International Journal of Electronics Signals and Systems

Volume 3 | Issue 3 Article 6

January 2014

# REMOVAL OF GAUSSIAN AND IMPULSE NOISE IN THE COLOUR IMAGE PROGRESSION WITH FUZZY FILTERS

P. VENKATESAN
*Department of ECE, SCSVMV University, Kanchipuram, India*, pv.ecekanchi@gmail.com

G. NAGARAJAN
*Department of ECE, Pondicherry Engineering College, Pondicherry, India*, nagarajanpec@yahoo.com



Recommended Citation

VENKATESAN, P. and NAGARAJAN, G. (2014) "REMOVAL OF GAUSSIAN AND IMPULSE NOISE IN THE COLOUR IMAGE PROGRESSION WITH FUZZY FILTERS," *International Journal of Electronics Signals and Systems*: Vol. 3 : Iss. 3 , Article 6.
DOI: 10.47893/IJESS.2014.1162
Available at: https://www.interscience.in/ijess/vol3/iss3/6

# REMOVAL OF GAUSSIAN AND IMPULSE NOISE IN THE COLOUR IMAGE PROGRESSION WITH FUZZY FILTERS

**P.VENKATESAN[1] & G.NAGARAJAN[2]**

[1]Senior Assistant Professor in department of ECE, SCSVMV University, Kanchipuram [T.N], India
[2]Professor in department of ECE, Pondicherry Engineering College, Pondicherry, India
E-mail: pv.ecekanchi@gmail.com, nagarajanpec@yahoo.com

**Abstract-** This paper is concerned with algebraic features based filtering technique, named as the adaptive statistical quality based filtering technique (ASQFT), is presented for removal of Impulse and Gaussian noise in corrupted colour images. A combination of these two filters also helps in eliminating a mixture of these two noises. One strong filtering step that should remove all noise at once would inevitably also remove a considerable amount of detail. Therefore, the noise is filtered step by step. In each step, noisy pixels are detected by the help of fuzzy rules, which are very useful for the processing of human knowledge where linguistic variables are used. The proposed filter is able to efficiently suppress both Gaussian noise and impulse noise, as well as mixed Gaussian impulse noise. The experiments shows that proposed method outperforms novel modern filters both visually and in terms of objective quality measures such as the mean absolute error (MAE), the peak-signal-to-noise ratio (PSNR) and the normalized color difference (NCD). The expectations filter achieves a promising performance.

***Keywords-*** *Gaussian noise, Impulse noise, Adaptive distance, fuzzy logic, image denoising, logic, nonlinear filters.*

## I. INTRODUCTION

Digital images are often corrupted by noise during their acquisition and transmission. A fundamental problem in image processing is to effectively suppress noise while keeping intact the desired image features such as edges, textures, and fine details. In particular, two common sources of noise are the so called additive Gaussian noise and impulse noise which are introduced -during the acquisition and transmission processes, respectively [1]–[3]. Noisy images can be found in many today's imaging applications. TV images are corrupted because of atmospheric interference and imperfections in the image reception. Noise is also introduced in digital artworks when scanning damaged surfaces of the originals. Digital cameras ma introduce noise because of CCD sensor malfunction, electronic interference or flaws in data transmission. cDNA microarray image data contains imperfections due to both source and detector noise in microarray technology, etc. In the past years, many methods have been introduced in the literature to remove either Gaussian or impulse noise. However, not all methods are able to deal with images which are simultaneously corrupted with a mixture of Gaussian and impulse noise.According to the above, the filter design is a challenging task for mixed Gaussian-impulse noise removal. A possible solution is to apply two consecutive filters to remove first impulse noise and then Gaussian noise, or vice versa. However, the application of two filters could dramatically decrease the computational efficiency of the method which implies that this solution could not be practical for real applications. Therefore, it is more interesting to devise specific filters to remove mixed noise. To date, a few methods in the literature are able to approach - this problem efficiently. The Adaptive Nearest Neighbor Filter (ANNF) and its variants [4], [5] use a weighted averaging where the weights are computed according to robust measures so that impulses that receive lower weights are reduced. The Fuzzy Vector Median Filter (FVMF) [6] performs a weighted averaging where the weight of each pixel is computed according to its similarity to the robust vector median. Another important family of filters are the partition based filters [7], [8] that classify each pixel to be processed into several signal activity categories which, in turn, are associated to appropriate processing methods. Other filters follow a regularization approach [9] [10] based on the minimization of appropriate energy functions by means of Partial Differential Equations (PDEs).Wavelet theory has also been used to design image filtering methods [11] [12] and the combination of collaborative and wavelet filtering is proposed in [13], [14]. In addition, other methods based on Principal Component Analysis (PCA) [15] have been studied.

The propose use a fuzzy representation. This leads us to introduce the fuzzy filter group concept which we use to devise a novel filtering procedure. The method presented in this paper is based on well established concepts. It uses fuzzy metrics [16], [17], which have been proven to be efficient and effective for noise detection [18] but, in this case, fuzzy metrics are applied to build the fuzzy filter groups. The proposed method is based on the consecutive application of a fuzzy rule-based switching impulse noise filter and a fuzzy average filtering. Both steps use the same the Adaptive Statistical Quality Based Filtering

Technique (ASQFT), which leads to computational savings. (i) ASQFT are represented as fuzzy sets instead of crisp sets used in [19] (ii) it employs a novel fuzzy method first to determine the fuzzy filter group members and then to assign their corresponding membership degrees, (iii) it uses fuzzy rules to detect impulse noise pixels, and (iv) it performs a fuzzy weighted averaging to generate the output. Hence, the combination of these fuzzy components is the main novelty of the proposed method. Experimental results will show that the proposed filtering technique exhibits competitive results with respect to other state-of-the-art methods

## II. STATISTICAL MODELS OF IMPULSE NOISE

Color images may be contaminated by various types of noise and impulse noise is the noise model frequently used and reported in digital restoration literature. Impulse noise corruption often occurs in digital image acquisition or transmission process as a result of photo-electronic sensor faults or channel bit errors. Image transmission noise may be caused by various sources, such as car ignition systems, industrial machines in the vicinity of the receiver, switching transients in power lines, lightning in the atmosphere and various unprotected switches. This type of transmission noise is often modeled as the impulse noise.

Let $C = \{c = (c_1,c_2) \ |1 \le c_1 \le H, 1 \le c_2 \le W\}$ denote the set of the pixel coordinates of a color image, where H and W are height and the width of the image, respectively at each pixel coordinate c € C ,a multivariate value vector in the RGB color space, $X(C) = [x_R(c), x_G(c), x_B(c)]^T$, is used to represent the RGB(Red,Green,Blue) pixels values.

Two approaches as reported in the literature are used in this paper to model the impulse noise for color image restoration. In the first approach, the impulse noise corruption of the color images in the RGB space is expressed by a multivariate model.

$$Y(c) = \begin{cases} s(c), & \text{with probability } (1-P_I) \\ n_T(c), & \text{with probability } P_I \end{cases} \quad (1)$$

and in the second approach the impulse noise corruption of the color images in the RGB space is expressed by a multivariate model.

$$Y(c) = \begin{cases} s(c), & \text{with probability } (1-P)^3 \\ n_t(c), & \text{with probability } 1-(1-P)^3 \end{cases} \quad (2)$$

Where S(c) and X(c) represent the original and the observed pixel (vector) values at coordinate c, respectively , and the value of $n_T(c)$ and $n_t(c)$ is generated by substituting at least one color component of the pixel S(c) by distinct value 'd' in both (1) and (2). In (1), $P_I$ is the impulse noise ratio; a factor r=0.5 is used to simulate the channel correlation for each corrupted pixel, namely if at least one of the three components of the pixel is corrupted by the impulse noise, its remaining noise free components will have a 50% probability to be corrupted. The second approach (2) is a more generalized impulse noise model of color images where $P = P_R = P_G = P_B$ is the impulse noise ratio for each channel of a corrupted color image, assuming that the image is corrupted by the impulse noise in a channel independent manner. In (1) and (2) ,if d, the component value of $n_t(c)$ or $n_T(c)$ equals the maximum or the minimum value of the digital image (e.gg,, 255 or 0 for an 8- bit channel of the 24- bit color image in the RGB space), the impulse noise is referred to as the salt – and –pepper impulse . Each pixel of the image may be corrupted by either the pepper or salt impulse with unequal probabilities. However, if the amplitudes of the impulse are distributed randomly with, e.gg, the uniform or the Gaussian distribution, in the range of [0,255], a more general type of the impulse noise is generated and named as the random impulse noise.

In this paper, an Adaptive Statistical Quality based Filtering Techniques (ASQFT) with a low computational complexity is proposed for restoration of digital color images corrupted by the impulse noise. This technique uses a set of novel noise detection criteria for detection of the corrupted pixels, which are based on 2-D geometric and dimension features of the noisy pixel or the noisy region of images. This is in contrast with the traditional noise detection techniques where only 1-D statistical information is used for estimation of the noise ratio and the noise statistical distribution model. Based on the result of the estimation, an adaptive progressive filtering operation is employed in combination with optimized dimension and shape of processing windows computational efficiency of the ASQFT is also investigated denoising performance of the ASQFT is evaluated to demonstrate noticeable gains against that of a number of well-known benchmark techniques mentioned above, in terms of standard objective measurements perceptual image quality and computational complexity ,especially for suppression of the impulse noise in medium-and large-size color images.

$$\begin{cases} S_1^a(n_1^a) = y[i.j]-y[\, i-n_1^a,j] \\ S_2^a(n_2^a) = y[i,j]-y[i,\, j-n_2^a] \\ S_3^a(n_3^a) = y[i,j]-y[i+n_3^a,j] \\ S_4^a(n_4^a) = y[i,j]-y[i,\, j+n_4^a] \end{cases} \quad (3)$$

Where $n^a = [n_1^a,n_2^a,n_3^a,n_4^a]^T$, $n^a_k > 0$ and the default value of $n^a_k$ is 1,for $1 \le k \le 4$, and subscript "T" represents the transpose operation.

When a derivative is only considered in the diagonal direction, $\partial y(c)/\partial c^d$ is approximated by $G^d$, the difference between the pixel and its other 8-neighbors, for each component of the color component, and defined as follows:

**Fig.1. Reconstruction of proposed filter compared with other techniques, where the test image Jovanov is corrupted by salt-and-pepper impulse with noise in noise model defined by (2). (a) Original image Jovanov; (b) 15% salt-and-pepper corruption; (c) ANNF output; (d) FVMF output; (e) PGA output; (f) ASQFT output.**

$$\begin{cases} G_1^d(n_1^d) = y[i,j]-y[i-n_1^d, j-n_1^d] \\ G_2^d(n_2^d) = y[i,j]-y[i+n_2^d, j-n_2^d] \\ G_3^d(n_3^d) = y[i,j]-y[i+n_3^d, j+n_3^d] \\ G_4^d(n_4^d) = y[i,j]-y[i-n_4^d, j+n_4^d] \end{cases} \tag{4}$$

Where $n^d = [n_1^d, n_2^d, n_3^d, n_4^d]^T$, $n_k^d > 0$ and the default value of $n_d^k$ is 1 , for $1 \le k \le 4$. The two special derivatives, $G^a$ and $G^d$, will be used to measure the edge feature (sharpness) and other geometric properties to determine whether center pixel at c = (i,j) is corrupted or not in the ASQFT procedure and the fig.1. Shows reconstruction of processed filter corrupted by salt -and-pepper nois.

## III. GAUSSIAN NOISE SMOOTHING PROCEDURE

The second step of the proposed method concerns the Gaussian noise smoothing task. As mentioned above, we propose to perform a weighted averaging operation among color vectors. So, to smooth the pixel we use the members of where the weighting coefficient for each color vector is its membership degree to the fuzzy filter group Notice that, unlike other smoothing filters based on weighting coefficients, such as those in [20], [21], and [22], the set of neighbor pixels involved in the proposed smoothing procedure is restricted to the members of the fuzzy filter group, which implies that only similar pixels are used. Fig.2 for diagram of the filtering process this approach should perform a better edge and detail preservation than those non restricted approaches since non similar color vectors out of the fuzzy filter group do not perturb the averaging.

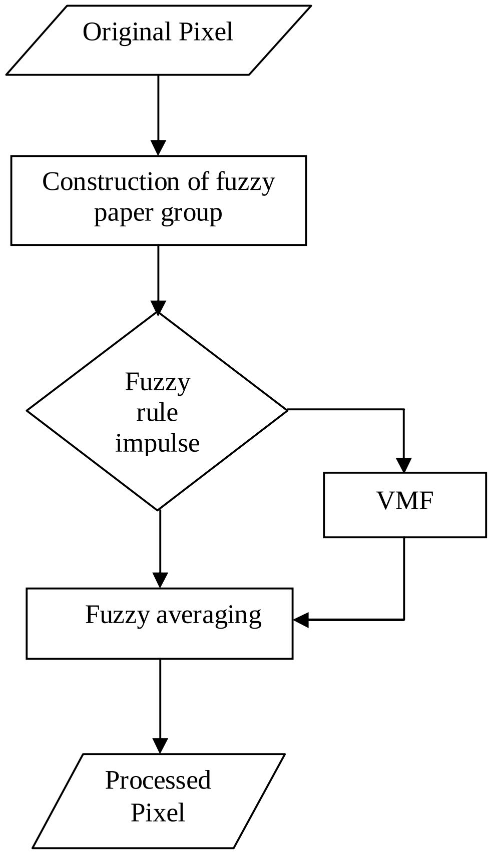
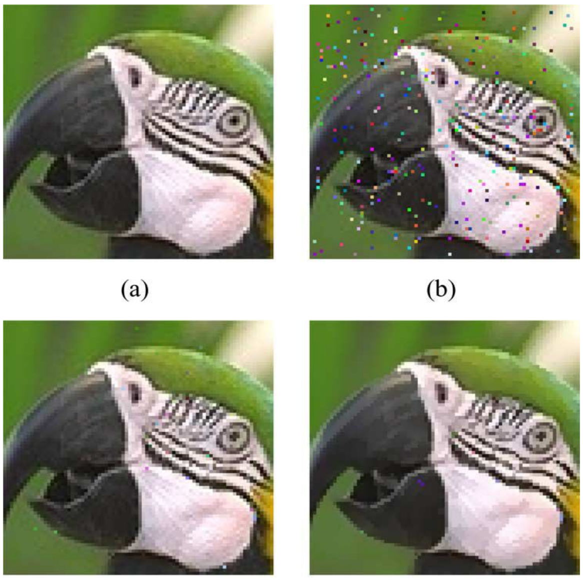



**Fig.2. Diagram of the filtering process applied to each image pixel.**

## IV. EXPERIMENTAL RESULTS

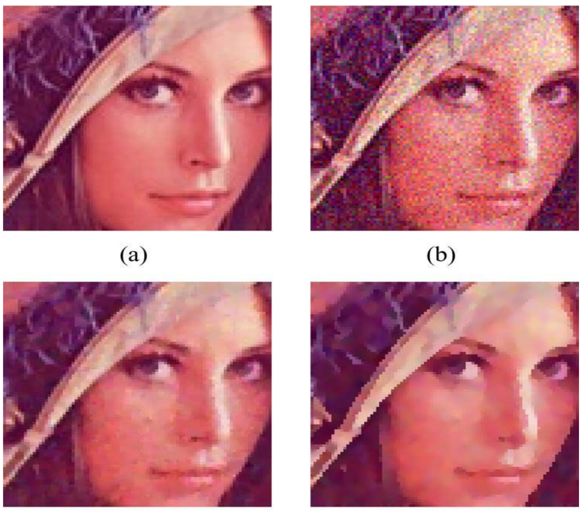
The test images Parrots and Lena in Fig.3 and fig.4 have been used to evaluate the performance of the proposed filter. In particular, a detail of each image has been used in order to better appreciate the performance differences among different parameter settings and filtering methods. These images have been corrupted with Gaussian and/or impulse noise. For Gaussian noise we have used the classical white additive Gaussian model [1] contaminating independently each color image channel where the standard deviation of the Gaussian distribution represents the noise intensity. On the other hand, the two most common impulse noise models assume that the impulse is either an extreme value in the signal range or a random uniformly distributed value within the signal range. These models are known as fixed-value and random-value impulse noise, respectively.

Since the removal of fixed-value noise has been extensively studied in the literature and there have been several methods developed and able to suppress this noise effectively. we will denote the probability of impulse appearance as. The filter performance is assessed by taking into account both the noise suppression and the detail preserving capabilities of the filter. To this end, we have used the Mean Absolute Error (MAE), the Peak Signal to Noise Ratio (PSNR), and the Normalized Color Difference (NCD) that measure the detail preserving capability, the noise suppression capability, and the results comparisons performances show in the Table I II and II the color preservation ability, respectively. The definitions of these objective quality measures can be found in [1]–[3].



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

**Fig.3.Filter outputs for visual comparison: (a) Parrots image, (b) image corrupted with p = 0.05 impulse noise and outputs from (c) ANNF, and (d) ASQFT.**



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

**Fig.4. Filter outputs for visual comparison: (a) Lena image, (b) image corrupted with σ= 20 Gaussian noise and outputs from (c) CRF, and (d) ASQFT.**

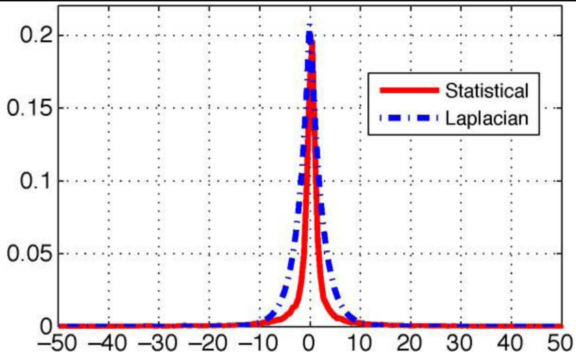
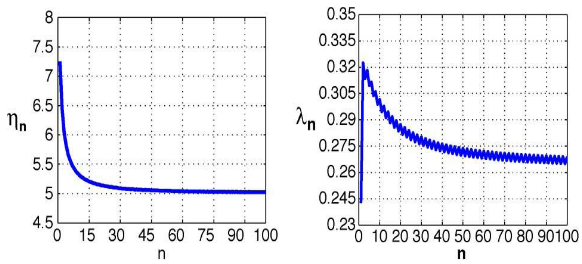



**Fig.5. Statistical distribution of fuzzy coefficients generated by the fuzzy filter for the "Lena" image, and the Laplace distribution with a scale parameter estimated by ML**

We first look at Fig.5, which shows the distribution of fuzzy coefficients by the filter for the "Lena" image. It can be seen that many fuzzy coefficients are close to zero and its statistical distribution (real line) is similar to Laplace distribution (dashed line). Motivated from this example, we model the tight fuzzy coefficients as samples from a Laplace random process with zero mean. Although this assumption does not fit real cases well due to the fact that the coefficients are statistically dependent, in the present study, we find that an approximate assumption of the fuzzy coefficients [cf. (24)] provides a way to select the parameter $\square_n$ .Experiments in Section VI will confirm the effectiveness of this assumption in deblurring images corrupted by Gaussian and impulsive noise.




(a) (b)

**Fig.6. Iterative trends of (a) $\square_n$ and (b) $\square_n$ for deburring the "Lena" image contaminated by salt–pepper plus Gaussian noise.**

Fig.6. (a) and (b) shows the records of $\square_n$ and $\square_n$ used in an experiment for deblurring the "Lena" image corrupted by salt–pepper plus Gaussian noise. This says that the parameter $\square_n$ converges to a constant while the parameter $\square_n$ wiggly tends to a constant when the number of iteration is large enough.

## V. CONCLUSION

In this paper the problem of image deblurring in the presence of impulse noise and Gaussian noise. A statistical features-based filtering technique has been proposed for removing impulse noise from corrupted digital color images. The special contribution of the new filtering technique is its novel impulse detection method, In order to preserve the details as much as possible; the noise is removed step by step. The detection of noisy color components is based on fuzzy rules in which information from spatial and temporal neighbors as well as from the other color bands is used. Detected noisy components are filtered based on block matching where a noise adaptive mean absolute difference is used and where the search region contains pixels blocks from both the previous and current frame. Experimental results have shown that the proposed method is able to reduce mixed Gaussian-impulse noise exhibiting an improved performance with respect to state-of-the-art methods mainly because of its ability to properly determine the ASQFT. The experiments showed that outperforms other state-of-the-art methods both in terms of objective measures such as MAE, PSNR and NCD and visually. Also, the proposed method is competitive when reducing noise from images which are corrupted only with Gaussian noise and only with impulse noise.

## REFERENCES


[1] I.Pitas and A. N. Venetsanopoulos, Nonlinear Digital FilterPrinciplesand Applications. Norwell, MA: Kluwer, 1990.Y. M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[2] 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 Trans. Image Process., vol. 5, no. 6, pp. 1012–1025, Jun. 1996.

[3] V. I. Ponomaryov, "Real-time 2D-3D filtering using order statistics based algorithms," J. Real-Time Image Process., vol. 1, no. 3, pp.173–194, 2007.

[4] X. Li, "On modeling interchannel dependency for color image denoising," Int. J. Imag. Syst. Technol., vol. 1, no. 3, pp. 163–173, Oct. 2007.

[5] O. Lezoray, A. Elmoataz, and S. Bougleux, "Graph regularization for color image processing," Comput. Vis. Image Understand., vol. 10, no. 1–2, pp. 38–55, Jul.–Aug. 2007.

[6] A. Elmoataz, O. Lezoray, and S. Bougleux, "Nonlocal discrete regularization on weighted graphs: A framework for image and manifold processing," IEEE Trans. Image Process., vol. 1, no. 7, pp. 1047–1060, Jul. 2008.

[7] P. E. Trahanias and A. N. Venetsanopoulos, "Vector direction filter: A new class of multichannel image processing filter," IEEE Trans. Image Process., vol. 2, no. 10, pp. 528–534, Oct. 1993.

[8] D. G. Karakos and P. E. Trahanias, "Combining vector median and vector direction filters: The directional-distance filter," in Proc. IEEE Int. Conf. Image Process., Washington, DC, Oct. 1995, vol. 1, pp. 171–174.

[9] 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

[10] V. Chatzis and I. Pitas, "Fuzzy scalar and vector median filters based on fuzzy distances," IEEE Trans. Image Process., vol. 8, no. 5, pp. 731–734, May 1999.

[11] H. H. Tsai and P. T. Yu, "Genetic-based fuzzy hybrid multichannel filters for color image restoration," Fuzzy Sets Syst., vol. 114, pp. 203–224, 2000.

[12] R. Lukac, K. N. Plataniotis, B. Smolka, and A. N. Venetsanopoulos, "cDNA microarray image processing using fuzzy vector filtering framework," J. Fuzzy Sets Syst., vol. 152, no. 1, pp. 17–35, May 2005

[13] L. Khriji and M. Gabbouj, "Adaptive fuzzy order statistic-rational hybrid filters in color image processing," Fuzzy Sets Syst., vol. 128, no. 1, pp. 35–46, Mar. 2000.

[14] E. S. Hore, B. Qiu, and H. R. Wu, "Improved color image vector filtering using fuzzy noise detection," Opt. Eng., vol. 42, no. 6, pp. 1656–1664, Jun. 2003.

[15] R. Lukac, B. Smolka, K. N. Plataniotis, and A. N. Venetsanopoulos,"Selection weighted vector directional filter," Comput. Vis. Image Understand., vol. 94, no. 1-3, pp. 140–167, Apr. 2004.

[16] Y. Dong and S. Xu, "A new directional weighted median filter for removal of random-valued impulse noise," IEEE Signal Process. Lett., vol. 1, no. 3, pp. 193–196, Mar. 2007

[17] V. Chatzis and I. Pitas, "Fuzzy scalar and vector median filters based on fuzzy distances," IEEE Trans. Image Process., vol. 8, no. 5, pp. 731–734, May 1999

[18] H. H. Tsai and P. T. Yu, "Genetic-based fuzzy hybrid multichannel filters for color image restoration," Fuzzy Sets Syst., vol. 114, pp. 203–224, 2000.

[19] R. Lukac, K. N. Plataniotis, B. Smolka, and A. N. Venetsanopoulos, "CDNA microarray image processing using fuzzy vector filtering framework," J. Fuzzy Sets Syst., vol. 152, no. 1, pp. 17–35, May 2005.

[20] L. Khriji and M. Gabbouj, "Adaptive fuzzy order statistic-rational hybrid filters in color image processing," Fuzzy Sets Syst., vol. 128, no. 1, pp. 35–46, Mar. 2000

[21] E. S. Hore, B. Qiu, and H. R. Wu, "Improved color image vector filtering using fuzzy noise detection," Opt. Eng., vol. 42, no. 6, pp. 1656–1664, Jun. 2003

[22] S. Schulte, V. D. Witte, M. Nachtegeal, D. V. Weken, and E. E. Kerre, "Fuzzy two-step filter for impulse noise reduction from colour images,"

[23] D. Kornack and P. Rakic, "Cell Proliferation without Neurogenesis in Adult Primate Neocortex," Science, vol. 294, Dec. 2001, pp. 2127-2130, doi:10.1126/science.1065467.'

[24] H. Goto, Y. Hasegawa, and M. Tanaka, "Efficient Scheduling Focusing on the Duality of MPL Representatives," Proc. IEEE Symp. Computational Intelligence in Scheduling (SCIS 07), IEEE Press,.


TABLE I

COMPARISON OF THE PERFORMANCE MEASURED IN TERMS OF MAE, PSNR, AND NCD ($\times 10^2$) USING THE PARROTS IMAGE CONTAMINATED WITH DIFFERENT DENSITIES OF MIXED NOISE

| Filter | σ=5 Gaussian and p=0.05 impulse noise MAE PSNR NCD | σ=10 Gaussian and p=0.1 impulse no MAE PSNR NCD | σ=20 Gaussian and p=0.2 impulse MAE PSNR NCD | σ=30 Gaussian and p=0.3 impulse MAE PSNR NCD |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| ANNF | 6.81 26.99 4.41 | 7.42 26.63 5.21 | 9.38 25.38 7.45 | 12.29 23.60 10.04 |
| FVMF | 6.53 27.04 4.35 | 7.27 26.64 5.13 | 9.37 25.04 6.80 | 11.87 23.75 9.14 |
| PGA | 5.20 29.81 4.05 | 7.26 27.61 6.09 | 10.14 24.95 8.42 | 12.91 23.00 10.74 |
| FWD | 7.62 21.10 7.50 | 12.16 19.45 12.45 | 18.12 18.70 17.50 | 22.40 18.17 20.30 |
| CWF | 6.37 24.07 5.60 | 9.32 25.71 7.61 | 16.75 21.70 13.97 | 21.55 19.81 17.82 |
| ASQFT | 4.22 31.03 3.26 | 5.76 29.15 4.60 | 8.11 26.35 6.71 | 10. 68 24.51 8.90 |

TABLE II
COMPARISON OF THE PERFORMANCE MEASURED IN TERMS OF MAE, PSNR, AND NCD ($\times 10^2$)
USING THE LENA IMAGE CONTAMINATED WITH DIFFERENT DENSITIES OF MIXED NOISE

| Filter | σ=5 Gaussian and p=0.05 impulse noise MAE PSNR NCD | σ=10 Gaussian and p=0.1 impulse noise MAE PSNR NCD | σ=20 Gaussian and p=0.2 impulse noise MAE PSNR NCD | σ=30 Gaussian and p=0.3 impulse noise MAE PSNR NCD |
|---|---|---|---|---|
| ANNF | 7.17 27.01 3.90 | 7.82 26.61 4.71 | 9.66 25.32 6.98 | 12.46 23.46 9.13 |
| FVMF | 6.70 27.27 3.93 | 7.83 26.52 4.82 | 9.55 25.37 6.74 | 12.07 23.74 8.71 |
| PGA | 5.95 28.84 4.07 | 7.49 27.49 6.00 | 10.55 24.75 8.72 | 13.28 22.89 10.91 |
| FWD | 7.42 21.60 7.27 | 12.15 19.69 12.31 | 16.72 19.46 15.80 | 20.63 18.87 16.99 |
| CWF | 7.05 21.63 7.25 | 9.53 25.42 6.30 | 14.73 22.31 9.29 | 19.38 20.33 11.78 |
| ASQFT | 4.55 30.90 3.09 | 6.88 28.24 4.34 | 8.70 26.35 6.62 | 11.03 24.45 8.75 |

TABLE III
COMPARISON OF THE PERFORMANCE MEASURED IN TERMS OF MAE, PSNR, AND NCD ($\times 10^2$)
USING THE JOVANOV IMAGE CONTAMINATED WITH DIFFERENT DENSITIES OF MIXED NOISE

| Filter | σ=5 Gaussian and p=0.05 impulse MAE PSNR NCD | σ=10 Gaussian and p=0.1 impulse MAE PSNR NCD | σ=20 Gaussian and p=0.2 impulse MAE PSNR NCD | σ=30 Gaussian and p=0.3 impulse MAE PSNR NCD |
|---|---|---|---|---|
| ANNF | 8.881 24.63 5.88 | 9.58 24.28 6.96 | 11.66 23.30 9.66 | 14.94 21.62 12.77 |
| FVMF | 8.66 24.37 6.18 | 9.60 23.87 7.04 | 11.49 22.97 9.13 | 14.16 21.73 11.99 |
| PGA | 7.05 27.03 5.90 | 8.59 25.76 8.22 | 11.75 23.24 11.25 | 14.91 21.39 14.28 |
| FWD | 7.42 21.44 8.65 | 12.50 19.34 15.03 | 18.60 18.64 20.25 | 23.19 17.83 22.07 |
| CWF | 6.11 24.08 6.24 | 10.67 23.85 9.97 | 18.04 20.68 14.85 | 23.63 18.56 17.98 |
| ASQFT | 5.50 28.77 4.72 | 6.61 27.14 6.24 | 9.70 24.31 8.96 | 12.46 22.68 11.80 |