Filtering of the Color Images Distorted by Impulse Noise

Csaba STUPÁK
Dept. of Electronics and Multimedial Communications
Technical University of Košice
Park Komenského 13, 040 21 Košice
Slovakia

Abstract

The paper deals with color image filtering distorted by impulse noise. The component, transformation, and vector filtering are analyzed. The filters are evaluated besides the classical criteria (mean absolute error and mean square error), and by the color difference criterion. Moreover, use of the impulse detectors in the color image filtration is analyzed.

Keywords

Color image processing, impulsive noise, median filter, impulse detector, color transformation.

1. Introduction

On the ground of developing fast signal processors that can process large number of data, the field of digital color image processing was opened. Well elaborated processing of grayscale images has been expanded to color image processing [5] - [7].

The color pixel can be described by the base colors red, green and blue (RGB) or by other base colors (YUV, YIQ etc). By these color triplets, all color can be created. Consequently, the color image is usually represented by triplet of matrixes RGB. In case of digital images, the image pixels are quantized by 8 bits. Similarly, color digital triplets are quantized by 3x8 bits.

The paper is organized as follows. The next section describes the color images used in the experiments. After it, the evaluation criterions are shown. The paper is divided into two major parts. In the first part, Section II, the component, transformation and vector filtering are compared. The second part, Section III, is devoted to color image filtering by impulse detectors. Comments and directions for future research are given in the last section.

1.1 Noise models

In the paper, two standard color images were used in experiments. The first one is the so-called Lena (Fig.1a), which is a monotonic, containing less details image. The second one is the Mandrill (Fig.1b), which contains more fine detailed parts as the image Lena. On that account, the filters give worse results on that image. In addition, other images were processed and analyzed too, but for the sake of saving the place, only the results of the images Lena and Mandrill are shown.

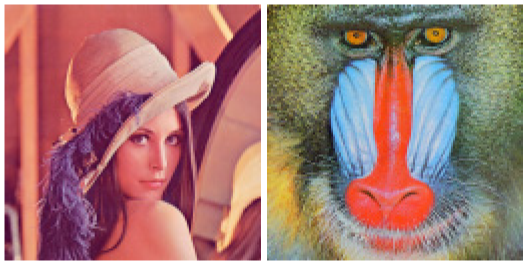

Fig. 1 The original noise free images: a) Lena, b) Mandrill

During the sampling, transmission and receiving of the data frequently result in its distorting. There are two types of noise in nature, the Gaussian additive and the impulsive noise. This paper deals with the impulsive noise. There were two models used of the impulsive noise. The first one is the classical impulsive noise, where the value of

Fig. 2 The distorted images of the Lena: a) correlated impulsive, b) correlated salt and pepper, c) non-correlated impulsive, d) non-correlated salt and pepper

the impulses is from the interval 0 and 255 in case of 8 bit quantized pixels. The second one is the so-called salt and pepper noise, where the impulses can be 0 and 255 only. Apart from these two models, in case of color images the noise can be correlated or not between the RGB channels. The correlated noise means that each color channel is distorted by similar value. In this paper, the full-correlated noise model was used, which denotes that each channel is distorted by the same value, in case of color images by gray pixels. On the other hand, the image is distorted by non-correlated noise if the pixels in the individual color channels are distorted independently.

1.2 Filter evaluation

Besides the subjective criteria each filter was evaluated also by objective criteria. The most common criteria are the *mean absolute error* (MAE) for evaluation of the image details conservation (1.1a), and the *mean square error* (MSE) for assessment of the noise suppression (1.1b) [5,10]. If the image is more blurred the value of the MAE is higher. In like manner, the higher is the MSE the higher is the noise presence in the image.

$$MAE_k = \frac{1}{N\,M}\sum_{i=1}^{N}\sum_{j=1}^{M}\left| x_{i,j}^{k} - o_{i,j}^{k} \right| \tag{1.1a}$$

$$MAE_k = \frac{1}{N\,M}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(x_{i,j}^{k} - o_{i,j}^{k} \right)^2 \tag{1.1b}$$

where $k = R$, G, B (color channels), x is the filtered image, o is the original image, N and M image size and i, j are indices. The overall value of the MAE and MSE is defined as the arithmetical mean value of the channels.

The grayscale images are well evaluated by both of the criteria. However, human eyes are more sensitive to color distortion. Therefore, another criterion should be introduced to calculate the *color difference* (CD) of two images. The computation of the CD cannot be performed directly in RGB color space. At first, the RGB image must be transformed to *Luv* color space by complex transformation (1.2-4) [2,11] and the comparison of the images only afterward can be done (1.5).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412 & 0.358 & 0.180 \\ 0.213 & 0.715 & 0.072 \\ 0.019 & 0.119 & 0.950 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1.2}$$

where X, Y, Z are the CIE XYZ transformation and R, G, B are the RGB color primaries. Computation of the *Luv* color space involves intermediate u' and v' quantities.

$$u' = \frac{4X}{X + 15Y + 3Z}, \quad v' = \frac{9Y}{X + 15Y + 3Z} \tag{1.3}$$

In the next step, u_n and v_n are computed for reference white X_n, Y_n, Z_n.

$$L^* = \begin{cases} 116 * \sqrt[3]{\dfrac{Y}{Y_n}} - 16 & \text{if } Y/Y_n > 0.008856 \\ 903.3\dfrac{Y}{Y_n} & \text{else} \end{cases} \tag{1.4a}$$

$$u^* = 13L^* \;\left(u - u_n \right), \; v^* = 13L^* \;\left(v - v_n \right) \tag{1.4b}$$

$$\Delta E_{uv}^* = \sqrt{\left(\Delta L^* \right)^2 + \left(\Delta u^* \right)^2 + \left(\Delta v^* \right)^2} \tag{1.5}$$

The CIE 1976 established a threshold [11], so-called just noticeable difference (JND), which tells the minimal value of the CD that human eyes can note. The value of the JND for Luv color space is around 2.9.

2. Color image filtering

This section is divided into three major parts. The first part describes the exploitation of the median filter on each color channel. The next part describes filtering the color images by several methods of color transformation. The last part encloses vector median filter.

In order to compare the filtering results, the objective criteria for distorted images are shown in Tab. 1. E.g., CI10 means 10% correlated impulsive noise in the table and NW20 20% non-correlated salt and pepper noise.

Image	Noise	MAE	MSE	CD
Lena	*CI10*	7.356	848.4	12.50
	NI10	7.312	832.0	32.72
	CW20	23.031	3564.3	26.44
	NW20	17.943	2772.0	90.94
Mandrill	*CI10*	7.324	823.7	13.04
	NI10	7.221	811.4	33.43
	CW20	23.056	3505.5	27.36
	NW20	23.152	3515.3	115.79

Tab. 1 Evaluation of the distorted images

The features of each criterion can be seen from the table. The larger the noise the higher is the value of the MAE and MSE. Further, the value of CD is higher in case of non-correlated noise because the color difference between the original and distorted image is larger.

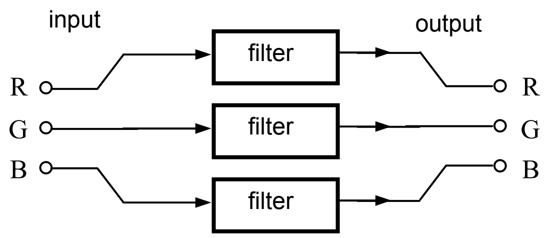

Fig. 3 RGB component filtering

2.1 Component wise filtering

From the above-mentioned three approaches, this is the simplest one. Each color channel (RGB) is filtered particularly [6]. On that account the filters developed for grayscale images can be employed easily. In this paper the well-known median filter (MF) was used with 3x3 operation window [8]. This filter is characterized by simplicity and high robustness. The principle is shown in Fig. 3.

Experimental results are shown in Tab. 2. The experiments were performed on the images *Lena* and *Mandrill*.

It can be seen that MF achieves quite good results. MF approximately 14 – 34 times suppresses the impulsive noise (Tab. 1, 2). On the other hand, the color information is not as good as preserved.

Image	Noise	MAE	MSE	CD
Lena	*CI10*	3.797	62.9	16.76
	NI10	3.703	56.8	17.78
	CW20	4.376	103.7	17.63
	NW20	4.029	78.0	20.21
Mandrill	*CI10*	10.674	288.5	31.63
	NI10	10.647	288.4	33.63
	CW20	11.353	342.6	32.37
	NW20	11.399	348.9	39.62

Tab. 2 Component filtering by MF

However the implementation of such approach is lucrative on the other hand it has a disadvantage. There are not utilized the correlation between RGB channels in case of component filtering.

2.2 Color image transformation

This approach should eliminate the drawback of the previous method. It should exploit the correlation between RGB channels and therefore to suppress color difference. This technique transforms RGB triplets to corresponding color space (YUV, YIQ, etc.). After conversion, filtering

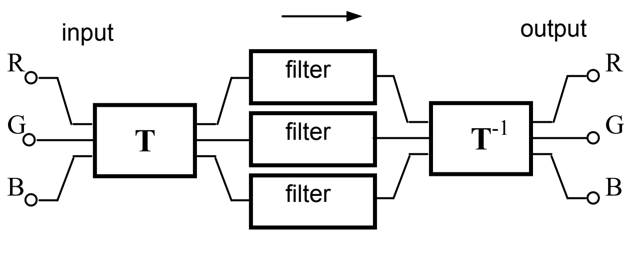

Fig. 4 Color image transformation filtering

was applied and the inverse transformation back to RGB color space. The whole process is shown in Fig. 4.

Four methods of color transformation were used: YUV, YIQ, YCbCr and HDTV. Principle and conversion equation of these transformations are presented in following sections [2], [9]. The further section of this part deals with statistical features of each transformation. In the last section of color transformation part the filters following the MAE, MSE and CD criteria are compared.

2.2.1 YUV color transformation

European TV (PAL and SECAM coded) uses YUV components. Y is similar to perceived luminance, U and V carry the color information and some luminance information. The conversion equations for linear signals for white point D65 are defined as follows:

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2.1a}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1.140 \\ 1 & -0.396 & -0.581 \\ 1 & 2.029 & 0 \end{bmatrix} \begin{bmatrix} Y \\ U \\ V \end{bmatrix} \tag{2.1b}$$

2.2.2 YIQ color transformation

American TV (NTSC coded) uses YIQ components. Again Y is similar to perceived luminance, I and Q carry color information and some luminance information and are derived by rotating the UV vector formed by color coding by 33 degrees. The conversion equations for linear signals for white point D65 are defined as follows:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2.2a}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1.140 \\ 1 & -0.396 & -0.581 \\ 1 & 2.029 & 0 \end{bmatrix} \begin{bmatrix} Y \\ I \\ Q \end{bmatrix} \tag{2.2b}$$

2.2.3 YCbCr color transformation

This is the international standard for digital coding of TV pictures. It is independent of the scanning standard and the system primaries, therefore there are no chromaticity co-ordinates, no CIE XYZ matrices, and no assumptions about white point or CRT gamma. It deals only with the digital representation of RGB signals in YCbCr form. The coding matrices are (ITU.BT-601 YCbCr):

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2.3a}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1.403 \\ 1 & -0.344 & -0.714 \\ 1 & 1.773 & 0 \end{bmatrix} \begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} \tag{2.3b}$$

2.2.4 HDTV studio production in YCbCr color transformation

This is a recent standard, defined only as an interim standard for HDTV studio production. It was defined by the CCIR (now the ITU) in 1988, but it is not yet recommended for use in broadcasting (ITU.BT-709 HDTV studio production in YCbCr). The conversion equations for D65 white point are:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.221 & 0.715 & 0.072 \\ -0.114 & -0.385 & 0.500 \\ 0.502 & -0.456 & -0.046 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2.4a}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1.570 \\ 1 & -0.187 & -0.466 \\ 1 & 1.856 & 0 \end{bmatrix} \begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} \tag{2.4b}$$

2.2.5 Statistical features of the color transformations

The main purpose of color transformations is to decorrelate components of RGB color space. As it can be seen from Tab. 3 the correlation among RGB components is high while among transformed components is less. The best decorrelation is achieved by the YIQ transformation. The statistical features of the color transformation were computed on the image *Lena*.

Transformation	1-2	2-3	1-3
RGB	0.88	0.92	0.68
YUV	0.76	0.46	**0.11**
YIQ	**0.20**	**0.08**	0.87
YCbCr	0.75	0.46	**0.11**
HDTV	0.79	0.30	0.21

Tab. 3 Component correlation

Transformation	1	2	3
RGB	36	39	25
YUV	63	16	21
YIQ	64	23	13
YCbCr	64	18	18
HDTV	**66**	**17**	**17**

Tab. 4 Energy compression

Moreover, the first component carries the major part of the energy in transformed domain (Tab. 4). This component is the grayscale transformation of the color image and the additional components interpret the color information. From this table can be seen that the transformation methods similarly compress the energy.

2.2.6 Filtering results

The experiments were performed on the same images and noise types as in case of component wise filtering. The filtering results are shown in the Tab. 5a for image *Lena* and in the Tab. 5b for image *Mandrill*. From the results, it is difficult to decide, which is the best color transformation method. They are altogether similar. For simple images (Lena) and small noise the YCbCr transformation seems good while for complex and highly distorted images the YIQ transformation gives better results.

Lena	Filter	MAE	MSE	CD
CI10	*YUV*	4.132	**66.1**	16.54
	YIQ	4.149	66.3	**16.44**
	YCbCr	**4.129**	**66.1**	16.53
	HDTV	4.633	69.7	17.13
NI10	*YUV*	4.007	**58.0**	**15.71**
	YIQ	4.025	**58.0**	16.39
	YCbCr	**4.006**	**58.0**	15.73
	HDTV	4.476	60.8	16.13
CW20	*YUV*	5.262	130.6	20.23
	YIQ	**5.249**	**130.2**	**19.33**
	YCbCr	5.255	130.6	20.18
	HDTV	5.732	136.8	20.83
NW20	*YUV*	4.431	77.4	**16.97**
	YIQ	**4.408**	**76.7**	17.32
	YCbCr	4.430	77.4	16.98
	HDTV	4.898	82.8	17.34

Tab. 5a Transformation filtering on Lena

Lena	Filter	MAE	MSE	CD
CI10	*YUV*	11.304	294.0	30.60
	YIQ	11.335	**293.7**	31.28
	YCbCr	**11.297**	293.9	**30.54**
	HDTV	11.461	298.3	31.03
NI10	*YUV*	11.196	289.3	29.85
	YIQ	11.221	**288.9**	30.47
	YCbCr	**11.192**	289.3	**29.81**
	HDTV	11.298	291.3	30.03
CW20	*YUV*	12.432	368.9	34.91
	YIQ	12.472	**368.7**	35.65
	YCbCr	**12.424**	368.8	**34.83**
	HDTV	12.602	376.2	35.40
NW20	*YUV*	11.983	329.9	31.93
	YIQ	**11.975**	**327.6**	32.47
	YCbCr	11.977	329.8	**31.89**
	HDTV	12.084	339.3	32.15

Tab. 5b Transformation filtering on Mandrill

The task of the color transformation method is to improve the performance of the grayscale filters, the filtering results it does not approve. The best decorrelation and filtering results were obtained by the YIQ transformation.This transformation does not give better results as the simple component wise filtering (Tab. 8).

2.3 Vector median filtering

In the last decade, the area of vector valued signal processing has dramatically increased [1,15]. Color image is also represented by a three-component vector per pixel. The vector contains the value of the pure red, green and blue components of the pixel's color. There are several vector-valued filters, the classical vector median filter (VMF) based on $L1$ or $L2$ norm, median filter based on reduced or conditional ordering, etc. In this part, the performance of the VMF is evaluated. The formula of the VMF is following [5].

$$\sum_{i=1}^{N} \left\| y_n - x_{n-i} \right\|_L \leq \sum_{i=1}^{N} \left\| x_{n-j} - x_{n-i} \right\|_L \qquad (2.5)$$

for j = 1, 2, …, N. Further, y is the output of the VMF, x is the input data, N is the size of the input data, L is the used norm ($L1$, $L2$) and i, j are indices.

The experiments for same images were performed as in case of component wise and transformation filtering. The results are listed in Tab.6. It is clear that the VMF based on L2 norm gives the best results. In case of detailed images, such as *Mandrill*, the VMF-L1 filter has a little bit better image details preservation (MAE) comparing to VMF-L2 but it cannot be noticed on images.

Lena	Filter	MAE	MSE	CD
CI10	*L1*	3.845	66.0	16.15
	L2	**3.825**	**65.0**	**15.65**
NI10	*L1*	3.699	57.2	15.98
	L2	**3.687**	**56.5**	**15.40**
CW20	*L1*	4.467	106.5	17.67
	L2	**4.453**	**105.8**	**17.15**
NW20	*L1*	3.947	70.2	16.81
	L2	**3.927**	**65.5**	**16.15**

Tab. 6a Vector median filtering on Lena

Lena	Filter	MAE	MSE	CD
CI10	*L1*	**10.860**	302.4	31.84
	L2	10.881	**300.8**	**30.67**
NI10	*L1*	**10.780**	299.0	31.89
	L2	10.818	**297.2**	**30.63**
CW20	*L1*	**11.557**	356.1	33.08
	L2	11.577	**353.6**	**31.89**
NW20	*L1*	11.315	338.5	33.74
	L2	**11.278**	**320.7**	**31.92**

Tab. 6b Vector median filtering on Mandrill

2.4 Comparison of filtering methods

For the sake of transparency, filtering results of the best filters in each category are summarized in Tab. 7. Comparing 3 methods MF, transformation filtering based on YIQ transformation and VMF-L2, roughly similar filtering results can be found. In case of correlated noise, MF achieves better result than VMF and vice versa.

Lena	Filter	MAE	MSE	CD
CI10	*MF*	**3.797**	**62.9**	16.76
	YIQ	4.149	66.3	16.44
	VMF	3.825	65.0	**15.65**
NI10	*MF*	3.703	56.8	17.78
	YIQ	4.025	58.0	16.39
	VMF	**3.687**	**56.5**	**15.40**
CW20	*MF*	**4.376**	**103.7**	17.63
	YIQ	5.249	130.2	19.33
	VMF	4.453	105.8	**17.15**
NW20	*MF*	4.029	78.0	20.21
	YIQ	4.408	76.7	17.32
	VMF	**3.927**	**65.5**	**16.15**

Tab. 7a Filter comparison on Lena

Lena	Filter	MAE	MSE	CD
CI10	*MF*	**10.674**	**288.5**	31.63
	YIQ	11.335	293.7	31.28
	VMF	10.881	300.8	**30.67**
NI10	*MF*	**10.647**	**288.4**	33.63
	YIQ	11.221	288.9	**30.47**
	VMF	10.818	297.2	30.63
CW20	*MF*	**11.353**	**342.6**	32.37
	YIQ	12.472	368.7	35.65
	VMF	11.577	353.6	**31.89**
NW20	*MF*	11.399	348.9	39.62
	YIQ	11.975	327.6	32.47
	VMF	**11.278**	**320.7**	**31.92**

Tab. 7b Filter comparison on Mandrill

The main disadvantage of the above mentioned methods that they process all the pixels of the image. By this way, the noise-free pixels are processed too, which bring error to the filter's output. The next part of this paper describes a principle, which well resolves this problem.

3. Impulse detectors in color image filtering

As mentioned, the classical filters step-by-step pass over the whole image and by help of an operator process each pixel. Thus, all the pixels are changed independently whether the pixel was or was not distorted. In that manner, usually the fine details of the image are blurred. The impulse detectors also called classifiers solve the problem. The principle is shown in Fig. 5.

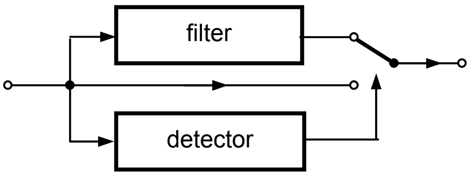

Fig. 5 Filtering by impulse detector

From Fig. 5, principle of the impulse detector is clear, if the detector decides that the processed pixel is distorted then the pixel is filtered else not. There are several impulse detectors: *E-detector*, *biased E-detector*, *E-detector controlled by fuzzy logic*, *SDV-detector*, etc [4], [7], [12]-[14], [16]-[17]. For the sake of robustness and simplicity of the SDV-detector, this detector was used in experiments.

If the central pixel of the operation window (OW) is more different than the rest pixels it should be filtered by a filter, otherwise leave it not filtered. In this paper, the SDV detector was combined by MF or VMF. The SDV detector is based on the following rule:

$$\textbf{IF}\ C > \sigma \quad \textbf{THEN}\ \textit{filter} \qquad \textbf{ELSE}\ \textit{not filter} \tag{3.1}$$

where $C = | x_{cent} - D |$ is the absolute difference of the central pixel in the OW from the mean value D of the pixels in OW and σ is the standard deviation of the OW's pixels.

Next subsections describe application of SDV detector in component wise, transformation and vector filtering.

3.1 Color image filtering by SDV detector

Principle of component wise filtering is the same as in section 2.1. The only difference is that the impulse detector is added to each channel in this case. Essentially, in case of transformation filtering with impulse detector the principle is also same as in the case without impulse detector. In both cases, the detector and filter work on each channel independently. In the last case, the SDV detector works with VMF. The detectors monitor each channel separately and if at least in one channel detects impulse all the channels are processed by VMF.

The results of the filters are shown in the Tab. 8. Besides the classical criteria (MAE, MSE, CD), which evaluate the whole filter with impulse detector, another criteria were also used, which appraise the features of the impulse detector. There were used two criteria. The first one evaluates the detector's misclassification (MCL). The smaller is the MCL the filter less processes noise-free pixels and the image details are more remained. The second criterion evaluates the successfully detected impulses (SCL). The larger is this value the impulses is more removed from the images.

Noise	Filter	MAE	MSE	CD	MCL	SCL
CI10	*MF*	**1.824**	55.0	8.93	**20.8**	62.7
	YIQ	2.100	54.8	7.33	24.5	77.4
	VMF	1.963	**50.0**	**7.12**	20.9	**95.1**
NI10	*MF*	**1.741**	49.7	10.14	**20.9**	57.6
	YIQ	2.325	64.3	9.63	24.7	57.8
	VMF	1.798	**36.9**	**6.73**	21.0	**98.6**
CW20	*MF*	2.176	91.9	12.11	**8.8**	78.6
	YIQ	2.793	113.9	10.05	14.8	86.2
	VMF	**1.892**	**70.5**	**6.23**	**8.8**	**99.0**
NW20	*MF*	1.701	54.5	11.80	**12.6**	81.8
	YIQ	3.327	139.9	14.20	16.0	54.4
	VMF	**1.581**	**34.7**	**5.82**	**12.6**	**99.9**

Tab. 8a Detector comparison on Lena

Noise	Filter	MAE	MSE	CD	MCL	SCL
CI10	*MF*	**5.665**	**212.9**	19.67	**29.2**	61.2
	YIQ	6.869	213.1	20.48	45.3	44.0
	VMF	6.639	229.0	**15.81**	**29.2**	**89.9**
NI10	*MF*	**5.683**	**213.5**	23.07	**31.4**	47.3
	YIQ	6.902	230.1	17.66	36.3	49.2
	VMF	6.911	230.5	**16.33**	31.5	**97.9**
CW20	*MF*	**5.055**	211.1	17.03	**13.3**	85.4
	YIQ	6.786	237.3	24.55	40.1	45.3
	VMF	5.360	**209.3**	**12.73**	**13.3**	**98.5**
NW20	*MF*	**5.045**	216.2	23.72	**14.9**	83.1
	YIQ	7.521	345.7	23.11	20.6	43.4
	VMF	5.408	**191.1**	**13.19**	**14.9**	**99.7**

Tab. 8b Detector comparison on Mandrill

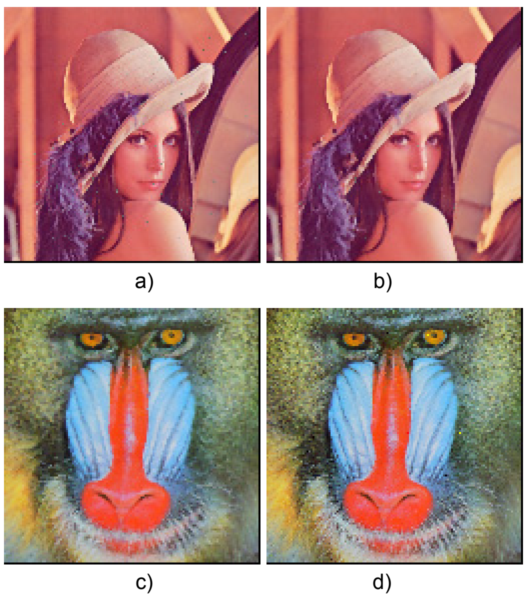

Fig. 6 Filtered images. a) VMF, b) VMF+SDV, c) VMF, d) VMF+SDV

The tables show that in most cases, the SDV detector gives the best results with VMF. In term of detail preservation (MAE) the component wise processing provides the best results.

Comparing the filters without impulse detectors (Tab. 7) with filters with impulse detectors (Tab. 8) shows that the use of impulse detectors improves the filtering results considerably. Values of the MAE and CD are even almost by half less. It can be noticed in Fig. 6, where the images at left side were filtered only by VMF and images at right side were filtered with impulse detectors. The images at right side are sharper, which acts better for human eyes than the blurred images at left. On the other hand, in the images processed by impulse detector can be noticed few number of impulses hardly.

4. Conclusion

The paper was devoted to color image filtering distorted by impulsive noise. There were analyzed the component, transformation and vector filtering, respectively. It can be stated that the three methods of filtering give roughly equivalent results. In spite of expectation the color transformation methods do not give better results comparing to component wise filtering. Evenly, the component wise filtering almost overcome the performance of the vector median filter. The best results give the VMF. Additionally, there were analyzed the usefulness of the impulse detectors in three domain (RGB, YIQ and vector processing), too. The best result gives the vector processing of the data.

As follows from the results, the usage of the impulse detectors is appropriate. The image detail preservation and color distortion are better using detectors. Therefore, the further developments should be oriented to improvement of the impulse detectors.

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About author...

Csaba STUPÁK received the M.S. degree from the Technical University of Košice, Slovak Republic, in Electronics and multimedial communications in 1997 and the Ph.D. degree in 2000 at the department of Electronics and multimedia communications of Technical University, Košice. Currently, he works at Slovak Air Force Institute of Research and Testing – Košice. His research interest includes image filtering, neural network, fuzzy logic and genetic algorithms.