

# Removal of Gaussian and Impulse Noise in the Colour Image Succession with Fuzzy Filters

Prof.P.Venkatesan, Prof.Dr.S, K.Srivatsa

**Abstract—** In this paper, a new fuzzy filter for the removal of impulse noise and Gaussian in colour is presented. By working with different successive filtering steps, 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 colour difference (NCD). The expectations filter achieves a promising performance.

**Index Terms—** Impulse noise, Adaptive distance, fuzzy logic, image denoising, logic, nonlinear filters.

## 1 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 introduces 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

*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

- Prof.P.Venkatesan is currently pursuing Phd program in image processing in SCSVMV University, India.  
E-mail: [pv.ecekanchi@gmail.com](mailto:pv.ecekanchi@gmail.com)
- Prof.Dr.S.K.Srivatsa, senior professor in ECE department  
St.Joseph's College of Engineering, Anna University.

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*

## 2. Fuzzy filter for Impulse noise

A colour image can be represented via several colour models such as RGB, CMY, CMYK, HSI, HSV and CIE. The most well known of these is the RGB model which is based on cartesian coordinate system. An image presented in the RGB colour model consists of three component images, one for each primary colour (Red, Green and Blue). Consider a colour image represented in the x-y plane, then the third coordinate  $z = 1, 2, 3$  will represent the colour component of the image pixel at  $(x, y)$ . Let  $f$  be the image function then  $f(x, y, 1)$  will represent the Red component of pixel at  $(x, y)$ . Similarly,  $f(x, y, 2)$  and  $f(x, y, 3)$  represent the Green and Blue components respectively. This notation is followed throughout this work.

### 2.1 Impulse noise in colour images

Images corrupted with impulse noise contain pixels affected by some probability. This implies that some of the pixels may not have a trace of any noise at all. Moreover, a pixel can have either all or one or two of its components corrupted with impulse noise. Mathematical modelling of impulse noise in colour images is as follows:

$$f(x, y, z) = \begin{cases} N(x, y, z) & \text{with probability } p_z \\ I(x, y, z) & \text{with probability } p(1-p_z) \end{cases} \quad (1)$$

Where,  $z = 1, 2, 3$  represents red, green and blue components. The probabilities  $p_z$ 's can have equal or unequal values. In Equ (1),  $f$  represents the final corrupted image, while  $N$  and  $I$  are the numbers of corrupted and uncorrupted pixels respectively.

### 2.2 Algorithm for Median of noise-free pixels

An algorithm to determine the median of noise-free pixels in the neighborhood of a pixel under interest is now presented. The median of the noise free pixels is utilized to modify the pixel corrupted with impulse noise. This median is computed separately for each colour component in the following steps:

Step1: Take a window of size  $w \times w$  centered on the pixel of interest in the corrupted image.

Step2: Arrange all the pixels of the window as a vector. Sort the vector in an Increasing order and compute the median of the sorted vector.

Step3: Calculate the difference between each window pixel and the median of the vector.

Step4: Arrange all the window pixels having the differences less than or equal to a parameter  $\delta_1$  in a vector.

Step5: Sort the new vector and obtain the median  $med$  of the sorted vector.

The procedure for the computation of the median  $med$  is illustrated below.

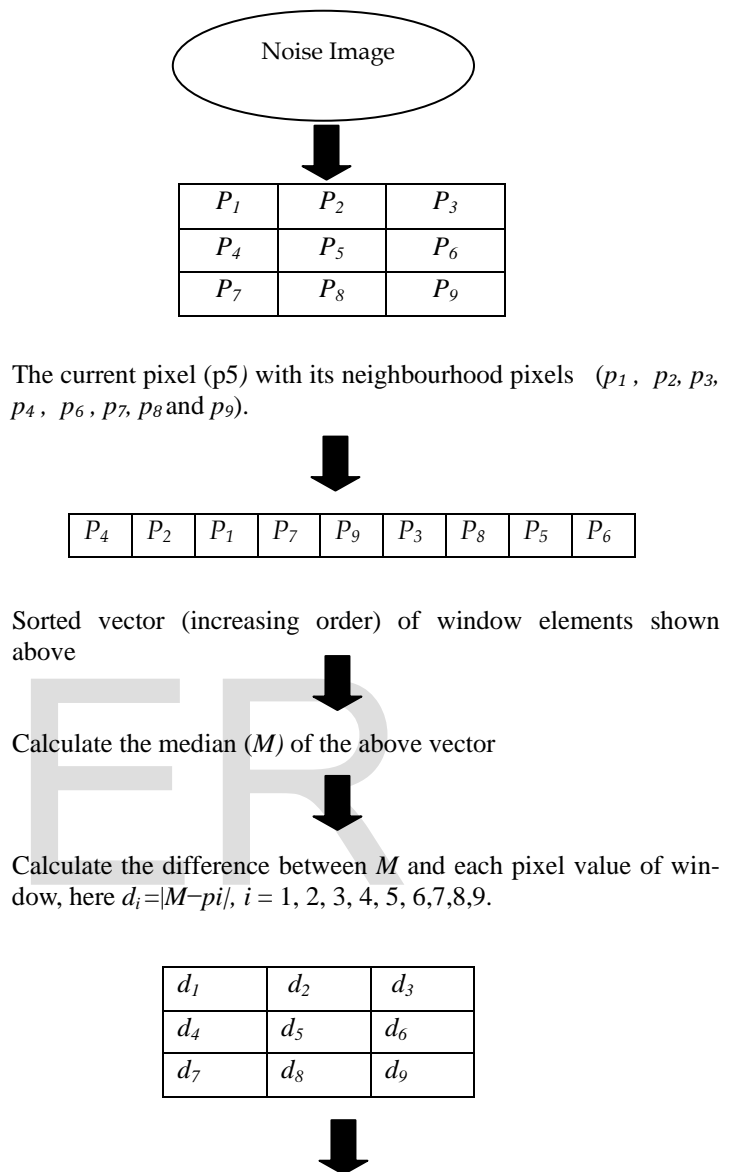


Figure 1: A scheme for the computation of Median of noise-free Pixel

The above median ( $med$ ) is used to find the correction term for each pixel in the noisy image.

### 2.3 Structure of Impulse Filter

The proposed filter is designed for the reduction of impulse noise in colour images by treating each colour component separately. Interactions among these colour components are used to determine the similarity of the central pixel vis-à-vis the neighboring pixels. The nature of impulse noise is random in the sense that it corrupts some pixels while leaving others untouched. So the

objective is to identify the noisy pixels along with the amount of noise present. It may be noted that the impulse noise bears similarity with the high frequency content of images like edges and fine details because both reflect sudden changes in pixel values. Three different membership functions, viz., **Large**, **Unlike** and **Extreme** are used to differentiate the noisy pixels from the high frequency contents. The proposed impulse filter consists of two sub filters in cascade now devise a membership function,  $\mu_1$  to represent a fuzzy set "**Large**" that indicates how large the difference is. A pixel with higher noise will have a larger difference with the median value. This is defined by the membership function,  $\mu_1$  as

$$\mu_1(D_m(x,y,1)) = \begin{cases} 1 & D_m(x,y,1) \geq \alpha_2 \\ \frac{D_m(x,y,1) - \alpha_1}{\alpha_2 - \alpha_1} & \alpha_1 \leq D_m(x,y,1) < \alpha_2 \\ 0, & D_m(x,y,1) < \alpha_1 \end{cases} \quad (2)$$

The parameters  $\alpha_1$  and  $\alpha_2$  in Equ(2) are obtained from experimentation. The membership function represented by Equation (2). A second membership function  $\mu_u$  is devised to measure the degree of similarity of the central pixel to the neighboring pixels. This membership function describes the fuzzy set called **Unlike** over the discrete universe of discourse  $N=\{0,1,2,3,4,5,6,7,8\}$ . Let,  $N$  be the number of similar pixels (excluding the central pixel) in the window of size  $w \times w$ . The number  $N$  is decided based on the differences calculated in the similarity criterion. Considering a  $3 \times 3$  window, the membership function is now defined as:

$$\mu_u(N, D_m) = \begin{cases} 0, & N \geq 4 \text{ and } D_m < \delta_2 \\ 0.5, & N=3 \text{ and } D_m < \delta_2 \\ 1, & \text{otherwise} \end{cases} \quad (3)$$

Note that  $D_m$  in Equ (3) and the parameter  $\delta_2$  is the same as used in the similarity criterion. Therefore if a pixel has more than half pixels similar in the window and its value is close to the median, then it can be considered as a noise-free pixel. The third membership function is characterized as follows. If we arrange pixels of the window in a vector  $V$  and sort them in an increasing order, we will obtain two extreme pixel values in the window, viz.,  $V_{\min}$  and  $V_{\max}$ . The closer the value of a pixel is to these extremes, the higher is the possibility of the pixel being noisy. This concept is used in obtaining Fuzzy set **Extreme**. The membership function for the fuzzy set Extreme applicable to each colour component is given as

$$\mu_e(\tau) = \begin{cases} \frac{1}{1 + \exp(100(\tau - V_{\min} - 0.1))} & V_{\min} \leq \tau \leq V_{\min} + 0.1 \\ \frac{1}{1 + \exp(100(\tau - V_{\max} - 0.1))} & V_{\max} - 0.1 \leq \tau \leq V_{\max} \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where,  $\tau$  represents the pixel value of each colour component.

### 3. EXPERIMENTAL RESULTS

The test images Parrots and Lena in Fig.2 and fig.3 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 colour 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 Colour 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 colour preservation ability, respectively. The definitions of these objective quality measures can be found in [1]–[3].

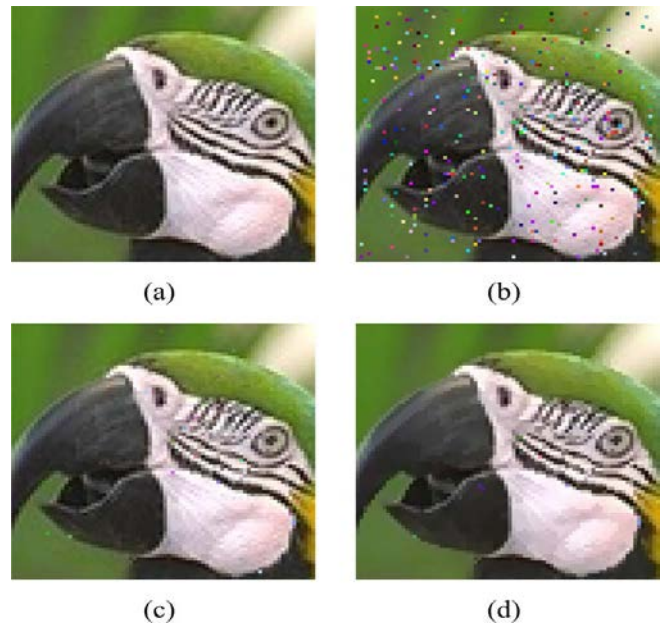


Fig.2. Filter outputs for visual comparison: (a) Parrots image, (b) image corrupted with  $p = 0.05$  impulse noise and outputs from (c) ANNF, and (d) ASQFT.



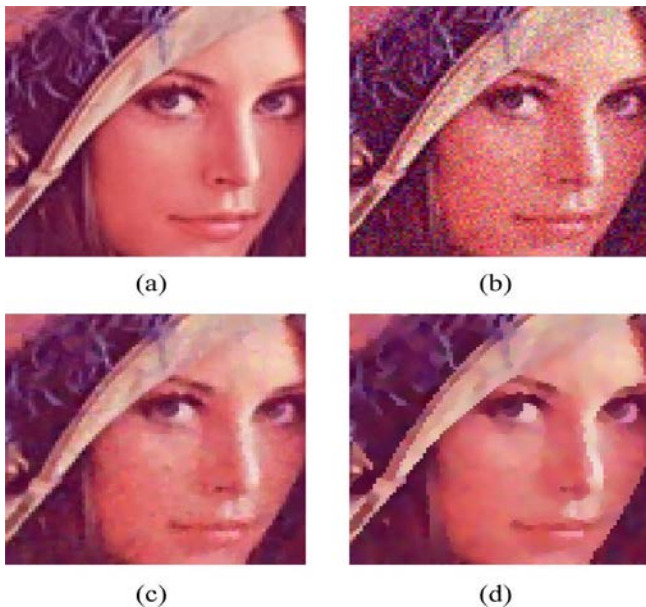


Fig.3. Filter outputs for visual comparison: (a) Lena image, (b) image corrupted with  $\sigma = 20$  Gaussian noise and outputs from (c) CRF, and (d) ASQFT.

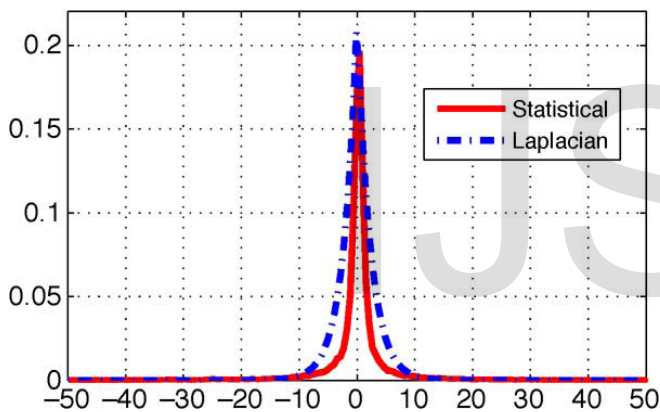


Fig.4. Statistical distribution of fuzzy coefficients generated by the fuzzy filter for the “Lena” image, and the Laplace distribution with a scale parameter estimated by ML

We first look at Fig.4, 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  $\lambda_n$ . Experiments in Section VI will confirm the effectiveness of this assumption in deblurring images corrupted by Gaussian and impulsive noise.

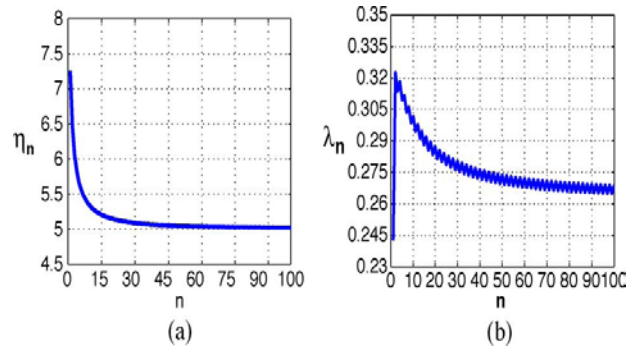


Fig.5. Iterative trends of (a)  $\eta_n$  and (b)  $\lambda_n$  for deblurring the “Lena” image contaminated by salt-pepper plus Gaussian noise.

Fig.5. (a) and (b) shows the records of  $\eta_n$  and  $\lambda_n$  used in an experiment for deblurring the “Lena” image corrupted by salt-pepper plus Gaussian noise. This says that the parameter  $\eta_n$  converges to a constant while the parameter  $\lambda_n$  wiggly tends to a constant when the number of iteration is large enough.



Fig.6. 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.

## 4 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 colour 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 colour components is based on fuzzy rules in which information from spatial and temporal neighbors as well as from the other colour 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 Filter Principles and Applications*. Norwell, MA: Kluwer, 1990. Y. M. Young, *The Technical Writer's Handbook*. Mill Valley, CA: University Science, 1989.
- [2] E. Abreu, M. Lighthstone, 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. Boughleux, "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. Boughleux, "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.

**TABLE I**

COMPARISON OF THE PERFORMANCE MEASURED IN TERMS OF MAE, PSNR, AND NCD ( $\times 10^3$ )  
USING THE PARROTS IMAGE CONTAMINATED WITH DIFFERENT DENSITIES OF MIXED NOISE

Filter	$\sigma=5$ Gaussian and $p=0.05$ impulse noise MAE PSNR NCD			$\sigma=10$ Gaussian and $p=0.1$ impulse no MAE PSNR NCD			$\sigma=20$ Gaussian and $p=0.2$ impulse MAE PSNR NCD			$\sigma=30$ 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
<b>ASQFT</b>	<b>4.22</b>	<b>31.03</b>	<b>3.26</b>	<b>5.76</b>	<b>29.15</b>	<b>4.60</b>	<b>8.11</b>	<b>26.35</b>	<b>6.71</b>	<b>10.68</b>	<b>24.51</b>	<b>8.90</b>

**TABLE II**

COMPARISON OF THE PERFORMANCE MEASURED IN TERMS OF MAE, PSNR, AND NCD ( $\times 10^3$ )  
USING THE LENA IMAGE CONTAMINATED WITH DIFFERENT DENSITIES OF MIXED NOISE

Filter	$\sigma=5$ Gaussian and $p=0.05$ impulse noise MAE PSNR NCD			$\sigma=10$ Gaussian and $p=0.1$ impulse noise MAE PSNR NCD			$\sigma=20$ Gaussian and $p=0.2$ impulse noise MAE PSNR NCD			$\sigma=30$ 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
<b>ASQFT</b>	<b>4.55</b>	<b>30.90</b>	<b>3.09</b>	<b>6.88</b>	<b>28.24</b>	<b>4.34</b>	<b>8.70</b>	<b>26.35</b>	<b>6.62</b>	<b>11.03</b>	<b>24.45</b>	<b>8.75</b>

**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	$\sigma=5$ Gaussian and $p=0.05$ impulse MAE PSNR NCD			$\sigma=10$ Gaussian and $p=0.1$ impulse MAE PSNR NCD			$\sigma=20$ Gaussian and $p=0.2$ impulse MAE PSNR NCD			$\sigma=30$ 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
<b>ASQFT</b>	<b>5.50</b>	<b>28.77</b>	<b>4.72</b>	<b>6.61</b>	<b>27.14</b>	<b>6.24</b>	<b>9.70</b>	<b>24.31</b>	<b>8.96</b>	<b>12.46</b>	<b>22.68</b>	<b>11.80</b>