Proceedings of the International MultiConference of Engineers and Computer Scientists 2012 Vol I,
IMECS 2012, March 14 - 16, 2012, Hong Kong

Random-Valued Impulse Noise Detection and Removal in Grayscale and Color Images

Vladimir V. Khryashchev, *Member, IAENG,* Andrey M. Shemyakov, Olga N. Gushchina and Dan Falcon

Abstract - **The paper presents a comparative analysis of random-valued impulse noise detectors for grayscale and color images. Experimental results demonstrate that vector median filter with directional detector outperforms other filters both in terms of objective criteria and visual appearance. The examples of reconstructed images are provided.**

Keywords - **color image restoration, noise detection, vector median filter, peer group filter, random-valued impulse noise**

I. INTRODUCTION

In many practical applications images are corrupted by noise caused either by faulty image sensors or due to transmissions corruption resulting from artificial or natural phenomena. Transmission noise, also known as salt-and-pepper noise in grey-scale imaging, is modeled by an impulsive distribution. However, a problem in the study of the effect of the noise in the image processing community is the lack of commonly accepted multivariate impulse noise model. A number of simplified models have been introduced recently, to assist the performance evaluation of the different color image filters [1, 2].

Based on trichromatic color theory, color pixels are encoded as three scalar values, namely, red, green and blue (RGB color space). Since each individual channel of a color image can be considered as a monochrome image, traditional nonlinear image filtering techniques have involved the application of scalar filters on each channel separately [3-5]. However, this disrupts the correlation that exists between the color components of natural images. As such the color noise model should be considered as a 3-channel perturbation vector in color space [5].

Let $\mathbf{x}_i$ be the vector, characterizing a pixel of a noisy image, $\mathbf{v}_i$ – the vector describing impulse noise model, $\mathbf{z}_i$ is the noise-free color vector, p – impulse noise probability, then

$$\mathbf{x}_i = \begin{cases} \mathbf{v}_i, & with \quad probability \quad p \\ \mathbf{z}_i, & with \quad probability \quad 1-p \end{cases}.$$

Vladimir Khryashchev, PhD, P.G. Demidov Yaroslavl State University, 14 Sovetskaya, Yaroslavl, Russia, 150000 (phone: +74852797775; e-mail: vhr@yandex.ru).

Andrey Shemyakov, Graduate Student, P.G. Demidov Yaroslavl State University, 14 Sovetskaya, Yaroslavl, Russia, 150000 (phone: +74852797775; e-mail: andrey.shemiakov@gmail.com).

Olga Gushchina, Graduate Student, P.G. Demidov Yaroslavl State University, 14 Sovetskaya, Yaroslavl, Russia, 150000 (phone: +74852797775; e-mail: olyagushchina@gmail.com).

Dan Falcon, M.ED, Pastukhov State Academy of Industrial Management, 42 Respublikanskaya, Yaroslavl, Russia, 150000 (phone: +74852305650; e-mail: difelcone@hotmail.com).

Depending on the type of vector $\mathbf{v}_i$ researchers consider either fixed-valued or random-valued impulse noise models [3-9].

In the case of fixed-valued impulse noise $\mathbf{v}_i$ is characterized by the following expression:

$$\mathbf{v}_i = \begin{cases} (d, z_i^G, z_i^B)^T, & with \quad probability \quad p_1 \\ (z_i^R, d, z_i^B)^T, & with \quad probability \quad p_2 \\ (z_i^R, z_i^G, d)^T, & with \quad probability \quad p_3 \\ (d, d, d)^T, & with \quad probability \quad p_4 \end{cases},$$

where d - an impulse value and $\sum_{m=1}^{4} p_m = 1$.

Random-valued impulse noise can be defined in several ways. In this paper we use the following model:

$$\mathbf{v}_i = \begin{cases} (d_1, z_i^G, z_i^B)^T, & with \quad probability \quad p_1 \\ (z_i^R, d_2, z_i^B)^T, & with \quad probability \quad p_2 \\ (z_i^R, z_i^G, d_3)^T, & with \quad probability \quad p_3 \\ (d_1, d_2, d_3)^T, & with \quad probability \quad p_4 \end{cases},$$

where d_1, d_2, d_3 - uniformly distributed independent random numbers.

The main approach for impulse noise removing is to use median-based filters [3]. However, these nonlinear filters also tend to modify pixels that are not affected by the noise. In addition, when impulse noise probability is high, they are prone to edge jitter, so that details and edges of the original image are usually blurred by the filter [6-11].

In order to improve performance of median-based filter approach, various decision-based filters have been proposed, where possible impulse noise pixels are first identified and then replaced by using median filter. The examples of decision-based filters for random-valued impulse noise removal from grayscale images are: adaptive center-weighted median filter [10] and directional weighted median filter [11].

The most popular vector filter is vector median filter (VMF). VMF is a vector processing operator that has been introduced as an extension of scalar median filter [4, 5]. To quantify relative magnitude differences of input samples, VMF utilizes either the well-known Euclidean distance or the generalized Minkowski metric.

Neuvo and Ku proposed the first peer group based filtering method [12]. Peer group filter (PGF) is based on the evaluation of statistical properties of a sorted sequence of accumulated distances used for the calculation of vector median of samples belonging to the filtering window. PGF output switches between vector median and the original central pixel [13, 19, 20].

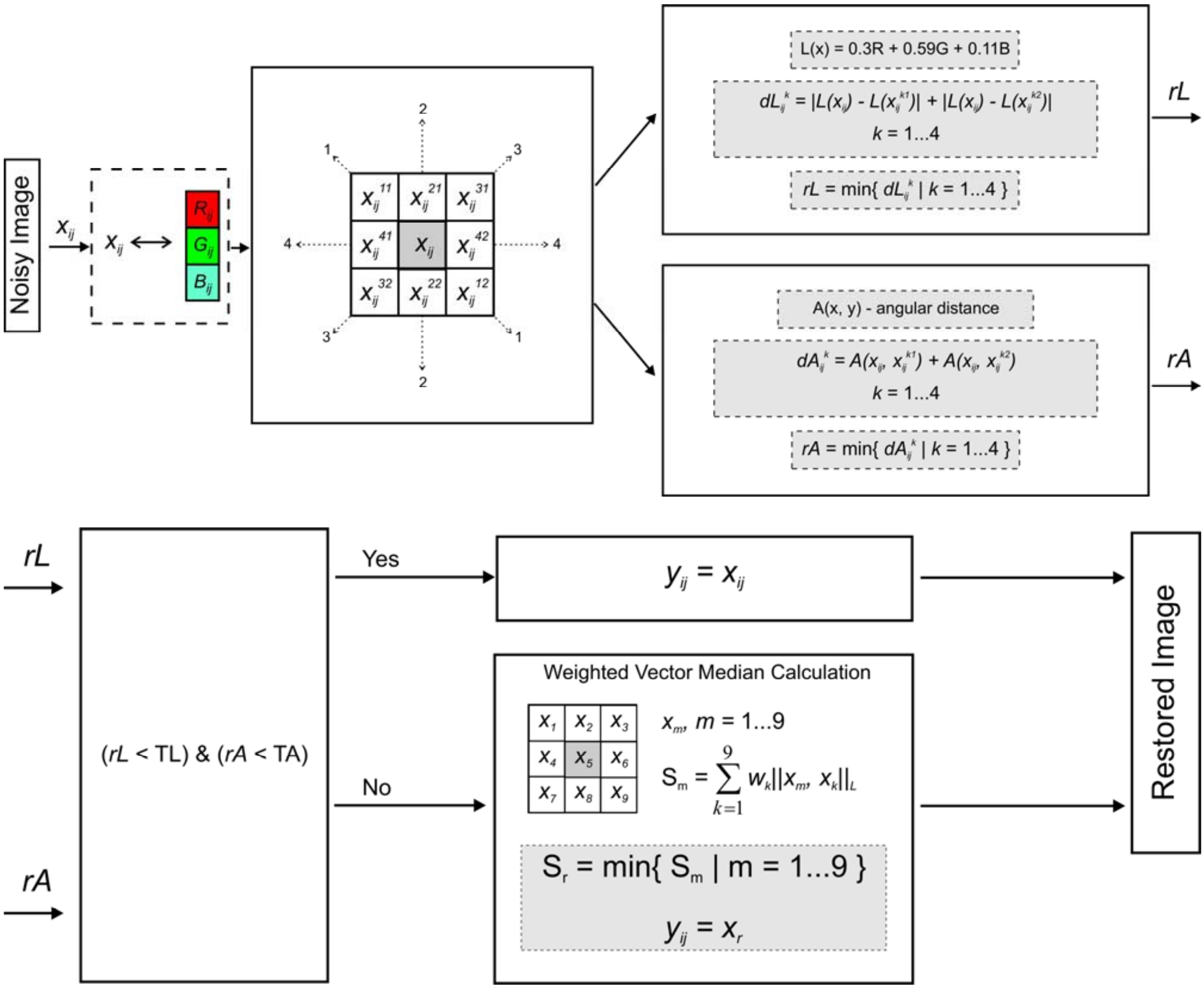

Fig. 1. The scheme of vector median filter with directional detector

Camarena *et al.* [14] proposed a fast peer group based filtering method in which a pixel is identified as non-corrupted when the size of peer group is larger than a threshold in the fuzzy metrics context. Morillas *et al.* [15] used a reduced ordering of color vectors to detect and replace the corrupted pixels for simultaneous reduction of impulse noises and preservation of the textured edges. Camarena *et al.* [16] further proposed a two-stage peer group filtering method to detect the corruption status of a pixel [17].

In our previous work [18] we introduce a novel filter for the purpose of random-valued impulse noise removal from RGB-color images which utilizes the advantages of both weighted vector median and decision-making filtration schemes - vector median filter with directional detector (VMF-DD). This paper focused mostly on detailed comparison of random-valued impulse noise detectors. New results of detectors and filters simulation are presented for grayscale and color test images.

The rest of the paper is organized as follows. In section 2, we shortly describe the vector median filter with directional detector. Section 3 focuses on comparison of random-valued impulse noise detectors performance for grayscale images. In section 4, we present new experimental results for color RGB- images. Section 5 concludes the paper.

II. Vector Median Filter with Directional Detector

The processing of each image pixel consists of two stages: impulse detection and filtration, as shown in fig. 1.

The VMF-DD detector works as follows. Let $\mathbf{x}_{ij}$ be the current pixel of the distorted image with coordinates (i, j), $\mathbf{y}_{ij}$ - the corresponding pixel of the processed image. On the stage of detection four basic directions passing through the central pixel $\mathbf{x}_{ij}$ are chosen inside the filter sub-window. They are designated by indexes $k = 1...4$. For each direction two sums are calculated:

– the sum of brightness value differences dL_{ij}^{k} $(k = 1...4)$ between pixels lying on the given direction $\mathbf{x}_{ij}^{k}$ and the central pixel $\mathbf{x}_{ij}$;

ISBN: 978-988-19251-1-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

– the sum of angular distances $dA_{ij}^{k}\ (k=1...4)$ between pixels lying on the given direction $\mathbf{x}_{ij}^{k}$ and the central pixel $\mathbf{x}_{ij}$.

The angular distance between two pixels we define as an angle between corresponding 3-channel vectors which contain color component values of pixels [21]:

$$\|\mathbf{x}_1,\mathbf{x}_2\| = arc\cos\left(\frac{\mathbf{x}_1,\mathbf{x}_2}{\|\mathbf{x}_1\|\|\mathbf{x}_2\|}\right) = = arc\cos\left(\frac{x_{11}x_{21}+x_{12}x_{22}+x_{13}x_{23}}{\sqrt{x_{11}^2+x_{12}^2+x_{13}^2}\sqrt{x_{21}^2+x_{22}^2+x_{23}^2}}\right).$$

The brightness of a pixel is calculated from its color component values by the following formula:

$$L(\mathbf{x}) = 0.3R + 0.59G + 0.11B,$$

where R, G, B - are red, green, and blue component values of pixel $\mathbf{x}$.

Among all calculated sums dL_{ij}^{k} the minimum is found: $rL = \min_k dL_{ij}^{k} \mid k = 1,...,4$. Similarly we find the minimum among all sums $dA_{ij}^{k}: rA = \min_k dA_{ij}^{k} \mid k = 1,...,4$. The resulted values rL and rA are compared to threshold values TL and TA respectively. If both $rL < TL$ and $rA < TA$, then pixel $\mathbf{x}_{ij}$ remains without changes. Otherwise, the current pixel is considered distorted and is replaced by weighted vector median calculated inside the filter's sub-window.

III. Simulations on Grayscale Images

Detectors performance can be compared using five measures: recall, specificity, precision, accuracy and F-measure [17]. Recall measure (R) shows the ratio between correctly deduced corrupted pixels and the overall number of corrupted pixels. Specificity (S) is the relation between the total number of pixels, correctly deduced as non-corrupted, and the number of non-corrupted pixels on the image. Precision (P) is the proportion of true corrupted pixels within the deduced corrupted pixels. Accuracy (A) is the proportion of correctly deduced pixels within the total number of pixels on the image. The F-measure (F) is the harmonic mean of the recall and precision measures. Let TP and TN be the number of pixels, correctly deduced as corrupted and non-corrupted respectively. FP and FN denote respectively the number of pixels that was falsely deduced as corrupted and non-corrupted. Using the notation, the measures can be given by:

$$R = \frac{TP}{TP+FN},\ S = \frac{TN}{TN+FP},\ P = \frac{TP}{TP+FP},$$
$$A = \frac{TP+TN}{TP+FP+TN+FN},\ F = \frac{2}{\frac{1}{R}+\frac{1}{P}}.$$

The grayscale test images used are Peppers, Lena and Barbara. The resolution of all images is 512×512. An image is being corrupted by random-valued impulse noise. The corruption is carried out with different noise probability – *p*, and the proposed filter is tested using these increasingly corrupted images. The filters used for comparison are: adaptive center-weighted median filter (ACWMF) [10], signal-dependent rank-ordered-mean filter (SD-ROM) [8] and directional weighted median filter (DWM) [11].

TABLE I
Comparison of detectors performance for grayscale images

p	Measure	"Peppers"			"Lenna"			"Barbara"		
		ACWMF	SD-ROM	DWM	ACWMF	SD-ROM	DWM	ACWMF	SD-ROM	DWM
0,1	R	91,46	90,46	4,06	90,54	89,60	5,32	86,38	86,04	5,65
	S	99,03	98,19	98,86	99,27	98,03	98,79	94,42	90,51	96,57
	P	91,28	84,78	27,71	93,27	83,47	32,84	63,18	50,21	15,46
	A	98,27	97,42	89,36	98,40	97,19	89,45	93,61	90,07	87,47
	F	91,33	87,50	7,07	91,80	86,38	9,16	72,94	63,38	8,28
0,2	R	85,10	86,57	5,62	85,40	86,44	5,43	81,05	83,13	5,72
	S	98,88	97,70	98,85	98,85	97,24	98,78	94,08	88,92	96,55
	P	95,02	90,41	54,87	94,98	88,72	52,59	77,44	65,28	29,31
	A	96,12	95,47	80,19	96,16	95,08	80,10	91,47	87,76	78,37
	F	89,77	88,44	10,19	89,90	87,56	9,84	79,18	73,12	9,57
0,3	R	80,60	85,24	5,98	80,30	84,68	5,89	76,37	81,93	6,21
	S	97,76	96,11	98,81	97,99	95,78	98,74	93,05	86,62	96,61
	P	93,99	90,39	68,29	94,56	89,60	66,72	82,52	72,39	43,94
	A	92,61	92,85	70,96	92,68	92,45	70,90	88,05	85,21	69,50
	F	86,77	87,74	10,99	86,85	87,07	10,83	79,32	76,86	10,88

ISBN: 978-988-19251-1-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

According to the results presented in Table 1, the following conclusions can be made. In terms of recall the SD-ROM algorithm demonstrated the best results, slightly outperform ACWMF. Low recall of DWM caused by the huge number of false negative errors. All of the detectors have about the same specificity (except highly detailed image “Barbara”, for which the worst performance shows SD-ROM detector). The ACWMF has significantly higher precision. However precision is depend on the test image and for all detectors precision is lower for highly detailed images. In terms of accuracy and F-measure the results of ACWMF and SD-ROM detectors are comparable and much lower for DWM (which is also caused by the huge number of false negative errors).

Presented results show that ACWMF and SD-ROM detectors outperform DWM detector. Fig. 2 shows the restoration results for grayscale “Lena” image in terms of peak signal to noise ratio (PSNR). The ACWMF outperforms other two filters for noise probability $p<0.15$, while the DWM has better performance for $p>0.15$.

IV. Simulations on color images

In this section, we provide the similar analysis of impulse noise detectors for color RGB-images. The color test images used are Peppers and Baboon. Each vector pixel is of 24 bits, with 8 bits for every channel. The resolution of all images is 512×512.

The filters used for comparison are: directional weighted median filter, applied for each color channel; peer group filter, and vector median filter with directional detector. The simulation results presented in Table 2.

Based on the simulation results, the following conclusions can be made. The VMF-DD has significantly higher recall (because of the less number of false negative errors). For highly detailed images the PGF has the minimum number of false positive errors and respectively the higher specificity. Meanwhile the DWM has highest specificity for low-detailed images. According to the results presented in Table 2, PGF outperforms other detectors for highly detailed and low-detailed images in terms of remaining three criteria.

Fig. 3 shows the restoration results for color “Peppers” image in terms of PSNR. For low impulse noise probability $p<0.1$ the proposed VMF-DD algorithm wins against PGF 2-4 dB in terms of PSNR metric. For the increased impulse noise probability $p>0.1$ the values of PSNR metric, measured for images processed by the proposed VMF-DD filter, are 1-2 dB higher than for images filtered by PGF.

Let’s consider visual results of test images restoration. Test image “Caps” and its corrupted version with random-valued impulse noise probability p = 0.15 are presented in fig. 4. Normalized color difference (NCD) criterion [22-23] was used for restored images quality assessment.

TABLE II
Comparison of detectors performance for color images

p	Measure	«Peppers»			«Baboon»		
		DWM	PGF	VMF-DD	DWM	PGF	VMF-DD
0,1	R	44,01	73,71	86,11	40,14	82,68	83,66
	S	88,98	89,98	73,58	99,21	95,89	94,72
	P	30,74	44,97	26,59	85,02	69,36	63,51
	A	84,48	88,35	74,83	93,30	94,67	93,51
	F	36,19	55,86	40,63	54,54	75,85	71,83
0,2	R	44,20	70,22	86,85	40,40	80,43	83,00
	S	88,83	90,80	70,08	99,16	95,35	93,04
	P	49,73	65,61	42,05	92,34	81,23	74,89
	A	79,9	86,68	73,43	87,41	92,37	91,03
	F	46,81	67,84	56,67	56,21	80,83	78,74
0,3	R	44,35	67,08	88,01	40,09	75,70	83,42
	S	88,67	91,84	65,38	99,11	95,69	89,85
	P	62,66	77,89	52,14	95,12	88,29	77,90
	A	75,38	84,41	72,17	81,41	89,69	87,92
	F	51,94	72,08	65,49	56,41	81,51	80,56

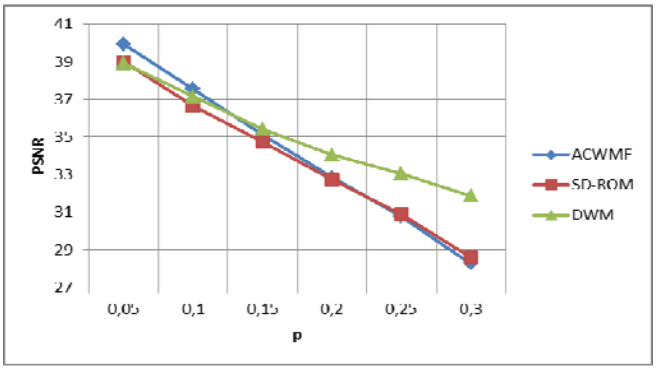

Fig. 2. Restoration performance (PSNR, dB) vs. probability of random-valued impulse noise for the grayscale "Lena" image

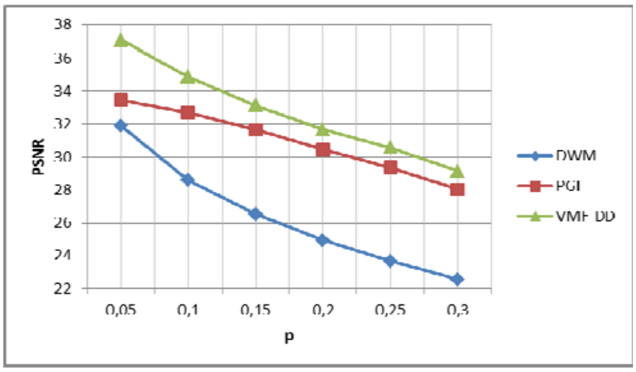

Fig. 3. Denoising performance (PSNR, dB) vs. probability of random-valued impulse noise for the color "Peppers" image

(a) NCD = 0 (b) NCD = 144.8

Fig. 4. Test image "Caps": (a) original image, (b) image corrupted by impulse noise (p = 0.15)

Fig. 5 shows enlarged fragments of test image "Caps" after their processing by different algorithms. After DWM filtration restored images turn out to be less blurred but they still contain some amount of impulse pixels. Better restoration results are achieved by the application of PGF algorithm which preserves image details and almost completely removes impulses from an image. The proposed VMF-DD algorithm demonstrates visual results close to that of PGF algorithm excelling the least in image edges preservation and the number of removed impulses. The values of NCD quality metric, presented in fig. 5, corroborate the conclusions drawn after the analysis of visual data.

Thus, from shown filtration results it is possible to draw a conclusion that VMF-DD algorithm, applied to random-valued impulse noise removal from color RGB-images, allows to achieve a significant increase of restored image quality in terms of both objective and subjective quality assessment criteria. Moreover experiments show that computational complexity of the proposed VMF-DD filter is lower than computational complexity of DWM and PGF filters.

(a) NCD = 12.2 (b) NCD = 11.2 (c) NCD = 8.3

Fig. 5. Zoomed restoration results of test image "Caps" corresponding to Figure 4:
(a) DWM output, (b) PGF output, (c) VMF-DD output

ISBN: 978-988-19251-1-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

V. Conclusions

The following conclusions can be drawn based on the obtained simulation results. The ACWMF and SD-ROM algorithms achieve better detection ability for grayscale images. Meanwhile, the DWM filter demonstrates better image restoration abilities in terms of PSNR.

The PGF algorithm is effective in noise detection for color RGB-images. Besides, earlier proposed VMF-DD algorithm outperforms PGF in terms of PSNR and NCD. Visual results of restored images prove the results of objective quality assessment.

The experimental results demonstrate the possibility for further improvement of the filters with detectors dealing with random-valued impulse noise removal from color images. Because of its low computational complexity, the proposed VMF-DD algorithm can be integrated in real-time denoising systems.

Acknowledgments

This work was supported by the Russian Ministry of Education and Science under Grant 2.1.2/7067 “The development of nonlinear theory of signal and image processing in radio engineering and communications”. Olga Gushchina was also supported by Google Anita Borg Memorial Scholarship - 2011.

References

[1] R. Szeliski, *Computer Vision: Algorithms and Applications*. Springer, 2010.

[2] R. Lukac, *Computational Photography: Methods and Applications.* CRC Press / Taylor & Francis, 2010.

[3] I. Pitas, A. Venetsanopoulos, *Nonlinear Digital Filters: Principles and Applications*. Boston, MA: Kluwer, 1990.

[4] J. Astola, P. Haavisto, Y. Neuvo, “Vector median filters,” *Proceedings of the IEEE*, vol. 78, 1990, pp. 678-689.

[5] R. Lukac, B. Smolka, K. Martin, K. Plataniotis, A. Venetsanopoulos, “Vector filtering for color imaging,” *IEEE Signal Processing Magazine, Special Issue on Color Image Processing*, vol. 22, 2005, pp. 74-86.

[6] I. Apalkov, V. Khryashchev, A. Priorov, P. Zvonarev, “Image denoising using adaptive switching median filter,” in *Proc. of the IEEE Int. Conf. on Image Processing (ICIP)*, 2005, pp. I-117 - I-120.

[7] L. Yin, R. Yang, M. Gabbouj, Y. Neuvo, “Weighted median filters: a tutorial,” *IEEE Trans. Circuits Systems*, vol. 43, 1996, pp. 157-192.

[8] E. Abreu, Mitra S, “A signal-dependent rank ordered mean (SD-ROM) filter - a new approach for removal of impulses from highly corrupted images,” *in Proc. of the Int. Conf. on Acoustics, Speech, and Signal Processing (ICASSP)*, 1995, vol. 4, pp. 2371-2374.

[9] R. Chan, C. Hu, M. Nikolova, “An iterative procedure for removing random-valued impulse noise,” // *IEEE Signal Processing Letters*, 2004, vol. 11, pp. 921-924.

[10] T. Chen, H. Wu, “Adaptive impulse detection using center-weighted median filters,” *IEEE Signal Processing Letters*, 2001, vol. 8, pp. 1-3.

[11] Y. Dong, S. Hu, “A new directional weighted median filter for removal of random-valued impulse noise,” *IEEE Signal Processing Letters*, 2003, vol. 14, pp. 193-196.

[12] Y. Neuvo, W. Ku, “Analisys and digital realization of pseudorandom gaussian and impulse noise source,” *IEEE Transactions on Communications*, vol. 23, 2003, pp. 1941-1953.

[13] B. Smolka, “Peer group filter for impulsive noise removal in color images,” *Lecture Notes in Computer Science (LNCS 5197)*. Springer-Verlag, 2008, pp. 699-707.

[14] J.G. Camarena, V.Gregori, S. Morillas, A. Sapena, “Fast detections and removal of impulsive noise using peer groups and fuzzy metrics,” *Journal of Visual Communications and Image Represenation*, vol. 19, 2008, pp. 20-29.

[15] S. Morillas, V. Gregori, G. Peris-Fajarnes, “Isolating impulsive noise pixels in color images by peer group techniques,” *Computer Vision and Image Understanding*, vol. 110, 2008, pp. 102-116.

[16] J.G. Camarena, V.Gregori, S. Morillas, A. Sapena, “Some improvements for image filtering using peer group techniques,” *Image and Vision Computing*, vol. 28, 2010, pp. 20-29.

[17] Y. Lai, K. Chung, W. Yang, C. Chen, L. Lin, “Novel Peer Group Filtering Method Based on the CIELAB Color Space for Impulse Noise Reduction,” *Proc. 21st International Conference on Computer Graphics and Vision*, 2011. P. 124-127.

[18] V. Khryashchev, D.K. Kuykin, A.A Studenova, “Vector median filter with directional detector for color image denoising ,” *Proc. World Congress on Engineering*, 2011. V. 2. P. 1699-1704.

[19] J. Y. F. Ho, “Peer region determination based impulse noise detection,” *Proceedings of International Conference on Acoustics, Speech and Signal Processing ICASSP*, vol. 03, 2003, pp 713-716.

[20] B. Smolka, A. Chydzinski, “Fast detection and impulsive noise removal in color images,” *Real-Time Imaging*, vol. 11, 2005, pp. 389-402.

[21] R. Lukac, “Adaptive color image filtering based on center-weighted vector directional filters,” *Multidimensional Systems and Signal Processing*, 2004, vol. 15, pp. 169-196.

[22] K. Plataniotis, D. Androutsos, A. Venetsanopoulos, “Adaptive fuzzy systems for multichannel signal processing,” *Proceedings of the IEEE*, 1999, vol. 87, pp. 1601-1622.

[23] K. N. Plataniotis, A.N. Venetsanopoulos, *Color Image Processing and Application*. Spring-Verlag, Berlin, 2000.

ISBN: 978-988-19251-1-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)