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Color Image Denoising with Multi-channel Circular Spatial Filtering

Sukadev Meher
Department of Electronics & Communication Engineering,
National Institute of Technology, Rourkela-769008, Orissa, India
smeher@nitrkl.ac.in, sukadevmeher@gmail.com

***Abstract*–A multi-channel circular spatial filter (MCSF) in YCbCr-color space is developed for color image denoising. In [2], Bhoi and Meher proposed and demonstrated that circular spatial filter performed very well for efficient suppression of additive white Gaussian noise (AWGN) from gray images. Here multi-channel versions of the circular spatial filter are proposed and developed. The developed filter is based on three-channel processing (e.g., RGB-processing, YCbCr-processing, etc.). The YCbCr version of MCSF is observed to yield quite superior performance as compared to the other versions in RGB, CMY and CIE Lab color spaces. The proposed filter outperforms the multi-channel versions of existing filters in terms of objective and subjective evaluation measures.**

Keywords - additive white Gaussian noise (AWGN); image denoising; color image denoising; bilateral filter; circular spatial filter

I. INTRODUCTION

In the last two decades, the field of digital image processing became more interesting, sustained by the continuous advancement in electrical, electronics and computer engineering. A typical image processing system comprises of several processing units that perform different tasks. Noise removal is one of the most basic processing units that are present in almost all image processing systems [1]. During the processes of acquisition and transmission, images are often contaminated by Additive White Gaussian Noise (AWGN). This results in severe degradation of image quality which can be improved by denoising. The aim of denoising is then to reduce the noise level, while preserving the image features. Most of the denoising techniques available in literature are developed and tested only for gray images [2-10]. In recent past, a few color image denoising filters are reported in the literature [11-14]. Some of them perform very well under low noise power only. Hence, there is sufficient scope for developing very good color image filters.

Helbert *et al.* [11], Kim *et al.*[12], Lian *et al.* [13] and Luisier *et al.* [14] have shown that the YCbCr color space is found to be quite effective color representation space for image (2-D) and video (3-D) denoising applications. Since the performance of denoising filters degrades in other color spaces, more concentrated efforts are made, in this research work, to develop color image denoising filter i.e., MCSF only in YCbCr-color space. Nevertheless, other standard color spaces: RGB, CMY and CIE Lab are also employed to study their performance.

The rest of the paper is organized as follows. Section II briefly introduces the circular spatial filter. Multi-channel circular spatial filter (MCSF) is discussed in Section III. Section IV gives the simulation results. Finally the paper is concluded in Section V.

II. CIRCULAR SPATIAL FILTER

Bhoi and Meher [2] have proposed Circular Spatial Filter (CSF) for suppression of AWGN under high noise variance conditions. In this method, a **circular spatial-domain window**, whose weights are derived from two independent functions: (i) spatial distance and (ii) gray-level distance, is employed for filtering. The name circular refers to the shape of the window being circular. In the proposed method, two weighting functions based on spatial distance and gray level distance are used to prepare the filtering kernel. This circular shaped kernel is moved invariably throughout the image to remove the noise.

The proposed CSF filter has got some resemblance with bilateral filter [4]. Both filters use filtering window which is a combination of distance kernel and gray-level kernel. The gray-level kernel of circular spatial filter is similar to that of a bilateral filter. But the distance kernels of both filters are different. The function used for the distance kernel is exponential in case of bilateral filter whereas it is a simple non-linear function in case CSF. Last but not the least, the extreme corner points in the CSF convolution matrix are necessarily zeros. This is the basic difference between the CSF and the bilateral filter. The proposed filter's kernel is mathematically derived below.

In spatial-domain filtering an image is sampled in space and a pixel (usually called center pixel) and its spatial neighbors are considered for the filtering

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operation. Thus, a sampled small region is only considered at a time for filtering. A simple 3×3 window (a sub-image) is shown, as an example, in Fig.1 for further reference. Fig.1 (a) shows the center pixel at location (x,y) and an arbitrary neighbor at (x_1,y_1). Fig. 1(b) shows the intensity values for a gray image. Euclidean distance (spatial distance) is computed and shown in Fig. 1(c) whereas the gray-level distance (difference in intensity) is calculated and shown in Fig. 1(d) for each pixel in the neighborhood.

(x_1,y_1)		
	(x,y)	

(a)

119	124	124
119	128	124
119	128	132

(b)

$\sqrt{2}$	1	$\sqrt{2}$
1	0	1
$\sqrt{2}$	1	$\sqrt{2}$

(c)

3	2	2
3	0	2
3	0	2

(d)

Figure 1. A 3×3 sub-image (window) of an input noisy image sampled for spatial-domain filtering

(a) center pixel at location (x,y) and an arbitrary neighbor at (x_1,y_1)
(b) the pixel intensity values (gray values in the range of 0-255)
(c) spatial distance of all pixels from the center pixel
(d) gray-level distance of all pixels from the center pixel

Spatial Distance

In an image, the spatial distance between any arbitrary pixel in a particular window at location (x_1,y_1) and the center pixel at location (x,y) is calculated as:

$$d_s = ((x - x_1)^2 + (y - y_1)^2)^{1/2} \tag{1}$$

Now the distance kernel is defined by:

$$w_d = 1 - \frac{d_s}{d_{max}} \tag{2}$$

where, d_{max} is the maximum radial distance from center.

The correlation between pixels goes on decreasing as the distance increases. Hence, when w_d becomes very small the correlation can be taken as zero. When the small values of distance kernel are replaced by zeros we get a circular shaped filtering kernel. The circular shaped kernel is denoted as w_{cd}.. Such a kernel is shown in Fig. 2.

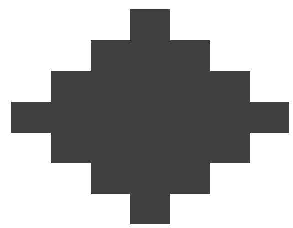

Figure 2. A circular kernel

Gray-level Distance

The gray-level distance between any arbitrary pixel $g(x_1,y_1)$, in a particular window, at location (x_1,y_1) and the center pixel $g(x,y)$ at location (x,y) is calculated as:

$$d_g = \left[\left| \; g^2(x_1,y_1) - g^2(x,y) \; \right|\right]^{1/2} \tag{3}$$

This distance function shows the dissimilarity between the intensity levels of the current (center) pixel and its neighboring pixel. Many spatial-domain filters consider only the spatial distance between the center pixel and its neighbor whereas only bilateral filters [4] and their derivatives take both the spatial distance and the gray-level distance into consideration. This makes the bilateral filters efficient in detecting true neighboring pixels whose weighted average yields better estimation of original pixel value.

The gray-level distance d_g is used to find the gray level kernel which is defined by:

$$w_g = \exp\left(\frac{-d^2{}_g}{2\sigma^2{}_g}\right) \tag{4}$$

where, σ_g is the standard deviation of the distribution function w_g.

CSF Kernel

The filtering kernel of the circular spatial filter is prepared from w_{cd} and w_g as:

$$w = w_{cd} . w_g \tag{5}$$

The filtering kernel w is slid throughout the image corrupted with noise, $g(x,y)$ to get the estimated output, $\hat{f}(x,y)$. The estimated pixel is computed as:

$$\hat{f}(x,y) = \frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t).g(x+s,y+t)}{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t)} \quad (6)$$

In the filtering window, the center coefficient is given the highest weight. The weight goes on decreasing as distance increases from center and it is zero when correlation is insignificant.

The filtering algorithm presented in (6) along with the kernel given by (5) represents the CSF meant for gray images. In this paper, a multi-channel version of it is developed and tested for color images. The next section presents the development of multi-channel circular spatial filter.

III. MULTI-CHANNEL CIRCULAR SPATIAL FILTER

The CSF is found to be quite efficient in suppressing AWGN under moderate and high noise conditions yielding less distortion to the filtered image. The filtering performance of CSF has already been examined and found to be very promising for gray images [2]. Therefore its multi-channel version i.e. multi-channel circular spatial filter (MCSF) is developed here for suppressing AWGN from color images. The block diagram of the proposed filter MSCF is shown in Fig. 3.

It has been verified that YCbCr is a better color-space as compared to RGB, CMY and many other standard color-spaces for color image denoising. Therefore, an RGB-to-YCbCr transformation is needed as a pre-processing task. Similarly, a YCbCr-to- RGB transformation is needed as a post-processing task after the 3-channel CSF filtering. This is illustrated in Fig.3. Thus, the proposed filter is simply a multi-channel extension of the CSF [2] in YCbCr color-space. This proposed filter is simulated and tested and its filtering performance is presented in the next section.

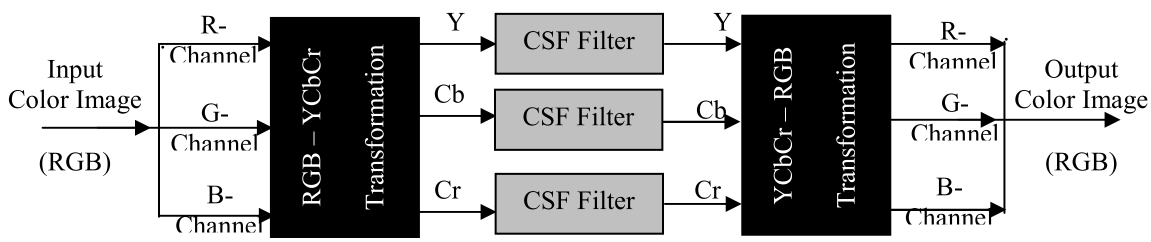

Figure 3. Block diagram of a multi-channel CSF filter

IV. SIMULATION RESULTS AND DISCUSSION

The simulation work is performed on color test image, Lena (512×512×3 pixels) corrupted with AWGN of standard deviation σ_n = 10, 25 and 40. Multi-channel CSF is compared with multichannel versions of *mean filter* (M-MF) [1] (simplest and oldest filter) and multichannel versions of *locally adaptive window based maximum likelihood* (M-LAWML) filter [7] (one of the best performers of existing wavelet-domain filters). The color-peak-signal-to-noise ratio (CPSNR) [13] is taken as performance measure. The PSNR of various filters are given in Table I.

From the table it is observed that the CPSNR of MCSF is higher than that of other filters. Also, it is observed that the filters perform better in YCbCr-color space. For subjective evaluation, the filtered output images of various multi-channel filters are shown in Fig. 4. From this figure, it is evident that the proposed filter MCSF gives a high quality filtered image even at very high noise power.

It is observed that the proposed filter: MCSF outperforms all other filters at moderate and high noise power though its performance is slightly less than M-LAWML only at low noise power. From Fig. 4 it is seen that the output of the proposed filter is quite noise-free and is having very little distortion even at high noise power. The proposed filter neither yields any artifacts in smooth regions nor produces any distortion at edges of the image. Thus, it preserves the integrity of the image to a great extent. Under high noise conditions, it is observed from Fig. 4 that the proposed filter M-CSF outperforms M-LAWML leaving M-MF far behind even at noise with σ_n = 40.

TABLE I. FILTERING PERFORMANCE OF COLOR IMAGE DENOISING FILTERS IN DIFFERENT COLOR SPACES, IN TERMS OF CPSNR (DB) [TEST IMAGE: LENA]

Sl. No	Denoising Filters	RGB color space			YCbCr color space			CMY color space			CIE LAB color space		
		Standard deviation of AWGN			*Standard deviation of AWGN*			*Standard deviation of AWGN*			*Standard deviation of AWGN*		
		10	25	40	10	25	40	10	25	40	10	25	40
1	M-MF [3×3]	33.50	28.68	25.72	37.45	33.26	30.03	33.11	28.49	25.55	32.40	27.89	24.99
2	M-MF [5×5]	30.29	28.88	27.01	34.37	33.22	31.59	29.90	28.69	26.84	29.19	28.09	26.28
3	M-MF [7×7]	28.20	27.71	26.60	32.42	31.95	31.10	27.81	27.53	26.43	27.10	26.92	25.87
4	M-LAWML [3×3]	34.25	29.25	25.83	**38.97**	34.16	31.59	33.86	29.16	25.66	33.15	28.46	25.10
5	M-LAWML [5×5]	34.55	30.11	27.12	38.57	33.41	30.08	34.16	29.93	26.95	33.45	29.32	26.39
6	M-LAWML [7×7]	**34.96**	30.48	27.55	38.24	32.66	27.93	**34.57**	30.28	27.38	**33.86**	29.69	26.82
7	MCSF [3×3]	33.57	26.54	22.45	37.64	30.44	26.59	33.18	26.31	22.28	32.47	25.75	21.72
8	MCSF [5×5]	33.30	**30.49**	26.86	37.51	**34.17**	30.80	32.91	**30.30**	26.69	32.20	**29.70**	26.13
9	MCSF [7×7]	31.01	29.98	**28.35**	34.58	33.57	**32.04**	30.62	29.79	**28.18**	29.91	29.19	**27.62**

Figure 4. Performance of Various Filters in YCbCr-Color Space for Color Lena Image with AWGN of $\sigma_n = 40$
(a) Original image (b) Noisy image
(c) – (e): Results of various filtering schemes
(c) M-MF (d) M-LAWML (e) Proposed Filter: MCSF

V. CONCLUSION

A multi-channel circular spatial filter is developed for denoising color images. The filter gives superior performance in terms of CPSNR as compared to other denoising schemes. The proposed filter shows very high performance when implemented in YCbCr color-space. This filter also retains the detailed information very well. It does not introduce any artifacts in smooth regions of the filtered image. Hence, the proposed filter is quite suitable for suppression of additive noise from color images under moderate and high noise power conditions.

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