Time Joint Bilateral Filtering Using Joint Histograms”, In IEEE Transactions on Image Processing, Volume: 21, Issue: 9, pp. 4309-4314, 2012.
[20] J. Liu, Z. Huan, H. Huan, “Image restoration under mixed noise using globally convex segmentation”, Journal of Visual Communication and Image Representation, vol. 22, no. 3, pp. 263-270, Apr. 2011.
[21] Joan-Gerard Camarena, V. Gregori, Samuel Morillas and Almanzor Sapena ,“A simple fuzzy method to remove mixed Gaussian-impulsive noise from colour images”, in IEEE transactions on fuzzy systems, vol. 21, issue 5, pp. 971-978, Oct. 2013.
[22] Sylvain Paris, Fredo Durand, “A Fast Approximation of the Bilateral Filter Using a Signal Processing Approach”, Springer Science and Business Media, vol. 81, pp. 24-52, 2009.
[23] Buyne Zhang and Allebach, “Adaptive Bilateral Filter for Sharpness Enhancement and Noise Removal”, in IEEE transactions on image processing, vol.17, no. 5, pp. 664-678 , May 2008.
[24] Malik, K. And Smolka, B., “Improved Bilateral Filtering Scheme For Noise Removal in Color Images,” In Proceedings of the International Conference on Informatics and Applications (ICIA 2012), pp. 118-130, 2012.
[25] G.C. Holst, CCD Arrays, Cameras, and Displays, 2nd ed. Bellingham, WA: SPIE, 1998.
[26] W.K. Pratt, Digital Image Processing, New York: Wiley, 1978.
[27] Tripathi, A.K.; Mukhopadhyay, S.; “Single image fog removal using bilateral filter,” In Proceedings of IEEE International Conference on Signal Processing, Computing and Control (ISPCC 2012), pp. 1-6, 2012.
[28] Rafael Gonzalez and Richard E. Woods. Digital Image Processing. Addison-Wesley, second edition, 2002.

