

COLOR IMAGE PROCESSING USING GENERALIZED WEIGHTED VECTOR FILTERS

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Abstract This paper focuses on generalized weighted vector filters which constitute a powerful filtering framework for multichannel signal processing. The utilization of a generalized multichannel sigmoidal adaptation scheme allows to accommodate the filter parameters to varying signal and noise statistics. Experimental results indicate that the presented multichannel filters are capable of removing impulsive noise present in color images and simultaneously they preserve color and structural information.

Keywords: Multichannel image processing; color image filtering; filter weights; adaptation algorithm.

1. INTRODUCTION

In the last decade, a number of nonlinear multichannel filters have been developed¹⁻³. Among them, vector filters take a great interest of the image processing community due to the importance of color image processing⁴. It is well-known that noise and other impairments introduced during recording and/or transmission of the image data degrade the value of the color information. This usually declines the perceptual quality and the fidelity of the images, and decreases the performance of the task for which the image was used⁵.

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Therefore, noise filtering is an essential part of any image processing based system. In this paper, we focus on impulsive noise removal in color images using generalized weighted vector filters⁵.

2. GENERALIZED WEIGHTED VECTOR FILTERS

Let us consider, a $K_1 \times K_2$ multichannel image $\mathbf{x} : Z^l \rightarrow Z^m$ representing a two-dimensional matrix of m -component samples $\mathbf{x}_i = [x_{i1}, x_{i2}, \dots, x_{im}]$. Note that standard color images such as Red-Green-Blue (RGB) images relate to parameters $l = 2$ and $m = 3$. Components x_{ik} , for $k = 1, 2, \dots, m$ and $i = 1, 2, \dots, K_1 K_2$, represent the k -th elements of the vectorial inputs \mathbf{x}_i . Thus, each multichannel sample \mathbf{x}_i can be considered as a m -dimensional vector. Operating on some type of sliding window $W = \{\mathbf{x}_i \in Z^l; i = 1, 2, \dots, N\}$ of finite size N , the window center $\mathbf{x}_{(N+1)/2}$ is replaced by some function of a local neighborhood area W . This window operator slides over the image to affect individually all the image pixels.

It has been widely observed that vector processing is the most effective way to process noisy color images¹⁻⁵. Since the noisy samples usually represent extremes of the input set, they can be effectively determined using the aggregated distance concept applied to the samples of W . The extreme observations maximize the aggregated distances to other samples of W and therefore, the most popular vector filters determine the output as the lowest ranked vector in a predefined sliding window^{4,5}. The well-known vector median filters (VMF)¹ utilize the aggregated Euclidean distance, whereas vector directional filters (VDF)² utilize the aggregated angular distance of the input vectors.

Employing the concept of generalized weighted vector filters (WVF)⁵: i) a number of previously developed vector filters (including VMF and VDF) are generalized, ii) more sophisticated filtering solutions can be designed, and iii) the characteristics of the solution can be adapt for various image and noise statistics. In the WVF design, the vectors $\mathbf{w} = [w_1, w_2, \dots, w_N]$ and $\mathbf{u} = [u_1, u_2, \dots, u_N]$ represent sets of positive real weights reflecting the magnitude and directional characteristics of the input samples \mathbf{x}_i associated with the weights w_i and u_i , for $i = 1, 2, \dots, N$. Using the minimization principle, the WVF scheme is defined as follows⁵:

$$\min_{\mathbf{x}_{(1)} \in W} \arg \left(\sum_{i=1}^N w_i \|\mathbf{x}_{(1)} - \mathbf{x}_i\|_2 \right)^{1-p} \left(\sum_{i=1}^N u_i A(\mathbf{x}_{(1)}, \mathbf{x}_i) \right)^p \quad (1)$$

where $\|\mathbf{x}_{(1)} - \mathbf{x}_i\|_2$ is the Euclidean distance, whereas $A(\mathbf{x}_{(1)}, \mathbf{x}_i)$ denotes the angular distance between two color vectors $\mathbf{x}_{(1)}$ and \mathbf{x}_i . The parameter p is a design parameter ranged from 0 to 1 and it can be used to tune the overall filter characteristics.

To adapt the WVF coefficients in required manner, a multichannel generalization of the sigmoidal adaptation scheme of⁶ has been provided⁵. Assu-

ming, for the simplicity, the equivalence between the weight vectors \mathbf{w} and \mathbf{u} so that $w_i = u_i$, for $i = 1, 2, \dots, N$, the WVF can be defined using $\mathbf{w} = [w_1, w_2, \dots, w_N]$, only. Employing the vector approach of,⁵ the generalized difference between two vectors \mathbf{x}_i and \mathbf{x}_j is defined as follows:

$$D(\mathbf{x}_i, \mathbf{x}_j) = S(\mathbf{x}_i, \mathbf{x}_j) (\|\mathbf{x}_i - \mathbf{x}_j\|_2)^{1-p} (A(\mathbf{x}_i, \mathbf{x}_j))^p \quad (2)$$

where $S(\mathbf{x}_i, \mathbf{x}_j) \in \{-1, 1\}$ is a polarity function given by $S(\mathbf{x}_i, \mathbf{x}_j) = 1$ for $\|\mathbf{x}_i\| \geq \|\mathbf{x}_j\|$, and $S(\mathbf{x}_i, \mathbf{x}_j) = -1$ for $\|\mathbf{x}_i\| < \|\mathbf{x}_j\|$. The use of $S(\cdot, \cdot)$ preserves the sign of the difference between the scalar image samples \mathbf{x}_i and \mathbf{x}_j , since for a scalar case, i.e. $m = 1$ and $p = 0$, the magnitude of \mathbf{x}_i and \mathbf{x}_j is equivalent to x_{i1} and x_{j1} , respectively.

During processing, the sliding filtering window is moving over an image domain. With respect to the filter weights at the previous points, the iterative algorithm adjusts the weights w_i , for $i = 1, 2, \dots, N$, as follows⁵:

$$w_i = P[w_i + 2\mu D(\mathbf{o}, \mathbf{y}) \text{sgn}(D(\mathbf{x}_i, \mathbf{y}))] \quad (3)$$

where \mathbf{o} denotes the desired (original) signal, μ is the regularization factor, \mathbf{y} is the output of the sigmoidally optimized WVF filter (1) related to the actual weight coefficients \mathbf{w} , $\text{sgn}(a) = (2/(1 + e^{-a})) - 1$ denotes the sign sigmoidal function and $P(\cdot)$ is a projection function which changes the negative values to zero during the weight adaptation. The initial weight vector \mathbf{w} should contain the equal weights corresponding to the robust smoothing functions⁵.

Since, original noise-free (training) samples may not be available in practical image processing applications, the desired signal \mathbf{o} in (3) should be replaced with the robust, easily achieved estimate \mathbf{y}^* . Using a component-wise median filter (MF),⁷ the adaptation formula (3) is modified as follows⁵:

$$w_i = P[w_i + 2\mu D(\mathbf{y}^*, \mathbf{y}) \text{sgn}(D(\mathbf{x}_i, \mathbf{y}))] \quad (4)$$

where $\mathbf{y}^* = [y_1^*, y_2^*, \dots, y_m^*]$ is the MF of the input set W .

To improve the detail-preserving characteristics of (4), it can be desirable to simultaneously use the MF output \mathbf{y}^* and the central sample $\mathbf{x}_{(N+1)/2}$,⁵:

$$w_i = P[w_i + 2\mu (D(\mathbf{y}^*, \mathbf{y}) + D(\mathbf{x}_{(N+1)/2}, \mathbf{y})) \text{sgn}(D(\mathbf{x}_i, \mathbf{y}))] \quad (5)$$

Such a filter should demonstrate the excellent balance noise smoothing and color/structural content preservation.

3. EXPERIMENTAL RESULTS

The adaptation capability of the WVF framework is tested using 256×256 test color image Lena (Fig.1a,b). In all subsequent experiments a 3×3 supporting window (i.e. $N = 9$) is used. The results are measured using the



Figure 1. 256 × 256 test color images: (a) original image Lena, (b) image Lena corrupted by 10% impulsive noise, (c) original image Parrots.

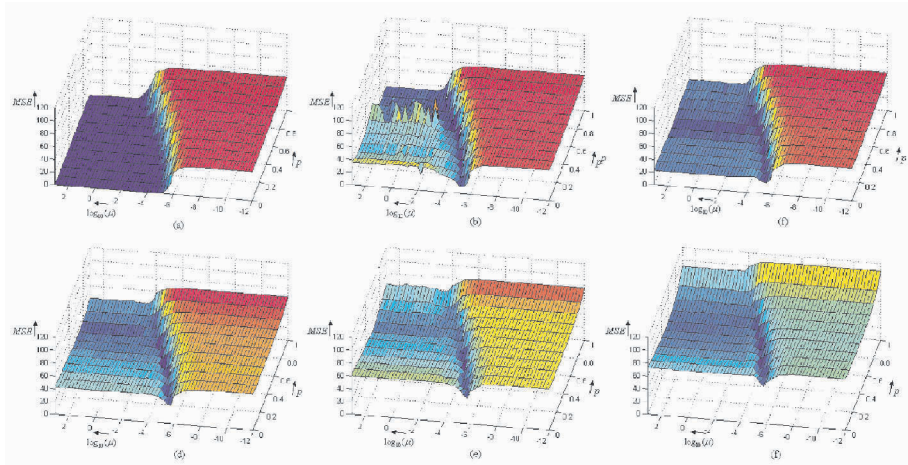


Figure 2. WVF adaptation capability v.s. MSE expressed for the image Lena corrupted by impulsive noise: (a) 0% noise, (b) 2% noise, (c) 5% noise, (d) 10% noise, (e) 15% noise, (f) 20% noise.

commonly accepted mean square error (MSE) and normalized color difference (NCD) criteria^{4,5}. Fig.2 shows the results, expressed in terms of MSE, are related to the training set represented by the test image Lena and its corrupted versions with 0% (no corruption), 2%, 5%, 10%, 15% and 20% impulsive noise, respectively. It can be seen that the error criteria increase with the noise corruption and that in all cases the WVF scheme achieved the best results for $\mu \geq 0.5$.

The WVF filters optimized using the image Lena corrupted by 10% impulsive noise are compared, in terms of performance related to the test color image

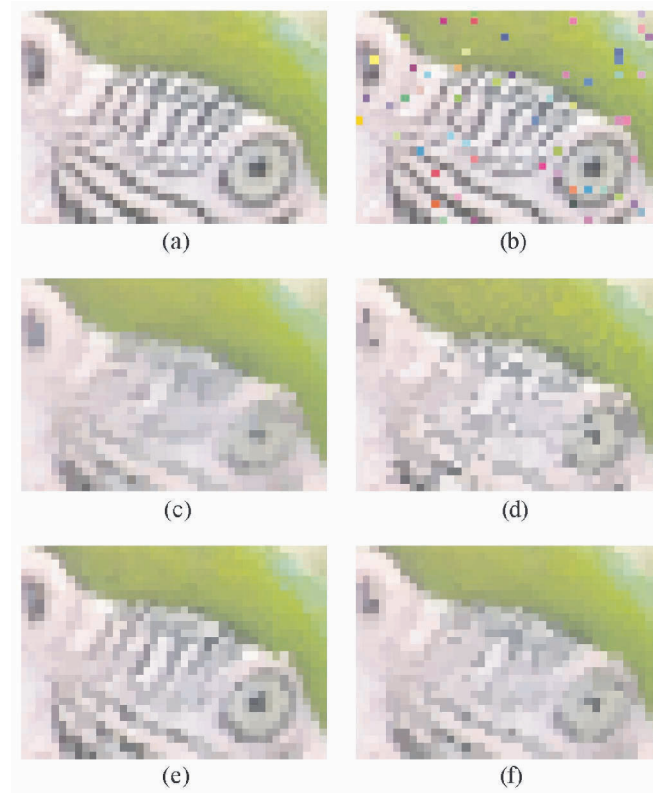


Figure 3. Enlarged parts of Parrots image: (a) original, (b) image corrupted by 5% impulsive noise, (c) VMF output, (d) BVDF output, (e) WVF output obtained via (3), (f) WVF output obtained via (5).

Parrots (Fig.1c) with other widely used color image filters such as VMF,¹ basic VDF (BVDF),² MF,⁷ and directional-distance filter (DDF)⁸.

Visual inspection of the results shown in Table 1 and Fig.3 reveals that the WVF schemes achieve excellent balance between noise attenuation and signal-detail preserving characteristics, and outperform well-known techniques, in terms of both objective (Table 1) and subjective (Fig.3) comparisons.

4. CONCLUSION

In this paper, a generalized vector signal processing framework based on the order-statistic theory was presented. A robust approach for weight adaptation was tested using noisy color images. The presented WVF filters are able

Table I. Comparison of the presented algorithms using image Parrots.

Noise	5% noise		10% noise	
Method/Criterion	MSE	NCD	MSE	NCD
Noisy	443.6	0.0432	882.0	0.0857
MF	63.1	0.0170	70.0	0.0198
VMF	64.2	0.0132	69.6	0.0142
BVDF	109.0	0.0116	113.5	0.0127
DDF	65.3	0.0117	69.7	0.0128
WVF (3), $p = 0.5$	18.5	0.0033	29.8	0.0049
WVF (5), $p = 0.5$	51.8	0.0091	58.2	0.0105

to achieve excellent balance between smoothing and detail preservation and outperform commonly used filtering schemes.

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