SINGLE-SENSOR MULTI-SPECTRAL IMAGE DEMOSAICING ALGORITHM USING LEARNED INTERPOLATION WEIGHTS

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ABSTRACT

Multi-spectral images capture more information about a scene as compared to RGB images and have various scientific applications. But the high resolution multi-spectral cameras are very expensive which limits their wide applicability as compared to normal digital RGB cameras. In this paper a multi-spectral filter array design is proposed to capture multiple bands using the single-sensor architecture. The use of single-sensor can help in reducing the cost and size of multi-spectral cameras while simultaneously eliminating the image registration problem. Fast linear demosaicing technique is also proposed to interpolate missing values from under-sampled raw image. Experimental results show the superiority of proposed technique over state of art multi-spectral demosaicing technique.

***Index Terms*—** Multispectral filter arrary, Multispectral imaging, Interpolation

1. INTRODUCTION

Multi-spectral images captured over multiple bands of electromagnetic (EM) spectrum have more information content compared to RGB color images captured over visible bands. Multi-spectral images have found applications in various domains such as: medicine, agriculture, security services, and military surveillance [1, 2, 3].

However multi-spectral cameras are very expensive compared to their RGB counterparts, e.g. a five sensor multi-spectral camera with resolution of only 1360×1024 costs several thousand US dollars whereas the cost of a single-sensor RGB camera with much higher resolution is only a few hundred US dollars. The high cost of multi-spectral cameras is the main deterrent in widespread applications of such devices in developing countries. The objective of this work is to bring down the cost of such multi-spectral cameras.

Most multi-spectral cameras have a separate sensor array for each band of the EM-spectrum. Image acquisition using such separate sensor arrays requires large number of optical and mechanical parts which contributes to the increased cost and size of the cameras. Owing to such separate sensor arrays, there is also the problem of pixel registration. This work is inspired from single-sensor architecture of modern RGB cameras to address the issues of cost, size and pixel registration.

There are many studies on color image demosaicing [4, 5] but only a handful of studies on demosaicing algorithms for multi-spectral imaging. A multi-spectral filter array design has been proposed in [6]. Based on this filter array design, a generic demosaicing algorithm has been proposed in [7] which exploits edge correlation to compute missing values at different bands. This algorithm is named Binary Tree based Edge Sensing method (BTES). However the proposed design of filter array is based on the prior knowledge about the importance of a particular band over others; such a prior knowledge based sampling approach may not be always advisable. Moreover it can only split the sampling space in a dyadic scale, such as 1/2 or 1/4 or 1/8 which is restrictive and cannot handle arbitrary prior probabilities.

In this paper, a generic single-sensor filter array for multi-spectral image acquisition has been proposed and a linear interpolation technique to impute the missing pixel values. The proposed algorithm performs one time offline training to compute interpolation parameters which makes it computationally cheap and accurate. Fast interpolation rate makes it applicable to be implemented on the board of the multispectral camera. A comparative study for existing multispectral demosaicing algorithm [7] has also been carried out.

2. PROPOSED TECHNIQUE

This work considers two aspects of multi-spectral camera design namely: design of multi-spectral filter (MSF) to capture multiple bands using single-sensor and the demosaicing technique to interpolate missing intensity values.

2.1. Proposed Multi-Spectral Filter Array

Color filter array used in many digital cameras are based on Bayer pattern [8] which captures 50% samples of green band and 25% each of red and blue bands. The reason for higher sampling of green band is the claim that the human eye is more sensitive to green color as compared to red and blue. In case of multi-spectral images, there is no prior information

H.K. Aggarwal is supported by TCS research fellowship.

Algorithm 1: Generate Uniform Multi-Spectral Filter

Input K: number of bands

e_j : K-dimensional row vecor having all elements as zero except j^{th} element which is one.

Output: UMSF (Uniform Multi-Spectral Filter)

Initialize $P = \begin{pmatrix} e_K \\ e_1 \\ \vdots \\ e_{K-1} \end{pmatrix}, \quad \text{UMSF} = \begin{pmatrix} row_1 \\ row_2 \\ \vdots \\ row_K \end{pmatrix}$

$row_1 = \begin{bmatrix} 1 & 2 & \dots & K \end{bmatrix}$

for $j = 2$ *to* K **do**

$\quad row_j = row_{j-1} \times P$

end

B_1	B_2	$\dots$	B_{K-1}	B_K
B_2	B_3	$\dots$	B_K	B_1
$\vdots$	$\vdots$	$\dots$	$\vdots$	$\vdots$
B_{K-1}	B_K	$\dots$	B_{K-3}	B_{K-2}
B_K	B_1	$\dots$	B_{K-2}	B_{K-1}

Fig. 1. Uniform Multi-Spectral Filter

about the preference of one band over the other and therefore we have designed the multispectral filter to collect equal number of samples for each band. Proposed Algorithm to generate the K-band multi-spectral filter is shown in Algorithm 1. There are two main multi-spectral filter design considerations namely *spectral consistency* and *spatial uniformity* which were introduced in [6]. Our proposed UMSF generation algorithm takes into consideration both of these requirements. Spectral consistency requirement is satisfied since neighborhood bands remain the same for each pixel in the image. Spatial uniformity requirement is also satisfied by the proposed UMSF because samples corresponding to each band are uniformly captured in the whole image. The generated Uniform Multi-Spectral Filter array (UMSF) design is shown in Fig. 1 to capture K-band multi-spectral image. Here $B_i \forall i \in [1, K]$ represents that only the intensity of i^{th} band will be captured by the image sensor at that pixel location. The captured under-sampled image is refereed as raw image which have only one sample at each pixel and remaining $K-1$ samples have to be interpolated.

The advantage of UMSF is that it can be easily extended to capture any number of bands with a repeatable deterministic architecture unlike random sampling patterns. Another advantage of having a uniform pattern is that, we can frame the demosaicing problem as a linear interpolation problem something which is not possible for random patterns.

2.2. Proposed Demosaicing Algorithm

Both spatial and spectral correlation information have been explored to interpolate missing band values in a raw multi-spectral image.The K-band raw image generated from proposed UMSF will have K different repeating patterns in the whole image. Each non-border pixel of raw image will be the central pixel in exactly one of the K patterns repeating in the whole raw image.

Consider a pattern for 3 band raw image in which at the central pixel location there is missing band values of band 1 and band 2. These two band values can be estimated by exploiting their relationship with the known neighboring pixels of same band as well as other bands. This relationship can be represented by expressing the central pixel value as the linear combination of neighboring pixel values. The unknown band 1 and band 2 pixel values for a pattern can be expressed as:

$$y_1 = \sum_{i=1}^{8} a_i x_{i1}, \quad y_2 = \sum_{i=1}^{8} a_i x_{i2}$$

The x_{i1} and x_{i2} values represent the weights of neighboring pixel values a_i's for the interpolation of unknown band 1 and band 2 values at the central pixel location. If the weights x_{i1} and x_{i2} are known then the unknown pixel values can be estimated. These weights remain constant for a particular pattern in the whole image.

In general, for each pattern in the K band raw image the interpolation process can be expressed as:

$$\begin{bmatrix} Y_1 & Y_2 & \dots & Y_{K-1} \end{bmatrix} = A \begin{bmatrix} X_1 & X_2 & \dots & X_{K-1} \end{bmatrix} \quad (1)$$

where $Y_i \; \forall i \in [1, K-1]$ represents unknown values,X_i represents interpolation weights, A represents known pixel values. This process is repeated for each pattern in the raw image to interpolate unknown pixel values at each central pixel location. The next section discusses how to estimate these weight vectors $X_i \; \forall i \in [1, K-1]$.

2.3. Learning Interpolation Parameters

When a camera is designed it is already known that corresponding to which wavelengths it will capture intensity values and for those particular wavelengths the weights can be learned in advance. A set of K band multi-spectral images can be used to learn the weights of neighboring pixels in the interpolation process. Since for full multispectral image the Y vector and the matrix A are known therefore weight vectors X_i in (1) can be learned by solving the convex optimization problem:

$$\arg\min_x \|AX - Y\|_p + \lambda \|X\|_2 \quad (2)$$

where $p \in \{1, 2\}$ and $\lambda \in [0, 1]$. Equation (2) can be solved $K-1$ times for each pattern and there are K different patterns in the K band imagery. Therefore total $K \times (K-1)$ weight vectors can be learned from full multispectral training images.

The interpolation process considers not only the same band values but also other band values in an interpolation window therefore these weight vectors X considers the spectral correlation of different bands and spatial correlation of the neighboring pixels.

A set of training images can be chosen such that they have various low and high frequency features so that the learned weight vectors are robust to different kinds of images. The interpolation window size should be such that there are samples from all the bands captured in the raw image e.g. a window size of 3×3 is not sufficient for 6 band multispectral images since in this window there will be too few samples to do effective interpolation. On the other hand a large window size will show image averaging effect. Experiments with different window sizes reveled that a window size of 5×5 is sufficient for four, five, and six band multispectral images.

The weight vector learning is a one-time process that can be done offline. These weights can be used in (1) to do the interpolation on any raw image captured over that particular wavelengths for which weights have been learned. There will be different weight vectors for different number of bands and different spectral gaps. This means that three band multispectral images may have different weights than three band RGB images due to different spectral gaps.

3. EXPERIMENTS AND RESULTS

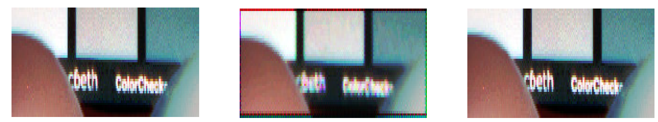
Experiments were done with multi-spectral and color images. Five images from multi-spectral dataset [9] were used to estimate interpolation parameters for three to six band multi-spectral images. Similarly five images from color image dataset [10] were used to estimate parameters for color images. The parameters were learned by solving (2) which is a least square regression problem and hence proposed algorithm is named Least-square based Multi-Spectral Demosaicing (LMSD) algorithm. Five images were used for learning parameters because parameter values were converging to fixed values and more training images had no effect on reconstruction quality. Since parameter learning is convex problem for which efficient solvers exists therefore learning time was few seconds.

After the weight vector estimation, experiments were performed with 20 three to six consecutive bands of multispectral images as well as 20 RGB color images from dataset [11]. Wiener filtering was applied on the reconstructed multi-spectral images to remove some patterned noise. Table 1 presents comparative results of LMSD and BTES for multi-spectral and color images. Average Peak Signal to Noise Ratio (PSNR) values shows that LMSD outperforms BTES in all five cases. The differences in average PSNR values are 2.29 dB for three bands, 2.96 for four bands, 1.87 dB for five bands, and 1.27 dB for six bands whereas for color images it is 4.82 dB.

Proposed UMSF was evaluated using static coefficient (SC) and consistency coefficient (CC) defined in [6]. Table 2 shows comparative values of SC and CC for the proposed UMSF and other existing MSF. In the column headings *B* stands for *bands* e.g. 3B means 3 bands. The values in Table 2 corresponding to MSF are taken from Miao paper [6]. For both SC and CC, the UMSF got zero value which indicates that the proposed filter array design is better as compare to existing MSF.

Table 2. Comparison of Multispectral Filter Arrays

	Miao [6]				UMSF			
Metric	3B	4B	5B	6B	3B	4B	5B	6B
SC	0	0	0	0	0	0	0	0
CC	0.29	0	0.49	0.29	0	0	0	0



(a) Original (b) BTES (c) LMSD

Fig. 2. Reconstruction results for a portion of 5-band multispectral image with BTES and proposed LMSD algorithms. Images are shown in false color composite.

Figure 2 shows reconstruction results for a 5 band multispectral image using LMSD and BTES algorithms. Multispectral images are shown in false color composite after doing histogram equalization for better visual contrast. There are no image artifacts visible for the proposed LMSD unlike BTES reconstruction where artifacts are clearly visible. Hence proposed reconstruction results are visually better than BTES. The reconstruction time of a five band multispectral image of size $512 \times 512 \times 5$ was around 80.91 seconds for BTES and 0.29 seconds for proposed LMSD technique on the same machine which indicates that proposed demosaicing technique is significantly faster. However these values are implementation dependent and shall vary on different machines.

4. CONCLUSIONS

The proposed single-sensor multi-spectral imaging technique can be used to develop low cost and small size multi-spectral cameras which will not suffer from the problem of image to image registration of multiple bands. Proposed UMSF has been experimentally proved to be more effective as compared to other MSF array.

Quantitative results proved that reconstruction quality of LMSD approach is better than the already existing algorithm. Currently experiments have been performed with three to six band multispectral images and more experiments needs to be carried out by increasing the number of bands and by varying spectral gap. Once offline training is done then the proposed algorithm is linear-time because every pixel is visited only

Table 1. Comparison of PSNR(dB) values for BTES and proposed LMSD algorithms on multispectral and RGB image datasets.

	BTES					LMSD				
Img No.	3band	4band	5band	6band	RGB	3band	4band	5band	6band	RGB
1	48.83	46.34	45.3	44.26	26.31	50.67	49.29	46.05	43.71	32.93
2	36.63	34.08	32.56	30.91	33.32	38.81	37.26	35.24	33.56	37.99
3	47.33	44.99	43.34	41.64	34.6	46.38	42.24	37.91	34.47	39.57
4	42.36	37.97	36	34.48	33.71	44.63	41.25	38.32	34.95	36.76
5	55.28	52.74	51.09	49.45	26.66	56.51	55.08	52.35	49.26	31.08
6	38.58	35.88	34.47	32.94	27.79	40.07	38.13	36.73	35.55	33.39
7	45.25	42.81	41.77	40.91	33.49	47.8	46.14	44.96	44.04	37.52
8	50.38	46.81	44.96	43.4	23.63	53.26	50.95	48.41	45.93	30.83
9	50.87	48.65	47.23	45.51	32.43	50.34	49.68	47.8	45.24	38.11
10	51.92	48.93	46.82	44.61	32.42	52.67	51.34	48.99	46.34	38.2
11	44.84	42.21	40.48	38.56	29.19	45.92	43.95	42.29	40.73	34.17
12	51.59	48.5	46.64	44.55	33.46	53.72	52.03	48.91	46.17	39.31
13	50.79	48.48	46.62	44.56	23.89	52.39	51.77	48.99	46.37	27.94
14	45.87	43.17	41.9	40.35	29.25	49.54	47.38	45.04	43.15	32.95
15	48.23	45.57	43.49	41.67	33.24	48.27	46.4	44.63	43.09	36.32
16	43.92	40.97	39.3	37.66	31.28	45.23	43.4	42.14	40.95	37.37
17	41.38	38.09	36.62	35.02	32.1	44.12	40.31	36.81	33.88	35.43
18	47.18	45.23	44.08	42.84	28.17	49.38	47.52	45.32	43.07	32.02
19	36.25	32.88	31.65	30.54	28.15	40.22	38.55	36.94	35.64	35.15
20	46.7	43.9	42.62	41.51	31.81	50.51	48.4	46.48	44.62	36.18
Avg.	**46.21**	**43.41**	**41.85**	**40.27**	**30.25**	**48.02**	**46.05**	**43.72**	**41.54**	**35.16**

once for doing interpolation. Since proposed algorithm is fast and more accurate as compare to previously existing technique therefore it is applicable to be implemented for real-time imaging in the multispectral cameras.

Following the philosophy of reproducible research, source code for BTES and LMSD implementation can be obtained from Matlab central web-link [12] or via email to corresponding author.

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