ABSTRACT
This paper presents a simple yet effective color filter array (CFA) interpolation algorithm. It is based on a linear interpolating kernel, but operates on YUV space, which results in a nontrivial boost on the peak signal-to-noise ratio (PSNR) of red and blue channels. The algorithm can be implemented efficiently. At the end of the paper, we present its performance compared with nonlinear interpolation methods and show that it’s competitive even among state-of-the-art CFA demosaicing algorithms.

Index Terms— color filter array, interpolation, linear kernel, YUV

1. INTRODUCTION
Most digital cameras capture color images using a single, monochrome sensor. The sensor is covered by a color filter array (CFA) such that incoming light is spectrally sampled. Due to the presence of the CFA, only one of R, G and B components is sampled at each pixel sampling location, resulting (together with other information) in the image known as the raw image. The most popular type of such mosaic is Bayer Filter Array [1], shown in figure 1. The raw image undergoes a chain of processing stages inside the digital camera before finally presented as a full-color image. One of the most important stages is demosaicing, in which the missing color components at each pixel are estimated using some prior knowledge. Demosaicing can be essentially formulated as an upsampling problem. The real image is first downsampled by the camera and then upsampled in the demosaicing process. Therefore, standard interpolation techniques such as bilinear interpolation can be directly applied. Such techniques are fast, memory-saving, but are subject to non-negligible artifacts such as false color and zipper effect [14]. They are primarily consequences of bad sampling and ringing effect across edges. Nonlinear methods make use of spatial and interchannel correlation to help restoration. State-of-the-art restoration techniques include smooth hue transition [14] [2] and edge-directed interpolation [4] [15]. They achieve excellent results in terms of peak signal-to-signal ratio (PSNR).

To our knowledge, all the state-of-the-art techniques mentioned make use of RGB information exclusively. We propose a new vision on demosaicing, with linear interpolating kernels, but in the YUV space. Although the PSNR obtained does not outperform all the techniques above on standard test images (lighthouse 1, lighthouse 2, sails, buildings) in this realm of research, we obtain a boost in the R and B channels (about 5 dB) for almost free (no prior knowledge on hue or edges is assumed). The linear interpolating kernels we experimented include B-spline family functions and O-MOMS functions.

2. COLOR FILTER ARRAY INTERPOLATION
2.1. Traditional Approach
Bayer color filter array samples in such a way that the number of samples in G channel double those in R and B channels respectively. The reason is based on human visual system, the luminance response of which peaks at around the frequency of green light.
An example of such a color space representation is the YUV color space. Our rationale is that this color space is characterized by a luminance (Y) component and two chrominance (U and V) components. The three components are less correlated in the sense that luminance and chrominance components are separated explicitly on the CFA [3]. Luminance component accounts for light intensity, whereas chrominance components are differential components used to discriminate colors. For example, R can be obtained by subtracting a weighted chrominance component (V) from the luminance component.

RGB space is related to YUV space by a linear transformation

\[
\begin{bmatrix}
Y \\
U \\
V
\end{bmatrix} = \begin{bmatrix}
R_D & B_D & G_D \\
R_{D1} & B_{D1} & G_{D1} \\
R_{D2} & B_{D2} & G_{D2}
\end{bmatrix} \begin{bmatrix}
R_n \\
G_n \\
B_n
\end{bmatrix}
\]

where

\[
\begin{bmatrix}
R_D & B_D & G_D \\
R_{D1} & B_{D1} & G_{D1} \\
R_{D2} & B_{D2} & G_{D2}
\end{bmatrix} = \begin{bmatrix}
0 & 0 & 1 \\
-1 & 0 & 1 \\
1 & -0.5 & 0
\end{bmatrix}
\]

The main disadvantage of RGB representation is the high correlation between its components. Tkalčík [5] reported that there is a 0.78 for \(\gamma_{BR} \) (cross correlation between B and R), 0.98 for \(\gamma_{RG} \) and 0.94 for \(\gamma_{GB} \).

RGB is HVS based, and RGB devices have a luminance response similar to figure 2, from which we observe a substantial channel overlap. Therefore, it is very likely that interpolating them separately and ignoring the interchannel correlation may not produce a “good” result. For this reason, it is desirable to look for alternative color spaces in which each component is isolated from the others.

2.3. New Prior Based on Alternative Color Space

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We relate equation 4 to the RGB samples captured by the camera. A $4 \times 4$ version of transformation matrix $M_{4 \times 4} = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & 1 & -0.39465 & -0.5806 \\ 1 & 1 & -0.39465 & -0.5806 \\ 1 & 1 & 2.03211 & 0 \end{bmatrix}$ by first replicating the first column, and then the second row.

$$\begin{bmatrix} R_{\text{int}}(r) \\ G_{1\text{int}}(r) \\ G_{2\text{int}}(r) \\ B_{\text{int}}(r) \end{bmatrix} = \sum_{k} M_{4 \times 4} \Phi(D^{-1}r - k) \Gamma(k) \quad (5)$$

3. DECONVOLVING AND INTERPOLATION

In order to perform the interpolation in equation 5, the coefficients in $\Gamma(k)$ must be found at first. This process is essentially a deconvolution operation. Substitute the captured samples in equation 1 to obtain

$$S_{\text{sample}}(n) = \sum_{k} \Phi'(n - k) \Gamma(k). \quad (6)$$

where $\Phi'(k)$ can be obtained directly from the sampled values of $M_{4 \times 4} \Phi(r)$. This equation can be solved efficiently by using DFT and solving a linear system in the Fourier domain. The step corresponds to the stage between (b) and (c) in figure 3.

Finally, the full image in YUV representation (figure 3 (d)) can be interpolated with equation 3. The RGB image is obtained using the color space transformation matrix $M_{4 \times 4}$.

4. EXPERIMENTS AND RESULTS

The algorithm is implemented with MATLAB. We test our algorithm by first applying the Bayer filter to a full color test image, mimicking the capturing operation in the digital camera, and then demosaicing the sampled image. For a 768 by 512 image, it takes about 1 second to reconstruct using $\beta^3$ kernel. We use Peak Signal-to-Noise Ratio (PSNR) as the metric for the demosaicing quality. The PSNR between the original image for reference $I_{\text{ref}}$ and the reconstructed image $I_{\text{cmp}}$ for a certain channel is given by

$$\text{PSNR} = 10 \cdot \log_{10} \left( \frac{\text{max}(\max(I_{\text{ref}}))^2}{\frac{1}{mn} \sum \sum ||I_{\text{ref}} - I_{\text{cmp}}||^2} \right) \quad (7)$$

where $mn$ is the total number of pixels in the image.

We tested the algorithm over a wide range of kernels, including $\beta^0$ through $\beta^5$ and O-MOMS functions $\varphi_0^p$ through $\varphi_5^p$, which generally outperforms the B-spline kernel of the same degree [11] [12]. Increasing the kernel degree does not affect the processing time significantly. Some of the representative results are tabulated in tables 1.

We observe a nontrivial improvement on PSNR with linear interpolation in YUV space, for any interpolating kernel, by 3 to 5 dB in R and B PSNRs. However, the G PSNR is actually a little bit smaller than if interpolated in RGB space. Nevertheless, the loss is tolerable. The loss can be compensated by performing another interpolation in the G channel using prior in equation 2 and swapping it back to the reconstructed image.

Since the interpolation is done in Fourier space, very little adaptive step could be applied within the process. It is our ongoing project to apply a nonlinear post-processing step (such as [14]) to improve the quality in artifact prone regions such as edges.

5. CONCLUSIONS AND DISCUSSIONS

We present an efficient algorithm for demosaicing a Bayer image in YUV space with a linear kernel function, which significantly improves the quality of blue and red channels. The generalized linear interpolation can be used as a basis for more sophisticated, nonlinear techniques, such as median filtering [13] or alternating projections [2] [16]. When a $3 \times 3$ median filter is applied to the U and V channels in the reconstructed image, the PSNR of G channel increases by about 0.7 dB, and 0.3 dB for R and B channels (on lighthouse 1).
<table>
<thead>
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Table 1. PSNR for Interpolation results. Each cell shows in turn the PSNR for R, G and B channel.

Experiments on YUV-siblings such as YPbPr, YCbCr or YIQ reveal similar performance.

Having shown that YUV space is good for improving the demosaicing quality, we hypothesize that there exists a non-standard color space that particularly leverages a certain channel. We are working in search of such a magic color space by modifying the linear transformation matrix $M_{4 \times 4}$.

6. REFERENCES


