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Multichannel filtering by gradient information☆

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Abstract

In this paper, multichannel image filtering using local gradient information is studied and evaluated which is simpler and more appropriate than the traditional approaches that have been addressed by means of groupwise vector ordering information. Two adaptive weighted multichannel filters based on local gradient information to noise removal in color images are introduced. The first proposed multichannel filter is rather highly effective for Gaussian and Uniform noise removal in preserving good edges. The second proposed multichannel filter is robust to Gaussian, Uniform, Impulse noise, and Gaussian noise mixed with outliers. © 2000 Elsevier Science B.V. All rights reserved.

Zusammenfassung

In dieser Arbeit wird eine mehrkanalige Filterung von Bildern unter Benützung lokaler Gradienteninformation untersucht und bewertet. Eine solche Methode ist einfacher und besser geeignet als traditionelle Ansätze, die Information über die gruppenweise Ordnung von Vektoren benützen. Es werden zwei adaptive, gewichtete, auf lokaler Gradienteninformation beruhende Mehrkanal-Filter zur Rauschunterdrückung in Farbbildern eingeführt. Das erste vorgeschlagene Mehrkanal-Filter unterdrückt Gauß-und gleichverteiltes Rauschen sehr wirkungsvoll, wobei Kanten weitgehend erhalten bleiben. Das zweite Filter ist robust gegenüber Gaußschem Rauschen, gleichverteiltem Rauschen, Impulsrauschen sowie Gaußschem Rauschen gemischt mit Ausreißern. © 2000 Elsevier Science B.V. All rights reserved.

Résumé

Dans cet article, nous étudions et évaluons le filtrage d'images à canaux multiples en utilisant l'information de gradient locale, ce qui est plus simple et plus approprié que les approches traditionnelles qui ont été adressées au moyen de l'information orientée par groupe de vecteurs. Nous introduisons deux filtres multicanaux pondérés adaptatifs reposant sur l'information de gradient local pour supprimer le bruit dans des images en couleurs. Le premier filtre multicanal proposé est assez hautement efficace pour la suppression de bruit gaussien et uniforme tout en préservant de bons contours. Le second filtre multicanal proposé est robuste aux bruits gaussiens, uniformes, impulsionnels, ainsi qu'au bruit gaussien mêlé à des points isolés. © 2000 Elsevier Science B.V. All rights reserved.

Keywords: Multichannel filters; Adaptive weighted filters; Gradient weighted filters

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Nomenclature

α	the parameter of the proposed Π filters
β	the common parameter for FVF1, FVF2, FVF3, FVF4 in Table 4
γ	the common parameter for FVF1, FVF2, FVF3, FVF4 in Table 4
f	a gray-scale image
X	a multichannel RGB color image
$g_p(k)$	the local gradients
$g_p^s(k)$	the symmetric local gradients
$\boldsymbol{g}_p(k)$	the vector gradients
$\boldsymbol{g}_p^s(k)$	the symmetric vector gradients

Abbreviations

MMF	marginal median filter
AMF	arithmetic (Linear) mean filter
VMF	vector median filter
DDF	directional-distance filter
FVDF	adaptive (Fuzzy) vector directional filter
ANNF	nearest-neighbor multichannel filter
ANNMF	adaptive nearest-neighbor multichannel filter
ANNMF2	adaptive nearest-neighbor multichannel filter
DWANNF	double-window adaptive nearest-neighbor filter
FVF1–4	combined fuzzy directional and fuzzy median filter
GIWF	gradient inverse weighted filter
AGWF	adaptive Gaussian weighted filter

1. Introduction

Multichannel filtering has received increased attention due to its importance in color image processing. Numerous filtering techniques proposed to date utilize correlation among multivariate vectors [1,3,4,6,7,10–16,22–24,26,27]. Some of these select directly the minimum as output from an ordering sequence using various distance and angle measures such as these in VMF [1], BVDF [23,24] and DDF [6]. These vector ordering filters do well for long-tailed noise (impulse) but are inferior to the arithmetic mean filter (AMF) for high-frequency noise (Gaussian) [15]. Other approaches, referred to as the adaptive vector weights filters, such as α-TM/GVDF [24], ANNF [12], ANNMF [16], ANNMF2 [16], FVDF [13,14], and DWANNF [13], yield output by the combination of image vectors in the local window. They cope with noise but at the same time smear sharpness of images such as edges. Besides, they require a great bulk of process time for sorting, arccosine function, and aggregating distance measure. Some approaches [15,13] reduce the aggregation time by prior estimating or predicting the reference vector (MMF). Other efforts [2,20] are devoted to reducing the complexity. They conclude that vector weighted filters with the techniques of parallel processing and weights determination can diminish the total process time.

In this paper, the main goal is to devise computationally efficient and reliable filtering structures. Many gray-scale adaptive weighted filters, such as GIWF [25], AGWF [21], Sigma filter [8], Rational filters [17–19], and Π filters [9], all of which migrate or diffuse gray levels in iterative filtering, show good performances in attenuating noise and preserving sharpness. We propose a scheme of weight determination by vector gradient information for reducing the aggregation times in color images, which is similar to that used in gray-scale adaptive weighted filters.

The paper is organized as follows. First, in Section 2, a Π filter [9] based on local gradient information for gray-scale image filtering is introduced. Then, in Section 3, a new multichannel Π filter, extended from the gray-scale one, is proposed, which results in a good performance for high-frequency noise (Gaussian and Uniform). In Section 4, another multichannel Π filter is proposed which is equipped with symmetrical local gradients having the robustness for impulsive noise. Experimental results on the effectiveness of the proposed methods are exhibited in Section 5. Our conclusions are given in Section 6.

2. Gray-scale image filtering

2.1. Noise removing and edge preserving by gradients

There has been some interest recently in a specific class of adaptive weighted filters. One of these is called adaptive gradient weighted filters. Examples include the gradient inverse weighted filter of Wang and Vernucci [25], Gaussian weighted filter of Spann and Nieminen [21], sigma filters of Lee [13], and the rational filters of Ramponi [17–19]. Let $f(x_1), f(x_2), f(x_3), \ldots, f(x_{n-k}), \ldots, f(x_n), \ldots, f(x_{n+k}), \ldots, f(x_m)$ be a sequence of 1-D signal, where x_n is defined as a noise point. A generalized 1-D adaptive gradient weighted filter can be expressed as

$$f'(x_n) = \Big(1 - \sum_{i=n-1, i\neq 0}^{n+1} F(g_{x_i}) f(x_n)\Big) + \sum_{i=n-1, i\neq 0}^{n+1} F(g_{x_i}) f(x_i), \quad (1)$$

where $g_{x_i} = f(x_i) - f(x_n)$ are the local gradients and F is the weighted function. In all the gradient weighted filters mentioned [17–19,21,25], the weighted function F is reciprocal to the absolute value of g_{x_i}. A variety of weighted functions of g_{x_i}'s was employed in the image processing. Wang [25] choose the absolute inverse of gradients as adaptive weights for noise suppression. Spann and Nieminen [21] used exponential function of gradients to remove Gaussian noise and segment images. The same exponential weighted function also was employed by Guillon [5] to design adaptive filter masks for improving the contrast enhancement. Also, iterative filtering techniques are followed to migrate and diffuse gray levels to perform noise attenuation. However, such gradient weighted filters have poor performance if impulse noise is present. Fig. 1(a) shows one such instance. The symmetric local gradients defined as $g^s_{x_n} = f(x_{n+1}) - f(x_{n-1})$ are then suggested to cope with such situation [17,18].

On the other hand, as a point x_n crossed on an edge with height H as delineated in Fig. 1(b) where N is the window size, $f(x_{n-l}) = a$ for $-1 \leqslant l \leqslant k-2$; $f(x_{n+r}) = b$ for $2 \leqslant r \leqslant N-k+1$, and $b - a = H$. The filtered output is $a + [(N-k)/N]H$; in mean filter. The resultant value amplifies the result in $[(N-k)/N]H$; therefore, signal points crossed on edges are blurred. By way of response of zero or small weights to x_n's neighbors with large local gradients, adaptive gradients weighted filters would be effective for edge preserving. Thus, the advantage of the adaptive gradient weighted filters is that they are able to smooth a noisy signal whilst maintaining sharp transitions in the signal. The idea of our methods is to extend the iterative nonlinear filtering using gradient information to multichannel image filtering. Our purpose is to design a function that is reciprocal to the gradients for removing noise and preserving edges. In our approach, π functions are chosen to substitute the weighted function $F(x)$. The reasons for choosing π functions are that (1) they match our purposes; (2) they are simple, only second degree with respect to x; (3) the parameter α provides the adaptability for the filters. The formulation is given as

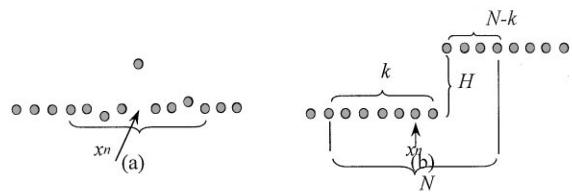

Fig. 1. Two 1-D signals: (a) a signal with nosiy points; (b) a signal crossed on edge points.

$$\pi(x) = \begin{cases} 1 - 2\left(\dfrac{x}{\alpha}\right)^2 & \text{if } |x| \leqslant \dfrac{\alpha}{2}, \\ 2\left(\dfrac{x}{\alpha} - 1\right)^2 & \text{if } \dfrac{\alpha}{2} \leqslant |x| \leqslant \alpha, \\ 0 & \text{if } |x| \geqslant \alpha \end{cases} \quad (2)$$

2.2. The structure of Π filters

Let $f: Z \times Z \rightarrow \{0, 1, \ldots, 255\}$ be a gray-level image. In a 3×3 window centered at p, the eight neighbors of p are in an order as shown below:

p_1	p_2	p_3
p_8	p	p_4
p_7	p_6	p_5

Then, the local gradients are defined as

$$g_p(k) = f(p_k) - f(p), \quad k = 1, 2, \ldots, 8 \tag{3}$$

and the symmetric local gradients $g_p^s(k)$, $k = 1, 2, \ldots, 8$, are given as

$$g_p^s(k) = g_p(k) - g_p((k+4) \bmod 8)$$
$$= f(p_k) - f(p_{(k+4)\bmod 8}). \tag{4}$$

A gradient weighted Π filter [19] can be formulated as below:

$$f_\Pi(p) = \left(1 - \sum_{k=1}^{8} w_p(k)\right) f(p) + \sum_{k=1}^{8} w_p(k) f(p_k), \tag{5}$$

where $w_p(k)$'s are π-functions of the local gradients or symmetric local gradients. In our experiments, $w_p(k)$ is set to $\frac{1}{8}\pi(g_p(k))$ or $\frac{1}{8}\pi(g_p^s(k))$ and the π-functions are those defined in the previous subsection for some constant or adaptive parameter α.

By way of fixing an appropriate α to all image points, Π filters equipped with local gradients have the advantages of simplicity and efficiency with respect to high-frequency noises such as Gaussian and Uniform noises. Section 5 will exhibit the evidential results by experiments. However, if the center pixel p is an outlier, this outlier will be preserved as an edge point using local gradients information due to the fact that π-functions pay small weights to the neighbors of the center pixel p and large weights for p itself. Iterative filtering and using symmetric local gradients would avoid the outlier being preserved under impulsive noise environment.

3. The first proposed multichannel filter

Color images compromised with R, G, and B components are generally regarded as extensions of gray-scale images. The marginal median filters, having the incoming of simple, parallel and non-expensive computational time, are the most instinctive extensions of gray-scale median filters for color image smoothing. The bulk of aggregation time would be reduced when the reference vector is chosen [15,13]. However, it suffers from the chromatic distortion if wrong reference is obtained. It is our goal in this section to develop a computationally effective algorithm, which utilizes the similarity between vector weighted and gray-scale adaptive weighted filters to remove noise and obtain good edge preserving property.

Let $X: Z \times Z \to \{0, 1, \ldots, 255\}^m$ be a multichannel image. Note that when $m = 3$, X represents a digital multichannel RGB color image. In a 3×3 window, the ordering of the eight neighbors of p is identical to the one shown in Section 2. Let $\boldsymbol{x}_p = X(p)$, and $\boldsymbol{x}_i = X(p_i)$, $i = 1, 2, \ldots, 8$. We define the vector gradients and the symmetric vector gradients as

$$\boldsymbol{g}_p(k) = \boldsymbol{x}_k - \boldsymbol{x}_p, \quad k = 1, 2, \cdots, 8, \tag{6}$$

$$\boldsymbol{g}_p^s(k) = \boldsymbol{x}_k - \boldsymbol{x}_{(k+4) \bmod 8}, \quad k = 1, 2, \ldots, 8. \tag{7}$$

A vector gradient weighted Π filter can then be formulated as below:

$$\boldsymbol{f}_\Pi(p) = \left(1 - \sum_{k=1}^{8} w_p(k)\right)\boldsymbol{x} + \sum_{k=1}^{8} w_p(k)\boldsymbol{x}_k \tag{8}$$

where $w_p(k) = \frac{1}{8}\pi(\|\boldsymbol{g}_p(k)\|)$ and $\|\cdot\|$ could be any norm of R^m. The Π filter equipped with vector gradients is referred to as Π1 filter.

A Π1 filter with a fixed parameter α has the advantages of the simplicity and efficiency with respect to high-frequency noises such as Gaussian and Uniform noises. Assume the image size of X

is $M \times N$. The parameter α is proportional to the noise amount or edge height in each image point. Here, we suggest that α is chosen by $(\kappa_1 \times \sum_{p=(i,j)\in M\times N} \mathrm{Mean}(\|g_p(k)\|))/(M \times N)$ to reflect the noise amount and edge height, where κ_1 is a constant and $\kappa_1 = 1.5$ in our investigations.

For adaptive parameter schemes, there are two goals for deciding α. The first is that plausible α should be obtained to remove noise on non-edge points. The larger the amount of noise corrupted, the larger the α needed. That is, the parameter α depends on the amount of noise. The second is that α should be obtained for preserving edge on edge points. Parameter α is proportional to the amount of noise and edge height. Empirically, it is set to be $\kappa \times \mathrm{Mean}(\|\boldsymbol{g}_p(k)\|)$ in each 3×3 window, where $\kappa = 1$ and $\mathrm{Mean}(\|\boldsymbol{g}_p(k)\|)$ using gradient information is an estimator about the noise amount or edge height.

4. The second proposed multichannel filter

In a 3×3 window W, the aforementioned adaptive vector weighted multichannel filters such as ANNF [12], ANNMF [16], and ANNMF2 [16], determine weighted coefficients by aggregating distance differences from other neighbors and then by ordering these vectors. The DWANNF [13] measures the distance differences from the predicted vector, such as MMF or VMF, instead of groupwise vectors. If a vector possesses the lower degree distance error, it is regarded as a higher correction of non-corrupted vector. A large weight is acquired. The other filter FVDF [13,14] was devised to hybridize aggregating distance and angle discrepancy measures. For our approach in Section 3, we consider the distance information between the current vector and the center vector only. The aggregation of distance difference is diminished drastically. The adaptive weights design discussed here differs from others structures. It is noticeable that the computation time is accelerated in the proposed filter.

As mentioned in Section 3, the fixed α $\Pi1$ filter equipped with vector gradients would perform reasonably well with respect to impulsive noise due to a large weight paid to the pixel corrupted by impulse noise or unsuitable α. Vector gradients with large norms usually result when a pixel is contaminated with outliers. The proposed filter equipped with the vector gradients pays a high weight to the center pixel due to the π-functions. This will delimit the ability of the proposed filter. Two intuitive recipes can be applied to make up such insufficiency. The first is that the adaptive approach indicated in above section can be used to solve unsuitable α. The second is that iterative filtering and symmetric vector gradients can be equipped in the Π filter structure to diminish large weights assigned to the pixels corrupted by outliers. In a 3×3 window shown in subsection 2.2, if there exists one or more than one large norm of symmetric vector gradients and the center point has large norm with most of its neighbors, then the center pixel is regarded as an edge point or fine detail to be preserved. If there are no large norms of symmetric vector gradients, then the center pixel is regarded as an outlier which is to be removed. A Π filter equipped with symmetric vector gradients is abbreviated as a $\Pi2$ filter.

Similarly, fixed and adaptive schemes of $\Pi2$ filter with regard to α are deduced. For fixed $\Pi2$ scheme, α is set to $(\kappa_2 \times \sum_{p=(i,j)\in M\times N} \mathrm{Mean}(\|g_p(k)\|))/(M \times N)$ to reflect the noise amount and edge height, where $\kappa_2 = 1$, empirically. For adaptive scheme, parameter α is the same with adaptive $\Pi1$ scheme.

5. Application to color image processing

We would show the performances of different multichannel filters evaluated in the color image filtering in this section. It would be found that the first proposed adaptive multichannel filter by fixed parameter α performs well with respect to high-frequency noises such as Gaussian and Uniform noises. The proposed filter can not only remove noise but also preserve sharpness. A synthetic wheel image composed of diversified colors and contaminated with Gaussian noise ($\sigma = 25$) is exhibited in Fig. 2. Fig. 3 shows the result of the first proposed method using 3 iterations and $\alpha = 90$.

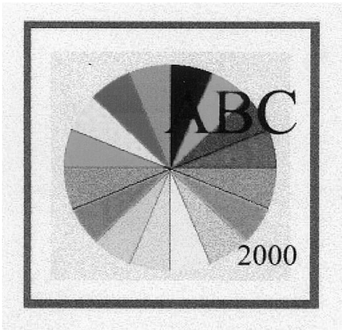

Fig. 2. A synthetic image corrupted with $\sigma = 25$ Gaussian noise.

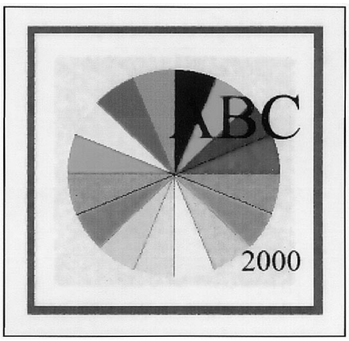

Fig. 3. The result of the first proposed method Section 3 to Fig. 2.

Fig. 4. The original 512×512 'Jet' image.

The proposed filter removes noise within uniformly color regions and preserves sharpness between color regions.

Comparisons with other pioneer's efforts will be made in the following. Fig. 4 shows the original 512×512 'Jet' image. Fig. 5 depicts its corrupted image using 25% uniform noise. Figs. 6–8 show

Fig. 5. The noisy 'Jet' image corrupted with 25% Uniform noise.

Fig. 6. The result of arithmetic mean filter (AMF) to Fig. 5.

Fig. 7. The result of fuzzy vector directional filter (FVDF) to Fig. 5.

Fig. 8. The result of adaptive nearest neighbor median filter (ANNMF2) to Fig. 5.

three objective competitions, AMF, FVDF, and ANNMF2, respectively. Fig. 9 displays the result of our first proposed filter where α is 50 and the iterative number is 3. It is apparent that edges and details such as the numbers attached on the body of the jet fighter are well preserved when our method is used. Moreover, the values of normalized mean square error (NMSE) and the mean chromaticity error (MCRE) are calculated for AMF, VMF [1], DDF [6], FVDF [14], ANNF [12], ANNMF2 [16], and DWANNF [13] to evaluate the quantitative measure of different multichannel filters. Here NMSE is defined as

$$\mathrm{NMSE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\|y(i,j)-\hat{y}(i,j)\|^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\|y(i,j)\|^2},$$

where $y(i,j)$ and $\hat{y}(i,j)$ represent the original image and noisy image, respectively. The MCRE that is based on the distances on Maxwell triangle plan is given as

$$\mathrm{MCRE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\|p(i,j)-\hat{p}(i,j)\|^2}{M\times N},$$

where $p(i,j)$ and $\hat{p}(i,j)$ are the intersection points of $y(i,j)$ and $\hat{y}(i,j)$ with Maxwell triangle plan, respectively. Table 1 shows their NMSE evaluations with 'Lena' images contaminated with $\sigma = 10, 15, 20, 25, 30$ of Gaussian noise. Table 2 also shows their NMSE evaluations with 'Jet' images contaminated with 20%, 25%, 30%, and 40% of uniformly noise. All experiments of our proposed methods in the following comparisons are set to three iterations with one accord. From Tables 1 and 2, it is easy to

Fig. 9. The result of the first proposed method in Section 3 to Fig. 5.

see that our proposed Π filters perform better than others under the investigated images.

Next, the second proposed multichannel filter by fixed parameter α is robust with respect to mixed noise type that would show up. It must be emphasized that parts of pioneer's works in Tables 1 and 2 are noise dependent [14]. For comparison, the 'Lena' image corrupted with Gaussian noise ($\sigma = 30$) mixed with 5% Impulse noise depicted in Fig. 10 is investigated. The evaluation of NMSE in Fig. 10 to compare with other known techniques is shown in Tables 3 and 4. In Table 4, it shows the

Table 1
The NMSE ($\times 10^{-2}$) for the noisy 'Lena' images corrupted with different amount of Gaussian noise, window 3×3

Noise	Noisy	AMF	VMF	DDF	FVDF	ANNF	ANN MF2	DWA NNF	Π1 filter
$\sigma = 10$	1.65	0.37	0.48	0.51	0.41	0.43	0.44	0.47	0.32
$\sigma = 15$	2.45	0.50	0.67	1.13	0.58	0.59	0.61	0.65	0.41
$\sigma = 20$	3.22	0.63	0.88	1.47	0.76	0.76	0.77	0.85	0.50
$\sigma = 25$	3.91	0.78	1.11	1.81	0.95	0.93	0.94	1.02	0.58
$\sigma = 30$	4.57	0.91	1.31	2.11	1.14	1.08	1.10	1.18	0.66

Table 2
The NMSE ($\times 10^{-2}$) for the noisy 'Jet' image corrupted with different amount of Uniform noise, window 3×3

Noise	Noisy	AMF	VMF	DDF	FVDF	ANNF	ANN MF2	DWA NNF	Π1 filter
20%	0.32	0.14	0.15	0.32	0.13	0.13	0.14	0.15	0.09
25%	0.53	0.17	0.20	0.42	0.16	0.18	0.18	0.20	0.12
30%	0.75	0.20	0.27	0.53	0.20	0.24	0.24	0.26	0.15
40%	1.29	0.29	0.45	0.81	0.30	0.37	0.36	0.40	0.22

Table 3
NMSE ($\times 10^{-2}$) for the 'Lena' image, corrupted with Gaussian noise mixed with 5% impulsive noise

Window-size	Noisy	AMF	VMF	DDF	FVDF	ANNF	ANN MF2	DWA NNF	Π2 filter
3×3	4.10	0.87	0.90	1.72	1.0	0.76	0.80	0.80	0.56
5×5	4.10	0.76	0.71	1.84	1.83	0.61	0.65	0.61	

Table 4
NMSE ($\times 10^{-2}$) for the 'Lena' image, corrupted with Gaussian noise mixed with 5% impulsive noise

Window-size	Parameters	FVDF (FVF1)	(FVF2)	(FVF3)	(FVF4)
3×3	$\gamma = 1, \beta = 2$	1.0	0.81	0.79	0.79
5×5		1.83	0.64	0.62	0.62

assessment of a FVF family [14], which possesses robustness on noise type and does not require any information about the noise characteristics. Results in Tables 3 and 4 reveal that the second proposed multichannel filter performs better than others do. In addition, Figs. 11 and 12 show the visual result of competitions FVDF (FVF1) [14] and DWANNF [16], respectively. Fig. 13 shows the

Fig. 10. The noisy 'Lena' image corrupted with Gaussian noise ($\sigma = 30$) mixed with 5% impulsive noise.

Fig. 12. The result of DWANNF to Fig. 10.

Fig. 11. The result of nearest neighbor multichannel filter (ANNF) to Fig. 10.

Fig. 13. The result of the second proposed Π filter to Fig. 10.

result of second proposed mutichannel filter with fixed $\alpha = 90$. In summary, our second proposed multichannel filter is pretty efficient under our experimental cases and has the advantage of robustness to mixed noise.

Note in Section 3, the fixed α $\Pi 1$ filter equipped with vector gradients would perform reasonably well with respect to impulsive noise. Adaptive scheme would make up the insufficiency of fixed $\Pi 1$ filter to impulsive noise. The second and third columns in Table 7 disclose the salient improvements. Fig. 14 also shows the improved result of adaptive $\Pi 1$ filter on a noisy 'Lena' image corrupted with 20% impulse noise.

Fig. 14. The result of the adaptive $\Pi 1$ filter to a noisy 'Lena' image contaminated with 20% impulse noise.

Then, we compare the difference between fixed and adaptive parameter α in Π filter schemes. Tables 5–7 show the comparison of three types of noise corruption including Gaussian, Uniform, and Impulse with respect to NMSE. The fixed α $\Pi 1$ and $\Pi 2$ filters used in Tables 5–7 indicate the corresponding $\Pi 1$ and $\Pi 2$ filters in Tables 1–3. For the fixed $\Pi 1$ filter, the experimental results in Figs. 1, 2, 4 and 5 and Table 7 show that it is effective for Gaussian and Uniform noise in preserving good edges but sensitive to outliers (impulse). Observe that the adaptive scheme performs as well as fixed scheme to Gaussian and Uniform noise from Tables 6 and 7, and it shows an excellent improvement for impulsive noise from Table 5. For the fixed and adaptive $\Pi 2$ filters, both are insensitive to impulse noise compared to the fixed $\Pi 1$ filter. Here we can claim that fixed α scheme performs better than adaptive for Gaussian and Uniform noise. Inversely, the performance of adaptive α scheme is better than the fixed one with respect to impulse noise. In summary, both exhibit a better improvement than the competitors mentioned above (see Table 8).

Finally, Figs. 15–17 show the NMSE and MCRE criteria of the competition and the proposed fixed and adaptive schemes, respectively, on Gaussian, Uniform and Impulse noise for clarifying the comparisons.

Table 5
The comparisons between fixed and adaptive α Π filter schemes: NMSE ($\times 10^{-2}$) for the 'Lena' image corrupted with Gaussian noise

Noise	Fixed α $\Pi 1$ filter	Adaptive α $\Pi 1$ filter	Fixed α $\Pi 2$ filter	Adaptive α $\Pi 2$ filter
$\sigma = 10$	0.32	0.33	0.33	0.34
$\sigma = 15$	0.41	0.43	0.41	0.43
$\sigma = 20$	0.50	0.52	0.49	0.52
$\sigma = 25$	0.58	0.62	0.57	0.62
$\sigma = 30$	0.66	0.70	0.64	0.70

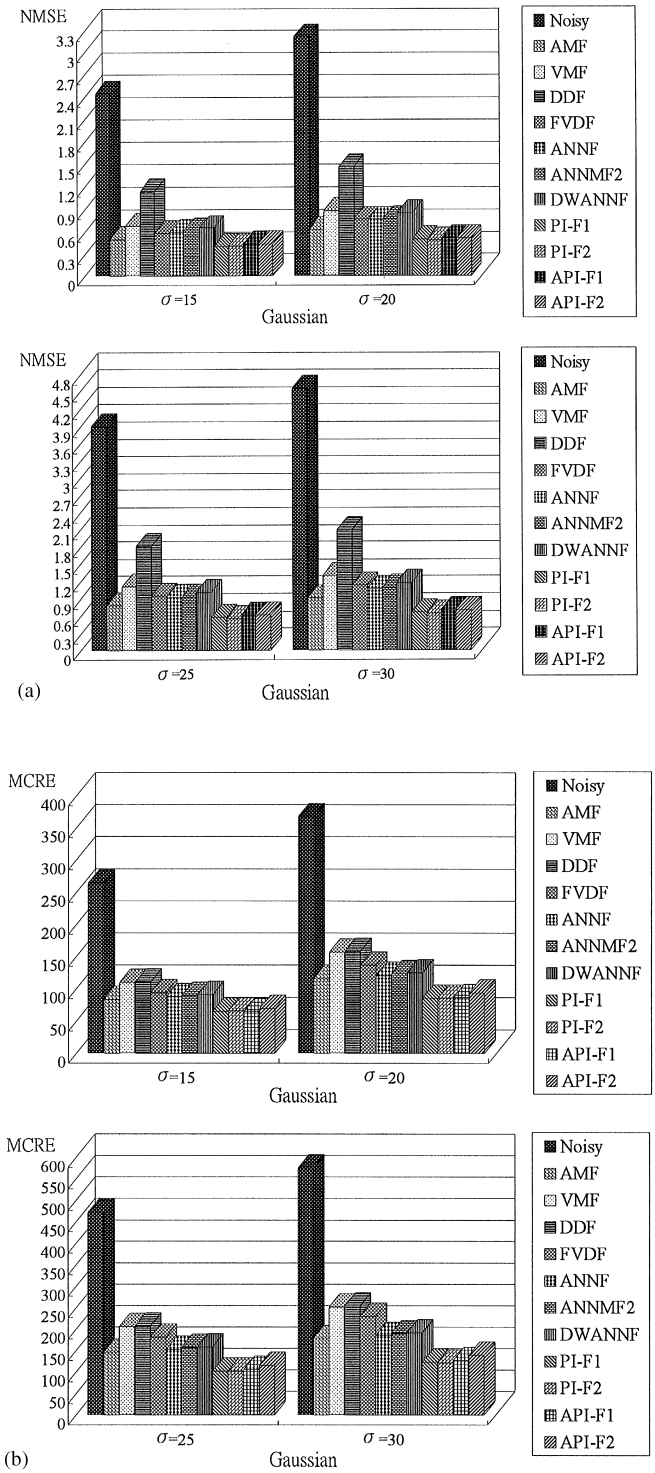

Fig. 15. The merit of (a) NMSE and (b) MCRE criteria on 'Lena' image contaminated with Gaussian noise.

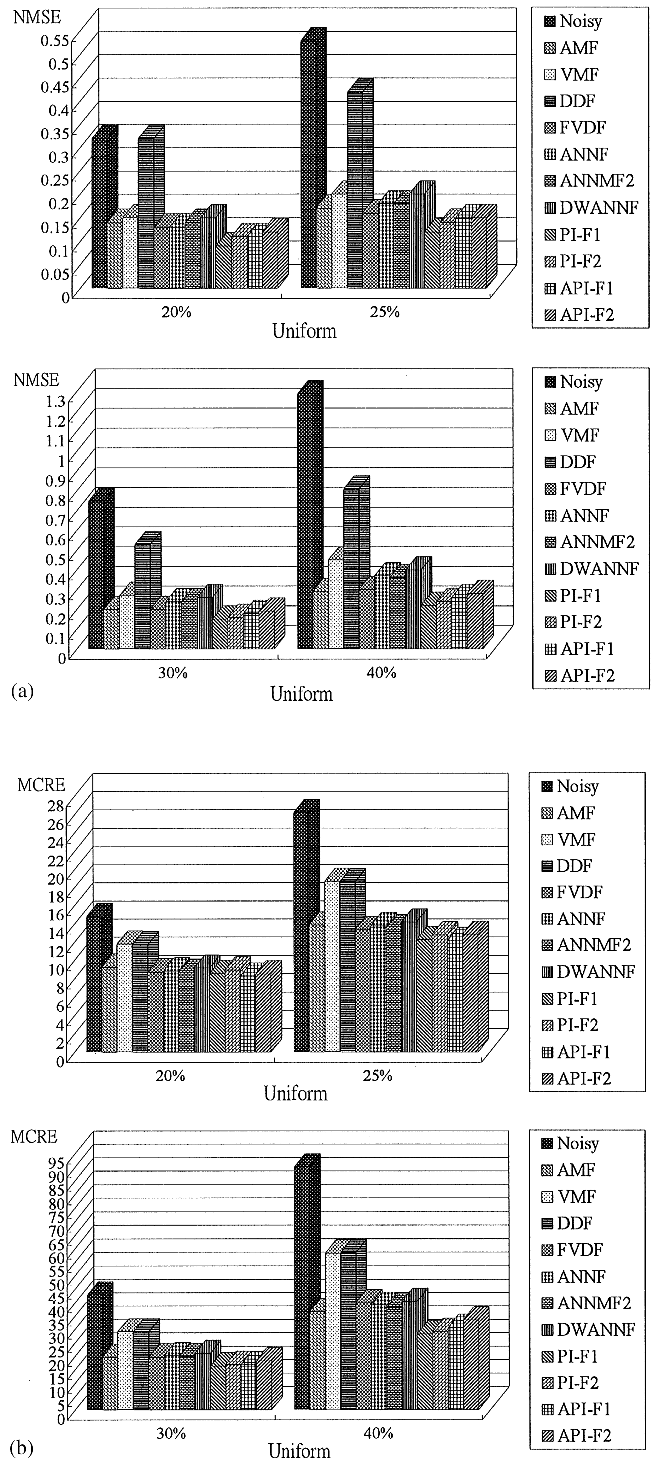

Fig. 16. The merit of (a) NMSE and (b) MCRE criteria on 'Jet' image contaminated with Uniform noise.

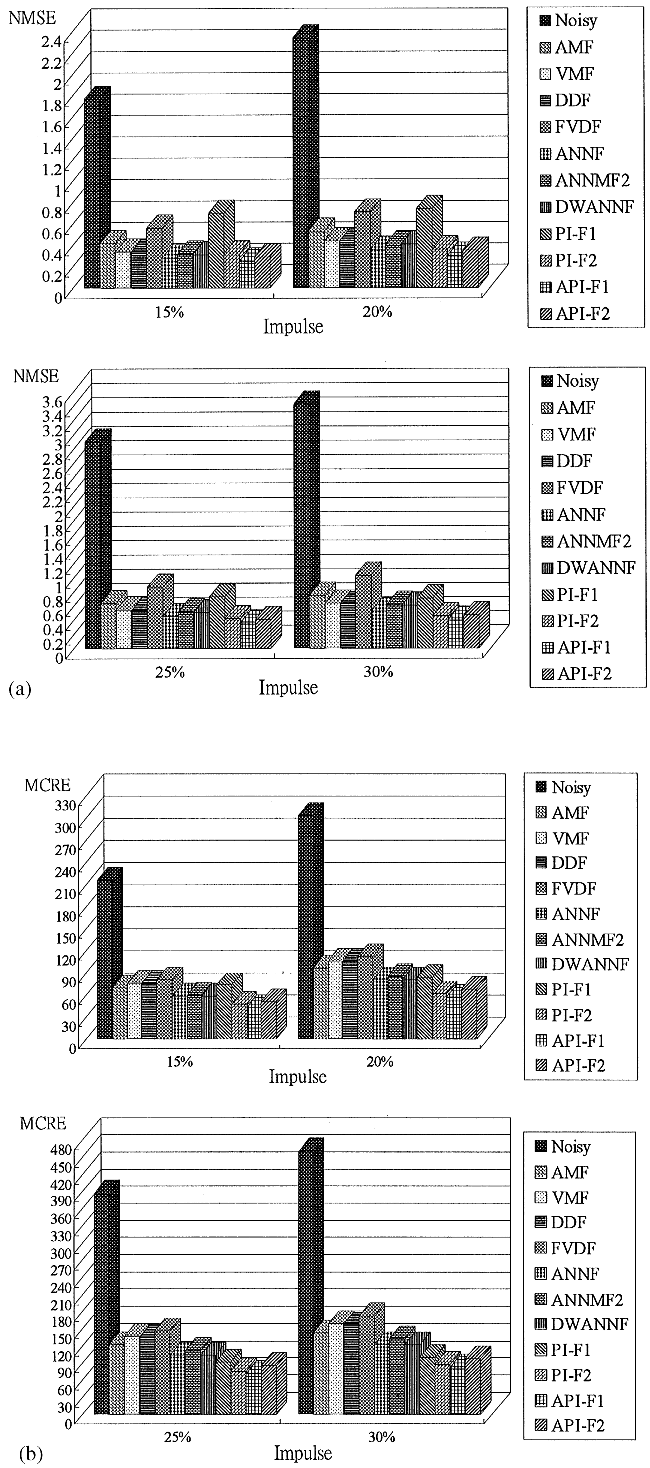

Fig. 17. The merit of (a) NMSE and (b) MCRE criteria on ‘Lena’ image contaminated with Impulse noise.

Table 6
The comparisons between fixed and adaptive α Π filter schemes: NMSE ($\times 10^{-2}$) for the 'Jet' image corrupted with Uniform noise

Noise (%)	Fixed α Π1 filter	Adaptive α Π1 filter	Fixed α Π2 filter	Adaptive α Π2 filter
20	0.09	0.11	0.11	0.12
25	0.12	0.15	0.14	0.15
30	0.15	0.18	0.16	0.19
40	0.22	0.26	0.24	0.28

Table 7
The comparisons between fixed and adaptive α Π filter schemes: NMSE ($\times 10^{-2}$) for the 'Lena' image corrupted with impulsive noise

Noise (%)	Fixed α Π1 filter	Adaptive α Π1 filter	Fixed α Π2 filter	Adaptive α Π2 filter
10	0.55	0.21	0.26	0.23
15	0.70	0.25	0.32	0.29
20	0.74	0.30	0.36	0.35
25	0.73	0.36	0.42	0.41
30	0.71	0.41	0.47	0.47

Table 8
NMSE ($\times 10^{-2}$) for the noisy 'Lena' images corrupted with different amounts of impulsive noises, window 3×3

Noise (%)	AMF	VMF	DDF	FVDF	ANNF	ANN MF2	DWA NNF	Adaptive Π1 filter	Adaptive Π2 filter
10	0.31	0.24	0.24	0.39	0.21	0.23	0.21	0.21	0.23
15	0.42	0.34	0.34	0.56	0.28	0.32	0.29	0.25	0.29
20	0.53	0.44	0.44	0.71	0.36	0.41	0.36	0.30	0.35
25	0.64	0.55	0.55	0.87	0.45	0.52	0.45	0.36	0.41
30	0.75	0.64	0.64	1.03	0.53	0.62	0.53	0.41	0.47

6. Conclusion

In this paper, two new adaptive multichannel filters are proposed. The proposed multichannel filters using local gradient information are simpler and more appropriate than the traditional approaches that have been addressed using groupwise vector ordering information. The first proposed adaptive multichannel filter has the advantages of computation efficiency and good edge preserving for high-frequency short-tail contamination (Gaussian and Uniform). The proposed method attenuates noise in uniform regions and preserves details across edges. Moreover, the second proposed filter is robust to noise type. In our experimental cases, they perform better than other known competitors.

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