A RETINAL MECHANISM BASED COLOR CONSTANCY MODEL

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Abstract. It has been generally accepted that the retina is the first level that plays critical role in the function of color constancy in human visual system. In this paper we propose a computational model which imitates the neural mechanisms of color information processing in retina. In this model we first compute a simple statistics of reflectance about the real scene by simulating bipolar cells. Then, the ganglion cells (e.g., the midget cells) receive both the computational statistics of reflectance of the scene from bipolar cells and the response from horizontal cells as well as amacrine cells. Subsequently, the ganglion cells provide a stable output independent of the color of illuminant. We tested our model on a commonly used large-scale linear image dataset, and the results demonstrate that our model provides better color constancy performance than those widely accepted color constancy models.

Keywords: color constancy, human visual system, retinal mechanisms, reflectance, illuminant, computer vision.

1 Introduction

Color constancy is an amazing phenomenon which represents the ability of human visual system stably perceiving the color of a real scene under variable illuminant environment [1-3]. In real natural scenes, the luminance represents the amount of visible light that comes into the eyes from a surface, which contains the information about the illuminant and reflectance. Accurately speaking, the illuminant lights the whole scene, then object reflects the light of certain wavelength, finally the specific light entering into the human visual system shapes the bases of color perceiving. Since the luminance is the product of illuminant and reflectance, when the illuminant changes (e.g., the sunshine in the morning is quite different from the sunshine in the afternoon), the luminance into the eye also changes. Obviously, if our visual system cannot adapt to those changes, the perceived color would be very different when we see the same object at different time. Fortunately, million of years of evolution endows our visual system the ability named color constancy[2-5]. Nevertheless, how the human visual system realizes the color constancy is still unclear. On one hand,

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although much research about human visual system through electrophysiological methods finds various neurons which maybe contribute to the color constancy, such as the single-opponent neuron in lateral geniculate nucleus (LGN) [1], double-opponent neuron in primary visual cortex (V1) [2], higher visual cortexes such as V2 [3], V4 [4] etc. Electrophysiological methods can record the properties of single neuron, but mathematic models are needed to simulate and predict how the neuronal circuits work as a group. On the other hand, most existing models about color constancy mechanisms only emphasize single neuron's function, e.g., the double-opponent neurons have the structure of spatial opponent and color opponent, the structure of receptive field can boycott the change of illuminant in environment; thus it can maintain an invariant response independent of illuminant. However, it is still an open question that how double-opponent neurons acquire the invariant response or color constancy. In addition, we have probably underestimated the complexity of retina and its ability to process the information from external environment [5].

The models about color constancy can be divided into physiological mechanism based and non-physiological mechanism based ones. The former contains Land's classical theory in color constancy field, i.e., Retinex [6], which is derived from psychophysical research. The other biologically based methods include the ones based on gain control of retina [7] or based on hexagonal-type cellular neural network [8]. The typical models of color constancy based on non-physiological mechanism include Grey World [9], Gamut mapping [10], Grey Edge [11] and so on, and these methods often need to first estimate the illuminant using different complicated techniques. In this work we proposed a simply but efficient color constancy model based on the physiological mechanisms at the level of retina.

2 Linear image and Computational color constancy

2.1 Linear image model

The linear image $f(x,y)$ recorded by a camera depends mainly on three factors [12]: the physical content of the scene, namely the scene reflectance $r(x,y,\lambda)$, the illumination incident on the scene $i(x,y,\lambda)$, and the response function of the camera $s(\lambda)$. The linear image model could be written as

$$f(x,y)=\int s(\lambda)i(x,y,\lambda)r(x,y,\lambda)d\lambda \tag{1}$$

Where λ is the wavelength of the light and (x,y) is the spatial coordinate.

2.2 Computational color constancy

One of the key problem in the traditional computer vision field is the object identification based on color, if we only use the linear image model mentioned above, we would face a ambiguous situation, because the image values $f(x, y, \lambda)$ will change accompanied with the change of illuminant $i(x, y, \lambda)$. For example, if the object in a scene is lighted by tungsten illumination (reddish), then object identification can fail when the object in a scene is lighted by very blue illumination of a clear sky. Then the purpose of computational color constancy is to compute the real illumination or surface reflectance about the scene [12].

3 Our Model

It is well known that the algorithms of traditional computational color constancy usually estimate the coefficient of illuminant first; then the illuminant estimate is used to correct the picture with color cast, such as the model of Grey World [9], White Patch [6], Grey Edge [11]. In contrast, according to Eq. (1), we first can estimate the coefficient of reflectance $r(x, y, \lambda)$; then we make use of the statistic of reflectance estimated by our algorithm to compute the illumination $i(x, y, \lambda)$ in the picture; finally, we adopt the von kries model [13]to correct the picture with color cast.

3.1 Hypothesis and mathematic computation

In the traditional computational color constancy field, it is generally assumed that the illuminant of environment is of uniform distribution [12, 14]. Our work is also based on this assumption, and the detailed process is described as follows.

3.1.1 The responses of three cones lead to the retinal image

In Eq. (1), if we replace the response function, $s(\lambda)$, of the camera with the spectral sensitivities of three cones in retina, $f(x, y)$, is equivalent to the response of cones. Furthermore, if we simplify $s(\lambda)$ to an impulse function $\delta(\lambda)$, we get

$$f_k(x, y) = \int \delta_k(\lambda) i_k(x, y, \lambda) r_k(x, y, \lambda) d\lambda = i_k(x, y) r_k(x, y) \tag{2}$$

Where $k \in (l, m, s)$ corresponds to the channels of L-, M- and S-cone, respectively. $f_l(x, y)$, $f_m(x, y)$ and $f_s(x, y)$ are the retinal image of red, green and blue channel; $i_l(x, y)$, $i_m(x, y)$ and $i_s(x, y)$ are the illuminant components of red, green, blue channel; $r_l(x, y)$, $r_m(x, y)$ and $r_s(x, y)$ represent the reflectance of red, green, blue channel, respectively.

3.1.2 Calculating the reflectance at local area

With the retinal image of three color channels $f_l(x, y)$, $f_m(x, y)$ and $f_s(x, y)$, we try to estimate the reflectance of local region in each channel. Taking L channel as an example, we chose a local region with the size of $3*3$ pixels, in which the illuminant $i_l(x,y)$ is assumed to be uniform. We have

$$\begin{bmatrix} f_l(x_1,y_1) & f_l(x_2,y_2) & f_l(x_3,y_3) \\ f_l(x_4,y_4) & f_l(x_5,y_5) & f_l(x_6,y_6) \\ f_l(x_7,y_7) & f_l(x_8,y_8) & f_l(x_9,y_9) \end{bmatrix} = \begin{bmatrix} i_l(x,y)r_l(x_1,y_1) & i_l(x,y)r_l(x_2,y_2) & i_l(x,y)r_l(x_3,y_3) \\ i_l(x,y)r_l(x_4,y_4) & i_l(x,y)r_l(x_5,y_5) & i_l(x,y)r_l(x_6,y_6) \\ i_l(x,y)r_l(x_7,y_7) & i_l(x,y)r_l(x_8,y_8) & i_l(x,y)r_l(x_9,y_9) \end{bmatrix} \quad (3)$$

We select (x_5,y_5) as the center of receptive field in this local region. By dividing the cone response at each location in this local region by the response of the central cone $f_l(x_5,y_5)=i_l(x_5,y_5)r_l(x_5,y_5)$, we could get the estimate of reflectance in this region:

$$\begin{bmatrix} \frac{f_l(x_1,y_1)}{f_l(x_5,y_5)} & \frac{f_l(x_2,y_2)}{f_l(x_5,y_5)} & \frac{f_l(x_3,y_3)}{f_l(x_5,y_5)} \\ \frac{f_l(x_4,y_4)}{f_l(x_5,y_5)} & \frac{f_l(x_5,y_5)}{f_l(x_5,y_5)} & \frac{f_l(x_6,y_6)}{f_l(x_5,y_5)} \\ \frac{f_l(x_7,y_7)}{f_l(x_5,y_5)} & \frac{f_l(x_8,y_8)}{f_l(x_5,y_5)} & \frac{f_l(x_9,y_9)}{f_l(x_5,y_5)} \end{bmatrix} = \begin{bmatrix} \frac{r_l(x_1,y_1)}{r_l(x_5,y_5)} & \frac{r_l(x_2,y_2)}{r_l(x_5,y_5)} & \frac{r_l(x_3,y_3)}{r_l(x_5,y_5)} \\ \frac{r_l(x_4,y_4)}{r_l(x_5,y_5)} & \frac{r_l(x_5,y_5)}{r_l(x_5,y_5)} & \frac{r_l(x_6,y_6)}{r_l(x_5,y_5)} \\ \frac{r_l(x_7,y_7)}{r_l(x_5,y_5)} & \frac{r_l(x_8,y_8)}{r_l(x_5,y_5)} & \frac{r_l(x_9,y_9)}{r_l(x_5,y_5)} \end{bmatrix} \quad (4)$$

However, actually we only obtain the estimate of reflectance, and the accurate reflectance at every single point of retinal image cannot be computed, because among the formula $f(x,y)=i(x,y)r(x,y)$, we only know $f(x,y)$, this is a ill-posed problem.

3.1.3 The statistic of reflectance of local region

Due that the color constancy is an ill-posed problem and we only need to compute the coefficient of illuminant at local area, therefore we calculate the statistic of reflectance Sr of the local region by simply computing the sum of reflectance of this local region as

$$\begin{aligned} Sr &= \sum_{i=1}^{9} \frac{f_l(x_i,y_i)}{f_l(x_5,y_5)} = \sum_{i=1}^{9} \frac{i_l(x,y)r_l(x_1,y_1)}{i_l(x,y)r_l(x_5,y_5)} \\ &= \frac{1}{r_l(x_5,y_5)} \sum_{i=1}^{9} r_l(x_i,y_i) \end{aligned} \quad (5)$$

Similarly, we can accumulate the original response Ac from cones of retinal image.

$$Ac = \sum_{i=1}^{9} f_l(x_i, y_i) = i_l(x, y) \cdot \sum_{i=1}^{9} r_l(x_i, y_i) \tag{6}$$

3.1.4 Estimate the illuminant

If we check the estimate of reflectance of each point on retina, it is clear that the value of reflectance, $\frac{r_l(x_1, y_1)}{r_l(x_5, y_5)}$, is much different from the true reflectance, $r_l(x_1, y_1)$. Nonetheless, as the central-limit theorem in probability theory says that "given certain conditions, the mean of a sufficiently large number of independent random variables, each with finite mean and variance, will be approximately normally distributed", thus we assumes the sufficiently large number of independent random reflectance will approximately a sort of distribution and the sum of this distribution will be stable to some extent. Based on these assumptions we can estimate the illuminant as

$$i_l(x, y) \approx \frac{1}{K} \sum_{k=1}^{K} \frac{Ac(k)}{Sr(k)} \tag{7}$$

Where K is the number of the non-overlapped local regions in the whole image, and $Sr(k)$ and $Ac(k)$ are the statistics of the k-th local region computed by Eqs (5) and (6). Note that since we assume that the illuminant of environment is of uniform distribution, the mean operation defined by Eq. (7) integrates the responses from whole visual field (or the whole image), which can smooth the noise. Similarly, we can estimate the illuminant components of another two color channels.

3.1.5 Image correction and Von kries model

The focus of this paper is on estimating the color of the illuminant. However, in many cases the color of the illuminant is of less importance than the appearance of the input image under a reference light (canonical illuminant). Therefore, the aim of most of the color constancy methods is to transform all colors of the input image, taken under an unknown light source, to colors as they appear under this illuminant. This transformation can be considered to be an instantiation of chromatic adaptation[12].

4 Evaluation criterion

In computational color constancy field, the angular error is often chosen as the evaluation criterion [14], which is computed by

$$Angel\_error(e_e, e_g) = \cos^{-1}\left(\frac{e_e \cdot e_g}{\|e_e\| \cdot \|e_g\|}\right) \tag{8}$$

Where $e_e \cdot e_g$ is the dot product of the estimated illuminant e_e and the ground truth e_g. $\|\cdot\|$ is the Euclidean norm of a vector.

5 Results

Because our model is based on the assumption of linear image model, and almost all of the existing models in color constancy assume the formation of image is linear, which means that the value at every pixel is directly related to the number of photons received at that location of the sensor array. Thus, we utilized the large scale linear image dataset to test our method and compare with other typical methods. The Gehler-Shi dataset [15, 16] contains 568 high quality images, accompanied with measured illuminant that can be used as ground truth. The images in this dataset are lossless compression, linear and uncorrected by camera.

Fig.1 shows the plots of whisker-and-box of the angular errors on the Gehler-Shi dataset with different models including GW (grey-world), WP (White-Patch), GE (Grey-Edge), SG (Shade-of-Grey), GG (General-Grey), and our model named CCBR (color constancy based on retinal mechanism). The result of 'Do nothing' means the angular error was directly computed between the color-biased images and the ground truth. From Fig.1 we find that our CCBR model provides clear improvement compared with other typical models. The right part of Fig. 1 also demonstrates the relationship of the model's performance (i.e. angular error) with the size of RF, the one main parameter in our model.

This improvement is further demonstrated by Fig.2, which lists the results of different models on an image in Gehler-Shi dataset.

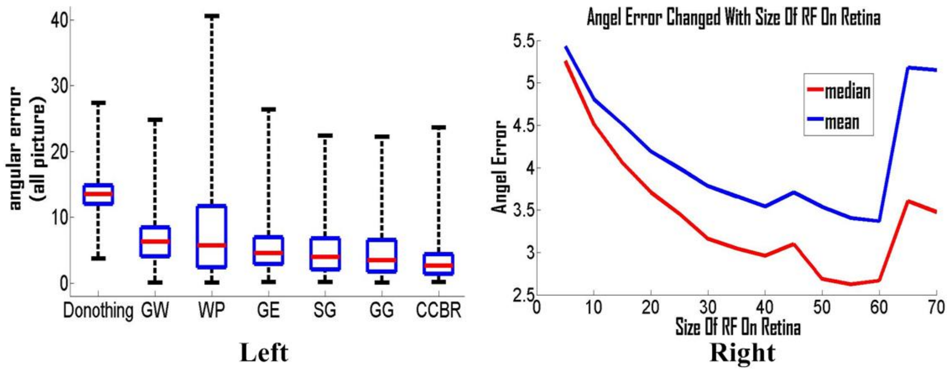

Fig. 1. Left: The plots of box-and-whisker of angular errors computed by seven methods on the Gehler-Shi image dataset, the methods include: Uncorrected (do-nothing), Grey world (GW), White patch (WP), Grey edge (GE), Shade of grey (SG), General of grey (GG), Our method (CCBR). Right: Angular error varies with the size of RF on retina. The blue and red lines denote the mean and median of angular error, respectively. It is clear that the best size of RF on retina in our model is 55 pixels.

Fig.2. The result of an image of the Gehler-Shi dataset, from left to right and from top to bottom represent respectively the original image, ideal image corrected by ground truth, estimated image corrected by Our method, Grey world, White patch, Shade of grey, General of grey, Grey edge of first order, Grey edge of second order. The corresponding angular errors are shown in the lower right corner of the images.

6 Conclusion

In this work a retinal mechanism based color constancy model was proposed, and the results on a commonly used large dataset demonstrated that the proposed model obtain better results than other typical methods. To explain the success of our model, we think that the ganglions on the retina, together with horizontal cells, amacrine cells and bipolar cells, work as a team to construct a physiological circuit, which can be used to compute the estimate of illuminant brought by luminance; after that, both the estimated information about illuminant and the response from cones input to ganglion neurons, for example, the midget cell, are used to remove the effect of illuminant, finally producing an invariant response, which is independent of illuminant. We verified our model on a large scale dataset and achieved the best result among all those static methods of color constancy.

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