On the reduction of impulsive noise in multichannel image processing

B. Smolka
A. Chydzinski
K. W. Wojciechowski
Department of Automatics, Electronics and Computer Science
Silesian University of Technology
Akademicka 16 Str
44-101 Gliwice, Poland
E-mail: bsmolka@ia.polsl.gliwice.pl

K. N. Plataniotis
A. N. Venetsanopoulos
Edward S. Rogers Sr. Department of Electrical and Computer Engineering
University of Toronto
10 King's College Road
Toronto, Ontario M5S 3G4, Canada
E-mail: kostas@dsp.toronto.edu

Abstract. A new approach to the problem of impulsive-noise reduction for color images is introduced. The major advantage of the technique is that it filters out the noise component while adapting itself to the local image structures. In this way the algorithm is able to eliminate strong impulsive noise while preserving edges and fine image details. As the algorithm is a fuzzy modification of the commonly used vector median operator, it is very fast and easy to implement. Our results show that the proposed method outperforms all standard algorithms for the reduction of impulsive noise in color images. [DOI: 10.1117/1.1367347]

Subject terms: color image processing; multichannel filters; impulsive noise; adaptive techniques.

Paper 200270 received July 6, 2000; revised manuscript received Dec. 29, 2000; accepted for publication Jan. 10, 2001.

1 Introduction

The processing of color image data has received much attention in recent years. The amount of research published to date indicates increasing interest in the area. It is widely accepted that color conveys very important information about the scene objects and this information can be used to further refine the performance of an imaging system.

The most common image-processing tasks are noise filtering and image enhancement. These tasks are an essential part of any image processor, whether the final image is utilized for visual interpretation or for automatic analysis.[1]

As it has been generally recognized that the nonlinear vector processing of color images is the most effective way to filter out noise and to enhance the images, the new filtering technique presented in this paper is also nonlinear and utilizes the correlation of a color image among the channels.[2,3]

This paper is divided into four main parts. In Sec. 2, a brief overview of the standard noise reduction operations for color images is presented. Section 3 shows the construction of the new algorithm of image enhancement. In Sec. 4 we focus on the computational complexity of the proposed filter, and Sec. 5 depicts the results of noise attenuation achieved using the proposed algorithm in comparison with the standard noise suppression techniques.

2 Standard Noise Reduction Filters

A number of nonlinear multichannel filters, which utilize correlation among multivariate vectors using various distance measures, have been proposed to date.[4–6] The most popular nonlinear multichannel filters are based on the ordering of vectors in a predefined moving window. The output of these filters is defined as the lowest-ranked vector according to a specific ordering technique.

Let $\boldsymbol{F}(x): Z^p \rightarrow Z^p$ represent a multichannel image, and let $W \in Z^p$ be a window of finite size n (filter length). The noisy image vectors inside the window W are denoted as $\mathbf{F}_j,\ j=1,2,\ldots,n$. If the distance between two vectors $\mathbf{F}_i, \mathbf{F}_j$ is denoted as $d(\mathbf{F}_i, \mathbf{F}_j)$, then the scalar quantity

$$D_i = \sum_{j=1}^{n} d(\mathbf{F}_i, \mathbf{F}_j), \tag{1}$$

is the distance associated with the noisy vector $\mathbf{F}_i$ inside the processing window. An ordering of the D_i's,

$$D_{(1)} \leqslant D_{(2)} \leqslant \cdots \leqslant D_{(n)}, \tag{2}$$

implies the same ordering to the corresponding vectors $\mathbf{F}_j$,

$$\mathbf{F}_{(1)} \leqslant \mathbf{F}_{(2)} \leqslant \cdots \leqslant \mathbf{F}_{(n)}. \tag{3}$$

Nonlinear ranked-type multichannel estimators define the vector $\mathbf{F}_{(1)}$ as the filter output. This selection is due to the fact that vectors that diverge greatly from the data population usually appear in higher-indexed locations in the ordered sequence. However, the concept of input ordering, initially applied to scalar quantities, is not easily extended to multichannel data, since there is no universal way to define ordering in vector spaces.

To overcome the problem, distance functions are often utilized to order vectors. As an example, the *vector median filter* (VMF) uses the L_1 or L_2 norm in Eq. (1) to order vectors according to their relative magnitude differences.[4,7]

The orientation difference between two color vectors can also be used as their distance measure. This so-called *vector angle criterion* is used by *vector directional filters*

(VDFs) to remove vectors with atypical directions.[5,8] The type of the distance metric used to order the color input vectors greatly affects the performance of the filter. For this reason, different kinds of vector distances are applied to increase the efficiency of the multichannel noise reduction algorithms.

The *basic vector directional filter* (BVDF) is a ranked-order, nonlinear filter that parallelizes the VMF operation. However, a distance criterion different from the L_1, L_2 norm used in VMF is utilized to rank the input vectors. The angular distance criterion used in BVDF is defined as a scalar measure

$$A_i = \sum_{j=1}^{n} a(\mathbf{F}_i, \mathbf{F}_j), \quad \text{with} \quad a(\mathbf{F}_i, \mathbf{F}_j) = \cos^{-1}\left(\frac{\mathbf{F}_i \mathbf{F}_j^T}{|\mathbf{F}_i|\,|\mathbf{F}_j|}\right), \tag{4}$$

as the distance associated with the noisy vector $\mathbf{F}_i$ inside the processing window of length n. The output of the BVDF is that vector from the input set that minimizes the sum of the angles with the other vectors. In other words, the BVDF chooses the vector most centrally located without considering the magnitudes of the input vectors.

To improve the efficiency of the directional filters, a new method called the *directional-distance filter* (DDF) was proposed.[5] This filter retains the structure of the BVDF, but utilizes a new distance criterion to order the vectors inside the processing window.

To enhance the rank-ordered operations, a technique called the *hybrid directional filter* was proposed.[9] This filter operates on the direction and the magnitude of the color vectors independently and then combines them to produce a unique final output. This hybrid filter, which can be viewed as a nonlinear combination of the VMF and BVDF filters, produces an output according to the following rule:

$$\mathbf{F}_{\mathrm{HyF}} = \begin{cases} \mathbf{F}_{\mathrm{VMF}} & \text{if } \mathbf{F}_{\mathrm{VMF}} = \mathbf{F}_{\mathrm{BVDF}}, \\ (\|\mathbf{F}_{\mathrm{VMF}}\| / \|\mathbf{F}_{\mathrm{BVDF}}\|)\mathbf{F}_{\mathrm{BVDF}} & \text{otherwise}, \end{cases} \tag{5}$$

where $\mathbf{F}_{\mathrm{BVDF}}$ is the output of the BVDF filter, $\mathbf{F}_{\mathrm{VMF}}$ is the output of the VMF, and $\|\cdot\|$ denotes the magnitude of the vector. Another, more complex hybrid filter, which involves the utilization of an arithmetic (linear) mean filter (AMF), has also been proposed.[9]

A different approach in the development of directional filters was taken with the introduction of a new class of adaptive directional filters.[10,11] The adaptive filters proposed there utilize data-dependent coefficients to adapt to local image characteristics. The weights of the adaptive filters are determined by fuzzy transformations based on features from local data.

The general form of the adaptive directional filters is given as a nonlinear transformation of a weighted average of input vectors inside the window W:

$$\hat{\mathbf{y}} = \sum_{i=1}^{n} w_i^* \mathbf{F}_i = \frac{\sum_{i=1}^{n} w_i \mathbf{F}_i}{\sum_{i=1}^{n} w_i}. \tag{6}$$

In the adaptive design, the weights provide the degree to which an input vector contributes to the output of the filter. The weights of the filter are determined adaptively, using fuzzy transformations of a distance criterion at each image position.

3 New Approach to Impulsive Noise Reduction

The output of the vector median of pixels belonging to a filter window W is a value that minimizes the appropriate cost function

$$R(\mathbf{\Theta}) = \sum_{j=0}^{n-1} \|\mathbf{F}(j) - \mathbf{\Theta}\|, \tag{7}$$

where $\|\cdot\|$ is the vector norm. This basic idea can be reformulated using the concept of a fuzzy similarity function, which describes the relation between neighboring pixels. Let the similarity between vectors $\mathbf{F}_i$ and $\mathbf{F}_j$ be defined as

$$\rho(\mathbf{F}_i, \mathbf{F}_j) = \exp(-\beta\|\mathbf{F}_i - \mathbf{F}_j\|), \tag{8}$$

where β is a filter coefficient. Then let the total similarity function be defined as

$$R(\mathbf{F}_0) = \sum_{j=1}^{n-1} \rho(\mathbf{F}_0, \mathbf{F}_j) \tag{9}$$

and

$$R(\mathbf{F}_i) = \sum_{j=1}^{n-1} (1 - \delta_{i,j})\rho(\mathbf{F}_i, \mathbf{F}_j), \quad i = 1, \ldots, n-1. \tag{10}$$

The new filter is constructed in such a way that the center pixel $\mathbf{F}_0$ is replaced by $\mathbf{F}_k$ only if $R(\mathbf{F}_0) < R(\mathbf{F}_k)$ and $R(\mathbf{F}_k)$ is the maximal value ($k = 1, 2, \ldots, n-1$). In other words, the center pixel is replaced by the one that maximizes the sum of similarities between the new central pixel and its neighbors. An actual replacement happens only when the center pixel is noisy, and that is just what gives our filter the property of preserving ‘‘good’’ image pixels.

The performance of the procedure was evaluated using the similarity function defined by Eq. (8); however, we expect that good results can be obtained with other monotonically decreasing convex functions.

The constraint regarding the total similarity measure introduced here is very important, as for very small β we have $R(F_0) \approx 4$ and $R(F_i) \approx 3$, $i = 1, \ldots, 4$, in the example illustrated by Fig. 1. This means that for small β all image pixels will be preserved; changes will occur only for large enough β. Without this constraint on the similarity measure, for small β the output of the filter would be the same as that of the median, and a lot of pixels would be unnecessarily replaced by their neighbors.

4 Computational Complexity of the New Filter

Apart from the numerical behavior of any proposed algorithm, its computational complexity is a realistic measure of its practicality and usefulness, since it determines the required computing power and processing (execution) time.

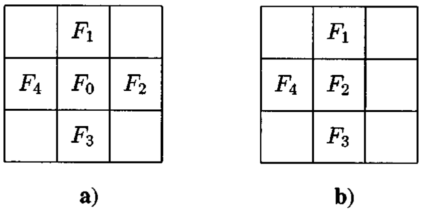

Fig. 1 Illustration of the construction of the new filtering technique (for the sake of simplicity the 4-neighborhood was chosen). If the value of the center pixel F_0 (a) is replaced by the value of its neighbor F_2, then the F_2 pixel is not taken into consideration while calculating the total similarity measure between the pixels (b).

In this section a comparison, in terms of computational complexity, between the proposed filter and the two standard methods, namely the vector median filter and the vector directional filter, is presented. A general framework to evaluate the computational requirements of image-filtering algorithms is given in Refs. 12 and 13. The framework of that analysis, originally introduced for filters utilizing a predefined moving window, is used here to evaluate the computational requirements of the algorithms.

The requirement of this approach is that the filter window W be symmetric $(n\times n)$ and contains n^2 vector samples of order p (Z^p). In most image-processing applications a value $n=3$ is considered.

The computational complexity of a specific filter is assumed to be a total time to complete an operation:

$$\text{Time}=\sum w_{\text{OPER}}\,\text{OPER}, \tag{11}$$

where OPER is the number of operations of type OPER that are required, and w_{OPER} is the weight of that type. In our analysis the following operations are used: ADD (additions), MULT (multiplications), DIV (divisions), SQRT (square roots), COMP (comparisons), ARCCOS (arccosines), and EXP (exponentiations). The weights used in the calculations do not pertain to any particular machine. Rather, they can be considered mean values of those coefficients commonly encountered. All qualitative results presented in the following hold even if the weighting coefficients in the above formula are different for a specific computing platform. Usually w_{ADD} is assumed to be 1, while other w_{OPER} values depend on the computing platform and are out of our interest. In this way the computational complexity of the presented filter can be determined step by step as follows:

1. Filtration of one pixel requires computation of n^2 total similarity measures $R(\mathbf{F}_j)$ and selection of their maximum n^2-1 comparisons.
2. Computation of one particular measure $R(\mathbf{F}_i)$ requires n^2-2 additions and n^2-1 calculations of $\rho\{\mathbf{F}_i,\mathbf{F}_j\}$.
3. Computation of one particular $\rho\{\mathbf{F}_i,\mathbf{F}_j\}$ requires 1 computation of Euclidean distance (if the L_2 metric is used), 1 multiplication, and 1 computation of an exponent.
4. Computation of one particular Euclidean distance requires p multiplications, $2p$ additions, and 1 square root.

Table 1 Computational complexity of VMF, BVDF, and proposed filter.

	Complexity					
Filter	ADD	MULT+DIV	SQRT	ARCCOS	EXP	COMP
VMF	$O(n^4)$	—	—	—	—	$O(n^2)$
BVDF	$O(n^4)$	$O(n^4)$	$O(n^4)$	$O(n^4)$	—	$O(n^2)$
Proposed	$O(n^4)$	$O(n^4)$	$O(n^4)$	—	$O(n^4)$	$O(n^2)$

Combining these steps, we conclude that the computational complexity of the presented method is

$$\begin{aligned} & n^2[(n^2-2)\ \text{ADD}+(n^2-1)(p\ \text{MULT}+2p\ \text{ADD} \\ &\quad +\text{SQRT}+\text{MULT}+\text{EXP})]+(n^2-1)\ \text{COMP} \\ &\quad = O(n^4)\ \text{MULT}+O(n^4)\ \text{ADD}+O(n^4)\ \text{SQRT} \\ &\qquad +O(n^4)\ \text{EXP}+O(n^2)\ \text{COMP}. \end{aligned}$$

In the same way we can obtain computational complexities for VMF and BVDF. Table 1 summarizes the results. As can be seen, the proposed filter has the same rank of complexity, $O(n^4)$, as VMF and BVDF and is a little slower than VMF, but as fast as BVDF.

It must be stressed that all results were obtained by straightforward application of the described algorithms and are not optimal. For instance, in Ref. 12 a way to reduce the complexity of VMF to $O(n^3)$ is described. Similar improvements might be applied to the presented filter as well.

5 Results

The performance of the new algorithm was compared with the standard procedures of noise reduction used in color image processing (Table 2). Two RGB color images were selected for our tests. The color images ''Lena'' and ''Peppers'' were contaminated by 4% of impulsive noise. The mean absolute error (MAE), the root of the mean squared error (RMSE), the signal-to-noise ratio (SNR), the peak signal-to-noise ratio (PSNR), the normalized mean squared

Table 2 Filters compared.

Abbr.	Name	Ref.
AMF	Arithmetic-mean filter	4
VMF	Vector median filter	7
ANNF	Adaptive nearest neighbor filter	11
BVDF	Basic vector directional filter	14, 15
HDF	Hybrid directional filter	9
AHDF	Adaptive hybrid directional filter	9
DDF	Directional-distance filter	5
FVDF	Fuzzy vector directional filter	10

Table 3 Comparison of the new filter with the standard techniques using ''Lena.''

Method	NMSE (10^{-4})	RMSE	PSNR (dB)	NCD (10^{-3})
None	51,495	32,165	17,983	43,211
AMF	82,863	12,903	25,917	44,496
VMF	23,304	6,842	31,427	19,923
ANNF	31,271	7,926	30,149	24,926
BVDF	29,074	7,643	30,466	21,012
HDF	22,845	6,775	31,513	20,201
AHDF	22,603	6,739	31,559	20,193
DDF	24,003	6,944	31,288	21,291
FVDF	26,755	7,331	30,827	23,319
Proposed	10,215	4,530	35,009	4,014

error (NMSE), and the normalized color difference (NCD) were used as quantitative measures for evaluation purposes. They are computed as

$$\mathrm{MSE}=\frac{\Sigma_{i=1}^{N_1}\Sigma_{j=1}^{N_2}\|\mathbf{F}(i,j)-\hat{\mathbf{F}}(i,j)\|^2}{N_1 N_2}, \tag{12}$$

$$\mathrm{MAE}=\frac{\Sigma_{i=1}^{N_1}\Sigma_{j=1}^{N_2}\Sigma_{k=1}^{3}|F_k(i,j)-\hat{F}_k(i,j)|}{3N_1 N_2}, \tag{13}$$

$$\mathrm{RMSE}=\sqrt{\mathrm{MSE}}, \quad \mathrm{PSNR}=20\log\left(\frac{255}{\mathrm{RMSE}}\right), \tag{14}$$

$$\mathrm{NMSE}=\frac{\Sigma_{i=1}^{N_1}\Sigma_{j=1}^{N_2}\|\mathbf{F}(i,j)-\hat{\mathbf{F}}(i,j)\|^2}{\Sigma_{i=1}^{N_1}\Sigma_{j=1}^{N_2}\|\mathbf{F}(i,j)\|^2}, \tag{15}$$

where N_1, N_2 are the image dimensions, and $\mathbf{F}(i,j)$ and $\hat{\mathbf{F}}(i,j)$ denote the original image vector and the estimate at pixel (i,j), respectively. Tables 3 and 4 summarize the results obtained for the test images for a 3×3 filter window and 8-neighborhood system. We have used the L_1 norm, and the β value in Eq. (8) was 0.75.

Table 4 Comparison of the results using ''Peppers.''

Method	NMSE (10^{-4})	RMSE	PSNR (dB)	NCD (10^{-3})
None	650,920	32,624	17,859	39,841
AMF	124,724	14,281	25,036	52,281
VMF	33,257	7,374	30,776	23,468
ANNF	50,647	9,104	28,949	31,047
BVDF	33,824	7,437	30,703	23,544
HDF	32,497	7,289	30,877	23,676
AHDF	32,086	7,243	30,931	23,603
DDF	33,848	7,439	30,699	23,545
FVDF	38,947	7,980	30,090	25,631
Proposed	13,616	4,718	34,655	5,143

As the MAE, RMS, NMSE, SNR, and PSNR do not take into account the perceptual characteristics of the human eye, they are not accurate measures of the manner in which the images are perceived by a human. The normalized color difference (NCD) is the mean squared in the Commission Internationale de l'Eclairage $L^*u^*v^*$ space, which is approximately uniform with respect to human visual perception.[16]

In the $L^*u^*v^*$ space, the L^* component defines the lightness, and the u^* and v^* components together define the chromaticity. In such a space, the perceptual color error between two color vectors is defined as

$$\Delta E_{uv}=[(\Delta L^*)^2+(\Delta u^*)^2+(\Delta v^*)^2]^{1/2}, \tag{16}$$

where ΔE_{uv} is the color error and ΔL^*, Δu^*, and Δv^* are the differences in the L^*, u^*, and v^* components, respectively, between the two color vectors under consideration. Once the ΔE_{uv} for each pixel of the images under consideration is computed, the NCD is estimated according to the formula[17]

$$\mathrm{NCD}=\frac{\Sigma_{i=1}^{N_1}\Sigma_{j=1}^{N_2}\|\Delta E_{uv}\|}{\Sigma_{i=1}^{N_1}\Sigma_{j=1}^{N_2}\|E_{uv}^*\|}, \tag{17}$$

where $E_{uv}^*=[(L^*)^2+(u^*)^2+(v^*)^2]^{1/2}$ is the *norm*, or *magnitude*, of the uncorrupted original image pixel vector in the $L^*u^*v^*$ space.

The efficiency of the new filtering technique is shown in Figs. 2 and 3. Figure 2 depicts the results of image filtering using the new method in comparison with VMF, AHDF, and DDF. For the comparisons, the standard test image ''Lena'' was used and the RGB channels were distorted by 4% impulsive noise. Figure 3 shows the performance of the new filter using the standard ''Peppers'' image, distorted with impulsive noise of the same intensity. Figure 3(e) and (f) illustrate the difference between the original undistorted image and the results of the filtering with VMF and the new method. In order to better visualize the changes introduced by both filters, the absolute differences of the RGB values were multiplied by 10 to get (e, f). As can be seen, the majority of the image pixels were changed by the VMF. As compared with VMF, using the new filtering technique, only a small fraction of the pixels was changed. This confirms the good results depicted in Tables 3 and 4.

Another important feature of the proposed filter is that it can be used in an iterative way and the number of iterations does not play an important role. Our experiments show that with each iteration the number of pixels that change their values decreases rapidly, so that after a few iterations the filter reaches its root and further iterations do not introduce any new pixel values into the filtered image.

Figure 4 and Table 5 show that the new filter is capable of reducing even strong random noise. The ''Lena'' image was distorted by $x=10\%$, 20%, 40%, and 70% random color noise (to x% of the image pixels random RGB values from the range [0,255] were assigned). As can be seen, the

Fig. 2 Efficiency of the proposed filter as compared with the standard methods: (a) color test image ''Lena,'' (b) image distorted by 4% impulsive noise, (c) new method (3×3 window, $\beta=0.75$), (d) VMF, (e) AHDF, (f) DDF.

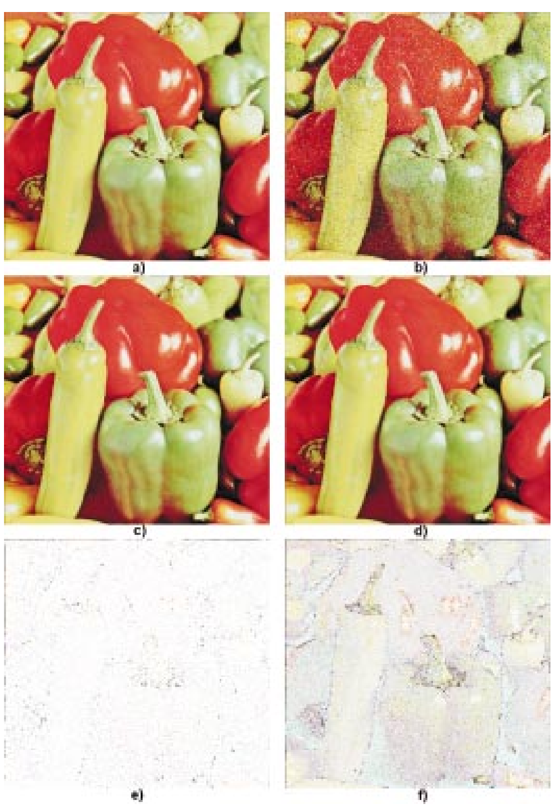

Fig. 3 Noise reduction effect of the proposed filter as compared with the standard methods: (a) color test image ''Peppers,'' (b) image distorted by 4% impulsive noise, (c) new method (3×3 window, $\beta=0.75$), (d) VMF, (e, f) the absolute difference between the original and filtered images [in (e, f) the RGB values have been multiplied by 10].

Fig. 4 Efficiency of the proposed filter: (a, c, e) color test images distorted respectively by 10%, 20%, and 40% random noise, beside (b, d, f) the results of the filtering with the new method (3×3 window, $\beta=1.5$).

Fig. 5 Random-noise reduction results: (a) test image distorted by 70% random noise, (b) the result of filtering with VMF (a 5×5 filtering window was used, and three iterations performed), (c) the results of filtering with the proposed method ($\beta=10$, 5×5 window, and three iterations).

Table 5 Results of random-noise reduction by the new filter compared with the vector median. The test image "Lena" was contaminated by $x=10\%$, 20%, 40%, and 70% random noise (to $x\%$ of the pixels random RGB values were assigned).

Noise contam. (%)	MAE	RMS	SNR	PSNR
No filtering				
10	7,714	29,814	13,542	18,642
20	15,430	42,168	10,599	15,631
40	31,113	59,865	7,625	12,587
70	54,288	79,105	5,304	10,167
Vector median filter				
10	3,496	6,086	27,343	32,444
20	3,901	6,906	26,245	31,345
40	5,135	8,965	23,979	29,080
70	16,691	27,816	13,883	19,245
Proposed filter				
10	0,587	3,351	35,523	37,627
20	1,133	4,499	29,964	35,067
40	2,560	7,093	26,003	31,114
70	6,579	12,805	20,837	25,093

filter is capable of reducing even strong random noise while preserving the image details. Figure 5 shows how the new filter copes with 70% random noise. Although only 30% of the image pixels retained their original values and the information on the rest of the image pixels was totally lost, by using the new method of noise reduction it was possible to restore the original image with much better accuracy than when using the standard VMF approach.

6 Conclusions

The new algorithm presented in this paper can be seen as a modification and improvement of the commonly used filters, which are based on the median or vector median. Although there exist a lot of different kinds of filters that seek to overcome the drawbacks of the median and vector median, the new approach is interesting in that the filter is not invasive, in the sense that it does not destroy the structure of the image unnecessarily as the median does. The comparison shows that the new filter outperforms all standard procedures used in color image processing when impulse noise is to be eliminated.

Acknowledgment

The work of B. Smolka was partially supported by KBN grant 8-T11E-013-19.

References

1. A. N. Venetsanopoulos and K. N. Plataniotis, "Multichannel image processing," in *Proc. IEEE Workshop on Nonlinear Signal/Image Processing*, Vol. I, pp. 2–6 (1995).
2. I. Pitas and A. N. Venetsanopoulos, *Nonlinear Digital Filters: Principles and Applications*, Kluwer Academic, Boston (1990).
3. K. N. Plataniotis and A. N. Venetsanopoulos, *Color Image Processing and Applications*, Springer-Verlag (2000).
4. I. Pitas and P. Tsakalides, "Multivariate ordering in color image processing," *IEEE Trans. Circuits Systems Video Technol.* **1**(3), 247–256 (1991).
5. D. G. Karakos and P. E. Trahanias, "Combining vector median and vector directional filters: the directional-distance filters," in *Proc. IEEE Conf. on Image Processing, ICIP-95*, pp. 171–174 (1995).
6. I. Pitas and A. N. Venetsanopoulos, "Order statistics in digital image processing," *Proc. IEEE* **80**(12), 1893–1923 (1992).
7. J. Astola, P. Haavisto, and Y. Neuovo, "Vector median filters," *Proc. IEEE* **78**, 678–689 (1990).
8. P. E. Trahanias and A. N. Venetsanopoulos, "Vector directional filters: a new class of multichannel image processing filters," *IEEE Trans. Image Process.* **2**(4), 528–534 (1993).
9. M. Gabbouj and F. A. Cheickh, "Vector median–vector directional hybrid filter for color image restoration," in *Proc. EUSIPCO-96*, pp. 879–881 (1996).
10. K. N. Plataniotis, D. Androutsos, and A. N. Venetsanopoulos, "Colour image processing using fuzzy vector directional filters," in *Proc. IEEE Workshop on Nonlinear Signal/Image Processing*, pp. 535–538 (1995).
11. K. N. Plataniotis, D. Androutsos, V. Sri, and A. N. Venetsanopoulos, "A nearest neighbour multichannel filter," *Electron. Lett.* **31**(22), 1910–1911 (1995).
12. M. Barni and V. Cappellini, "On the computational complexity of multivariate median filters," *Signal Process.* **71**, 45–54 (1998).
13. K. N. Plataniotis and A. N. Venetsanopoulos, "Vector processing," in *The Colour Image Processing Handbook*, S. J. Sangwine and R. W. E. Horne, Eds., pp. 188–209, Chapman & Hall, Cambridge, UK (1997).
14. P. E. Trahanias, I. Pitas, and A. N. Venetsanopoulos, "Color image processing," in *Advances in 2D and 3D Digital Processing (Techniques and Applications)*, C. T. Leondes, Ed., Academic Press (1994).
15. P. E. Trahanias and A. N. Venetsanopoulos, "Vector directional filters: a new class of multichannel image processing filters," *IEEE Trans. Image Process.* **IP-2**(4), 528–534 (1993).
16. C. Poynton, "Color science for video," Chap. 7 in *A Technical Introduction to Digital Video*, pp. 110–151, Wiley (1996).
17. K. N. Plataniotis, D. Androutsos, V. Sri, and A. N. Venetsanopoulos, "Color image processing using adaptive multichannel filtering," *IEEE Trans. Image Process.* **7**(6), 933–949 (1997).

B. Smolka received the Diploma in Physics degree from the Silesian University in Katowice, Poland, in 1986, and the PhD degree in automatic control from the Department of Automatic Control, Silesian University of Technology, Gliwice, Poland. From 1986 to 1989 he was a teaching assistant in the Department of Biophysics, Silesian Medical University, Katowice, Poland. From 1992 to 1994 he worked as a teaching assistant at the Technical University of Esslingen, Germany. Since 1994 he has been at the Silesian University of Technology. In 1998 he was appointed as an associate professor in the Department of Automatic Control at the Silesian University of Technology. His current research interests include application of Markov fields and random walks in low-level image processing, wavelet-based methods of image compression, and the visual aspects of image quality.

A. Chydzinski received the Diploma in Engineering degree and the MS in applied mathematics from the Silesian University of Technology, Gliwice, Poland in 1997 and is a PhD student at present. Since 1997, he has been at the Silesian University of Technology in the Department of Mathematics, where he researches and teaches probability theory and its applications in computer sciences, especially in image processing, data compression, and queueing systems. He coauthored, with M. Bratiychuk, a book on *Probability Theory* (published in December 2000), and he has published several papers in refereed journals and conference proceedings on the mentioned subjects.

K. Wojciechowski received the MSc diploma in electrical engineering from the Academy of Mining and Metallurgy, Cracow, Poland, in 1967, and the PhD and DSc (habilitation dissertation) in control

theory from Silesian University of Technology, Gliwice, Poland, in 1976 and 1991, respectively. He joined the Department of Automatic Control, Electronics, and Computer Science, Silesian University of Technology, in 1968 as a doctoral student, and he was promoted to assistant professor in 1976 and to professor in 1991. He lectures in linear and nonlinear control theory, adaptive control, image processing and pattern recognition, signal processing, and elements of artificial intelligence. He has been given an award by the chancellor for scientific results and also an award of the Polish Ministry of Education. Since 1995 he has been a member of the Institute of Theoretical and Applied Informatics, Polish Academy of Sciences, Gliwice. He has published 150 papers in refereed journals and conference proceedings on control theory, decision making, image processing, and digital communications. Since 1996, Prof. Wojciechowski has been dean of the Department of Automatic Control, Electronics and Computer Science. He is the head of the Laboratory of Computer Vision, chair of doctoral studies in automation and robotics, and chair of postgraduate studies in spatial information systems. He has been a director of the Summer School on Morphological Image and Signal Processing and a member of the program committees and organizing committees of numerous conferences. He is a member of the Executive Board of the Society of Image Processing and a member of Polish Electrical Engineering Society. His current research interests include control and adaptive systems, control based on visual information, artificial intelligence, image processing, spatial information systems, and multimedia.

K. N. Plataniotis received the BEng degree in computer engineering from the Department of Computer Engineering and Informatics, University of Patras, Patras, Greece, in 1988, and the MS and PhD degrees in electrical engineering from the Florida Institute of Technology (Florida Tech), Melbourne, Florida, in 1992 and 1994, respectively. He was a research associate at the Computer Technology Institute (CTI), Patras, Greece, from 1989 to 1991, and a postdoctoral fellow at the Digital Signal & Image Processing Laboratory, Department of Electrical and Computer Engineering, University of Toronto, from 1995 to 1997. From August 1997 to June 1999 he was an assistant professor at the School of Computer Science at Ryerson Polytechnic University. While at Ryerson, Prof. Plataniotis served as a lecturer to industry in 12 courses and in continuing education programs. Since 1999 he has been at the University of Toronto as an assistant professor in the Department of Electrical & Computer Engineering, where he researches and teaches adaptive systems and multimedia signal processing. He coauthored, with A.N. Venetsanopoulos, a book on *Color Image Processing & Applications* (Springer-Verlag, August 2000), he is a contributor to three books, and he has published more than 100 papers in refereed journals and conference proceedings in the areas of adaptive systems, signal and image processing, and communication systems and stochastic estimation. Prof. Plataniotis is a member of the IEEE Technical Committee on Neural Networks for Signal Processing, and is the technical cochair of the Canadian Conference on Electrical and Computer Engineering, CCECE 2001, May 13–16, 2001, in Toronto. His current research interests include adaptive systems, statistical pattern recognition, multimedia data processing, statistical communication systems, and stochastic estimation and control.

A. N. Venetsanopoulos received the Diploma in Engineering degree from the National Technical University of Athens (NTU), Greece, in 1965, and the MS, MPhil, and PhD degrees in electrical engineering from Yale University in 1966, 1968, and 1969, respectively. He joined the Department of Electrical and Computer Engineering of the University of Toronto in September 1968 as a lecturer, and he was promoted to assistant professor in 1970, associate professor in 1973, and professor in 1981. Since July 1997, he has been associate chair (graduate studies) of the Edward S. Rogers Sr. Department of Electrical and Computer Engineering, and was acting chair during the spring term of 1998–1999. In 1999 a chair in multimedia was established in the ECE Department and Prof. Venetsanopoulos assumed the position as inaugural chairholder in July 1999. He has served as chair of the Communications Group, associate chair of the Department of Electrical Engineering, and associate chair (graduate studies) for the Department of Electrical and Computer Engineering. Professor Venetsanopoulos has been on research leave at Imperial College of Science and Technology, the National Technical University of Athens, the Swiss Federal Institute of Technology, the University of Florence, and the Federal University of Rio de Janeiro, and has also served as adjunct professor at Concordia University. He has served as lecturer in 138 short courses to industry and in continuing education programs, and as consultant to numerous organizations; he is a contributor to 28 books, a coauthor of *Color Image Processing and Applications*, (Springer-Verlag, August 2000), *Nonlinear Filters in Image Processing: Principles Applications*, (Kluwer, 1990), *Artificial Neural Networks: Learning Algorithms, Performance Evaluation and Applications* (Kluwer, 1993), and *Fuzzy Reasoning in Information Decision and Control Systems*, (Kluwer, 1994). He has published 750 papers in refereed journals and conference proceedings on digital signal and image processing and on digital communications. Professor Venetsanopoulos has served as chair on numerous boards, councils, and technical conference committees of the Institute of Electrical and Electronic Engineers (IEEE), such as the Toronto Section (1977–1979) and the IEEE Central Canada Council (1980–1982); he was president of the Canadian Society for Electrical Engineering and vice president of the Engineering Institute of Canada (EIC) (1983–1986). He has been a guest editor or associate editor for several IEEE journals, and the editor of the *Canadian Electrical Engineering Journal* (1981–1983). Professor Venetsanopoulos is the technical program cochair of the IEEE International Conference on Image Processing, ICIP-2001, to be held in Thessaloniki, Greece, October 7–10, 2001. He is a member of the IEEE Communications, Circuits and Systems, Computer, and Signal Processing Societies, as well as of Sigma Xi, the Technical Chamber of Greece, the European Association of Signal Processing, the Association of Professional Engineers of Ontario (APEO), and Greece. He was elected as a Fellow of the IEEE ''for contributions to digital signal and image processing,'' he is also a Fellow of the EIC, ''for contributions to electrical engineering,'' and he was awarded an honorary doctorate from the National Technical University of Athens in October 1994. In October 1996 he was awarded the Excellence in Innovation Award of the Information Technology Research Centre of Ontario and Royal Bank of Canada, ''for innovative work in color image processing.''