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Weighted Bilinear Interpolation Based Generic Multispectral Image Demosaicking Method

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Abstract
Multispectral imaging systems acquire images having more than three spectral bands and these images play crucial role in various applications such as remote sensing, medical imaging, military surveillance, vision inspection for food quality control, archaeological surveys etc. But the high cost of multispectral imaging systems limit their usage. Similar to the use of color-filter-array interpolation methods in development of low cost RGB color cameras, researchers have been exploring the use of multispectral image demosaicking technologies for developing affordable multispectral imaging systems. In this paper, we present a generic simple weighted bilinear interpolation based multispectral image demosaicking method. This method is applicable for any number of spectral bands image, however it critically depends upon the multispectral filter array that needs to be carefully designed for the weighted bilinear method to be easily applicable. We use two publically available multispectral image datasets for the performance evaluation of the proposed approach and present some interesting insights derived from the experimental results.

Keywords- Multispectral Images, Demosaicking, Interpolation, Weighted Bilinear, Multispectral Filter Array (MSFA).

1. Introduction
The standard digital color cameras capture only three spectral bands of the visible electromagnetic spectrum. It curtails the applicability of these imaging systems for the applications where better color reproduction and more spectral bands information is needed. The multispectral imaging systems that capture larger number of spectral bands data content in images are highly demanded, and these multispectral images can be used in various fields such as remote sensing (MacLachlan et al., 2017; Galidaki et al., 2017; Addesso et al., 2017; Brennera et al., 2017), satellite imaging (Mangai et al., 2010; Kalkan et al., 2010), medical imaging (Pearce et al., 2016; Shinoda et al., 2015), vegetation analysis, military surveillance, cyber forensics, etc. Acquiring raw multispectral images requires multi-camera-one-shot imaging system that is embedded with multiple cameras and various mechanical and optical parts. These systems are however quite expensive and heavy, and therefore their usage is restricted (Monno et al., 2011; Yamaguchi et al., 2006).

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The use of color-filter-array interpolation methods played helpful role in the development of low cost RGB color cameras. The commonly used RGB color cameras consist of single imaging sensor along with color filter array (CFA) in front of the sensor. Most commonly used CFA is Bayer CFA (Bayer and Bryce, 1976) as shown in Figure 1(a). Using CFA in RGB cameras, only one color sample is acquired at each pixel location, and this acquired image data is called CFA image or mosaiced image. Other missing color samples are estimated through neighboring pixels in CFA image. To reconstruct the full RGB color image by evaluating missing color samples from raw CFA image (mosaiced image), reconstruction operation, called CFA demosaicking, is applied. There are many CFA demosaicking methods which have been proposed for RGB imaging system (Losson et al., 2010; Popescu and Farid, 2005; Li et al., 2008; Goyal et al., 2014).

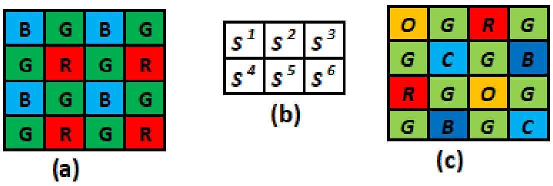

Figure 1. (a) Bayer CFA (b) 2×3 MSFA pattern for *6*-Bands (c) 4×4 MSFA pattern for *5*-bands

The idea of an extension of single-camera-one-shot systems for multispectral imaging using multispectral filter array (MSFA) in multispectral domain provides the advantage of low cost, less weight and real time video capturing. An MSFA is a mosaic pattern similar to CFA with each element being a wavelength specific optical filter. Multispectral camera along with multispectral filter array (MSFA) captures only one spectral band information at each pixel location, and the captured image is called MSFA image. To reconstruct the full multispectral image from a MSFA image, the reconstruction operation, called MSFA demosaicking or multispectral image demosaicking, is required. However, extension from CFA to MSFA and CFA demosaicking to MSFA demosaicking is not directly generalized because of very sparse sampling of each spectral band in MSFA. The Bayer CFA pattern is designed based on a human visual system. As the human eye is more sensitive to green color, 50% samples are of green color and 25% samples are of red and blue each in Bayer CFA. But designing a MSFA pattern is challenging task because of a large number of bands and each having specific characteristics. Brauers and Aach (2006), proposed six-band MSFA pattern 2×3 grid, as shown in Fig. 1(b). Miao and Qi described the first generic algorithm to systematically design MSFA patterns for any number of bands (Miao and Qi, 2006) given the probability of appearance (PoA) of each spectral band. This binary tree driven method starts from a checkerboard pattern and then generates MSFA pattern considering spatial uniformity and spectral consistency. In Figure 1(c), there is shown a 4×4 size 5-band MSFA designed using this method where PoA for green band is 50% and 12.5% for rest of the 4 bands. Aggarwal and Majumdar (2014; 2015) presented two different types of MSFA patterns: random MSFA

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and uniform multispectral filter array (UMSF). Developing efficient multispectral image demosaicking method is more complicated because of very sparse sampling of each spectral band in MSFA pattern. The quality of the reconstructed image highly depends on the MSFA pattern and the multispectral image demosaicking algorithm. In recent years, a few multispectral demosaicking methods have been proposed. Many of these demosaicking methods are not generic and are limited in their applicability for only specific number of bands.

In this paper, we extend the weighted bilinear interpolation method to be used as generic multispectral demosaicking method which is applicable for reconstructing images with any number of multispectral bands. Section 2 describes the multispectral image demosaicking related prior works. This is followed by description of the proposed approach in next section. The details of the dataset and performance metrics used are presented in Section 4, and the experimental results and analysis are discussed in Section 5. Finally, we present the conclusion of this work in Section 6.

2. Related Works

Miao et al. (2006), had proposed a multispectral image demosaicking method using the MSFA patterns that were generated using the binary tree approach given by Miao and Qi (2006). In this binary tree edge sensing (BTES) method, same binary tree as used in generating MSFA pattern were to be used to reconstruct the full multispectral image from raw MSFA image. In BTES method, each band is interpolated independently and no inter-band correlation is applied. This binary tree based method is known to be generic method applicable for any number of multispectral bands. For each spectral band, edge correlation is explored to find the missing intensities. As number of spectral band increases, the spatial resolution decreases and the edge information from low resolution spectral band is unreliable. Therefore, it suffers from severe color artifacts especially in edge and texture regions. The method is also computationally expensive and somewhat complicated. Aggarwal and Majumdar (2014; 2015) discussed about compressive sensing based demosaicking methods applied to two different types of MSFA patterns: random MSFA and uniform multispectral filter array (UMSF). In (Aggarwal and Majumdar, 2015), the compressed sensing based formulation was used to recover images exploiting the sparsity of the images in the wavelet domain. In the other work also, Aggarwal and Majumdar (2014) proposed another learning interpolation parameter based demosaicking approach applicable for UMSF. These methods require original multispectral images for learning the parameters which are used later in interpolation, but this information will not be available in real time, so these methods are not feasible.

Brauers and Aach (2006) extended the CFA demosaicking algorithms - bilinear interpolation and color differences based color interpolation, and accordingly presented weighted bilinear (WB) interpolation and spectral channel differences (SCD) based interpolation algorithms for

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2×3 MSFA pattern based multispectral images. The WB method uses convolution operations and it is computationally faster. However, the method was shown to be applicable for 6-band multispectral images only. Mizutani et al. (2014), extended an earlier method (Brauers and Aach, 2006) using 16-band MSFA pattern set (4×4 pixels in raster order) by repeating interpolations to strengthen the cross correlation of demosaiced bands. Mihoubi et al. (2015), discussed two new demosaicking methods: Intensity Difference (ID) method and Iterative Intensity Difference (IID) method for square non-redundant MSFA pattern, using spatial and spectral correlations to estimate each missing spectral band. Intensity level is used for demosaicking based on assumption that the correlation between each band and the intensity is higher on average than the correlation between spectral bands considered pairwise. These methods were based on WB method. However, the applicability of these demosaicking methods were restricted to multispectral images having square size (n=4, 9 or 16) spectral bands.

Monno et al. (2012), and Monno et al. (2015), proposed 5-band MSFA pattern with higher density of green band 50% among all other bands (Fig. 1 (c)). For reconstruction, an adaptive kernel based method is used. In Monno et al. (2012), a guided image is generated from green band which is highly dense band, and it is used as reference image to demosaic other bands. This method is further improved by Monno et al. (2015) by developing multiple guided images. Jaiswal et al. (2016) modified the color difference interpolation (CDI) assumptions (Li et al., 2008) and proposed an adaptive method based on frequency domain analysis of spectral correlation on 5-band MSFA pattern that was proposed by Monno et al. (2015). But these methods are applicable only for 5-band MSFA pattern and cannot be generalized to any number of bands or any other MSFA pattern. To the best of our knowledge, the recently proposed multispectral demosaicking methods are applicable only for multispectral images with a specific number of bands and/or require original multispectral image data values for getting optimal parameters used in that method, and this limits their applicability and feasibility in practice.

3. Generic Weighted Bilinear Multi-Spectral Image Demosaicking Method

As highlighted above, the weighted bilinear interpolation based demosaicking method is one of the simple and computationally faster multispectral image demosaicking method. It also serves as basis for many other multispectral image demosaicking methods. However, in the research works so far, the applicability of this method is restricted to only specific size multispectral images. Here, we present the process for designing appropriate MSFA patterns and the corresponding filter so that the WB method can be extended and generalized to be applied for performing demosaicking for any K-band size multispectral images.

Let A denotes an M×N size raw (mosaicked) multispectral image having K spectral bands. At any pixel location, it contains the information for only one of the K spectral bands as per the MSFA pattern used in the single sensor multispectral camera used to acquire this image A.

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The aim of the multispectral image demosaicking method is to reconstruct the full multispectral image, let's say B, of size M×N×K, using raw image A. The WB demosaicking method is performed primarily in two steps.

Step 1: Obtain the sparse raw image A^k for each spectral band $k \in \{1, 2, 3, \ldots K\}$ as follows:

$$A^k = A \boxdot m^k ,$$

where, m^k is defined as binary mask for *band-k* and $\boxdot$ denotes element wise product. The mask m^k is dependent on the MSFA pattern for K-band multispectral image.

Step 2: To obtain full image B, the missing pixel values in each sparse image A^k are estimated as follows

$$B^k = A^k * H$$

where * is convolution operator and H is a low pass filter dependent on the MSFA pattern.

In order to extend and generalize the WB method so that it can be applied to any K-band size multi-spectral images, we need to devise an approach to generate the MSFA pattern for K-band size multispectral images. Here, we propose the approach for the same.

- If K is prime, then MSFA pattern would be of size 1×K. For example, the MSFA patterns for 7-band and 11-band multispectral images would be of size 1×7 and 1×11, respectively.
- If K is perfect square, then MSFA pattern would be of size $\sqrt{K} \times \sqrt{K}$. For example, the MSFA patterns for 9-band and 16-band multispectral images would be of size 3×3 and 4×4, respectively.
- In other cases, find the integer factors of K that are closest to $\sqrt{K}$ and use that to design the MSFA pattern. For example, the MSFA patterns for 10-band and 12-band multispectral images would be of size 2×5 and 3×4, respectively.

Table 1 presents the MSFA patterns for some different size multispectral images. In Table 2, we also show the corresponding filter H for 5, 6, 7, 8 and 9-band multispectral images related MSFA patterns shown in Table 1.

4. Datasets and Performance Evaluation Metrics Used

We use two well-known publically available multispectral image datasets in our experiments:

- CAVE dataset (http://www.cs.columbia.edu/CAVE/databases/multispectral/) - It comprises of high quality multispectral images, each of 31-bands ranging between 400nm-700nm with spectral gap of 10nm, and these images were captured using tunable filter (VariSpec Liquid Crystal Tunable Filter) and cool CCD camera (Apogee Alta U260, 512x512 pixels).

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- TokyoTech dataset (Monno et al., 2015) - This dataset contains 31-band hyperspectral images, from 420nm to 720nm at 10nm intervals, of colorful objects with rich textures. The images were captured using a monochrome camera with a VariSpec liquid crystal tunable filter (VariSpec VIS).
- Out of 31 bands of these multispectral images, we use K-bands information, taken at equal spectral gaps, in our experiments and performance analysis. And, we present the performance analysis using peak signal to noise ratio (PSNR) and structure similarity (SSIM), given by Wang et al., (2004).

Table 1. MSFA patterns for multispectral images with K-bands, here K varies from 5 to 16

No. of bands (K)	MSFA pattern (uniformly distributed; same PoA of all channels)
5	S^1 S^2 S^3 S^4 S^5
6	S^1 S^2 S^3 S^4 S^5 S^6
7	S^1 S^2 S^3 S^4 S^5 S^6 S^7
8	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8
9	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8 S^9
10	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8 S^9 S^{10}
11	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8 S^9 S^{10} S^{11}
12	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8 S^9 S^{10} S^{11} S^{12}
13	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8 S^9 S^{10} S^{11} S^{12} S^{13}
14	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8 S^9 S^{10} S^{11} S^{12} S^{13} S^{14}
15	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8 S^9 S^{10} S^{11} S^{12} S^{13} S^{14} S^{15}
16	S^1 S^2 S^3 S^4 S^5 S^6 S^7 S^8 S^9 S^{10} S^{11} S^{12} S^{13} S^{14} S^{15} S^{16}

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Table 2. The low pass filer H used in WB method for reconstructing multispectral images with K-bands, here K varies from 5 to 9

No. of bands (K)	Size of the MSFA pattern	Filter kernel H
5	1×5	[1 2 3 4 5 4 3 2 1] (1/5)
6	2×3	$\begin{bmatrix} 1 & 2 & 3 & 2 & 1 \\ 2 & 4 & 6 & 4 & 2 \\ 1 & 2 & 3 & 2 & 1 \end{bmatrix} (^1/_6)$
7	1×7	[1 2 3 4 5 6 7 6 5 4 3 2 1] (1/7)
8	2×4	(1/2) [1 2 1]^T. (1/4) [1 2 3 4 3 2 1] $= \begin{bmatrix} 1 & 2 & 3 & 4 & 3 & 2 & 1 \\ 2 & 4 & 6 & 8 & 6 & 4 & 2 \\ 1 & 2 & 3 & 4 & 3 & 2 & 1 \end{bmatrix} (^1/_8)$
9	3×3	(1/3) [1 2 3 2 1]^T. (1/3) [1 2 3 2 1] $= \begin{bmatrix} 1 & 2 & 3 & 2 & 1 \\ 2 & 4 & 6 & 4 & 2 \\ 3 & 6 & 9 & 6 & 3 \\ 2 & 4 & 6 & 4 & 2 \\ 1 & 2 & 3 & 2 & 1 \end{bmatrix} (^1/_9)$

5. Experimental Results and Analysis

We objectively compare the performances of the extended WB based multispectral image demosaicking method using two different publically available datasets for K =5, 6, …, 15 and 16 bands size multispectral images. Table 3 presents the average PSNR and average SSIM for different datasets based multispectral images with varying size of spectral bands (K) generated using extended WB multispectral image demosaicking method. It is generally expected that as the number of bands, K, increases, the average PSNR value decreases. Larger the number of bands, more will be the sparseness, lesser will be the PoA for each band and therefore more will be the reconstruction error leading to lower PSNR and SSIM. However, this trend is not so observed with this extended weighted bilinear interpolation based multispectral image demosaicking method. The deeper analysis reveals the reason for this observation and brings out the significance of MSFA pattern design. In our analysis, we consider three cases: (1) when MSFA pattern is of row vector shape; (2) when number of rows in MSFA pattern is 2 and it is seemingly less compact; and (3) when K is a perfect square and/or MSFA pattern size is more compact with number of rows more than 2. From the plots as shown in Figures 2 and 3, it can be observed that for each case, the average PSN shows expectedly almost decreasing trend with the increase in the number of band. Case 3 is more preferred to case 2 and case 2 is more preferred to case 1. The average PSNR for 13-band, 11-band and even 7-band multispectral images is significantly lower than 16-band multispectral images. This is because of non-compact or say row/column vector shape MSFA patterns when K is prime. The average PSNR for 16-band images is slightly higher compared to 15-band images and that is because of slightly more compact MSFA pattern when K=16. The average SSIM values also follow the similar trend as of average PSNR values with varying K values.

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Table 3. Average PSNR and SSIM for different datasets based multispectral images with varying size of spectral bands (K) generated using extended WB multispectral image demosaicking method

No. of bands (K)	MSFA Band size	Case	CAVE dataset		Tokyo dataset	
			PSNR	SSIM	PSNR	SSIM
4	**2×2**	**2,3**	40.51	0.9917	38.58	0.9881
5	**1×5**	**1**	34.45	0.9620	32.27	0.9276
6	**2×3**	**2**	37.26	0.9816	35.56	0.9682
7	**1×7**	**1**	32.31	0.9380	29.79	0.8848
8	**2×4**	**2**	35.31	0.9690	33.49	0.9471
9	**3×3**	**3**	36.00	0.9752	34.12	0.9570
10	**2×5**	**2**	33.95	0.9583	31.91	0.9253
11	**1×11**	**1**	29.70	0.8987	27.19	0.8189
12	**3×4**	**3**	34.66	0.9645	32.76	0.9372
13	**1×13**	**1**	29.03	0.8864	26.69	0.7982
14	**2×7**	**2**	32.04	0.9362	29.78	0.8852
15	**3×5**	**3**	33.38	0.9521	31.15	0.9149
16	**4×4**	**3**	33.71	0.9547	31.06	0.9184

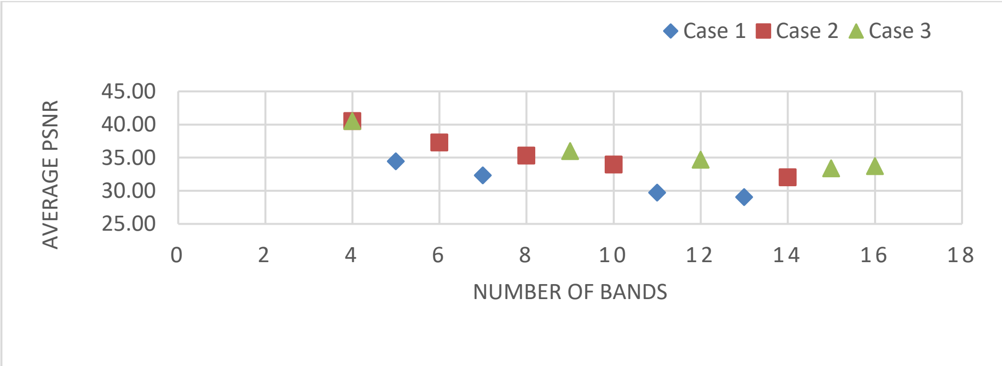

Figure 2. Plot showing how average PSNR Varies for different K-band size CAVE dataset multispectral images reconstructed using extended WB multispectral image demosaicking method (in 3 different cases)

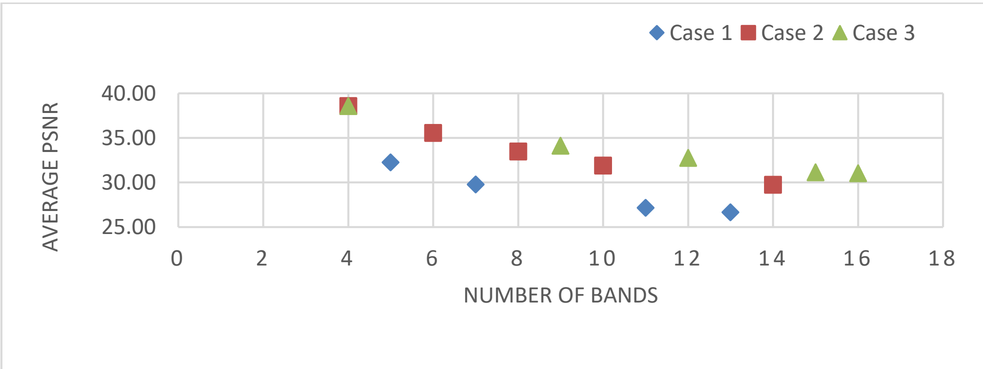

Figure 3. Plot showing how average PSNR varies for different K-band size Tokyo dataset multispectral images reconstructed using extended WB multispectral image demosaicking method (in 3 different cases

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6. Conclusions and Future Work

In this work, we presented an approach to design the MSFA patterns for any K-band multispectral imaging systems so that the computationally efficient and easy to implement weighted bilinear interpolation based multispectral image demosaicking method can be easily extended and applied for reconstructing any K-band size multispectral images. The experiments are performed using two publically available multispectral images dataset and the analysis is performed using PSNR and SSIM metrics. Counterintuitively, the performance of extended WB method is noted to be better at times despite increase in number of bands. In this analysis, the importance of compact shape MSFA patterns is highlighted. We observe that the MSFA pattern design also plays the crucial role in the performance of multispectral image demosaicking method; the row/column vector shape linear MSFA patterns are least preferred and the compact shape MSFA patterns are more preferred. WB method serves also as the basis for many other multispectral image demosaicking methods. In future, we would be therefore interested to generalise the other multispectral image demosaicking methods.

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