

# Rank Order Weighted Vector Median Filter

Bogdan Smolka

Silesian University of Technology,  
Department of Automatic Control  
Akademicka 16, 44-100 Gliwice, Poland  
Bogdan.Smolka@polsl.pl

*Abstract*— In this paper a novel adaptive noise attenuating and edge enhancing filter for color image processing is proposed. The new filtering design is based, like the vector median filter, on the minimization of aggregated weighted distances between pixels in a sliding filtering window. The weights which are assigned to the sequence of the sorted distances are decreasing functions of their ranks. In this way, the largest distances are taken to the aggregated distance with the smallest weights, which ensures much better noise reduction properties of the described filter. Additionally, the proposed method has a unique ability to strengthen the edges of the noisy image objects. This valuable deblurring property can be useful in many applications which require reliable impulse noise reduction and efficient edge sharpening of color images.

*Keywords*- color image enhancement; impulse noise reduction; edge sharpening; vector median filter.

## I. INTRODUCTION

Noise, arising from a variety of sources, is inherent to all electronic image sensors and therefore the noisy signal has to be processed by a filtering algorithm that suppresses the noise component, while preserving original image structures [1-3].

Quite often color images are corrupted by impulse noise caused by malfunctioning sensors in the image formation pipeline, faulty memory locations in hardware, aging of the storage material or transmission errors due to natural or man-made processes. Common sources of impulse noise include also lightning, industrial machines, car starters, faulty or dusty insulation of high voltage powerlines and various unprotected electric switches. These noise sources generate short time duration, high energy pulses which block the regular signal, resulting for example in bothering spots on the TV screen.

The most popular family of nonlinear filters used for impulsive noise removal in color images is based on the concepts of order statistics [4]. These filters perform the vector ordering of the set of pixels from the filtering window to determine the output sample which is defined as the lowest ranked vector.

The main drawback of such filtering design lies in introducing too much smoothing which results in an extensive blurring of the output image [5]. To remove this disadvantage, a modification of the aggregated vector ordering scheme is proposed in this paper.

This modification is based on the application of the information on the ranks of distances used for the computation of the aggregated distances utilized in the weighted vector median filtering schemes, as it enables to design efficient noise reducing filtering methods.

## II. ADAPTIVE RANK ORDER WEIGHTED VMF

Let the color image  $\mathbf{x}$  be defined as a mapping  $Z^2 \rightarrow Z^3$  and let the set  $W = \{\mathbf{x}_i \in Z^2, i = 1, 2, \dots, n\}$  denotes a square filtering window consisting of  $n$  samples centered at the pixel  $\mathbf{x}_1$ .

The most popular impulsive noise reduction methods are based on a *vector ordering* which works on *aggregated distances*. The aggregated distance  $D_i$  assigned to a sample  $\mathbf{x}_i$ , ( $i = 1, 2, \dots, n$ ), is defined as

$$D_i = \sum_{\mathbf{x}_k \in W} d(\mathbf{x}_i, \mathbf{x}_k) = \sum_{k=1}^n d_{ik}, \quad (1)$$

where  $d(\mathbf{x}_i, \mathbf{x}_k) = d_{ik}$  denotes the Euclidean distance between pixels  $\mathbf{x}_i$  and  $\mathbf{x}_k$ . Sorting the scalar quantities  $D_1, \dots, D_n$  an ordering of the corresponding vectors can be achieved:  $D_{(1)}, D_{(2)}, \dots, D_{(n)} \rightarrow \mathbf{x}_{(1)}, \mathbf{x}_{(2)}, \dots, \mathbf{x}_{(n)}$ , where  $\mathbf{x}_{(1)}$  is the vector median of the set of samples belonging to the window  $W$ . In this way the Vector Median Filter (VMF) output is the sample  $\mathbf{x}_{(1)}$  minimizing the sum of distances to all other pixels contained in  $W$  [4].

The distances between a given pixels and all other pixels belonging to  $W$  can also be ordered:  $d_{i1}, d_{i2}, \dots, d_{in} \rightarrow d_{i(1)}, d_{i(2)}, \dots, d_{i(n)}$  and the ranks of the ordered distances can be used for building the accumulated distances in (1). If  $r$  denotes the rank of a given distance, then  $d_{i(r)}$  will denote the corresponding distance value and instead of the aggregated distances in (1) we can build a weighted sum of distances, utilizing the distance ranks

$$\Delta_i = \sum_{r=1}^n f(r) \cdot d_{i(r)}, \quad (2)$$

where  $f(r)$  is a function of the distance rank  $r$ . Then, the new weighted aggregated distances  $\Delta_i$  can be sorted and a new sequence of vectors is obtained

$$\Delta_{(1)}, \Delta_{(2)}, \dots, \Delta_{(n)} \rightarrow \mathbf{x}_{(1)}^*, \mathbf{x}_{(2)}^*, \dots, \mathbf{x}_{(n)}^*, \quad (3)$$

where the vector  $\mathbf{x}_{(1)}^*$  will be the output of the proposed Rank Order Weighted Vector Median Filter denoted as ROWVMF. Applying the constant function:  $f(r)=1$ ,  $r=1,2,\dots,n$ , we obtain  $\Delta_i = D_i$  and  $\mathbf{x}_{(1)}^* = \mathbf{x}_{(1)}$ . For a step-like function  $f(r)=1$  for  $r \leq \alpha$ ,  $\alpha \leq n$  and 0 otherwise the Sharpening Vector Median Filter (SVMF) is obtained, [6].

In order to evaluate the effectiveness of the novel filtering design the test images were contaminated with uniform impulse noise defined as  $x_{iq}$  with probability  $\pi$ ,  $o_{iq}$  with probability  $1-\pi$ , where  $o_{iq}$  denotes the  $q$ -th component of the original pixel at position  $i$  and the contamination component  $\rho_{iq}$  is a random variable in the range  $[0,255]$ . The fraction of contaminated pixels is then equal to  $p = 1 - (1-\pi)^3$ .

TABLE I. DEPENDENCE OF PSNR FOR THE PROPOSED ROWVMF, SVMF AND VMF ON THE IMPULSIVE UNIFORM NOISE INTENSITY CONTAMINATING LENA IMAGE FOR VARIOUS WEIGHTING FUNCTIONS  $f(r)$  AND  $\alpha$  PARAMETERS OF THE SVMF.

$p$	$r^{-1}$	$r^{-2}$	$e^{-\left(\frac{r}{h}\right)^2}$	$e^{-\frac{r}{h}}$	$\alpha = 3$	$\alpha = 4$	VMF
0.1	31.62	30.30	<b>32.61</b>	32.57	29.51	30.40	32.50
0.2	30.90	29.95	<b>31.52</b>	31.46	29.37	30.11	31.04
0.3	29.86	29.53	29.88	<b>29.89</b>	29.01	29.40	28.42
0.4	27.48	<b>27.78</b>	27.61	27.68	27.08	26.93	24.73
0.5	23.86	<b>24.48</b>	24.44	<b>24.48</b>	23.48	23.20	21.16
0.6	19.98	<b>20.42</b>	20.28	20.32	19.50	19.25	17.95

Table 1 shows the performance of the new denoising scheme in terms of PSNR as compared with the VMF and SVMF using a  $3 \times 3$  filtering window, when restoring the LENA image contaminated with uniform impulsive noise using decreasing functions of  $r$ . As can be observed, the design based on the Gaussian function  $\exp\{-r^2/h^2\}$  outperforms the SVMF and yields satisfactory results for a wide range of contamination levels and therefore this function was chosen for the experiments.

Figure 1 shows the dependence of the PSNR on the noise intensity using the color test image PEPPERS utilizing the Gaussian weighting function  $f(r)$  used in (2). As can be seen, the optimal parameter  $h$  depends heavily on the noise intensity level  $p$ , which evokes the need for an adaptive design of choosing the optimal smoothing parameter. It can be also observed that for high values of  $h$ , the VMF is obtained and for high noise intensity the difference in terms of PSNR between VMF and the proposed filter is quite significant.

In order to estimate the impulsive noise intensity contaminating the image, the difference between the aggregated distance  $D_1$  assigned to the central pixel of the filtering window and the value of  $D_{(1)}$  corresponding to the vector median output can be

used. The strength of the impulse is then estimated as as the difference between  $D_1$  and  $D_{(1)}$ .

Figure 2 shows an example of the detected noise using a part of the test PEPPERS image. The visual comparison of the noise map 2(d) with the impulses visible in (a) confirms that the map of the detected noise corresponds very well with the real corruption. The average value  $\hat{D}$  of the differences  $D = D_1 - D_{(1)}$  gives direct information on the intensity of contamination.

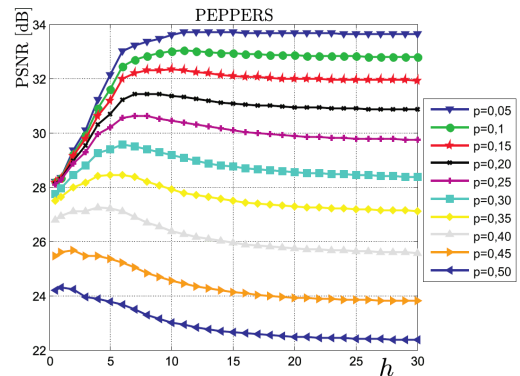


Figure 1. Plot of the dependence of the PSNR on the  $h$  parameter for various noise intensity  $p$ , (PEPPERS test image).

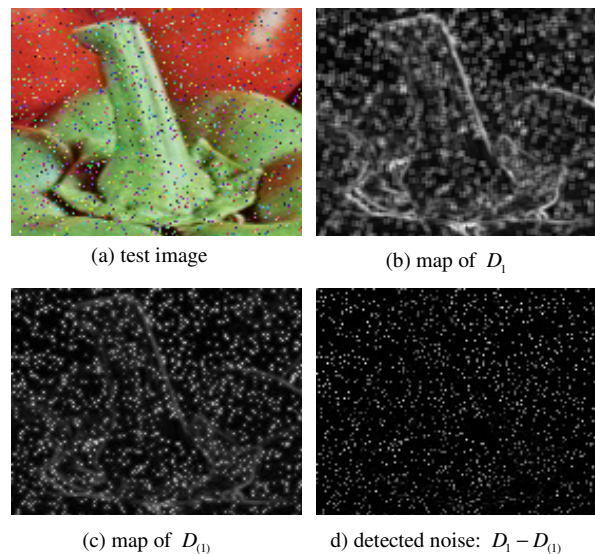


Figure 2. Illustration of the noise detection scheme.

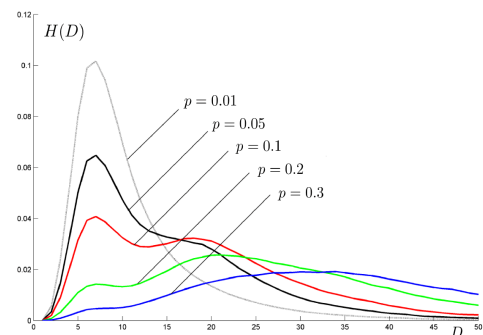


Figure 3. Histogram of the values of  $D = D_1 - D_{(1)}$  for the PEPPERS image contaminated by uniform impulsive noise normalized to the range  $[0; 255]$ .

Figure 3 depicts the histograms of the  $D$  values using the contaminated PEPPERS test image. As can be observed, the main mode of the histogram of  $D$  is shifted towards higher values with increasing noise intensity.

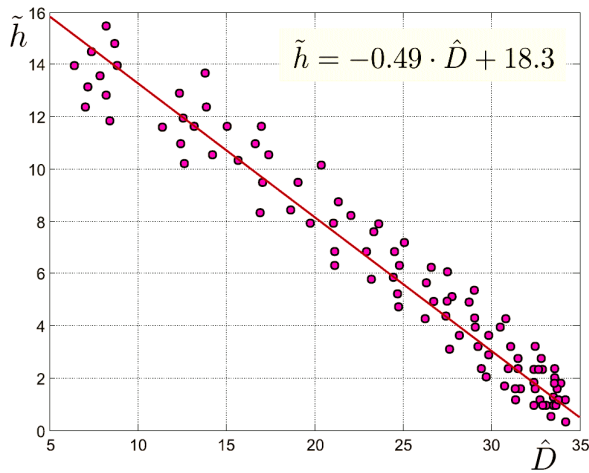


Figure 4. Dependence of the optimal smoothing parameter  $\tilde{h}$  on the noise intensity strength  $\hat{D}$  obtained using the test images depicted in Fig. 5 contaminated by uniform impulsive noise.

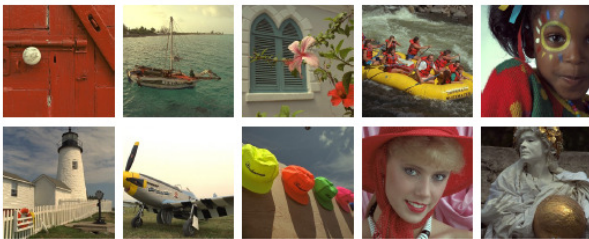


Figure 5. Test images used for the simulations

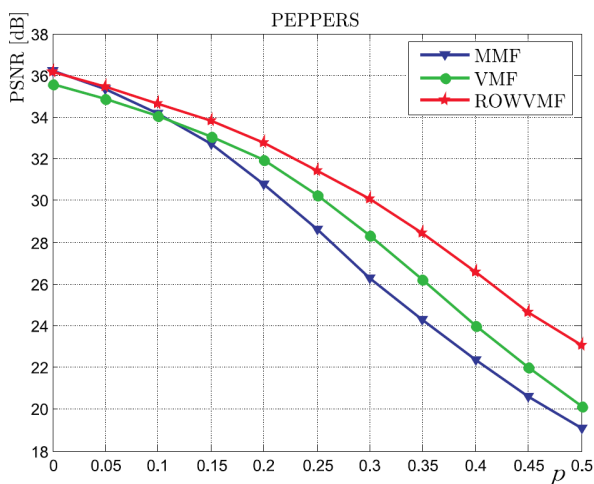


Figure 6. Dependence of PSNR on noise intensity for the proposed filter as compared with VMF and marginal median filter (MMF).

Figure 4 shows a plot of the optimal (giving the maximum PSNR values) of the  $h$  smoothing parameter denoted as  $\tilde{h}$  of the Gaussian weighting function on the mean value of  $D$  referred to as  $\hat{D}$  for contaminations ranging from 5% to 30%. This dependence, evaluated using a set of test images shown

in Fig. 5, is linear, which enables to adaptively adjust the smoothing parameter  $h$  of the Gaussian weighting function utilizing the rank information.

### III. EXPERIMENTAL RESULTS

Figure 6 shows the dependence of the PSNR restoration quality measure on the noise intensity  $p$  for the PEPPERS image using the adaptive noise intensity estimation procedure. The apparently lower effectiveness of the proposed filtering scheme for low contamination levels is due to its edge enhancing properties.

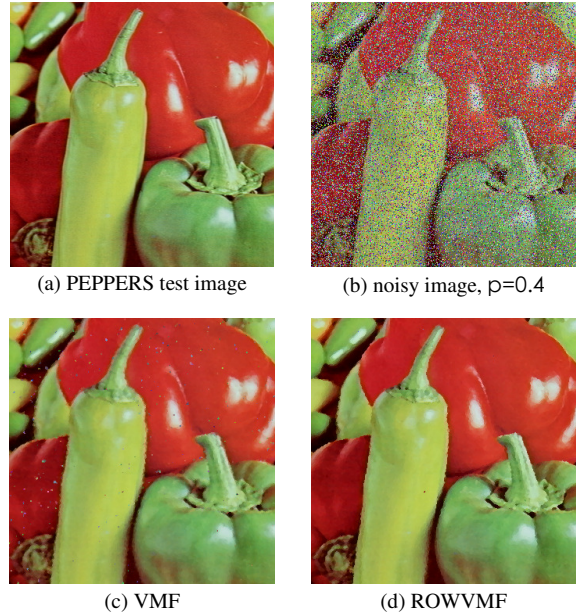


Figure 7. Efficiency of ROWVMF as compared with VMF: (a) part of the PEPPERS image, (b) noisy test image,  $p = 0.4$ , (c) and (d) VMF and ROWVMF output, (two iterations)

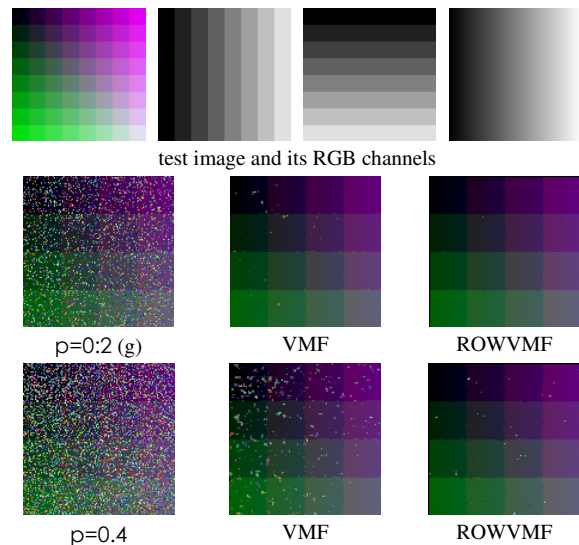


Figure 8. Comparison of the noise reduction efficiency of the adaptive ROWVMF and VMF evaluated on an artificial test image shown with its RGB components for noise intensity  $p=0.2$  and  $p = 0.4$ . As can be observed the VMF outputs contain much more impulse noise than the images filtered with ROWVMF

The enhanced edges are treated by the PSNR measure as a distortion, but in fact the edge enhancing effect is very beneficial and improves the restoration quality of the new filter. The edge enhancing effect is visible in Fig. 7, which depicts the results of the filtering of the PEPPERS color test image distorted by 40% of impulse uniform noise.

The comparison with the output of the VMF shows that the noise is better suppressed and image details are better preserved. Moreover, the edges are much sharper, which can help in further stages of image processing like edge detection or segmentation.

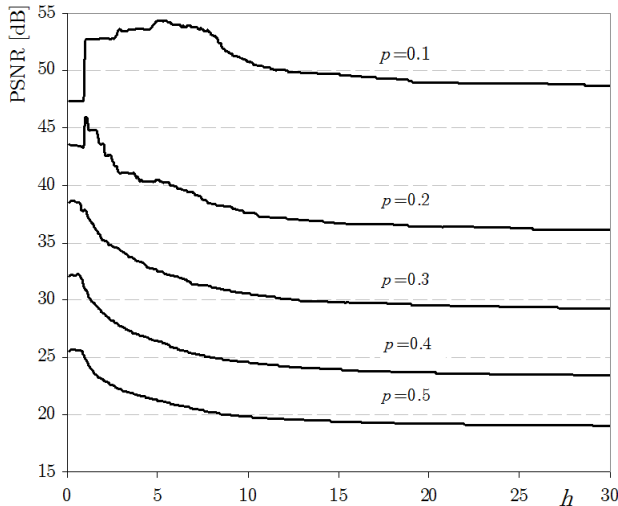


Figure 9. Dependence of the PSNR on the  $h$  parameter for the artificial test image shown in Fig. 8 contaminated with impulsive noise. Note that for large values of  $h$  the VMF is obtained.

The ability of the proposed filter to sharpen the image edges makes that the PSNR measure poorly describes the noise reduction ability of the ROWVMF for low noise intensity levels. For the evaluation of the efficiency of the new filter an artificial image has been generated (Fig. 8). The test image does not change after the filtering with VMF and ROWVMF and the edges are not affected by both filters. In this way, contaminating and restoring this test image, the real noise reducing properties of the proposed filter can be evaluated. As can be seen in Fig. 9 the proposed filtering solution offers much better performance than the VMF. As can be observed, the difference is quite significant for large contamination levels.

Figure 10 presents the dependence of the PSNR on the number of the filter passes evaluated using the PEPPERS image polluted with uniform impulsive noise. As can be observed for moderate noise intensity best results are obtained in the second iteration which is optimal for the filter performance.

Figure 11 shows that the proposed algorithm can be used not only for noise reduction but also for image sharpening. As can be noticed the processed image has much sharper edges without overshots typical for linear edge enhancing methods.

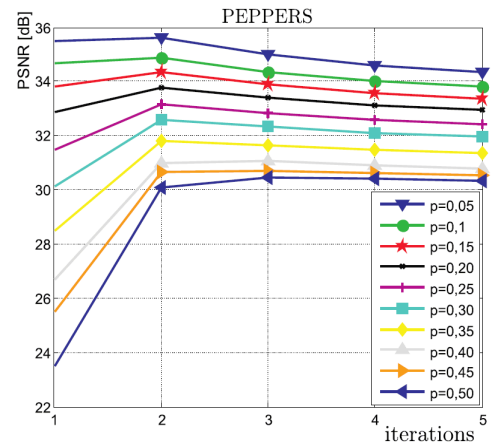


Figure 10. Dependence of PSNR on the iteration number for the PEPPERS image with various noise levels.



Figure 11. Edge enhancing property of the proposed filter: blurry test image (left) and its sharpened version (right)

#### IV. CONCLUSIONS

In this paper a novel filtering design utilizing the information of the pixels ranks in the ordered sequence of distances between a pixel and its neighbors has been proposed. The described method is an extension and improvement of the well known Vector Median Filter. Extensive simulations revealed very good noise attenuation properties of the proposed filtering scheme combined with its unique ability to sharpen image edges. As a result, color image noise removal is combined with edge enhancement.

#### ACKNOWLEDGMENT

This work has been supported by the Polish Ministry of Science and Higher Education under grant R13 046 02.

#### REFERENCES

- [1] K.N. Plataniotis, A.N. Venetsanopoulos, Color Image Processing and Applications, Springer Verlag, August 2000.
- [2] R. Lukac, B. Smolka, K. Martin, K.N. Plataniotis, A.N. Venetsanopoulos, "Vector filtering for color imaging," IEEE Signal Processing Magazine, vol. 22, no. 1, pp. 74-86, 2005.
- [3] I. Pitas, A.N. Venetsanopoulos, Nonlinear Digital Filters, Principles and Applications, Kluwer Academic Publishers, Boston, 1990.
- [4] J. Astola, P. Haavisto and Y. Neuvo, "Vector median filters," Proceedings of the IEEE, vol. 78, no. 4, pp. 678-689, 1990.
- [5] M. Ciuc, V. Vrabie, M. Herbin, C. Vertan, P. Vautrot, "Adaptive-neighborhood best mean rank vector filter for impulsive noise removal," Proc. of IEEE ICIP, pp. 813-816, 2008.
- [6] R. Lukac, B. Smolka, K.N. Plataniotis, "Sharpening vector median filters," Signal Processing, vol. 87, no. 9, pp. 2085-2099, 2007.