CHAPTER 5
DEVELOPMENT OF FULL COLOR IMAGES FROM GAP CAMERA MOSAIC IMAGES BY HYBRID APPROACH

5.1 INTRODUCTION

Digital cameras are extremely popular and have replaced traditional film-based cameras in most applications. To produce a color image in a digital camera, there should be at least three color components at each pixel location. This can be achieved by sensors, each of which receives a specific primary color. Due to this, the cost and space is more in cameras. As a result, most digital cameras use single sensor camera. To render a full-color image, an image reconstruction process, known as demosaicing, is required to estimate the other two missing color values for each pixel. In this research work, an approach is developed to demosaic generalized assorted pixel camera images. Even though several demosaicing approaches for Bayer pattern have come up in recent years there are still challenges in demosaicing for GAP camera images.

5.2 DEMOSAICING GAP APPROACH

An immense number of methods have been proposed for demosaicing to reconstruct images. Fumihito (2010) presented a comprehensive optimization method to provide the spatial and spectral layout of the color filter array of a GAP camera. And also developed an algorithm for reconstructing the under-sampled channels of the image while minimizing aliasing artifacts, demonstrating how the user can capture a single image and then control the tradeoff of spatial resolution to generate a variety of images, including monochrome, high dynamic range (HDR) monochrome, RGB, HDR RGB and
the performance of the GAP camera has been verified through extensive simulations that use multispectral images of real world scenes.

In DEMGAP (Boyed, 2018), at each pixel of the GAP Mosaic there is only one primary color measurement which means the other primary colors must be estimated from neighboring pixels in order to produce interpolated output image. The bilinear approach is useful to understand since many advanced algorithms still adopt bilinear interpolation as an initial step; additionally, these algorithms usually use the results of bilinear interpolation for performance comparison. The bilinear interpolation method fills the missing color values with weighted averages of their neighboring pixel values. The existing technique uses the bilinear interpolation for estimating the missing primary colors. Initially the high exposure image is estimated, refined, and then interpolating the CMY image with strong inter channel correlation, then complimenting the CMY image for the Low exposure image and developing the monochrome image for the high exposure image and the low exposure image. The HDR images for high exposure and low exposure images were generated by the merging technique.

In CFCGAP, a novel GAP demosaicing approach was proposed which deals with demosaicing by directional filtering and a posteriori decision to construct the high exposure image and demosaicing by directional filtering and a posteriori decision with up-sampling technique to construct the low exposure image.

The New Joint demosaicing and zooming algorithm for color filter array (Kuo, 2009) proposed for the Bayer pattern by (a) recovering the G channel to obtain the complete G channel by using the edge-sensing demosaicing algorithm (b) zooming the recovered complete G channel to obtain the zoomed G channel and (c) recovering and
zooming R and B channels by using the color difference value to obtain the zoomed R channel and finally (d) after refinement the zoomed full color image can be obtained. Based on the extracted more accurate edge information and the color difference concept, the developed joint demosaicing and zooming algorithm for mosaic images was used. Further, a new refinement method, which combines the concept of the local color ratios and the proposed proper weighting scheme.

5.3 DEMOSAICING GAP USING DIRECTIONAL AND ZOOMING TECHNIQUE

The proposed approach deals both Demosaicing Directional filtering with posteriori decision technique to construct the high exposure image and the Joint Color Demosaicing and Zooming approach to construct the low exposure image. Daniele (2006) presented the Demosaicing Directional filtering with posteriori decision technique. Kuo-Liang (2009) presented the New Joint Demosaicing and Zooming Algorithm for Color Filter Array.

From the GAP mosaic image R,G,B values were extracted as high exposure image and r, g, g, b as low exposure image. The GAP pattern was used for this proposed approach which is shown in fig.5.1.

![Fig.5.1. CFCGAP Color mosaic pattern](image)

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Fig. 5.2. Block diagram of DFCGAP approach

Extract High Exposure Mosaic Image → Estimate the missing G components in the mosaic image → Demosaicking with Directional filtering and a posteriori decision → Reconstructed High Exposure Image

Extract Low Exposure Mosaic Image → Joint Color Demosaicking and Zooming Technology → Reconstructed Low Exposure Image

GAP Mosaic Image

Low Exposure Image → High Exposure → CMY Image → HDR RGB Image → Low Exposure Monochrome Image → High Exposure Monochrome Image → HDR Monochrome Image

Fig. 5.3. High Exposure Mosaic Image

Fig. 5.4. Low Exposure Mosaic Image
5.3.1 Reconstruction of high exposure image

Directional filtering and a posteriori decision demosaicing technique was adopted to reconstruct the high exposure image after estimating the green components in the empty locations.

5.3.1.1 Estimation of Green component in the empty locations

Initially 25% of the pixel components in the empty locations are estimated. The green component is estimated in the empty location. The green component is estimated by using neighboring green component values. The equation (5.1) is applied to calculate the missing green components at the empty location. \(x\) and \(y\) denotes the row and column.

\[
\hat{G}(x, y) = \frac{1}{4}(G(x - 1, y - 1) + G(x - 1, y + 1) + G(x + 1, y - 1) + G(x + 1, y + 1))
\] (5.1)

Now the high exposure mosaic image is complete and is similar to Bayer mosaic image. So the directional demosaicing technique can be adapted to this complete high exposure mosaic image.

5.3.1.2 Directional Demosaicing

The steps involved in this approach are:

5.3.1.2.1 Directional green interpolation

To reconstruct the green image along horizontal and vertical directions, five coefficient FIR filters are applied to interpolate the Bayer samples. Along a row and the column of the Bayer pattern, the green values are sub sampled by a factor of 2. In the row or column of the Bayer sampled image is represented as follows
.... \( R_{-2}G_{-1}R_0G_1R_2 \) ....

where \( R_k \) is \( R(x,y+k) \) if row sample is considered and 
\( R(x+k,y) \) if column

Likewise other components are also considered.

The generalized missing green sample \( G_0 \) is estimated as

\[
\hat{G}_0 = R_0 + \frac{1}{2} \left( G_1 - \frac{R_0 + R_2}{2} + G_{-1} - \frac{R_0 + R_{-2}}{2} \right) \tag{5.2}
\]

Two green images \( G_V \) and \( G_H \) are produced using the equation (5.2) by taking row samples and column samples respectively.

5.3.1.2.2 Decision

A decision has to be made to select the filtering vertical or horizontal direction that gives the best performance.

The chrominance values \( R-G^H \) (or) \( R-G^V \) in a red pixel and \( B-G^H \) (or) \( B-G^V \) in a blue pixel is calculated using the equations.

\[
C_H(x, y) = R_{x,y} - G^H_{x,y} \quad \text{if} \ (x, y) \text{ is a red location}
\]

\[
C_H(x, y) = B_{x,y} - G^H_{x,y} \quad \text{if} \ (x, y) \text{ is a blue location}
\]

\[
C_V(x, y) = R_{x,y} - G^V_{x,y} \quad \text{if} \ (x, y) \text{ is a red location}
\]

\[
C_V(x, y) = B_{x,y} - G^V_{x,y} \quad \text{if} \ (x, y) \text{ is a blue location}
\]

The vertical gradient \( D_V \) for chrominance \( C_V \) and the horizontal gradient \( D_H \) for chrominance \( C_H \) are computed as follows.

\[
D_H(x, y) = \left| C_H(x, y) - C_H(x, y + 2) \right|
\]

\[
D_V(x, y) = \left| C_V(x, y) - C_V(x + 2, y) \right|
\]
The classifiers $\delta_V(x,y)$ and $\delta_H(x,y)$ is computed as the sum of gradients $D_V$ and $D_H$ for the 5x5 window.

For all the red and blue pixels, the green values are estimated as follows.

if $\delta_V(x,y) < \delta_H(x,y)$

then

$$\hat{G}_{x,y} = G^V_{x,y}$$

else

$$\hat{G}_{x,y} = G^H_{x,y}$$

A full color green image $G$ is estimated by considering the known green samples.

5.3.1.2.3 Red and blue interpolation

After the green channel has been reconstructed, estimate the red and blue color components. In a blue position, the red color component is estimated as follows:

if $\delta_V(x,y) < \delta_H(x,y)$

then

$$\hat{R}_{x,y} = B_{x,y} + \frac{1}{2}(\hat{R}_{x-1,y} - \hat{B}_{x-1,y} + \hat{R}_{x+1,y} - \hat{B}_{x+1,y})$$

else

$$\hat{R}_{x,y} = B_{x,y} + \frac{1}{2}(\hat{R}_{x-1,y} - \hat{B}_{x-1,y} + \hat{R}_{x+1,y} - \hat{B}_{x+1,y})$$

To estimate the blue values in red pixels, the same strategy is applied.

5.3.2 Reconstruction of low exposure image

To reconstruct the low exposure image, the following steps were carried out.
5.3.2.1 Estimation of Green channel

Initially the green channel has to be estimated as per the following steps:

5.3.2.1.1 Estimation of the missing G components horizontally

The missing green color components (horizontally) can be calculated using the following equation. i and j denotes the row and column.

\[
\hat{G}_h(i, j) = \frac{1}{2} (I(i, j + 1) + I(i, j - 1)) + \frac{1}{4} (2I(i, j) - I(i, j + 2) - I(i, j - 2))
\]

5.3.2.1.2 Estimation of the missing G components vertically

The missing green color components (vertically) can be calculated using the following equation.

\[
\hat{G}_v(i, j) = \frac{1}{2} (I(i + 1, j) + I(i - 1, j)) + \frac{1}{4} (2I(i, j) - I(i + 2, j) - I(i - 2, j))
\]

where I is the mosaic image

5.3.2.1.3 Estimation of the missing G components in other positions

The missing green color components in other positions can be calculated using the following equation.

\[
\hat{G}_{\alpha}(i, j) = \frac{1}{2} (\hat{G}_h(i, j) + \hat{G}_v(i, j))
\]

5.3.2.2 Refinement of edge based Green channel

To refine the edge based green component, the horizontal chrominance and the vertical chrominance have to be estimated.

5.3.2.2.1 Horizontal Chrominance

The horizontal chrominance (\(C_h\)) can be calculated using the following equation.
\[ C_v(i, j) = \sum_{m=-2}^{2} |I(i + m, j + n) - m(i + m, j)| \]

\[ n=-2,-1,1,2 \]

where I is the mosaic image

### 5.3.2.2 Vertical Chrominance

The vertical chrominance \( C_v \) can be calculated using the following equation.

\[ C_v(i, j) = \sum_{m=-2}^{2} |I(i + m, j + n) - I(i, j + n)| \]

\[ m=-2,-1,1,2 \]

where I is the mosaic image

### 5.3.2.3 Finding green on edges

Estimation of green on edges can be calculated using the following criteria.

\[ \tilde{G}(i, j) = \hat{G}_v(i, j) \]

\[ \text{if} \ C_v(i, j) < C_h(i, j) \]

\[ \tilde{G}(i, j) = \hat{G}_v(i, j) \]

\[ \text{if} \ C_v(i, j) > C_h(i, j) \]

\[ \tilde{G}(i, j) = \hat{G}_v(i, j) \]

\[ \text{if} \ C_v(i, j) = C_h(i, j) \]

### 5.3.2.3 Zooming Green channel

Zooming the green channel can be implemented using the following steps.
5.3.2.3.1 Estimation of green

In the gray color shaded locations which is shown in the fig.5.5, green color component has to be estimated by using the following equation

\[ \tilde{G}(i, j) = \frac{1}{4}(\tilde{G}(i-1, j-1) + \tilde{G}(i-1, j+1) + \tilde{G}(i+1, j-1) + \tilde{G}(i+1, j+1)) \]

where \( i=2,4,\ldots,m \)

\[ j=2,4,\ldots,n \]

Fig.5.5 Estimation of Green

Fig.5.6 Resulting G color

The output of estimation of green is shown in the fig.5.6.
5.3.2.3.2 Estimation of green in other pixels

In the gray color shaded locations which is shown in the fig.5.7, green color component has to be estimated by using the following equation

\[
\hat{G}(i, j) = \begin{cases} 
\frac{1}{2} (\hat{G}(i, j - 1) + \hat{G}(i, j + 1)) & \text{if } (C_v(i,j)<C_h(i,j)) \\
\frac{1}{2} (\hat{G}(i + 1, j) + \hat{G}(i - 1, j)) & \text{if } (C_v(i,j)<C_h(i,j)) \\
\frac{1}{4} (\hat{G}(i + 1, j) + \hat{G}(i - 1, j) + \hat{G}(i, j + 1) + \hat{G}(i, j - 1)) & \text{if } (C_v(i,j)=C_h(i,j))
\end{cases}
\]

where

\[
i = 1, 3, \ldots, m \\
\hat{G}(i, j) = 1, 3, \ldots, m \\
j = 2, 4, \ldots, n
\]

The resultant green color mosaic image is shown in fig.5.8.
5.3.2.4 Estimating and zooming red and blue channel

For estimation and zooming of red and blue channel, color difference concept is used. In the sample block fig.5.5, it is known that red and the blue values are in the four corners. The color difference values of the four corner pixels can be calculated using

\[ D_r^z (i + m, j + n) = \sum_{\delta_1} \frac{1}{4} (2 + \delta_1 n) \sum_{\delta_2} \frac{1}{4} (2 + \delta_2 m) D_r^z (i + 2\delta_2, j + 2\delta_1) \]

where \( \delta_1, \delta_2 \in [-1, 1] \) -2 \( \leq m, n \leq 2 \)

5.4 RESULTS AND DISCUSSION

In order to evaluate the performance of the DFCGAP proposed method, the standard Mean Square Error (MSE), Peak Signal-to-Noise-Ratio (PSNR) and the Structural Similarity Index (SSIM) were calculated. The test was carried out using MATLAB in the Windows 9 environment. All the compared methods along with the proposed methods share the same sample pictures in the same testing environment. PSNR measures quantitatively the fidelity of the restoration in comparison with the ground truth and the SSIM measures the structural similarity with the ground truth.
5.4.1. **PSNR**

PSNR is defined as

\[
\text{PSNR} = 10 \log_{10} \left( \frac{255^2}{\text{MSE}} \right)
\]

where MSE is the Mean Square Error.

5.4.2  **Mean Square Error**

Mean Square Error is defined as

\[
\text{MSE} = \frac{1}{HW} \sum_{y=1}^{H} \sum_{x=1}^{W} (I_o(x,y) - I_r(x,y))^2
\]

\(I_o\) and \(I_r\) represents the original image and reconstructed images of size \(H \times W\) each.

5.4.3  **Structural similarity Index (SSIM)**

Another improved metrics Structural similarity (Allan, 2008) can distinguish between structural and nonstructural distortions, giving results that agree with perception visibly distorted images (supra threshold distortions). The structural similarity index metrics take values from in the range from 0.0 to 1.0, where zero corresponds to a loss of all structural similarity and one corresponds to having an exact copy of the original image. Note that the image domain SSIM implementation can also take negative values when the local image structure is inverted.

The values of the peak signal to noise ratio and the SSIM for the high exposure image and the low exposure image were calculated. CPSNR is the combined PSNR value and is computed similar to PSNR with the combined MSE values of RGB color channels. The complex wavelet structural similarity (CWSSIM) is computed by the following equation

\[
\text{CWSSIM}(Cx, Cy) = \frac{2\sum_{i=1}^{N} Cx_i Cy_i + k}{\sum_{i=1}^{N} |Cx_i|^2 + \sum_{i=1}^{N} |Cy_i|^2 + k}
\]

where \(Cx\) and \(Cy\) are the complex wavelet coefficients corresponds to image patches \(x\) and \(y\) and \(k\) is a small positive constant set to 0.03. The comparison chart of
PSNR and MSE values between the proposed method and the existing method for HDR and related images is shown in Fig. 5.9a (i) to (v).

The column charts shown in figure (5.10) to (5.13) shows the values of CPSNR and CWSSIM measured using the proposed method. It is observed that the quality of the reconstructed image is much improved than the existing methods. The computational time is quite efficient than the previous methods. For a 24 bit High exposure and low exposure images need each of 3 x m x n bytes. But for a Generalised Assorted pixel camera images needs m x n bytes only. So the size reduces to 1/6 in size.

Fig 5.9  Sample high exposure and low exposure test images
### Table 5.1 MSE, CPSNR & CWSSIM values

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**Fig. 5.9a (i) CMY image**  
**Fig. 5.9a (ii) HDR RGB image**  
**Fig. 5.9a (iii) Low Exposure Monochrome**  
**Fig. 5.9a (iv) High Exposure Monochrome**  
**Fig. 5.9a (v) HDR Monochrome**
Table 5.2 Comparative PSNR analysis of existing methods with the proposed method

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Fig. 5.10  PSNR chart for High Exposure Images

Fig 5.11  CWSSIM for High Exposure Images
Generalized assorted pixel camera arrays offer the following advantages compared to traditional imaging systems: are (a) Flexibility and (b) Adaptability.

5.5 CONCLUSION AND FUTURE WORK

In this work new novel GAP mosaic pattern has been proposed. Also the proposed approach deals to enhance the quality of the images. Based on twenty-six sets
of popular testing high exposure and low exposure mosaic images, experiments have been carried out to demonstrate the quality advantage of the proposed algorithm in terms of CPSNR and CWSSIM when compared with several previous demosaicing algorithms. And also it was noted that the CPSNR values for the low exposure image is less than the high exposure images. In future algorithms can be developed to increase the CPSNR values for the low exposure images.