BM3D-Based Denoising of CFA Images for Single-Sensor Digital Cameras

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Abstract

Most existing Digital Color Cameras use a Single -sensor with a color filter array (CFA) to capture images. 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. Few denoising schemes that work directly on the CFA images have been presented because of the difficulties arisen from the red, green and blue interlaced mosaic pattern, yet a well designed "denoising first and demosaicking later" scheme can have advantages such as less noise-caused color artifacts and cost-effective implementation. Lie Zahng *et al*. has extended and developed a method called PCA-based denoising method on CFA image denoising [8]. However, when noise level is high, accurate estimation of the PCA basis is not possible and the image denoising performance is decreased. The weaknesses of PCA method are the high computational burden they enforce to processors and the more time they need. This paper proposes a new procedure that is improved block matching and 3-D filtering (BM3D) image denoising algorithm. Using an improved version of BM3D, it is possible to achieve a better performance than directly using of BM3D algorithm in a variety of noise levels. This method changes BM3D Algorithm parameter values according to noise level, removes pre-filtering, which is used in high noise level; therefore Peak Signal-to-Noise Ratio (PSNR) and visual quality get improved, and BM3D complexities and processing time are reduced. This improved BM3D algorithm is used to denoise color filter array (CFA) images.

Keywords –*Color Filter Array (CFA), Improved BM3D Denoising, Block-wise estimates, Collaborative filtering, Color Demosaicking.*

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). 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). Many CDM algorithms proposed in the past are based on the unrealistic assumption of noise-free CFA data. 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 principle component analysis (PCA)-based denoising scheme which directly operates on the CFA domain of captured images. Single-sensor digital color cameras use a process called color Denoising principle component analysis (PCA)-based denoising scheme which directly operates on the CFA domain of captured images. 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. Few denoising schemes that work directly on the CFA images have been presented because of the difficulties arisen from the red, green and blue interlaced mosaic pattern, yet a well designed "denoising first and demosaicking later" scheme can have advantages such as less noise-caused color artifacts and cost-effective implementation. An approach called principle component analysis (PCA) based spatially-adaptive denoising algorithm, works directly on the CFA data using a supporting window to analyze the local image statistics, but when noise level is high, accurate estimation of the PCA basis is not possible and the image denoising performance is decreased.

Recently, a powerful method for image denoising by K. Dabov at al, based on block matching and 3-D Transform-Domain collaborative filtering (BM3D), is proposed [3]. This procedure proposed in transform domain improved sparse representation based a new image denoising method. The enhancement of the sparsity is achieved by grouping similar 2-D fragments of the image into 3-D data arrays, which we call groups''. Collaborative filtering developed based on a special method for handling these 3- Dimensional groups. It includes three successive steps: 3-D transformation of a group, shrinkage of transform spectrum, and inverse 3-D transformation. Therefore, a 3- Dimensional group is obtained that comprise of a joint array from filtered 2-Dimensional fragments. Block Matching and 3-Dimensional filtering (BM3D) can achieve a high level of sparse representation of the noise –free signal, thus, the noise can be set apart well from signal by shrinkage. In this manner, the transform displays all of tiny details of image by grouped fractions; simultaneously the necessary unique feature of each individual fragment is protected.

Generally, denoising performance should gradually weaken with growing noise level. However, when noise standard deviation goes more than 39, denoising performance sharply drops. To avoid this problem, [3] proposes measuring the block-distance, using coarse prefiltering. It is shown in the following that by removing the prefiltering from the algorithm, its compatibility enhances [5]. Results show that by removal of prefiltering from BM3D algorithm and modification of parameters, such as maximum d-distance (τ_{match}^{ht}) maximum number of grouped blocks (N_2), wiener filter parameter (N_{step}), PSNR and visual quality are augmented. The proposed method improves the output PSNR significantly even with the standard deviation less than 39.

This paper is divided into the following sections: In section 2, the PCA based Denoising is described. Section 3 briefly surveys the concept of Block Matching and 3-Dimentional filtering (BM3D). In section 4, a method is proposed to improve the BM3D algorithm. Extension of the proposed algorithm for denoising CFA images and the comparison of its performance with the PCA-based method. Finally, Section 5 is devoted to conclusions.

I. Existing Method: PRINCIPAL COMPONENT ANALYSIS

PCA is a classical de-correlation technique which has been widely used for dimensionality reduction with direct applications in pattern recognition, data compression and noise reduction. Besides decorrelation, another important property of PCA is that it is optimal by using a subset of its principal components to represent the original signal. To fully exploit the spatial and spectral correlations of the CFA sensor readings during the denoising process, the mosaic samples from different color channels were localized by using a supporting window to constitute a vector variable, whose statistics are calculated to find the PCA transform matrix. The dimension reduction and LMMSE were conducted in the PCA transformed domain to suppress the CFA image noise. The denoising procedure is completed by inversing the PCA transform to produce the enhanced CFA image. To further reduce the noise residual in smooth areas and phantom artifacts around the boundary between edges and background, the procedures of CFA image decomposition and training sample selection were introduced before PCA transformation. 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. But when noise level is high, accurate estimation of the PCA basis is not possible and the image denoising performance is decreased. And also the computational processing time is very high, nearly 236sec.

II. Proposed Method: BLOCK MATCHING AND 3-D FILTERING

In this algorithm, the grouping is realized by block-matching, and the collaborative filtering is accomplished by shrinking in a 3-D transform domain. The used image fragments are square blocks of fixed size. The general procedure carried out in the algorithm is as follows: The input noisy image is processed by successive extraction of every reference block:

• Finding blocks that are similar to the reference one (block-matching), and stacking them together to form a 3-D array (group).
• Performing collaborative filtering of the group and returning the obtained 2-D estimates of all grouped blocks to their original locations. After processing all reference blocks, the obtained block estimates can overlap; thus, there are multiple estimates for each pixel. These estimates are aggregated to shape a overall estimate of the entire image.

The general concept of the BM3D denoising algorithm is the following.

1. Block-wise estimates*:* For each block in the noisy image the filter performs:

a) Grouping: Finding blocks that are similar to the currently processed one, and then stacking them together in a 3-D array (group).

b) Collaborative filtering: Applying a 3-D transform to the formed group, attenuating the noise by shrinkage (e.g., hard-thresholding) of the transform coefficients, inverting the 3-D transform to produce estimates of all grouped blocks, and then returning the estimates of the blocks to their original places. Because the grouped blocks are similar, Block Matching and 3- Dimensional filtering (BM3D) can achieve a high level of sparse representation of the noise –free signal, thus, the noise can be set apart well from signal by shrinkage.

2. Aggregation: The output image is estimated by weighted averaging of all achieved block estimates that have overlap.

For a noisy image Z, one reference block within Z is determined. Grouping discovers Z_x that is similar to Z_{x_R} by l^2-distance which can be calculated from the noisy blocks as

$$d^{noisy}(Z_{x_R}, Z_x) = \frac{\left\| Z_{x_R} - Z_x \right\|^2}{(N_1^{ht})^2} \qquad (1)$$

Where $\| \cdot \|$- denotes the l^2 -norm and the blocks Z_{x_R} and Z_x are respectively located at x_R and $x \in X$ in Z.

In [1], when noise standard deviation is more than 39 denoising performance have a sharp drop. To avoid this problem, it is proposed to measure the block-distance using a coarse prefiltering. This prefiltering is realized by applying a normalized 2-D linear transform on both blocks and then hard-thresholding the obtained coefficients, which results in

$$d(Z_{x_R}, Z_x) = \frac{\left\| \gamma'(\tau_{2D}^{ht}(Z_{x_R})) - \gamma'(\tau_{2D}^{ht}(Z_x)) \right\|_2^2}{(N_1^{ht})^2} \qquad (2)$$

Where γ' is the hard-thresholding operator with threshold $\gamma_{2D}\sigma$ and τ_{2D}^{ht} denotes the normalized 2-D linear transform. Using the l^2-distance, the result of BM is a set that contains the coordinates of the blocks that are similar to Z_{x_R}

$$S_{x_R}^{ht} = \{ x \in X : d^{noisy}(Z_{x_R}, Z_x) \leq \tau_{match}^{ht} \} \qquad (3)$$

Where the fixed τ_{match}^{ht} is the maximum l^2 -distance for which two blocks are considered similar. These parameters are selected by deterministic conjectures (the acceptance value of the ideal distinction) it principally neglects the noisy components of the signal. Obviously $d^{noisy}(Z_{x_R}, Z_x) = 0$, which implies that $|S_{x_R}^{ht}| > 1$ where $|S_{x_R}^{ht}|$ denotes the cardinality of $S_{x_R}^{ht}$. After obtaining a $S_{x_R}^{ht}$ a group is formed by stacking the matched noisy blocks $Z_{x \in S_{x_R}^{ht}}$ to form a 3-D array of size $N_1^{ht} \times N_1^{ht} \times |S_{x_R}^{ht}|$, which we denote $Z_{S_{x_R}^{ht}}$.

III. BM3D MODIFICATION

In [3], prefiltering is used to avoid sharp drop in denoising performance. However, using this filter will cause the removal of some noiseless data [5]. In the proposed method here, the algorithm parameters are set according to the added noise level to the image. Classifying the noise levels into low, medium, high and very high, the algorithm parameters can be set as mentioned in Table1. As can be seen in Table 1, when the noise standard deviation is increased, the maximum size of grouped blocks N_2, should increase to improve the denoising performance. As mentioned in [3], N_2 is a power of 2 so it is allowed to change among 16, 32, 64 and so on.

TABLE1: COMPARISON OF PARAMETER VALUES OF THE IMPROVED BM3D AND BM3D

Standard deviation of noise added to the image	**Changeable Parameter values of BM3D**	**Parameter value of improved BM3D**
σ < 30 Low	N_{step_wiener}=3 τ_{match}^{ht}=2500	N_{step_wiener}=2 τ_{match}^{ht}=3000
30 ≤ σ < 50 medium	N_{step_wiener}=3 τ_{match}^{ht}=2500	N_{step_wiener}=2 τ_{match}^{ht}=6500
50 ≤ σ < 80 High	N_1^{ht}=11 τ_{match}^{ht}=5000 N_2=16	N_1^{ht}=8 τ_{match}^{ht}=15000 N_2=32
80 ≤ σ < 100 Very High	N_1^{ht}=11 N_2=16 τ_{match}^{ht}=5000	N_1^{ht}=8 N_2=64 τ_{match}^{ht}=30000

τ_{match}^{ht} must be greater than its primitive value to ensure that there are enough blocks in 3D array for better image denoising performance. There is a trade-off between processing time and the output PSNR. Also, in noise level with standard deviation less than 50, wiener filter parameter N_{step} should decrease from 3 to 2.

The output PSNR of the BM3D method [3], LPG-PCA method [4] and the proposed method are compared in Table 2 and in Figures (1). PSNR is defined as follows:

$$PSNR = 10 \log_{10} \frac{(255^2)}{(MSE)} \qquad (4)$$

Where MSE is the mean square error.

According to Table 2, it can be seen that the output PSNR values increase significantly with the noise level increment.

TABLE2. THE COMPARISON OF THE OUTPUT-PSNR OF THE PROPOSED METHOD WITH TWO STATE-OF-THE-ART RECENT METHODS BM3D AND LPG-PCA

Peppers image256*256			
σ / *PSNR*	**PCA**	**BM3D**	**Improved BM3D**
10 /28.1	34.08	34.65	**34.69**
20 / 22.1	30.53	31.26	**31.30**
30 / 18.5	28.48	29.27	**29.30**
35 / 17.2	27.68	28.49	**28.54**
40 / 16.7	26.99	27.51	**27.9**
45 / 15.1	26.37	27.17	**27.19**
50 / 14.1	25.8	26.41	**26.70**
75 / 10.6	23.52	24.49	**24.74**
100/ 8.1	21.9	22.92	**23.40**

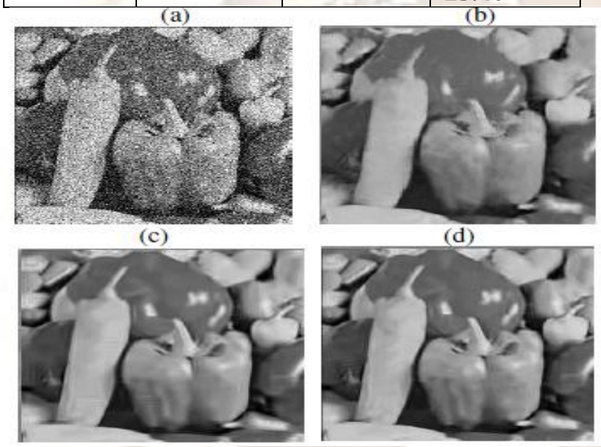

Figure 1: (a) Part of the noisy peppers Image (PSNR=14.13, s =50). (b) Result of the LPGPCA: PSNR=25.8. (c) Result of the BM3D: PSNR=26.41. (d) Result of the proposed method (improved BM3D): PSNR=26.70.

IV. EXPERIMENTAL RESULTS OF BM3D-BASED DENOISING OF CFA MOSAIC IMAGES

The output of the Single sensor digital cameras uses a process called CDM [Color Demosaicking] to produce full color images from data captured by a color filter array. Images quality degrades during image acquisition procedure as a result of sensor noise. Conventional solution for noise reduction is demosaicking first and then denoising the image. Color artifacts in the demosaicking process cause these conventional methods to produce many noise in image which will then make the noise removal process hard and difficult.

Recently a method based on PCA is proposed for CFA image denoising. In this method, despite conventional methods, first denoising is done with PCA and then the image is demosaicked. As mentioned before, the PCA algorithm consumes lots of time to implement and imposes a very high computational burden, therefore it has practical applications difficulties for digital cameras. To solve this problem, modified BM3D method can be used instead of PCA in denoising procedure. For simulation of CFA image with channel-dependent sensor noise, Gaussian white noise is added separately with standard deviations $\sigma_r = 30$, $\sigma_g = 27$, $\sigma_b = 25$ to red, green, and blue channels of the image, respectively. Then digital image resolution is decreased (downsampling). The PSNR of the output of the proposed method is compared with adaptive PCA method in Figure (2). It can be seen that the proposed method has better performance than the PCA method considering both PSNR and visual quality. In addition, computational processing time of the proposed algorithm is decreased significantly. The processing time for PCA and the proposed algorithms last 236sec and 45sec, respectively.

TABLE3. THE COMPARISON OF THE OUTPUT-PSNR OF THE PROPOSED METHOD AND PCA DENOISING

Kodak Fence Image 256*256				
Denoising Method	**PSNR Results** $\sigma_r = 30;\ \sigma_g = 27,\ \sigma_b = 25$			**Execution Time**
	R	**G**	**B**	
Existing Method: PCA Denoising	25.993	26.525	25.3929	236 seconds
Proposed Method: BM3D Denoising	29.5715	30.038	28.4861	45 seconds

(a)

(b)

Figure 2(a) Reconstructed by the adaptive PCA-based CFA denoising method followed by demosaicking method [8]: $PSNR_R$= 26.8508 dB,$PSNR_B$= 27.5306 Db, $PSNR_G$ = 27.6283 dB (b)Reconstructed by the proposed BM3D-based CFA denoising method followed by demosaicking method: $PSNR_R$= 29.57 dB,$PSNR_B$=30.038 Db, $PSNR_G$=28.4861 dB (Standard deviation of noisy CFA data is ($\sigma_r = 30$, $\sigma_g = 27$, $\sigma_b = 25$)).

CONCLUSION

In this paper a BM3D algorithm and improved BM3D algorithm for image denoising was presented. The results show that by removal of prefiltering from BM3D algorithm and modifying parameters such as maximum d-distance (τ_{match}^{ht}), maximum number of grouped blocks (N_2), wiener filter parameter (N_{step}), the PSNR and visual quality gets better than that of PCA. Also when this algorithm is developed to CFA images denoising, it has superior PSNR and visual quality than adaptive PCA algorithms. In addition, it significantly reduces the processing time. Using the proposed method here in medical image processing can be considered as future research.

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