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Adaptive fuzzy order statistics-rational hybrid filters for color image processing

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Abstract

In this paper, multichannel image processing using an adaptive approach is studied. The proposed approach is simpler and more appropriate than the traditional approaches that have been addressed by means of groupwise vector ordering information. These adaptive techniques are formed by a two-layer filter based on rational functions using fuzzy transformations of either the Euclidean or angular distances among the different vectors to adapt to local data in the color image. The output is the result of a vector rational operation taking into account three fuzzy sub-function outputs. Extensive simulation results illustrate that the new adaptive fuzzy filters are computationally attractive and achieve noise attenuation, chromaticity retention, and edges and details preservation. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Vector rational filters; Fuzzy membership functions; Vector magnitude filters; Vector directional filters; Color image processing

1. Introduction

The development of image processing methods for filtering multidimensional signals has received increased attention recently due to its importance for applications in remote sensing, robot motion, biomedical image processing and high-definition television (HDTV) [7].

A number of sophisticated multichannel filters have been developed to date for image filtering [3,6]. On the one hand, nonlinear filters applied to images are required to suppress noise while preserving the integrity of edges and detail information. To this end, vector processing of multichannel images is more appropriate compared to traditional approaches that use componentwise operators, instead [14]. For instance, the vector median filter (VMF) [2] minimizes the distance in the vector space between the image vectors as an appropriate error criterion. It inherently utilizes the inner correlation between the channels and retains the desirable properties of the scalar median; namely, the zero impulse response and the preservation of signal edges. VMFs are derived as the maximum likelihood estimators for an exponential distribution when the filter output is restricted to be one of the input samples. They perform accurately when the noise follows a long-tailed distribution

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(e.g. exponential or impulsive); moreover, outliers in the image data are easily detected and eliminated by VMFs. A second class of filters, called vector directional filters (VDF) [23], uses the angle between the image vectors as an ordering criterion. VDFs are optimal directional estimators and, consequently, are very effective in preserving the chromaticity of the image vectors. A drawback of VDF lies in the fact that they do not consider the magnitude of the image vectors, separating in this way the processing of vector data into *directional processing* and *magnitude processing*. However, the resulting filter structures are complex and the corresponding implementations may be slow since they operate in two steps. A third class of filters uses rational functions (RF) in its input/output relation, and hence the name "vector rational filters" (VRF) [10]. There are several advantages to the use of such a function. Similarly, to a polynomial function, an RF is a universal approximator (it can approximate any continuous function arbitrarily well). However, it can achieve a desired level of accuracy with a lower complexity, and possesses better extrapolation capabilities. Recently, a new nonlinear filter structure, the vector median-rational hybrid filter (VMRHF), in a hybrid form was developed in [11]. The VMRHF is a two-stage filter, which exploits in an effective way the features of the VMF and those of the VRFs.

Fuzzy techniques have been successfully applied and used for low-level signal and image processing tasks, such as non-Gaussian noise elimination, nonlinear/non-Gaussian stochastic estimation, image enhancement, video coding, signal sharpening, and edge detection [1,12,20,5]. Because of the underlying power of fuzzy set theory and fuzzy logic, fuzzy rules are flexible and powerful enough to model complex control systems [13]. The local correlation in the data is utilized by applying fuzzy rules directly on the pixels which lie within the operational window. The output value depends on the fuzzy rules and the defuzzifying process, which combines the effects of these different rules [21,22,24]. However, the increase in the local characteristics for such a filter causes a rapid increase in the number of rules. There is no optimal way to optimize such filters constructed by a large number of fuzzy rules.

In this paper, a new adaptive class of nonlinear hybrid filters is introduced. The filter acts based on two stages. It basically combines a fuzzy and non-fuzzy component. Its basic structure can be described as follows: in the first stage, three adaptive subfilters are computed using fuzzy membership functions based on two distance criteria: (1) Euclidean distance (L_2-norm), the resulting subfilter is called fuzzy vector magnitude filters [4]; and (2) angular distance and hence, the name fuzzy VDFs [23]. In the second stage, the outputs of the three subfilters in stage one constitute the input set of the vector rational operation. The behavior of the new filter class can be viewed as a simple control system, since it depends on two control values as will be shown later. Moreover, the new filter also possesses a highly robust capability which is examined in simulations.

This paper is organized as follows: Section 2 defines the adaptive fuzzy order statistics rational hybrid filters (FOSRHF) and points out some of its important properties. The proposed filter structures with different distance functions are presented in Section 3. Section 4 includes simulation results and discussion of the improvement achieved by the new adaptive filter class. In order to incorporate perceptual criteria in the comparison, the error is measured in the uniform $L^*a^*b^*$ color space, where equal color differences result in equal distances [19]. Section 5 concludes the paper.

2. Adaptive fuzzy order statistics rational hybrid filters (FOSRHF)

The new filters are two-stage-type hybrid filters. They combine in the first stage the L_p-norm criteria (angular distance criteria) with weighted mean filters and fuzzy transformations to produce three output vectors in which two are fuzzy vector median (fuzzy vector directional) outputs and one is a fuzzy center weighted vector magnitude filter (fuzzy center weighted VDF) output. In the latter subfilter, we give more importance to the central pixel value. In the second stage, a vector rational operation acts on the above three output vectors to produce the final output vector. The weights of the filter are determined using fuzzy membership functions at each image location.

Let $\underline{\mathbf{f}}(x): Z^l \to Z^m$, represent a multichannel signal and let $W \in Z^l$ be a window of finite size n (filter length). l represents the signal dimensions and m the number of signal channels. The pixels in W will be denoted as x_i, $i = 1, 2, \ldots, n$ and $\underline{\mathbf{f}}(x_i)$ will be denoted as $\underline{\mathbf{f}}_i$. $\underline{\mathbf{f}}_i$ are m-dimensional ($m \geqslant 2$) vectors in the vector space defined by the m signal channels. The FOSRHF is defined as follows:

Definition 2.1. The output vector $\underline{y}(\underline{\mathbf{f}}_i)$ of the FOSRHF is the result of a vector rational function taking into account three input sub-functions which form an input functions set $\{\underline{\Phi}_1, \underline{\Phi}_2, \underline{\Phi}_3\}$, where the "central one" ($\underline{\Phi}_2$) is fixed as a fuzzy center weighted vector magnitude sub-filter (fuzzy center weighted vector directional sub-filter)

$$\underline{y}(\underline{\mathbf{f}}_i) = \underline{\Phi}_2(\underline{\mathbf{f}}_i) + \frac{\sum_{j=1}^{3} \alpha_j \underline{\Phi}_j(\underline{\mathbf{f}}_i)}{h + kD[\,\underline{\Phi}_1(\underline{\mathbf{f}}_i), \underline{\Phi}_3(\underline{\mathbf{f}}_i)]}, \qquad (1)$$

where $D[\cdot]$ is a function of scalar output which plays an important role in RF as an edge sensing term, $\alpha = [\alpha_1, \alpha_2, \alpha_3]$ characterizes the constant vector coefficient of the input sub-functions. In this approach, we have chosen very simple prototype filter coefficients which satisfy the condition: $\sum_{i=1}^{3} \alpha_i = 0$. In our study, $\alpha = [1, -2, 1]^{\mathrm{T}}$. h and k are some positive constants. The parameter k is used to control the amount of the nonlinear effect.

The sub-filters $\underline{\Phi}_1$ and $\underline{\Phi}_3$ are chosen so that an acceptable compromise between noise reduction and edge and chromaticity preservation is achieved. It is easy to observe that this FOSRHF differs from a linear low-pass filter mainly in the scaling, which is introduced on the $\underline{\Phi}_1$ and $\underline{\Phi}_3$ terms. Indeed, such terms are divided by a factor proportional to the output of an edge-sensing term characterized by the function $D[\underline{\Phi}_1, \underline{\Phi}_3]$. The weight of the fuzzy vector magnitude output term is accordingly modified, in order to maintain the gain constant. The behavior of the proposed FOSRHF structure for different positive values of parameter k is as follows:

(1) $k \simeq 0$, the form of the filter is given as a linear low-pass combination of the three nonlinear sub-functions:

$$\underline{y}(\underline{\mathbf{f}}_i) = c_1 \underline{\Phi}_1(\underline{\mathbf{f}}_i) + c_2 \underline{\Phi}_2(\underline{\mathbf{f}}_i) + c_3 \underline{\Phi}_3(\underline{\mathbf{f}}_i), \qquad (2)$$

where the coefficients c_1, c_2, and c_3 are some constants.

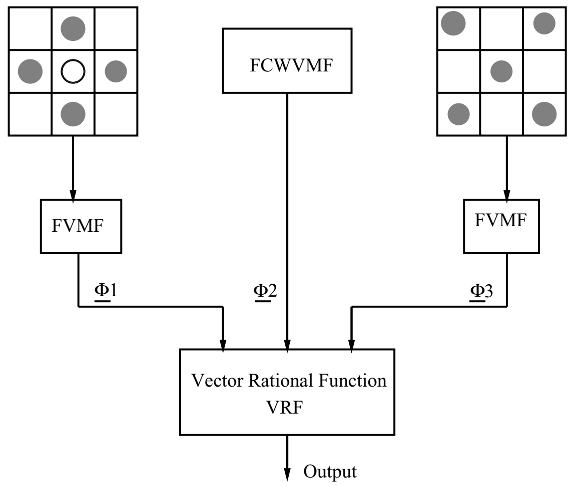


Fig. 1. Structure of the adaptive FVMRHF using bidirectional sub-filters.

(2) $k \to \infty$, the output of the filter is identical to the central sub-filter output and the vector RF has no effect:

$$\underline{y}(\underline{\mathbf{f}}_i) = \underline{\Phi}_2(\underline{\mathbf{f}}_i). \qquad (3)$$

(3) For intermediate values of k, the $D[\underline{\Phi}_1(\underline{\mathbf{f}}_i), \underline{\Phi}_3(\underline{\mathbf{f}}_i)]$ term perceives the presence of a detail and accordingly reduces the smoothing effect of the operator.

Therefore, the FOSRHF operates as a linear low-pass filter between three nonlinear sub-operators, the coefficients of which are modulated by the edge-sensitive component. If the subfilters are fuzzy vector magnitude filters, then the resulting filter is called adaptive fuzzy vector magnitude rational hybrid filter (FVMRHF). If the subfilters are fuzzy VDFs, then the resulting filter is called adaptive fuzzy vector directional rational hybrid filter (FVDRHF). The proposed structure of the FVMRHF is shown in Fig. 1 using two bidirectional fuzzy vector magnitude sub-filters and one fuzzy center weighted vector magnitude filter.

The general form of each adaptive sub-filter proposed in the first layer is given as a fuzzy weighted average of the input vectors inside the window

Table 1
Different distance measures

	Magnitude distances	Angular distances
Normalized sum of absolute distance	$\tilde{a}_i = (1/N)\sum_{j=1}^{N} \|\mathbf{x}_i - \mathbf{x}_j\|$	$\tilde{a}_i = (1/N)\sum_{j=1}^{N} \theta(\mathbf{x}_i, \mathbf{x}_j)$
Normalized sum of square distance	$\tilde{a}_{2i} = (1/N)\sum_{j=1}^{N} \|\mathbf{x}_i - \mathbf{x}_j\|_2$	$\tilde{a}_{2i} = (1/N)\sum_{j=1}^{N} \theta^2(\mathbf{x}_i, \mathbf{x}_j)$

W ($\underline{\Phi}_i$ is the output of the sub-filter i, $i = 1, 2, 3$)

$$\underline{\Phi}_i = \frac{\sum_{j=1}^{n} W_j \underline{\mathbf{f}}_j}{\sum_{j=1}^{n} W_j}. \tag{4}$$

The weighting coefficients are transformations of the sum of distances between the center pixel in the window (pixel under consideration) and all input vectors inside the filter window.

The adaptive weight represents the confidence that the vectors under consideration come from the same region: Thus, it is reasonable to make the weights in (4) proportional to the difference in terms of a distance measure between a given vector and its neighbors inside the filtering window. The design objective is to: *assign the maximum weight to the vector that is most centrally located inside the processing window*. Thus, the vector with the maximum weight will be the one that has the minimum distance from all the other vectors. In this way, atypical vectors due to noise or missing components (outliers), which are placed far away from the centermost vector, will be assigned smaller weights and will contribute less to the final output. The weighting transformation is essentially a membership function with respect to the specific window components. In accordance with our design objective, it is reasonable to select an appropriate fuzzy transformation so that the vector with minimum distance will be assigned the maximum weight. The membership function value can be regarded as the comparison of the vector under consideration with the ideal vector that results in a distance, which can be defined as

$$W_j = \frac{\beta}{1 + \gamma(\underline{\mathbf{f}}_j)}, \tag{5}$$

where $\gamma(\cdot)$ is a distance function yet to be determined. If the vector under consideration $\underline{\mathbf{f}}_j$ has all the features of the ideal vector, then the distance should be zero resulting in $W_j \to 1$, otherwise, if no similarity between the ideal and the vector $\underline{\mathbf{f}}_j$ exists, then the distance shall be ∞ with $W_j \to 0$.

The parameter β is a soft parameter used to adjust the limit of the S-shaped membership function (weight scale threshold). In order to use membership functions that deliver an output in the interval [0, 1], we assigned the value $\beta = 2$.

3. Distance functions

In this framework, there is no requirement for fuzzy rules or local statistics estimations. Features extracted from local data, here in the form of sums of distances, are used as inputs to the fuzzy weights. The form of (4) provides the means to generate a variety of different fuzzy membership strengths depending on the type of distance function used as input to the fuzzy membership function. Here, we adopted two well-known distance functions: the magnitude distance and the angular distance (Table 1 shows different forms of the distance functions).

3.1. Magnitude processing: (magnitude distance)

The criterion adopted here is the minimum Euclidean distance. It was pointed out in [2], that the VMF selects the vector that is most centrally located using as a criterion the minimization of the sum of the Euclidean distances with the other vectors. The average of the sum of the Euclidean absolute distances with the other vectors in the window is the distance criterion used here as the input to the fuzzy transformation.

Let $\tilde{a}_i$ correspond to $\underline{\mathbf{f}}_i$ defined as

$$\tilde{a}_i = \frac{1}{N}\sum_{j=1}^{N} \|\underline{\mathbf{f}}_i - \underline{\mathbf{f}}_j\|, \tag{6}$$

where $\|.\|$ denotes L_1-norm. The weights of the new sub-filter are determined using a fuzzy membership function of the above distances. Usually, the fuzzy transformation depends on the distance measure used. Since the Euclidean distance criterion is used, the fuzzy weight adopted is a sigmoid,

$$W_j = \frac{2}{1+\exp(\tilde{a}_j^r)}, \tag{7}$$

where parameter r is used to adjust the smoothness of the output. As a general rule, smaller values of r can smooth out noisy vectors, while larger values can make the overall output as nonlinear as required to preserve details and discard impulsive-type noise. Thus, the parameter should be properly chosen to provide a balance between smoothing and detail preservation.

Thus, the first layer of the entire structure is formed by two fuzzy vector magnitude filters ($\underline{\Phi}_1, \underline{\Phi}_3$) and one fuzzy center weighted vector magnitude filter ($\underline{\Phi}_2$). The edge sensor of the vector RF in the second layer uses the magnitude difference between the vectors in the L_2-norm sense and is given by

$$D[\underline{\Phi}_1, \underline{\Phi}_3] = \|\underline{\Phi}_1 - \underline{\Phi}_3\|_2,$$

where $\|.\|_2$ denotes the L_2-norm.

3.2. *Directional processing:* (*angular distance*)

The previous operators use the difference of the vector magnitudes as edge sensors. In the color space, transitions are also represented by angles between the color vectors. At a fixed luminance, small angles between color vectors denote "color" homogeneous regions, whereas large angles indicate edges. In the following, a modified VRF is proposed in which the edge sensors rely on the angles between the color vectors instead of the difference of their magnitudes.

Color images are two-dimensional three-channel signals, where each pixel can be represented as a vector in the 3-D color space. Color image pixels are thus regarded as vectors in the color cube, as shown in Fig. 2. The points marked with a cross "x" denotes the intersection point of the color vector with the *Maxwell triangle* (the triangle drawn between the three primaries, R, G, B). θ represents the angle between two vectors **u** and **v**.

The angle between the directions of the color vectors is now used as the edge sensitivity measure. The goal is to sustain the sharpness of the filtered image by preserving the transitions detected in the color space. The vector angle criterion orders the input vectors according to the normalized sum of angles with all other vectors.

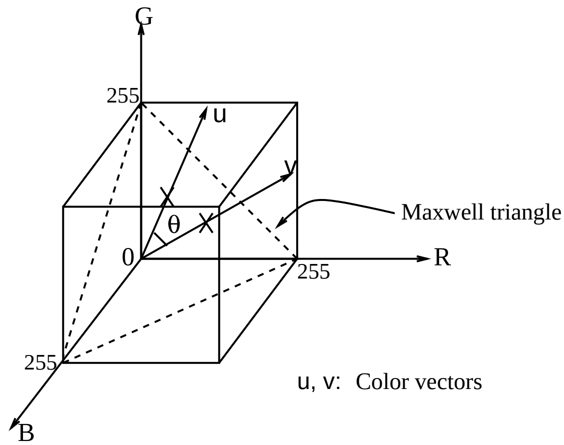


Fig. 2. Vectorial representation of the color image pixels in the RGB color space.

Let $\tilde{a}_i$ correspond to $\underline{\mathbf{f}}_i$ defined as

$$\tilde{a}_i = \frac{1}{N}\sum_{j=1}^{N} \theta(\underline{\mathbf{f}}_i, \underline{\mathbf{f}}_j) \tag{8}$$

and

$$\theta = \arccos\left(\frac{\langle \underline{\mathbf{f}}_i, \underline{\mathbf{f}}_j\rangle}{\sqrt{\|\underline{\mathbf{f}}_i\|_2^2 . \|\underline{\mathbf{f}}_j\|_2^2}}\right),$$

where $\theta(\underline{\mathbf{f}}_i, \underline{\mathbf{f}}_j)$ denotes the angle between the vectors $\underline{\mathbf{f}}_i, \underline{\mathbf{f}}_j$ and $0 \leqslant \theta(\underline{\mathbf{f}}_i, \underline{\mathbf{f}}_j) \leqslant \pi$. If input ordering is required, then an ordering of the $\tilde{a}_i$'s as $\tilde{a}_{(1)} \leqslant \tilde{a}_{(2)} \leqslant \cdots \leqslant \tilde{a}_{(N)}$ implies the same ordering to the corresponding $\underline{\mathbf{f}}_i$'s: $\underline{\mathbf{f}}_{(1)} \leqslant \underline{\mathbf{f}}_{(2)} \leqslant \cdots \leqslant \underline{\mathbf{f}}_{(N)}$.

The edge sensor for the vector rational operation is

$$D[\underline{\Phi}_1, \underline{\Phi}_3] = \theta^2(\underline{\Phi}_1, \underline{\Phi}_3).$$

3.3. *Combined magnitude directional processing*

The magnitude distance is used for its noise attenuation property in contrast to the angular distance that is used for its chromaticity retention. Therefore, it is very important to express a third distance measure combining these two distances [9]. Such a criterion would be more relevant to the human visual system. Let $\tilde{a}_i$ correspond to $\underline{\mathbf{f}}_i$ defined as

$$\tilde{a}_i = \frac{1}{N}\left[\sum_{j=1}^{N}\theta(\underline{\mathbf{f}}_i,\underline{\mathbf{f}}_j)\right]^p\left[\sum_{j=1}^{N}\|\underline{\mathbf{f}}_i-\underline{\mathbf{f}}_j\|\right]^{1-p},$$

$$p\in[0,1],\quad i=1,2,\ldots,N,$$

where $\theta(\underline{\mathbf{f}}_i,\underline{\mathbf{f}}_j)$ denotes the directional (angular) distance defined in (8) with the second term in (6) to account for the differences in magnitude in terms of L_1 metric. The power parameter p controls the importance of the angle criterion versus the distance criterion in the overall fuzzy membership function. In the two extremes, $p=0$ or 1, the operator behaves as either magnitude processing or directional processing, respectively. The case of $p=0.5$ gives equal importance to both criteria.

We have adopted a constant operational value $p=0.25$ as explained in [9]. This represents a compromise between the different values implied by the different noise models. Moreover, since the performance measures remain practically unchanged for a range of p values, which includes the value $p=0.25$, this is a “safe” value independent of the noise distribution [9].

The VRF edge sensor is now expressed as a function of the angles between the color vectors and the difference of their magnitudes. Using the same methodology, the edge sensor is written as

$$D[\underline{\Phi}_1,\underline{\Phi}_3]=[(\theta(\underline{\Phi}_1,\underline{\Phi}_3))^p(\|\underline{\Phi}_1-\underline{\Phi}_3\|)^{1-p}]^2.$$

Actually, the resulting filter is called adaptive fuzzy vector directional magnitude rational hybrid filter (FVDMRHF).

3.4. Comments

It is easy to make the following observations:

- Using the above sub-filter formulations, there is no requirement for fuzzy rules. The fuzzy weights are determined through the distance and the fuzzy transformation. The fuzzy membership function selected here derives its output in the range [0, 1] and is smooth over the entire input range.
- The new fuzzy sub-filters do not require any ordering. It is well known [17] that nonlinear filters based on order statistics are computationally expensive. The ranking process for multichannel images is computationally demanding, especially for a large window.
- Every sub-filter output (4) provides a vector valued signal, which is not included in the original set of inputs. Thus, some problems for image restoration can be solved, mainly when the desired output is not one of the observation samples.

4. Experimental results

The new filters are compared quantitatively with the widely known multidimensional nonlinear filters such as, the VMF, the vector distance directional filter and the VMRHF. For convenience, the simulated filters are denoted as follows:

- VMF: vector median filter,
- DDF: distance and directional filter,
- VMRHF: vector median-rational hybrid filter,
- FVMRHF: adaptive fuzzy vector magnitude rational hybrid filter,
- FVDRHF: adaptive fuzzy vector directional rational hybrid filter,
- FVDMRHF: adaptive fuzzy vector directional magnitude rational hybrid filter.

The noise attenuation properties of the different filters are examined by utilizing the real color images, Lena Fig. 3(a) and Peppers Fig. 3(b). The test images have been contaminated using various noise source models in order to assess the performance of the filters under different scenarios:

(1) *Gaussian noise*: Implies corruption by zero mean additive noise with a varying standard deviation σ.
(2) *Implusive noise*: Each image channel is corrupted independently using “salt and pepper” noise. We assume that both “salt” and “pepper” impulses are equally likely to occur.
(3) *Mixed Gaussian-impulsive noise*: The impulsive noise is fixed (“salt and pepper” 2% in each image channel). The standard deviation of the Gaussian noise is varied.

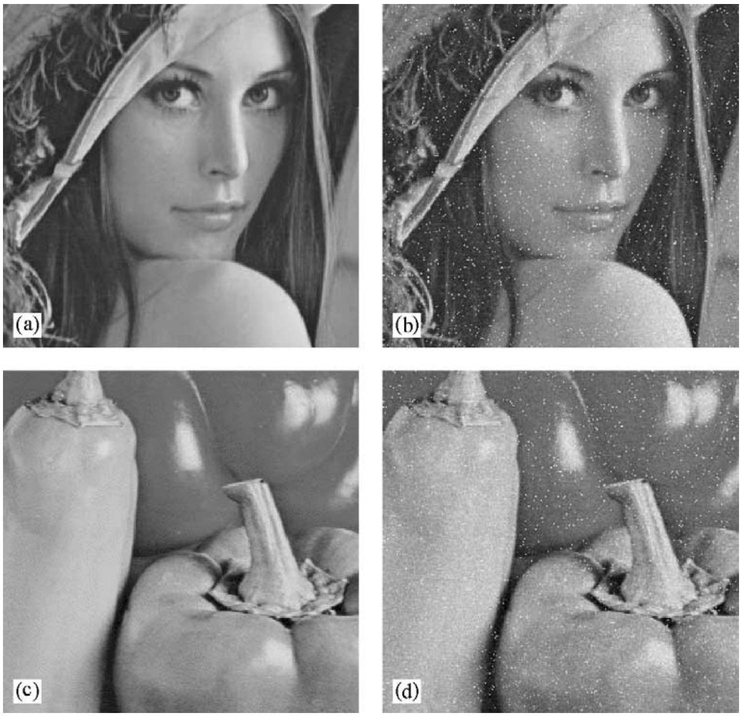


Fig. 3. Test images: (a) Lena image; (b) Peppers image (*left*: noise free, *right*: contaminated). The noise is a mixed impulsive-Gaussian noise (*impulsive* 2% in each component and *Gaussian* with zero mean and variance 100).

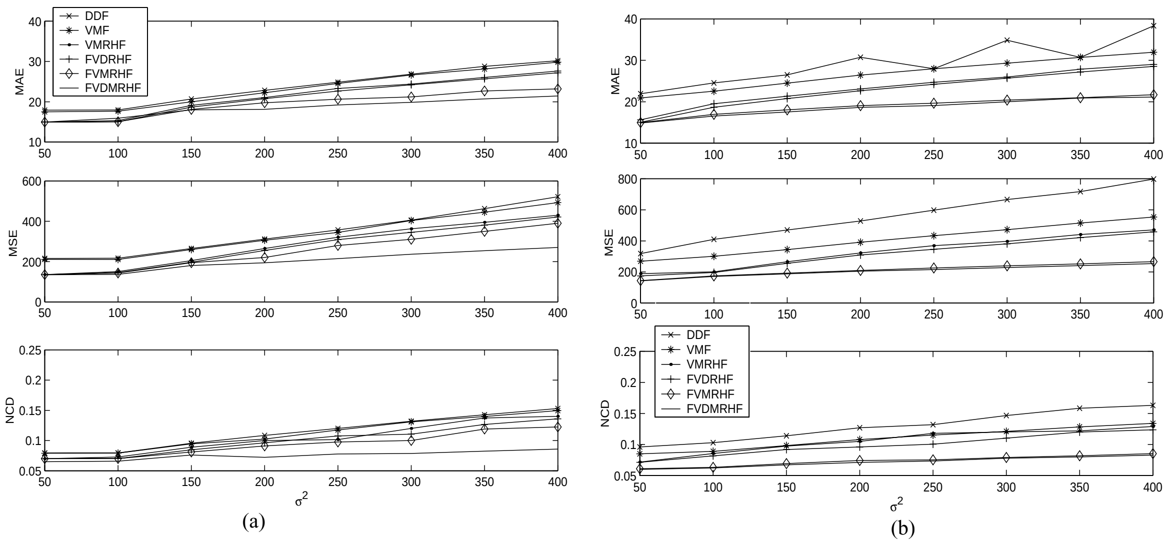
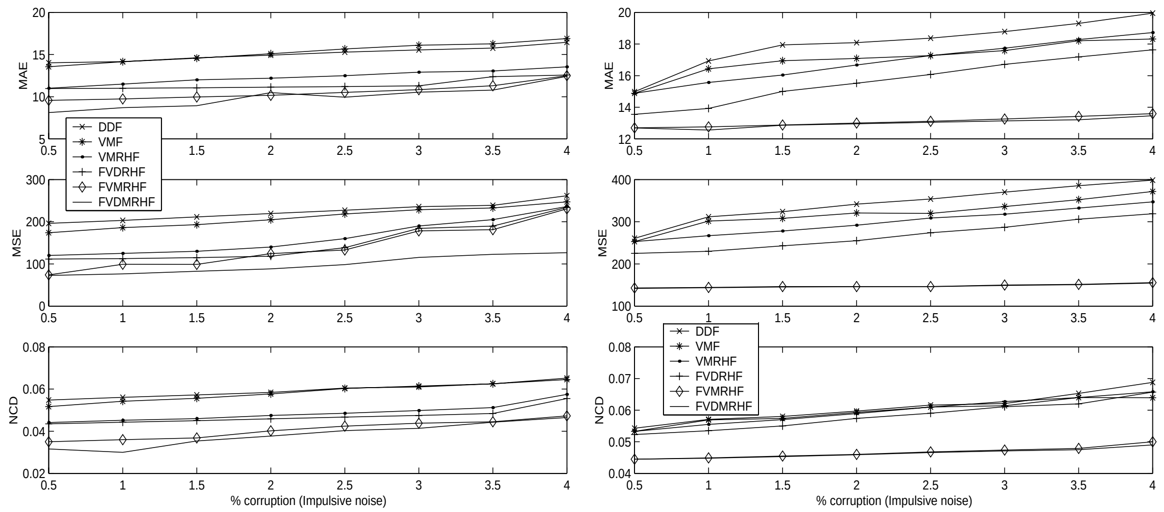


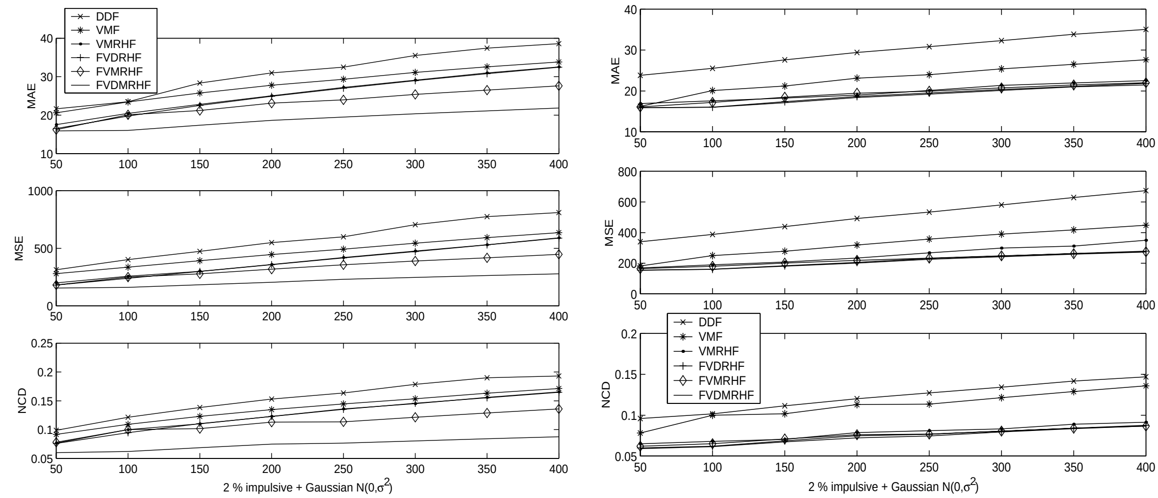
Fig. 4. Comparative results for the images in Fig. 3 contaminated by Gaussian noise: (a) Lena image; (b) Peppers image.

The original images, as well as their noisy versions, are represented in the RGB color space. This color coordinate system is considered to be objective, since it is based on the physical measurements of the color attributes. The filters operate on the images in the RGB color space.



(a) (b)

Fig. 5. Comparative results for the images in Fig. 3 contaminated by impulsive noise (salt and pepper): (a) Lena image; (b) Peppers image.



(a) (b)

Fig. 6. Comparative results for the images in Fig. 3 contaminated by mixed noise (salt and pepper 2% in each component, and Gaussian with zero mean and variable variance): (a) Lena image; (b) Peppers image.

A number of different objective measures can be utilized for quantitative comparison of the performance of the different filters. All of them provide some measure of proximity between two digital images by exploiting the differences in the statistical distributions of the pixel values [6]. The most widely used measures are the mean absolute error (*MAE*), the mean square error (*MSE*), and the normalized color difference (*NCD*). The latter measure is used to quantify the perceptual error between images in the perceptually uniform $L^*a^*b^*$ color space which is known as a space, where equal color differences result in equal distances [19]. Conversion from RGB to $L^*a^*b^*$ color space is explained in detail in [8].

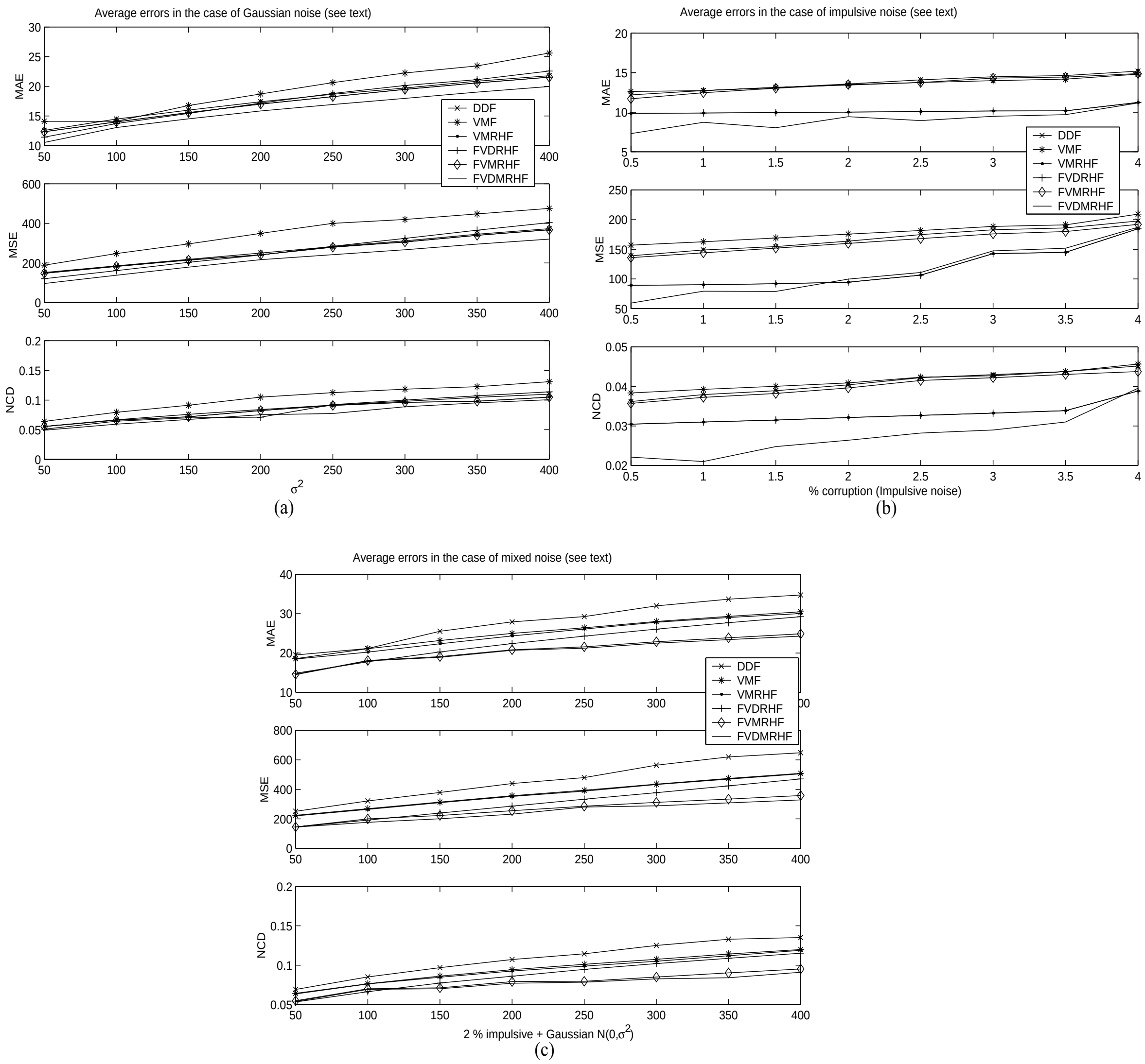


Fig. 7. Comparative average results using four color images: (Lena, Peppers, Rose, and Mandrill), and the same error criteria: (a) Gaussian noise; (b) impulsive noise; (c) mixed Gaussian with impulsive.

RGB values of both the original noise free and the filtered image are converted to the corresponding $L^*a^*b^*$ values for each of the filtering method under consideration.

In $L^*a^*b^*$ color space, we computed the *NCD* [18] which is estimated according to the following expression:

$$NCD = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\Delta E_{Lab}}{\sum_{i=1}^{M}\sum_{j=1}^{N}E^*_{Lab}}, \qquad (9)$$

where ΔE_{Lab} is the perceptual color error between two color vectors and defined as the Euclidean distance between them, given by

$$\Delta E_{Lab} = [(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2]^{1/2}, \qquad (10)$$

where ΔL^*, Δa^*, and Δb^* are the differences in the L^*, a^*, and b^* components, respectively. E^*_{Lab} is the magnitude of the original image pixel vector in

Fig. 8. Images (a)–(f) are the processed Lena image (Fig. 3(a)) by the DDF, VMF, VMRHF, FVDRHF, FVMRHF and FVDMRHF, respectively.

the $L^*a^*b^*$ space and is given by

$$E^*_{Lab} = [(L^*)^2 + (a^*)^2 + (b^*)^2]^{1/2}.$$

The comparisons of filtering performance results with three distinct measures are shown in the form of plots in Figs. 4–6 for the three noise models: Gaussian, impulsive, and Gaussian mixed with impulsive, respectively. It is obvious to conclude from the plots, that the performance of the new fuzzy filters (FVMRHF, FVDRHF, FVDMRHF) is better than that of the other simulated filters under consideration (i.e. VMF, DDF and VMRHF). Moreover, consistent results have been obtained when using a variety of other color images and the same evaluation procedure.

The filtered images are presented in Figs. 8 and 9 for visual and qualitative comparison, since in many cases they are the best measure of performance. Figs. 8(a)–(f) (Figs. 9(a)–(f)) are the filtered images of the corrupted Lena image (Peppers image) by mixed impulsive-Gaussian noise (impulsive 2%

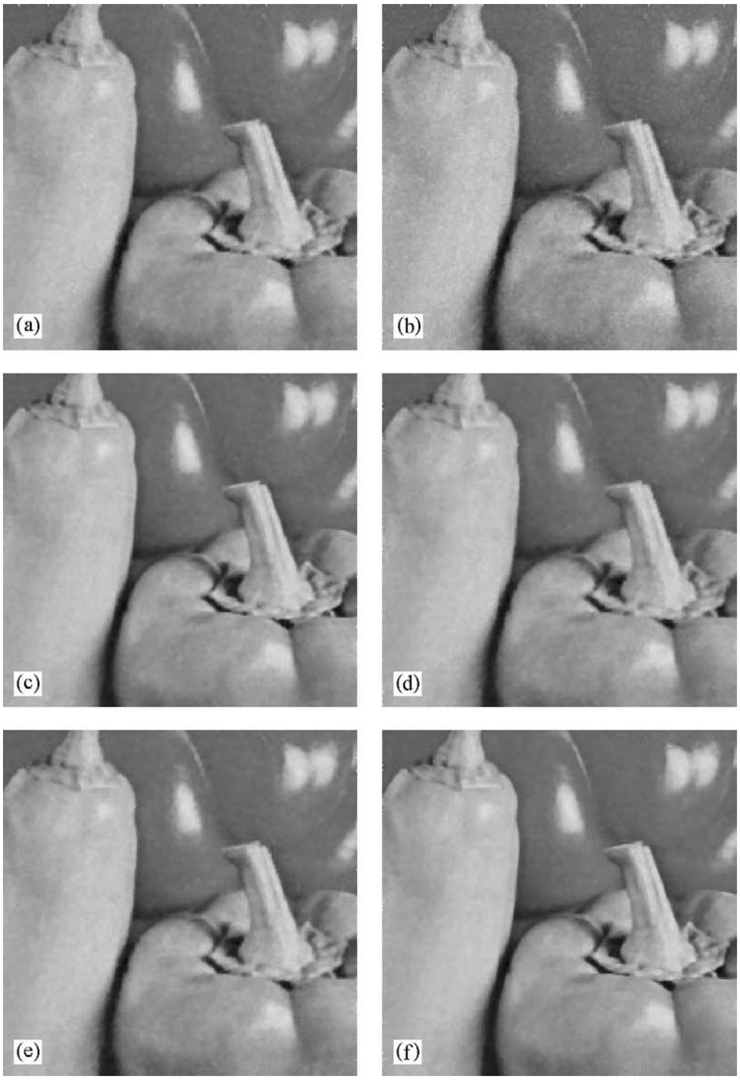


Fig. 9. Images (a)–(f) are the processed Peppers image (Fig. 3(b)) by the DDF, VMF, VMRHF, FVDRHF, FVMRHF and FVDMRHF, respectively.

in each component and Gaussian with zero mean and variance 100), using DDF, VMF, VMRHF, FVDRHF, FVMRHF and FVDMRHF, respectively. All the filters considered, operate using a square 3×3 processing window. The new adaptive fuzzy filters can preserve edges and smooth noise under different scenarios, outperforming the other widely used multichannel filters. A comparison of the images clearly favors our new adaptive fuzzy filters over their counterparts VMF and DDF, and slightly better than the VMRHF. These new filters do not suffer from VMF's inefficiency in a Gaussian noise environment and a small filtering window. Moreover, it has a better visual quality than the others, particularly, with Lena image Fig. 8(f). The proposed fuzzy filters can effectively remove impulses, smooth out nominal noise and preserve edges, details and color uniformity.

An additional sample processing results are presented in Figs. 7(a)–(c) as an average of the MAE, MSE, NCD errors over the four natural color images (Lena, Peppers, Rose and Mandrill) to recapitulate the comparison performances with respect to the nonlinear multichannel filters used.

Considering the number of computations needed for the implementation of the adaptive fuzzy filters and specially the adaptive FVMRHF filter, it should be noted that it does not require any ordering, which makes it faster than those based on order statistics. In addition, the different sub-filters can be computed in parallel thus reducing the execution time and making the new Fuzzy filters suitable for real-time implementation with digital signal processors.

5. Conclusion

A novel class of nonlinear multichannel filters, adaptive fuzzy order statistics-rational hybrid filters, has been proposed in this paper. These filters are two-stage filters which combine in a novel way, fuzzy memberships, average filters and distance criteria to provide the outputs of their first stage. They combine the good behavior of RF and fuzzy logic with vector approach (i.e. fuzzy vector magnitude filters, fuzzy VDFS and fuzzy vector directional magnitude filters). Simulation results and subjective evaluation of the filtered images indicate that the new filters with their three subclasses (FVMRHF, FVDRHF, FVDMRHF) outperform all other filters used in the study. Moreover, as seen from the images, FVMRHF, FVDRHF and FVDMRHF not only possess the capabilities of noise attenuation and edges or details preservation but also preserve the chromaticity components that are very important in the visual perception of color images.

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