An improved edge-adaptive color interpolation method for Bayer pattern images of single-sensor digital cameras is proposed in this paper. We derive a more accurate color edge classifier by using both intra-channel and inter-channel correlation. In order to reduce the aliasing artifacts, missing channel values are interpolated along the edge direction. Experiment results show that the proposed method can preserve the edge information better, reduce color-bleeding artifacts and achieve higher image quality and signal fidelity against the existing schemes.

Key words: demosaicing, Bayer pattern, color filter array

1. Introduction

Most digital cameras sample the projected scene with a color filter array (CFA) overlaid on a CCD such that each pixel is read by a single color channel only. The values of the other colors must be interpolated using neighboring samples. This color plane interpolation is known as demosaicing.

The most commonly used color sensor pattern in a digital camera is the “Bayer” pattern [1], as shown in Figure 1.

![Bayer CFA pattern](image)

The density of the green sensors is set as twice as that of the red and blue ones. This is due to a well-known fact that the Human Visual System (HVS) is more sensitive to luminance changes than chrominance changes. The spectral sensitivity of the HVS to luminance is close to the spectral power distribution of the green channel while the HVS to chrominance is similar to that of the red and blue channels.

There are a variety of demosaicing methods available. The simplest linear interpolation scheme estimates the unknown colors with average color values from their nearest neighbors. Although such a method is very simple, it often introduces visible color bleeding or color aliasing artifacts around high frequency regions, resulting in a poor reconstruction of edge information.

More sophisticated demosaicing methods attempt to limit hue transitions. Such smooth hue transition algorithms are based on the assumption that there are no sudden jumps in hue between neighboring pixel locations [2,3]. In these methods, G channel is interpolated with bilinear interpolation, R and B channels are then interpolated by color ratios (R/G, B/G) to avoid false color. This approach gives better results than pure bilinear interpolation. However, artifacts are still visible around sharp transition or edge regions where the assumption of constant hue does not hold.

In order to improve the quality in reconstructing edge regions, some edge-sensing algorithms have been developed [4-6]. The method proposed by Laroche and Prescott [5] first detects the second derivatives of red or blue channel in a local image neighborhood, and then makes effective choice of neighboring pixels to interpolate the missing color values. Adaptive color plan interpolation method, proposed by Hamilton and Adams [6], is a modification of the method by Laroche and Prescott. In addition to using second derivatives as the estimate, the missing green values are estimated by a combination of second derivatives and the green channel gradient estimate. The inter-channel correlation is also used as a correction term in the interpolation.

Another method proposed by Kimmel [7], combined the smooth hue transition and edge-directed interpolation in a three-time iterative correction scheme. This algorithm takes advantage of the fact that at each missing pixel, the gradient is known from the existing neighboring pixels.
The bilinear interpolation is then weighted by the estimated green channel gradient.

Since human visual system (HVS) has increased sensitivity to luminance (green channel) when compared to chrominance, the emphasis will be placed on the G channel reconstruction in this paper. Natural images are characterized by high correlation between their RGB color components [8-9], therefore the interpolation for G channel can take full advantage of the available R and B information. Taking these into account, we propose a new edge classifier to improve G channel reconstruction. Moreover, each yielded component has been fine-tuned after the interpolation of all channels for higher accuracy. The proposed demosaicing algorithm based on the new edge classifier is presented in Section 2, while its performance is demonstrated in Section 3. The last section gives several concluding remarks.

2. The Proposed Algorithm

The edge signals significantly change in luminance, chromaticity, or both. Taking this into account, our approach is based upon a green channel edge classifier that detects edge locations using chrominance and luminance information, intra-channel and inter-channel correlations, aiming at more accurate edge detection than the existing edge-sensing methods [4-7]. The missing channel values are interpolated along the edge direction, not across the edges, so that the aliasing artifacts are reduced.

2.1 G Channel Interpolation

We compute both first and second order directional derivatives in a window of $5 \times 5$ pixels around the missing green pixel. Since the gradient at each missing pixel is known from the existing neighboring pixels, we use all these 25 pixels to estimate it in order to make use of more information about the existing neighboring pixel values therefore obtain more accurate edge information than other existing edge-sensing methods [4-7].

Due to hardware limitations, single CCD arrays in digital cameras capture a sparsely sampled image such that each pixel is read by a single color channel only, like Bayer pattern in Figure 1. In traditional edge-sensing methods [4-7], the edge classifiers and edge-directed function defined by second derivatives or gradients are always detected from the same color plane, so that some fine details in a local area will not be detected accurately, thus introduce inevitable color aliasing artifacts.

In our method, besides the intra-channel directional derivatives of all the RGB components, notice that we also define edge classifier $\Delta H_{GR}$ and $\Delta V_{GR}$ from different color planes by using inter-channel information because of high correlation between the RGB color components. Correlation means that all components have similar derivatives. In a RGB image, all the color channels are very likely to have the same edge content, if the red channel value gets higher in one direction, it is very probable that the green and blue channel values get higher too. Therefore we can make use of this kind of inter-channel correlation to detect fine details in a local region and then improve the accuracy of the edge detection.

In Figure 1, for estimation of missing $G_{34}$ at $R_{34}$, we define edge classifiers as follows:

$$
\Delta H_{GR} = |G_{33} − G_{35}| + |G_{32} + G_{36} − 2G_{34}| + |G_{42} + G_{46} − 2G_{44}|
$$

$$
\Delta V_{GR} = |G_{24} − G_{44}| + |G_{41} + G_{43} − 2G_{33}| + |G_{15} + G_{45} − 2G_{55}|
$$

$$
\Delta H_{B} = |B_{23} − B_{25}| + |B_{43} − B_{45}|
$$

$$
\Delta V_{B} = |B_{23} − B_{43}| + |B_{25} − B_{45}|
$$

$$
\Delta H_{GR} = |G_{33} + G_{35} − 2R_{34}|
$$

$$
\Delta V_{GR} = |G_{24} + G_{44} − 2R_{34}|
$$

(1)

Then we compose the edge classifier as below and perform the interpolation using color difference model [8].

$$
\Delta H = \Delta H_{R} + \Delta H_{G} + \Delta H_{B} + \Delta H_{GR}
$$

$$
\Delta V = \Delta V_{R} + \Delta V_{G} + \Delta V_{B} + \Delta V_{GR}
$$

(2)

If $\Delta H > \Delta V$, then

$$
G_{34} = R_{34} + \frac{(G_{24} − R_{24}′) + (G_{44} − R_{44}′)}{2}
$$

(3)

else if $\Delta H < \Delta V$, then

$$
G_{34} = R_{34} + \frac{(G_{33} − R_{33}′) + (G_{35} − R_{35}′)}{2}
$$

otherwise

$$
G_{34} = R_{34} + \frac{\sum_{j=24,33,35,44}(G_{ij} − R_{ij}′)}{4}
$$

(5)

Where $R_{ij}′$ is calculated by the bilinear interpolation.

2.2 R, B Channels Interpolation

After interpolating the G channel, we use the gradient-based weighted average and also color difference model to
interpolate the R, B channel values, and make use of the available G information to calculate weighting factors. The performance of the R, B channels reconstruction directly depends on the accuracy of the G channel interpolation.

For instance,

\[
B_{34} = G_{34} + \frac{\beta_{23}k_{23} + \beta_{25}k_{25} + \beta_{43}k_{43} + \beta_{45}k_{45}}{\beta_{23} + \beta_{25} + \beta_{43} + \beta_{45}} \\
B_{33} = G_{33} + \frac{\gamma_{23}k_{23} + \gamma_{43}k_{43}}{\gamma_{23} + \gamma_{43}} \\
\]

where \( k_{ij} = B_{ij} - G_{ij} \)

and \( \beta_{ij} = \frac{1}{\sqrt{1 + \left(\frac{G_{ij} - G_{34}}{\sqrt{2}}\right)^2}} \)

\( \gamma_{ij} = \frac{1}{\sqrt{1 + \left(\frac{G_{ij} - G_{33}}{\sqrt{2}}\right)^2}} \)

A similar computation also applies to R channel interpolation.

### 2.3 G Channel Correction

After interpolation, we update the resulting values by adding a correction process. In contrast with the above interpolation steps which utilize four neighboring pixel values, the correction process includes four original values and four interpolated values that are obtained from the above two steps. The G channel correction scheme is similar to the interpolation method above except for the definition of G channel edge classifier.

For correction of \( G_{34} \), first and second directional derivatives of all the RGB channels are used to define the edge classifier.

\[
\Delta H_{G1} = |G_{33} - G_{35}| \quad \Delta V_{G1} = |G_{24} - G_{44}| \\
\Delta H_{R1} = |R_{33} - R_{35}| \quad \Delta V_{R1} = |R_{24} - R_{44}| \\
\Delta H_{B1} = |B_{33} - B_{35}| \quad \Delta V_{B1} = |B_{24} - B_{44}| \\
\Delta H_{G2} = |G_{33} + G_{35} - 2G_{34}| \quad \Delta V_{G2} = |G_{24} + G_{44} - 2G_{34}| \\
\Delta H_{R2} = |R_{33} + R_{35} - 2R_{34}| \quad \Delta V_{R2} = |R_{24} + R_{44} - 2R_{34}| \\
\Delta H_{B2} = |B_{33} + B_{35} - 2B_{34}| \quad \Delta V_{B2} = |B_{24} + B_{44} - 2B_{34}| \quad (11)
\]

then,

\[
\Delta H = \Delta H_{R1} + \Delta H_{G1} + \Delta H_{B1} + \Delta H_{G2} + \Delta H_{R2} + \Delta H_{B2} \\
\Delta V = \Delta V_{R1} + \Delta V_{G1} + \Delta V_{B1} + \Delta V_{R2} + \Delta V_{G2} + \Delta V_{B2} \quad (12)
\]

if \( \Delta H > \Delta V \), then

\[
G_{34} = R_{34} + \frac{(G_{34} - R_{34}) + (G_{34} - R_{34})}{2} \quad (13)
\]

else if \( \Delta H < \Delta V \), then

\[
G_{34} = R_{34} + \frac{(G_{33} - R_{33}) + (G_{35} - R_{35})}{2} \quad (14)
\]

otherwise

\[
G_{34} = R_{34} + \frac{\sum_{ij=23,24,25,33,35,43,44,45} (G_{ij} - R_{ij})}{8} \quad (15)
\]

### 2.4 R, B Channels Correction

Just as in Section 2.3, the correction of the R and B channels also uses eight neighboring pixel values:

\[
B_{ij} = G_{ij} + \frac{k_{i-1,j-1} + k_{i-1,j} + k_{i,j-1} + k_{i,j}}{8} + \frac{k_{i,j+1} + k_{i+1,j} + k_{i+1,j+1}}{8} \quad (16)
\]

where \( k_{ij} = B_{ij} - G_{ij} \)

A similar computation also applies to R channel correction.

### 3. Experimental Results

We applied our demosaicing method to the lighthouse, sailboat, window and statue images. Table 1 shows the Mean Square Error of the interpolation results for the bilinear method, Hamilton and Adams’ method [6], Kimmel’s method [7] and the proposed method. The results of Kimmel’s method [7] were calculated by using the color images obtained directly from the author’s web page in a lossless PPM format, and they reflect the author’s implementation of the algorithm. As expected, the bilinear method gives the worst performance, Kimmel’s method outperforms Hamilton and Adams’ method in most cases. The proposed method is doing better consistently as compared with other approaches in all cases.

Figure 2 (a) shows the magnified details of the original sailboat image. The image is sampled with Bayer CFA pattern to produce the mosaic image that is used as the input for interpolation. Figure 2 (b~d) display the interpolated ones using different methods, (e~f) illustrate the proposed method before and after correction. It can be

3
seen that our proposed method produces much less color-bleeding and color aliasing artifacts around edge and fine details than the other three methods, e.g., the number region. The improvements are more obvious when the visual comparison is made on a monitor.

<table>
<thead>
<tr>
<th>Images</th>
<th>Bilinear</th>
<th>H&amp;A</th>
<th>Kimmel (after correction)</th>
<th>Proposed (before and after correction)</th>
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</tr>
</tbody>
</table>

Table 1: MSE of different interpolation methods

Our new edge classifier for green channel preserves edge information better, and the follow-up correction scheme also contributes to the improved performance demonstrated in Table 1 and Figure 2.

4. Conclusion

An improved edge-adaptive color interpolation method for Bayer pattern images of single-sensor digital cameras is presented in this paper. We devise a more accurate color edge classifier by using all the RGB intra- and inter-channel correlation information. The emphasis is placed on the G channel reconstruction since G channel is important to human perception and the performance of the R, B channels reconstruction directly depends on the accuracy of the G channel interpolation. The correction phase is also meaningful after all missing components have been recovered, since more information is available for decision.

Experimental results show that the proposed method can preserve the edge information better, reduce color-bleeding artifacts and achieve higher data fidelity.

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References


