Denoising methods have been proposed for CFA images, and the choice of method depends on the specific application and the level of noise present in the image.

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Abstract- Single sensor digital color still/video cameras capture images using a color filter array (CFA) and require color interpolation (demosaicking) to reconstruct full color images in demosaicking, sensor noises can cause color artifacts that are hard to remove later by a separate denoising process, because the demosaicking process complicates the noise characteristics by blending noises of different color channels. 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. The Paper shows different types of denoising process of CFA images.

Index Term-CFA(Color Filter Array),Denoising, Demosaicking, Transform Domain.

1. INTRODUCTION

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the image. Most existing digital color cameras use a single sensor with a color filter array (CFA) [1] 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).Many CDM algorithms [2]–[8] 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 process.

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 .All these traditional methods consider the signal and noise as the same status but not consider the independence of signal and noise, so they may tend to affect the denoising effect, while independent component analysis renders the images as statistically independent as possible by evaluating higher-order statistics of observation images, so it performs well in noise removal and it preserves edge sharpness. 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 [2]–[11], [14]–[17] proposed in the past are based on the unrealistic assumption of noise-free CFA data of images.

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 [19]–[26], 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 suppress the effect of noise on the demosaicked image, three strategies are possible: denoising after demosaicking; denoising before demosaicking; and joint demosaicking-denoising.

II. BACKGROUND OF CFA

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

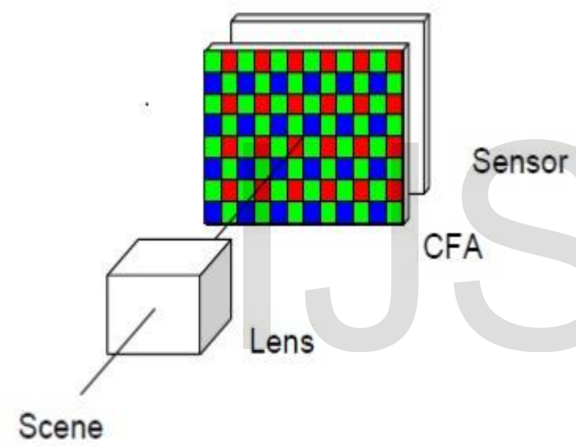

Figure 1- Demonstration of optical path digital camera

As we have discussed in the last section the sensor cell can record only one color value. There are 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 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 eyelid in medium wavelengths, corresponding to the G portion of the spectrum.

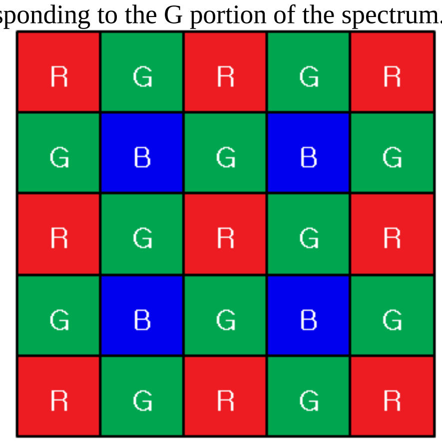

Figure 1.2 Bayer Pattern

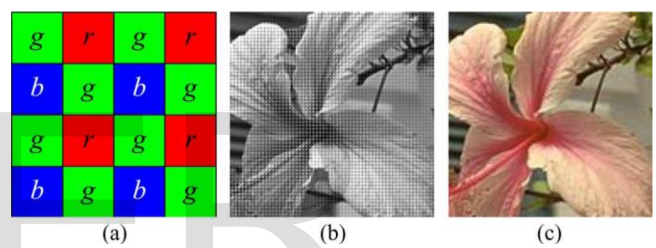

Figure 1.3 Single-sensor imaging concept: (a) Bayer CFA pattern; (b) a CFA image; (c) demosaicked full-color version of (b).

III.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

III.1 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 compound noise that is difficult to characterize.

III.2 Joint demosaicking-denoising

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 demosaicking denoising 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 red green 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.

III.3 Denoising before demosaicking (Proposed Method)

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.

IV. Proposed Algorithm

The proposed CFA denoising algorithm is summarized as follows.

1. Estimate the noise standard deviations $\boldsymbol{\sigma_r}$,$\boldsymbol{\sigma_g}$ **and** $\boldsymbol{\sigma_b}$ of the red, green and blue channels.
2. Decompose the noisy CFA image $\mathbf{I}$ into $\mathbf{I_l}$ and $\mathbf{I_h}$.Apply the following denoising steps 3 and 4 to $\mathbf{I_h}$.
3.Set the sizes of variable block and training block. The noise co-variance matrix $\mathbf{C_m}$ can then be determined.
4. For each training block:

Perform the training sample selection procedure.

(a) Denote by $\mathbf{X}$ the selected training dataset.
(b) Calculate the co-variance matrix $\mathbf{C_m}$;
(c) Estimate the co-variance matrix of signal as
$\mathbf{C_s = C_m - C_v}$.
(d)Factorize $\mathbf{C_m = F_x * A_x * F_t}$ and set the transformation matrix $\mathbf{P_x = F_t}$.;
(e)Transform the dataset to domain: $\mathbf{Y = P_x * X}$.;
(f)By resetting the last several rows of $\mathbf{Y}$ to zeros, reduce $\mathbf{Y}$ to (dimension reduction);
(g)Shrink each row of $\mathbf{Y_d}$ as $\mathbf{Y_{di} = C_i * Y_{di}}$.
(h)Transform back $\mathbf{Y_d}$ to time domain as $\mathbf{X = P_x * Y_d}$.;
(i)Reformat $\mathbf{X}$ to get the denoised CFA block.
End

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

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

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

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

The high pass image is then obtained as

$$I_{vh} = Iv – I_{vl} \quad ....(2)$$

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).

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

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.

V. Conclusion and Discussion

In this paper, the authors provide efficient new method of removing the noises in the CFA data by providing the denoising operation before the demosaicking. The different methods for improving the color balancing and color correction of CFA data has been also discussed by the authors. The complete information of noise produced in the Bayer filter has been explained. The new proposed method of denoising 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.
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.

VI.REFERENCES

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