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Impulsive Noise Suppression and Analysis in Color Imaging

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ABSTRACT

We present the analysis and simulation results for some modifications of the vectorial color imaging procedures those use at the second stage of magnitude processing the different order statistics filters.

The technique of non-parametric filtering is presented and investigated in this paper too. For unknown functional form of noise density estimated from the observations we use the gray scalar filters to provide the reference vectors needed to realize the calculations. The performances of the traditional order statistics algorithms such as, median, Vector Median, alfa-trimmed mean, Wilcoxon, other order statistics M KNN are analyzed in the paper.
For comparison analysis of the color imaging we use the following criterions: MAE; PSNR; MCRE; NCD.
Numerous simulation results which characterize the impulsive noise suppression and fine detail preservation are presented in the paper using different test images) such as: Lena, Mandrill, Peppers, etc. (256x256, 24 bits, RGB space). The algorithms those demonstrated good performance results have been applied to process the video sequences: "Miss America", "Flowers" and Foreman" corrupted by impulsive noise.
The results of the simulations presented in the paper show differences in color imaging by mentioned filtering technique and help to choose the filter that can satisfy to several criterion at dependence on noise level value.

Keywords: Impulsive Noise, Non-linear Filters, Color Imaging

1. INTRODUCTION

Random fluctuations in intensity, color, texture, object boundary, or shape can be seen in most real- images. The causes for these fluctuations are diverse and complex, and they are often due to different factors. One of the important reasons of such a distortion is a noise, in particularly impulsive noise.
Usually the image or video data are degraded through random impulsive noise caused in the channel and can significantly distorts an image or video sequence.

The nonlinear filtering has changed into a full-grown field of signal processing with its characteristic features because there are several application areas where linear filters cannot give satisfactory results. Nonlinear filters have proven to be useful in many image restoration applications[1-4]. They are very popular over the last decades, particularly in different applications. Because of their robust properties, some of these filters have been used when the images are corrupted by non-Gaussian noise [1-3]. For instance, the *median,* especially *median vector filters*[4] and, in general, *order statistics* (OS) filters have demonstrated good proficiency in the removal of noise[2,3,5]. There are different proposals to use such the filters in color imaging[6-11].

So, the principal goal of this paper is the proposal a novel filtering scheme that followed from before proposed *RM* type filters[12] and could be able to decrease the noise influence by filtering of the corrupted color image providing preservation of fine details and taking care chromaticity properties of color images.
It is known that noise can occur as thermal circuit noise, communication channels noise, sensor noise, and so on.

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In color image processing the assumption of additive white noise seldom holds. There are many models for impulsive noise. Impulses are also referred to as outliers. In statistics, outliers can be defined as observations which appear to be inconsistent with the pure data.

The acquisition or transmission of digitized images through sensor or digital communication link is often interfered by impulsive noise.

Common for the models of impulsive noise in images are the appearance of noise as of the spots of different color in images, i.e., the noisy color pixels have either a very small or a very large value. More realistic noise is implied by bit errors in the received signal values. Let each pixel be quantized to several (24 in real color image) bits. Assume the channel is a binary symmetric one. If an each bit is flipped with the same probability, it is easy to prove that the contribution to the mean square error from the most significant bit is approximately 3 times that of all the other bits. Such an impulsive noise is an example of very heavy-tailed noise.

The employed here is the following model of image degradation in presence of impulsive noise for each color channel:[1-3]:

$$r(i,j) = n_{im}(R(i,j)) \qquad g(i,j) = n_{im}(G(i,j)) \qquad b(i,j) = n_{im}(B(i,j)) \qquad ,(1)$$

where the result of impulsive noise influence in each channel (R - red, G -green and B – blue) is given by the following equation:

$$n_{im}(C(i,j)) = \begin{cases} \text{values of impulsive noise with probability } P \\ C(i,j) \text{ in another case} \end{cases} \qquad , \quad (2)$$

and $C(i,j)$ represents each channel for RGB 24 bit color image.

One of the first approaches in color imaging was the directional processing[4,6]. These filters use the characteristics, which identify the unique vector that represents the color image. Such the characteristics are the vector direction and its magnitude. These filters order the vectors which get during the calculation process in agree to the direction of each a vector. So, the complete processing procedure is separated in "directional processing" and "magnitude processing". Usually the Vector Directional Filter realizes the vector direction processing and eliminates the vectors with atypical directions having vector`s angle as ordering criterion. The remaining set is a vector group with approximately the same direction into the vector space. After that there is carried out to this group of vectors a magnitude processing to obtain an only vector which represents the algorithm output. The second stage of filtering is the magnitude processing and may be carried out with any grey level image processing filter[6,7].

Another scheme presented here is the filtering procedure that uses non parametric approaches. This approach is realized for filters those use the vector approximation, transferring any color image to a vector set. Such a set contains each vector`s direction and magnitude related with pixel chromaticity properties. The unknown noise density functional is estimated from available sample using non-parametric techniques[8].

An important property of order statistics filtering techniques is the robust parameter estimation where median and Wilcoxon are the first examples of robust estimators[13].

This paper presents the investigation and implementation different known filters such as: Median Filtering (MF), α-Trimmed Mean Filter (ATMF), Vector Median Filter (VMF)[14]; and proposed ones: MM-KNN[15] (Median M-Type K-Nearest Neighbor), WM-KNN[16] (Wilcoxon M-Type K-Nearest Neighbor) and ABSTM-KNN[16] (Ansari-Bradley-Siegel-Tukey M-Type K-Nearest Neighbor) adapted to color imaging problems or used as a reference filter in cascade filters. .

2. APPLIED FILTERING SCHEMES

a) The **Order Statistics Filters** employed here were: *Median Filter*, *Median Vector Filter*, α*-Trimmed Mean Filter*, *MM-KNN Filter*, *WM-KNN filter* and *ABSTM-KNN filter*.

It is very known that **Median Filter** forms the median of a pixel set given for every sliding window: $med\{x_1, x_2, \dots, x_N\} = x_{Med}$.

The **Median Vector Filter** selects the vector that minimizes the sum of the distances to the other $N-1$ vectors in respect to the norm L (Euclidian distance)[4,7].

$$\sum_{i=1}^{N}\left\|x_{VM}-x_i\right\|_L \le \sum_{i=1}^{N}\left\|x_j-x_i\right\|_L, \quad j=1,2,...,N \qquad (3)$$

The α **-Trimmed Mean Filter** joins the properties of Mean Filter and Median Filter to obtain the estimate in such a form: $y_i = \dfrac{1}{N-2P}\sum_{i=P}^{N-P} x_i$

The **MM-KNN filter** processes the grey level images[15] and can be written in such a form:

$$\hat{e}^{(q)}_{MMKNN}(i,j) = med\left\{g^{(q)}(i+m, j+n)\right\} \qquad (4)$$

Here it is only adapted to color imaging giving sufficiently good results.

The influence functions applied as data restriction functions during the filtering process were: the *Simplest Cut*, *Bernoulli*, *Tukey*, *Andrews* and *Hampel* functions[1,2,12]. These influence functions are the same for other filters employed here; WM-KNN and ABSTM-KNN filters.

WM-KNN filter adapted to color imaging in this paper is presented in such a form:

$$\hat{e}^{(q)}_{WM-KNN}(i,j) = MED\left\{\frac{g^{(q)}(i+m,j+n)+g^{(q)}(i+m_1,j+n_1)}{2}\right\} \qquad (5)$$

where $g^{(q)}(i+m, j+n)$ and $g^{(q)}(i+m_1, j+n_1)$ are the members of the set of K_c number of pixels that are weighted in accordance with the used influence function in a sliding filter window and are the closest to the estimated obtained at previous step. The filtering window size is $N=(2L+1)^2$, $m \le m_1$, $n \le n_1$, and $m,n,m_1,n_1 = -L,\dots,L$.

The RMKNN (MM-KNN; WM-KNN) filtering approach employs an iterative procedure, which uses the median of a sample data as the initial approximation, so algorithm forms the estimate based on the center element of the sliding window as the initial estimate in order to preserve the small feature of the image. At the current iteration, which we index by *q*, the procedure uses a data sample to form a set of elements whose values are most close to the estimate calculated at the previous step[15,16]. Subsequently, the procedure calculates a median of this set and then, it uses such a median at next (q+1)th step as the previous estimation. The number of neighbors K_c in the sample with closest values is calculated prior to iterations and is kept unchanged. The number K_c is calculated in this manner for each element (i,j) in order to fit the filter to local characteristics of the image, which helps to preserve the small feature. Iterations should be terminated when the current estimate becomes equal to the previous one. The current number K_c reflects the local data activity within the sliding window and spike presence and can be determined as[15]

$$K_c(i,j) = \left[K_{\min} + aD_S(i,j)\right] \le K_{\max} \qquad (6)$$

The parameter a in the eq. (6) controls the filter sensitivity to the local data activity in order to provide the best detection of the small details of the image. $K_{\min}$ determines the minimal number of the neighbors needed for noise rejection performance in the uniform regions of the image, $K_{\max}$ places a limit on the blue of the object edges and on the smoothing of its features. $D_S(i,j)$ is the used spike detector[15]

$$D_S(i,j) = \frac{\mathrm{MED}\left\{\left|x(i,j)-x(i+m,j+n)\right|\right\}}{\mathrm{MAD}\{x(i,j)\}} + 0.5\frac{\mathrm{MAD}\{x(i,j)\}}{\mathrm{MED}\{x(i+k,j+l)\}} \qquad (7)$$

Another algorithm using novel *RM*-estimators such as in eqs. (4) and (5) is the **ABSTM-KNN filter**[16], and its description is the following:

$$\hat{e}^{(q)}_{ABSTM-KNN}(i,j) = MED\left\{\begin{array}{ll} R^{(q)}(k), & k \le [K_c/2] \\ \dfrac{R^{(q)}(k)+R^{(q)}(l)}{2}, & [K_c/2] < k \le K_c, k \le l \end{array}\right\} \qquad (8)$$

where $R^{(q)}(k)$ represents the value of the pixel having the k rank among the sliding window elements $g^{(q)}(i+m, j+n)$ which are the members of the set of K_c number of pixels which are weighted in accordance with the used influence function and are the closest to the estimated obtained at previous step.

b) The processing steps of **Vector Directional Filters** (VDF) are divided in "magnitude processing" and "vector processing", where the first one is used to process like as grey level images and the second one is received the name as ***chromaticity processing***.

The **Basic Vector Directional Filter** (BVDF) realizes the processing procedure taking into account the pixels as vectors in the directional processing and obtaining the output vector that results a less deviation of its angles under ordering criterions in respect to the other vectors. In a vector set $\{f_i, i = 1,2,...,n\}$, the filtering procedure gives:

$$f_{BD} = BVDF[f_1, f_2,..., f_n] \quad , \quad (9)$$

where the ordering procedure is realized in the following way: $\sum_{i=1}^{n} A(f_{BD}, f_i) \le \sum_{i=1}^{n} A(f_j, f_i)$, $\forall j = 1,2,...,n$, and $A(f_{BD}, f_i)$, is the minimum angle value between the vectors obtained for f_i y f_j; $0 \le A(f_i, f_j) \le \pi/2$.

Another filter employed here was **Generalized Vector Directional Filter** (GVDF)[7]. In this case from an initial vector set $\{f_i, i = 1,2,...,n\}$ another vector set is obtained in such the form $S_{GD} = GVDF[f_1, f_2,..., f_n]$ and output vector is represented as:

$$f_O = \Im\{f^{(1)}, f^{(2)},..., f^{(k)}\} = \Im\{GVDF[f_1, f_2,..., f_n]\} \quad , \quad (10)$$

and output vector is calculated by magnitude processing, which is carried out by any grey level processing filter $\Im$.

The **Generalized Vector Directional Filter Adaptive** (GVDFAD) is an adaptive filter that uses the derivative of ordering sequence $\alpha_{(i)}$ according to ordering criterion. It uses the angles between different angles, cutting the sequence for the first discontinuity that exceeds some value $\tau\%$ of the maximum sequence derivative ($\tau = 25$). The GVDF filter has to be combined with the magnitude filter to result an only vector output for each pixel.

Double processing window is sufficiently powerful tool to suppress impulsive noise but it blurs the image. So, we used two windows: a small window of 3x3 and a larger window of 5x5. This gives the algorithm **Generalized Vector Directional Filter of Double Window** (GVDF_DW)[6,7]. The GVDF_DWAD works of the similar manner as GVDFAD described in[6,7].

c) The **Adaptive non Parametric Approach Filters** determine the functional form of density probability of noise that is obtained from data into the sliding filtering window. We applied some of such the filters.
Adaptive Multichannel non Parametric Filter (AMNF)[8]:

$$\hat{x}(y)_{AMNF} = \sum_{l=1}^{n} y_l \left(\frac{h_l^{-M} K\left(\frac{y - y_l}{h_l}\right)}{\sum_{l=1}^{n} h_l^{-M} K\left(\frac{y - y_l}{h_l}\right)} \right) \quad , \quad (11)$$

where y_l represents the vector references, which in this case are noisy vectors; h_l is the smooth parameter that is determined as: $h_l = n^{-k/M} A_l = n^{-k/M} \left(\sum_{j=1}^{n} |z_j - z_l| \right)$; and the function $K(z)$ is the kernel function that for impulsive noise has the exponential form $K(z) = \exp(-|z|)$[8].

Another filter that has been implemented is the **AMNF2** that in difference with eq. (11) uses the Median Vector Filter (MVF) as the reference to calculate the needed vectors:

$$\hat{x}(y)_{AMNF2} = \sum_{l=1}^{n} x_l^{VM} \left(\frac{h_l^{-M} K\left(\frac{y - y_l}{h_l}\right)}{\sum_{l=1}^{n} h_l^{-M} K\left(\frac{y - y_l}{h_l}\right)} \right) \quad , \quad (12)$$

Next investigated proposal of the paper is the novel processing procedure, **AMNF3** filter where the MM-KNN filter is applied as the reference one to provide the reference vectors:

$$\hat{x}(y)_{AMNF3} = \sum_{l=1}^{n} x_l^{MMKNN} \left(\frac{h_l^{-M} K\left(\frac{y - y_l}{h_l}\right)}{\sum_{l=1}^{n} h_l^{-M} K\left(\frac{y - y_l}{h_l}\right)} \right) \quad . \tag{13}$$

The simplest Cut Influence function is used in the MM-KNN filter to provide the reference vectors needed.

Finally, the **Multiple Adaptive non Parametric Multichannel Filter Exponential** (MAMNFE) has been implemented and investigated:

$$\hat{x}_{np} = \frac{\sum_{i=1}^{P} \hat{m}_i(x) f_\xi(y - \hat{m}_i(x))}{\sum_{i=1}^{P} f_\xi(y - \hat{m}(x))} = \sum_{i=1}^{P} \hat{m}_i(x)\omega_{npi} \quad . \tag{14}$$

The mentioned MAMNFE filter uses the AMNF and AMNF2 filters in cascade to provide an output vector trying to reduce the error obtained during the processing stage.

3. PERFORMANCE CRITERIA

To define the error criteria to accurately quantify the image distortion on the particular applications where the filters are used is difficult. During the simulation different criteria have been used for testing the edges and details preservation as well the noise suppression level too.

We also used a subjective visual criterion presented by error images for each filter applied to compare the capabilities of noise suppression of the algorithms. Such an error image provides information about the spatial distortion and artifacts introduced by different filters, as well as the noise suppression capabilities of the algorithm and present performance of the filter

The presented algorithms were evaluated with agree to criteria mentioned. Besides, it has been characterized the chromaticity error in filtered images and visual perceptual error of color images.

- **Mean Absolute Error** (MAE). It is used to evaluate the edges and fine detail preservation[2,3]:

$$MAE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left[\frac{|(R(i,j) - R'(i,j))| + |(G(i,j) - G'(i,j))| + |(B(i,j) - B'(i,j))|}{3} \right] \quad . \tag{15}$$

- **Mean Square Error** (MSE). It is the objective measure more common to compare the quality of the filtering between the original and filtering image:

$$MSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left[\frac{|R(i,j) - R'(i,j)|^2 + |G(i,j) - G'(i,j)|^2 + |B(i,j) - B'(i,j)|^2}{3} \right] \quad .$$

- **Pick Signal to Noise Relation** (PSNR). It is used to compare the filter ability to suppress a noise and is given in dB.

$$PSNR = 10 \cdot \log \left[\frac{(255)^2}{MSE} \right] dB \quad . \tag{16}$$

- **Normalized Color Difference** (NCD). It estimates the perceptual error among two color vectors[8].

$$NCD = \frac{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \|\Delta E_{Luv}\|}{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \|E^*_{Luv}\|} \quad . \tag{17}$$

- **Normalized Mean Square Error** (NMSE). It gives a relation in similarity between two digital images exploiting differences in statistical distribution of pixel values[6].

$$NMSE = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left\|[R(i,j),G(i,j),B(i,j)]-[R'(i,j),G'(i,j),B'(i,j)]\right\|^2}{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left\|[R(i,j),G(i,j),B(i,j)]\right\|^2} \quad . \qquad (18)$$

- **Mean Chromaticity Error** (MCRE). It is the criterion related to the color chromaticity and it characterizes the chromaticity error among two images[6].

$$MCRE = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} c\left[f(i,j),\hat{f}(i,j)\right]}{MN} \quad , \qquad (19)$$

4. SIMULATION RESULTS

Each channel R, G, B of the color image has been corrupted with impulsive noise independently according to eqs. (1)-(2) with different occurrence rate of noise: 0, 5, 10, 15, 20, 25, 30 and 30%. To determine the processing performances in case of color imaging by different filters the test images "Lena", "Mandrill", and "Peppers" have been used.

The results obtained for different color images have given the significant differences in performance of the algorithms MVF, MF, α -Trimmed Mean Filter with RM-estimators, but better than VDF filters and similar with non Parametric Filters.

To process color images we have selected the semi-optimal parameters values which were applied during the grey image processing[15,16]. This analysis has been done using multiple tests.

The results are presented in Table 1, 2 and 3, respectively, for MM-KNN, WM-KNN and ABSTM-KNN. The parameters a presented in eq. (6) controls the noise suppression and detail preservation, and the influence functions parameters can improve the robustness properties of the filter as it is shown below.

Table 1. Semi-optimal values of parameters for **MM-KNN** Filter

Influence Function	Semi-optimal parameters by MM-KNN				
	a	Kmin	α	β	r
Simplest Cut	≥0.6	5	–	–	255
Andrews Sine	10.7	5	–	–	120
Tukey	10.1	5	–	–	350
Hampel	11	5	150	160	550
Bernoulli	8.8	5	–	–	340

Table 2. Semi-optimal values of parameters for **WM-KNN** Filter

Influence Function	Semi-optimal parameters by WM-KNN				
	a	Kmin	α	β	r
Simplest Cut	40	5	–	–	255
Andrews Sine	40	5	–	–	350
Tukey	20	5	–	–	350
Hampel	40	5	150	160	550
Bernoulli	20	5	–	–	350

Table 3. Semi-optimal values of parameters for **ABSTM-KNN** Filter

Influence Function	Semi-optimal parameters by ABSTM-KNN				
	a	Kmin	α	β	r
Simplest Cut	40	5	–	–	255
Andrews Sine	40	5	–	–	400
Tukey	20	5	–	–	350
Hampel	40	5	100	230	550
Bernoulli	40	5	–	–	450

Table 4 presents PSNR values for image "Lena". One can see in here that the better results are demonstrated by AMNF2 and AMNF3 filters in the case of impulsive noise occurrence rate more than 15%. The MM-KNN, WM-KNN and ABSTM-KNN filters present good results in its PSNR values for small impulsive noise occurrence rate.

Table 4. PSNR values for image "Lena" degraded by impulsive noise with occurrence rate 0, 5, 15, 25 and 35% in the case of different filters used.

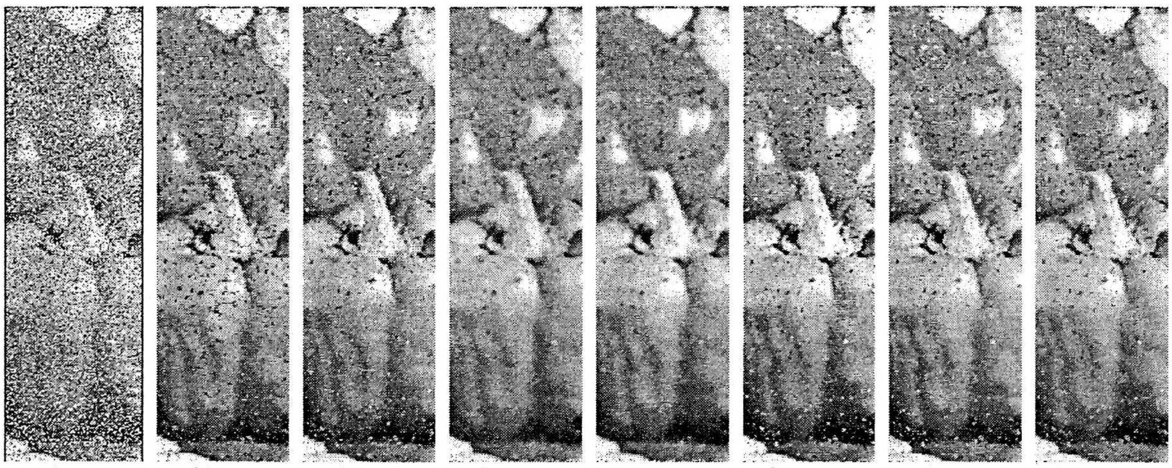
FILTERS/Noise rate		0	5	15	25	35
MF		30.72147	29.984219	24.914757	17.475109	13.545074
MVF		30.471371	30.047707	25.788	17.070684	12.582614
ATMF (p=2)		30.377804	29.856369	24.759146	17.656471	13.81483
BVDF		29.769039	28.88007	22.600193	14.563734	11.077305
GVDF		30.060499	29.292667	25.355745	16.816786	12.616925
GVDFAD		**30.756817**	**30.25304**	26.269354	18.093641	13.567474
GVDF_DW (MF)		29.392038	28.464939	25.303171	18.90444	13.78318
MAMNFE		29.482975	29.151171	26.381971	**18.907701**	**14.316879**
AMNF2 (MVF)		29.480999	29.217768	**27.265032**	**20.066677**	**14.610831**
AMNF3 (MM-KNN)		29.450153	29.191975	**27.47418**	**20.59968**	**14.84548**
MM-KNN	Simplest Cut	30.705856	30.240301	**26.42907**	18.150047	13.403153
	Bernoulli	30.649475	30.153433	26.22735	18.182432	13.605738
	Hampel	30.566624	30.083618	26.235106	18.212595	13.623626
	Andrews sine	30.612064	30.11743	26.203127	18.199255	13.617124
WM-KNN	Simplest Cut	**30.754028**	**30.25753**	26.24461	18.063856	13.561396
	Bernoulli	30.746546	30.101631	26.209414	18.088009	13.571087
	Hampel	30.734621	30.124018	26.185797	18.062668	13.561621
	Andrews sine	30.742943	30.147329	26.181713	18.064188	13.561532
ABST	Simplest Cut	**30.749613**	**30.252306**	26.261379	18.065668	13.561625
	Bernoulli	30.748667	30.224279	26.249329	18.065458	13.561627
	Hampel	30.748016	30.219999	26.247347	18.065401	13.561687
	Andrews sine	30.727785	30.206276	25.222626	16.692932	12.342652

Table 5. NCD criterion values for image "Mandrill" degraded by impulsive noise with occurrence rate 0, 5, 15, 25 and 35% in the case of different filters used.

FILTERS/ Noise rate		0	5	15	25	35
MF		**0.026983**	**0.029352**	**0.043702**	0.080204	0.126729
MVF		**0.033647**	**0.034019**	**0.042713**	0.080455	0.134334
ATMF (p=2)		0.038069	0.039164	0.05177	0.090531	0.134211
BVDF		0.050963	0.051136	0.062452	0.115284	0.18205
GVDF		0.044432	0.043302	0.04887	0.089753	0.146316
GVDFAD		0.034633	0.035105	**0.04338**	0.07751	0.128414
GVDF_DW (MF)		0.052755	0.053993	0.059809	0.090483	0.146815
MAMNFE		0.041701	0.042988	0.053246	0.085778	0.129754
AMNF2 (MVF)		0.041683	0.042597	0.04914	**0.077182**	**0.124745**
AMNF3 (MM-KNN)		0.041175	0.042151	0.047738	**0.072707**	**0.120682**
MM-KNN	Simplest Cut	**0.03301**	**0.0343**	0.04397	**0.076696**	0.128417
	Bernoulli	0.035365	0.035805	0.04394	0.077301	0.128397
	Hampel	0.035511	0.035987	0.044112	0.07726	**0.12838**
	Andrews sine	0.035489	0.035943	0.044067	0.077297	0.128382
WM-KNN	Simplest Cut	0.035146	0.035611	0.043827	0.078109	0.128654
	Bernoulli	0.035059	0.035584	0.043704	0.077697	0.128477
	Hampel	0.035444	0.035912	0.044011	0.078109	0.128656
	Andrews sine	0.035463	0.035943	0.044026	0.078111	0.128657
ABST	Simplest Cut	0.035322	0.035734	0.043835	0.078099	0.128655
	Bernoulli	0.035362	0.035815	0.043895	0.078103	0.128655
	Hampel	0.035332	0.035783	0.043885	0.078102	0.128655
	Andrews sine	0.03533	0.035778	0.043882	0.078102	0.128655

The Table 5 shows the values of NCD criterion that used to characterize chromaticity error between filtered and references images for the test image "Mandrill", We can conclude that for low level of impulsive noise the MF and MVF have shown the best results in minimum chromaticity error until 15 % impulsive noise occurrence. When the image has been contaminated by impulsive noise with the occurrence rate more than 15% the better NCD values are demonstrated by AMNF2 and AMNF3 filters.

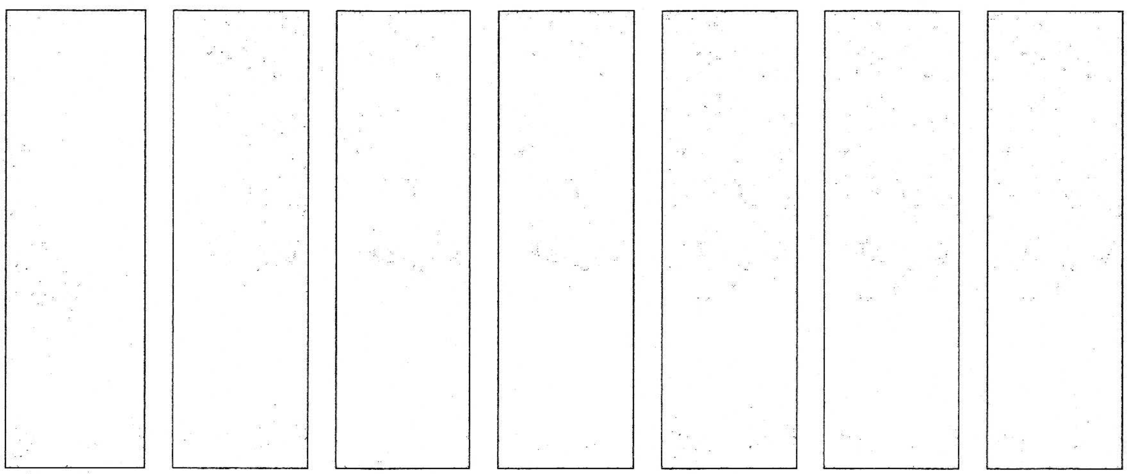
Figure 1 shows the subjective comparative results of noise suppression in the case of impulsive noise with 20% occurrence that contaminates the image when different filters are applied. We can notice the visual differences in filtered images obtained by different processing techniques.



a) b) c) d) e) f) g) h)

Figure 1. a) Subjective comparative results of impulsive noise (with 20% occurrence) suppression in the image "Peppers" when different filters have been applied: a) Noisy image, b) MF, c) MVF, d) AMNF2, e) AMNF3, f) MM-KNN (Simplest cut), g) WM-KNN (Hampel) and h) ABSTM-KNN (Andrews Sine).

Figure 2 shows the error images in image "Peppers" obtained by applying the different filters. Error images are used to compare in a subjective manner the quality of algorithm performance and characterize the robustness of the algorithm.

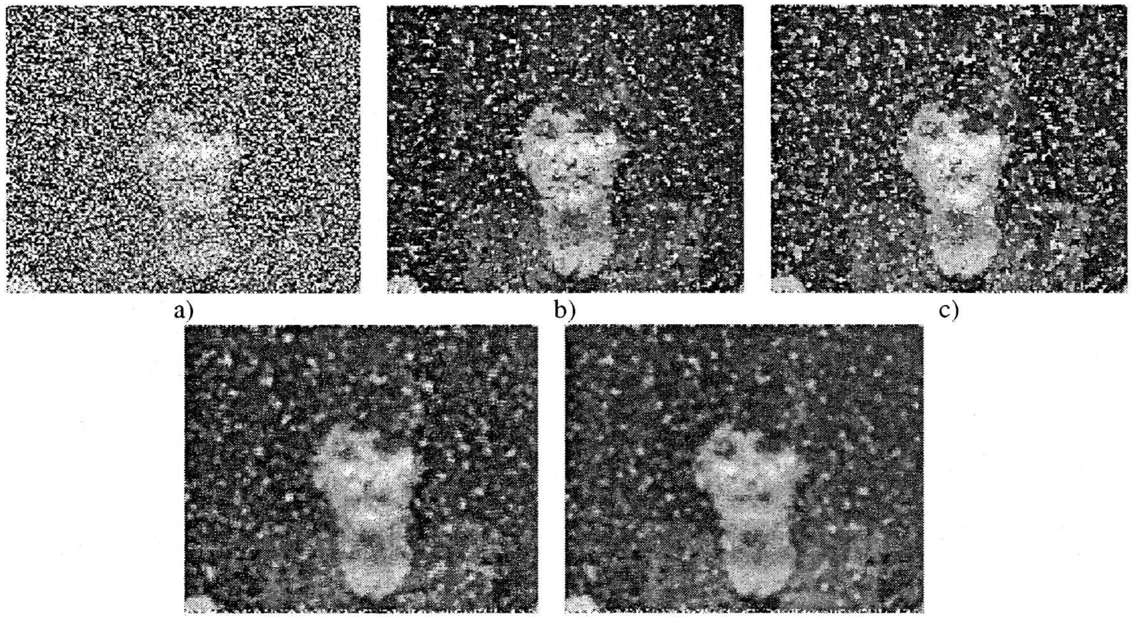


b) c) d) e) f) g) h)

Figure 2. Error Images b) MF, c) MVF, d) AMNF2, e) AMNF3, f) MM-KNN (Simplest cut), g) WM-KNN (Hampel) and h) ABSTM-KNN (Andrews Sine).

We have applied the mentioned and investigated filter to process the frame of the video sequence in QCIF format (176x144 pixels).

Figure 3 shows the subjective comparative results of noise suppression in the case of impulsive noise with 25% occurrence for video sequence "Miss America" when different filters are applied in processing. We can notice the visual differences in filtered images obtained by different techniques applied.



a) b) c)

d) e)

Figure 3. Subjective comparative results of impulsive noise (with 25% occurrence) suppression in the frame of sequence "Miss America" when different filters have been applied: a) Noisy image, b) MF, c) MVF, d) AMNF2, e) AMNF3.

5. CONCLUSIONS

It has been analyzed different techniques in the color image processing.

Besides, it has been proposed and investigated a novel *RM*-estimators, which are applicable to grey color image processing and have been adapted to color imaging.

RM-estimators are applied in non parametric approach processing algorithms to form the reference values needed in such a scheme. It has been concluded that such the compound algorithms give the best results of impulsive noise suppression in high levels of noise corruption.

AMNF3 has presented the better results when it uses MM-KNN algorithm with "Simplest Cut" influence function.

The NCD, MCRE and NMSE criteria characterizing the preservation of chromaticity properties in the color edges and fine details have demonstrated that the best results are obtained by AMNF3 and AMNF2 filters in the high level of impulsive noise corruption and by MF and MVF filters in low levels of noise corruption.

It has been proposed several efficient procedures which used to improve the performance of algorithms in non parametric approach. These algorithms can be used in cascade or to provide reference values needed to obtain a satisfactory estimation of pixel value.

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