Efficient Demosaicing Through Recursive Filtering

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***Abstract*— We present a computationally efficient demosaicing algorithm based on a luminance-chrominance model of the Color Filter Array (CFA) image. We show that the chrominance information can be estimated using simple low-pass filtering. This algorithm allows us to use separable recursive filters, which are particularly adapted for real-time processing. Moreover, while most of demosaicing algorithms are specific to a particular CFA (usually the popular Bayer CFA), our method can be applied to any CFA. We present a linear version of the algorithm and an adaptive extension.**

I. Introduction

Color demosaicing refers to the operation of constructing a color image from a mosaic of chromatic samples. In digital cameras today, the color information is sampled with a single sensor in front of which is placed a Color Filter Array (CFA). The resulting image has a single color value per pixel and should be interpolated to retrieve the corresponding color image. The interpolation is generally not perfect and there may appear artifacts in the reconstructed image. The most used CFA is the one proposed by Bayer [1].

Two main types of methods have been proposed in the literature : linear ones and adaptive ones, each one corresponding to a characteristic of color images [2]. Linear methods (such as [3], [4]) exploit the spectral correlation or inter-plane correlation (the color planes are very similar one to each other in high frequencies). Since this correlation depends only on the spectral sensitivities of the color filters, it is assumed constant over the image and a linear uniform algorithm is used. Nonlinear or adaptive methods (such as [5]–[9]) exploit in addition the spatial correlation or intra-plane correlation (there is a stronger correlation between pixels along a contour than across it). The visual artifacts of the demosaicing process can be substantially reduced by taking into account both correlations. However, an adaptive algorithm means analyzing the image content, and hence increasing the computational complexity of the algorithm. At the opposite, linear methods are computationally efficient, but there may remain some artifacts in areas of high frequency content. Thus, demosaicing always results in a compromise between image quality and computation time. The search for the optimal tradeoff is becoming more and more determining with the advent of cameras on embedded systems such as mobile phones. In this context, we propose a linear method that uses recursive filtering to reduce computation time. We also propose an extension with adaptive processing to increase the quality of the reconstructed image.

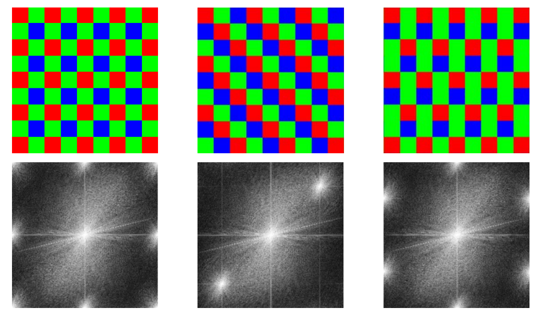

(a) (b) (c)

Fig. 1. CFA patterns and amplitude specta of a corresponding CFA image: (a) Bayer CFA; (b) diagonal stripes CFA; (c) CFA proposed by Lukac [2].

Moreover, every demosaicing algorithm is designed for a specific mosaic, generally the Bayer CFA. The method we propose here can be applied on any mosaic, in particular on pseudo-random mosaics, which reveal interesting properties in terms of false colors reduction. To our knowledge, the only attempts of demosaicing a general mosaic can be found in [2] and [10], but they are computationally heavy.

The paper is organised as follows. We first recall the spectral model of Alleysson *et al.* [4] in Section II. Then, we describe our new approach in Section III. We finally discuss its implementation in both linear and adaptive manners, using recursive filters (Section IV).

II. Color opposition model

Let m be the global sampling lattice (or mosaic), without distinction of the color filter types. We restrict ourselves to the case where m is a square lattice of Dirac impulses. m can be decomposed into three sub-mosaic m_R, m_G and m_B:

$$m = m_R + m_G + m_B \quad (1)$$

where $m_i(x,y)$ is 1 or 0 whether the filter i (with $i \in \{R,G,B\}$) is present or not at pixel (x,y). In the Fourier domain, we have:

$$\hat{m} = \delta_0 \quad \text{and} \quad \begin{cases} \hat{m}_R = r_0\delta_0 + \sum_{n\neq 0} r_n\delta_n \\ \hat{m}_G = g_0\delta_0 + \sum_{n\neq 0} g_n\delta_n \\ \hat{m}_B = b_0\delta_0 + \sum_{n\neq 0} b_n\delta_n \end{cases} \quad (2)$$

where δ_n denotes the Dirac impulse at spatial frequency n. For instance, for the Bayer pattern n describes the set [4]:

$$\left\{(\frac{k}{2}, \frac{l}{2}), \text{ with } (k,l) \in \{-1,0,1\} \text{ and } (k,l) \neq (0,0)\right\} \quad (3)$$

r_0, g_0 and b_0 are the mean values of each submosaic, or in other words, the probability at each spatial location to have a sample of the respective color channel. Let us call them respectively p_R, p_G and p_B. By unicity of the Fourier transform, we may conclude:

$$\begin{cases} p_R + p_G + p_B = 1 \\ r_n + g_n + b_n = 0 \qquad (\forall n \neq 0) \end{cases} \quad (4)$$

Now, let $I = \{C_R, C_G, C_B\}$ be a color image, *i.e.* with three color planes. The resulting CFA image I_m (a grayscale image containing the color mosaic) is obtained by:

$$I_m(x,y) = \sum_{i\in\{R,G,B\}} C_i(x,y).m_i(x,y) \quad (5)$$

and its Fourier transform is:

$$\hat{I}_m(\nu) = \underbrace{\sum_i p_i \hat{C}_i(\nu)}_{\hat{\phi}(\nu)} + \sum_{n\neq 0} \underbrace{\begin{array}{l} \quad r_n\hat{C}_R(n-\nu) \\ + \quad g_n\hat{C}_G(n-\nu) \\ + \quad b_n\hat{C}_B(n-\nu) \end{array}}_{\hat{\psi}_n(n-\nu)} \quad (6)$$

ϕ is a linear combination of color signals with positive weights, it is a luminance term. $\psi_n(n-\nu)$ is a linear combination of color signals with coefficients whose sum vanishes, modulated at frequency n. It is a modulated chrominance. Fig. 1 shows three examples of CFA's and the amplitude spectra of an image sampled by those CFA's. We can see on that figure that the CFA pattern guides the location of the chrominance carriers, and controls thus the amount of aliasing between the baseband luminance and the modulated chrominances.

This model has been used for designing a linear space-invariant demosaicing algorithm [4] and two adaptive algorithms [7], [8], which all apply on the Bayer CFA.

III. Description of the novel approach

Let f be a lowpass filter, whose characteristics will be specified later. Let us call I_m^{LF} the CFA image filtered by f:

$$I_m^{LF} = f * I_m \quad (7)$$

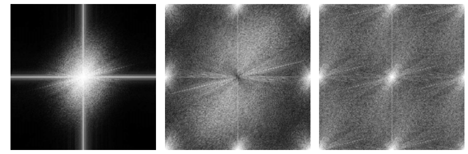
where $*$ denotes the convolution product. Using Eqn. (6) - chrominances are modulated to high frequencies - we have:

$$f * \sum_{n\neq 0} \psi_n \approx 0 \quad (8)$$

and hence

$$I_m^{LF} = f * \phi = \phi^{LF} \quad (9)$$

The last equation holds if the frequency cutoff f_c of filter f is lower than $(n - f_{max})$, with f_{max} the highest frequency of the chrominance signals. I_m^{LF} thus contains a coarse (but alias-free) estimate of the luminance image ϕ (Fig. 2(a)). Let I_m^{HF} be the complementary signal (Fig. 2(b)):



(a) (b) (c)

Fig. 2. Amplitude spectra: (a) LF luminance ϕ^{LF}; (b) HF mosaic image I_m^{HF}; (c) channel R of the demultiplexed HF mosaic image I_m^{HF}. Each figure corresponds to the Bayer case.

$$I_m^{HF} = I_m - \phi^{LF} \quad (10)$$

I_m^{HF} conveys the modulated chromatic oppositions and the details of luminance (high-frequency luminance ϕ^{HF}). In the frequency domain we have:

$$\hat{I}_m^{HF}(\nu) = \hat{\phi}^{HF}(\nu) + \sum_{n\neq 0} \hat{\psi}_n(n-\nu) \quad (11)$$

with $\phi = \phi^{LF} + \phi^{HF}$.

Let us now examine the demultiplexing of I_m^{HF}. The demultiplexing of a mosaic image is the conversion from the grayscale image to the color image, with still one color per pixel. It is equivalent to multiplying the mosaic image I_m^{HF} by the submosaics m_i to get the three color channels $\{I_m^{HF}\}_i$:

$$\{I_m^{HF}\}_i(x,y) = I_m^{HF}(x,y)m_i(x,y) \quad (12)$$

Using Eqn. (10), it comes:

$$\{I_m^{HF}\}_i = I_m m_i - \phi^{LF} m_i \quad (13)$$

where in fact $I_m m_i = C_i m_i$, and $C_i = \phi + \{\psi\}_i$. So we have:

$$\begin{array}{rl} \{I_m^{HF}\}_i & = (\phi + \psi_i)m_i - \phi^{LF} m_i \\ & = (\phi^{HF} + \psi_i)m_i \end{array} \quad (14)$$

The submosaic m_i can be decomposed into the sum of a constant part p_i and a modulating part $\tilde{m}_i$, $m_i = p_i + \tilde{m}_i$ as in Eqn. (2), which yields to:

$$\{I_m^{HF}\}_i = \underbrace{p_i(\phi^{HF} + \psi_i)}_{\text{baseband}} + \underbrace{(\phi^{HF} + \psi_i)\tilde{m}_i}_{\text{modulated}} \quad (15)$$

We thus have two terms in the expression of $\{I_m^{HF}\}_i$: one term is baseband, the other one is HF modulated (Fig. 2(c)). Moreover, if the frequency cutoff f_c of filter f was chosen to match the chrominance bandwidth, ϕ^{HF} and ψ_i have disjoint supports (the chrominance of natural images ψ being generally a lowpass signal). Consequently, simple lowpass filters on the demultiplexed HF image are sufficient to recover the full chrominance components of the image. In practice we use the same filter f used for the estimation of ϕ^{LF}:

$$\psi_i = \frac{1}{p_i} f * \{I_m^{HF}\}_i \quad (16)$$

Knowing the mosaic image and the chrominance components, one can retrieve the full luminance component by subtraction:

$$\phi = I_m - \sum_{i \in \{R,G,B\}} \psi_i m_i \tag{17}$$

An error-free recovery is illusory for real images, in practice there is spectral overlapping between chrominance and modulated luminance which expresses itself through false colors and/or zipper noise. To improve the visual rendering, an adaptive extension of the algorithm will be introduced in the next section.

To sum up, the approach can be divided into 5 steps:

1) separation of the mosaic image I_m into low and high frequency components ϕ^{LF} and I_m^{HF},
2) demultiplexing of the HF component,
3) filtering of each color plane in order to get the chrominance components ψ_R, ψ_G and ψ_B,
4) retrieving of the luminance ϕ by subtraction between the mosaic image and the "remodulated" chrominances,
5) addition of luminance to each chrominance to get C_R, C_G and C_B.

IV. Implementation

In the following section, we present two implementations of the approach that was described in the preceding section. One is a linear version whereas the other one is an edge-adaptive extension.

A. Linear method

The crucial point of the linear method is the design of the filter f. f has the only constraint to be lowpass, and to match the chrominance bandwidth. For computational efficiency, we chose to implement it using a separable recursive filter whose z-transform is $F(z_1, z_2) = F_1(z_1)F_2(z_2)$, where z_1 and z_2 are the horizontal and vertical variables, and with

$$F_k(z_k) = (1-a)^2 \frac{1}{1-az_k^{-1}} \frac{1}{1-az_k} \qquad (k \in \{1,2\}) \tag{18}$$

Note that F involves only 4 neighbors. Its frequency response is represented in Fig. 3. As the reader can see, F attenuates much more in diagonal than in horizontal/vertical directions. Hence, a one-order numerator is needed for mosaics whose m_i modulate at horizontal or vertical direction (*e.g.* the Bayer pattern for R/B channels). However, this FIR part is superfluous for CFA's that do not modulate chrominance in horizontal and vertical directions.

The parameter a controls the cutoff frequency, and hence, the tradeoff between false colors and zipper noise. For the Kodak database, we empirically found $a = 0.5$.

Note that in Eqn. (16), the densities p_i of the color filters are involved. For the Bayer CFA, these are constant and have values $\{0.25, 0.5, 0.25\}$. In a general case, these densities may vary locally around the mean values. These variations have to be taken into account in the filtering process in order to match the luminance definition of Eqn. (6). Eqn. (16) will be thus rewritten (for $i \in \{R,G,B\}$):

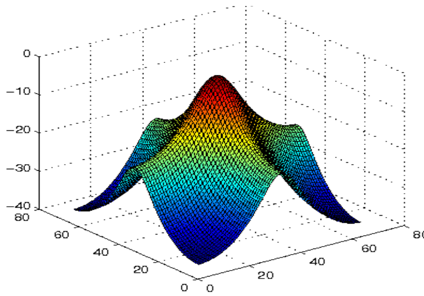


Fig. 3. Frequency response of the IIR filter (dB).

$$\psi_i = \frac{f * \{I_m^{HF}\}_i}{f * m_i} \tag{19}$$

This technique is called normalised convolution [11]. Note that $f * m_i$ depends only on the mosaic and can thus be hard coded. The same precaution holds for the estimation of ϕ^{LF}.

B. Adaptive extension

The coarse, alias-free luminance ϕ^{LF} can be exploited in order to filter more accurately the chrominances. This "rough" estimate may appear sub-optimal to the reader who is aware that classical demosaicing methods use the mosaic image I_m directly (*e.g.* [7], [9]), without any lowpass filtering. However these methods must compute gradients between pixels of the same class (R, G or B), wich are not adjacent on the CFA. Therefore, ϕ^{LF} contains the same amount of spatial information as the marginal planes of the mosaic image do. Moreover ϕ^{LF} has the property of being totally independent from the mosaic, since it contains pure spatial information. The edge detection on ϕ^{LF} will thus be mosaic blind.

We propose a voluntary simple adaptive method, in order not to increase to much the computation time, consisting in rendering edge adaptive the chrominance filtering. We compute the horizontal and vertical gradients on ϕ^{LF}. These gradients are used to choose the direction of interpolation of the chrominance filtering, using F_1 or F_2. Residus of luminance are then removed from the interpolated chrominances:

$$\psi_i(x,y) = \psi_i(x,y) - \sum_{j \in \{R,G,B\}} p_j \psi_j \tag{20}$$

As other adaptive methods, a postprocessing step improves the quality, due to potential misguidings of the adaptive filter. A solution consists in updating the chrominance values using the estimated luminance.

C. Results

We have reported in Table I both the PSNR values (computed over the Kodak databse) of our linear and adaptive methods and of some methods of the litterature, and an estimation of the complexities in terms of operations per pixel.

The linear version has the same quality than the linear algorithm in [4]. However it drastically reduces the computation

(a) (b)

Fig. 4. Crop of a demosaiced image using (a) the linear version and (b) the adaptive version of the proposed method, with (from top to bottom) the Bayer's, Lukac's and the diagonal stripes mosaics.

time, because of the recursive filtering. The complexity is approximately of 22 op./pixel (for the Bayer case, a bilinear prefiltering needs to be added).

The adaptive method substantially removes the zipper noise that arises with the linear method (Fig. 5(b)). While the results are visually improved, the PSNR values are close to those of the linear method. This may be due to the fact that the proposed adaptive method is very simple. A more sophisticated solution should give better objective quality. Interestingly, the fact that a filter type is missing at each line and each column compels us to perform iterative calculations for the Bayer CFA (as most adaptive methods do), and the method loses its efficiency. It is much more efficient on CFA's that do not have the property of carriers at vertical and horizontal directions. With respect to the linear version, adding the gradient computation, the luminance residus subtraction and the postprocessing step leads to approximately 50 op./pixel.

It is noteworthy that the visual quality is not the same with every CFA. Pseudo-random CFA's show interesting results in terms of false color suppression (Fig. 5).

V. Conclusion

We presented a new demosaicing approach that is applicable to any CFA arrangement. The linear version is extremely fast, for a reasonable quality. The adaptive extension gives interesting results, in particular on pseudo-random mosaics, but should be improved with a more sophisticated exploitation of the edges.

This algorithm makes an analogy with the visual system. The human retina provides a coarse estimate of the achromatic spatial information at its output, called magno-cellular pathway. This channel is thought to prepare the information for the brain before the arrival of the details of spatial information (high frequencies of luminance) and color oppositions, which are conveyed by the parvo-cellular pathway.

	Linear methods			Adaptive methods			
	Here	[3]	[4]	Here	[7]	[9]	[5]
R	37.89	35.36	37.83	38.23	38.77	38.02	38.40
G	40.53	38.87	40.74	40.62	42.12	39.59	41.37
B	36.70	34.15	36.48	36.98	38.62	36.76	37.46
Comp.	25	21	77	50	63	161	405

TABLE I

PSNR values (dB) and complexity (op./pix.)

(a) (b)

Fig. 5. Reconstruction from the Bayer mosaic (left) and from a pseudo-random mosaic (right), illustrating the false color suppression of the pseudo-random mosaic.

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