ISSN 2047-3338

Adaptive Denoising of CFA Images for Image Demosaicking

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***Abstract*– In single sensor digital color cameras at each pixel it captures only one of the three primary colors so the full color image is obtained by interpolating all other missing color samples at that pixel this process is the color demosaicking process. When we capture the images using digital cameras there is some sensor noise is introduced in image. This type of noise is introduced in all type of digital cameras that is low cost to high cost. So in reconstructing the images there are different strategies used to obtain the good quality images. Basically there are three different strategies, first strategy is demosaicking the image and after that denoise the image but in that process the artifacts occurs in initial color demosaicking method is hard to remove in subsequent denoising process. Second strategy is joint denoising demosaicking and third strategy is denoising before demosaicking so here last strategy is used. In this paper here first denoise the CFA image to remove sensor noise for that here use PCA based adaptive denoising method and after that demosaicking the image with nonlocal adaptive thresholding method. So here main advantage of this implementation is that by the use of Principal component analysis (PCA) based denoising this algorithm remove the sensor noise and by using the Nonlocal adaptive thresholding for demosaicking it reconstruct good quality images which having sharp color transition in it.**

***Index Terms*– Adaptive, Denoising, Demosaicking and Nonlocal**

I. INTRODUCTION

WHEN we capture images with single sensor digital cameras the reconstructed image quality depends upon two factors that is denoising of image and color demosaicking of the image. For images captured with digital cameras some sensor noise is introduced in the image. When we demosaick that image because of the sensor noise there are some initial color demosaicking artifacts present and these artifacts are hard to remove in subsequent Denoising process. There are many advanced denoising algorithms [5]–[15], which are designed for monochromatic (or full color) images, are not directly applicable to CFA images due to the underlying mosaic structure of CFAs. Most CDM algorithms assume noise free CFA data but this assumption is not valid in practice. Thus the restoration of color images from noisy CFA data is a challenging problem. Basically there are three strategies to denoise the CFA image. Convenient strategy to remove noise is to denoise the demosaicked images. There are many algorithms based on this strategy [10]-[21]. But problem of this method is that the artifacts present initial color demosaicking cannot be removed in subsequent denoising process. Recently, some schemes that perform demosaicking and denoising jointly have been proposed. 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 third way to reconstruct the image is denoising CFA image first and then demosaicking takes place. But due to the mosaic structure of CFAs, many existing effective monochromatic image denoising methods cannot be applied to the CFA data directly. To overcome this CFA image can be subdivided into many sub images using the approach known as CFA image compression [5]. The desired CFA image can be obtained by considering all sub images.

This paper is based on an efficient scheme for image demosaicking which uses the adaptive denoising for removal of sensor noise. For adaptive denoising principal component analysis (PCA) approach is used. After denoising the input CFA image then demosaicking takes place. For demosaicking here nonlocal adaptive thresholding method [2] is used. So the main advantage of this approach is that it effectively removes the sensor noise in CFA image also by using nonlocal adaptive thresholding method for demosaicking effectively reconstruct the natural images in which there is weak spectral correlation around the object boundaries.

The rest of paper is structured as follows. Section II gives brief explanation about the algorithm. Section III describes the PCA based denoising method. Section IV explains nonlocal adaptive thresholding method. In section V experimental results are provided to show the efficiency of algorithm.

II. ADAPTIVE DENOISING ALGORITHAM

For input CFA image to remove the sensor noise in the image here first denoise the CFA image. For that this algorithm uses principle component analysis approach.

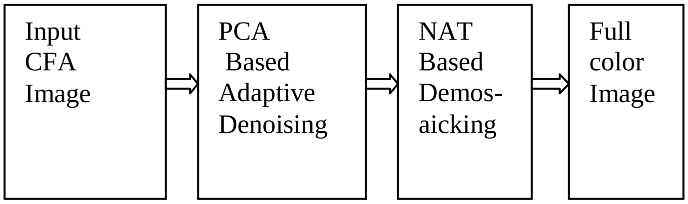

Figure 1: Adaptive Denoising of CFA Images for Image Demosaicking

Adaptive PCA denoising scheme works directly on the CFA image and it can effectively exploit the spatial and spectral correlation simultaneously [1]. PCA [6] [7] 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.

Another important property of PCA is that it is optimal by using a subset of its principal components to represent the original signal. By using the principal component analysis it can analyze the local structure of each CFA block variable block which contains color component from different channel [1]. This algorithm adaptively computing the co-variance matrix of each variable block, it could transform noisy signal into another space where the signal energy can be better clustered and noise can be efficiently removed from the image. In PCA denoising method it uses the training sample selection procedure as there are different and varying structure in each local training window, so to increase estimation accuracy of PCA transformation matrix select the similar blocks to underlying one and use only this block instead of considering all blocks for PCA training. Such process can better preserve the image local structure. After this the noise free image obtained, so to reconstruct the full color image here use nonlocal adaptive thresholding method [2]. This is demosaicking algorithm spatially developed for images where there is weak correlation around the object boundaries [3]. In that algorithm for denoised input CFA image first initial interpolation of green channel takes place with the help of local directional interpolation method (LDI) [3]. As there is weak correlation around the object boundaries some initial CDM artifacts are present in LDI method.

To remove these artifacts this algorithm enhance the G channel by applying nonlocal adaptive thresholding algorithm for that consider the patch matching technique. So here initial CDM output is modeled as true signal to be stored with addition of the noise artifacts. After that use the regularization solution and optimize the true signal by decreasing the noise artifacts. For that consider a local patch and compare this patch with nonlocal patch similar to it. In that method apply some threshold for nonlocal patch and if this patch attains the threshold value then this patch is consider for enhancing the G channel. Once the good estimation of G channel is obtained then good estimation of R and B channel is possible. By using the reconstructed G channel and Input denoised CFA image, then obtain the initial interpolation of R/B channel using LDI method. Here again enhancement of R/B channel takes place with nonlocal adaptive thresholding method to remove initial CDM artifacts. After that by using reconstructed G channel and R/B channel full color image is obtained which is noise

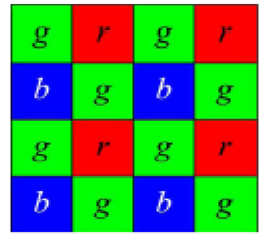

Figure 2: Bayer CFA

free. This algorithm is mainly efficient for natural images in which there is weak correlation around the object boundaries.

III. DENOISING USING SPACIALY ADAPTIVE PCA

Here Bayer pattern is used and this algorithm extended to other CFAs. Most CDM algorithm assume that there noise free data but practically there is some noise is added when the images is captured with digital cameras. As result of this noise, digital photographs become visually unpleasant. Foi *et al.* [9] pointed out that the noise variance depends on the signal magnitude, while Poisson, film-grain, multiplicative and speckle models can be used to model the noise. Previously there are different noise models developed, Hirakawa [4] modeled the raw sensor output as $y= x + (k_0+k_1x)v$ where x is the desired noise signal.

V is white Gaussian noise k_1 and k_0 are noise parameters. Also there is signal independent additive noise model defined as $y= x+v$. This algorithm use the Zhang *et al.* [1] a channel-dependent additive noise model, which is a tradeoff between the signal-dependent noise model and the signal-independent additive noise model, here consider different type of color filters [1]:

$$\bar{r} = r + Vr\,,\quad \bar{g} = g + Vg\,,\quad \bar{b} = b + Vb$$

Where Vr,Vg and Vb are the noise signals in the red, green and blue locations of the CFA image. In channel dependant noise model it allows the noise statistics vary in different channels as given type of sensor behaves differently in different wavelengths. Also in channel-dependent noise model the sensor noise is independent of signal within each channel to simplify the Denoising algorithm [1]. In this paper it use a strategy which is used by Lei Zhang [1] for PCA-Based Spatially adaptive denoising algorithm. Here Denoising and demosaicking algorithms can be independently designed. By using PCA based Denoising which works directly on CFA images here fully exploit the correlation among the three color channels. In this paper it considers the special structure of CFA pattern and uses this algorithm to mosaic CFA images. Here w the algorithm is improved and extends the PCA-based Denoising. In figure2 consider the variable block which consist at least one red, one blue, and one green sample [1]. Practically it can extend the size of variable block. Here it take the variable block having one red, one blue, and two green samples. Then obtain the column vector as:

$$x = [g_1 \quad r_2 \quad b_3 \quad g_4]^T \quad \ldots.. (1)$$

The variable block is associated with training block which contains the enough number of samples for the training. Variable block is matched with training block and when the match is occurred the corresponding pixels are considered for variable vector.

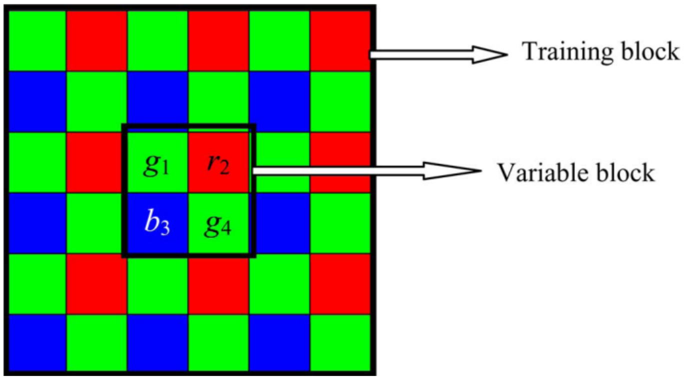

Figure 3. Variable block and training block in the spatially adaptive PCA-based CFA image denoising. Image taken from [1]

For each element of X, there are nine samples are associated with it. For example variable r_2 is associated with red samples at position (1,2), (1,4), (1,6), (3,2), (3,4), (3,6), (5,2), (5,4), and (5,6). In similar way the samples for other variable can be calculated. R_2 be the row vector which contains all the samples associated with r_2.similaraly G_1, B_3, and G4 denotes the row vector for g_1, b3 and g_4 respectively. So the complete dataset for x can be calculated as:

$$X= \begin{bmatrix} G_1^T & R_2^T & B_3^T & G_4^T \end{bmatrix}^T \quad \ldots (2)$$

The mean values of variables g_1, r_2, b_3 and g4 are denoted by $\mu_{g1}, \mu_{r2}, \mu_{b3}$ and μ_{g4} respectively. The mean vector for X is denoted as

$$\mu = \begin{bmatrix} \mu_{g1} & \mu_{r2} & \mu_{b3} & \mu_{g4} \end{bmatrix}^T \quad \ldots (3)$$

X is centralized as $\bar{X} = X - \mu$ and

$$\bar{X} = \begin{bmatrix} G_1^T - \mu_{g1} & R_2^T - \mu_{r2} & B_3^T - \mu_{b3} & G_4^T - \mu_{g4} \end{bmatrix} \quad \ldots (4)$$

By using additive noise model the variable of noisy observation is expressed as

$$\bar{X} = X + V \quad \ldots (5)$$

Where $V = \begin{bmatrix} v_{g1} & v_{r2} & v_{b3} & v_{g4} \end{bmatrix}^T$ is the noise variable vector. Now obtain the centralized dataset as

$$\bar{\bar{X}} = \bar{X} + V \quad \ldots (6)$$

Now the main aim is to estimate $\bar{X}$ from the noisy measurement $\bar{\bar{X}}$ [1]. The middle part of the training block can be extracted as the denoising block because boundary samples do not usually contribute to the denoising performance as much as the samples from the middle part. The whole algorithm is implemented as follows:

First estimate the noisy standard deviation σ_g, σ_r and σ_b of the red, green and blue channel the decompose the noisy image CFA image I_v into I_v^l and I_v^h. After that set the sizes of variable block and training block. Then the noise co-variance matrix Ω_v can be determined. For each training block perform the training sample selection procedure. Denote by $\Omega_{\bar{x}}$ the selected training dataset. Calculate the co-variance matrix $\dddot{X}$. Then Estimate the co-variance matrix of signal as $\Omega_{\bar{x}} = \Omega_{\bar{\bar{x}}} - \Omega_v$ .Factorize $\Omega_{\bar{x}} = \Phi_{\bar{x}} \Lambda_{\bar{x}} \Phi_{\bar{x}}^T$ and set the PCA transformation matrix $p_{\bar{x}} = \Phi_{\bar{x}}^T$. Then transform the dataset to PCA domain $\bar{\tilde{Y}} = P_{\bar{x}} . \bar{\tilde{X}}$ By resetting the last several rows of $\bar{\tilde{Y}}$ to zeros, reduce $\bar{\dddot{Y}}$ to $\bar{\dddot{Y}}^d$. After that shrink each row of $\bar{\tilde{Y}}^d$ as $\hat{\bar{Y}}_i^d = c_i * \bar{\tilde{Y}}_i^d$. Then transform $\hat{\bar{Y}}^d$ to time domain as $\hat{\bar{X}} = P_{\bar{x}}^{-1} * \hat{\bar{Y}}^d$. Then reformat the $\hat{\bar{X}}$ to get the denoised CFA block. Denote by $\hat{I}_v^h$ the denoised output of I_v^h final denoised image is. $\hat{I} = I_v^l + \hat{I}_v^h$ Up to that part we get the denoised CFA image. After that apply the Lei Zhang [3] nonlocal adaptive thresholding method for demosaicking the denoised CFA image.

IV. NONLOCAL ADAPTIVE THRESHOLDING METHOD FOR DEMOSAICKING

For the input CFA image first initial demosaicking of green channel takes place by using Local Directional Interpolation. After that to remove CDM errors in Initial interpolation here Non–local adaptive thresholding is used. In that, PCA method is used. Then with the help of reconstructed G channel & input CFA image, the initial CDM of R/B channels are obtained. After that NAT of R/B channel is done to remove the initial CDM errors. At the end using reconstructed G and R/B full color image is obtained.

A. Local Directional Interpolation Of Green Channel

Usually, a better reconstruction of G will lead to a better reconstruction of R and B [3]. Initially interpolate the G channel by using local redundancy, and then enhance it by using nonlocal redundancy.

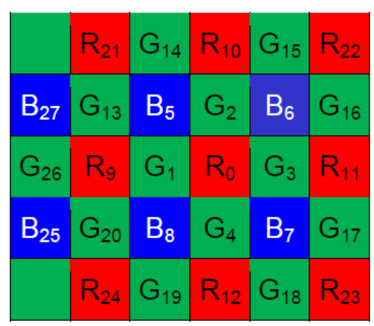

Figure 4: CFA Block

In SOLC, at each R or B position two filtering outputs of G are computed along horizontal and vertical directions respectively, and then one of them is selected based on the gradients in the two directions. However, SOLC has two problems. First, it considers only two directions in the interpolation. This limits its capability in preserving edge structures along other directions. Second, SOLC simply selects one of the two directions for interpolation, but this will lose much useful information in the local area, resulting in many interpolation errors. In this section, it proposes to fuse the directional information for more robust color interpolation. Since there can be sharp color transitions in highly saturated regions, it use a compact local window for the initial interpolation.

Refer to Fig. 2, considering a CFA block and let's focus on the red pixel R0, where the green color is to be estimated. If we could know the color difference between G and R at position Ro denoted by $d_{gr} = G_0 - R_0$, the missing green sample can then be recovered as $G_0=R_0+d_{gr}$ Therefore, how to estimate the color difference d_{gr} is a key in the interpolation of G. $d^n_{gr}, d^s_{gr}, d^e_{gr}, d^w_{gr}$ for that compute the color difference along four directions: north (n), south (s), west (w) and east (e). Refer to Fig. 2, the four directional estimates are calculated as follows:

$$d^n_{gr} = G_2 - (R_0 + R_{10})/2 \qquad \ldots (7)$$

In similar way calculate the color difference signal along other directions. The interpolation error of the four directional estimates relates to the edge direction and color transition at R_o. In order to evaluate which estimate is better, calculate the gradients at R_o along the four directions. There are many forms to define the directional gradients at R_o. For that following considerations is used. First, the gradient should be calculated using the pixels from the same channel; second, to make the calculation of gradients more stable, involve neighboring columns/rows of the central column/row in calculation; third, the central column/row should have higher contribution to the gradient than the neighboring columns/rows. Based on the above three considerations, use the following formula to calculate the gradients along north, south, west and east directions:

$$\nabla_n = |G_2 - G_4| + |R_0 - R_{10}| + \frac{1}{2}|G_1 - G_{14}| + \frac{1}{2}|G_3 - G_{15}| + \varepsilon \qquad \ldots (8)$$

Similarly the gradients along other direction are calculated. Where ε is a small positive number to avoid the gradient being zero. In general, a bigger gradient along a direction means more variations in that direction and hence it is more difficult to accurately estimate the color difference, vice versa. Therefore, use the gradients as indices to weight the four estimates into a final estimate. An optimal weighting scheme needs to know the joint distribution of the gradient and the color difference. However, such information is unknown in advance or hard to estimate online. This paper simply let the weight assigned to a directional estimate be inversely proportional to the gradient along that direction:

$$w_n = \frac{1}{\nabla_n}, w_s = \frac{1}{\nabla_s}, w_w = \frac{1}{\nabla_w}, w_e = \frac{1}{\nabla_e} \qquad \ldots (9)$$

Then normalize the four weights to make the sum of them be 1. There is

$$\overline{w_n} = \frac{w_n}{c}, \overline{w_s} = \frac{w_s}{c}, \overline{w_w} = \frac{w_w}{c}, \overline{w_e} = \frac{w_e}{c} \qquad \ldots (10)$$

Where $c = w_n + w_s + w_w + w_e$

The four directional estimates are then fused into one estimation.

$$\hat{d}_{gr} = \overline{w_n} d^n_{gr} + \overline{w_n} d^s_{gr} + \overline{w_w} d^w_{gr} + \overline{w_e} d^e_{gr} \ldots (11)$$

Finally, the missing green component at Ro can be estimated as:

$$\hat{G}_0 = R_0 + \hat{d}_{gr} \qquad \ldots (12)$$

By applying the above procedures to all the R and B positions, then reconstruct the G channel.

B. Nonlocal Enhancement of G Channel

Since only the local redundancy in a compact local window is exploited, the interpolation may not be accurate, especially around object boundaries where sharp color or intensity changes will occur. In natural images there are many similar patterns or structures, while a similar structure to the given one may appear far from it. Such nonlocal redundancy can be exploited to enhance the CDM results. In this section, use the nonlocal redundancy to reduce the initial interpolation errors and enhance the color reproduction quality of G channel.

Nonlocal enhancement by NAT.

Initial CDM output can be modeled as:

$$y = x + \upsilon \qquad \ldots (13)$$

Where

x= true signal to be stored;

υ = additive noise,

y= is the initial CDM result

To estimate the original signal x from the degraded observation y, a regularized solution is used [1]

$$\hat{x} = \arg\min J(x) \text{ is } \|y - x\|_2^2 \le \tau \qquad \ldots (14)$$

Therefore, apply a soft threshold t [1] to Γ to remove Γ*V* from Γ [1] so that the desired Λ can be obtained as follows [1] where Λ is a sparse matrix.

$$\Lambda(i,j) = \begin{cases} sign(\Gamma(i,j)).(|\Gamma(i,j) - t|) & if \Gamma(i,j) > t \\ 0 & if \Gamma(i,j) \le t \end{cases} \qquad \ldots (15)$$

C. Initial Interpolation of R and B Channels

With the non-locally enhanced G channel, first compute the initial estimates of R and B channels by exploiting the local spatial-spectral correlation, and then enhance them by nonlocal redundancy. Since the interpolations of R and B channels are symmetric, in the following only discuss the reconstruction of B. Interpolate the missing B samples by using a two-step strategy. First interpolate the B samples at the R positions, and then with these interpolated B samples, all the other B samples at the G positions can be interpolated. Refer to Fig. 3, suppose interpolate the missing sample Bo at Ro. Note that all the G samples have been recovered and are available now, then estimate the color differences between B and G along the four diagonal directions at Ro as:

$$d^{nw}_{bg} = B_5 - G_5 \qquad \ldots (16)$$

Similarly difference signal along other direction is calculated.

The four directional estimates are weighted for a more robust estimate. To determine the weights, the gradients along the four directions are calculated as follows

$$\nabla_{nw} = |B_5 - B_7| + |R_{21} - R_0| + |G_5 - G_0| + \varepsilon \quad \ldots (17)$$

Similarly other three gradients are calculated.

Weight vector set as

$$\overline{w}_{nw} = \frac{1}{C\nabla_{nw}} \quad \text{Where } C = \frac{1}{\nabla_{nw}} + \frac{1}{\nabla_{ne}} + \frac{1}{\nabla_{se}} + \frac{1}{\nabla_{sw}} \quad \ldots (18)$$

Final blue and green color difference at position R_0 is estimated by [1]

$$\hat{d}_{bg} = \overline{w}_{nw} d_{bg}^{nw} + \overline{w}_{ne} d_{bg}^{ne} + \overline{w}_{se} d_{bg}^{se} + \overline{w}_{sw} d_{bg}^{sw} \quad \ldots (19)$$

The missing blue component at Ro is estimated as

$$\hat{B}_0 = G_0 + \hat{d}_{bg} \quad \ldots (20)$$

Once the B samples at the R positions are interpolated as described above, consequently interpolate the B samples at all the other G positions. Take the position G1 in Fig. 4 as an example. Note that the blue samples at R9 and Ro have been interpolated, and denote them as $\hat{B}_9$ and $\hat{B}_0$

D. Nonlocal Enhancement of R and B Channels

Once the R and B channels are interpolated with the help of nonlocal enhanced G channel, they can then be enhanced by exploiting nonlocal redundancies in R and B channels respectively. The process is the same as that for the G channel. For each interpolated red (blue) sample $\hat{R}_0(\hat{B}_0)$ search for similar pixels to $\hat{R}_0(\hat{B}_0)$ it in a large window centered on it. The *N* most similar pixels to it, including itself are used to enhance it via NLM or NAT.

VII. RESULTS

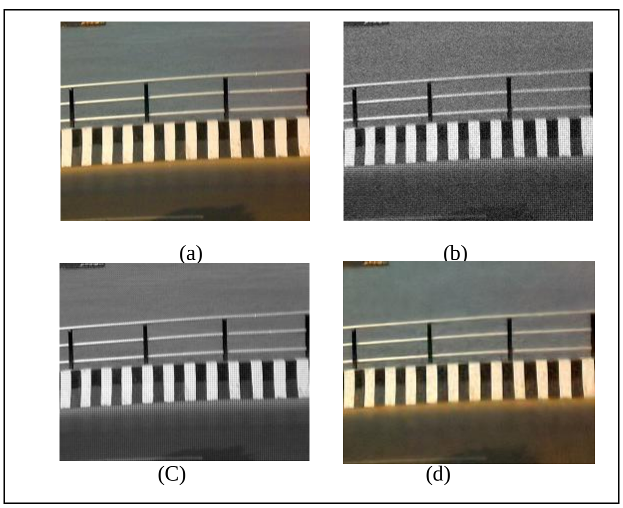

Figure 5. Image 1 (a) Original image (b) Noisy image (c) Denoised Image (d) CDM image

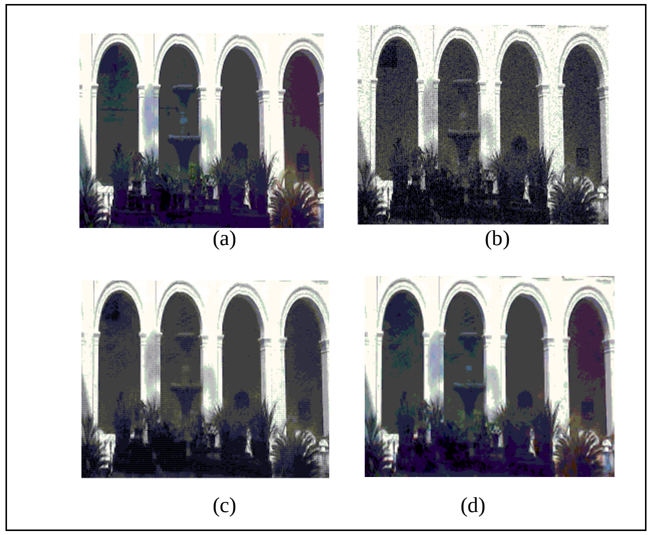

Figure 6. Image 2 (a) Original image (b) Noisy image (c) Denoised Image (d) CDM image

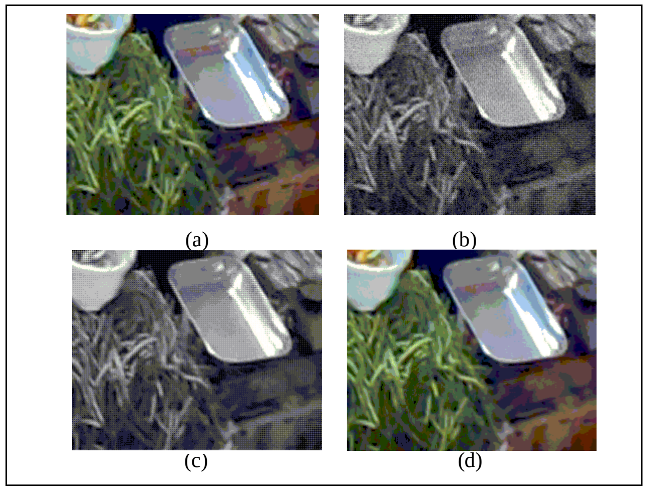

Figure 7. Image 3 (a) Original image (b) Noisy image (c) Denoised Image (d) CDM image

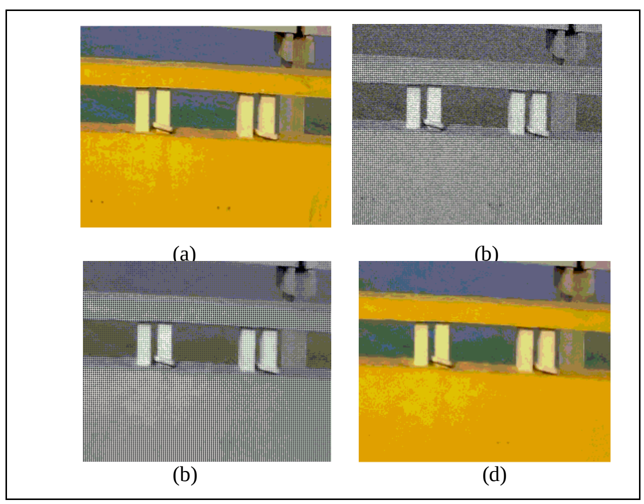

Figure 8. Image 4 (a) Original image (b) Noisy image (c) Denoised Image (d) CDM image

TABLE I
PSNR (DB) RESULTS OF THE CFA IMAGES

Image	PSNR of noisy CFA image	PSNR of Denoised and CDM Image		
		R	G	B
Image1	26.6954	31.1390	32.1954	31.3034
Image2	26.6932	30.0140	30.7502	30.3802
Image3	26.6932	31.8257	31.0195	32.0410
Image4	26.6954	32.6107	33.8290	33.1220

VIII. CONCLUSION

This algorithm is combination of two methods that is, first it denoise the CFA image with adaptive denoising method and after that it demosaick the image with nonlocal adaptive thresholding method. So the advantage of this algorithm is that, as denoising is done before demosaicking the color artifacts are not generated in that method. Also this algorithm effectively removes the sensor noise in the image and it is efficient algorithm for images having sharp color transition around the object edges.

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