color image processing,
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ON THE ADAPTIVE IMPULSIVE NOISE REDUCTION IN COLOR IMAGES

In this paper a novel class of noise attenuating and edge enhancing filters for color image processing is introduced and analyzed. The proposed adaptive filter design is minimizing the cumulative dissimilarity measure of a cluster of pixels belonging to the sliding filtering window and outputs the centrally located pixel. The proposed filter is computationally efficient, easy to implement and very effective in suppressing impulsive noise, while preserving image details and enhancing its edges. Therefore it can be used in any application in which simultaneous denoising and edge enhancement is a prerequisite for further steps of the color image processing pipeline.

1. INTRODUCTION

During image formation, acquisition, storage and transmission many types of distortions limit the quality of digital images [1, 2, 3, 4]. Quite often, images are corrupted by *impulsive noise* caused mainly either by faulty image sensors or due to transmission errors. Common sources of impulse noise include also lightening, 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 and sharp click sounds in the audio.

The Vector Median Filter (VMF) is the most popular filter intended for smoothing out spikes injected into the color image by the impulse noise process [5]. This filter is very efficient at reducing the impulses, preserves sharp edges and linear trends, however it does not preserve fine image structures, which are treated as noise and therefore generally the VMF tends to produce blurry images. This unwanted feature of the VMF is very important as much of the image information is contained in its edges and sharp edges are pleasing to humans and are desirable for machine processing. As a result much research has been devoted to the construction of filters which can cope with image noise, while simultaneously preserving image details and enhancing image edges.

In this paper a solution to the problem of image noise filtering with edge enhancing abilities is presented. Extending the VMF using the *peer group* concept introduced in [6], it is possible to efficiently remove impulse noise, while sharpening the color image edges. The proposed filtering design excels over the VMF, preserves much better image details and produces images with sharp object boundaries.

2. VECTOR MEDIAN FILTER

In this paper the color image is defined as a two-dimensional matrix of size $N_1 \times N_2$ consisting of pixels $\mathbf{x}_i = (x_{i1}, x_{i2}, x_{i3})$, indexed by i, which gives the pixel position on the image domain. Components x_{ik}, for $i = 1,2,\ldots,N$, $N = N_1 \cdot N_2$ and $k = 1,2,3$ represent the color RGB channel values quantified into the integer domain. As color images are highly non-stationary, the filtering operators work on the assumption that the local image features can be extracted from a small image region centered at a given pixel called a *sliding filtering window* denoted as *W*. The size and shape of the window influence the properties and efficiency of the image processing operations, however, in order to preserve image details mostly a 3×3 window is used to process the central pixel surrounded by its neighbors.

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To remove the impulse noise, various filtering approaches based on the order statistics theory have been devised. The most popular filtering class operating on a sliding window is based on the *reduced* or *aggregated ordering* which assigns an aggregated dissimilarity measure to each color pixel from the filtering window [1].

The aggregated dissimilarity measure assigned to pixel $\mathbf{x}_i$ is defined as

$$R_i = \sum_{j=1}^{n} \rho(\mathbf{x}_i, \mathbf{x}_j), \quad \mathbf{x}_i, \mathbf{x}_j \in W, \tag{1}$$

where $\rho(\cdot)$ denotes the chosen dissimilarity measure. The scalar accumulated dissimilarity measures are then sorted and the associated vectors are correspondingly ordered,

$$R_{(1)} \leq \ldots \leq R_{(n)} \Rightarrow \mathbf{x}_{(1)} \leq \ldots \leq \mathbf{x}_{(n)}. \tag{2}$$

The dissimilarity measure depends on the kind of relationship between the sample vectors used to measure their difference. Usually the distance between vectors and the angle between them is utilized. In this paper we will focus on the *vector median filter* defined using the accumulated sum of distances between vectors, which serves as a dissimilarity measure. The vector median of a set of vectors belonging to a filtering mask W is defined as the vector $\mathbf{x}_{(1)}$ from W for which the sum of distances to all other vectors in W is minimized, [5]

$$\mathbf{x}_{(1)} = \arg\min_{\mathbf{x} \in W} \sum_{j=1}^{n} \left\| \mathbf{x} - \mathbf{x}_j \right\|, \tag{3}$$

where $\|\cdot\|$ denotes the Euclidean distance. The construction of the VMF is illustrated in Fig. 1, where the Euclidean distance is used. As can be seen, the vector median of the set of pixels is centrally located within the samples from the filtering window, meaning that the sum of distances to all other samples from W is minimized.

3. PEER GROUP VECTOR MEDIAN FILTER

As in the definition of the VMF the sum of distances is used (Eqs. 1, 3), we can say that the vector median is the vector $\mathbf{x}_{(1)}$ whose average distance to the n vectors from W is minimized. So we see that the vector median and also the scalar median is utilizing the concept of averaging, which is a little bit surprising, taking into account its highly nonlinear properties, which are clearly opposed to the filters based on the concept of arithmetic average.

In this paper we propose to generalize the definition of the vector median. In the new approach the vector median will be the vector $\mathbf{x}_{(1)}^{\alpha}$ for which the sum of α smallest distances to other vectors from W is minimized. For $\alpha = n$ the output of the Peer Group VMF (PGVMF) is identical with the standard VMF and for $\alpha = 1$ the identity filter is obtained, as the smallest distance is always zero, because it is the distance of the reference pixel to itself.

If the distance between the vector $\mathbf{x}_i$ and $\mathbf{x}_j$ is denoted as $\rho_{i,j}$, then we can order the set of distances $\rho_{i,j}$, for $j = 1, \ldots, n$ and obtain the following sequence: $\rho_i^{(1)} \leq \ldots \leq \rho_i^{(\alpha)} \leq \ldots \leq \rho_i^{(n)}$, where $\rho_i^{(k)}$ is the k-th smallest distance from $\mathbf{x}_i$ and $\rho_i^{(1)} = \left\| \mathbf{x}_i - \mathbf{x}_i \right\| = 0$. For each pixel in the filtering window the cumulated sum R_i^{α} is calculated

$$R_i^{\alpha} = \sum_{k=1}^{\alpha} \rho_i^{(k)}, \tag{4}$$

and the output of the generalized VMF is the pixel for which the trimmed sum of distances R^{α} is minimized.

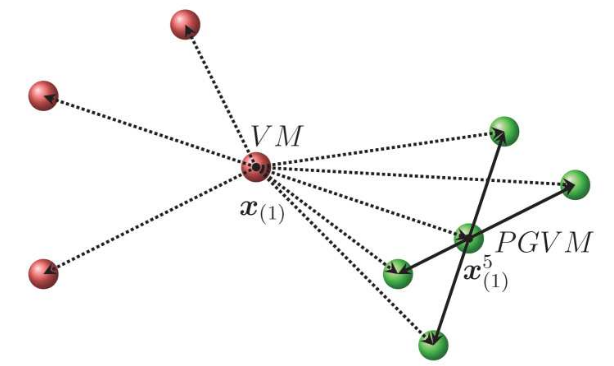


Fig. 1. Output of the VMF, (window size 3×3, $n=9$) and PGVMF for $\alpha=5$.

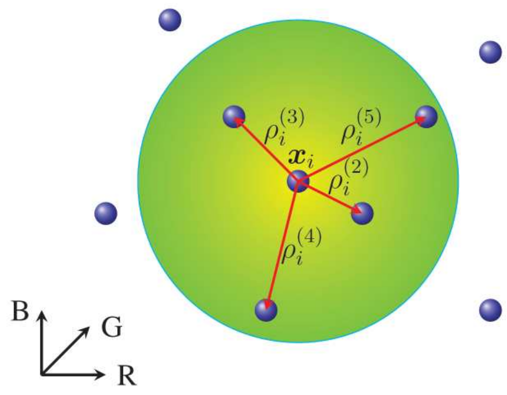


Fig. 2. Peer group associated with $\mathbf{x}_i$, $\alpha=5$.

In [6] a concept of the so called *peer group* filtering was introduced. This concept can be used to describe the construction of the proposed filtering approach. The *peer group* $P(\mathbf{x}_i,\alpha)$, denotes the set of α pixels consisting of $\mathbf{x}_i$ and $(\alpha-1)$ nearest pixels belonging to W. Using the *peer group concept* we can define the generalized vector median filter output as the sample $\mathbf{x}$ whose peer group of size α has the smallest accumulated sum of distances R^{α}, (see Figs. 1 and 2). In other words the output of the PGVMF is the pixel centrally located within a peer group of pixels with minimal dispersion, expressed as the sum of distances.

It is worth noticing the similarity of the new filter design with the α*-trimmed vector median filter*. The trimming operation in the α-trimmed filter is however being performed on the ordered set of vectors, whereas in the construction of the new filter, the trimming is applied to the ordered set of distances associated with a pixel from the filtering window.

So, the new filtering design is utilizing the concept of a peer group which has been already successfully utilized for impulse noise removal [7-9] and can be regarded as a generalization of the vector median filter, which is obtained as a special case of the new filtering technique.

4. ADAPTIVE DESIGN

For the evaluation of the efficiency of the proposed adaptive denoising design a set of standard color images has been contaminated with uniform random noise defined as

$$x_{iq} = \begin{cases} \rho_{iq}, & \text{with probability} \quad \pi, \\ o_{iq}, & \text{with probability} \quad 1-\pi, \end{cases} \tag{5}$$

where o_{iq} denotes the q-th component of the original pixel at a position i and the contamination component ρ_{iq} is a random variable in the range $[0,255]$. The fraction of contaminated pixels is then equal to $p=1-(1-\pi)^3$.

For the measurement of the restoration quality, the *Root Mean Squared Error* (RMSE) expressed through the *Peak Signal to Noise Ratio* (PSNR) was used. For the evaluation of the detail preservation capabilities of the proposed filtering design the *Mean Absolute Error* (MAE) has been utilized.

As can be observed in Fig. 3, the PSNR and MAE quality measures depend significantly on the choice of the α parameter of the PGVMF, which evokes the need for an adaptive scheme of adjusting this parameter to the local image structures.

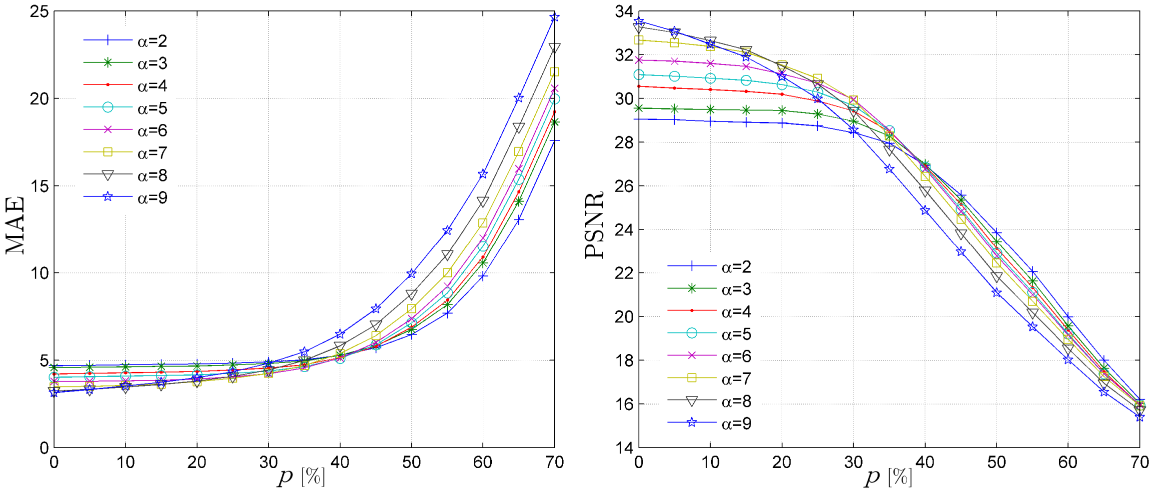


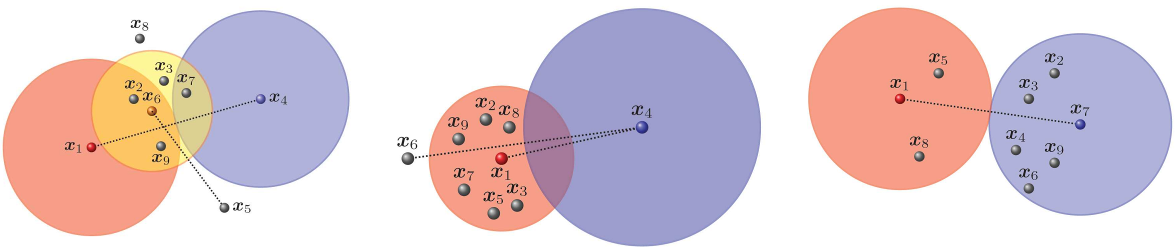
Fig. 3. Dependence of the MAE and PSNR image quality measures on the contamination intensity p for the uniform impulsive noise contaminating the *LENA* test image.

In [10] the following criterion for determining the α parameter has been proposed

$$\alpha = \max \alpha^* \quad \text{subject to} \quad \left(\sum_{j=1}^{\alpha^*} \rho_i^{(j)} \right) \leq \rho_i^{(n)}, \mathbf{x}_i \in W, \tag{6}$$

where $\rho_i^{(n)}$ is the largest distance between the central pixel $\mathbf{x}_i$ and its neighbors from W. This rule for the setting of the α values works well for pixels corrupted by impulsive noise, however for uncorrupted pixels in homogeneous image areas, usually the number of the pixels α in the peer-group is quite small, as the distances between pixels are comparable. Therefore a new scheme for the adaptive determination of the choosing the α value has been elaborated.

The adaptive algorithm requires to calculate for each pixel $\mathbf{x}_k$, the distances $\rho_{k,l}, l = 1,\ldots,n, l \neq k$ to other pixels belonging to the filtering window. The largest distance denoted as $\rho_k^{(n)}$ is used for building the peer-group $P(\mathbf{x}_k, \alpha_k)$ which consists of α_k pixels contained in a sphere centered at $\mathbf{x}_k$ with a diameter $\rho_k^{(n)}$. In this way the peer group consists of pixels $\mathbf{x}_l$ satisfying: $\rho_{k,l} \leq \rho_k^{(n)}/2$. The highest value of the α_k for $k = 1,\ldots,n$ serves as a parameter of the proposed filter. Its output is the pixel $\mathbf{x}_k$ for which the aggregated, trimmed distance R_k^{α} defined in (4) is minimized.



(a) (b) (c)

Fig. 4. Illustration of the adaptive determination of the maximum size cluster.

Figure 4a shows an exemplary configuration of pixels. For the pixel $\mathbf{x}_1$ the most distant neighbor is the outlying pixel $\mathbf{x}_4$ and in the sphere centered at $\mathbf{x}_1$ with the diameter equal to the distance $\rho_{1,4}$ four pixels are contained. The peer group of pixel $\mathbf{x}_4$, whose most distant neighbor is $\mathbf{x}_1$ contains 2 pixels and the largest peer group consisting of 5 pixels is assigned to pixel $\mathbf{x}_6$ whose most distant pixel is $\mathbf{x}_5$. In this way the proposed filter is searching for a cluster of $\alpha = 5$ pixels with the lowest trimmed sum of distances.

As can be observed in Fig. 4b the proposed design is able to cope with the outliers introduced by the noise process, as their peer groups do not contain any other pixels or like in a situation depicted in Fig. 4c the peer group size is quite low.

As often a few clusters with the same maximum number of pixels is found, then the pixel centrally located in the most compact cluster is chosen as the filter output. In other words, the output is the center of the peer-group whose aggregated distances to its members attains a minimum value.

5. EXPERIMENTS

The overall good noise reduction abilities of the proposed filtering design are presented in Fig. 5, which show the dependence of the PSNR and MAE on the noise intensity p when restoring the *LENA* noisy image. As can be observed the efficiency of the proposed adaptive PGVMF (APGVMF) is superior to that of the Sharpening VMF (SVMF) proposed in [10] and the Peer Group VMF (PGVMF) with fixed parameter $\alpha = 6$. Apart from the good denoising efficiency and detail preservation, depicted in Fig. 6, the proposed technique has the unique ability to sharpen the edges present in the color images, as can be observed in Fig. 7, which shows the filtering results delivered by the new filter as compared with the VMF in a case of high noise contamination ratio.

The novel filtering technique can be applied for various tasks in which the noise reduction capabilities combined with the strong edge enhancing properties are beneficial. One of such applications is the analysis of the cDNA microarrays which quantify the genes expression levels [11]. As can be observed in Fig. 8, the impulse noise is efficiently removed and the spots have sharp edges, which enable their reliable detection and estimation of the mean expression level calculated as an average intensity over the spot area.

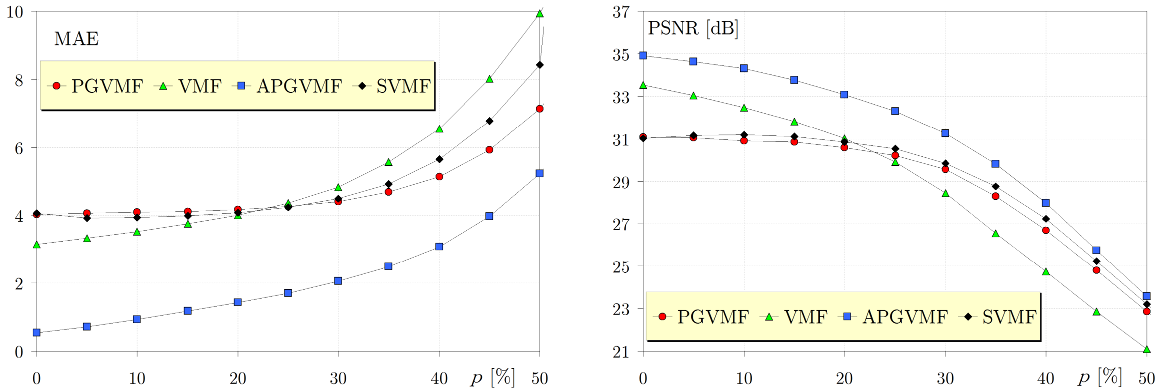


Fig. 5. Dependence of the MAE and PSNR image quality measures on the contamination intensities p for the uniform impulsive noise contaminating the *LENA* test image.

(a) test image (i) (b) noisy image (c) VMF output

(d) APGVMF (e) PGVMF $\alpha = 6$ SVMF output

Fig. 6. Comparison of the proposed filtering technique with the modified vector median filters: (a) color test image, (b) test image distorted by 10% impulsive noise, (c) VMF output, (d) APGVMF output, (e) PGVMF with $\alpha = 6$, (f) SVMF output.

(a) test image (i) (b) noisy image (c) VMF (d) APGVMG

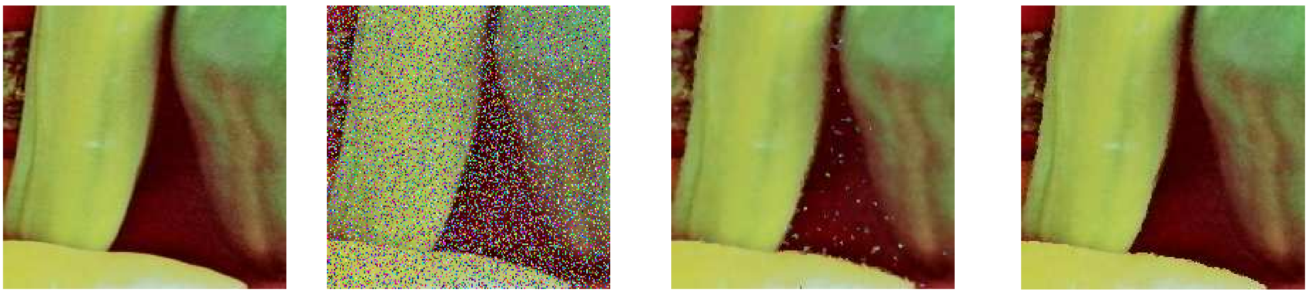
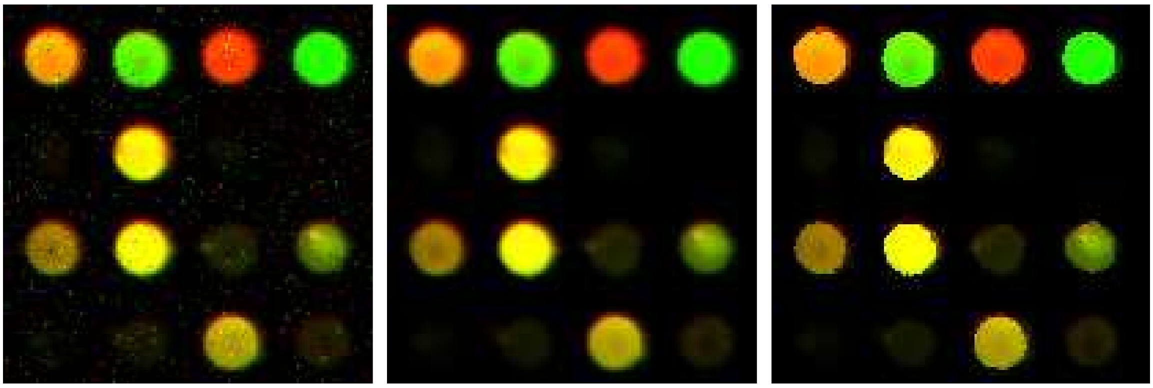


Fig. 7. Comparison of the proposed filtering technique with the modified vector median filters:
(a) color test image, (b) test image distorted by 40% impulsive noise, (c) VMF output, (d) APGVMF output, below the cropped and zoomed parts of the images are shown.



(a) noisy cDNA omage (b) VMF (c) APGVMG

Fig. 8. Illustration of the noise reduction and edge enhancing capabilities of the new filter as compared with the VMF: (a) cDNA test image, (b) VMF output, (c) image restored with the proposed APGVMF.

6. CONCLUSIONS

In the paper an adaptive filtering design for impulsive noise removal has been presented. The proposed adaptive scheme of choosing the optimal value of the peer group size used in the construction of the filter exhibits very good denoising properties outperforming the vector median based solutions.

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, the novel class of filters exhibits very good noise reduction efficiency which combined with its edge enhancing properties makes the new filtering design an attractive tool for low level color image processing. The simplicity of the new algorithm and its computational speed, which is comparable to that of the VMF makes the new noise removal method very useful in the preprocessing of color images corrupted by impulse noise.

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