An Automatic White Balance Algorithm Based on Pixel Luminance and Chromaticity

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Abstract. Automatic white balance (AWB) is a crucially important part of digital still camera. It keeps constant color of an image by eliminating the color cast caused by non-canonical illuminant. A dynamic threshold is used to remove outliers in C_b and C_r components and detect the near-white region in an image. And we also describe a technique using both the internal illumination and all pixels in the near-white region to estimate the illuminant. The results show that the proposed technique is superior or comparable to the existing AWB algorithms. The algorithm is attractive for practical applications because of the low complexity.

Keywords: Automatic white balance · Near-white region · YC_bC_r color space · Illuminant estimation

1 Introduction

Illumination affects the color distribution of a certain object in a digital camera [1]. It can result in color instability such that when illuminated by different light sources, the same object appears to have different colors. A white object will appear reddish under a low color temperature. Conversely, it will appear bluish under a high color temperature. And maintaining color constancy is critical in plenty of image processing applications, such as object detection [2], color enhancement [3], etc. Therefore, we can process the image with AWB method to eliminate the color cast [4]. They usually consist of two steps: illuminant estimation and color compensation [5].

In the step of illuminant estimation, AWB algorithms try to find achromatic color (the neutral color). Since the neutral color is achromatic, we can consider that any color component of the neutral color comes from the light source [6]. Therefore, most AWB algorithms try to find the neutral color and then to estimate the illuminant.

Early AWB algorithms always make certain assumptions about low-level features, including gray world method (GWM) [7], perfect reflector method (PRM) [8], fuzzy rule method (FRM) [9], etc. And in the recent years, some new methods using high-level features have emerged, including correlation of color [10] and neural network method based on color constancy [11]. While high-level-feature-based methods typically have better performance than low-level-feature-based methods, they spend more time on computation. Starting from reality, in the digital cameras, low-level-feature-

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based methods can perform reasonably in a short time with limited computing capability [12].

We propose a technique using image statistics to get the near-white region in the YC_bC_r color space. The proposed method takes pixels' weighted average in the near-white region to estimate the illuminant. Experimental results show that the proposed method performs better than other AWB methods in subjective and objective evaluation.

2 Related Work

We denote the image value with $f(x)$. It relates to the power distribution of illuminant spectrum $i(\lambda)$, the surface reflectance of spectrum $r(x, \lambda)$ where x is the pixel location and the camera spectral response function $c(\lambda)$ for a Lambertian surface corresponding to a light with wavelength λ by

$$f(x) = \int_w i(\lambda) r(x, \lambda) c(\lambda) d\lambda. \tag{1}$$

Where w is the visible spectrum.

Assuming only one light source illuminates the scene, then the observed illumination of the light source depends on the power distribution of illuminant spectrum and the camera spectral response function [10]. The illuminant I is defined by:

$$I = \int_w i(\lambda) c(\lambda) d\lambda. \tag{2}$$

Because only the image value f is known, estimating illuminant is an inappropriate problem without other assumptions.

GWM works under the assumption that, we can get an achromatic image by the average of reflectance of a scene if the original image has sufficient color variations [7].

PRM assumes that the brightest pixel in an image conveys many information about the illumination of the scene [8]. And the brightest pixel is defined as the reference white point [7].

In the FRM, the image is processed in the YC_bC_r color space. They proposed the idea of near-white region and considered the C_r to C_b ratio of white objects was between −1.5 to −0.5 [9]. The method obtains the gains of C_b and C_r to adjust images through several fuzzy rules [7].

Based on FRM, Weng et al. proposed the mean absolute deviation (MAD) method to remove outliers that have large C_b and C_r values. The method depends on mean absolute deviation in C_b and C_r component. Then the method computed the average reflectance by remaining pixels that have small C_b and C_r values, not the entire image [13].

3 The Proposed Method

A dynamic threshold is used to detect the near-white region in an image, which is different to predefined threshold in previous methods. Similar to previous methods, our method consists of white point detection and image adjustment. First, we can convert the image values from RGB to YC_bC_r color space to obtain the chromatic components easily.

As discussed in [6], for a neutral color, the chromaticity C_b and C_r are considered to come from the light source. Conversely, for a chromatic color, its values contain illumination from the scene and illumination from the light source. In order to represent the level of illumination from the light source contained in a color, Thai et al. proposed an illumination factor $h(x)$ where x is the pixel location [12]. The illuminant is given by:

$$I = \frac{\int f(x)h(x)dx}{\int h(x)dx}. \tag{3}$$

The role of $h(x)$ is to lower the influence of chromatic color pixels to the illuminant estimation. Liu et al. [9] observed that the smaller C_b and C_r values pixels have, the more neutral pixels are. We define $h(x)$ as following:

$$h(x) \propto \exp\left(-\frac{|C_b(x) + C_r(x)|}{\delta^2}\right). \tag{4}$$

$C_b(x)$, $C_r(x)$ denote chromaticity C_b and C_r of a pixel, where x is the pixel location. And δ is the parameter that controls the influence of a pixel in the illuminant estimation process. Setting a smaller value for δ, a pixel has less influence.

Based on the color characteristics observed by Liu et al. [9], we define a near-white region composed of pixels that satisfy the following relationships:

$$|C_b(i,j)| < \frac{Y(i,j)}{\sigma}. \tag{5}$$

$$|C_r(i,j)| < \frac{Y(i,j)}{\sigma}. \tag{6}$$

Where $C_b(i,j)$, $C_r(i,j)$, $Y(i,j)$ denote chromaticity C_b, C_r and luminance Y of pixel (i,j), and $\sigma \geq 1$ is the parameter which controls the range of the near-white region. Setting a larger value for σ, less pixels are selected as the near-white region.

Let $T_k(i,j)$ denote corresponding values of the pixel (i,j), where $k = \{1, 2, 3\}$ represent R, G and B channels. From Eqs. (3) to (6), the illuminant in the image defined as $\bar{T}_k$ is computed by:

$$\bar{T}_k = \sum_N \rho(i,j)T_k(i,j). \tag{7}$$

Where N is the number of image pixels in the near-white region. The averaging coefficient $\rho(i,j)$ is defined as:

$$\rho(i,j) = \frac{1}{\bar{\rho}} \exp\left(-\frac{|C_b(i,j) + C_r(i,j)|}{\delta^2}\right). \tag{8}$$

Where $\bar{\rho}$ is the normalized factor such that $\sum_N \rho(i,j) = 1$.

The following step is adjusting the image color to the estimated illuminant. The Von Kries model is used to adjust the image color [14]. Each channel gain ∂_k is computed by counting the luminance $\bar{Y}$ in the near-white region:

$$\partial_k = \frac{\bar{Y}}{\bar{T}_k}. \tag{9}$$

Where $\bar{Y} = \sum_N \rho(i,j) Y(i,j)$.

The value of each image pixel is adjusted by:

$$T_k^*(i,j) = \partial_k T_k(i,j). \tag{10}$$

Where $T_k^*(i,j)$ is the adjusted image value of channel k at pixel (i,j).

4 Experimental Results

In order to demonstrate the performance of our method, we present many experimental results to test our algorithm against other low-level-feature-based AWB algorithms including GWM [7], PRM [8], FRM [9] and MAD [13].

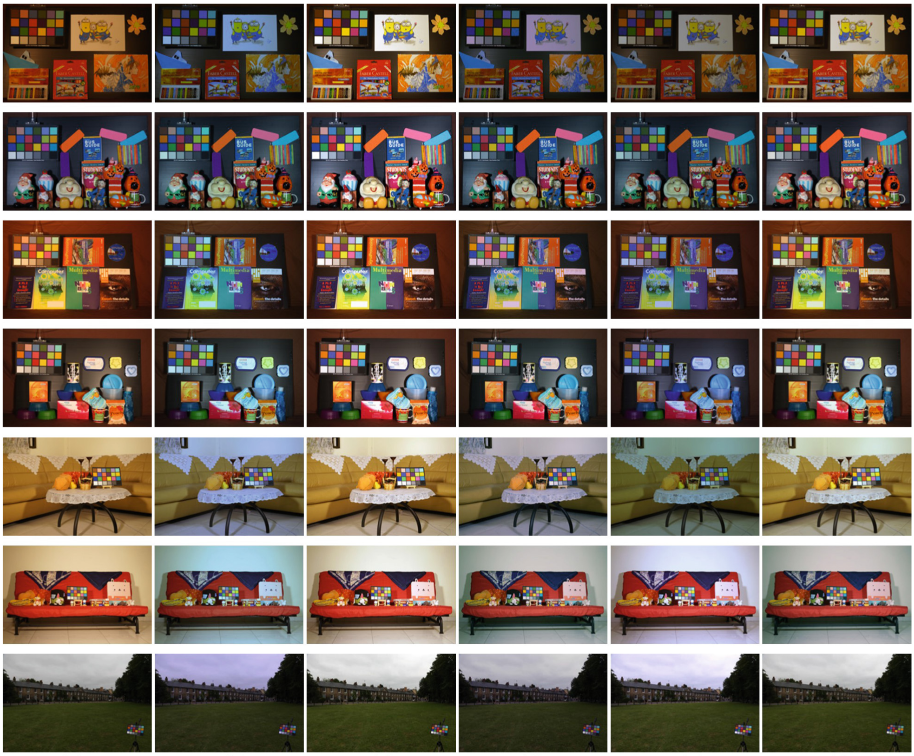
The experiments were conducted on datasets supplied by Gehler et al. [15] and Cheng et al. [16]. Every image in the datasets contains a Macbeth ColorChecker chart.

We used the average chromaticity of the achromatic patches of Macbeth ColorChecker as objective evaluative values to compare different methods [17]. The average chromaticity is defined by:

$$d = \sqrt{C_b^2 + C_r^2}. \tag{11}$$

If the value of d is smaller, the method has better performance.

We first studied the parameters σ, δ by setting them to different values and observing the values of average chromaticity. Experiments show that for most images we can obtain the best results when $\sigma = 4$, $\delta = 1$. Therefore, we used these values for all the experiments presented in this paper. Performance of AWB methods are demonstrated in Fig. 1. As can be seen, our method can eliminate color cast.



(a) (b) (c) (d) (e) (f)

Fig. 1. Results of AWB methods on image datasets. From *top* to *bottom*: pictures, toys, books, snacks, table, sofa and outdoors image. From *left* to *right*: original images, GWM, PRM, FRM, MAD and our method. (a) The original image. (b) GWM. (c) PRM. (d) FRM. (e) MAD. (f) Our method.

We use Eq. (11) to evaluate the AWB algorithms objectively. The results are shown in Table 1, which demonstrate that our algorithm performs better than other algorithms in the test. The subjective evaluation shows that our algorithm can improve the image quality significantly.

Table 1. Average chromaticity values obtained from the Macbeth ColorChecker in images.

Test image	Original	GWM	PRM	FRM	MAD	Ours
Pictures	27.99	2.85	19.88	13.59	11.30	**1.72**
Toys	5.05	2.71	3.93	4.60	4.44	**1.82**
Books	43.50	7.51	13.62	9.87	5.47	**4.15**
Snacks	23.44	5.86	14.95	6.91	8.41	**3.38**
Table	23.96	10.90	12.28	12.67	6.15	**3.97**
Sofa	24.58	9.30	12.40	13.20	2.91	**2.86**
Outdoors	9.48	7.39	8.10	7.51	9.24	**2.08**

5 Conclusion

In this paper, we have proposed an automatic white balance algorithm. In our method, we attempt to use a dynamic threshold to remove outliers in C_b and C_r components and detect the near-white region in an image. The proposed method takes pixels' weighted average in the near-white region to estimate the illuminant. And the weight of each pixel is determined in the YC_bC_r color space. Compared to other methods, our method performs better in the objective evaluation. The subjective results also show that our algorithm is superior or comparable to other algorithms. Therefore, our method can be applied in digital cameras as a robust technique for automatic white balancing.

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