



**Extension of Demosaicing Algorithms to Multi-Spectral Images**  
**Tutorial Project: Introduction to Image Processing**

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**06/01/2013**

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# Extension of Demosaicing Algorithms to Multispectral Images

## I. Introduction

The camera works as our visual system works. In human visual system the light passes through the cornea and hits the cones which then transformed into electrical information and sent to the brain. Brain then process the information and we get the sensation of color, size, shape etc. The camera also works in the same way, Instead of cornea the light passes through the lens and hits the sensors. Sensors then transform the information into electrical signal and send the information for further processing to the processor. Through examination of our visual system we came to know that our cones are more sensitive to green than the other primary colors red and blue. That's why the camera also has similar sensitivity to different colors. But instead of using different sensors for different colors, we use only one sensor and a Color Filter Array (CFA) so that for each pixel only one color is passed to the sensor. So it is obvious that for each color the information is not presented at each pixel. These images are called mosaiced image, because the pattern looks like a mosaic. The most popular CFA arrangement is the Bayer CFA.

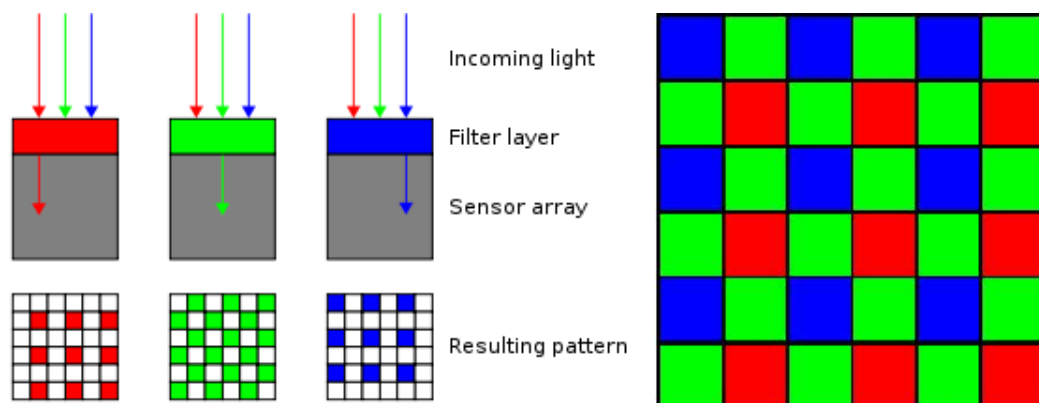


Figure 1: Bayer CFA for RGB colors

Many different demosaicing algorithms exist to get the final image from this mosaiced image. The process of filling up the empty pixels in each plane is called interpolation. The simplest interpolation to fill up the empty pixels is called bilinear interpolation. Many improvement of this bilinear algorithms has been studied and implemented during our Laboratory work namely Edge preserve bilinear interpolation which uses the edge information of green channel to interpolate other channels to improve the

artifacts in the edges, and hue Constance which uses the ratio of luminance's to reduce artifacts.

Now a day's three classic primary colors are not enough for collecting desired information from a particular scene. Researcher and scientists felt the need to introduce more bands and thus the concept of multispectral images was introduced. The use of multispectral images is increasing day by day. The reason for this increased interest is due to the fact that multispectral images can reveal much more information that are not available in a single band or color image. So it is necessary to find a new arrangement of CFA namely Multi-Spectral Color Filter Array (MCFA) that can accommodate more than three color bands and also new extensions of demosaicing algorithms have to be made in order to handle new MCFA arrangements to get final images. In recent years many research works have been conducted on these topics. They will be discussed in the Literature Review section. Then based on the literature reviews Best Filter Arrangements (MCFA) and Best channels will chosen in order to find the state of art in this field in section III. Finally a few implementations of demosaicing algorithms will be mentioned and compared in the later parts.

## II. Literature Review

**2.1.** In 2006 Lindao Miao *et al.* described a very precise and detailed way to work with multi-spectral images [1, 2]. They proposed to use binary tree based algorithm. For example a 5-band multispectral images can be mosaiced into five bands namely Green, Red, Blue, Cyan and Magenta. They will form a binary tree based of their Probability of Appearance (POA). Their spatial arrangement and the binary tree can be shown in the Fig 2. Then to apply the demosaicing they proposed to consider two commonly used spectral correlations, namely Constant Color Difference (ratio) and constant edge location.

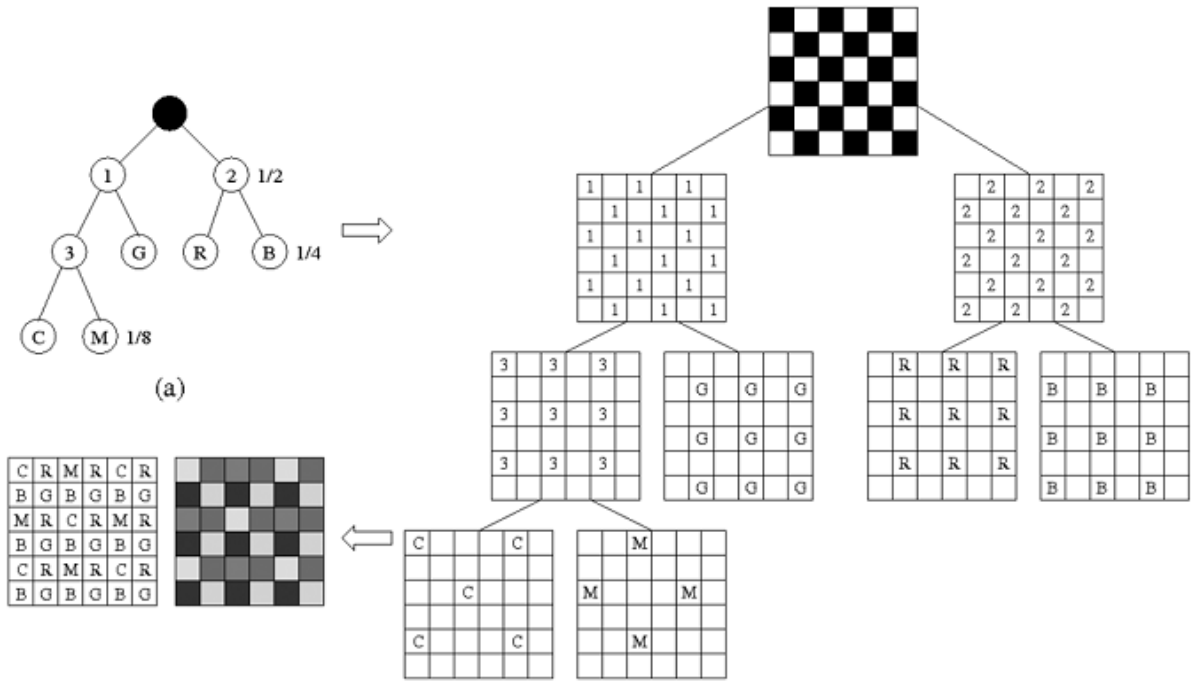


Figure 2: Binary Tree based Spatial Arrangement of color Filters

It is observed that the ratio or the differences between different color channels are very similar. So instead of finding the absolute values in each color channel, the color ratio or difference can be used to derive the chrominance value (what we did in Lab for edge preserve algorithm). And since human visual system is more sensitive to color artifacts than to luminance or saturation errors, these schemes can reconstruct full color images with less visible artifacts and sharp edges. Although very promising in the color domain, these rules might not hold in the multispectral domain.

To compare the ratio and difference correlations in set of multispectral images they proposed a metric “std” to quantify the inter band correlation based on color difference as:

$$std = \frac{\sum_{i=0}^{N_r-1} \sum_{j=0}^{N_c-1} \sqrt{\sum_{s,t \in \mathcal{N}_{i,j}} [d(i+s, j+t) - \bar{d}(i, j)]^2}}{N_r N_c}$$

where  $N_r$  and  $N_c$  denote the number of image rows and columns,  $\mathcal{N}_{i,j}$  is the neighborhood of pixel  $(i, j)$ ,  $d(i, j)$  represents the intensity difference between two spectral planes at the  $(i, j)$  location, and  $\bar{d}(i, j)$  is the mean of the difference image within  $\mathcal{N}_{i,j}$ . The metric based on color ratio can be immediately obtained by substituting the color difference image  $d$  by the color ratio image. The larger the metric “std”, the less the correlation between spectral bands.

Another important inter-band correlation that they considered is that all color bands possess similar edge information; they have showed by adding up all the chromatic images (edges only) of one multispectral image that almost all the edges are in the same location in all images.

Now finally for demosaicing, they propose the binary tree based edge sensing method (BTES). This method uses the same binary tree that generates the MSFA and approach progressively to estimate the missing pixel values. This generic demosaicing algorithm consists of three interrelated components:

- i. Band selection or the determination of the interpolation order of different spectral bands;
- ii. Pixel selection or the determination of the interpolation order of pixel locations within each spectral band;
- iii. Interpolation or applying the interpolation algorithm that uses the edge correlation information.

In order to determine the order of the band to interpolate, the binary tree provides a clear picture; the binary tree is directly related with the POA, It is intuitive that more detailed information is kept in the spectral band with higher POAs and that these bands contribute more in obtaining a reconstructed image that better resembles the real scene. And in tree

higher the node possesses higher POA's. So authors start from the first level of the binary tree. If there is a leaf node at this level, it will be the first selected spectral band for interpolation. This process continues as the tree level goes deeper. If there exists more than one leaf at a certain level, the selection order among these nodes is random.

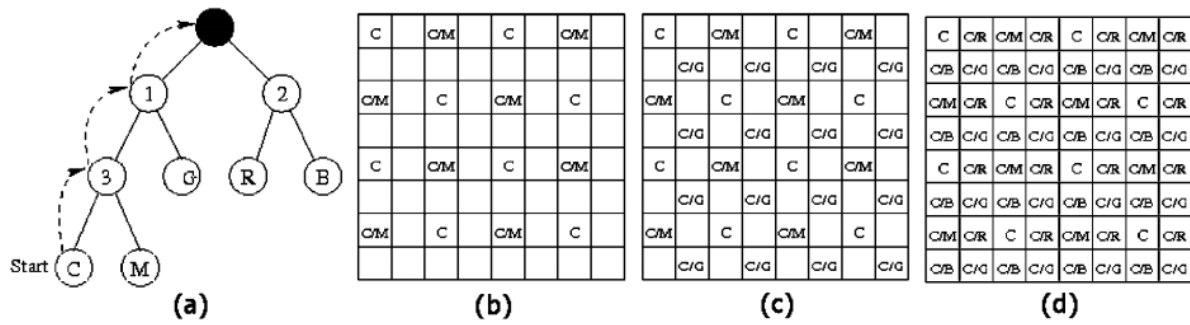


Figure 3: Illustration of pixel selection process of band "C." (a) The directed dash lines indicate the trace of traversal. (b) The "C" values at pixel locations with known "M" are first estimated based on known "C"s. (c) The "C" values at pixel locations with known "G" are second estimated based on both known and estimated "C"s from (b). (d) At node "1," pixel locations at "2" positions are selected, which are combinations of pixel locations at node "R" and "B."

Pixel selection in multispectral domain is more difficult than in RGB domain, because here we have more missing pixels and less known pixels, so only using known MSFA samples will not generate best results. So the authors propose a "progressive" demosaicing method which considers the sparse samples exist in MSFA patterns. They again use the binary tree to do that. Their algorithm first interpolates the missing band information at pixel locations where its sibling pattern locates, and then algorithm goes up one level of the binary tree and finds the sibling of its parent pattern. If its parent's sibling is an internal node, then the leaf patterns of the subtree under this sibling pattern are investigated. This process continues until the root node is visited. It is also observed that it can be seen that, at each step, after interpolating the selected pixel locations, the resulted pattern is the same as the parent pattern. Thus, the pixel selection scheme guarantees that all the intermediate patterns during the demosaicing process are those presented in the binary tree.

And finally the in interpolation part the missing pixels have to be estimated based on the neighboring pixel information. Here in this paper, first, they identify a basic pattern and then developed the demosaicking algorithm based on this patterns.

So first, a transformation has to be found that transforms all patterns present in the binary tree to the basic pattern. The operation of transforming a certain pattern to the basic pattern is called the forward transform and the reverse process the inverse transform. For a pattern in the binary tree, if we apply forward transform first, followed by interpolating the missing pixel values and the inverse transform, the resulting pattern is exactly the same as its parent. These three step processes (i.e., forward transform, interpolation, and inverse transform) together called the one-step interpolation. The reconstruction of a certain spectral band at level “X” of the binary tree consists of “X” number of one-step interpolations. Therefore, now only one more algorithm is needed to interpolate the basic pattern.

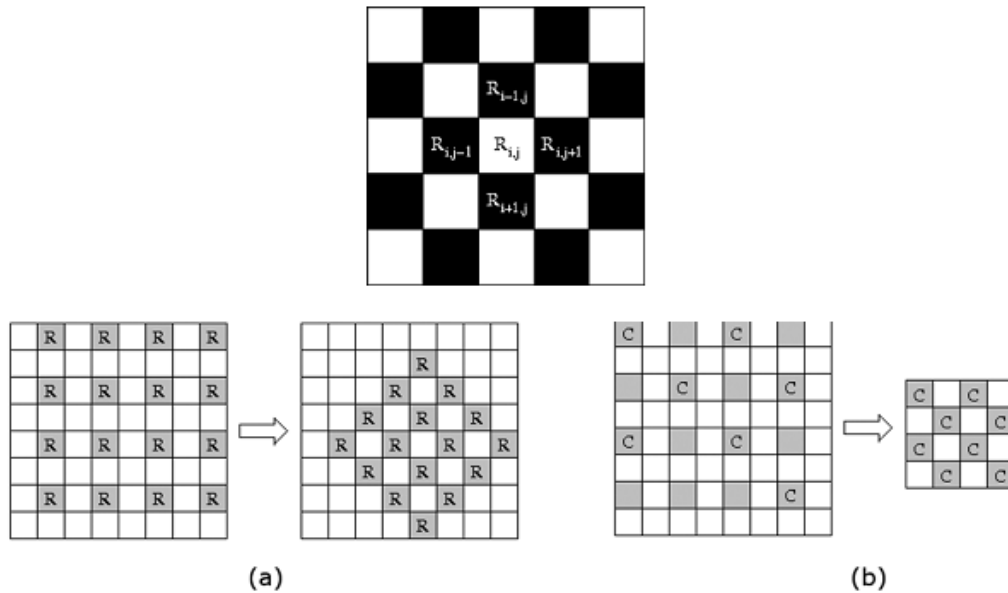


Figure 4: Basic Pattern and Transformation of other patterns to basic pattern

All patterns in the binary tree can be transformed into this basic pattern through two operations, namely, resampling and resampling combined with rotation. The basic pattern is actually the decomposed result of the original checkerboard, where the spectral information at the black pixels are known, and the intensity value at spatial location  $(i,j)$  is denoted by  $R_{ij}$ .

For patterns at the odd levels of the binary tree, only resampling is needed to transform them to the basic pattern, that is, the pattern need to be downsampled by  $2^{(X-1)/2}$ ,  $X > 0$ .



To transform patterns at the even levels of the binary tree, the pattern should be first downsampled by  $2^{(X)/2-1}$ ,  $X>1$  and then rotated clockwise or counterclockwise by  $45^\circ$ .

Then when the basic pattern is found unknown pixel  $R_{ij}$  can be estimated as:-

$$\hat{R}_{i,j} = \frac{\sum_{s,t(|s+t|=1)} W_{i+s,j+t} R_{i+s,j+t}}{\sum_{s,t(|s+t|=1)} W_{i+s,j+t}}$$

The weights of two neighboring pixels along the vertical direction are calculated by

$$V : W_{m,n} = \left( 1 + |R_{m+2,n} - R_{m,n}| + |R_{m-2,n} - R_{m,n}| + \frac{1}{2}|R_{m-1,n-1} - R_{m+1,n-1}| + \frac{1}{2}|R_{m-1,n+1} - R_{m+1,n+1}| \right)^{-1}$$

where  $m \in \{i-1, i+1\}$ ,  $n = j$ , and that along the horizontal direction is

$$H : W_{m,n} = \left( 1 + |R_{m,n+2} - R_{m,n}| + |R_{m,n-2} - R_{m,n}| + \frac{1}{2}|R_{m+1,n-1} - R_{m+1,n+1}| + \frac{1}{2}|R_{m-1,n-1} - R_{m-1,n+1}| \right)^{-1}$$

with  $m = i$ ,  $n \in \{j-1, j+1\}$ .

This edge-sensing approach interpolates the unknown according to pixel weights derived from edge information. Thus, the estimation of edge information directly affects the quality of reconstructed images. In multispectral imaging, as the number of spectral bands increases, the spatial resolution decreases in certain spectral bands and the edge information based on the low resolution spectral band information would not be reliable. As analyzed before, the edge information in different spectral bands are either similar or partly overlapped. The spectral band with the highest POA preserves the edge information the best. Therefore, the edge information in high resolution spectral band can be used to calculate the weights in low resolution spectral band since the band selection scheme guarantees the high resolution spectral bands are reconstructed first.

**2.2.** In 2006 Gourav A. Baone and Hairong Qi [3] proposed another demosaicing methods using mosaic focal plane array technology. They explore ways of extending the existing demosaicing methods to multispectral images. They also address the problem of noise and degradations present during the acquisition process. They developed a maximum a posteriori probability (MAP) based method that performs demosaicing that at the same time reduces noise and degradations in the output. Their approach treats the demosaicing problem as an image restoration problem and solves the optimization problem using the gradient descent method.

Their logic is that, demosaicing takes a single-band mosaiced image and reconstruct a multi-band image out of it. That means the key function is to reconstruct an image from an imperfect image. This can be thought as a traditional image restoration problem since we know that the traditional image restoration problem restores an image from its degraded version.

**2.3.** In 2011 Raju Shrestha, Jon Yngve Hardeberg and Rahat Khan proposed new scheme for spatial arrangements of color filter array for multispectral image acquisition [4]. They compared results using different number of filters/channels in terms of spectral RMS errors and distances. They mention the fact that design of MSFA is not oriented toward the human visual system (where CFA is totally based on human visual system), rather, the filters are arranged such that the array would have the best performance for certain purpose. So the probability of appearance (POA) depends on the application.

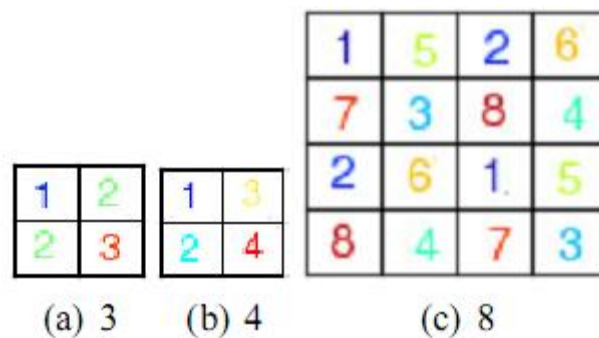


Figure 5: Generalised MCFA mention in [3] for 3, 4 and 8 channels

Their algorithm starts with a checker board pattern. The algorithm progresses by the process of decomposition and sub sampling with the knowledge of probability of appearance of each spectral band on the scene (*just like [1]*). It means the more the probability of appearance of a spectral band, the more it will appear on the MCFA. It terminates when all the bands on MCFA has the predefined probability. Fig. 5 illustrates CFA arrangements based on this algorithm for 3, 4 and 8 channels used in this literature; here all the spectral bands have equal probability of appearance because they all the channels have appeared equal number of times in the MCFA except in the case of 3 channels.

**2.4.** Another new concept is for multispectral demosaicing is proposed in [5] using a novel concept of adaptive kernel upsampling. They consider the spectral planes as severely undersampled data and use an adaptive kernel as a spatial weight and apply them to multispectral demosaicking to upsample the bands. They also propose a new CFA and direct adaptive kernel estimation from the raw data of the proposed CFA. The adaptive kernel is a spatially variant kernel estimated based on image structures [6]. But in the case of an upsampling, the adaptive kernel cannot be estimated from raw data because of the sparsity of input data. Therefore, an initial interpolation is required.

To describe the adaptive kernel upsampling, first upsampling algorithms have to be discussed. Upsampling can be done by Gaussian Upsampling (GU) and joint bilateral upsampling (JBU). Each upsampled result for a location  $\mathbf{x}_p$  is obtained as:

$$S^{GU}(\mathbf{x}_p) = \frac{1}{w_{\mathbf{x}_p}^{GU}} \sum_{\mathbf{x}_i \in N_{\mathbf{x}_p}} k(\mathbf{x}_i - \mathbf{x}_p) M(\mathbf{x}_i) S(\mathbf{x}_i),$$

$$S^{JBU}(\mathbf{x}_p) = \frac{1}{w_{\mathbf{x}_p}^{JBU}} \sum_{\mathbf{x}_i \in N_{\mathbf{x}_p}} k(\mathbf{x}_i - \mathbf{x}_p) r(I(\mathbf{x}_i) - I(\mathbf{x}_p)) M(\mathbf{x}_i) S(\mathbf{x}_i),$$

where  $N_{\mathbf{x}_p}$  is the set of neighbor pixel locations of the location  $\mathbf{x}_p$ ,  $S(\mathbf{x}_i)$  is the sampled value at the location  $\mathbf{x}_i$ ,  $M(\mathbf{x}_i)$  is the binary mask at the

location  $x_i$ ,  $I(x_i)$  and  $I(x_p)$  are pixel values of a guide image,  $k(x_i - x_p)$  is the spatial weight,  $r(I(x_i) - I(x_p))$  is the range weight of the guide image, and  $w_{xp}^{GU}$  and  $w_{xp}^{JBU}$  are normalizing factors which are sums of filter weights. The binary mask is set to one if the data is sampled at an associated location and set to zero for other cases.

The idea of these two non-adaptive upsampling is extended to an adaptive kernel upsampling using adaptive kernel as a spatial weight. The adaptive kernel for the location  $x_p$  is represented as:

$$k_{\mathbf{x}_p}(\mathbf{x}) = \exp \left[ -\frac{\mathbf{x}^T \mathbf{C}_{\mathbf{x}_p}^{-1} \mathbf{x}}{2h^2 \mu_{\mathbf{x}_p}^2} \right]$$

where  $C_{xp}$  is the covariance matrix of the Gaussian kernel,  $h$  stands for a global smoothing parameter, and  $\mu_{xp}$  is a local density parameter, which controls the kernel size. The covariance matrix  $C_{xp}$  is estimated based on the derivatives around the location  $\mathbf{x}_p$  as:

$$\mathbf{C}_{\mathbf{x}_p}^{-1} = \frac{1}{|N_{\mathbf{x}_p}|} \begin{pmatrix} \sum_{\mathbf{x}_j \in N_{\mathbf{x}_p}} z_u(\mathbf{x}_j) z_u(\mathbf{x}_j) & \sum_{\mathbf{x}_j \in N_{\mathbf{x}_p}} z_u(\mathbf{x}_j) z_v(\mathbf{x}_j) \\ \sum_{\mathbf{x}_j \in N_{\mathbf{x}_p}} z_u(\mathbf{x}_j) z_v(\mathbf{x}_j) & \sum_{\mathbf{x}_j \in N_{\mathbf{x}_p}} z_v(\mathbf{x}_j) z_v(\mathbf{x}_j) \end{pmatrix},$$

\*\*Where  $z_u$  is the horizontal derivative,  $z_v$  is the vertical derivative,  $N_{xp}$  denotes neighbor pixels around the location  $x_p$ , and  $|N_{xp}|$  is the pixel number of  $N_{xp}$ . The equations of GU and JBU are extended by replacing the spatially invariant Gaussian kernel  $k(x)$  with the adaptive  $K_{xp}(x)$  and the corresponding new adaptive kernel upsampling are called adaptive Gaussian upsampling (A-GU) and adaptive joint bilateral upsampling (A-JBU).

These kernels cause severe artifacts due to very narrow values in the edges. This can be removed by setting a limitation on the kernel size.

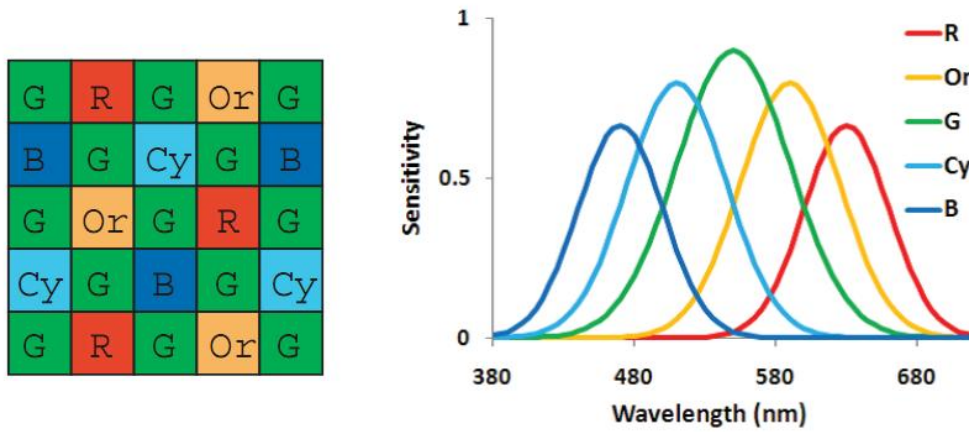


Figure 6: Proposed CFA and spectral sensitivities in [4]

Their proposed CFA and corresponding schematic spectral sensitivities of each spectral band are shown in Fig. 6. They used R, Or, G, Cy and B bands. G-band data is higher than other spectral bands because of the human eye's sensitivity. In the case of an upsampling, the derivatives cannot be calculated for all pixels because of the sparsity of input data. Therefore, an initial interpolation is necessary for the adaptive kernel estimation. Their algorithm can be summarized in the block diagram below.

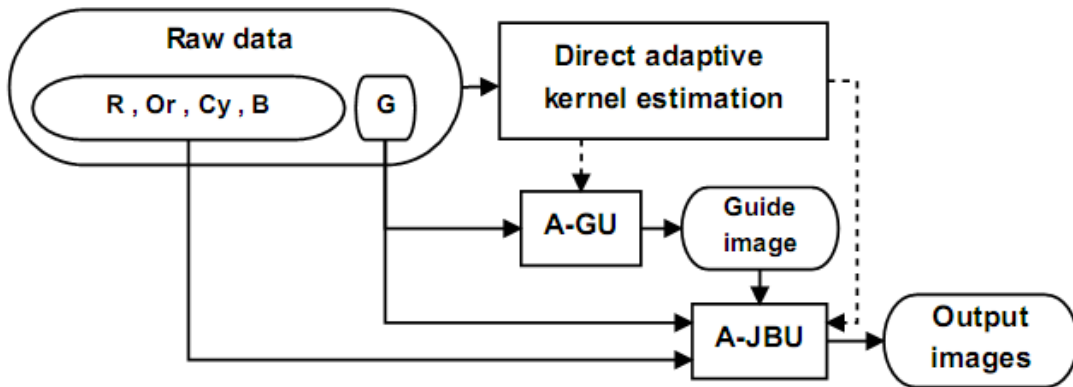


Figure 7: Block diagram of demosaicing algorithm using adaptive kernel upsampling

Their proposed algorithm includes three steps. First, the adaptive kernel is estimated directly from the raw data. Second, the guide image for A-JBU is generated from the G-band data using A-GU. Finally, A-JBU is applied to each spectral band data. Each upsampling is progressively performed similarly.

**2.5.** In 2012 the same authors proposed another method for multispectral demosaicing using guided filters [7]. It also requires the guide image like their previous work. The guide image is obviously generated using the most densely sampled spectral component in the MCFA. Then, other spectral components are interpolated by the guided filter. Experimental results demonstrate that this algorithm outperforms other existing demosaicking algorithms both visually and quantitatively.

The guided filter generates the output by a linear transform of a given guide image. In the guided filter, the filter output in each window is modeled by the linear transformation of the guide image as:

$$q_{\mathbf{x}_i} = a_{\mathbf{x}_p} I_{\mathbf{x}_i} + b_{\mathbf{x}_p}, \quad \forall \mathbf{x}_i \in \omega_{\mathbf{x}_p}$$

where  $\omega_{x_p}$  denotes the window centered at the pixel location  $x_p$ ,  $x_i$  is a pixel location in the window,  $q_{x_i}$  is the filter output at the location  $x_i$ , and  $I_{x_i}$  is the intensity of the guide image at the location  $x_i$ . Linear coefficients ( $a_{x_p}$ ,  $b_{x_p}$ ) for each window are estimated by minimizing the cost function:

$$E(a_{\mathbf{x}_p}, b_{\mathbf{x}_p}) = \sum_{\mathbf{x}_i \in \omega_{\mathbf{x}_p}} M_{\mathbf{x}_i} ((a_{\mathbf{x}_p} I_{\mathbf{x}_i} + b_{\mathbf{x}_p} - p_{\mathbf{x}_i})^2 + \epsilon a_{\mathbf{x}_p}^2)$$

where  $p_{x_i}$  is the intensity of the input image at the location  $x_i$ ,  $M_{x_i}$  is a binary mask at the location  $x_i$ , and  $\epsilon$  is a smoothing parameter. The binary mask is set to one if data is sampled at an associated location and set to zero for other cases. The location  $x_i$  is involved in the windows that contain the location  $x_i$ , thus the final output at the location  $x_i$  is calculated by averaging as:

$$q_{\mathbf{x}_i} = \bar{a}_{\mathbf{x}_i} I_{\mathbf{x}_i} + \bar{b}_{\mathbf{x}_i}$$

where

$$\bar{a}_{\mathbf{x}_i} = \frac{1}{|\omega|} \sum_{\mathbf{x}_p \in \omega_{\mathbf{x}_i}} a_{\mathbf{x}_p}, \quad \bar{b}_{\mathbf{x}_i} = \frac{1}{|\omega|} \sum_{\mathbf{x}_p \in \omega_{\mathbf{x}_i}} b_{\mathbf{x}_p},$$

and  $|\omega|$  is the number of pixels in the window.

They used the same spectral band as their previous article. There are two advantages in their proposed MCFA: (i) the sampling density of the G - band data is as high as the Bayer CFA, (ii) an adaptive kernel can be estimated directly from the raw data observed by their proposed MCFA. These two advantages are used to obtain the effective guide image. They uses adaptive kernel (adaptive Gaussian Upsampling) for high-performance upsampling of G band data to generate the effective guide image. Then the guided filter is applied to interpolate each spectral component with the help of guide image. The whole process can be shown in a block diagram.

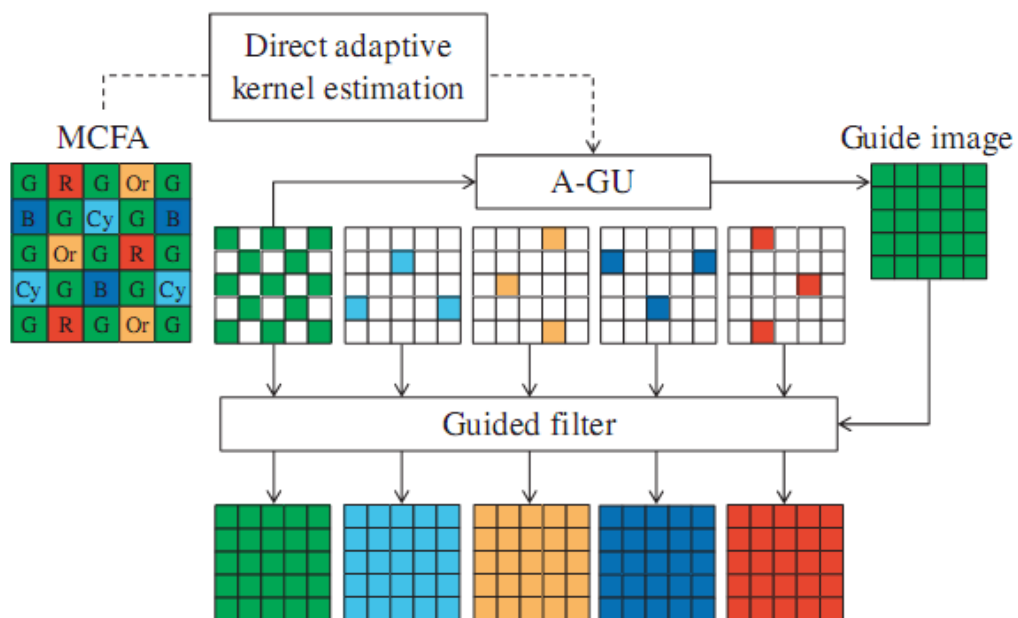


Figure 8: Block diagram of demosaicing algorithm using guided filter

### III. State of Art in Multispectral Demosaicing

In our literature review we have discussed about five different articles. All of them provide new and novel ideas for spatial arrangement of filters, color channels to be used and multispectral demosaicing algorithms. Among all the ideas the idea of binary tree [1] is surely a great solution to find the best solution for spatial arrangement. The multispectral images are used in a variety of fields. So which color channels should be used largely depends on the application of the images. For example, medical imaging researchers may choose to have information from ultra-violet region where for military use infrared spectrum is more important. But whatever the field is the most important spectrum must have higher spatial density in mosaiced image or in other words most important spectrum band should be placed in higher position in the binary tree. For example, human visual system is more sensitive to green, so if the images are for general use, then green channel should be placed at higher position in binary tree.

Among the demosaicing algorithm we discussed, the latest algorithm or demosaicing using guided filter produces the best result. A comparison between three main algorithms namely binary tree based edge sensing (BTES), adaptive kernel upsampling (A-KU) and Guided filter (Proposed) has been presented in [7]. According to their result the guided filter demosaicing produce the best image both in terms of PSNRs and visual interpretations.

Image index	Demosaicking algorithm	PSNR				
		R	Or	G	Cy	B
CHINADRESS	BTES	48.53	44.09	49.24	47.34	49.38
	A-KU	<b>52.74</b>	47.17	49.31	50.05	52.47
	Proposed	<b>52.74</b>	<b>50.33</b>	<b>50.28</b>	<b>53.11</b>	<b>54.02</b>
BUTTERFLY	BTES	45.71	42.20	45.29	37.57	40.54
	A-KU	50.48	46.24	46.70	41.88	45.17
	Proposed	<b>52.48</b>	<b>50.30</b>	<b>47.33</b>	<b>45.02</b>	<b>45.86</b>
COLOR	BTES	47.34	43.60	50.17	44.23	46.50
	A-KU	<b>51.23</b>	46.97	53.32	47.31	50.06
	Proposed	50.54	<b>49.02</b>	<b>54.17</b>	<b>51.29</b>	<b>52.07</b>

Table 1: Comparison of Algorithms Mention in Literature Review











Figure 9: Comparison of Algorithms a) original image b) zoomed image c) BTES d) A-KU e) Guided Filter

To summarize the concepts, we can say, best MCFA arrangement can be found by using binary tree; where application depended most important color band or channel should be placed in higher position so that it can have high spatial resolution and high probability of appearance (POA). For demosaicing first this band should be interpolated and then the information of this band can be used to interpolate other bands using BTES, A-KU or GF algorithms. And between these three algorithms guided filter algorithm produces the best result.

## IV. Implementations of few Methods

Our implementation is divided into two parts. The first part of the implementations is related with classical RGB images. We have implemented the algorithms mentioned in the article given with the project description in the website [8]. The authors proposed a new algorithm to improve the bilinear demosaication. Our whole program is under a function named *run\_program.m*. The input arguments of this function should be the name the image files and their corresponding start and end numbers. The function then performs bayer mosaicing using *bayer* function. The output of this function then passed to the *bilinear\_conv* function which performs the bilinear interpolation though convolution method. Then the bayer output is then passed to their proposed function *lu\_interp* to apply their proposed the interpolation process. Finally a comparison between bilinear and their proposed algorithm was made through *measure\_metric* function.

The images we worked on were collected from the author's website. The results can be shown in the next figures and tables. The results clearly show the effectiveness of the new algorithm both visually and in terms of distances, MSEs and PSNRs.

							
Image1: Original		Bilinear Interpolation		Proposed Interpolation			
							
Image 2: Original		Bilinear Interpolation		Proposed Interpolation			
**more images are available in the attached folders							
		MSE			PSNR		
		Red	Green	Blue	Red	Green	Blue
Image 1	Bilinear	17.8038	7.8896	19.3804	35.6257	39.1603	35.2572
	Proposed	<b>3.2089</b>	<b>1.4388</b>	<b>3.1133</b>	<b>43.0672</b>	<b>46.5507</b>	<b>43.1986</b>
Image 2	Bilinear	110.2275	40.0154	106.0576	27.7079	32.1085	27.8754
	Proposed	<b>9.6700</b>	<b>6.2974</b>	<b>11.1468</b>	<b>38.2765</b>	<b>40.1392</b>	<b>37.6593</b>

The second and the main part of our implementation is the mosaicing and demosaicing of multispectral image using the binary tree based spatial filter arrangement. We implemented our code for 5 spectral band images where green band has the same spatial density like bayer CFA and all other band have equal POA. The binary tree of our implemented mosaication algorithm can be given as below:

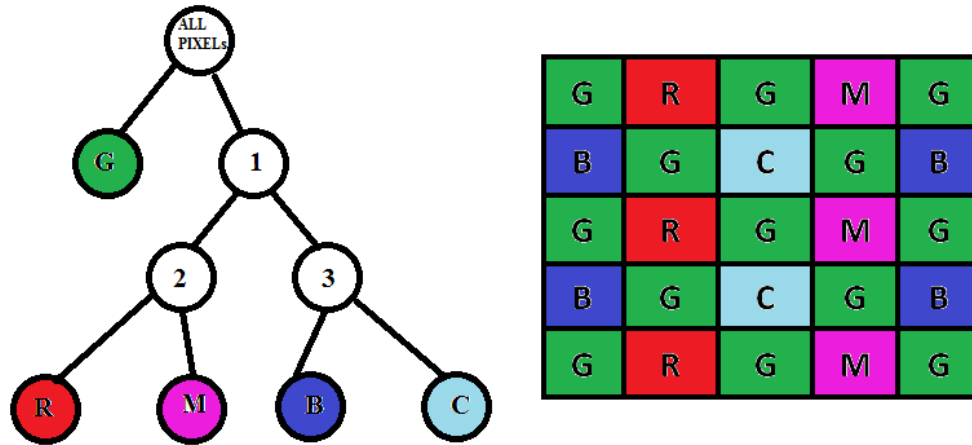


Figure 10: Binary Tree and MCFA arrangement for our implementation

We used two images from our laboratory tutorial no. 3 namely *Macbeth\_7.mat* and *flowers\_7.mat*. As we were working 5 spectral images, we deleted the last two bands and created *Macbeth\_5.mat* and *flowers\_5.mat*. We also collected two different images from internet database [9] and created corresponding 5 spectral images called *feathers\_5.mat* and *ballons\_5.mat*. The MATLAB code for the file creation and corresponding image files can be found as *multi725.m* under the folder name “*Creation of 5 Spectral image database*”.

Then demosaicing is done according to the above figure on those 5-spectral images. The code can be found as *demosaication.m*. The mosaiced files are then saved as *Macbeth\_5\_demosaiced.mat*, *flowers\_5\_demosaiced.mat*, *feathers\_5\_demosaiced.mat* and *ballons\_5\_demosaiced.mat*.

For demosaication part we implemented bilinear interpolation and two improvements of bilinear interpolation namely smooth hue and edge preserve bilinear interpolations.

For bilinear interpolation, corresponding codes can be found in folder named “*bilinear\_interpolation*”. As the green channel is exactly similar to the bayer CFA green channel, bilinear interpolation of the

unknown pixel is just the average of neighboring known pixels. For other channels we need to traverse the binary tree in the reverse order. The process is already illustrated in Fig. 3. First we need to fill up the siblings positions in the band, we then go one step up, then the empty diagonal positions can filled up by averaging the diagonal neighbors, then we reach the last level in binary tree, the final blank locations can filled up like the green band, by averaging the neighbors.

In the implementation of the smooth hue bilinear interpolation, the interpolation of the green plane doesn't change but the interpolations of other planes are modified by the corresponding green values. The related codes can be found in folder "*smooth hue interpolation*".

Finally the implementation for edge preserve bilinear algorithm only the green interpolation changes, other colors bands keeps the same interpolation as smooth hue. For green plane now we take care off the edges, we find two gradient of change in green values in horizontal and vertical directions, then according to the lower gradient the average is taken to interpolate values in the blank space. This implementations can be found in the folder "*edge preserve interpolation*". Result of all these interpolation is saved as *.mat* file with the name of corresponding interpolation methods. Finally the PSNRs are found by comparing the original and interpolated images. They can found in the next table.

For displaying the multispectral images we used the idea gained in the third tutorial and modified the code to handle 5-spectral images. Two different illumination conditions are used for displaying each image.

Image Name	PSNR					
	Method	Green	Red	Magenta	Blue	Cyan
Macbeth	Bilinear	43.3630	<b>36.2956</b>	<b>36.1620</b>	<b>34.4843</b>	<b>35.0253</b>
	Smooth hue	43.3630	30.5476	27.7982	26.8326	27.4833
	Edge preserve	<b>45.0968</b>	30.6230	27.7920	26.8057	27.0886
Flowers	Bilinear	<b>55.5957</b>	<b>48.3460</b>	<b>47.3915</b>	<b>45.1074</b>	<b>43.4657</b>
	Smooth hue	<b>55.5957</b>	45.3956	34.3160	41.9400	37.6090
	Edge preserve	55.2489	45.4325	34.2843	41.6726	37.6403
Feathers	Bilinear	45.0087	31.8678	<b>30.9413</b>	<b>32.7985</b>	33.4151
	Smooth hue	45.0087	32.6834	26.7864	30.6954	33.4369
	Edge preserve	<b>46.3002</b>	<b>32.9077</b>	27.1331	30.8000	<b>33.5789</b>
Balloons	Bilinear	52.1667	<b>42.7755</b>	<b>41.3782</b>	<b>44.6094</b>	<b>42.0538</b>
	Smooth hue	52.1667	29.6488	26.7965	27.0708	30.6543
	Edge preserve	<b>53.7531</b>	29.6362	26.8291	27.0605	30.6596

**Table 2: Comparison of Implemented Algorithms**



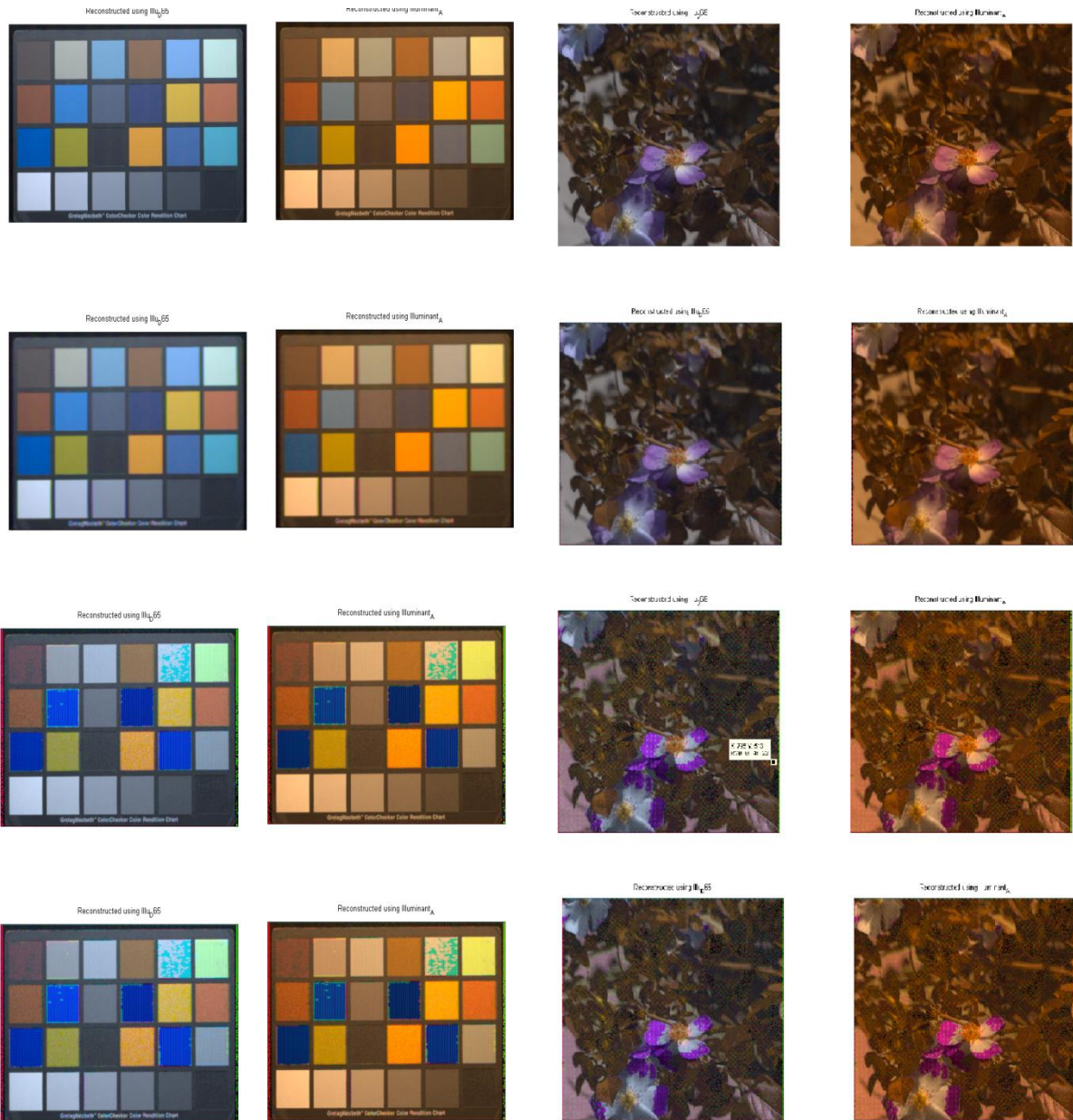


Figure 11: Output Figures of our Implementations Top to Bottom: Original, Bilinear, Smooth Hue, Edge Preserve; Left to right: Macbeth under  $illu_{D65}$ , Macbeth under  $illu_{A}$ , flowers under  $illu_{D65}$ , flowers under  $illu_{A}$



Figure 12: Output Figures of our Implementations Top to Bottom: Original, Bilinear, Smooth Hue, Edge Preserve; Left to right: feathers under illu\_D65, feathers under illu\_A, balloons under illu\_D65, balloons under illu\_A

## V. Discussion

In this project we have gone through some literatures containing novel ideas about multispectral demosaicing. We have tried to discuss the key points mentioned in those literatures in order find the state of the art in this field. Those ideas enriched our knowledge about multispectral images and their effective filter arrangements, demosaication processes. The demosaicing algorithm has been improved so much since 2006 when the BTES algorithm was first introduced. The application of Adaptive Kernel Upsampling Method and Guided Filter are the latest demosaicing algorithm which outperforms all the previous algorithms.

In the implementation part we observe from the comparison table (Table 2) that the smooth hue and edge preserve algorithm do not improve the multispectral demosaicing process much. It only shows improvement in the green band, but for the other bands the PSNR decreases. There may have been many reasons behind this. Our implementation may have been wrong, although we have checked our codes for several times. Or maybe the correlation between color bands are not good enough in multispectral images to apply smooth hue and edge preserve interpolation. Both of these two are based on the RGB images where the correlation between R – G and B – G are strong enough. Multispectral images may not hold these strong correlations and may result in low PSNR for those two algorithms.

## VI. Conclusion

In our theory classes we have covered the CFA pattern and many existed algorithms for standard RGB images. As RGB images have been used for long times, the domaisaic pattern and their demosaication have been standardized by many researched. In contrast of the RGB images, multispectral imaging possesses a lot of difficulties. The first question to answer is that how many spectrums have to be used for multispectral imaging? The answer is different based on different situation or application. Most researchers used 5, 7 and 8 spectrums. For our implementation we choose the 5 spectral images. Once the number of the spectrum is found, next question arises, "Which bands should be used?" The answer for this question also depends on the application of the images. For collecting information on the infrared region, infrared region can be covered. To see the effect of ultraviolet rays in the environment, ultraviolet spectrum can be chosen. Or to see more colors all the spectrum band can be chosen from visible spectrum ranges. Now when we know the number of the bands we are taking and we also know which bands are to be taken; then we should think about how to arrange the spectrum filters in order to achieve the best image. The arrangement of filters obviously depends on the number of the spectral plane. There is a trade of between the number of spectral planes and the spatial resolution of the planes. Higher number of spectral planes results in low spatial resolutions. So a perfect balance between these have to be made in order to achieve desired result. The arrangement can be generalized by using binary tree. Where we can keep the important band in higher level and less important band in lower levels. Finally when the best spatial arrangement mosaication is done, next thing is to demosaic the spectral planes to reconstruct the image perfectly. Demosaication have to done also following the same binary tree, first the band with highest spatial resolution should be interpolated as this band possess more information than other bands. Then using the knowledge of this band other band can also be interpolated using either BTES or A-KU or state of the art Guided Filter method.



## VII. References

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## VIII Appendix: MATLAB files and instructions

MATLAB Files are in the *MATLAB Codes.zip* file.

There are two folders inside; Multi Spectral Implementation and RGB Implementation.




### Multi Spectral Implementation



-  1. Creation of 5 Spectral image database
-  2. Binary tree based Mosacing
-  3. Bilinear interpolation
-  4. Smooth hue interpolation
-  5. Edge preserve interpolation
-  6. Measure Metrics
-  7. Display
-  Results

### RGB Implementation



-  Codes for Bayer CFA, Interpolation and Their Input Files
-  Codes for Metric Measurements with original and interpolated files
-  Results, Output Figures and Metrics

1. First folder contains the data and the script multi725.m used to create the database we worked on.
2. Second folder contains the script for performing demosaication with the needed input files.
3. Contain all the functions and input mosaiced figure needed to do bilinear interpolation.
4. Contain all the functions and input mosaiced figure needed to do smooth hue bilinear interpolation.
5. Contain all the functions and input mosaiced figure needed to do edge preserve bilinear interpolation.
6. Contains the outputs of all the algorithms and original file in order to find the PSNRs using measure metric script.
7. Contains the files needed to display multispectral images.
8. The last folder contains all the Results, Output figures and Metrics.

1. The first folder contains the codes for RGB bayer CFA mosaication, bilinear interpolation and new interpolation method used in [8].
2. The second folder contains the metric measurement scripts, functions and needed input files for comparing the algorithms.
3. Third and the last folder contains all the output figures and metric results.