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Adaptive Denoising of CFA Images for Single-Sensor Digital Cameras Using Principle Component Analysis

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ABSTRACT

Single-sensor digital color cameras use a process called color demosaicking to produce full color images from the data captured by a color filter array (CFA). The quality of demosaicked images is degraded due to the sensor noise introduced during the image acquisition process. The conventional solution to combating CFA sensor noise is demosaicking first, followed by a separate denoising processing. This strategy will generate many noise-caused color artifacts in the demosaicking process, which are hard to remove in the denoising process. This paper presents a principle component analysis (PCA) based spatially-adaptive denoising algorithm, which works directly on the CFA data using a supporting window to analyze the local image statistics. By exploiting the spatial and spectral correlations existed in the CFA image, the proposed method can effectively suppress noise while preserving color edges and details. Experiments using both simulated and real CFA images indicate that the proposed scheme outperforms many existing approaches.

Keywords: Adaptive denoising, Bayer pattern, Color Filter Array (CFA), Demosaicking, Principle Component Analysis (PCA).

I. INTRODUCTION

Single-sensor digital color cameras use a process called color demosaicking to produce full color images from the data captured by a color filter array (CFA). The quality of demosaicked images is degraded due to the sensor noise introduced during the image acquisition process. The conventional solution to combating CFA sensor noise is demosaicking first, followed by a separate denoising processing. This strategy will generate many noise-caused color artifacts in the demosaicking process, which are hard to remove in the denoising process. Our paper will present a naïve spatially-adaptive denoising algorithm based on the principle component analysis using a supporting window to analyze the local image statistics. By exploiting the spatial and spectral correlations existed in the CFA image, the proposed method can effectively suppress noise while preserving color edges and details.

MOST existing digital color cameras use a single sensor with a color filter array (CFA) to capture visual scenes in color. Since each sensor cell can record only one color value, the other two missing color components at each position need to be interpolated from the available CFA sensor readings to reconstruct the full-color image. The color interpolation process is usually called color demosaicking (CDM).

The presence of noise in CFA data not only deteriorates the visual quality of captured images, but also often causes serious demosaicking artifacts which can be extremely difficult to remove using a subsequent denoising process. Note that many advanced denoising algorithms, which are designed for monochromatic (or full color) images, are not directly applicable to CFA images due to the underlying mosaic structure of CFAs. To overcome the problem, we will propose a principle component analysis (PCA)-based denoising scheme which directly operates on the CFA domain of captured images. Though most existing CDM techniques assume noise-free CFA data, this assumption does not hold well in practice. For almost all kinds of color imaging devices, ranging from the low-cost and/or resource-constrained ones such as wireless camera phones to the high-end ones such as digital cinema cameras, image corruptive noise is inherent and can be severe; thus, the restoration of color images from noisy CFA data is a challenging problem.

II. BRIEF LITERATURE SURVEY

An intuitive and convenient strategy to remove noise is to denoise the demosaicked images. Algorithms developed for gray-scale imaging, for example [4]–[5], can be applied to each channel of the demosaicked color image separately whereas some color image filtering techniques [2], [3] process color pixels as vectors. The problem of this strategy is that noisy sensor readings are roots of many color artifacts in demosaicked images and those artifacts are difficult to remove by denoising the demosaicked full-color data. In general the CFA readings corresponding to different color components have different noise statistics. The CDM process blends the noise contributions across channels, thus producing compound noise that is difficult to characterize. This makes the design of denoising algorithms for single-sensor color imaging very difficult.

Recently, some schemes that perform demosaicking and denoising jointly have been proposed [6]–[13]. In [12], Trussell and Hartig presented a mathematical model for color demosaicking using minimum mean square error (MMSE) estimator. The additive white noise is considered in the modeling. Ramanath and Snyder [34] proposed a bilateral filter based demosaicking method. Hirakawa and Parks [6] developed a joint demosaicking-denoising algorithm by using the total least square (TLS) technique where both demosaicking and denoising are treated as an estimation problem with the estimates being produced from the available neighboring pixels. In [7] and [8], Hirakawa et al. proposed two wavelet based schemes that can perform CDM simultaneously with denoising. The joint demosaicking-denoising scheme developed by Zhang et al. [9] first performs demosaicking-denoising on the green channel. Inspired by the directional linear minimum mean square-error estimation (DLMMSE) based CDM scheme in [1], Paliy et al. [10], [11] proposed an effective nonlinear and spatially adaptive filter by using local polynomial approximation to remove the demosaicking noise generated in the CDM process and then adapted this scheme to noisy CFA inputs for joint demosaicking-denoising.

III. PROBLEM FORMULATION

To test comprehensively the performance of the proposed PCA-based CFA denoising algorithm, we will carry out extensive experiments in three different types. First, we evaluate its denoising outputs in comparison with those by applying other denoising schemes to CFA images. Second, joint assessment of the proposed CFA denoising scheme with demosaicking schemes is carried out in comparison with many "demosaicking first and denoising later" and "joint denoising and demosaicking" algorithms. At last, a real raw CFA image is used to illustrate the performance of the proposed method. In the final paper, we will report all the experimental results in details.

IV. SUMMARY OF THE ALGORITHM

The proposed spatially adaptive PCA-based CFA denoising algorithm is summarized as follows.

1. Estimate the noise standard deviations σ_g, σ_r, and σ_b of the red, green and blue channels.
2. Decompose the noisy CFA image I_v into I_v^l and I_v^h using (3-16) and (3-17). Apply the following denoising steps 3 and 4 to.
3. Set the sizes of variable block and training block. The noise co-variance matrix Ω_v can then be determined.
4. For each training block:

Perform the training sample selection procedure.

Denote by $\bar{\bar{X}}$ the selected training dataset.

Calculate the co-variance matrix $\mathbf{\Omega}_{\bar{\bar{x}}}$ using **(3-5)**;

Estimate the co-variance matrix of signal as $\mathbf{\Omega}_{\bar{\mathbf{x}}} = \mathbf{\Omega}_{\bar{\bar{\mathbf{x}}}} - \mathbf{\Omega}_{\mathbf{V}}$;

Factorize $\mathbf{\Omega}_{\bar{\mathbf{x}}} = \mathbf{\Phi}_{\bar{\mathbf{x}}}\mathbf{\Lambda}_{\bar{\mathbf{x}}}\mathbf{\Phi}_{\bar{\mathbf{x}}}^{\mathbf{T}}$ using **(3-8)** and set the PCA transformation matrix $\mathbf{P}_{\bar{\mathbf{x}}} = \mathbf{\Phi}_{\bar{\mathbf{x}}}^{\mathbf{T}}$;

Transform the dataset to PCA domain: $\bar{\bar{\mathbf{Y}}} = \mathbf{P}_{\bar{\mathbf{x}}}\bar{\bar{\mathbf{X}}}$;

By resetting the last several rows of $\bar{\bar{\mathbf{Y}}}$ to zeros, reduce $\bar{\bar{\mathbf{Y}}}$ to $\bar{\bar{\mathbf{Y}}}^d$ (dimension reduction);

Shrink each row of $\bar{\bar{\mathbf{Y}}}^d$ as $\hat{\bar{\mathbf{Y}}}_i^d = c_i \cdot \bar{\bar{\mathbf{Y}}}_i^d$ using **(3-14)**;

Transform back $\hat{\bar{\mathbf{Y}}}^d$ to time domain as $\hat{\bar{\mathbf{X}}} = \mathbf{P}_{\bar{\mathbf{x}}}^{-1} \cdot \hat{\bar{\mathbf{Y}}}^d$;

Reformat $\hat{\bar{\mathbf{X}}}$ to get the denoised CFA block.

End

5. Denote by $\hat{I}_v^h$ the denoised output of I_v^h, the final denoised image is $\hat{I} = I_v^l + \hat{I}_v^h$.

V. RESULTS AND DISCUSSION

Following table shows the PSNR (Db) results of the reconstructed houses images by different demosaicking and denoising methods

TABLE 1. PSNR RESULTS OF THE RECONSTRUCTED HOUSES IMAGES

Demosaicking Methods	Denoising Methods	PSNR Results (dB)					
		$\sigma_r = \sigma_g = \sigma_b = 12$			$\sigma_r = 13, \sigma_g = 12, \sigma_b = 10$		
		R	G	B	R	G	B
[4]	[24]	25.9	27.9	25.9	25.8	27.9	26.2
	[25]	25.6	28.0	25.5	25.5	28.0	25.8
[9]	[24]	28.2	29.1	28.2	28.0	29.1	28.5
	[25]	28.2	28.8	28.3	28.0	28.9	28.6
[10]	[24]	27.4	28.3	27.5	27.4	28.4	27.7
	[25]	27.6	28.5	27.8	27.6	28.7	28.1
[15]	[24]	28.4	29.5	28.6	28.3	29.6	28.8
	[25]	**28.6**	**29.6**	28.9	28.5	**29.7**	**29.2**
Joint Demosaicking-Denoising [27]		24.7	26.3	24.9	24.7	26.3	25.0
Joint Demosaicking-Denoising [30]		28.3	29.3	28.5	28.2	29.3	28.8
PCA-based CFA Denoising + Demosaicking [4]		26.4	28.7	26.5	26.3	28.8	26.6
PCA-based CFA Denoising + Demosaicking [9]		**28.6**	29.5	**29.0**	**28.6**	29.5	29.1
PCA-based CFA Denoising + Demosaicking [10]		28.2	29.1	28.6	28.2	29.2	28.7
PCA-based CFA Denoising + Demosaicking [15]		28.5	29.4	28.9	28.5	29.5	29.1

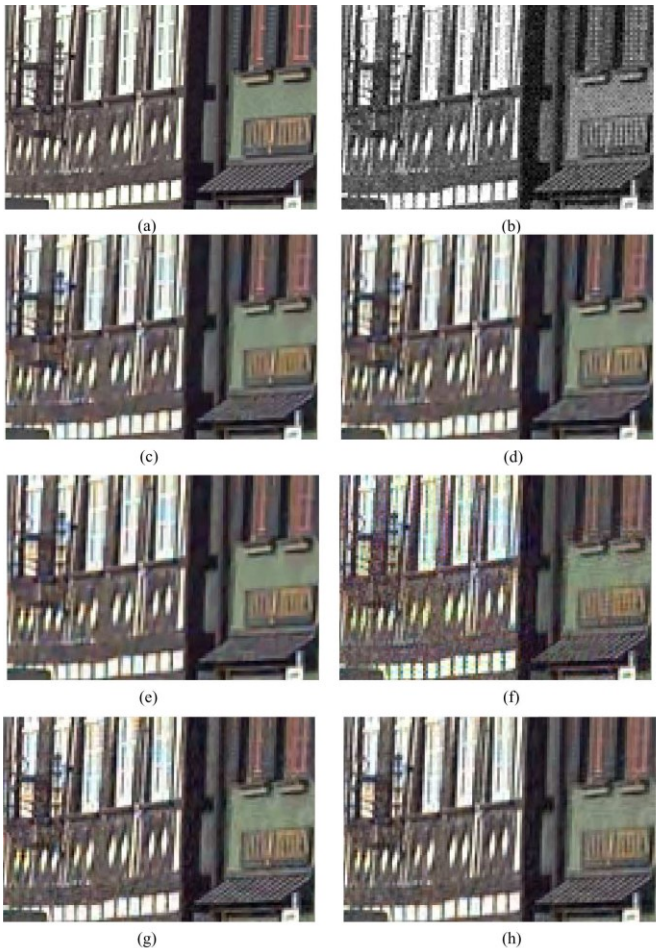

Figure 1. Cropped and zoom-in images of the reconstructed color "house" image. (a) Original image; (b) noisy CFA data (σr =13, σr =12, σr =10); (c)–(e) are reconstructed by demosaicking methods [9], [10] and [15] followed by denoising method [25]; (f) and (g) are reconstructed by joint demosaicking-denoising methods [27] and [30]; (h) is reconstructed by the proposed adaptive PCA-based CFA denoising method followed by demosaicking method [9].

VI. CONCLUSION

This paper presented a PCA-based CFA image denoising scheme for single-sensor digital camera imaging applications. The proposed direct CFA image denoising scheme, followed by a subsequent demosaicking scheme, reduces significantly the noise-caused color artifacts in the demosaicked images. Such artifacts often appear in the output full-color images of many "demosaicking first and denoising later" schemes as well as some joint demosaicking-denoising schemes. While suppressing noise, the proposed scheme preserves very well the fine structures in the image, which are often smoothed by other denoising schemes.

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