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IMPULSE DETECTION IN NOISED COLOUR IMAGES

Rastislav Lukáč — Stanislav Marchevský *

In environments corrupted by impulse noise a problem of desired signal features preservation with simultaneous removing of noise elements is an adequate motivation for looking for systems where the desired features would be invariant to the filtering operation and only noise would be affected. The connection of an impulse detector with some filter, *eg* most frequently a well- known median, is creeping to the mentioned optimum situation. In the case of multivariate or vector valued signals such as colour images the problem is extended to the next dimension. For these signal, where correlation of colour channels is included, vector methods such as vector medians are successfully used. Even thought we show that excellent improvement and reduction of colour distortion can be obtained by componentwise filtering by an impulse detector with a well-known standard median filter. Similar results can be obtained by the vector median connected with an impulse detector, too.

K e y w o r d s: colour images, vector median, impulse detector, median, impulse noise

1 INTRODUCTION

In vector valued signals such as colour images [1,13,17] every sample is represented by multiple components. There exist a number of colour transformations [1] such as RGB, CMY, HSV, YUV, etc. Common sign of colour transformations is the fact that a colour image is represented by a set of three colour primaries [1,13,17]. In the case of RGB model, the set of primaries is created by red (R), green (G) and blue (B). During the scanning, transfer over transmission channel or display, noise is introduced into the desired signal. The introduced noise attacks all channels in dependence on the correlation between channels. The impulse noise is the most frequent case of damage.

Many filtering methods for gray scale images [7,18] are well used in colour image processing, too. However, in componentwise filtering the dependence between colour channels is not considered and on that account it is suboptimal. Exactly this suboptimality is presented in the form of colour artefacts [13,17,18] since the channels are filtered separately and the resulting colour is composite from outputs of individual channels. Thus, the error of individual outputs increases colour distortion.

Therefore, in the case of vector valued signals (multivariate signals) corrupted by impulse noise, on the ground of a colour artefacts reduction, vector smoothing techniques are used such as vector median [1,7,18] or spherical median that achieve a smaller colour difference from the original in comparison with the standard (componentwise) median [1,7,14,18]. However, vector methods do not perform excellent noise suppression and image reconstruction. The main drawback of standard componentwise filtering methods and vector processing is the fact that samples are processed without the knowledge about the noise presence. Thus, the deviation is increased, since the used filter introduces blurring. An optimal situation would arise if a filter could be designed such that the desired features would be invariant to the filtering operation and only noise would be affected. Since filters for impulse noise suppression belong to the class of nonlinear filters and superposition does not apply, the optimal situation can never be fully obtained.

On that account impulse detectors were developed for classification of input data. Thus, the input data are classified in two classes, *ie* noised samples and noise free samples. While the impulse detector is connected with some filter, *eg* most frequently a well-known median filter, it is possible to obtain a system that performs optimal filtering, *ie* noise free samples are passed on the output without change (system works as an identity filter) whereas corrupted elements are estimated by the median filter.

From our experience it is evident that the role of impulse detectors in impulse noise filtering is underrated, even though the connection of impulse detectors and standard median represents a simple and effective solution. In our previous works the impulse detectors were successfully used in gray scale images [15] or noised image sequences [8,9]. In this paper we present results achieved by impulse detectors in connection with a standard componentwise 3×3 median filter. The second approach leads to a connection of vector median and impulse detectors, too. Thus, on impulse position the vector median is applied and the output vector is determined by a vector from the input set.

2 NOISE MODELS AND CRITERIA

To test the performance of the methods, some well-known tested images such as Lena (Fig. 3a), Mandrill,

* Department of Electronics and Multimedial Communications, Technical University of Košice, Park Komenského 13, 041 20 Košice, Slovakia, e-mail: lukacr@tuke.sk, marchs@tuke.sk

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Table 1. Evaluation of methods (IF noised images, MF filtered by 3×3 componentwise median, VF filtered by 3×3 vector median)

Noise	CI10			2NI10			CBW20			NBW20		
Method	MAE	MSE	CD	MAE	MSE	CD	MAE	MSE	CD	MAE	MSE	CD
IF	7.356	848.4	12.496	7.312	832.0	32.717	23.031	3564.3	26.436	17.943	2772.0	90.937
MF	3.797	62.9	16.762	3.703	56.8	17.777	4.376	103.7	17.633	4.029	78.0	20.211
VF L2	3.825	65.0	15.652	3.687	56.5	15.396	4.453	105.8	17.151	3.927	65.5	16.151

Fruit, Train and some types of impulse noise were used. Thus, the robustness of methods is tested, too. However, to save the paper space, the results are presented for image Lena only.

2.1 Noise models

To illustrate various degrees of damage the following types of impulse noise [3,14] were used (Fig. 3b-e). The first one is the classical impulse noise (also called impulse noise with variable random value), of which mathematical model is given by

$$n_{i,j} = \begin{cases} o_{i,j} & 1 - p_\nu \\ \nu & \nu \end{cases} \tag{1}$$

where ν represents in the case of 8 bit quantized pixels, the value of the impulse from the interval 0 and 255, p_n is the impulse noise probability and $o_{i,j}$ is the original sample on the pixel position i, j

The second one is the so-called salt and pepper noise, where the impulses can be 0 and 255 only as determined by

$$n_{i,j} = \begin{cases} o_{i,j} & 1 - (p_0 + p_{255}) \\ 0 & p_0 \\ 255 & p_{255} \end{cases} \tag{2}$$

where p_0 and p_{255} are probabilities of the occurrence for minimum value (p_0) and maximum value (p_{255}).

In the case of colour images the noise can be correlated or not between the colour channels [7,14]. The correlated noise means that each colour channel is distorted by a similar value. In this paper, both extremes were considered: the fully-correlated noise model which causes gray impulses since each channel is distorted by the same value. On the other hand, the image is distorted by non-correlated noise if the pixels in individual colour channels are distorted independently.

In this paper, separate types of impulse noise were marked as

- CI10 - 10% full correlated impulse noise with a variable random value (Fig. 3b)
- NI10 - 10% non-correlated impulse noise with variable random value (Fig. 3c)
- CBW20 - 20% full correlated salt and pepper noise (Fig. 3d)
- NBW20 - 20% non-correlated salt and pepper noise (Fig. 3e)

However, mathematical model of impulse noise for colour images is not a simple concern and thus a simplified model for two channels was presented in [13].

2.2 Objective criteria

Besides the subjective criteria, the performance of methods was evaluated by objective criteria (evaluation of noised images is shown in Table 1) also. The well-known and widely used criteria in image processing are the mean absolute error (MAE) that evaluates the image details preservation, and the mean square error (MSE) to characterize the noise suppression. The mentioned criteria are defined as follows [15]

$$MAE = \frac{}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} |x_{i,j} - o_{i,j}| \tag{3}$$

$$MSE = \frac{}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} \left(x_{i,j} - o_{i,j}\right)^2 \tag{4}$$

where N, M characterize the image dimension, $x_{i,j}$ is an image point of noised or filtered image, $o_{i,j}$ is an image point of original image and i, j are indices of the pixel location.

Usually, two approaches of the use of objective criteria exist. The first is the evaluation of each colour channel separately and thus, for every criterion a number of measures equal to the number of colour channels are needed. On that account, we preferred the second method where objective criteria such as MAE and MSE are computed as the mean value over three channels.

However, these criteria provide information about signal-detail preservation and noise suppression only. In the case of colour image processing, the colour distortion, *ie* a measure [14] for colour artefacts must be included, too. Thus, in many works the colour difference (CD) is used

$$\Delta E^*_{u\nu} = \sqrt{(\delta L^*)^2 + (\delta u^*)^2 + (\delta \nu^*)^2} \tag{5}$$

$\Delta L^*, \Delta u^*, \Delta \nu^*$ present the difference between original and filtered (or noised) images in $Lu\nu$ colour space [14]. Note that a threshold value of CD for $Lu\nu$ colour space *ie* a minimal value that human eyes are able to differentiate was establish around 2.9. This value is called just noticeable difference (JND).

To evaluate the performance of impulse detectors (Table 2), two criteria for succesful impulse detection and missclassified impulses were introduced [15,16]. The first one is SCL that gives the measure about success classification. Mathematically, SCL is defined as

$$SCL = \frac{\eta - \varepsilon_c}{\eta} 100 \tag{6}$$

whereas the second one MCL is a mirror of missclassification given by

$$MCL = \frac{\varepsilon_m}{MN - \eta} 100. \tag{7}$$

In equations (6) and (7) ε_m presents a number of noise free samples marked as impulses, ε_c is the number of non-classified impulses, η presents the total number of impulses and N, M characterize image dimension. Note that in the case of colour images, a sample, *ie* a vector is considered as an impulse or noised vector if at least one of colour channels is corrupted.

2.3 Used detector window

The principle of many filtering algorithms is based on sequential processing with utilizing of the local image information given by an operation window as shown in Fig. 1. Exactly, windowing plays an important role in the choice of processed sample neighbourhoods since the local information about image details and edges is the basis for well estimating the original sample. The most frequently used operation windows are shown in Fig. 2. The use of a concrete window depends on edge positions in the image. Next, in many cases the interaction between the window shape and the used algorithm cannot be described analytically, however, under a number of experiments.

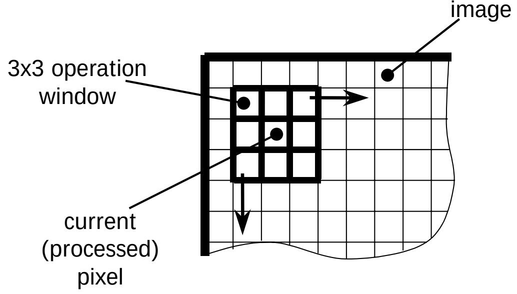

Fig. 1. Principle of image windowing

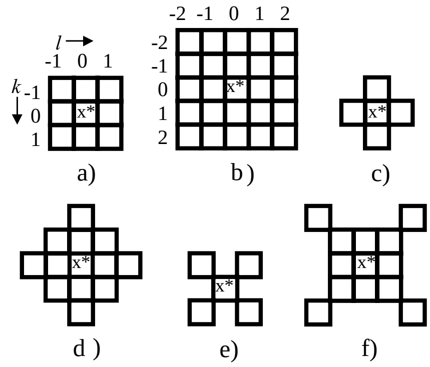

Fig. 2. Most frequently used filter window a) 3×3, b) 5×5, b) $+3$, b) $+5$, b) $\times 3$, b) $\times 5$

3 IMPULSE DETECTORS

In our previous works [6,15,16] the used detectors were described in detail, therefore in this section we restrict the detector description on the definition and basic properties only. A general detector rule can be expressed as

$$\begin{aligned} \text{IF} \quad Val \geq Tol \quad & \text{THEN} \quad 1 \\ & \text{ELSE} \quad 0 \end{aligned} \tag{8}$$

where Val is characterized by detector operation and Tol is a decision threshold. In the case of impulse detection, *ie* the condition is valid, the detector output is equal to 1, otherwise 0. As shown below, this simple decision of data classifying is the basis for excellent filtering results (Table 5 and Table 6). Note that detector rule (8) is applied to each colour channel independently, however, at least in one colour channel the detector output is equal to 1, the sample *ie* vector is considered as an impulse.

3.1 E detector

The name of E detector [10,15] follows since it is based on the mean value μ of the input set. The decision rule of E detector is given by

$$\begin{aligned} \text{IF} \quad D \geq M \quad & \text{THEN} \quad 1 \\ & \text{ELSE} \quad 0 \end{aligned} \tag{9}$$

where

$$D = |x^* - \mu| \tag{10}$$

$$M = \max_{i=1}^{N} \big(|x_i - \mu| \big). \tag{11}$$

and N is the window size, x^* is the central sample, for represents a simplified notation of samples from the input set W.

Table 2. Performance of impulse detection

Noise		CI10		NI10		CBW20		NBW20	
Method	W	MCL	SCL	MCL	SCL	MCL	SCL	MCL	SCL
E	3×3	5.751	77.495	5.789	88.297	5.789	88.297	3.493	95.829
	5×5	0.519	51.670	0.521	66.876	0.521	66.876	0.128	90.101
	$+3$	16.696	87.432	16.601	93.960	16.601	93.960	13.331	95.398
	$+5$	2.415	69.019	2.424	83.093	2.424	83.093	1.228	93.952
	$\times 3$	16.264	86.618	16.435	92.435	16.435	92.435	13.057	94.425
	$\times5$	1.845	68.559	1.815	81.254	1.815	81.254	0.925	94.008
E_p	3×3	0.259	76.430	0.277	86.834	0.277	86.834	0.157	95.329
	5×5	0.156	51.169	0.173	66.270	0.173	66.270	0.041	89.851
	$+3$	0.339	85.449	0.367	91.912	0.367	91.912	0.720	95.204
	$+5$	0.266	68.017	0.292	81.818	0.292	81.818	0.121	93.549
	$\times3$	0.916	84.405	0.888	90.763	0.888	90.763	1.112	94.091
	$\times5$	0.240	67.578	0.257	80.146	0.257	80.146	0.132	93.619
SDV	3×3	20.821	95.157	20.836	98.579	20.836	98.579	12.586	99.930
	5×5	8.249	96.367	8.654	98.537	8.654	98.537	2.653	100.00
	$+3$	30.670	93.570	30.734	98.182	30.734	98.182	24.082	98.888
	$+5$	14.497	95.303	14.685	98.516	14.685	98.516	7.137	99.972
	$\times3$	31.130	93.695	31.483	97.764	31.483	97.764	24.866	98.902
	$\times5$	12.777	95.303	12.987	98.621	12.987	98.621	6.415	99.972
E_f	3×3	0.730	92.317	0.827	96.677	0.827	96.677	0.855	99.917
	5×5	1.858	94.280	1.990	97.011	1.990	97.011	1.162	100.00
	$+3$	0.529	86.388	0.618	93.250	0.618	93.250	1.176	98.860
	$+5$	1.080	93.090	1.275	97.011	1.275	97.011	1.087	99.972
	$\times3$	1.156	86.806	1.354	92.915	1.354	92.915	1.928	98.818
	$\times5$	1.152	92.672	1.307	96.761	1.307	96.761	1.035	99.958
LCP	3×3	30.480	97.662	31.123	99.415	31.123	99.415	19.060	100.00
	5×5	19.503	98.685	20.097	99.498	20.097	99.498	7.964	100.00
	$+3$	38.431	94.843	38.686	98.809	38.686	98.809	30.119	99.500
	$+5$	25.072	98.225	25.722	99.436	25.722	99.436	13.331	100.00
	$\times3$	39.403	94.948	39.936	98.558	39.936	98.558	31.183	99.611
	$\times5$	23.338	98.017	24.104	99.478	24.104	99.478	12.531	100.00
H	3×3	21.155	94.864	21.272	98.474	21.272	98.474	12.693	99.750
	5×5	8.156	96.180	8.559	98.391	8.559	98.391	2.463	99.917
	$+3$	31.351	93.403	31.274	98.119	31.274	98.119	24.561	98.721
	$+5$	14.832	95.031	14.912	98.328	14.912	98.328	7.064	99.833
	$\times3$	31.500	93.257	31.838	97.450	31.838	97.450	25.073	98.526
	$\times5$	12.946	94.969	13.024	98.433	13.024	98.433	6.403	99.805
OSD	3×3	1.823	97.077	1.866	97.743	1.866	97.743	5.187	100.00
	5×5	2.994	96.848	3.070	97.555	3.070	97.555	3.676	100.00
	$+3$	3.234	96.576	3.821	97.889	3.821	97.889	9.587	99.986
	$+5$	2.059	97.015	2.169	97.576	2.169	97.576	3.500	100.00
	$\times3$	4.989	97.056	5.595	97.638	5.595	97.638	11.469	99.972
	$\times5$	2.335	97.161	2.437	97.722	2.437	97.722	3.721	100.00
$COSD$	3×3	0.987	96.013	0.944	97.241	0.944	97.241	3.202	100.00
	5×5	2.491	96.472	2.510	97.409	2.510	97.409	3.106	100.00
	$+3$	1.512	93.779	1.689	96.385	1.689	96.385	7.262	99.930
	$+5$	1.378	96.388	1.495	97.304	1.495	97.304	2.384	100.00
	$\times3$	2.230	93.612	2.456	95.883	2.456	95.883	8.163	99.917
	$\times5$	1.618	96.367	1.616	97.262	1.616	97.262	2.555	100.00
$LUMsm$	3×3	0.488	96.493	0.525	97.994	0.525	97.994	0.843	99.986
	5×5	0.724	95.825	0.817	97.576	0.817	97.576	0.786	100.00
	$+5$	0.773	96.806	0.842	98.307	0.842	98.307	0.759	99.972
	$\times5$	0.767	96.472	0.868	98.182	0.868	98.182	0.759	99.986

$\mathbf{E}_p$ detector

By modifying the E detector rule (9), the E_p impulse detector (called a threshold or biased E detector, too) was obtained [10]:

$$\text{IF } D \geq M \text{ AND } D \geq bias \text{ THEN } 1 \quad \text{ELSE } 0 \tag{12}$$

where $bias$ is an introduced threshold to create the second condition. In the case of gray scale images the optimal value was found $bias = 30$.

3.3 SDV detector

To improve the detection property of E detector and E_p detector the SDV detector based on standard deviation σ was developed [15]:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \mu\right)^2} \tag{13}$$

and the detector rule of SDV detector is given by

$$\text{IF } D \geq \sigma \text{ THEN } 1 \quad \text{ELSE } 0 \tag{14}$$

Thus, if the absolute differences D (10) is greater than the standard deviation σ (13), the central sample is probably distorted because it is more different from other input samples.

3.4 $\mathbf{E}_r$ detector (fuzzy E detector)

Detector rule of E_f impulse detector [16] is similar to E_p detector (12), however, in the case of E_f detector $bias$ is not fixed but adaptively changed according to local image complexity:

$$bias = \mu_{low} b_{low} + \mu_{high} b_{high} \tag{15}$$

where

$$\mu_{low} = \min\left(1, \max\left(0, \frac{\sigma_{high} - \sigma}{\sigma_{high} - \sigma_{low}}\right)\right) \tag{16}$$

$$\mu_{high} = 1 - \mu_{low}. \tag{17}$$

In equations (15-17), $b_{low}, b_{high}, \sigma_{low}, \sigma_{high}$ are parameters of a fuzzy system. In [1] the sub-optimal values of these fuzzy parameters for gray scale images were provided as follows $\sigma_{low} = 8$, $\sigma_{high} = 16$, $b_{low} = 20$, $b_{high} = 40$. Thus, the bias is changed according to the dependence of the standard deviation σ (13) on local image complexity.

3.5 Order-statistic detector

The principle of order-statistic detectors requires ordering of the input set W The detector rule of the order-statistic detector is given by [16]:

$$\text{IF } |\mu_{mid} - x^*| \geq Tol \text{ THEN } 1 \quad \text{ELSE } 0 \tag{18}$$

where Tol is the threshold (optimal value is equal 40) and μ_{mid} is the mean of n mid-positioned ordered samples. However, two types of order statistic detectors exist:

- **OSD detector**
  The first is the detector, called OSD [6,12], where the ordered set is created without the central sample x^*
- **COSD detector**
  On the other hand, COSD detector [6] utilizes an ordered set that include the central sample x^* too.

The set of control parameter n of order-statistic detectors is determined by Table 3.

Table 3. Parameters of order-statistic detectors

window	n(OSD)	n(COSD)
3×3	2	5
5×5	12	13
$+3$	2	3
$+5$	6	7
$\times 3$	2	3
$\times 5$	6	7

3.6 LCP detector

The idea of LCP detector [2,4] is based on the following rule:

$$\text{IF } P^* \geq P_C \text{ THEN } 1 \quad \text{ELSE } 0 \tag{19}$$

where P_C is a critical value defined as $P_C = 1/N$ and P^* is for $i = (N+1)/2$ the local contrast probability (LCP) of processed pixel given by

$$P_i = \frac{|x_i - D|}{\sum_{i=1}^{N}|x_i - D|}. \tag{20}$$

Thus, if the local contrast probability P^* of the central sample is greater than or equal to P_C, then central pixel is considered as a noise and the output value is equal to 1.

3.7 H detector

Unlike LCP detector, H detector based on the entropy [4] utilizes the adaptive critical threshold value defined by the following equation: vskip 1mm

$$\eta = \frac{-P^* \log P^*}{H} = \frac{-P^* \log P^*}{-\sum_{i=1}^{N} P_i \log P_i}. \tag{21}$$

The local contrast entropy H is computed in every location of detector window by

$$H = -\sum_{i=1}^{N} P_l og P_i \tag{22}$$

where P_i is the local contrast probability (20) associated with input sample $x+i$. The control rule of H detector is determined by the following formula:

$$\begin{aligned} \text{IF} \quad P^* \geq \eta \quad & \text{THEN} \quad 1 \\ & \text{ELSE} \quad 0 \end{aligned} \tag{23}$$

3.8 LUMsm detector

The name of LUMsm [5] detector derives from LUM smoothers [5,7], since the outputs for all smoothing levels of the LUM smoother are used as a base for detector decision:

$$\begin{aligned} \text{IF} \quad Val \geq Tol \quad & \text{THEN} \quad 1 \\ & \text{ELSE} \quad 0 \end{aligned} \tag{24}$$

where

$$Val = \sum_{\lambda}^{\lambda+2} |x^* - y_\lambda| \tag{25}$$

is the reduced sum of absolute differences between the central sample x^* and the outputs of LUM y_k smoothers for each possible value of tuning parameter k. The output of LUM smoother is given by

$$y_k = med\left\{x_{(k)}, x^*, x_{(N-k+1)}\right\} \tag{26}$$

where $x_{(k)}$ and $x_{(N-k+1)}$ are lower and upper order statistics of the ordered set and med is a median operator. In (19) Tol presents a threshold (optimal value 60 or 90 [5] for various degree of damage).

Table 4. The set of parameter λ

window	I10	BW20
3×3	2	3
5×5	5	7
$+5$	3	4
$\times 5$	3	4

The set of control parameter λ of LUMsm detector is most appropriate according to Table 4. In this table, the setting of control parameter λ depends on the operation window size N and the degree of damage. From the principle of LUMsm detector it is evident that operation windows with size $N \leq 5$ (N is odd) are not suitable since LUMsm detector requires three outputs of standard LUM smoother. In the case of $N = 5$, *ie* $+3$ and $\times 3$ windows the whole potential of outputs includes an identity filter and a median filter could be used, however, in the case of high noise corruption there is needful to exercise filtering with a larger smoothing level.

4 USED FILTERS

After detecting noise corruption, *ie* positive impulse detection (it means that the detector output is equal to 1), the processed sample is delivered to additional processing. Thus, the pulse-wise distortion is reduced by replacing the processed sample, *ie* the central sample of the input set by the most appropriate estimate according to the filter algorithm.

On the other hand, in the case of noise free samples the central sample is passed on the filter output without the change, *ie* the system works as an identity filter. For colour images, the filter output is identical to the central vector of the input vector set.

To show the difference between componentwise and vector medians, noised images were processed by both filters (Table 1). Next, the improvements achieved by placing an impulse detector in front of the mentioned filters are provided in Table 5 and Table 6. Now, both standard median and vector median are described in brief.

4.1 Median filter

The first is the well-known median [18] filter that is a basic nonlinear filter used in smoothing applications. The median filter is widely used because of its robustness and performance.

The output of median filter with input set of N samples is determined by

$$y = med\{x_1, x_2, \ldots, x_N\} \tag{26}$$

Thus, the algorithm of median filtering requires ordering of input samples and consecutive choice of the central sample from the ordered sequence. In the case of colour image filtering, the median filter is applied to each colour channel separately and thus it produces artefacts in the form of colour distortion. On that account the vector median was developed that utilizes the correlation between colour channels.

Table 5. Performance of impulse detectors with 3×3 componentwise median

Noise		CI10			NI10			CBW20			NBW20		
Method	W	MAE	MSE	CD	MAE	MSE	CD	MAE	MSE	CD	MAE	MSE	CD
E	3×3	2.008	138.2	5.554	1.370	67.2	6.235	3.265	260.5	8.273	1.486	79.1	7.487
	5×5	3.185	281.4	7.400	2.294	180.0	10.649	3.823	306.3	9.860	1.924	133.8	10.311
	$+3$	1.840	86.4	5.931	1.457	45.5	6.420	3.757	343.0	8.811	2.010	123.3	9.610
	$+5$	2.336	184.8	5.918	1.509	91.4	6.950	3.484	278.8	8.855	1.585	94.6	8.219
	$\times3$	2.015	97.5	6.690	1.622	52.9	7.134	3.888	353.1	9.320	2.237	146.7	10.996
	$\times5$	2.273	178.6	5.875	1.544	97.2	7.133	3.467	278.5	8.866	1.562	94.2	8.106
E_p	3×3	1.812	136.9	4.735	1.196	67.8	5.538	3.190	259.8	7.925	1.412	82.9	7.170
	5×5	3.181	282.1	7.378	2.296	181.1	10.685	3.822	306.3	9.854	1.944	136.0	10.377
	$+3$	1.310	82.5	3.762	0.937	41.9	4.292	3.442	339.8	7.456	1.629	120.9	7.965
	$+5$	2.272	185.7	5.649	1.454	93.4	6.797	3.463	278.6	8.765	1.582	98.2	8.213
	$\times3$	1.517	94.1	4.340	1.114	49.5	4.765	3.579	349.9	7.774	1.875	145.6	9.236
	$\times5$	2.238	179.9	5.696	1.517	99.0	7.044	3.454	278.4	8.805	1.571	97.9	8.144
SDV	3×3	1.930	49.1	7.241	1.775	37.1	7.275	1.860	69.9	6.183	1.627	43.3	7.088
	5×5	1.464	39.0	5.347	1.433	33.7	5.689	1.387	47.8	4.658	1.225	34.4	5.396
	$+3$	2.164	64.8	7.977	1.922	38.8	8.147	3.066	220.9	8.509	2.012	64.5	9.151
	$+5$	1.706	44.3	6.212	1.606	35.4	6.308	1.584	54.9	5.268	1.427	37.8	6.188
	$\times3$	2.330	67.0	8.931	2.100	43.7	9.121	3.176	218.1	9.032	2.196	68.8	10.092
	$\times5$	1.617	42.7	5.945	1.522	34.1	6.048	1.574	55.7	5.212	1.380	36.9	6.002
E_f	3×3	1.019	37.7	3.537	0.855	24.5	3.442	1.521	65.0	4.711	1.113	35.6	4.874
	5×5	1.104	34.6	3.957	1.010	27.2	4.033	1.354	47.3	4.522	1.120	32.5	4.957
	$+3$	1.174	57.7	3.866	0.867	29.0	3.754	2.426	212.3	5.754	1.198	53.1	5.607
	$+5$	1.046	36.0	3.611	0.924	25.8	3.629	1.414	52.3	4.596	1.129	33.2	4.937
	$\times3$	1.295	59.5	4.257	1.035	34.8	4.350	2.517	209.6	5.997	1.346	57.4	6.161
	$\times5$	1.053	35.8	3.677	0.930	26.0	3.660	1.420	53.1	4.592	1.108	32.5	4.859
LCP	3×3	2.320	51.2	9.147	2.254	43.1	9.580	2.122	73.1	7.303	2.064	52.9	8.957
	5×5	2.023	45.4	8.014	1.997	41.0	8.517	1.718	57.3	5.922	1.678	44.3	7.336
	$+3$	2.463	65.7	9.456	2.245	42.1	9.694	3.224	218.5	9.227	2.266	62.0	10.250
	$+5$	2.159	47.4	8.440	2.145	42.3	9.043	1.888	61.5	6.472	1.887	47.7	8.128
	$\times3$	2.625	68.1	10.416	2.406	45.9	10.686	3.334	215.2	9.845	2.435	64.1	11.112
	$\times5$	2.084	46.2	8.271	2.063	41.3	8.744	1.879	62.9	6.499	1.829	46.9	8.002
H	3×3	1.889	48.2	7.095	1.739	36.1	7.135	1.984	80.9	6.526	1.581	42.2	6.979
	5×5	1.432	38.4	5.212	1.391	32.6	5.508	1.412	50.0	4.681	1.188	33.0	5.269
	$+3$	2.141	64.0	7.910	1.892	38.0	8.060	3.080	224.1	8.502	2.001	66.0	9.162
	$+5$	1.672	43.3	6.118	1.574	34.7	6.204	1.672	62.5	5.416	1.387	36.9	6.065
	$\times3$	2.303	67.4	8.833	2.072	43.5	9.022	3.215	225.5	9.064	2.207	75.4	10.250
	$\times5$	1.585	42.1	5.824	1.476	33.0	5.868	1.646	61.2	5.390	1.354	36.5	5.918
OSD	3×3	1.101	34.7	3.697	1.009	28.3	3.944	1.967	77.0	6.106	1.531	50.7	6.884
	5×5	1.205	35.9	4.137	1.125	29.8	4.372	1.802	65.9	5.807	1.483	45.5	6.390
	$+3$	1.073	32.6	3.772	0.987	25.6	4.107	1.982	79.3	6.369	1.553	47.1	7.228
	$+5$	1.124	34.6	3.771	1.050	28.9	4.057	1.850	73.6	5.733	1.486	49.2	6.507
	$\times3$	1.323	38.7	4.607	1.261	33.2	5.014	2.192	84.1	7.083	1.773	53.5	8.123
	$\times5$	1.143	35.1	3.875	1.064	29.0	4.135	1.861	74.0	5.836	1.494	49.4	6.528
$COSD$	3×3	0.952	30.5	3.297	0.848	23.5	3.404	1.768	71.4	5.516	1.337	45.2	6.111
	5×5	1.152	34.8	3.972	1.064	28.4	4.116	1.724	62.3	5.551	1.414	43.5	6.057
	$+3$	0.927	30.0	3.355	0.799	20.7	3.466	1.835	79.3	5.859	1.328	39.8	6.345
	$+5$	1.014	31.6	3.458	0.942	25.7	3.637	1.721	69.8	5.340	1.353	45.4	5.909
	$\times3$	1.086	35.8	3.842	0.986	27.6	4.066	1.966	83.3	6.213	1.471	45.3	6.840
	$\times5$	1.037	32.2	3.546	0.956	26.2	3.747	1.734	70.6	5.414	1.355	45.5	5.965
$LUMsm$	3×3	0.808	26.4	2.825	0.738	19.8	2.997	1.515	65.4	4.776	1.141	39.0	5.005
	5×5	0.870	28.7	3.035	0.811	22.5	3.194	1.391	51.3	4.530	1.072	31.3	4.713
	$+5$	0.868	27.3	2.959	0.804	21.4	3.137	1.438	57.1	4.592	1.083	32.7	4.774
	$\times5$	0.871	27.7	2.986	0.814	21.8	3.161	1.470	61.6	4.620	1.083	32.5	4.745

Table 6. Performance of impulse detectors with 3×3 KL_2 norm vector median

Noise		CI10			NI10			CBW20			NBW20		
Method	W	MAE	MSE	CD	MAE	MSE	CD	MAE	MSE	CD	MAE	MSE	CD
E	3×3	2.022	138.5	5.560	1.375	67.0	5.903	3.288	261.0	8.327	1.449	73.7	6.540
	5×5	3.188	281.4	7.401	2.291	179.7	10.412	3.842	306.7	9.913	1.883	128.3	9.390
	$+3$	1.867	87.0	5.896	1.475	45.3	6.036	3.791	343.5	8.867	1.976	116.7	8.580
	$+5$	2.344	185.0	5.917	1.510	91.2	6.649	3.504	279.3	8.909	1.547	89.4	7.267
	$\times3$	2.038	98.2	6.643	1.634	52.7	6.751	3.919	353.6	9.354	2.202	141.0	9.952
	$\times5$	2.279	178.7	5.876	1.543	97.0	6.840	3.489	279.0	8.911	1.522	88.6	7.173
E_p	3×3	1.817	137.1	4.739	1.194	67.6	5.212	3.210	260.3	7.984	1.371	77.5	6.238
	5×5	3.183	282.1	7.382	2.294	180.9	10.450	3.841	306.7	9.909	1.902	130.6	9.455
	$+3$	1.315	82.7	3.753	0.934	41.5	3.953	3.462	340.2	7.517	1.579	114.3	6.990
	$+5$	2.276	185.8	5.648	1.453	93.2	6.506	3.482	279.1	8.821	1.543	93.0	7.266
	$\times3$	1.525	94.5	4.330	1.109	49.2	4.431	3.599	350.4	7.844	1.829	139.7	8.247
	$\times5$	2.242	180.0	5.700	1.514	98.8	6.756	3.475	278.9	8.851	1.529	92.3	7.218
SDV	3×3	1.963	50.0	7.120	1.798	36.9	6.728	1.892	70.5	6.228	1.581	34.7	5.818
	5×5	1.480	39.8	5.260	1.441	33.7	5.114	1.413	48.4	4.728	1.188	28.6	4.259
	$+3$	2.202	65.6	7.850	1.946	38.5	7.549	3.110	221.7	8.546	1.970	56.1	7.770
	$+5$	1.730	45.2	6.100	1.621	35.3	5.762	1.610	55.5	5.317	1.383	31.5	4.985
	$\times3$	2.365	68.0	8.709	2.123	43.6	8.414	3.216	218.9	9.031	2.159	61.6	8.652
	$\times5$	1.637	43.3	5.846	1.535	33.9	5.503	1.601	56.2	5.262	1.345	30.7	4.843
E_f	3×3	1.024	38.2	3.496	0.853	24.1	2.997	1.545	65.5	4.784	1.053	27.0	3.680
	5×5	1.110	35.1	3.910	1.006	27.0	3.545	1.379	47.9	4.596	1.083	26.8	3.864
	$+3$	1.176	57.9	3.840	0.858	28.3	3.326	2.449	212.8	5.813	1.133	44.6	4.395
	$+5$	1.051	36.4	3.595	0.923	25.6	3.177	1.438	52.9	4.666	1.082	27.0	3.801
	$\times3$	1.301	60.1	4.203	1.031	34.4	3.884	2.540	210.2	6.066	1.292	50.1	4.875
	$\times5$	1.057	36.2	3.640	0.926	25.6	3.190	1.444	53.6	4.659	1.066	26.3	3.758
LCP	3×3	2.363	52.4	8.936	2.287	43.0	8.834	2.158	73.8	7.329	2.018	43.3	7.450
	5×5	2.048	46.4	7.787	2.017	41.1	7.748	1.745	58.0	5.992	1.646	38.3	6.034
	$+3$	2.507	66.7	9.254	2.273	41.7	8.932	3.272	219.4	9.240	2.220	52.7	8.649
	$+5$	2.195	48.6	8.210	2.173	42.4	8.292	1.917	62.2	6.496	1.855	41.3	6.722
	$\times3$	2.668	69.4	10.113	2.429	45.7	9.776	3.378	216.2	9.802	2.395	56.1	9.423
	$\times5$	2.117	47.3	8.063	2.088	41.3	8.001	1.911	63.7	6.547	1.800	40.4	6.633
H	3×3	1.922	49.1	6.997	1.760	35.8	6.607	2.015	81.4	6.563	1.536	33.7	5.746
	5×5	1.447	39.0	5.143	1.399	32.5	4.950	1.437	50.6	4.750	1.148	27.2	4.155
	$+3$	2.180	64.8	7.797	1.919	37.7	7.475	3.124	224.9	8.544	1.961	57.6	7.812
	$+5$	1.695	44.1	6.012	1.589	34.6	5.684	1.698	63.0	5.463	1.344	30.7	4.875
	$\times3$	2.339	68.4	8.632	2.095	43.4	8.349	3.255	226.3	9.069	2.170	68.1	8.853
	$\times5$	1.604	42.5	5.739	1.490	32.8	5.343	1.673	61.8	5.444	1.318	30.4	4.786
OSD	3×3	1.107	35.6	3.655	1.000	27.5	3.311	1.985	77.6	6.142	1.433	38.2	4.833
	5×5	1.211	36.8	4.058	1.123	29.6	3.799	1.829	66.8	5.864	1.430	37.8	4.884
	$+3$	1.077	33.2	3.700	0.970	24.6	3.383	2.006	80.1	6.384	1.444	34.9	5.091
	$+5$	1.132	35.5	3.720	1.045	28.4	3.463	1.870	74.3	5.778	1.403	37.7	4.727
	$\times3$	1.330	39.8	4.492	1.243	32.4	4.188	2.219	85.0	7.111	1.676	42.0	5.867
	$\times5$	1.150	36.0	3.807	1.057	28.4	3.523	1.887	74.9	5.887	1.413	37.9	4.782
$COSD$	3×3	0.958	31.2	3.281	0.843	22.9	2.904	1.787	72.0	5.570	1.244	33.1	4.284
	5×5	1.155	35.5	3.894	1.061	28.2	3.583	1.749	63.1	5.599	1.362	36.0	4.636
	$+3$	0.930	30.3	3.336	0.790	20.1	2.936	1.858	79.8	5.896	1.231	28.3	4.511
	$+5$	1.020	32.2	3.432	0.942	25.5	3.157	1.743	70.5	5.395	1.277	34.4	4.323
	$\times3$	1.094	36.7	3.785	0.976	27.0	3.467	1.992	84.1	6.254	1.384	34.5	4.946
	$\times5$	1.039	32.8	3.509	0.951	25.7	3.226	1.759	71.3	5.473	1.279	34.2	4.373
$LUMsm$	3×3	0.813	26.7	2.816	0.735	19.4	2.634	1.540	66.1	4.851	1.072	28.6	3.700
	5×5	0.874	28.9	3.020	0.808	22.2	2.803	1.417	52.0	4.602	1.029	25.4	3.631
	$+5$	0.874	27.7	2.941	0.801	21.0	2.736	1.462	57.6	4.671	1.039	26.6	3.657
	$\times5$	0.876	28.1	2.980	0.811	21.4	2.770	1.496	62.3	4.689	1.042	26.7	3.633

Fig. 3. (a) Original image (b) 10% correlated impulse noise - CI10 (c) 10% uncorrelated impulse noise -NI10 (d) 20% correlated salt and pepper noise - CBW20 (e) 20% uncorrelated salt and pepper noise - NBW20 (f) CI10 filtered by 3×3 LUMsm detector + 3×3 vector median

4.2 Vector median

In dependence on the used norm L the output of vector median (VMF) [1,18] is given by

$$\sum_{i=1}^{N} ||\vec{y}-\vec{x}_{)}i|| \leq \sum_{i=1}^{N} ||\vec{x}_j-\vec{x}_{)}i||. \tag{27}$$

$\vec{y}$ is the output vector and $\vec{x}_i$ is a vector from the input set. For norm L of vector median the L_1 or L_2, *ie* componentwise distance or Euclidean distance are used, separately. The selected norm affects the detail preservation and noise reduction properties of VMF. The output of VMF is always one of the input vectors and thus new artefacts can not be introduced into the image. Vector medians have better performance near edges and other high-frequency elements than the scalar median.

5 CONCLUSION

Processing of noised colour images is performed not only with consideration of signal detail preservation and noise suppression, however, a measure of colour artefacts must be employed. Note that the threshold value of CD for Luv colour space, *ie* a minimal value, that human eyes are able to differentiate was establish around 2.9.

This paper was focused on impulse noise suppression by utilizing the impulse detectors with a median filter or vector median. As shown in Table 1, the vector median has its substantion, since achieves small colour difference in comparison with componentwise median. In addition, in the case of non correlated impulse noise, in term of MAE and MSE the vector median achieves better results than the median.

However, both median and vector median introduce blurring into the output image by filtering each image sample and, thus, small signal features are removed. On that account impulse detectors were developed that make decision about the noise presence. In this case, filter is used in the case of impulse detection only, whereas noise free samples are passed on the filter output without any change.

As shown in Table 5 and Table 6, excellent results can be obtained in this simple way. Besides extremely low values of MAE and MSE, *eg* in the case of LUMsm detector or LCP, H, COSD, E_f detectors, it is possible to perform image reconstruction so that the achieved colour difference is smallest or very near around the threshold value 2.9. Results under the threshold value were obtained by excellent LUMsm detector in the suppression of 10% correlated and non-correlated impulse noise.

The performance of singe impulse detectors was evaluated through MCL and SCL as shown in Table 2. From these results it can be seen that non-correlated impulse noise is more easily detected than the correlated variant of impulse noise. In addition, in the case of salt and pepper noise the successful detection (SCL) was performed near or to maximum value of 100%. Thus, the performance of the impulse detector with a median or vector median filter was dependent on a number of miss classified impulses (MCL). The excellent LUMsm detectors achieve very high SCL and their MCL is very low and, thus, LUMsm detectors provide the best compromise between success and miss classification.

Other detectors are distinguished by good performance of success classification, *eg* SDV, LCP or H detector, however, their MCL is relatively high, too.

By this work, we finish a two year long research in area of impulse detection in the standard gray and colour static and dynamic images. We would like to point at the underestimated position of impulse detectors in image filtering. In our previous works we presented detection properties and performance of impulse detectors in gray scale images [4,5,6,11,15,16] and dynamic images [8,9], too. Now, impulse detectors were used in vector environments [11] corrupted by impulse noise. Besides standard image applications, *ie* office and administration, as a next use of impulse detectors we tried to find the place in modern satellite technologies as CDMA, where impulse detectors with an appropriate filter would play the role of signal recovering.

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Rastislav Lukáč (Ing, PhD) received the Ing (MSc) degree from the Technical University of Košice, Slovakia. In 2001 he finished his PhD study and currently is Assistaant Professor at the Department of Electronics and Multimedia Communications at the Technical University of Košice. His research interest includes image filtering, impulse detection, neural network and permutations.

Stanislav Marchevský (Doc, Ing, PhD) received the MSc degree in electrical engineering from the Faculty of Electrical Engineering, Czech Technical University in Prague, in 1976 and PhD degree in radioelectronics from the Technical University in Košice in 1985. Since 2001 he has been Full Professor at FEI TU in Košice. His research interest includes image filtering and multimedia communication.