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A spatially variant total variational model for chromatic aberration correction ☆,☆☆

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ABSTRACT

In this paper, we propose a spatially variant total variational model to correct chromatic aberration (CA) that causes false color artifacts near edges in captured images. In general, it may be very difficult to determine suitably CA regions in captured images. Instead of using local image processing methods, our idea is to make use of spatially variant model to control the gradient and intensity matching between the red and blue color channels and the green color channel at the edges. The total variation regularization is also employed to constraint the change of the intensity of red and blue color channels during the gradient and intensity matching. We present both theoretical results and algorithms for the proposed model. Experimental results are given to illustrate the effectiveness of the proposed model and algorithm and show that their corrected images are visually better than those corrected by the other testing methods.

1. Introduction

Digital cameras are widely used in recent years. The main component of a digital camera is its image sensor that determines the image resolution. Because camera lens have different refractive indices for different wavelengths of light, they are not possible to make all color components convergence to the same local point, see [1,2,13]. This phenomenon occurs especially in the regions of sharp edges in captured images. These visible color artifacts in captured images are called chromatic aberration (CA). Usually, there are two types of chromatic aberration: axial CA and lateral CA. The axial CA often causes the effect of image blurring, and the lateral CA often causes geometric errors [2].

In order to correct CA, we may consider to use two or more pieces of lenes with different refractive indices [3]. This hardware method may be perfect, and the main issue is that the cost of camera would be very expensive. Another approach is to use image processing methods to correct CA [4–8]. In most of these works, the methods are to employ global warping methods to distort the geometry between different color channels of degraded images. These global warping methods need a pre-calibration process to estimate registration parameters that can compensate for misalignments in degraded images.

By using the fact that CA usually occurs near the edges, some CA correction methods are studied in [9,10]. In [9], Kim and Park proposed a two stage method to detect and correct purple fringing. Their detection is based on color information with large gradient magnitudes, and pixels in these detected purple fringing regions are desaturated to correct the color suitably. The main issue of this method is that it works for purple fringes but it fails for the other color fringes. In [10], Kang et al. developed a partial differential equation based local CA correction method. Their idea is to consider CA artifacts near edges, and study that the edge in the green channel is shaper than the edges in the red and blue channels. Their proposed method is to match the edges in the red channel and blue channels to the edge in the green channel. In their two stage method, the first step is to estimate the regions with CA artifacts and the second step is to match red and blue edges to green edges in these regions via image processing techniques based on partial differential equations. The maximum and gradient operations within these CA regions are employed in the computational process. The crucial step of this method is how to determine CA regions suitably so that the maximum and gradient operations can be calculated appropriately. Later, Chang et al. [11] developed a local CA correction algorithm by introducing adaptive weights in both gradient and color differences calculation. Moreover, a transient improvement technique is applied to control slow transitions

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of the edges of red and blue channels that are caused by the CA. The main issue of this method is to control many parameters in the algorithm. Recently, Korneliussen and Hirakawa [12] presented a new camera processing scheme aimed at correcting the chromatic aberration. This is also a two stage method. This method is consisted by a demosaicking method that tolerates chromatic aberration and post-demosaicking chromatic aberration correction.

The main contribution of this paper is to propose a spatially variant total variational model to correct chromatic aberration. As it may be difficult and complicated to identify CA regions to correct red and blue channels at the edges of captured images, we study to employ spatially variant model to control the gradient matching between the green color channel and the corrected red/blue color channels, and the intensity matching between the given red/blue color channels and the corrected red/blue color channels. Here the spatially variant model is based on the gradient magnitudes of green channel. When the gradient magnitudes of the green channel are large (i.e., at the neighborhood of edges), the gradient matching between the green color channel and the corrected red/blue color channels should be more dominant than the intensity matching between the given red/blue color channels and the corrected red/blue color channels. We can consider similarly when the gradient magnitudes of the green channel is small. This mechanism can be incorporated adaptive weighting for CA and non-CA regions of captured images so that the CA correction can be performed appropriately. We formulate the optimization problem consisting of three terms: the gradient matching between the green color channel and the corrected red/blue color channels; the intensity matching between the given red/blue color channels and the corrected red/blue color channels; the total variational regularization for the corrected red/blue color channels. The last term is used to regularize the intensity of red and blue color channels during the gradient and intensity matching, i.e., it is used to avoid their oscillation in the matching process. The existence of the minimizer of the optimization model is analyzed. The fast algorithm is developed to solve the resulting model. Experimental results are given to illustrate the effectiveness of the proposed model and algorithm and show that their corrected images are visually better than those corrected by the other testing methods.

The organization of the this paper is as follows. In Section 2, we describe the proposed spatially variant total variational model. Some theoretical results are shown. In Section 3, the algorithm is presented. In Section 4, numerical examples are shown to demonstrate the performance of the proposed model and algorithm. Finally, some concluding remarks are given in Section 5.

2. The proposed model

Chromatic aberration usually occurs as "fringes" of color near boundaries with contrasting color in the captured image. Most of auto-focus cameras focus on the green channel when images are captured. Both red and blue colors of different wavelengths may not be focused at a single common point with the green color [13]. It is natural to make use of green channel in captured images as a reference to the red and blue channels in order to correct CA artifacts. As an example, we show in Fig. 1 the ground-truth image and the image with chromatic aberration [11]. For the illustration, we show the intensity values of red, green and blue colors along the line. In this example, both red and blue colors intensity values are different from green color intensity values near the edge position. Therefore, the CA artifacts appear.

According to this example, we propose the following three components in the CA correction:

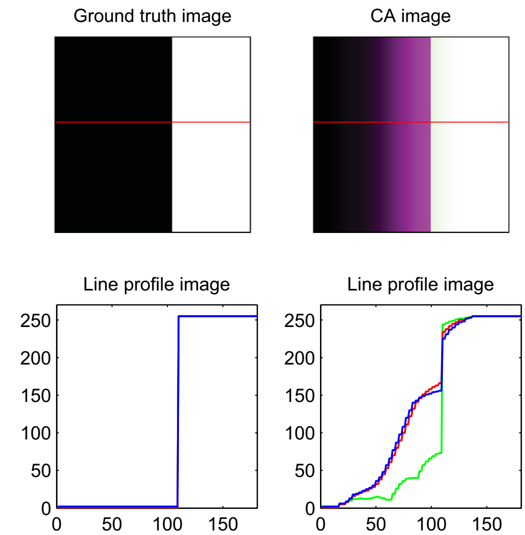

Fig. 1. The upper row shows the ground-truth image and the image with chromatic aberration image. The lower row shows the intensity values of red, green and blue colors along the lines in the upper row images. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

- the intensity matching between the given red/blue color channels and the corrected red/blue color channels;
- the gradient matching between the green color channel and the corrected red/blue color channels;
- the total variation regularization of the corrected red/blue color channels.

The first term is used to keep the intensity values of red/blue color channels in the regions being far away from edges. For instance, we see the graphs in the lower row of Fig. 1 the region in between the position 0 to the position 50, and the region after the position 150. We see from Fig. 1 (upper row, right) that the color in these two regions are kept and it does not have any CA artifacts. The second term is used in the regions near edges as CA artifacts appear. Both the gradients of red and blue color channels should match with the gradient of green channel.

For example, when we use an optimization model with these two terms only with a single balance parameter β:

$$\min_{Y} \|\nabla Y(x) - \nabla G(x)\|^2 + \beta \|Y(x) - Y_0(x)\|^2$$

where Y refers to red or blue channel intensity values, $Y_0(x)$ and $G(x)$ are the given red/blue color and green color respectively at the pixel location x in the captured image, ∇ is a gradient operator and $\nabla = \left(\frac{\partial}{\partial x_i}, \frac{\partial}{\partial x_j}\right)$, and $\|\cdot\|$ is the L^2 norm. However, we find that it is not straightforward to control where we should pay more attention to gradient matching or intensity matching. In Fig. 2, we show the results of the combination of the intensity and gradient matching terms with a single parameters. Because the effect of CA is not the same as the left and right hand sides of the edge, a single parameter may not be effective for controlling the two terms in the objective function. When we use a small parameter value of β, CA artifacts disappear, but the red and blue colors in the other regions (without CA artifacts previously) are changed. When we use a large parameter value of β, CA artifacts cannot be corrected. Based on this observation we propose to use a spatially variant function to determine the balance between the intensity and gradient matching terms at different pixel locations. In particular, when $\|\nabla G(x)\|$ is large (it is near the edge location), the effect of the intensity