Proceedings of the World Congress on Engineering 2011 Vol II
WCE 2011, July 6 - 8, 2011, London, U.K.

Vector Median Filter with Directional Detector for Color Image Denoising

Vladimir V. Khryashchev, *Member, IAENG*, Denis K. Kuykin, and Alina A. Studenova

Abstract – **In this paper a new approach to the problem of impulse noise removal from color images is presented. The proposed method is based on noise detection algorithm and weighted vector median filter. The results of its analysis compared to other known median-based vector filters are presented. The analysis shows that the proposed algorithm is more efficient in random-valued impulse noise removal from color digital images than other considered filters.**

Index Terms – **color image processing, impulse noise removal, vector median filter, order statistic, genetic algorithm optimization**

I. INTRODUCTION

IMAGE noise reduction without structure degradation is perhaps the most important low-level image processing task [1, 2]. Faulty sensors, optic imperfectness, electronics interference, and data transmission errors may introduce noise to digital images. In considering the signal-to-noise ratio over practical communication media, such as microwave or satellite links, there can be degradation in quality due to low received signal power.

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 often 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 [6, 7].

The noise encountered in digital image processing applications cannot always be described in terms of commonly used Gaussian model. Very often, it can be characterized in terms of impulse sequences which occur in the form of short duration, high energy spikes attaining large amplitudes with probability higher than those predicted by Gaussian density model. Transmission noise, also known as salt-and-pepper noise in grayscale imaging, is modeled by an impulsive distribution [4, 5, 7].

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".

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

Denis Kuykin is Post-Graduate Student, P.G. Demidov Yaroslavl State University, 14 Sovetskaya, Yaroslavl, Russia, 150000 (phone: +74852797775; e-mail: denis.kuykin@ gmail.com).

Alina Studenova is Post-Graduate Student, P.G. Demidov Yaroslavl State University, 14 Sovetskaya, Yaroslavl, Russia, 150000 (phone: +74852797775; e-mail: alina.studenova@ gmail.com).

There are many types of impulse noise. 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

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

Depending on the type of vector $\mathbf{v}_i$ researchers consider either fixed-valued or random-valued impulse noise models [4-6].

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:

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

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, 8-10]. 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 [11-13].

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

ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

removal from grayscale images are: adaptive center-weighted median filter [14] and directional weighted median filter [15]. These filters are good in locating the noise even in the case of high noise probability.

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 [6, 7]. To quantify relative magnitude differences of input samples, VMF utilizes either the well-known Euclidean distance or the generalized Minkowski metric. To improve detail-preserving characteristics of VMF, the simple basic idea has been modified and extended VMF-based filters [16-18] were designed.

The family of vector directional filters (VDF) represents a different type of vector processing filters. These filters operate on the directions of image vectors, aiming to eliminate vectors with atypical directions in the color space [16]. Weighted vector directional filters (WVDF) extend the flexibility of VDF-based designs and provide a powerful color image filtering tool capable of tracking varying signal and noise statistics.

Recently developed 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 [18].

In this paper 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.

The rest of the paper is organized as follows. In section 2, we introduce the proposed vector median filter with directional detector (VMF-DD). Section 3 focuses on the genetic algorithm optimization of the VMF-DD parameters. In section 4, we present experimental results of applying of the proposed filter. Section 5 concludes the paper.

II. Vector Median Filter with Directional Detector

The proposed filter utilizes a decision-making scheme to improve the efficiency of impulse noise removal algorithm. 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 $k = 1...4$.

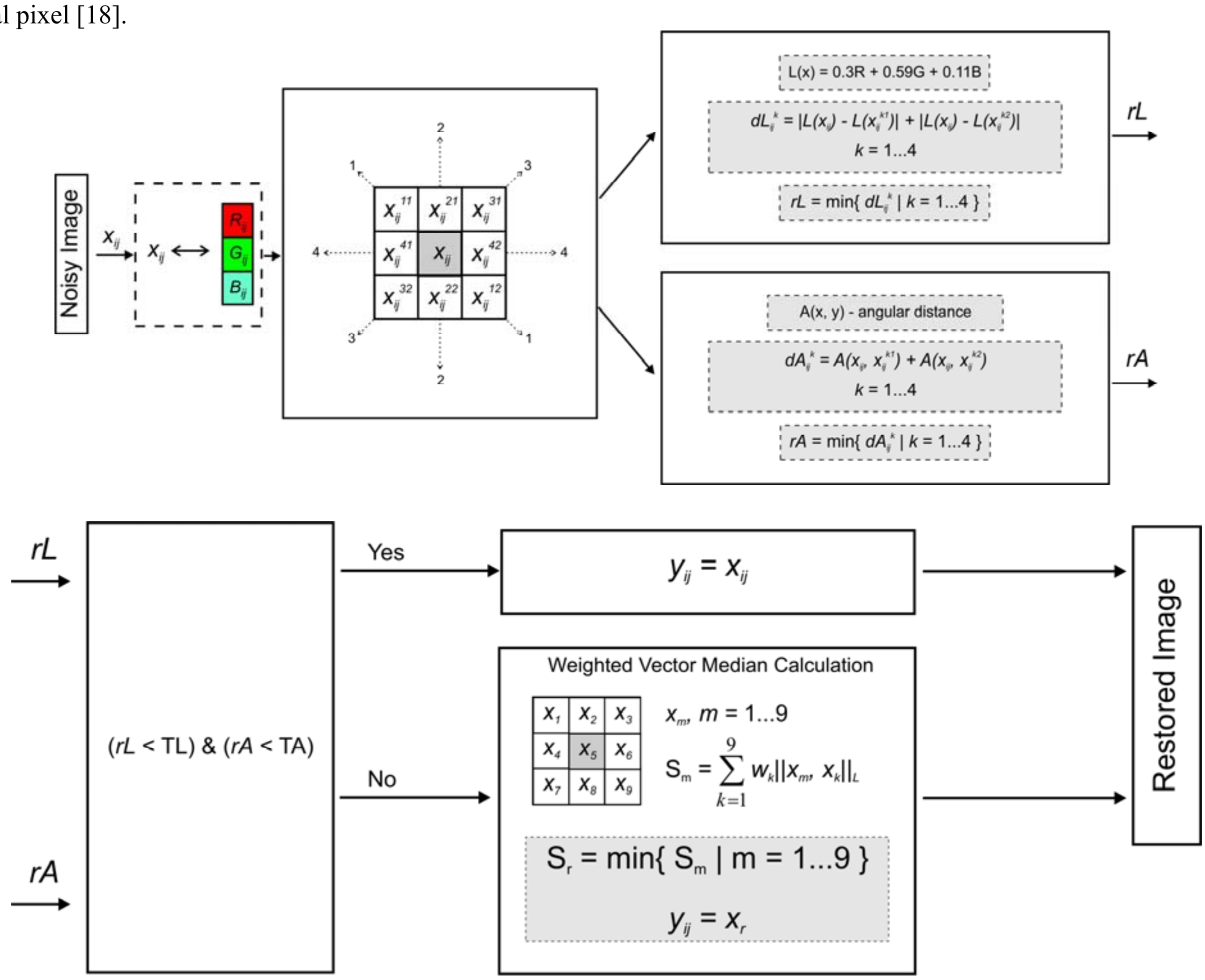


Fig. 1. The scheme of vector median filter with directional detector

ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

For each direction two sums are calculated: the sum of brightness value differences dL_{ij}^{k} $(k = 1 \ldots 4)$ between pixels lying on the given direction $\mathbf{x}_{ij}^{k}$ and the central pixel $\mathbf{x}_{ij}$; the sum of angular distances dA_{ij}^{k} $(k = 1 \ldots 4)$ 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 [16]:

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

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:

$$rL = \min_k dL_{ij}^{k} \mid k = 1,\ldots,4 .$$

Similarly we find the minimum among all sums dA_{ij}^{k}:

$$rA = \min_k dA_{ij}^{k} \mid k = 1,\ldots,4 .$$

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. Filter Parameters Optimization

From the description of VMF-DD algorithm presented above it follows that the efficiency of its work depends on the choice of threshold values TL and TA, and also on the choice of vector median filter weighting coefficients $w_1, \ldots, w_9$. Thus, there is a problem of mentioned above parameters optimization relative to one of restored image quality estimation criteria. In our work this problem has been solved by the utilization of classical genetic algorithm (GA) [19], which scheme is shown in fig. 2.

In order to solve the problem of VMF-DD algorithm parameters optimization we use chromosomes, representing an 11 element vector which consists of real values. First 9 elements of this vector represent the values of vector median filter weighting coefficients; the 10th element contains the threshold value TL; the 11th element – the threshold value TA

$$H = \begin{bmatrix} w_1 \\ \vdots \\ w_9 \\ TL \\ TA \end{bmatrix}.$$

Mean square error (MSE) between the original image and the restored image is used as a fitness function. MSE is calculated by the following formula [2]:

$$MSE(Z, Y) = \frac{1}{3N} \sum_{i=1}^{N} \sum_{k=1}^{3} \left(Z_i^k - Y_i^k \right)^2,$$

where Z_i^k, Y_i^k - k-th component value of i-th pixel in the original image and the restored image respectively, N – the total number of pixels in an image.

During the process of genetic algorithm operation the value of fitness function gradually decreases while the number of generations grows. This process for test color images "Lena" and "Airplane" [20, 21] is demonstrated in fig. 3

The analysis of presented dependences shows that during the process of genetic algorithm operation and hence during the growth of the number of generations the value of fitness function gradually decreases, reaching approximately 20% relative to its initial value. And it is possible to achieve this result after only 15-20 generations. Performed experiments show that optimized parameters of the filter, averaged on several runs of genetic algorithm, differ insignificantly from each other for different test images. Further for VMF-DD filter we use optimized parameters acquired on test image "Lena".

IV. Simulations on Color Images

The color test images used are Peppers, Lena and Parrots. Each vector pixel is of 24 bits, with 8 bits for every channel. 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: median filter (MF) [3] applied for each color channel; directional weighted median filter (DWM) [15], applied for each color channel; vector median filter (VMF) [6]; weighted vector directional filter (WVDF) [16]; peer group filter (PGF) [18], and the proposed vector median filter with directional detector (VMF-DD).

ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

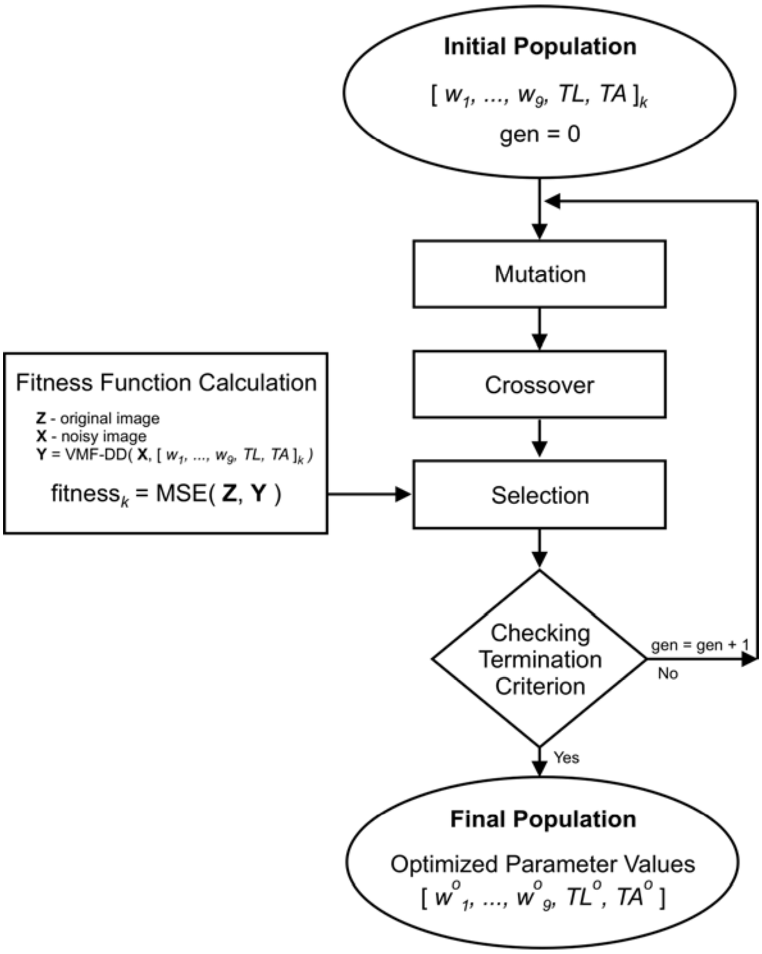
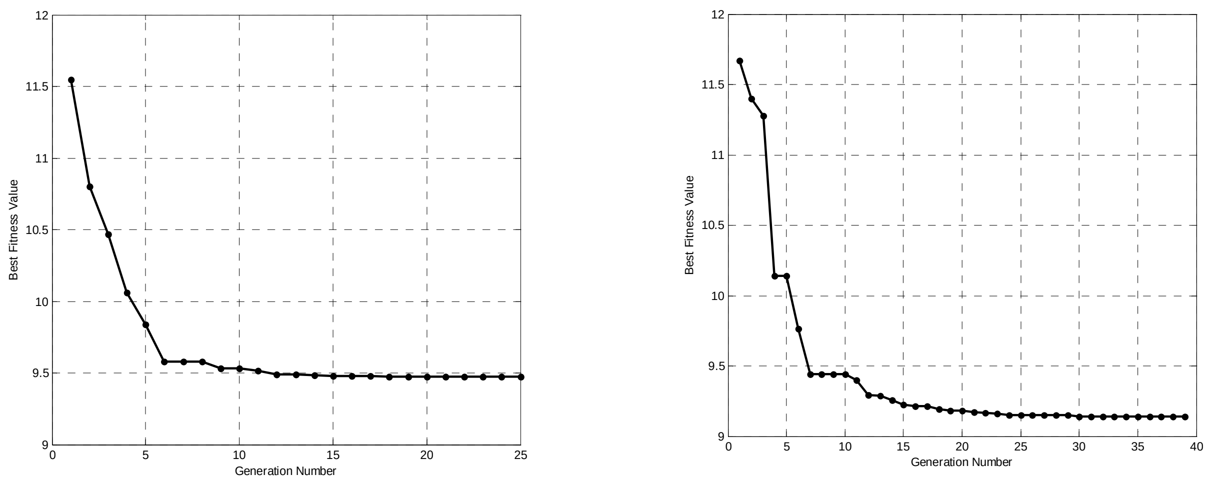


Fig. 2. GA optimization of the VMF-DD parameters



(a) (b)

Fig. 3. Convergence of the GA-VMF-DD optimization: (a) test image "Lena", (b) test image "Airplane"

Following the traditional practice of image quality evaluation in the area of color image processing, peak signal to noise ratio (PSNR), mean absolute error (MAE) and normalized color difference (NCD) criterion [17] were used for restored images quality assessment. While both PSNR and MAE are defined in RGB domain, NCD criterion is defined in CIE LUV color space [1, 2]. Thus, NCD criterion is useful for the evaluation of color chromaticity differences between color vectors, and it allows us to quantify the error in the uniformly perceived color space. On the other hand, MAE and PSNR are commonly accepted in image processing community as the measures of signal-detail preservation and noise attenuation, respectively. For convenience, the values of NCD criterion were multiplied by 10^3. Table I lists the performance of various filters applied to the task of random-valued impulse noise removal from various color test images.

ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

TABLE I
COMPARISON OF PRESENTED ALGORITHMS USING IMPULSIVE NOISE CORRUPTION

p	Quality measure	"Peppers"						"Lena"						"Parrots"					
		MF	DWM	VMF	WVDF	PGF	**VMF-DD**	MF	DWM	VMF	WVDF	PGF	**VMF-DD**	MF	DWM	VMF	WVDF	PGF	**VMF-DD**
0.02	PSNR, dB	32.7	33.9	30.3	33.6	33.8	**38.9**	33.8	34.2	33.4	37.2	40.6	**43.6**	36.3	35.4	36.1	38.9	41.2	**44.6**
	MAE	3.66	1.30	4.02	2.22	0.46	**0.35**	3.04	1.38	3.18	1.49	0.29	**0.16**	1.63	0.60	1.62	0.73	0.18	**0.09**
	NCD	48.3	24.1	50.7	25.5	6.3	**4.70**	44.2	29.3	42.9	18.6	3.5	**2.2**	18.7	11.0	15.9	6.5	1.7	**1.0**
0.06	PSNR, dB	32.3	33.1	30.1	32.7	33.1	**36.1**	33.5	33.8	33.1	36.1	38.5	**40.2**	36.0	34.9	35.8	37.5	39.7	**41.8**
	MAE	3.74	1.59	4.12	2.35	0.74	**0.62**	3.12	1.50	3.29	1.62	0.52	**0.37**	1.69	0.70	1.70	0.83	0.32	**0.21**
	NCD	49.5	26.5	51.8	27.4	10.1	**8.5**	45.6	31.1	44.0	20.2	7.1	**5.2**	20.1	12.9	16.8	7.7	3.6	**2.8**
0.10	PSNR, dB	32.1	32.5	29.9	31.6	32.5	**34.9**	33.3	33.5	32.8	34.7	36.8	**38.3**	35.6	34.5	35.4	35.7	38.4	**40.1**
	MAE	3.81	1.45	4.22	2.53	1.01	**0.88**	3.19	1.61	3.39	1.78	0.76	**0.59**	1.75	0.79	1.78	0.97	0.45	**0.34**
	NCD	50.7	28.6	53.0	29.6	13.8	**12.0**	46.9	33.0	45.2	22.3	10.9	**8.5**	21.5	14.8	17.7	9.4	5.7	**4.6**
0.14	PSNR, dB	31.7	31.8	29.8	30.4	31.9	**33.5**	33.1	33.1	32.6	33.2	35.3	**36.8**	35.3	34.1	35.0	34.1	36.4	**38.2**
	MAE	3.91	1.76	4.33	2.74	1.26	**1.16**	3.28	1.74	3.51	1.98	0.99	**0.82**	1.81	0.89	1.87	1.13	0.62	**0.49**
	NCD	52.2	31.1	54.3	33.0	17.6	**16.1**	48.5	34.9	46.5	25.3	14.8	**12.0**	23.1	16.9	18.8	11.6	8.7	**6.8**
0.18	PSNR, dB	31.2	31.1	29.5	29.0	31.0	**32.2**	32.7	32.8	32.2	31.5	33.8	**35.5**	34.8	33.6	34.5	32.2	34.9	**36.9**
	MAE	4.01	1.93	4.45	3.05	1.55	**1.47**	3.37	1.86	3.62	2.25	1.25	**1.07**	1.89	1.00	1.97	1.36	0.80	**0.65**
	NCD	53.9	33.7	55.7	37.5	22.1	**20.5**	50.2	37.0	47.8	29.3	19.2	**15.8**	24.7	18.8	19.9	15.3	12.2	**9.1**

The results presented in table 1 show that the proposed VMF-DD algorithm, applied to the problem of random-valued impulse noise removal, achieves the best performance relative to any of considered quality assessment criteria and for all color test images used.

For low impulse noise probability $p = 0.02 - 0.10$ the proposed VMF-DD algorithm wins against PGF 2-4 dB in terms of PSNR metric, and provides 30-60% smaller error relative to NCD criterion. For the increased impulse noise probability $p = 0.14 - 0.18$ 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. In terms of NCD criterion the advantage of VMF-DD algorithm at the same impulse noise probability range is about 10-40%. Same dependences are observed concerning MAE criterion.

Fig. 4 shows enlarged fragments of test image "Parrots" after their processing by different algorithms. The application of median filter to each color channel leads to almost complete removal of noise but it also introduces significant image blur and causes the appearance of artifacts in the form of pale color regions on restored images. After DWM filtration restored images turn out to be less blurred but they still contain some amount of impulse pixels. The application of VMF also lead to significant image blur.

Among algorithms, that don't contain noise detector, high quality of restored images is demonstrated by WVDF algorithm. But after WVDF filtration separate impulse noise pixels, which are visible for human perception, remain on an image. 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. 4, corroborate the conclusions drawn after the analysis of visual data.

Thus, from shown results it is possible to draw a conclusion that VMF-DD algorithm, applied to random-valued impulse noise removal from RGB color images, allows to achieve a significant increase of restored image quality in terms of both objective and subjective quality assessment criteria.

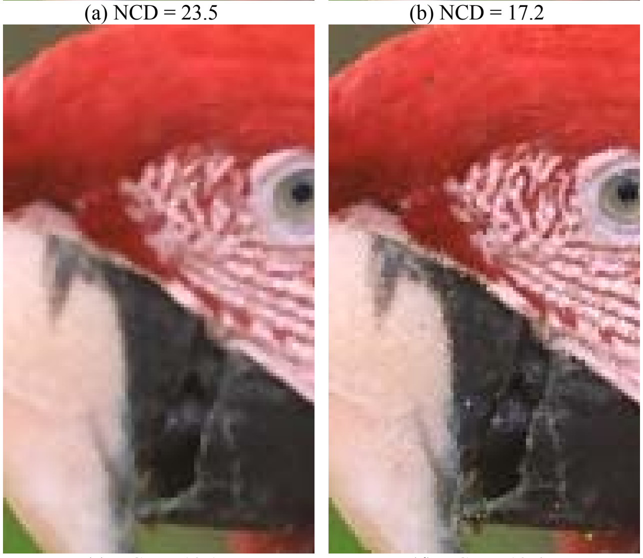
V. CONCLUSION

The following conclusions can be drawn based on obtained simulation results. The proposed VMF-DD filter shows best results for all three test images, evaluated both by classical quality metrics (PSNR and MAE) and by NCD metric which is specialized for color images. The presence of detector allows reducing the level of distortions, introduced into an image by filtration algorithm, due to the reduction of the number of pixels directly subjected to changes. Visual results of test images restoration prove the results of the analysis held on the basis of objective quality assessment metrics. Experiments show that computational complexity of the proposed VMF-DD filter is comparable to that of VMF and WVDF filters and is lower than computational complexity of DWM and PGF filters.

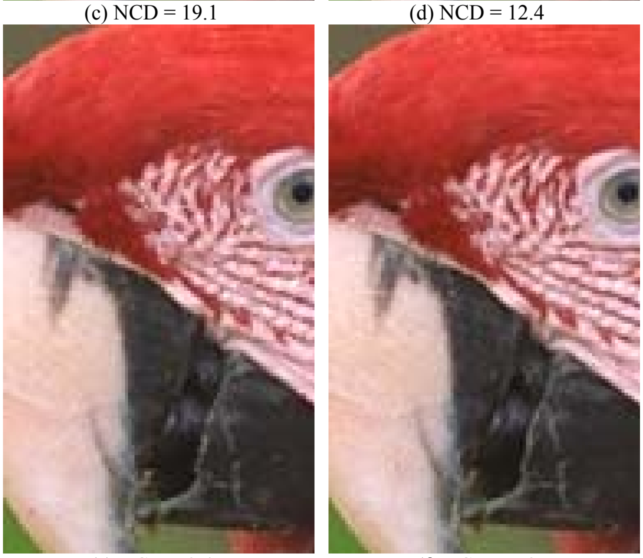
Thus, the efficiency of VMF-DD filter, applied to random-valued impulse noise removal from color images, has been shown.

ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

(a) NCD = 23.5 (b) NCD = 17.2



(c) NCD = 19.1 (d) NCD = 12.4



(e) NCD = 9.4 (f) NCD = 7.2

Fig. 4. Zoomed restoration results of test image “Parrots”:
(a) MF output, (b) DWM output, (c) VMF output, (d) WVDF output,
(e) PGF output, (f) VMF-DD output

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. Kuosmanen, Fundamentals of Nonlinear Digital Filtering. Boca Raton, FL: CRC, 1997.

[5] G. Arce, Nonlinear Signal Processing: A Statistical Approach. John Wiley & Sons. New Jersey, 2005.

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

[7] 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.

[8] 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.

[9] I. Apalkov, V. Khryashchev, A. Priorov, P. Zvonarev, “Adaptive switching median filter with neural network impulse detection step,” Lecture Notes in Computer Science (LNCS 3696). Springer-Verlag, 2005, pp. 537-542.

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

[11] D. Kuykin, V. Khryashchev, I. Apalkov, “Modified progressive switched median filter for image enhancement,” in Proc. of the 19th Int. Conf. on Computer Graphics and Vision (GraphiCon), 2009, pp. 303-304.

[12] 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.

[13] 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.

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

[15] 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.

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

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

[18] 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.

[19] D. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning. MA: Addison-Wesley, 1989.

[20] Signal and Image Processing Image Database. Available: http://sipi.usc.edu/database.

[21] Kodak Lossless True Color Image Suite. Available: http://www.cipr.rpi.edu/resource/stills/kodak.html.

ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)