PCA Based CFA Denoising and Demosaicking For Digital Image

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Abstract

Principal component analysis (PCA) is an orthogonal transformation that seeks the directions of maximum variance in the data and is commonly used to reduce the dimensionality of the data. In image denoising, a compromise has to be found between noise reduction and preserving significant image details. PCA is a statistical technique for simplifying a dataset by reducing datasets to lower dimensions. It is a standard technique commonly used for data reduction in statistical pattern recognition and signal processing. This paper proposes a denoising technique by using a new statistical approach, principal component analysis with spatial adaptive technique This procedure is iterated second time to further improve the denoising performance, and the noise level is adaptively adjusted in the second stage. 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 paper presents a principle component analysis (PCA) based spatiall-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, including those sophisticated demosaicking and denoising schemes, in terms of both objective measurement and visual evaluation.

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

I. INTRODUCTION

In the time of embedded system, the digital camera's are one of the popular consumer electronic product. The personal digital assistance (PDA's), mobile cell phones, iPods are embedded with the expansive digital camera's instead of film camera's for capturing or recording of the activities of everyday life. The removing of noise or providing a correction of non-linearity's of sensor of camera's non uniformities, adjusting the white balance and many more needs a significant processing for users viewable image [3]. These camera's are generally uses a sensor with CFA (color Filter Array) which is a very important part of processing chain. Any color image is consisting of three basic primary color R, G, B. the only one third or single color is to be measured at each pixel by CFA and the remaining missing true color image is estimated by camera and this estimated process by the camera is known as demosaking [1-5].

PCA is a statistical procedure that uses an orthogonal property to transform to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables. The denoising phenomenon goal is to remove the noise while retaining the maximum possible the important signal or image features. At the time of acquisition and transmission the images are often corrupted by additive noise. The main aim of a denoising algorithm is to reduce the noise level, while preserving the image features. To achieve a good performance in this respect, a denoising algorithm has to adapt to image discontinuities. Generally the quality of image can be measured by the peak signal-to-noise ratio (PSNR). However, sometimes a denoised image with a high PSNR value does not have satisfactory visual quality [12].

PCA is a pre-processing transformation technique that creates new images from the uncorrelated values of different images [13]. This is accomplished by a linear transformation of variables that corresponds to a rotation and translation of the original coordinate system. PCA is used to find out principal components in accordance with maximum variance of a data matrix. Based on the principle components a new technique, based on maximization of SNR was also proposed in [3]. The grouping procedure guarantees that only the sample blocks with similar contents are used in the local statistics calculation for PCA transform estimation, so that the image local features can be well preserved after coefficient shrinkage in the PCA domain to remove the noise. Experimental results shows this method gives better performance, especially in image fine structure preservation, compared with general denoising algorithms [4-9].

II. PCA(PRINCIPAL COMPONENT ANALYSIS)

It is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analyzing data, main advantage of PCA is that once you have found these patterns in the data, and you compress the data, ie. by reducing the number of dimensions, without much loss of information Principal component analysis is a variable reduction procedure. It is useful when you have obtained data on a number of variables (possibly a large number of variables). PCA is a classical decorrelation technique which has been widely use for dimensionality reduction with direct application in pattern recognition, data compression and noise reduction.Denote by X=[x1 x2…..xm]ˆT an m component vector variable and denoted by

$$\mathbf{X} = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^n \\ x_2^1 & x_2^2 & \cdots & x_2^n \\ \vdots & \vdots & \vdots & \vdots \\ x_m^1 & x_m^2 & \cdots & x_m^n \end{bmatrix}$$

The sample matrics of x, Where xi^j,j=1,2….,n is the discrete sample of variable xi, i=1,2,……m. th ith row of sample matrix x,

A. PROPOSED ALGORITHM

The proposed CFA denoising algorithm is summarized as follows.

(1) Estimate the noise standard deviations σ_r ,σ_g and σ_b of the red, green and blue channels.
(2) Decompose the noisy CFA image **I** into I_l and I_h.Apply the following denoising steps 3 and 4 to I_h.
(3) Set the sizes of variable block and training block. The noise co-variance matrix C_m can then be determined.
(4) 4. For each training block:
    Perform the training sample selection procedure.
    (1) Denote by **X** the selected training dataset.
    (2) Calculate the co-variance matrix C_m ;
    (3) Estimate the co-variance matrix of signal as : $C_s = C_m - C_v$.
    (4) Factorize $C_m = F_x * A_x * F_t$ and set the transformation matrix $P_x = F_t$.;
    (5) Transform the dataset to domain: $Y = P_x * X$.;
    (6) By resetting the last several rows of **Y** to zeros, reduce **Y** to (dimension reduction);
    (7) Shrink each row of Y_d as $Y_{di} = C_i * Y_{di}$.
    (8) Transform back Y_d to time domain as $X = P_x * Y_d$.;
    (9) Reformat **X** to get the denoised CFA block.

End.

(5) Denote **I** by the denoised output of I_{dh}, the final denoised image is $I_{di} = I_l + I_{dh}$.

The proposed denoising algorithm will use a local training block to estimate the transformation matrix. All the possible samples in the training block are used in the calculation. However, sample structures may change within a block, especially if the block contains object boundaries with smooth background. Involving such samples in the training may lead to much bias in the estimation of transformation matrix and consequently reduce the denoising performance, e.g., generating many phantom artifacts.

To overcome the above two problems, we propose two preprocessing steps before applying the PCA-based denoising. First, we decompose the noisy CFA image into two parts: the low-pass smooth image and the high-pass image. Denote by I_v the noisy CFA image. We use a 2-D Gaussian low-pass filter

$$G(x,y) = 1/\sqrt{2\Pi s}\ \exp(-x^2+y^2/2s^2) \text{ to smooth } I_v.$$

$$I_{vl} = I_v * G \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The high pass image is then obtained as

$$I_{vh} = I_v - I_{vl} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

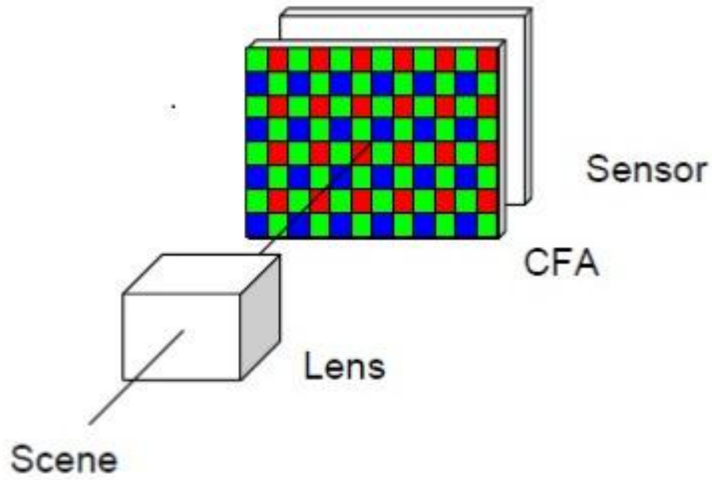
Assuming that n training samples are available for each element of x , the covariance matrix of x can be estimated using maximal likelihood estimation (MLE).

$$C_x = E[(x-E[x]) * (x-E[x])^T] \ \ldots\ldots\ldots(3)$$

With a suitable scale parameter s in the Gaussian filter, the low-pass image I_{lv} will be almost noiseless and most of the noise is contained in the high-pass output I_{vh}, which also contains the image edge structures to be preserved. Since I_{vl} is almost noiseless, we do not make further processing on it. The proposed CFA denoising scheme will be applied to the high-pass image I_{vh}, where the noise will be dominant in the smooth areas and they can then be better suppressed by LMMSE filtering in the PCA domain. Denote by I_{di} the denoised image of I_{vh} , the final denoised CFA image is obtained as $I_{di} = I_l + I_{dh}$. It can be validated that in a local window of I_{vh}, the mean value of red, green or blue variable will be nearly zero for smooth areas. In some sense, the Gaussian smoothing operation can be viewed as a procedure to better estimate the mean values of red, green and blue variables so that the noise residual in smooth areas can be reduced effectively. Now let's focus on how to reduce the phantom artifacts around edge boundaries with smooth background. As mentioned before, such artifacts are caused by the inappropriate training samples in the training block. Intuitively, one solution to this problem is to select the similar blocks to the underlying variable block and use them only but not all the blocks for training. Such a training sample selection procedure can better estimate the co-variance matrix of the variable block and, hence, lead to a more accurate transformation matrix. Finally, image local edge structures can be better preserved by removing the phantom artifacts.

III. BACKGROUND OF CFA

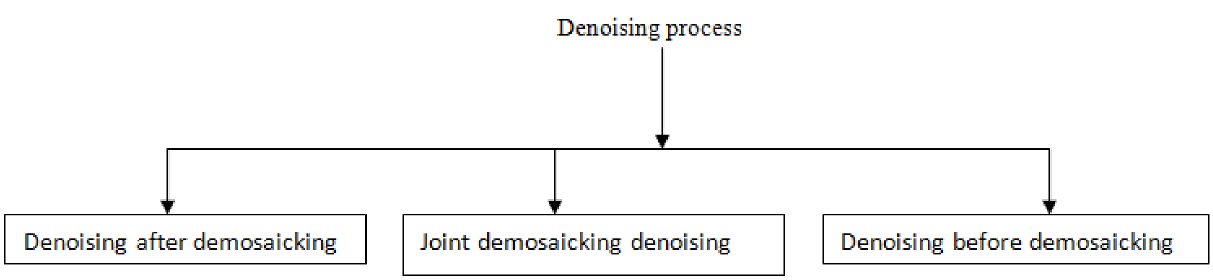
The digital cameras uses a very precious part i.e., single sensor with a colour filter array (CFA) for capturing the visual scene in color form as shown in fig.1.



As we have discussed in the last section the sensor cell can record only one colour value.The other two missingcolour components at each position need to be interpolated from the available CFA sensor readings to reconstruct the full colour image. The colour interpolation process is usually called colour demosaicing (CDM). There are many patterns out of which a CFA can have any pattern. The most commonly used CFA pattern is Bayer pattern shown in fig. 2. A Bayer filter mosaic is a color filter array (CFA) for arranging RGB color filters on a square grid of photo sensors. Its particular arrangement of color filters is used in most single-chip digital image sensors used in digital cameras, camcorders, and scanners to create a color image. The filter pattern is 50% green, 25% red and 25% blue, hence is also called RGBG, GRGB, or RGGB. The Bayer array measures the G image on a quincunx grid an the R & B images on rectangular grids. The G image is measured at higher sampling rate because sensitivity of human eyelie in medium wavelengths, corresponding to the G portion of the spectrum. There are number of applications where noise is present in the CFA. The presence of noise in CFA data not only deteriorates the visual quality of captured images but also often cause serious demos icing artifacts which can be extremely difficult to remove using a subsequent denoising process.

IV. METHODOLOGY FOR DENOISING

Many CDM algorithm [1]-[8] proposed in the past are based on unrealistic assumptions of noise free CFA data.To suppress the effect ofnoise on the demosaicked image, three strategies are possible.

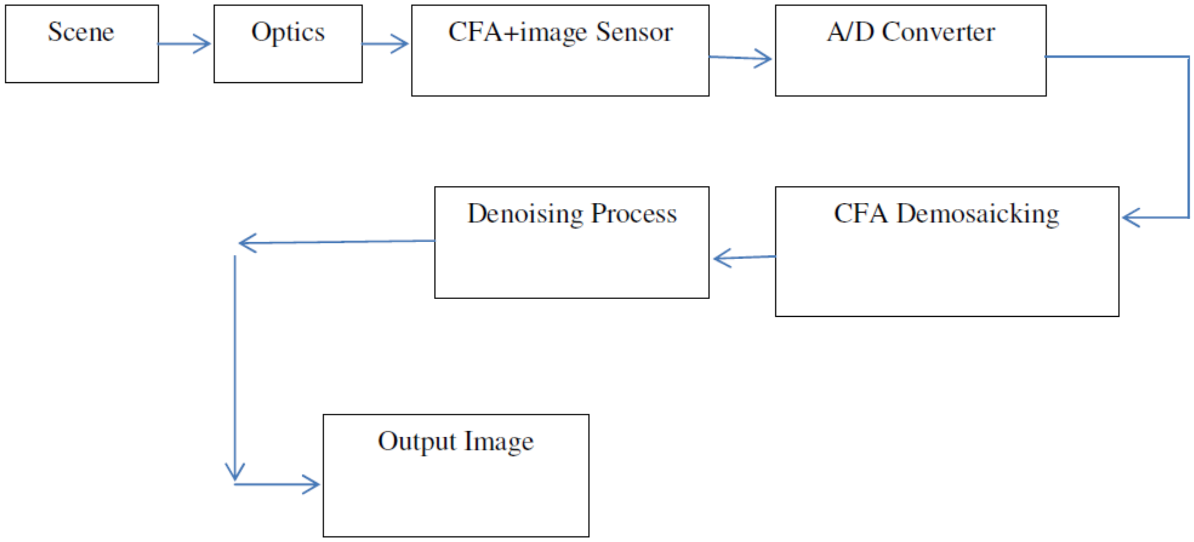


Joint demosaicking-denoising(Proposed Method):

Recently, some schemes that perform demosaicking and denoising jointly have been proposed [16]–[18]. In [17], 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 [20] proposed a bilateral filter based demosaicking method. Since bilateral filtering exploits the similarity in both spatial and intensity spaces, this scheme can handle light noise corrupted in the CFA image. Hirakawa and Parks [4] 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. The filter used for joint demosaicking-denoising is determined adaptively using the TLS technique under some constraints of the CFA pattern. The joint demosaickingdenoising scheme developed by Zhang *et al.* [13] first performs demosaicking-denoising on the green channel. The restored green channel is then used to estimate the noise statistics in order to restore the red and blue channels. In implementing the algorithm, Zhang *etal.*estimated the redgreen and blue-green color difference images rather than directly recovering the missing color samples by using a linear model of the color difference signals. Inspired by the directional linear minimum mean square-error estimation (DLMMSE) based CDM scheme in 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.

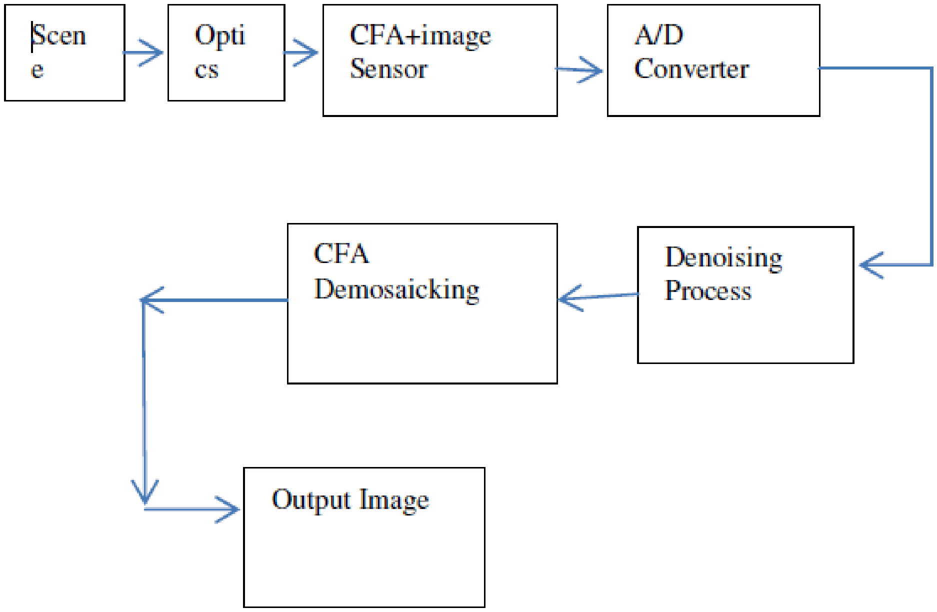
B. Denoising after demosaicking:

A convenient strategy to remove noise is to denoise the demosaicked images. Algorithms developed for gray-scale imaging, for example [12]–[15], can be applied to each channel of the demosaicked color image separately whereas some color image filtering techniques [11] 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 compoundnoise that is difficult to characterize. This makes the design of denoising algorithms for single-sensor color imaging very difficult as demonstrated below.



C. Denoising before demosaicking:

The third way to remove noise from CFA data is to implement denoising before demosaicking which is our proposed method. However, due to the underlying mosaic structure of CFAs, many existing effective monochromatic image denoising methods cannot be applied to the CFA data directly. To overcome the problem, the CFA image can be divided into several sub-images using the approach known from the CFA image compression literature, e.g.[19].Since each of the sub-images constitutes a gray-scale image, it can be enhanced using denoising algorithms from grayscale imaging. The desired CFA image is obtained by restoring it from the enhanced sub-images. Nonetheless, such a scheme does not exploit the inter channel correlation which is essential to reduce various color shifts and artifacts in the final image [11]. Since the volume of CFA images is three times less than that of the demosaicked images, there is a demand to develop new denoising algorithms which can fully exploit the inter channel correlations and operate directly on CFA images, thus achieving higher processing rates.



V. DEMOSAICKING

A representation of a full color image requires all the primary colors red, green, and blue at each pixel location. The output image of SSAC is monochromatic mosaic image, which consists of any one of the three primary color component values at each pixel location. As a result, the missing two other colors at each pixel location have to be interpolated to get a full color image The process of interpolating the missing colors is called as demosaicing or CFA interpolation. The aim of demosaicing is to reconstruct the missing colors as close as possible by keeping the computational complexity very low. Color CFA interpolation process to reconstruct the full RGB images collected from a single- sensor digital camera images. The single - sensor camera of the color information of the image obtained through the color filter array (CFA) , but the collected images at each pixel location only one of the original color component , in order to recover the other two components to obtain a full-color image , it must be interpolated this process is also called color demosaicking .

In Single-sensor digital camera, a mosaic image with any one of the primary color component is resulted because of the color filter array. A representation of a full color image requires reconstruction of the other two primary colors at each pixel location. A demosaicing algorithm is a digital image process used to reproduce the complete color image from the partial color image data received from a SSAC. The SSDCI consists of any one color component value at each pixel location. The missing other two color information at each pixel location in the SSDCI is interpolated (Demosaicing) from the adjacent pixels as close as possible by keeping the computational complexity very low. The demosaicing algorithms can be classified as adaptive and non-adaptive algorithms.

Non-adaptive Demosaicing

Non-adaptive algorithms perform interpolation in a fixed pattern for every pixel i.e. by averaging neighboring pixels indiscriminately. This causes an artifact, the zipper effect in the interpolated image. Nearest Neighborhood Interpolation, Bilinear Interpolation, Smooth Hue Transition, Median Based Interpolation are examples of non adaptive algorithm.

D. Adaptive Demosaicing

Adaptive algorithms use both spectral and spatial features present in the pixel neighborhood, to interpolate the missed pixel as close to the original as possible. Like other color image processing problems, modeling the correlation among three color channels (planes) plays the critical role in demosaicing. All color channels have very similar characteristics such as texture and edge location. Ignoring such inter-plane dependency (e.g., straightforward intra-plane linear interpolation) often renders the demosaiced image suffering from annoying artifacts caused by incorrect interpolation. To restore more accurate and visually pleasing results, many sophisticated demosaicing methods have been proposed by exploiting image spatial or spectral correlation, or both. Various techniques have been proposed to obtain a more faithful and higher quality reproduction of color images by exploiting the inter-plane correlation. The grand challenge is to find the best tradeoff between image quality and computational cost.

VI. EXPERIMENT RESULTS

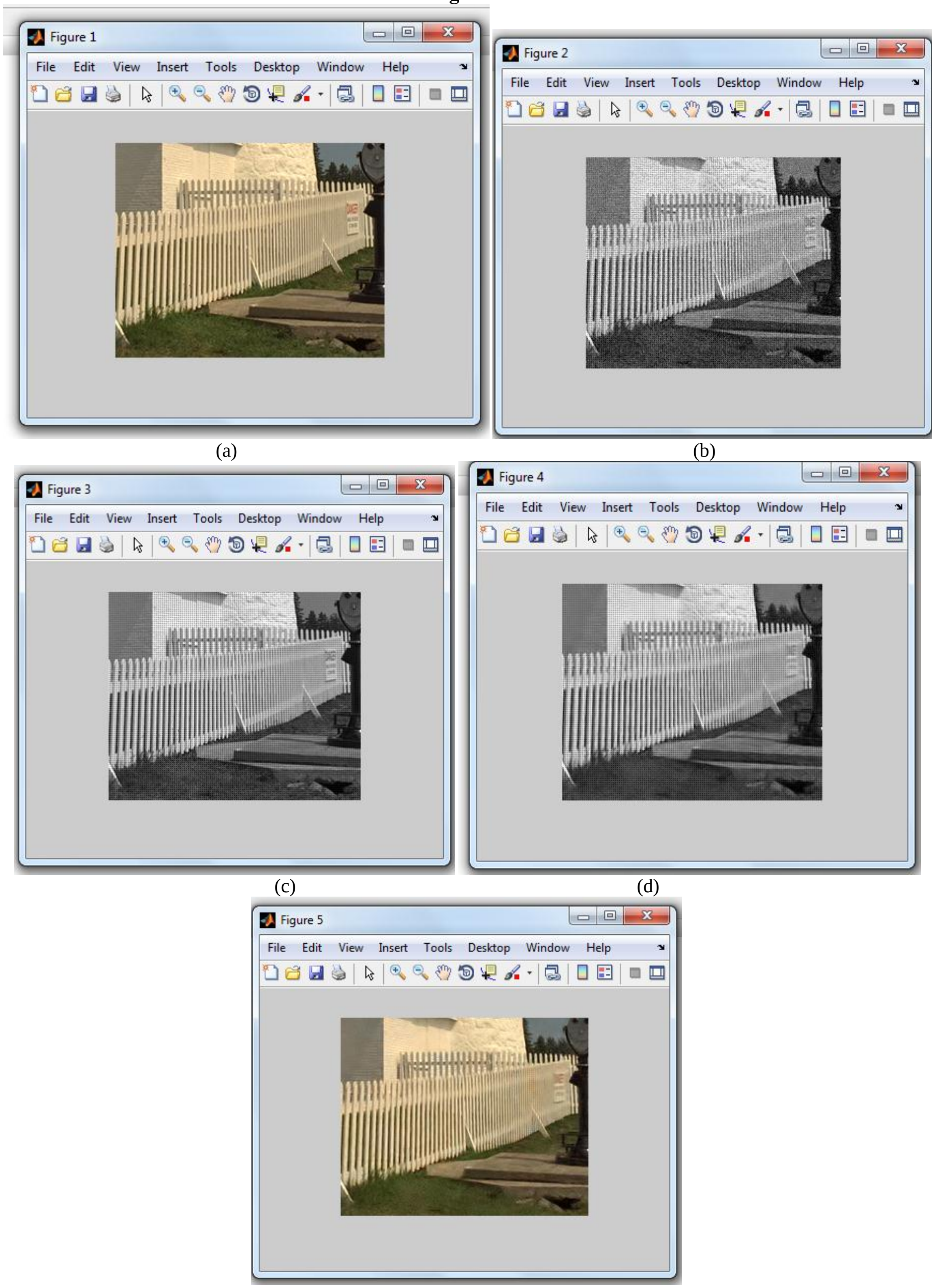
We performed simulations in an attempt to confirm the theoretical results above. 512×768 image is taken to examine the result. We examine the signal-noise ratio (SNR) The SNR is defined as:

$$SNR\ 10\log (Ps / Pn)\ (dB)$$

where Ps is the power of signals, Pn is the power of noise.

PSNR DB Result of the recontructed FENCE IMAGE by different demosaicking and denoising method

σr=σg=σb=12



(a) (b) (c) (d) (e)

Fig.2 Cropped images of the re constructed fence image. (a) Original image; (b) CFA noisy image (c) CFA noiseless image (d) PCA based denoised image (e) is reconstructed by the proposed PCA-based CFA denoising method followed by demosaicking.

PSNR result of the reconstructed FENCE Images by σr= 13 σb= 10 σg=12

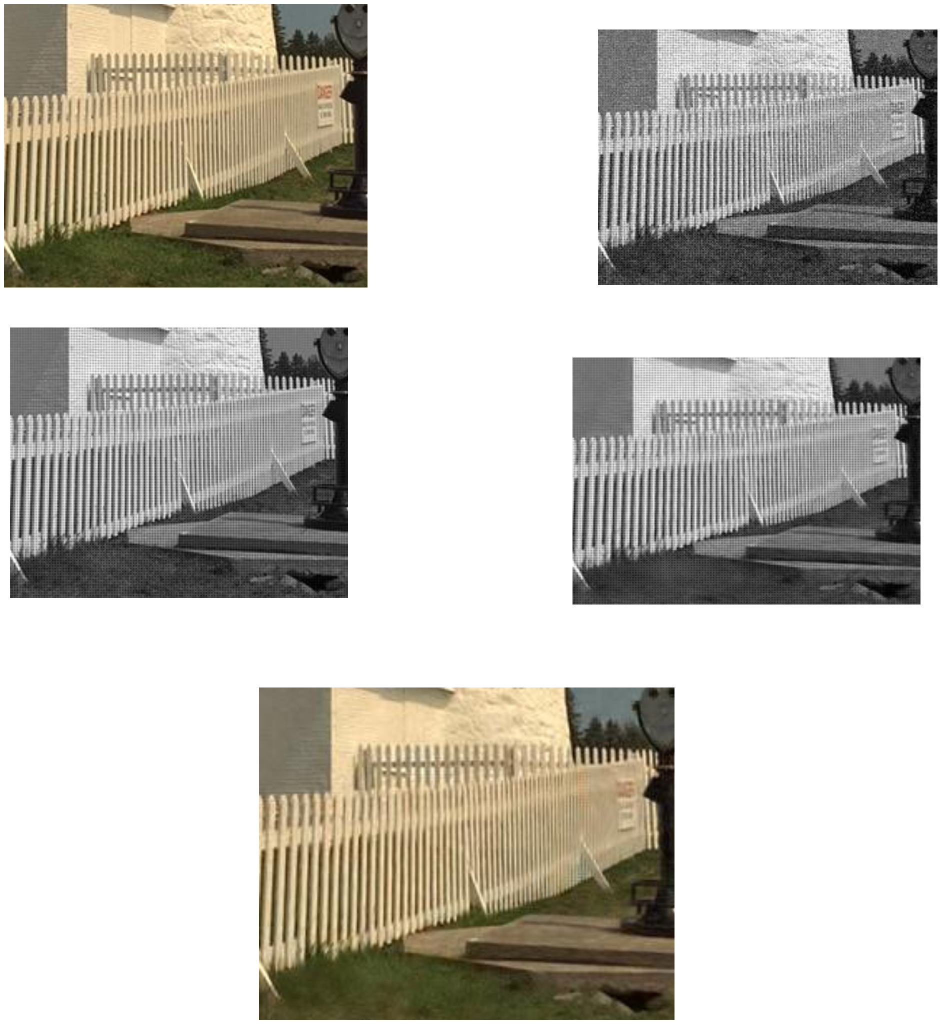
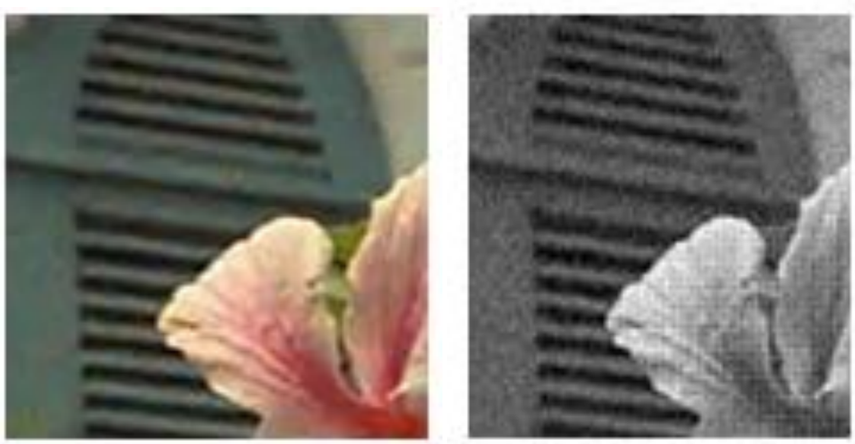


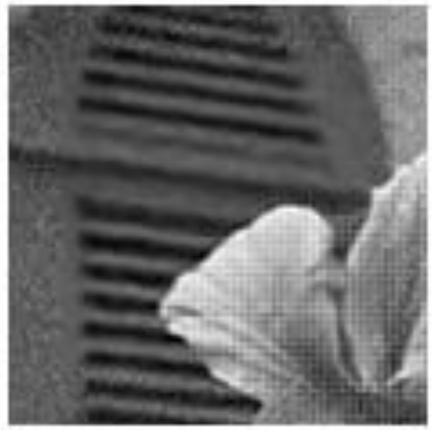
Fig. 3: Cropped Images of The Re Constructed Fence Image. (A) Original Image; (B) CFA Noisy Image (C) CFA Noiseless Image (D) PCA Based Denoised Image (E) Is Reconstructed By The Proposed PCA-Based CFA Denoising Method Followed By Demosaicking.

PSNR result of the reconstructed FENCE Images by $\sigma r= 13$ $\sigma b= 10$ $\sigma g=12$



(a) (b)

(C)



(D)

(e)

Fig. 4: Cropped Images Of The Re Constructed Flower Image. (A) Original Image; (B) CFA Noisy Image (C) CFA Noiseless Image (D) PCA Based Denoised Image (E) Is Reconstructed By The Proposed PCA-Based CFA Denoising Method Followed By Demosaicking.

Table - I.
PSNR (dB) Results of The Reconstructed *Fence* Images By Different Demosaicking and Denoising Methods.

Demosaicking Method	DenoisingMethod	PSNR RESULT(dB)					
		$\sigma r = \sigma b = \sigma g = 12$			$\sigma r = 13, \sigma b = 10, \sigma g = 12$		
		R	G	B	R	G	B
[1]	[5]	28.0	30.3	28.8	28.4	30.3	28.6
	[6]	28.1	30.6	28.3	27.9	30.6	28.6
[2]	[5]	30.5	31.3	30.8	30.3	31.3	31.2
	[6]	30.5	31.3	30.9	30.3	31.3	31.2
[3]	[5]	29.9	30.7	30.1	29.7	30.7	30.3
	[6]	30.2	31.1	30.6	30	31.2	30.9
[4]	[5]	30.4	31.5	30.7	30.2	31.5	31.1
	[6]	30.4	31.5	31.0	30.2	31.6	31.3
Joint Demosaicking –Denoising[7]		27.1	28.6	28.2	27.1	28.8	28.5
Joint Demosaicking –Denoising[8]		30.7	31.5	31.2	30.5	31.6	31.5
PCA based CFA Denoising + Demosaicking[1]		29.6	31.4	30.2	29.5	31.4	30.3
PCA based CFA Denoising+Demosaicking		30.90	31.6	31.6	30.8	31.7	31.6
PCA based CFA Denoising + Demosaicking[3]		30.8	31.5	31.4	30.7	31.5	31.5
PCA based CFA Denoising + Demosaicking[4]		30.7	31.5	31.5	30.7	31.6	31.7

Table - II
PSNR (dB) Results of The Reconstructed FLOWER Images By Different Demosaicking And Denoising Methods.

Demosaicking Method	Denoising Method	PSNR Result(DB) σr = 13 σb = 10 σg = 12		
		R	G	B
[2]	[6]	32.1	33.1	32.9
[3]	[6]	32.8	33.20	32.4
[4]	[6]	32.1	33.6	32.88
Joint Demosaicking-Denoising[7]		30.16	30.15	29.67
PCA Based CFA Denoising +Demosaicking		**31.13**	**31.45**	**31.81**

VII. CONCLUSION

In this paper an efficient ways new method of removing the noises in the CFA data by providing the joint denoising and demoisckіng. The complete information of noise produced in the Bayer filter has been explained. The new proposed method of joint denoising demoisckіng is also a better option and efficient option for the color improvement which is proposed in this paper. This proposed method is also a better option in the field of image processing.

Performance of denoising algorithms is measured using quantitative performance measures such signal-to-noise ratio(SNR) as well as in terms of visual quality of the images. In reality, this assumption may not always hold true due to the varied nature and sources of noise. An ideal denoising procedure requires a priori knowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise variance of the noise and the noise model to compare the performance with different algorithms. Noise with different variance values is added in the natural images to test the performance of the algorithm. The performance of different denoising methods can be evaluated by using signal-to-noise ratio (SNR) with respect to the original images. The PCA based CFA denoising method achieves highest SNR values. While suppressing noise, the proposed scheme preserves very well the fine structures in the image, which are often smoothed by other denoising schemes and the result of colour demosaicing in terms of red, green, blue are analyzed.

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