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Bogdan SMOLKA, Robert BIEDA*

APPLICATION OF THE ADAPTIVE NOISE REMOVAL TECHNIQUE TO THE ENHANCEMENT OF cDNA MICROARRAY IMAGES

In this paper a novel class of filters designed for the removal of impulsive noise in colour images is presented. The proposed filter family is based on the kernel function which controls the noise suppression properties of the new filtering scheme. The comparison of the new filtering method with the standard techniques used for impulsive noise removal indicates its superior noise removal capabilities and excellent structure preserving properties. The proposed filtering scheme has been successfully applied to the denoising of the cDNA microarray images. Experimental results proved that the new filter is capable of removing efficiently the impulses present in multichannel images, while preserving their textural features.

1. INTRODUCTION

The correction of the signal distorsions is a digital process, by which disturbances introduced by the sensor system are rectified, with the goal being to obtain the image or generally the signal, which corresponds as closely as possible to the output of an ideal imaging system. Thus, correcting signal artifacts, in practice means adjusting the characteristics of the imaging system to meet specific demands of the human observer or the computer vision system, [17,18,21].

Digital image processing is based on the conversion of a continuous image field into an equivalent digital form. The synthesis of images from the signals arising from various sensor systems is accomplished by a digital process directed to transforming the signal into a form allowing visual or machine perception. The requirements for an ideal conversion system are usually expressed in terms of certain technical properties such as the resolution of the imaging systems, photometric accuracy, quantization levels, intensity of intrinsic noise and many others.

Improvement of the image quality has always been one of the central tasks of digital image processing. In modern terms, improvements in sensitivity, resolution and noise reduction have equated higher quality with greater informational throughput. Image noise is an unwanted feature, which is either contained in the relevant light signal or is added by the imaging process and it compromises a precise evaluation of the light signal distribution, which should be measured.

During image *formation*, *acquisition*, *storage* and *transmission* many types of distorsions limit the quality of digital images. Transmission errors, periodic or random motion of the camera system during exposure, electronic instability of the image signal, electromagnetic interferences, sensor malfunctions, optic imperfections or aging of the storage material, all disturb the image quality.

* Silesian University of Technology, Dept. of Automatic Control, Akademicka 16, 44-100 Gliwice, Poland

In many practical situations, images are corrupted by the so called *impulsive noise* caused mainly either by faulty image sensors or due to transmission errors resulting from man-made phenomena such as ignition transients in the vicinity of the receivers or even natural phenomena such as lightning in the atmosphere.

In this paper we address the problem of impulsive noise removal in colour images and propose an efficient adaptive technique capable of removing the impulsive noise and preserving important colour image features.

The paper is organized as follows. In Section 2 a short overview of the basic multichannel filtering schemes is provided. Then the new filtering approach is introduced and its similarity to existing filtering schemes is discussed. Section 4 covers the experimental results performed on the test images contaminated with impulsive noise. Section 5 is devoted to the application of the proposed technique to the denoising of the images of microarrays. The paper ends with a brief conclusion.

2. VECTOR MEDIAN BASED FILTERS

Mathematically, a $N_1 \times N_2$ multichannel image is a mapping $Z^l \rightarrow Z^m$ representing a two-dimensional matrix of m-component samples (pixels), $\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{im}) \in Z^l$, where l is the dimension of the image domain and m denotes the number of channels, (in the case of standard color images, parameters l and m are equal to 2 and 3, respectively). Components x_{ik}, for $k = 1, 2, \ldots, m$ and $i = 1, 2, \ldots, N$, $N = N_1 \cdot N_2$, represent the colour channel values quantified into the integer domain, [11].

The majority of the nonlinear, multichannel filters are based on the ordering of vectors in a sliding filter window. The output of these filters is defined as the lowest ranked vector according to a specific vector ordering technique, [2,8].

Let the colour images be represented in the commonly used RGB color space and let $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$ be n m-dimensional samples from the sliding filter window W, with $\mathbf{x}_1$ being the central element in W. The goal of the vector ordering is to arrange the set of n vectors $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$ belonging to W using some sorting criterion. In [22] the ordering based on the cumulative distance function $R(\mathbf{x}_i)$ has been proposed

$$R(\mathbf{x}_i) = \sum_{j=1}^{n} \rho(\mathbf{x}_i, \mathbf{x}_j), \tag{1}$$

where $\rho(\mathbf{x}_i, \mathbf{x}_j)$ is a function of the distance between $\mathbf{x}_i$ and $\mathbf{x}_j$. The increasing ordering of the scalar quantities $\{R_1, R_2, \ldots, R_n\}$ generates the ordered set of vectors $\{\mathbf{x}_{(1)}, \mathbf{x}_{(2)}, \ldots, \mathbf{x}_{(n)}\}$.

One of the most important noise reduction techniques is the *Vector Median Filter* (VMF), [2] for which $\sigma(x_i, x_j) = \left\| x_i - x_j \right\|$. Given a set W containing n vectors, the *Vector Median* of the set is defined as vector $\mathbf{x}_{(1)} \in W$ satisfying

$$\sum_j \left\| \mathbf{x}_{(1)} - \mathbf{x}_j \right\| \leq \sum_j \left\| \mathbf{x}_i - \mathbf{x}_j \right\|, \quad \mathbf{x}_i, \mathbf{x}_j \in W. \tag{2}$$

In [1, 24, the VMF concept has been generalized and the so-called *Weighted Vector Median Filter* (WVMF) has been proposed. Using the *Weighted Vector Median* approach, the filter output is the vector $\mathbf{x}_{(1)}$ belonging to W, for which the following condition holds

$$\sum_{j=1}^{n} \psi_j \, \rho(\mathbf{x}_{(1)}, \mathbf{x}_j) \le \sum_{j=1}^{n} \psi_j \, \rho(\mathbf{x}_k, \mathbf{x}_j), \quad k = 1, \ldots, n. \tag{3}$$

If $\psi_1 > 1$ and $\psi_k = 1$ for $k = 2, \ldots, n$, ($\psi = \{\psi_1, 1, 1 \ldots, 1\}$), then the *Central Weighted VMF* (CWVMF) is obtained, [20,19,3].

An efficient modification of the CWVMF called *Modified CWVMF* (MCWVMF) was proposed in [14-16]. The modified technique has the ability of noise removal, while preserving fine image details, (lines, edges, corners, texture) and it outperforms the standard CWVMF as shown in [14,15].

Within the framework of the ranked type nonlinear filters, the orientation difference between input vectors can also be used to remove samples with atypical directions. The *Basic Vector Directional Filter* (BVDF) is a ranked order filter, similar to the VMF, which uses the angle between two vectors as the *distance measure*. In the directional processing of colour images, [13,23] each input vector $\mathbf{x}_k$ is associated with the aggregated *angular measure*.

The sample $\mathbf{x}_{(1)}$ associated with the minimal angular distance, i.e. the sample minimizing the sum of angles with other vectors, represents the output of the BVDF, [23]. A drawback of the BVDF is that since it uses only information about vector directions (chromaticity information), it cannot remove achromatic noisy pixels.

To improve the efficiency of the directional filters, another method called *Directional-Distance Filter* (DDF) was proposed, [6]. The DDF is a combination of VMF and BVDF and is derived by simultaneous minimization of their defining functions,[23]. Another efficient rank-ordered operation called *Hybrid Directional Filter* (HDF) was proposed in [5]. This filter operates on the direction and the magnitude of vectors independently and then combines them to produce a final output.

3. PROPOSED FILTERING DESIGN

The well known local statistic filters constitute a class of linear minimum mean squared error estimators and are based on the non-stationarity of the signal and the noise model, [7]. These filters make use of the local mean and the variance of the input set $W = \{x_1, x_2, \ldots, x_n\}$ and define the filter output for the grey-scale images as

$$y_i = \hat{x}_i + \alpha\left(x_i - \hat{x}_i\right) = \alpha x_i + (1-\alpha)\hat{x}_i, \tag{4}$$

where $\hat{x}_i$ is the arithmetic mean of the image pixels belonging to the filter window W centered at a pixel position i and α is a filter parameter usually estimated through, [20]

$$\alpha = \frac{\sigma_x^2}{\sigma_n^2 + \sigma_x^2}, \; \hat{x}_i = \frac{1}{n}\sum_{k=1}^{n} x_k, \; \nu^2 = \frac{1}{n}\sum_{k=1}^{n}\left(x_k - \hat{x}_i\right)^2, x_k \in W,$$

$$\sigma_x^2 = \max\left\{0, \nu^2 - \sigma_n^2\right\}, \alpha = \max\left\{0, 1 - \sigma_n^2/\nu^2\right\}, \tag{5}$$

where ν^2 is the local variance calculated from the samples in the filter window and σ_n^2 is the estimate of the variance of the noise process. If $\nu >> \sigma_n$, then $\alpha \approx 1$ and practically no changes are introduced. When $\nu < \sigma_n$, then $\alpha = 0$ and the central pixel is replaced with the local mean. In this way, the filter smooths with the local mean, when the noise is not very intensive and leaves the pixel value unchanged, when a strong signal activity is detected. The major drawback of this filter is that it **fails to remove impulses** and leaves noise in the vicinity of high gradient image features.

Equation (4) can be rewritten using the notation $x_i = x_1$, as

$$y_1 = \alpha x_i + (1-\alpha)\hat{x}_i = \alpha x_1 + (1-\alpha)\hat{x}_1 = (1-\alpha)\left(\psi_1 x_1 + x_2 + \ldots + x_n\right)/n, \tag{6}$$

with $\psi_1 = (1 - \alpha + n\alpha)/(1-\alpha)$ and the local statistic filter defined by (4) is reduced to the *Central Weighted Average*, with a weighting coefficient ψ_1. In this way the set of weights $\{\psi_1, 1, 1, \ldots, 1\}$ is assigned to the set of pixels in the filtering window $\{x_1, x_2, \ldots, x_n\}$

$$y_1 = \frac{1}{n + \psi_1 - 1}\sum_{k=1}^{n} \psi_k x_k = \frac{n}{n + \psi_1 - 1}\left[\hat{x}_1 + \frac{\psi_1 - 1}{n} x_1\right] = \tag{7}$$

$$= \left(\frac{n}{n + \psi_1 - 1}\right)\hat{x}_1 + \left(\frac{\psi_1 - 1}{n + \psi_1 - 1}\right) x_1 = (1-\alpha)\hat{x}_1 + \alpha x_1, \alpha = \frac{\psi_1 - 1}{n + \psi_1 - 1}.$$

If the weighting is applied to the ordered sequence of grey-scale samples belonging to $W := \{x_{(1)}, \ldots, x_{(\mu)}, \ldots, x_{(n)}\}$, where $x_{(1)}$ and $x_{(n)}$ are the minimal and maximal pixel values and $x_{(\mu)}$, $(\mu = (n+1)/2)$ denotes the median of the input set, then

$$y_1 = \frac{1}{\sum_{k=1}^{n} \psi_k}\sum_{k=1}^{n} \psi_k x_{(k)}. \tag{8}$$

Taking the weighting set $\{1, 1, \ldots, \psi_\mu, \ldots, 1\}$ special emphasis is given to the median of the input set $x_{(\mu)}$. Hence

$$y_1 = \left(\frac{n}{n + \psi_\mu - 1}\right)\hat{x}_1 + \left(\frac{\psi_\mu - 1}{n + \psi_\mu - 1}\right) x_{(\mu)} = (1-\alpha)\hat{x}_1 + \alpha x_{(\mu)}, \tag{9}$$

which is a compromise between the median $x_{(\mu)}$ and the average $\hat{x}_1$ controlled by the parameter α.

Let us now apply a weighting structure defined by the weights $\{1, 0, \ldots, \psi_\mu, \ldots, 0\}$. Such a setting of the weights leads to the output defined by

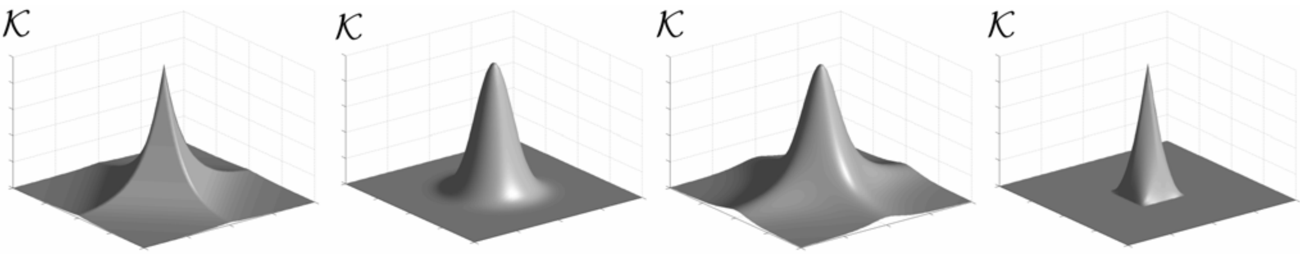
$$y_1 = \frac{1}{1 + \psi_\mu}\left(x_1 + \psi_\mu x_{(\mu)}\right) = \alpha x_1 + (1-\alpha) x_{(\mu)}. \tag{10}$$

If we work on the set of ordered vectors $\{\mathbf{x}_{(1)}, \mathbf{x}_{(2)}, \ldots, \mathbf{x}_{(n)}\}$ then (11) can be rewritten as

$$y_1 = \frac{1}{1+\psi_1}\left(\mathbf{x}_1 + \psi_1 \mathbf{x}_{(1)}\right) = \alpha \mathbf{x}_1 + (1-\alpha)\mathbf{x}_{(1)}\,, \tag{11}$$

where the weighting set is defined as: $\{\psi_1, 0, \ldots, 0, 1, \ldots, 0\}$ in which the weight ψ_1 is assigned to the *Vector Median* $\mathbf{x}_1$ of the input set from W and 1 is assigned to the central pixel $\mathbf{x}_1$.

Clearly, the new filter structure, which will be denoted as KVMF (*Kernel based VMF*), defined by (11) is similar to approaches defined by (4), (6) and (9). However, as our aim is to construct a filter capable of removing impulsive noise, **instead of the mean value, the VMF output is utilized** and the noise intensity estimation mechanism is accomplished through the coefficient α, which can be defined as a kernel function, known from the nonparametric probability density estimation, (Tab. 1, Fig. 1).



(L) (G) (C) (T)

Fig. 1. Plots of the kernel functions: L-Laplacian, G-Gaussian, C-Cauchy, T-Triangle, (see Tab. 1).

Table 1. Krenel function, x=<-1,1>, h = <0,∞), $[f(x)]^+$ denotes f(x) for x>0 and 0 otherwise

Kernel	$\mathrm{K}(x)$	$\kappa(x) = \gamma_h \mathrm{K}(x)$	γ_1
(L)	$e^{-\left\|\frac{x}{h}\right\|}$	$\frac{1}{2h} e^{-\left\|\frac{x}{h}\right\|}$	$\frac{1}{2}$
(G)	$e^{-\frac{x^2}{2h^2}}$	$\frac{1}{\sqrt{2\pi}h} e^{-\frac{x^2}{2h^2}}$	$\frac{1}{\sqrt{2\pi}}$
(C)	$\dfrac{1}{1+\frac{x^2}{h^2}}$	$\dfrac{1}{\pi h}\dfrac{1}{1+\frac{x^2}{h^2}}$	$\dfrac{1}{\pi}$
(T)	$[1-\left\|\frac{x}{h}\right\|]^+$	$\left[\dfrac{h(1-\left\|\frac{x}{h}\right\|)}{2h-1}\right]^+$	1
(E)	$[1-\left\|\frac{x^2}{h^2}\right\|]^+$	$\left[\dfrac{3h^2(1-\left\|\frac{x^2}{h^2}\right\|)}{6h^2-2}\right]^+$	$\frac{3}{4}$

The proposed KVMF technique is a **compromise** between the VMF and identity operation. When an impulse is present, then it is being detected by $\alpha = f\left(\left\|x_1 - x_{(1)}\right\|\right)$, which is a decreasing function of the distance between the central pixel $x_i = x_1$ and the *Vector Median* $x_{(1)}$, and the output y_1 is close to the VMF as α approaches 0. If the central pixel is not disturbed by the noise process, then α is close to 1 and the output is close to the original value x_1. If the central pixel in x_i is denoted as x_1, the vector norm as $\|\cdot\|$ and the coefficient α is replaced by kernel function κ, then

$$y_i = x_{(i)} + \mathrm{K}\left(x_1, x_{(1)}\right) \cdot \left(x_1 - x_{(1)}\right), \tag{12}$$

Table 2. Efficiency of the proposed filter in comparison with standard multichannel filters using the LENA image; h_{opt} and h_{est} denote the optimal (best possible) and estimated value of the bandwidth parameter of the appropriate kernel function.

Filtering efficiency, (PSNR, [dB])						
Noise	p = 1%		p = 3%		p=5%	
Kernel	h_{opt}	h_{est}	h_{opt}	h_{est}	h_{opt}	h_{est}
L	40.75	40.70	37.92	37.90	36.38	36.35
G	39.22	39.22	36.96	36.95	35.68	35.67
C	39.65	39.39	37.11	37.03	35.72	35.67
T	40.46	40.45	37.76	37.76	36.27	36.27
E	40.87	40.81	37.96	37.94	36.39	36.34
VMF	33.33		32.94		32.58	
DDF	32.90		32.72		32.25	
BDF	32.04		31.81		31.14	
HDF	33.28		32.89		32.49	
CWVMF	36.98		34.04		32.52	
MCWVMF	38.54		34.88		33.42	

$$y_i = \kappa x_1 + (1-\kappa)x_{(1)}, \kappa = f\left(\left\|x_1 - x_{(1)}\right\|\right) \tag{13}$$

In this way the proposed structure can be seen as a modification of the commonly used techniques applied for the suppression of the Gaussian noise. However, in the described technique we replace the arithmetic mean of the pixels in *W* with the *Vector Median* and such an approach proves to be capable of removing strong impulsive noise, while preserving the image details.

It is interesting to observe that the filter output y_i lies on the line joining the vectors $x_i(x_1)$ and $x_{(1)}$ and depending on the value of the kernel function κ, it slides from the identity operation (x_1) to the vector median $x_{(1)}$, (Fig. 2).

The efficiency of the proposed filtering scheme depends strongly on the bandwidth parameter *h* in the kernel function, (Tab. 1). The experiments performed on a wide range of natural images contaminated by different types of impulsive noise with varying intensities have shown that satisfactory efficiency of the proposed algorithm is achieved when using the following approximation of the optimal bandwidth

$$h_{est} = \frac{\gamma_1}{\sqrt{\hat{\sigma}}}, \hat{\sigma}^2 = \sum_{i=1}^{N} \frac{(x_i - \hat{x}_i)^2}{N^2} \tag{14}$$

where $\hat{\sigma}$ is the mean value of the approximation of standard deviation, calculated using the whole image or randomly selected image pixels and γ_1 is the coefficient of the kernel function taken from Tab. 1. The comparison of the real and estimated values of the bandwidth is shown in Fig. 3. As can be seen, a very good approximation has been achieved for the simplest linear triangle function (T), which is also reflected in terms of the achieved PSNR values presented in Tab. 2. Therefore the use of the triangular kernel function is recommended in applications in which the processing time plays a crucial role.

4. EXPERIMENTAL RESULTS

The noise modelling and evaluation of the efficiency of noise removal methods using the widely used test images allows the objective comparison of the noisy, restored and original images. In this paper we assume a noise model, [12,17] which reflects well the signal corruption and allows to simulate the correlation among noisy image channels. The sample distortion is given by

$$x_i = \begin{cases} o_i, & \textit{with probability } 1-p \\ \{v_i, o_{i2}, o_{i3}\}, & \textit{with probability } p_1 p \\ \{o_{i1}, v_i, o_{i3}\}, & \textit{with probability } p_2 p \\ \{o_{i1}, o_{i2}, v_i\}, & \textit{with probability } p_3 p \\ \{v_i, v_i, v_i\}, & \textit{with probability } p_4 p \end{cases} \tag{15}$$

where **o** is the original signal, p is the sample corruption probability and p_1, p_2, p_3 are corruption probabilities of each colour channel, so that $\sum_1^4 p_k = 1$. The impulses v_i are random-valued variables in the range [0,255] and p_k=0,25 was chosen for the evaluations. The impulsive noise suppression efficiency was measured using the PSNR

$$PSNR = 20\log_{10}\left(\frac{255}{\sqrt{MSE}}\right), MSE = \frac{\sum_{i=1}^{N}\sum_{k=1}^{m}(x_{ik}-o_{ik})^2}{Nm} \tag{16}$$

The efficiency of the proposed filtering approach is summarized in Tab. 2 and also presented in Fig. 4. As can be seen the dependence on the kind of the kernel function is not, as expected, very strong. The main problem however, is to find an optimal bandwidth parameter h, as the proper setting of the bandwidth guarantees good performance of the proposed filtering design.

The comparison of the efficiency of the proposed scheme in terms of PSNR for the optimal values of h and estimated by the *rule of thumb* defined by (14) is shown in Tab. 2 and in Fig. 3. Practically the h_{est} yields almost the best possible impulsive noise attenuation for all applied kernels.

The illustrative examples depicted in Fig. 5 show that the proposed filter efficiently removes the impulses and preserves edges and small image details. Additionally due to its smoothing nature it is also able to suppress to some extent the Gaussian noise present in natural images.

5. APPLICATION TO DENOISING OF MICROARRAY IMAGES

The cDNA microarray is a popular and effective method for simultaneous assaying the expression of large numbers of genes and is perfectly suited for the comparison of gene expression in different populations of cells. A microarray is a collection of spots containing DNA, deposited on the surface of a glass slide. Each of the spots contains multiple copies of a single DNA sequence, [9,4,10].

The probes are tagged with fluorescent reporter molecules, which emit detectable light when stimulated by laser. The emitted light is captured by a detector, which records the light intensity. When the laser scans the entire slide, a large array image containing thousands of spots is produced. The fluorescent intensities for each of the two dyes are measured separately, producing a two-channel image of very large dimensions.

The intensities provided by the array image can be quantified by measuring the average or integrated intensities of the spots. However, the evaluation of microarray images is a difficult task as the natural fluorescence of the glass slide and non-specifically bounded DNA or dye molecules add a substantial noise floor to the microarray image. To make the task even more challenging, the microarray images are also afflicted with discrete image artifacts, such as highly fluorescent dust particles, unattached dye, salt deposits from evaporated solvents, fibers and various airborne debris. So, the task of fast microarray image enhancement and especially the removal of artifacts is of paramount importance.

The good performance of the proposed switching scheme, when applied to the denoising of the microarray images can be observed in Fig. 6, which depicts the results of impulsive noise suppression. It can be noticed that the proposed filter removes the spikes only, while preserving the textural information. Therefore the application of the proposed filter is advantageous, as it is extremely fast and does not change the statistical properties of the spots, which enables accurate determination of the spots intensities.

6. CONCLUSION

In this paper an adaptive soft-switching scheme based on the *Vector Median* and a kernel-based similarity function has been presented. The proposed filtering structure is superior to the commonly used standard filtering schemes and can be applied for the removal of impulsive noise in natural images. It is relatively fast and the proposed adaptive bandwidth estimator enables automatic filtering independent of noise intensity.

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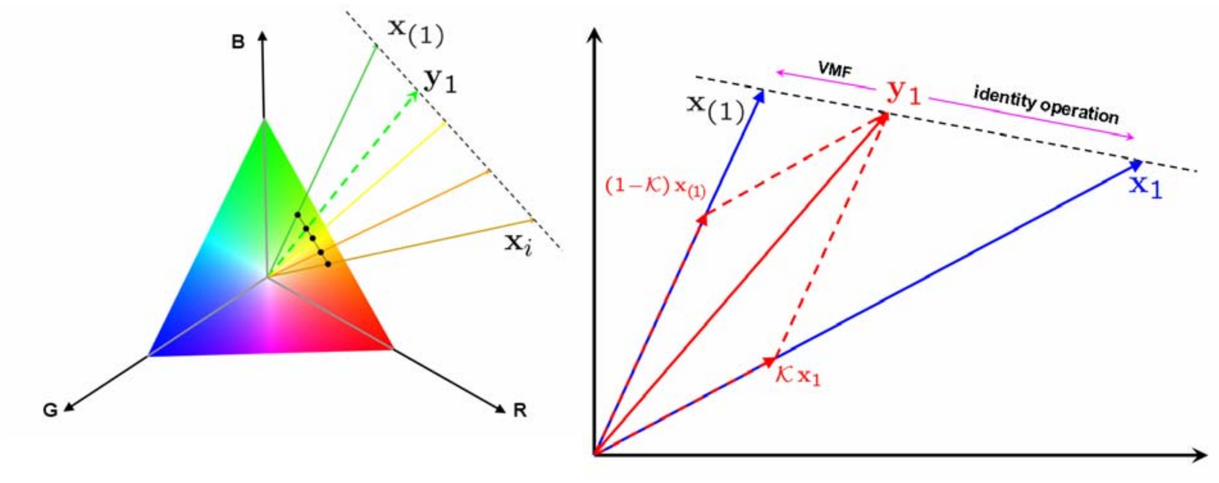

Fig. 2. Vector y_i lies on the line connecting the vector x_i and $x_{(1)}$ in the RGB space.

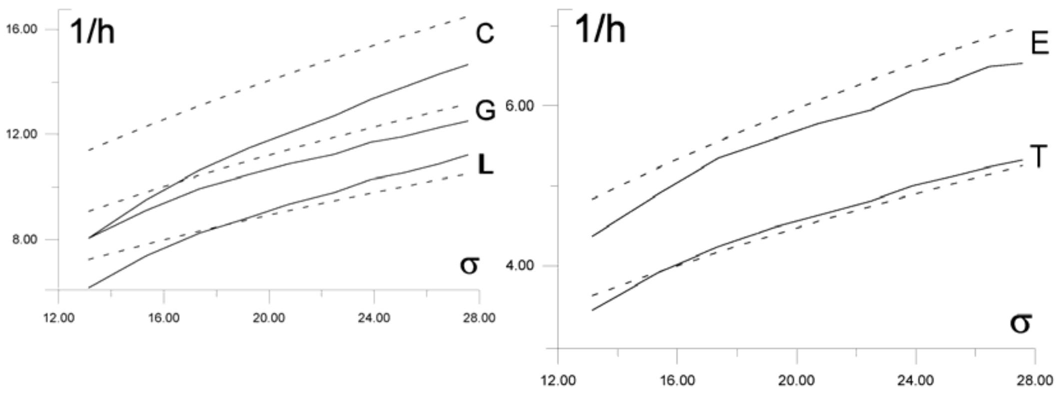

Fig. 3. Comparison of the estimated, (dashed line) and optimal bandwidth, (solid line) as functions of the noise intensity expressed through σ for the *LENA* image.

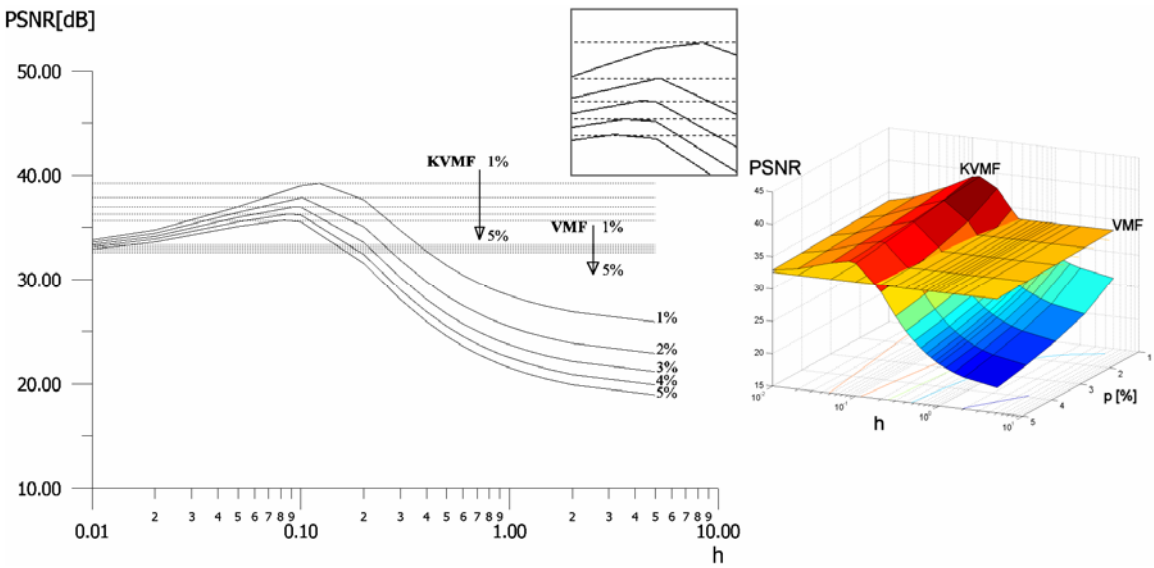

Fig. 4. Dependence of the PSNR on the *h* parameter of the L kernel, forp=1% - 5% in comparison with VMF, (*LENA* image). The dotted lines indicate the optimal value of PSNR achievable by the KVMF filter and the VMF. In the corner the magnified parts of the plots are presented. Besides, the dependence of the PSNR on the *h* parameter for the KVMF with the L kernel in comparison with the VMV for *p* ranging from 1% to 5% is presented.

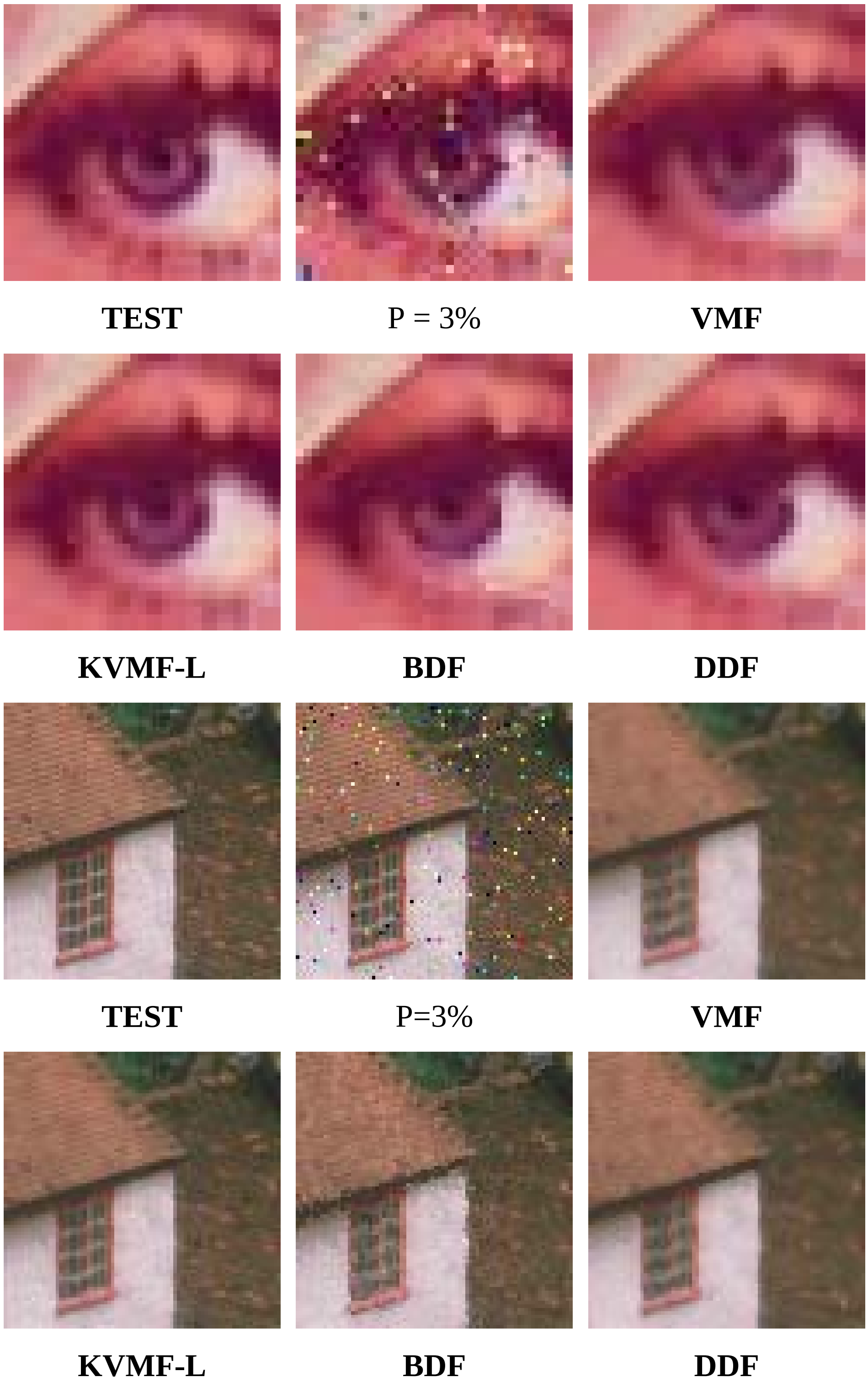

Fig. 5. Comparison of the filtering efficiency of the proposed filter with the Laplace kernel (KVMF-L) with the VMF, BDF and DDF methods.

(a)
(b)
(c)

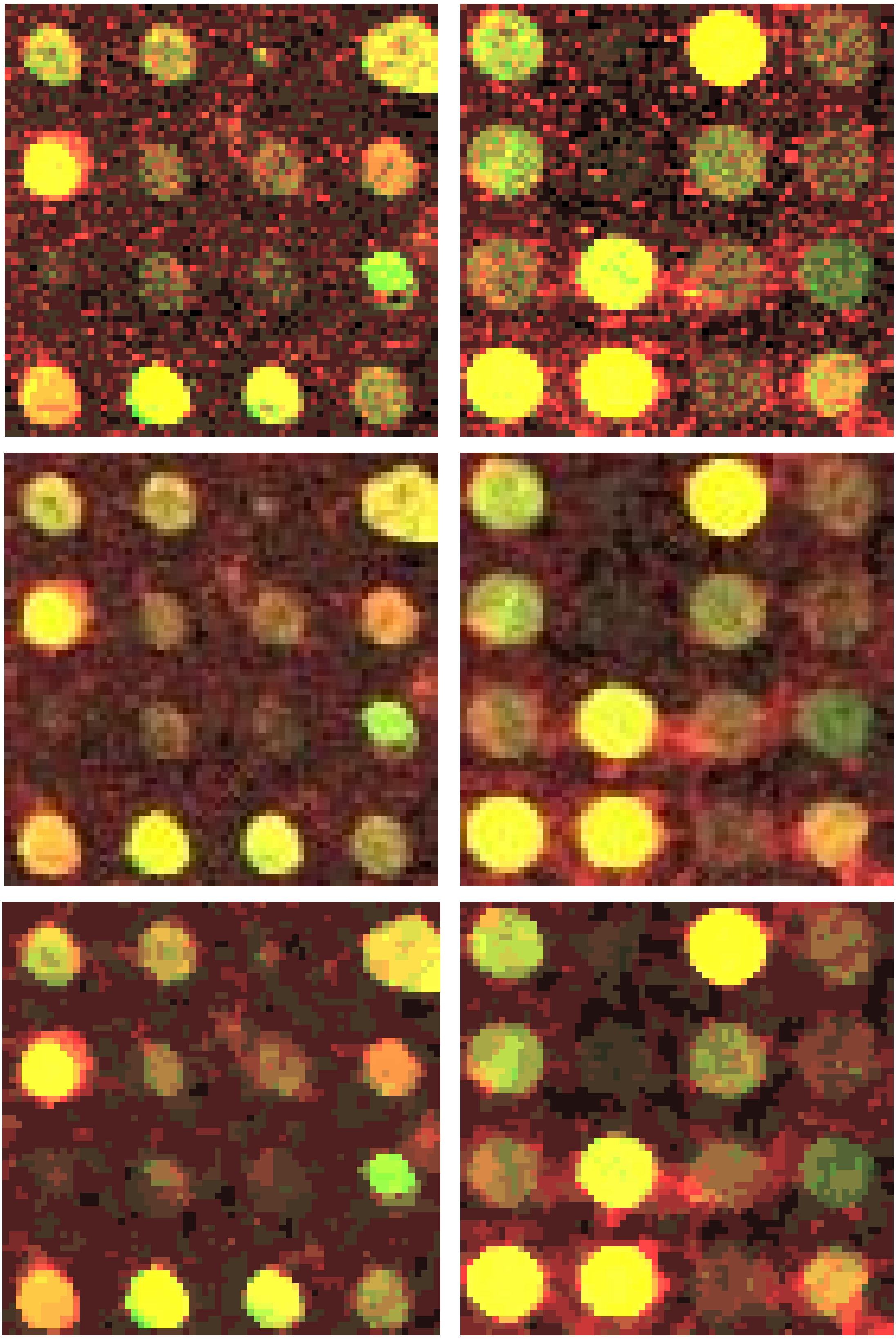

Fig. 6. Efficiency of the proposed noise removal technique when applied to the images of microarrays:
a) test images, b) filtered with the new method, c) output of the VMF. Note that the proposed method does not generate the artificial bloches visible in the VMF output.