CLASSIFICATION BASED ADAPTIVE VECTOR FILTER FOR COLOR IMAGE RESTORATION

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ABSTRACT

A new adaptive vector filter is proposed for restoring color images corrupted by impulse noise. The local image structure is estimated by a series of central weighted vector median filtering operations. Then a classification process is applied to map the local estimate errors into a group of mutually exclusive structure partition cells. For each partition, an optimal weighted filter is applied to provide the best image structure restoration. The new filter has demonstrated satisfactory results in suppressing various distinct types of impulse noise. Noticeable performance gains have been demonstrated over other existing methods in terms of objective measures and perceptual quality.

1. INTRODUCTION

Nonlinear filters have been widely used for restoration of noisy gray-scale images [1]. However, a straightforward extension of scalar techniques into the color space often results in drawbacks such as pixel value re-arranging or chromatic shifting [2]. Multivariate order statistics filters [3–5] have been formulated to take the advantage of inter-channel correlation of the RGB color space. Adaptive vector filtering structures are also developed to deal with the variation of color image characteristics and noise distribution [2, 6].

In the case of impulse noise removal, central weighted vector median (CWVM) filter was first reported [7] for its superior detail preservation. Soon adaptive vector filters based on different vector distance measures were developed, which use the CWVM structure to detect the impulse noise and to preserve fine image details [8, 9]. However, most of these adaptive filters rely on binary noise detection rules and switch-based filtering reconstruction, which highly limit their performance with different image structure and noise ratio.

In this paper a classification-and-filtering framework is proposed for restoration of color images corrupted by impulse noise. The new vector filter classifies the corrupted image structure according to the estimates coming from a series of central weighted vector median filters. Then the corrupted image is reconstructed using an adaptive weighted vector filter optimized for each classified structure group. The organization of this paper is as follows. In Section 2 the local structure classification are formulated. Section 3 discusses the adaptive weighted filtering method tailored for different classified cells and its parameter optimization. Experimental results are summarized in Section 4. Finally, the conclusion is drawn in Section 5.

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2. LOCAL STRUCTURE CLASSIFICATION

2.1. CWVM reference filter

Let $\mathbf{C} \equiv \{\mathbf{c} = (c_1, c_2) \mid 1 \leq c_1 \leq H,\ 1 \leq c_2 \leq W\}$ denotes the set of pixel coordinates for a color image, where H and W are the height and the width of the image, respectively. At each pixel coordinate $\mathbf{c} \in \mathbf{C}$, a vector $\vec{x}(\mathbf{c}) = [x^R(\mathbf{c}), x^G(\mathbf{c}), x^B(\mathbf{c})]^T$ is used to represent the RGB values of the sample, and an $n \times n$-pixel square window, $\mathbb{W}(\mathbf{c})$, is defined which is centered at the position $\mathbf{c}$, where n is an odd integer. Let the number of pixels in the window $\mathbb{W}(\mathbf{c})$ be represented by $N \equiv n^2$, and let $L = (N+1)/2$. Then the pixel samples contained in the window, $\mathbb{W}(\mathbf{c})$, can be expressed in a lexicographic scan order as

$$\mathcal{X}(\mathbf{c}) = \{\vec{x}_0, \vec{x}_1, \cdots, \vec{x}_i, \cdots, \vec{x}_{2L}\} \tag{1}$$

Note that the central pixel (CP) $\vec{x}(\mathbf{c}) \equiv \vec{x}_L$ in such an order. The output of the CWVM filter with an integer central weight $0 \leq \omega < L$ is given by [7, 9]

$$\vec{y}_\omega(\mathbf{c}) = \vec{x}_k : k = \arg_i \min(R_i^\omega(\mathbf{c})),\ \ \vec{x}_k \in \mathcal{X}(\mathbf{c}) \tag{2}$$

where for $i = 0, \cdots, 2L$, the aggregated weighted vector distance is defined as

$$R_i^\omega(\mathbf{c}) = (2\omega+1) \parallel \vec{x}_i - \vec{x}_L \parallel + \sum_{j=0, j\neq L}^{2L} \parallel \vec{x}_i - \vec{x}_j \parallel, \tag{3}$$

where $\parallel \cdot \parallel$ denotes a vector distance measure. In this paper, the *Euclidean* distance is used.

2.2. CP-reference distance classification

The CWVM filter with different central weights has demonstrated different levels of image structure preservation in color image restoration [7, 9]. In order to evaluate the local information about the CP, $\vec{x}(\mathbf{c})$, as well as the image structure in the window, $\mathbb{W}(\mathbf{c})$, We formulate a CP-reference distance vector based on a series of CWVM filters, i.e.,

$$\mathbf{e}(\mathbf{c}) = [e_1(\mathbf{c}), e_2(\mathbf{c}), \cdots, e_w(\mathbf{c}), \cdots e_L(\mathbf{c})]^T \tag{4}$$

where $e_\omega(\mathbf{c}) = \|\vec{y}_w(\mathbf{c}) - \vec{x}(\mathbf{c})\|$ is the estimated error for the CWVM filter with central weight $\omega = 1, 2, \cdots, L$. Such a CP-reference distance vector as a whole can reveal more local structure information than any individual output of the CWVM filter. To take advantage of such structure information, an classifier is formulated on the $\mathbf{e}(\mathbf{c})$ to partition the entire CP-reference distance vector space into M mutually exclusive cells $\{\Psi_i, i = 1, 2, \cdots, M\}$. The classifier follows the scalar quantization (SQ) structure for its robustness and efficiency. A group of threshold values are defined within each component of the CP-reference distance vector, $e_j(\mathbf{c})$ with $j = 1, 2, \cdots, L$, as follows:

$$\{T_{j,k},\ k = 0, \cdots, K\} \text{ with } T_{j,k-1} < T_{j,k} \tag{5}$$

where $K^L = M$ indicates the total partition cell number. Such thresholds are used to transfer the input$\mathbf{e}(\mathbf{c})$ into a series of level indices given by

$$\psi(\mathbf{c}) = \{\psi_1, \psi_2, \cdots, \psi_j, \cdots, \psi_L\} \tag{6}$$

where for $j = 1, 2, \cdots, L$

$$\psi_j = k, \text{ if } e_j(\mathbf{c}) \in [T_{j,k-1}, T_{j,k}),\ 1 \leq k \leq K \tag{7}$$

Based on the level indices, the input difference vector $\mathbf{e}(\mathbf{c})$ is finally classified into the partition cell $\Psi_{p(\mathbf{c})}$, with the cell index $p(\mathbf{c})$ given by

$$p(\mathbf{c}) = \sum_{j=1}^{L} \psi_j K^{L-j} \tag{8}$$

In order to obtain a group of well-functioned partition thresholds, we specified the number of quantization level and the start value of each threshold with the exploitation of our knowledge at the very begining. Then the genetic algorithm [10] is used to optimized the threshold values over a wide range of color test images. It is clear that the set of threshold we obtained is not globally optimized. However, we find that the obtained partition threshold set works quite robustly in most of the test conditions. Table 1 lists the partition threshold values we used throughout our experiments, where a 3×3 filter window is assumed. The number of quantization levels is set as $K = 8$, which implies the total partition number $M = 4096$.

Table 1. The threshold $T_{\omega,k}$ for a 3×3 filter window, where $T_{\omega,0} = 0$ and $T_{\omega,8} = +\infty$

ω	Index k						
	1	2	3	4	5	6	7
1	12.8	18.5	27.7	37.7	48.7	66.7	200.6
2	11.0	18.4	29.6	43.5	60.2	87.5	199.9
3	9.3	14.6	21.7	25.3	39.5	61.1	135.8
4	5.0	10.1	13.2	23.9	32.2	53.0	131.7

3. PARTITION BASED VECTOR FILTERING

3.1. Weighted filtering formulation

At each pixel coordinate $\mathbf{c} \in \mathbf{C}$, a weighted linear combination of the outputs of all reference CWVM filters as well as the CP sample is formed to reconstruct the original image pixel value as follows:

$$\hat{\vec{x}}(\mathbf{c}) = \mathbf{w}_i^T \mathbf{y}(\mathbf{c}) \tag{9}$$

where $i = p(\mathbf{c})$ corresponds to the partition cell index given by (8), and

$$\mathbf{y}(\mathbf{c}) = [\vec{y}_1(\mathbf{c}), \vec{y}_2(\mathbf{c}), \cdots, \vec{y}_L(\mathbf{c}), \vec{x}(\mathbf{c})]^T \tag{10}$$

where $\vec{y}_\omega(\mathbf{c})$ denotes the output of the CWVM filter given by (2), and

$$\mathbf{w}_i = [w_{1,i}, w_{2,i}, \cdots, w_{L,i}, w_{0,i}]^T \tag{11}$$

represents the weighting vector for the partition cell Ψ_i with $1 \leq i \leq M$, which is indexed by $p(\mathbf{c}) = i$. Local invariance constraint is applied on the weighting vector to achieve an unbiased estimation, so that

$$w_{0,i} = 1 - \widetilde{\mathbf{w}}_i^T \mathbf{1} \tag{12}$$

where $\widetilde{\mathbf{w}}_i = [w_{1,i}, w_{2,i}, \cdots, w_{L,i}]^T$ is the reduced weighting vector, and $\mathbf{1} = [1, 1, \cdots, 1]^T_{1\times L}$.

3.2. Constrained LMS Training

The weighting vector $\mathbf{w}_i$ for each partition cell $\Psi_i, 1 \leq i \leq M$, is trained to minimize the *mean square error* (MSE) defined as follows:

$$J = E[\|\vec{s}(\mathbf{c}) - \hat{\vec{x}}(\mathbf{c})\|^2],\ \mathbf{c} \in \mathbf{C} \tag{13}$$

where $E[\cdot]$ denotes the expectation operator, $\vec{s}(\mathbf{c})$ and $\hat{\vec{x}}(\mathbf{c})$ represent the original and the reconstructed pixel value, respectively. Since all distance vector partition cells are mutually exclusive to each other, the MSE minimization above can be equivalently achieved by the independent MSE minimization with respect to each partition cell, Ψ_i with $1 \leq i \leq M$, over the entire test image, that is

$$J_i = E[\|\vec{s}(\mathbf{c}) - \hat{\vec{x}}(\mathbf{c})\|^2], \forall \mathbf{c} : p(\mathbf{c}) = i, \mathbf{c} \in \mathbf{C} \tag{14}$$

Following the the steepest-descent method in [11], the updating formulas for the weighting vector $\mathbf{w}_i$ at n-th iteration can be given by

$$\widetilde{\mathbf{w}}_i^{n+1} = \widetilde{\mathbf{w}}_i^{n} + 2\lambda_i \, \widetilde{\mathbf{y}}_r(\mathbf{c}) \, \vec{\varepsilon}(\mathbf{c}) \quad (15)$$

$$w_{0,i}^{n+1} = 1 - [\widetilde{\mathbf{w}}_i^{n+1}]^T \mathbf{1} \quad (16)$$

where $\widetilde{\mathbf{y}}_r(\mathbf{c}) = [\widetilde{\mathbf{y}}(\mathbf{c}) - \mathbf{1}\vec{x}(\mathbf{c})]$ is the CP-reference difference vector matrix at position $\mathbf{c}$, and

$$\vec{\varepsilon}(\mathbf{c}) = \vec{s}(\mathbf{c}) - \hat{\vec{x}}(\mathbf{c}) = \vec{s}(\mathbf{c}) - \mathbf{w}_i^T \mathbf{y}(\mathbf{c}) \quad (17)$$

denotes the estimation error vector of the proposed filter.

In order to obtain a steady convergence in a non-stationary environment such as image processing, energy normalization is further applied to the updating step-size parameter λ_i following the method in [11]

$$\lambda_i = \frac{\lambda_0}{\|\widetilde{\mathbf{y}}_r(\mathbf{c})\|^2} = \frac{\lambda_0}{\sum_{k=1}^{L} \|\vec{y}_{r,k}(\mathbf{c})\|^2} \quad (18)$$

where $\lambda_0 \in (0, \frac{2}{3})$ is required to guarantee the sufficient condition of strict convergence. In our experiments, satisfactory results have been obtained with $\lambda_0 = 0.08$. The trained weights always converge to a steady solution within $n = 150$. Further increase of the iteration step has demonstrated very little improvement on the final performance.

4. EXPERIMENTAL RESULTS

The proposed filter structure has been extensively evaluated using a wide range of RGB color images and different impulse noise corruption. The restoration performances have quantitatively measured by the normalized mean square error (NMSE) in the RGB color space, and the normalized color difference (NCD) in the perceptual uniform CIELab color space [2]. Subjective quality is also evaluated by side-by-side comparisons of reconstructed images.

The noise corruptions are simulated according to the channel correlation method developed in [4, 6], where the Pepper-and-Salt (PS) impulse is simulated using the value 0 or 255 with equal probability, and the random impulse is simulated using random values randomly distributed within the range of $[0, 255]$. The inter-channel correlation factor for all impulse noise simulations is set to 0.5.

Due to the page limitation, only the results with 512×512 24-bit RGB test image *Lena* and *Peppers* are summarized in Table 2, where a 3×3 filter window is used throughout the test, and a 256×256 24-bit RGB image *Lake* with 15% random impulse corruption is used for weights training of the proposed filter. Fig. 1 shows detailed parts of test image *Peppers* for perceptual quality assessment. The proposed filter performs noticeably better than all other state-of-the-art filters, regardless the different test images and impulse noise corruption. Image structures are highly preserved while impulse noise are efficiently removed.

Table 3 shown some execution time recorded on same simulation platform (Dual P4 3.0GHz/ 2048MB DDR/ Window XP Pro) with a 512×512 RGB image *Lena* corrupted by 10% random impulse noise. All the vector filters are tested with a 3×3 window size without any code optimization. The SAA filter works on its normal mode, bypassing the noise estimator but activating the bisection to estimate its parameter. The computation cost of the proposed filter is slightly better than the SAA filter working in the normal mode. On the other hand, the SCWVDF, which utilizing a central weighted filtering structure with the vector directional distance, demands almost 1.8 the computation time as the proposed filter to process the same corrupted image.

Table 2. Restoration of color images corrupted by different types of channel correlated impulse noise with noise ratio $p = 10\%$, where a 3×3 window size is used.

(a) 10% Pepper-and-Salt impulse noise (10^{-2})

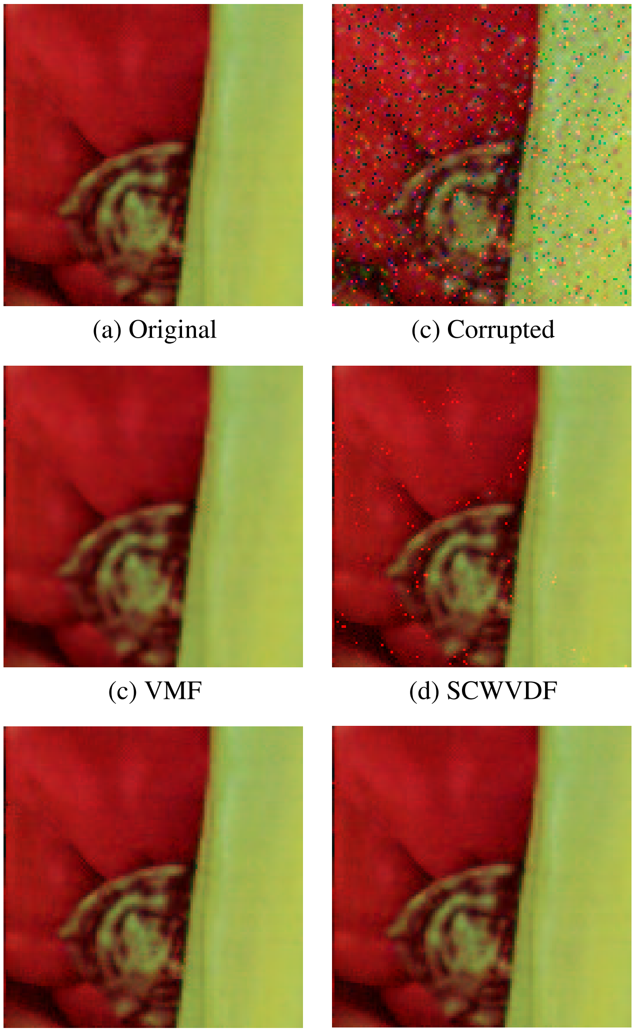
Filters	*Lena*		*Peppers*	
	NMSE	*NCD*	*NMSE*	*NCD*
None	6.3936	9.6306	8.2825	9.5064
VMF [3]	0.1730	3.1748	0.2715	4.5638
GVDF [4]	0.1943	3.4348	0.3385	4.8943
HDF [5]	0.1736	3.2682	0.2687	4.5608
SAA [8]	0.0550	0.5107	0.0757	0.6851
SCWVDF [9]	0.0587	0.4775	0.2509	0.9123
NAVF [12]	0.0448	0.5052	0.0713	0.6918
Proposed	0.0315	0.4916	0.0611	0.6767

(b) 10% random impulse noise (10^{-2})

Filters	*Lena*		*Peppers*	
	NMSE	*NCD*	*NMSE*	*NCD*
None	2.9240	5.4807	3.9321	5.9132
VMF [3]	0.1708	3.1810	0.2743	4.5925
GVDF [4]	0.1790	3.3543	0.3107	4.7644
HDF [5]	0.1710	3.2652	0.2728	4.5833
SAA [8]	0.0575	0.5439	0.0864	0.7202
SCWVDF [9]	0.0713	0.5368	0.1656	0.8949
NAVF [12]	0.0500	0.5575	0.0831	0.7492
Proposed	0.0382	0.5359	0.0659	0.7270

Table 3. The execution time of the new filter compared to other techniques, where 512×512 RGB image *Lena* corrupted by 10% random impulse noise is used. All filters run on a 3×3 window, and time is recorded in seconds.

Filter	VMF	BVDF	SAA	SCWVDF	Proposed
Time	8.4	13.8	34.3	54.9	30.2



(a) Original (c) Corrupted

(c) VMF (d) SCWVDF

(e) SAA (f) Proposed

Fig. 1. Zoomed reconstruction of the test image *Peppers* corrupted by 10% random impulse noise.

5. CONCLUSION

A novel adaptive vector filter is proposed for restoring digital color images corrupted by impulse noise. The filter classifies the local structure according to the output from a series of reference filters. Then for each classified partition, weighted adaptive filtering is applied to achieve the best image structure restoration. Despite its simple vector distance measure, the proposed filter has shown promising results in suppressing a wide variety of impulse noises that often occur in digital color images, with a significant performance improvement compared with most of up-to-date restoration techniques. Other distance functions and classification algorithms will be tested in the near future to achieve further performance improvement.

6. REFERENCES

[1] J. Astola and P. Kuosmanen, Eds., *Fundamentals of Nolinear Digital Filtering*, CRC, Boca Raton, FL, 1997.

[2] K. N. Plataniotis and A. N. Venetsanopoulos, Eds., *Color Image Processing and Applications*, Springer, Berlin, 2000.

[3] J. Astola, P. Haavisto, and Y. Neuov, “Vector median filter,” *Proc. IEEE*, vol. 78, no. 4, pp. 678–689, Apr. 1990.

[4] P. E. Trahanias and A. N. Venetsanopoulos, “Vector directional filters: a new class of multichannel image processing filter,” *IEEE Trans. Image Processing*, vol. 2, no. 4, pp. 5288–534, Oct. 1993.

[5] M. Gabbouj and F. A. Cheikh, “Vector median-vector directional hybrid filter for color image restoration,” in *Proc. EUSIPCO*, Trieste, Italy, Sept. 10–13, 1996, vol. 2, pp. 879–881.

[6] K. N. Plataniotis, D. Androutsos, and A. N. Venetsanopoulos, “Adaptive fuzzy systems for multichannel signal processing,” *Proc. IEEE*, vol. 87, no. 9, pp. 1601–1622, Sept. 1999.

[7] T. Viero, K. Oistamo, and Y. Neuvo, “Three-dimensional median-related filters for color image sequence filtering,” *IEEE Trans. Circuits Syst.*, vol. 4, no. 2, pp. 129–142, Apr. 1994.

[8] B. Smolka, A. Chydzinski, K. Wojcieshowski, K. N. Plataniotis, and A. N. Venetsanopoulos, “Self-adaptive algorithm for impulsive noise reduction in color images,” *Patt. Recogn.*, vol. 35, no. 8, pp. 1771–1784, 2002.

[9] R. Lukac, “Adaptive color image filtering based on center-weighted vector directional filters,” *Multidimensional Syst. Signal Process.*, vol. 15, no. 2, pp. 169–196, Apr. 2004.

[10] K.F. Man, K.S. Tang, and S. Kwong, Eds., *Genetic Algorithms:Concept and Design*, Springer Verlag, London, 1999.

[11] C. Kotropoulos and I. Pitas, “Adaptive *LMS L*-filter for noise suppression in image,” *IEEE Trans. Image Processing*, vol. 5, no. 12, pp. 1596–1609, Dec. 1996.

[12] Z. Ma and H. R. Wu, “A neighborhood adaptive vector filter for color image restoration,” in *Proc. IEEE Int. Symp. Intell. Signal Process. Comm.,Syst. (ISPACS’03)*, Awaji Island, Japan, Dec. 7–10, 2003.