A WINDOW ADAPTIVE HYBRID VECTOR FILTER FOR COLOR IMAGE RESTORATION

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ABSTRACT

A novel window adaptive hybrid filter for the removal of different types of noise which contaminate color images is proposed in this paper. At each pixel location the image vector is first classified into several different signal activity areas through a modified quadtree decomposition on the luminance of the input image, with only one empirical parameter required to be controlled. Then an optimal window and weight adaptive vector filtering operation is activated for the best tradeoff between noise suppression and detail preservation. The proposed filter has demonstrated superior performance in suppressing several distinctive types of color image noise, which include Gaussian, impulse, and mixed noise. Significant improvements have been achieved in terms of standard objective measurements as well as the perceived image quality.

1. INTRODUCTION

Many nonlinear filters have been widely applied for the restoration of corrupted monochrome images [1-3] with satisfactory performance on noise suppression and detail preservation. In color images, however, luminance and chrominance information are strongly inter-correlated, and a straightforward extension of monochrome restoration techniques to color space often resulted in severe drawbacks such as pixel rearrangement and chromatic drifts [3]. Multivariate order statistics techniques [4] have been strongly proposed for color image restoration, which include the Vector Median Filters (VMF), the Vector Direction Filter (VDF), and the Hybrid Directional Filter (HDF), to name a few. The Adaptive Nearest Neighbor Filter (ANNF) [5] can adaptively update the filtering weights to suppress the noise degradation in color image. The Peer Group Filter (PGF) [6] is proposed to preserve fine image structure for restoration. Restoration techniques based on fuzzy logic systems [7] also showed their power on noise detection and classification. Almost all of these are processed using fixed window. It is well known that the human eye is quite sensitive to little distortion in a flat area, while it tolerates larger amount of noise in "busy" areas. Thus, a filtering scheme with adaptive window sizes is naturally desirable. The filter can achieve smaller distortion through a bigger window to suit human perception in flat areas, while near an edge it can reduce the window size to result in better detail preservation.

In this paper a Window Adaptive Hybrid Vector Filter (WAHVF) is proposed for color image restoration. The new vector filter not only adapts its weight according to the local statistics, but also adaptively updates window size to achieve optimal noise suppression and detail preservation. The organization of this paper is as follows. In Section 2 the scalar pre-filtering structure and the image signal activity detector are described. Section 3 discusses the proposed adaptive hybrid vector filtering method tailored for different kinds of activity area. Experimental results are presented in Section 4. Finally, the conclusion is drawn in Section 5.

2. PRE-PROCESSING BLOCK

It is well known that images in digital RGB color space have high channel inter-correlation that any scalar processing of each channel will certainly lead to strong color distortion [3]. Thus a color de-correlated transform is highly desirable before a scalar process is implemented. Whereby the noisy image is first transformed into YC_rC_b spaces to separate luminance and chrominance. Then a pre-processing filter is employed to smooth the noisy image before the signal activity detector is applied. The signal activity detector proposed here is to classify the image pixels into different type of pixel groups such as smooth areas, edge areas, and possible image details according to their signal activity. This is followed by a decision mechanism which select proper filtering methods as well as window dimension adaptation for the best restoration performance.

2.1 Scalar Wiener Pre-Smoothing

Wiener filter is able to smooth out the flat area contaminated by additive noise while keeping the high frequency area intact. This makes it as one of the best

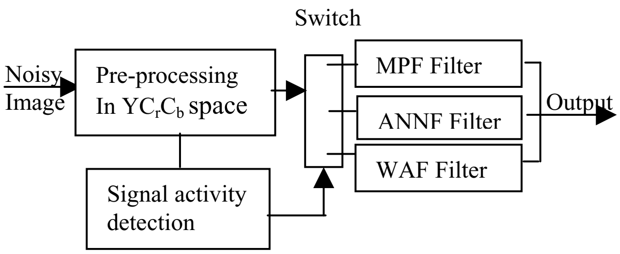

Fig. 1 The Window Adaptive Hybrid Vector Filter

candidates for pre-processing in gray image processing [1]. Here the filter is applied on each YC_rC_b channel independently a scalar smoothing process. Assuming the filtering window includes $w=N\times N$ pixels centered at (i,j), where N is an odd number, the output of scalar Wiener filter in YC_rC_b space will be

$$y_c(i,j)=\overline{m}_c(i,j)+\frac{\hat{\sigma}_x^2(i,j)}{\hat{\sigma}^2(i,j)}\cdot\left[x_c(i,j)-\overline{m}_c(i,j)\right], c\in\{Y,C_r,C_b\} \quad (1)$$

where $\overline{m}_c(i,j)$ and $\hat{\sigma}^2(i,j)$ are the local mean and variance in each YC_rC_b channel of the noisy image. $\hat{\sigma}_x^2(i,j)$ is the estimated local image variances in each channel. The assumption of independency between image signal and additive noise yields

$$\hat{\sigma}_x^2(i,j)=\begin{cases}\hat{\sigma}_c^2(i,j)-\hat{\sigma}_n^2\,, & \text{if } \hat{\sigma}_c^2(i,j)>\hat{\sigma}_n^2\\ 0\,, & \text{Otherwise}\end{cases} \quad (2)$$

In order to avoid the impact of possible impulsive outlier, in each channel the variance of noise is calculated from a robust median estimation of all the local variances throughout entire image as following:

$$\hat{\sigma}_n^2=\underset{i,j}{median}\left[\hat{\sigma}^2(i,j)\right] \quad (3)$$

2.2. Signal Activity Detection

The image after the scalar Wiener pre-filtering is decomposed into non-overlapping rectangular blocks with very similar luminance varying range between each other. The modified quadtree decomposition involves:

(a) Start from the entire image, the luminance of all four divided rectangular blocks denoted as $I=\{I_1,I_2,I_3,I_4\}$ are calculated. If any range of the pixel set I_i is smaller is smaller than a predetermined threshold T, the observed block is claimed as a *homogeneous* block. Otherwise further splitting is applied.
(b) Repeat splitting defined in step (a) on each block independently until all blocks are either *homogeneous* block, or reaching the size of one pixel.
(c) For *homogeneous* blocks bigger than 16x16, the quadtree decomposition further divides them directly until all the sub-block reach size of 16x16.

The value of threshold T is set as

$$T=\eta\cdot\hat{\sigma}_{3x3} \quad (4)$$

where $\hat{\sigma}_{3x3}$ is the median of all the 3x3 sliding window standard deviations of the noisy luminance image. η is an empirical value fixed for each image. It does not need to be highly accurate as long as it perform reasonably well in decomposing the whole luminance image into small *homogeneous* rectangular blocks.

2.3 Filtering Window Adaptation

After the quadtree decomposition, a sliding window filtering method is proposed to avoid the block artifacts commonly occurred in block image processing. The size of the window centered at each position (i,j) is calculated by averaging the quadtree decomposition result of its neighborhood. Let $W(i,j)$ denote the sliding window size at (i,j), and $B(i+k,j+l)$ describes the block size related to the Central Pixel (CP) and its eight neighborhood. Then

$$W(i,j)=\frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}B(i+k,j+l) \quad (5)$$

The value $W(i,j)$ is then used as the signal activity index to select a proper odd sliding window size for the filters.

3. SWITCH BASED HYBRID VECTOR FILTER

To deal with various noises in color image effectively, a switch based hybrid-filtering scheme performed on RGB color space with three adaptive vector sub-filters is adopted in this paper. Here the Modified Peer Filter (MPF) is optimal for removing noise degradation in image detail areas, the ANNF filter can effectively remove the noise while preserving the image edge structure, and the Weighted Average Filter (WAF) is able to smooth the small color distortion in large flat areas.

3.1. Modified Peer Filter

The MPF filter proposed here is different form the original PGF filter [5] in three aspects:

(a) A new vector distance function combining the vector magnitude and angle bias is proposed to replace the simple Euclidean distance between two vectors.
(b) An L-filter structure is proposed which adaptively updates its weights according to the new vector distance function value between the CP and its neighbor pixels.
(c) Instead of picking up the pixel maximizing the Fisher function as the boundary, the pixel with first positive Fisher function maximum is treated as the boundary.

Assuming the size of the local window is $w=N\times N$, and the color image pixels in the local window are

$\{\mathbf{x}_1, \mathbf{x}_2, \cdots \mathbf{x}_w\}$, the proposed vector distance between $\mathbf{x}_{CP}$ and its neighbor pixel $\mathbf{x}_i$ is calculated by

$$d_i = 1 - \left(\frac{\mathbf{x}_{CP} \mathbf{x}_i^T}{\|\mathbf{x}_{CP}\| \cdot \|\mathbf{x}_i\|} \right) \cdot \left(1 - \frac{\left| \|\mathbf{x}_{CP}\| - \|\mathbf{x}_i\| \right|}{\max\left(\|\mathbf{x}_{CP}\|, \|\mathbf{x}_i\| \right)} \right). \tag{6}$$

where $\|\cdot\|$ means the magnitude of vector pixel.

The Fisher discrimination is applied to determine the CP peer group based on the ordered vector distances above:

$$F(k) = \frac{\|m_1 - m_2\|^2}{v_1 + v_2} \tag{7}$$

where $m_1 = \frac{1}{k} \sum_{i=1}^{k} d_{(i)}$, $m_2 = \frac{1}{w-k} \sum_{i=k+1}^{w} d_{(i)}$ (8)

$$v_1 = \sum_{i=1}^{k} \left(d_{(i)} - m_1 \right)^2, \; v_2 = \sum_{i=k+1}^{w} \left(d_{(i)} - m_2 \right)^2$$

The pixel $\mathbf{x}_{(k)}$ with $F(k)$ approaching first positive maximum is entitled as the boundary of the CP peer group:

$$k = \min_{N \le i \le w} \left\{ i \; \middle| \left(F(i+1) - F(i) < 0 \right) \cap \left(F(i) - F(i-1) > 0 \right) \right\} \tag{9}$$

For the CP peer group, an adaptive L-filter [3] is adopted to preserve fine image details while removing possible noise distortion. The reconstruction of the CP is calculated from the weighted sum of its peer members:

$$\mathbf{y}_{CP} = \sum_{i=1}^{k} a_i \mathbf{x}_i \Big/ \sum_{i=1}^{k} a_i \tag{10}$$

where a_i is the adaptive weight defined using the ordered vector distances [4] such as

$$a_i = \frac{\left(d_{(k)} - d_{(i)} \right) + \alpha \left(d_{(k)} - d_{(1)} \right)}{(1 + \alpha)\left(d_{(k)} - d_{(1)} \right)} \tag{11}$$

where α is the regulating parameter controlling non-linearity of distance measure among image vectors. We set $\alpha = 1 / \left(d_k - d_{(1)} \right)$ as proposed in [5].

3.2. Adaptive Nearest Neighbor Filter

An ANNF filter [4] using 5x5 local window is adopted here to produce stronger smooth result while preserving possible significant edge structures and removing impulse noise. In each window the reconstruction of the CP is yielded similar from formula (10) and (11). However, the distance function d_i is different in order to verify the vector distance of each pixel and other pixels under current window, that is

$$d_i = \sum_{j=1}^{25} \left[1 - S\left(\mathbf{x}_i, \mathbf{x}_j \right) \right] \tag{12}$$

$$S(\mathbf{x}_i, \mathbf{x}_i) = 1 - \left(\frac{\mathbf{x}_i \mathbf{x}_j^T}{\|\mathbf{x}_i\| \cdot \|\mathbf{x}_j\|} \right) \cdot \left(1 - \frac{\left| \|\mathbf{x}_i\| - \|\mathbf{x}_j\| \right|}{\max\left(\|\mathbf{x}_i\|, \|\mathbf{x}_j\| \right)} \right). \tag{13}$$

3.3. Weighted Average Filter

The WAF filter is proposed to deal with the small distortion remained in big areas without significant computational complexity overhead. The detecting result $W(i, j)$ from formula (5) are adopted here as the weight for each pixels under filter window to avoid possible distortion spreading for those impulsive noise in flat area. Thus for the CP pixel located at (i, j), the filter output is

$$\mathbf{y}_{CP} = \frac{\sum_k \sum_l W(i+k, j+l) \cdot \mathbf{x}(i+k, j+l)}{\sum_k \sum_l W(i+k, j+l)} \tag{14}$$

where the filter window size $N \in \{5,7,9,11\}$ according to the smooth level of its neighbor area as in Table 1.

4. RESULTS AND ANALYSIS

Extensive simulation on a variety of test images had used to evaluate the restoration performance of proposed filter through quantitative measure the normalized mean square error (NMSE) and the normalized color difference (NCD) [4]. Several distinct types of noise have been generated to contaminate the test images for restoration verification. Due to the page limitation, here we only state the results for 24-bit RGB image *Barbara* corrupted by Gaussian nose, impulse noise, and mixed noise. The Gaussian noises are added into image with zero mean and σ=30 on each RGB channel. The 10% color impulsive noise that following uniform distribution among [0, 255] is inserted into image according to the two-step channel correlation simulation procedure as proposed in [4]. The mixed noise is introduced into image in two steps as in [4], the Gaussian noise with zero mean and σ=30 is first add into each RGB channel independently. Then 10% color impulsive noise is inserted into images for mixed effect.

The performance of WAHVF filter is compared with classic standard filters in [4], multi-pass vector filters such as CANNMF and CBNNMF [5], and the most recent Multiple Window Configuration (MWC) filter [8]. The window for all standard filters is set to 5, and η=7.0 for the WAHVF filter. The results are shown in Table 2. The performances of the mean filter and the ANNF filter for additive noise corrupted images are better than the rest vector filters, but their performance are inferior for images corrupted impulse and mixed noise. The scalar wiener filter performs well under additive noise but poorly for heavy-tail noise. The MWC filter works well for impulse noise but leaves too much distortion under Gausisan noise. It is obvious that the WAHVF filter yields significant improvement over other filters against all noises in terms of the NMSE and the NCD.

Fig. 2 shows detailed parts of *Barbara* for visual quality assessment. Large blocks of color distortion are remained in all the results of fixed vector filters.

Excessive blurring is observed for the ANNF filter and the MWC filter. The Wiener filter kept too much impulse distortion. The image details after PGF filtering is better but background areas show insufficient smoothing. A better result has been achieved by the WAHVF filter, with better noise suppression on flat backgrounds and superior preservation of image detail.

In addition to its superior performance, the proposed WAHVF filter proved to been computational efficiency. All its parameters can be trained offline. No dynamic parameter optimization is needed during filtering process. In fact, we found that the time the WAHVF filter cost for restoring a 24bit RGB 512x512 image is only about two times longer than the ANNF filter with 3x3 window size.

5. CONCLUSION

A new window adaptive hybrid vector filtering scheme is proposed and studied for color image restoration. The filter includes a novel scalar pre-processing block which is able to effectively detect the signal activity for each pixel position, and a switch-based window and weight adaptive hybrid vector filter tailored for each specific class of activity areas. The interaction between these two parts makes the proposed filter efficient in suppressing a wide variety of noises that often occur in digital color images, with significant performance improvement compared with most of up-to-date restoration schemes.

6. REFERENCES

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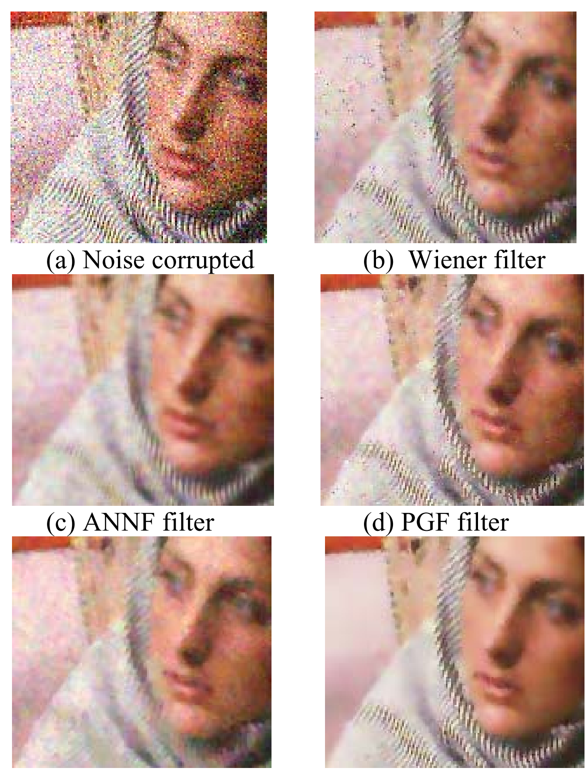
Table 1. Relation for detector output and window adaptation

$W(i,j)$	1~3.5	3.5~5.5	5.5~7.5	7.5~9.5	9.5~16
Window size	3x3	5x5	7x7	9x9	11x11

Table 2. Comparison on *Barbara* under various noises, (1e-2)

Noise / Filter	Gaussian		Impulse		Mixed	
	NMSE	NCD	NMSE	NCD	NMSE	NCD
None	4.195	34.89	3.086	7.228	7.039	39.14
Mean	2.037	8.411	2.076	9.053	2.325	9.734
VMF	2.543	13.03	1.841	4.968	2.665	13.42
VDF	2.784	10.37	1.929	5.502	2.936	10.71
HDF	2.329	10.61	1.830	4.963	2.438	11.02
AHDF	2.195	10.48	1.817	4.966	2.319	10.94
FVDF	2.892	10.38	1.921	5.340	3.154	10.98
ANNF	2.017	8.772	1.823	5.479	2.079	8.866
CANNMF	1.985	9.254	1.655	4.960	2.077	9.581
CBNNMF	1.987	9.554	1.657	4.955	2.077	9.863
PGF	1.962	11.27	0.873	4.782	1.873	9.976
MWC	1.859	12.65	1.216	3.828	2.060	13.86
Wiener	0.962	10.70	1.623	7.399	1.882	13.70
WAHVF	**0.984**	**6.772**	**0.951**	**4.767**	**1.291**	**7.491**



(a) Noise corrupted (b) Wiener filter

(c) ANNF filter (d) PGF filter

(e) MWC filter (f) WAHVF filter

Fig.2 Restoration for the *Barbara* corrupted by mixed noise