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Simultaneous image fusion and demosaicing via compressive sensing

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ABSTRACT

In this paper, a compressive sensing based simultaneous fusion and demosaicing method for raw data of single-chip imaging camera is introduced. In order to meet the incoherence constraints of compressive sensing theory, the popular Bayer CFA is replaced with a random panchromatic color filter array. Then, the demosaicing problem is cast as an ill-posed inverse problem inherently and the compressive sensing technology is employed to solve the inverse problem. The restored sparse coefficients of different images are further fused with ℓ_1-norm of the coefficients being served as activity measurements. The final fused image is reconstructed from the fused sparse coefficients. The extended joint sparse model is further used to exploit the inter-channel correlation of different color components. The simulation results illustrated in Experimental Section demonstrate that the proposed method gives both superior quantitative and qualitative performances.

1. Introduction

Image fusion is defined as the process of integrating the redundant and complementary information of two or more source images of the same scene and the aim is to get a more reliable and informative description of the scene [1–3]. Up to now, various fusion methods have been proposed and they have been applied in many fields of information processing, such as medical imaging, remote sensing, and digital camera. The multi-resolution analysis such as stationary wavelet transform (SWT) [4], dual-tree complex wavelet transform (DTCWT) [5], curvelet transform (CVT) [6] and nonsubsampled contourlet transform (NSCT) [7] are widely used to solve the image fusion problems since the multi-resolution coefficients can effectively represent the underlying local salient features of the images. In recent years, sparse representation attracts more attention in image fusion applications and the methods based on sparse representation got superior performances [8]. The reason is that sparse representation decomposes an image with a overcomplete dictionary which is much richer to describe images effectively.

In most visual application systems, the images are captured by the single-chip cameras which capture only one sample out of three channels per color image pixel with the color filter arrays (CFAs) [9]. The other two channels for each color pixel are needed to recover to obtain the full-color image. Such recovering process has been widely known as 'demosaicing'. The simplest demosaicing approaches treat image color channels separately and fill in missing pixels in each channel. Such simple spatial non-adaptive algorithms are known as interpolation. Numerous improved algorithms have also been proposed [9–11,20]. Based on the assumption that the hue of an image does not change abruptly, the authors proposed an improved interpolation method in [12]. In [13], a novel alternating projection scheme was introduced by considering the strong inter-channel correlations between different high frequency sub-bands of the color image.

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Traditional image fusion systems perform demosaicing and fusion separately. When the fusion processing of raw mosaic image data is needed, a separate demosaicing preprocessing step must be previously performed before the fusion operation. With such framework, the artifacts created during demosaicing may be propagated to the fusion step. Obviously, the demosaicing and fusion can be integrated since the a priori models such as multi-resolution, sparsity, inter-channel correlation used in demosaicing methods are also often employed by various image fusion methods. In addition, the efficiency of the integrated scheme can also be enhanced. Therefore, a novel approach that performs image demosaicing and fusion simultaneously under the CS framework is proposed in this paper.

Compressive sensing theory (CS) provided a new signal sensing framework, which guarantees the sparse or compressible signal can be accurately reconstructed from a small set of its incoherent projections [14]. In the proposed method, the imaging process of the consumer-level single-chip cameras is seen as the compressive sensing encoding process. Thus, the demosaicing problem can be cast as an ill-posed inverse problem inherently and the compressive sensing is employed to recover its corresponding sparse coefficients which are further fused with the predefined fusion rule. Then, the fused color image is constructed from the fused sparse coefficients. The experimental results on both natural and artificial multi-focus mosaic images validate the effectiveness of the proposed method.

The remainder of this paper is organized as follows. Section 2 reviews the theory of compressive sensing in brief and the demosaicing method with compressive sensing. Section 3 presents the proposed jointed image demosaicing and fusion scheme. Section 4 gives the experimental results. Finally, we conclude this paper in Section 5.

2. Compressive demosaicing

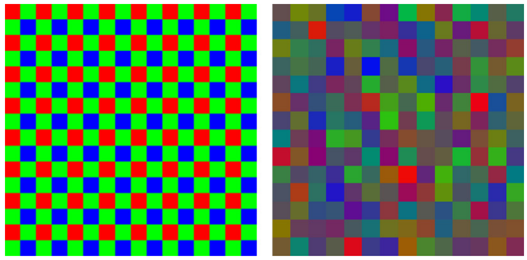
Consider a sparse signal $\boldsymbol{x} \in \boldsymbol{R}^N$ with only k $(k \ll N)$ non-zero entries. CS theory indicates that $\boldsymbol{x}$ can be accurately reconstructed from the measurements $\boldsymbol{y} = \mathbf{L}\boldsymbol{x}$, where $\mathbf{L}$ is a measurement matrix with size of $M \times N$ $(M \ll N)$ [14]. In practical applications, if the natural signal $\boldsymbol{x}$ is not sparse in spatial domain, it can be represented as a sparse vector with respect to a overcomplete dictionary as $\boldsymbol{x} = \mathbf{D}\boldsymbol{\alpha}$, which can be recovered by solving the following optimization problem:

$$\hat{\boldsymbol{\alpha}} = \arg\min \|\boldsymbol{\alpha}\|_1 \quad \text{s.t. } \boldsymbol{y} = \mathbf{LD}\boldsymbol{\alpha} \tag{1}$$

where $\mathbf{LD}$ is referred to projection matrix, which should adhere to certain conditions [14]. This problem can be solved tractably, for instance using Basis Pursuit (BP) [15] or the orthogonal matching pursuit (OMP) [16]. Finally, the estimated original signal is constructed by $\hat{\boldsymbol{x}} = \mathbf{D}\hat{\boldsymbol{\alpha}}$.

For most consumer-level single-chip ordinary cameras, only one sampled value for per pixel can be obtained. Let $\boldsymbol{y}_{i,j}$ denote the pixel value of the sensed image at location (i, j). It can be modeled as CS measurement as:

$$\boldsymbol{y}_{i,j} = \begin{pmatrix} a_{i,j} & b_{i,j} & c_{i,j} \end{pmatrix} \begin{pmatrix} R_{i,j} \\ G_{i,j} \\ B_{i,j} \end{pmatrix} \tag{2}$$



(a) (b)

Fig. 1. The CFA patterns. (a) the Bayer pattern; (b) the random panchromatic CFA. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

where $a_{i,j}$, $b_{i,j}$ and $c_{i,j}$ are the positive weights associated with the red, green and blue sample with constrain $a_{i,j} + b_{i,j} + c_{i,j} = 1$. The vector $\begin{pmatrix} R_{i,j} & G_{i,j} & B_{i,j} \end{pmatrix}^{\mathrm{T}}$ is consisted of the color values of the pixel located at the location (i, j). If the weight equals to one, a complete pass is carried out while zero indicates total blockage. So, this formulation is also valid for famous Bayer CFA as shown in Fig. 1(a). A random panchromatic CFA as Fig. 1(b) will be more attractive for compressive demosaicing [14]. For any pixel in (2), we have an under determined system with one sample value $\boldsymbol{y}_{i,j}$ and three unknowns $R_{i,j}$, $G_{i,j}$, $B_{i,j}$. Therefore, the demosaicing task is finding the three unknowns from one measurement, which cannot be solved by linear algebraic directly. So we cast the demosaicing task as the compressive sensing model as (1). In order to take advantage of local structure information of image signals, we extend (2) to image patch with size of $N \times N$ as

$$\boldsymbol{y} = \mathbf{L}\boldsymbol{x}, \tag{3}$$

where $\boldsymbol{x} \in R^{N\times N\times 3}$ is the vectorized color image patch with lexicographically order; the measurement matrix is defined as $\mathbf{L} = [\bar{\boldsymbol{a}}\bar{\boldsymbol{b}}\bar{\boldsymbol{c}}]$, where $\bar{\boldsymbol{a}}$, $\bar{\boldsymbol{b}}$, and $\bar{\boldsymbol{c}}$ are diagonal matrices with random CFA channel values are listed in diagonal position respectively; $\boldsymbol{y}$ is the vectorized mosaic image patch with lexicographically order. The illustrated relationship between the original color image and the sensed CFA image is shown in Fig. 2 with $N = 2$. Since the CS framework utilizes the a priori knowledge that an image to be sampled is sparse under some dictionary, the sparsity is important for effectively image recover. Therefore, the vectorized image patch $\boldsymbol{x}$ can be represented as sparse coefficients with an overcomplete dictionary $\mathbf{D}$ as

$$\boldsymbol{x} = \mathbf{D}\left[\boldsymbol{\alpha}_{\mathrm{R}}^{\mathrm{T}}\boldsymbol{\alpha}_{\mathrm{G}}^{\mathrm{T}}\boldsymbol{\alpha}_{\mathrm{B}}^{\mathrm{T}}\right]^{\mathrm{T}}, \tag{4}$$

where $\boldsymbol{\alpha}_{\mathrm{R}}$, $\boldsymbol{\alpha}_{\mathrm{G}}$ and $\boldsymbol{\alpha}_{\mathrm{B}}$ are the sparse representations of the R, G and B planes respectively.

Combining (3) and (4), we get

$$\boldsymbol{y} = \mathbf{LD}\left[\boldsymbol{\alpha}_{\mathrm{R}}^{\mathrm{T}}\boldsymbol{\alpha}_{\mathrm{G}}^{\mathrm{T}}\boldsymbol{\alpha}_{\mathrm{B}}^{\mathrm{T}}\right]^{\mathrm{T}} = \mathbf{P}\boldsymbol{\alpha}^{\mathrm{T}}. \tag{5}$$

The demosaicing problem can be solved in compressive sensing framework as

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\alpha} \|\boldsymbol{\alpha}\|_1 \quad \text{subject to } \boldsymbol{y} = \mathbf{P}\boldsymbol{\alpha}. \tag{6}$$

The color image is reconstructed as $\boldsymbol{x} = \mathbf{D}\hat{\boldsymbol{\alpha}}$.