Demosaicking Multispectral Images by Sphere Packing Filter Design

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Abstract: We propose an optimal distribution of spectral filters in a multispectral filter array based on packing congruent spheres in a 3D-euclidean space, promoting uniformity in the sensing of the 3D-datacube while leading to improved reconstructions.
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1. Introduction

The color filter array (CFA) sample spatial-spectral signals into a two dimensional sensor array, acquiring a grayscale mosaic projection in order to recover a color image through demosaicking algorithms [1].The multispectral filter array (MSFA) extends the CFA three-band base (tri-chromatic) to several spectral bands [2], leading to a trade-off between spatial and spectral resolution.

An important benefit of an well-designed MSFA would be improve the spectral resolution without heavy losses in the spatial resolution. This can be achieved with the help of demosaicking algorithms, where the simplest case would be just to apply independent spatial interpolation [2] per-band. Nonetheless, demosaicking algorithms can take better advantage of the prior-knowledge of the image statistics and the existent spatio-spectral correlations to deliver state-of-the-art reconstructions [3]. However, demosaicking for the MSFA deals with two main challenges. Firstly, dealing with more spectral bands comes with a higher computational burden during the rendering of the spatial-spectral image. Secondly, most demosaicking algorithms assume fixed pattern spectral filters. Therefore, we propose a novel MSFA pattern with an uniform distribution of optical filters, following a sphere packing optimization strategy recently used for snapshot temporal imaging [4]. Our approach maximizes the minimal spectral distance between filters, which reduce the aliasing when demosaicking the MSFA leading to improved reconstructions, while facilitating the scalability of the demosaicking algorithms.

2. Methods

The acquisition of the grayscale mosaic compressive multispectral projection of N_f spectral bands is

$$\mathbf{Y} = \sum_{l=1}^{N_f} \mathbf{X}_l \odot \mathbf{C}_l + \Omega \tag{1}$$

where $\mathbf{X}_l \in \mathbf{R}^{N_x \times N_y}$ is the l^{th} spectral band with $N_x \times N_y$ number of pixels, $\mathbf{C}_l \in \mathbf{R}^{N_x \times N_y}$ denote the positions of the filters at l^{th} wavelength, $\odot$ is the Hadamard product, and Ω is the Gaussian noise. The discrete model is similar to the sensing model of the CACTI presented in [5]. The proposed design for the MSFA is equivalent to packing spheres in a cubic container [6]. One of the optimal solutions to the $3DN_x^2$ Queens Problem associated to the MSFA sensing is:

$$\mathbf{G} = (a \odot \mathbf{I} + b \odot \mathbf{J}) \mod N_f + \mathbf{1}, \tag{2}$$

where $\mathbf{I} = \mathbf{x}^T \otimes \mathbf{y}$ such that $\mathbf{I} \in \mathbb{R}^{N_x \times N_x}$, being $\mathbf{x}$ a vector of all ones such as $\mathbf{x} \in \mathbb{R}^{N_x}$, and $\mathbf{y} = [1, \ldots, N_x]^T$ such as $\mathbf{y} \in \mathbb{R}^{N_x}$, $\odot$ denotes the Hadamard product, and $\otimes$ represents the Kronecker product, $\mathbf{J} = \mathbf{I}^T$, $\mathbf{1} \in \mathbb{R}^{N_x \times N_y}$ $i \in \{1, \ldots, N_x\}$, $j \in \{1, \ldots, N_y\}$. The resulting positions for the MSFA are:

$$C_{i,j,l} = \begin{cases} 1 & \text{if } l = G_{i,j} \\ 0 & \text{if } l \neq G_{i,j}, \end{cases}$$

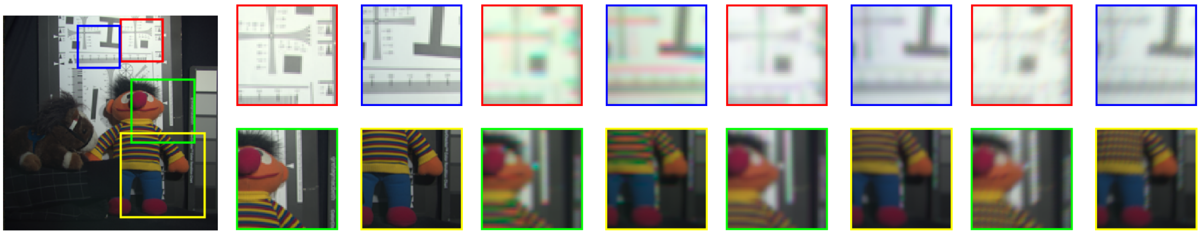
where $l \in \{1, \ldots, N_f\}$. Thus, the distance between a set of n spheres is given by

$$d^*(n) = \max\Big(\min_{1 \le u < v \le n} \|\mathbf{p}_u - \mathbf{p}_v\|_2\Big), \tag{3}$$

where $\mathbf{p}_u$ and $\mathbf{p}_v$ are the centers of the u^{th} and v^{th} sphere, respectively [4].

3. Results

To compare the performace of the proposed MSFA design, we used the CAVE dataset [7], with datacubes of $N_x = N_y = 256$ and $N_f = 16$ for our experiment. The evaluation includes a comparison of the proposed mosaic filter with two state-of-the-art MSFAs, the BTES [2] and the IMEC [8]. Fig. 1 compares the groundtruth RGB representation and the MSFA reconstructions. Despite generating blur, by solely using interpolation we can observe the benefits of our MSFA design in Fig. 1(e), where it is clear that both BTES and IMEC show artifacts and color distortions due to aliasing in high-frequency areas. These artifacts are even more clear in the red, blue, and green crops for IMEC Fig. 1(c) and BTES Fig. 1(d).



(a) (b) Groundtruth (c) IMEC16 (d) BTES (e) Our Method

Fig. 1: MSFA reconstruction comparison using interpolation. (a) RGB Grountruth; (b) cropped groundtruth; (c) IMEC16 recosntruction; (d) BTES reconstruction; Our MSFA reconstruction.

Furthermore, we adapted a novel neural network [9] developed for compressive hiperspecrtral imaging to our MSFA demosaicking problem. This network consists of an autoencoder with a reversible neural network in the middle section and implements 3D-Convolution blocks as layers. The network is trained to demosaic the multispectral datacubes from the different MSFAs using 70 datacubes between of the CAVE dataset [7] and TokyoTech [3], using also data augmentation procedures. The average PSNRs achieved by the MSFAs are depicted in Table 1, where the advantages of our novel MSFA for enhanced reconstructions are even more evident.

	Random	IMEC	BTES	Our Method
Groundtruth 1a (Interpolation)	24.09[dB]	24.02[dB]	24.09[dB]	24.55[dB]
Groundtruth (Neural Network Demosaicking)	26.55[dB]	25.84[dB]	27.95[dB]	28.90[dB]

Table 1: PSNR for preliminary results of Neural Network and Interpolation.

4. Conclusions

We designed a novel MSFA design procedure by using a sphere packing filter approach improve the spatio-spectral sampling for multispectral images. Results show promising results with interpolation which are enhanced when using advanced demosaicking algorithms. We are working on the experimental demonstration of the superiority of our new MSFAs.

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