Object Color Constancy for Outdoor Multiple Light Sources

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Abstract. Color is one of the mostly applied features for object recognition and tracking. Most work for color constancy is often based on the assumption of spatial uniformity or smooth illuminant transaction, which is not always true due to the presence of multiple light sources. In this paper, without these assumptions, we deal with the problem of color constancy in multiple light sources by computing the color constancy on a given object rather than the whole image. It keeps the color constancy for a given object under different outdoor lighting conditions, especially for an object under different shadows. We first calculate a transfer vector based on the given object and the illuminants ratio vector. This vector is then added to the original image to make the object be perpendicular to the illuminants ratio vector. Finally, an object color constant image is obtained by performing an orthogonal decomposition along the illuminants ratio vector on the new image. Compared with color constancy on whole image, this proposed method can reduce color distortion in the object and keep mostly color constancy for an object to be recognized and tracked regardless of lighting conditions. Both quantitative and qualitative experiments validate our method.

Keywords: Object color constancy · Illumination invariant · Outdoor multiple light sources · Object detection

1 Introduction

Although color is commonly experienced as an indispensable feature in describing the world around us, the color variation caused by different lighting conditions often introduces undesirable effects in digital images. It may negatively affect the performance of computer vision methods for different applications such as object recognition, tracking and surveillance [1,2]. Consider, for example, an object recognition application which identifies the DARK SKIN checker of Macbeth ColorChecker by color in Fig. 1. It may successfully identifies the DARK SKIN checker in Fig. 1 (a) but fails when the ColorChecker partly lies in shadow (Fig. 1 (b)) and totally lies in shadow (Fig. 1 (c)). This is because the change in the illumination affects object color and further hampers the robustness of

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Fig. 1. Sequence of images under different lighting conditions

object recognition and tracking. Therefore, recovering the object color invariant to changing lighting conditions (color constancy) is necessary and worthwhile.

A majority of methods advanced so far for illuminant invariant and color constancy are usually based on the assumption of spatial uniformity. Assuming that the spectral distribution of a light source is uniform across scenes, these methods (such as grey-world [3], white-patch [4], and gamut mapping [5]) get a color constant image by a color correction on original image after globally estimating the color of the light source [2]. More recently, Gijsenij et al. [6] proposed an photometric edge weighting color constancy algorithm based on photometric properties of different edges. Although this assumption works well in most cases, it is often violated as there might be more than one light source illuminating the scene [7].

Retinex theory [8], which assumes that an abrupt change in chromaticity is caused by a change in reflectance properties, is considered as one of the first color constancy methods for multiple light sources. It implies that the illuminant varies smoothly across the image. More specifically, the shadow removal problem [9–11] can be considered as a category of color constancy problem involving two light sources. Even though these shadow removal methods exhibit impressive results for shadow regions, they cannot yield an identical color consistent result regardless of lighting condition (e.g., Fig. 1(c)). Recently, Gijsenij et al. [7] proposed a color constancy method for multiple light sources by applying color constancy locally on small sampled patches. Greatly affected by the effectiveness of sampling method, this method may fail when the distribution of the lighting source is varying.

In order to deal with complex multiple illuminants successfully, these previous mentioned methods either resort to spatial uniformity assumption or smooth illuminant transaction assumption, which are not often true in real situation. In some applications, such as object recognition and tracking, the color constancy on a whole image maybe not necessary, but only the color constancy on the given object is required. In this paper, without spatial uniformity or smooth illuminant transaction, we deal with the color constancy problem for outdoor multiple light sources by computing the color constancy on a given object rather than the whole image. It keeps the color constancy for a given object under different outdoor ligting conditions, especially for an object under different shadows.

This work is based on our previous research on shadow linear model [10] and the color illumination invariant image [12] from the view of atmosphere transmittance effects. As be compressed, our previous color illumination invariant image has some color distortions. In order to make the color of the object keep the same as the canonical color, in this paper, we first calculate a transfer vector based on the given object and illuminants ratio vector. Then we add this transfer vector to the original Log-RGB image to obtain a new transferred image. This will make the object in the new transferred image be perpendicular to the illuminants ratio vector. Finally, the object color constant image is obtained by performing an orthogonal decomposition on the transferred image. Compared with our previous color illuminant invariant on whole image, this method can reduce color distortion in orthogonal decomposition processing and keep mostly color constancy for an object to be recognized and tracked. Both the quantitative and qualitative experiments and comparisons with other methods demonstrate that the color information of our object color constant image can serve as a stable feature for object recognition.

2 Background and Our Previous Work

In this section we first give a brief introduction of the formation of an outdoor image [10] and then we present our pixel-wise orthogonal decomposition for color illumination invariant image [12].

Light emitted from the sun will scattered by atmospheric transmittance effects that causes the incident light to be split into direct sunlight and diffuse skylight. It's revealed that the sRGB tristimulus values of a surface illuminated by daylight are proportional to those of the same surface illuminated by skylight in each of the three color channels [10], i.e.,

$$\log(F_H) = \frac{\log(K_H)}{2.4} + \log(f_H) \tag{1}$$

where F_H denotes the RGB values of a surface in non-shadow area and f_H denotes the RGB values for the same surface in shadow area, $H = \{R, G, B\}$. The proportional coefficients K_H are independent of reflectance and are approximately equal to constants determined by Eq. 2.

$$K_H = \arg\min \sum_{\lambda=400}^{700} |Q_H(\lambda) \cdot (E_{day}(\lambda) - K_H \cdot E_{sky}(\lambda))| \tag{2}$$

Expanding Eq. 1 and letting $\boldsymbol{u} = (u_R, u_G, u_B)^T$ defines a Log-RGB value vector of a pixel, $u_H = log(v_H)$, we have

$$A\boldsymbol{u} = \boldsymbol{I} \tag{3}$$

where $A = \begin{bmatrix} 1 & 1 & -\beta_1 \\ 1 & -\beta_2 & 1 \\ -\beta_3 & 1 & 1 \end{bmatrix}$ and $\boldsymbol{I} = (I_1, I_2, I_3)^T$. $\boldsymbol{I}$ represent a shadow invariant for a pixel in a image [12]. The β_1, β_2 and β_3 in matrix A are calculated as following,

$$\beta_1 = \frac{\log(K_R) + \log(K_G)}{\log(K_B)}, \beta_2 = \frac{\log(K_R) + \log(K_B)}{\log(K_G)}, \beta_3 = \frac{\log(K_G) + \log(K_B)}{\log(K_R)} \tag{4}$$

According to the definitions and calculations of β_1, β_2 and β_3, we have $rank(A) = 2$. Then for a Log-RGB value vector $\boldsymbol{u}$, from algebraic theory, we can obtain an orthogonal decomposition (for more information please refer to [12]):

$$\boldsymbol{u} = \boldsymbol{u_p} + \alpha \boldsymbol{u_0} \tag{5}$$

where $\boldsymbol{u_0}$, satisfying $A\boldsymbol{u_0} = 0$ and $\|\boldsymbol{u_0}\| = 1$, is the normalized free solution of Eq. 3; $\alpha \in R$ and $\boldsymbol{u_p}$ is a particular solution of Eq. 3 such that $\boldsymbol{u_p} \perp \boldsymbol{u_0}$. The symbol $\|\cdot\|$ denotes L^2 norm. Here the free solution has no relationship with the image itself but is determined by matrix A, i.e. illumination condition. $\boldsymbol{u_p}$, $\boldsymbol{u_p} \perp \boldsymbol{u_0}$, is only determined by illumination invariant $\boldsymbol{I}$ and $(\beta_1, \beta_2, \beta_3)^T$. It means that for a pixel with Log-RGB value vector $\boldsymbol{u}$, no matter how different the values of the pixel are with different lighting conditions (within shadow, without shadow or other illuminating), $\boldsymbol{u_p}$ is invariant and only α reflects the variation of pixel RGB values caused by shadow or different illuminating.

Shown in Fig. 2, we use three Macbeth ColorCheckers taken in outdoor scenes at different times on a sunny day to verify these illuminants invariant. It shows that although the three original images are different largely, their color illumination invariant images are almost the same (Fig. 2 (r2)). However, even this color illumination invariant image eliminates the influence of illumination, there still exist some color distortions, which may bring some wrong results for computer vision algorithms, such as object recognition and tracking.

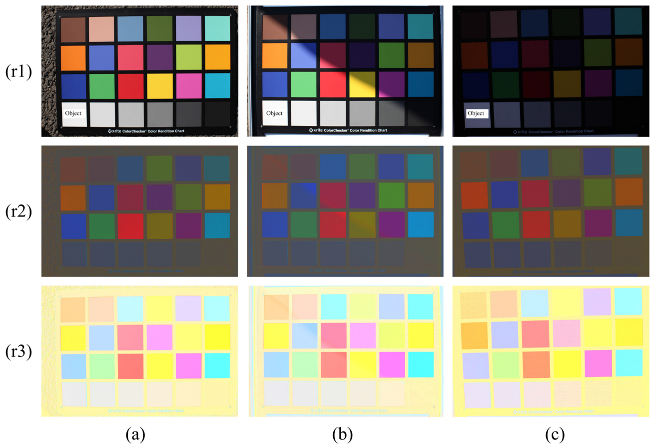

Fig. 2. Orthogonal decomposition and object color constancy. (r1) Original images under different lighting conditions (the WHITE check marked with **object** is the object needs to keep color constancy); (r2) Our color illumination invariant images; (r3) Our object color constant images.

3 Object Color Constancy

For a good prerequisite processing method for object recognition and tracking, it is expected that it can keep the similarity of the object in different lighting conditions meanwhile eliminate or diminish the similarity between the object and the background. In this section, from this point of view, we will introduce a color constancy algorithm for a given object, which will make the color of the object in different lighting conditions keep constant.

Even though the previous color illumination invariant image eliminates the influence of illumination, there still exist some color distortions. In order to make the object have no color distortion, a transfer vector should be added to the object's Log-RGB value vector to make this vector be perpendicular to the illuminants ratio vector. Let the Log-RGB value vector of the object we want to keep color constancy be $\boldsymbol{u}$ and its normalized illumination invariant vector $\boldsymbol{u}_{\boldsymbol{p}}^{t}$ can be calculated according to Eq. 5. Then this transfer vector can be calculated as following,

$$\boldsymbol{T} = \|\boldsymbol{u}\| \cdot \boldsymbol{u}_{\boldsymbol{p}}^{t} - \boldsymbol{u} \tag{6}$$

After this transfer, the Log-RGB value vector of this object is perpendicular to the illuminants ratio, which will make the object have no color distortion in our orthogonal decomposition operation.

Given the object we want to keep color constancy in an image, the overview color constancy algorithm can be calculated in the following four steps:

1) Calculating the transfer vector $\boldsymbol{T}$ according to Eq. 6;

2) Adding the transfer vector $\boldsymbol{T}$ to original Log-RGB image to get a new transferred image $\boldsymbol{I}^{t}$;

3) Making an orthogonal decomposition on the new transferred image $\boldsymbol{I}^{t}$ according to Eq. 5 to get a new color illumination invariant image $\boldsymbol{I}_{\boldsymbol{p}}^{t}$. Since

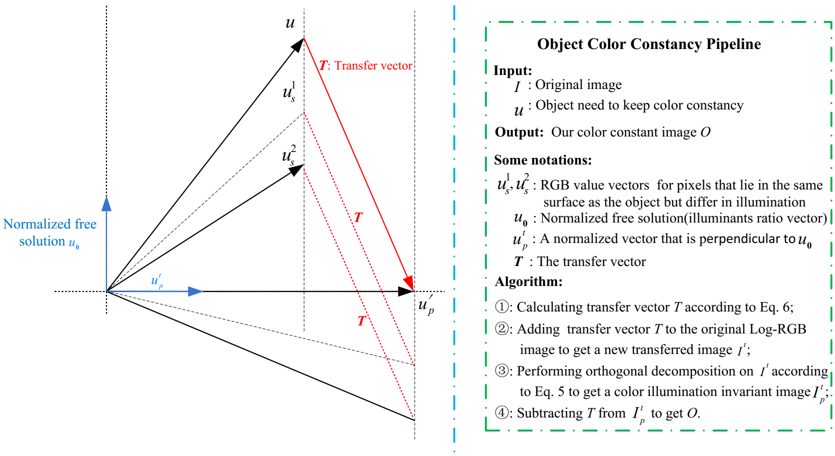

Fig. 3. An illustration of our object color constancy method.

adding the same transfer vector $\boldsymbol{T}$ on original Log-RGB image does not change the physical properties of the image, performing orthogonal decomposition on $\boldsymbol{I}^t$ will still get an color illumination invariant image like previous section. This can be shown more clearly in Fig. 3. Here, $\boldsymbol{u}$ denotes the pixel value of the pixel that we need to keep color constancy (lies in the canonical lighting condition). $\boldsymbol{u_s^1}$ and $\boldsymbol{u_s^2}$ denote the pixel values of the same pixel lie partly in shadow and totally in shadow, respectively. It shows that, after be added with the transfer vector $\boldsymbol{T}$, these pixels can still be projected along the vector $\boldsymbol{u_0}$ (illuminants ratio vector) into an illumination invariant vector, $\boldsymbol{u_p'}$. Also, as these newly obtained pixels are perpendicular to the illuminants ratio vector, the orthogonal decomposition operation will no longer cause color distortion on these pixels.

4) Subtracting transfer vector $\boldsymbol{T}$ from $\boldsymbol{I_p^t}$ to get the object color constant image.

In Fig. 2, we show our object color constancy method for WHITE checker under different lighting conditions. Unlike the color illumination invariant images in Fig. 2 (r2), the object color constant images (Fig. 2 (r3)) maintain the color information of the original WHITE checker. An more accurate experiment with quantitative analysis will be shown in our experiment section.

4 Experiment

In our experiment, we applied our proposed method for object color constancy on both Macbeth ColorCheckers and real images. We first compare our method with Grey-World method [3] and Weighted Grey-Edge method [6] respectively. And then a set of object recognition experiments based on our results of object color constant images will show the utility of our method.

4.1 Analysis on ColorCheckers

Similar to the previous experiment for object color constancy, in this section we will further give a more accurate experiment with quantitative analysis on those outdoor Macbeth ColorCheckers. A comparison with Grey-World method and Weighted Grey-Edge method will show the effectiveness of our method.

We use the angular error to evaluate the performance of our object color constancy algorithm for its frequent use in the literature [13]. As the angular error is computed pixel by pixel throughout the object, the overall metric of performance of an algorithm for that set of objects can be the mean of errors. For accuracy, in this paper we calculate both mean and median as well as the max error as our measurement to compare different color constancy algorithms. In Fig. 4, we give some examples of object color constant images based on Grey-World, Weighted Grey-Edge methods and our method. The first checker (DARK SKIN checker) marked with **Object** in Fig. 4 (r1,a) is the object we need to keep color constancy. We use the color of this **Object** in daylight as the canonical object color. It can be seen from Fig. 4 (b), the color of the object based on our method are almost the same as the canonical color regardless of lighting

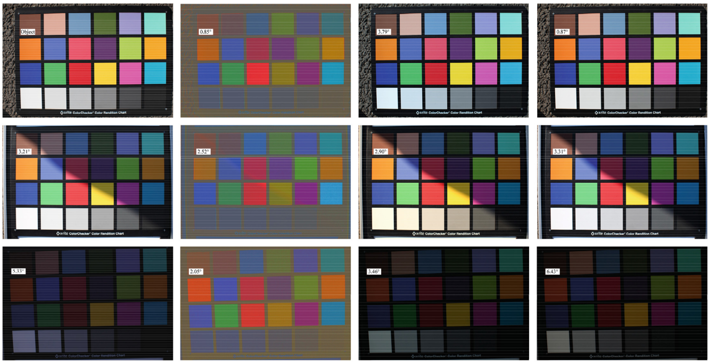

Fig. 4. Examples of object color constant images based on our method, compared to Grey-World method [3] and Weighted Grey-Edge method [6], along with their mean angular error compared to the canonical object color. The first checker in (r1,a) (DARK SKIN checker) marked with **Object** is the object we need to keep color constancy. The color of this DARK SKIN checker is used as the canonical color (ground truth color). The mean angular error is indicated in the left bottom corner of the object. For columns: (a) Original images taken under different lighting conditions, (b) Object color constant images by our method, (c) Color constant images by Grey-World method [3], (d) Color constant images by Weighted Grey-Edge method [6].

conditions. Whereas, even though the Grey-world method [3] and the Weighted Grey-Edge method [6] yield a pleasing result when the input image is illuminated by a uniform illuminant (Fig. 4 (r1)), they cannot deal with images with multiple varying lighting conditions (Fig. 4 (r2, r3)). The relevant quantitative measurement is given in Tab.1. Both the qualitative and the quantitative measurements demonstrate that our object color constant images are considerably closer to generate an canonical object color regardless of lighting condition than both the Grey-World method and Weighted Grey-Edge method.

Table 1. Angular errors for the ColorCheckers in terms of mean, median and max errors for several color constancy algorithms.

	Fig. 4 (r1)			Fig. 4 (r2)			Fig. 4 (r3)		
Methods	Mean	Median	Max	Mean	Median	Max	Mean	Median	Max
Do Nothing	-	-	-	$3.21°$	$2.08°$	$13.16°$	$5.33°$	$4.04°$	$17.12°$
Grey-World	$3.79°$	$3.77°$	$8.09°$	$2.90°$	$2.60°$	$8.90°$	$3.48°$	$3.20°$	$14.00°$
Grey-Edge	$0.87°$	$0.80°$	$6.54°$	$3.34°$	$2.32°$	$17.47°$	$6.43°$	$6.81°$	$14.27°$
Ours	$0.86°$	$0.78°$	$4.94°$	$2.52°$	$2.57°$	$8.23°$	$2.05°$	$2.02°$	$6.30°$

4.2 Applications of Our Object Color Constant Image

As a concrete test of the utility of our calculated object color constant image, we carried out a set of object recognition experiments which identify the object purely by color. Fig. 5 gives one example of this application. In this experiment, we choose the book with bluish green envelope as the object for recognition. These original images were imaged under three different illuminants, one without shadow, one partly in shadow and one totally in shadow. In our experiment, for original images, we adopt angular error to measure the color similarity of different objects. Besides, for comparison, we also evaluate an object recognition experiment based on an illumination and intensity invariant color descriptor: ***rg*histogram** [14] . In our method for object recognition, the root mean square error (RMSE) is used to measure the color similarity.

As shown in Fig. 5, the detection results shows that the using of angular error and the ***rg*histogram** color descriptor are variant to the illumination changes. Therefore, the recognition of this object on original images fails when the object lies partly in shadow (Fig. 5 (r2, b)) or totally in shadow (Fig. 5 (r2, c)). Whereas the object recognition on our object color constant image works quite well (Fig. 5 (r4)). These two experiments on real images show that our proposed method properly gets a color constancy for the given object in the presence of outdoor multiple light sources and can be directly applied to object recognition or tracking.

In addition to the above qualitative experiments, we also give a quantitative result on our proposed new dataset of five objects by comparing the recognition results with the ground truth identified objects. Shown in Fig. 6, our dataset contains 50 images, each of which consists of an original image and a manually marked object image (ground truth identified object). The five objects marked with "**Object1**, **Object2**, **Object3**, **Object4** and **Object5**" are the objects

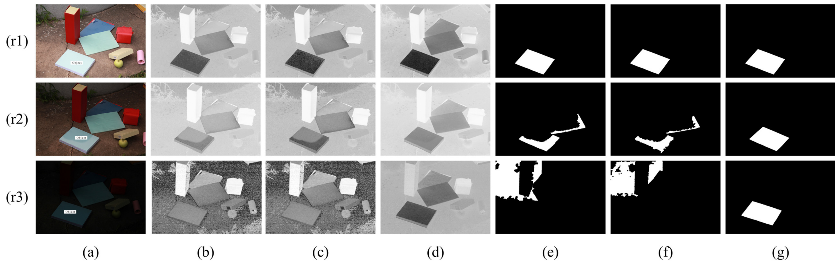

Fig. 5. Object recognition based on our object color constant images and the comparison with original images using angular error and one color descriptor (***rg*histogram**), respectively. For columns: (a) Original images under different lighting conditions. The book with bluish green envelope marked with **Object** is the object we want to identify and its color is used as the canonical color; (b), (c) and (d) The color difference of the original color and the canonical color using angular error, ***rg*histogram** color descriptor and our method, respectively; (e), (f) and (g) The recognition results based on angular error, ***rg*histogram** color descriptor and our object color constant image, respectively.

Fig. 6. Example images from our proposed dataset of five object viewed under different illuminants.

Table 2. Comparison of different methods for object recognition on our proposed dataset.

	Angular error			*Rg*histogram			Ours		
Object dataset	PPV	TPR	F1	PPV	TPR	F1	PPV	TPR	F1
Object1	0.6375	0.7332	0.6688	0.6099	0.7027	0.6394	0.9873	0.9367	0.9608
Object2	0.6339	0.4687	0.5375	0.6304	0.5742	0.6000	0.9968	0.9232	0.9570
Object3	0.6505	0.6145	0.6152	0.6655	0.6841	0.6739	0.9963	0.9911	0.9936
Object4	0.8305	0.4011	0.5212	0.7121	0.5185	0.5886	0.9901	0.9394	0.9636
Object5	0.4913	0.4529	0.4708	0.5828	0.5980	0.5866	0.9998	0.9839	0.9917
Mean	0.6487	0.5341	0.5627	0.6401	0.6155	0.6177	0.9941	0.9548	0.9734

that we use to evaluate our method. Each of the object were imaged with ten different illuminants. The precision rate (PPV), recall rate (TPR) and F1 score (F1) are used as the measurement to evaluate the recognition performance.

Table. 2 give the comparison of different methods for object recognition on our dataset of five object. The mean recognition precision rate of the object recognition on original image (angular error) is only 64.87%. Even the so called illuminant invariant color descriptor ***rg*histogram** is applied, the precision rate is still 64.01%. It reveals that this ***rg*histogram** color descriptor isn't really illuminant and shadow invariant and it cannot improve the recognition performance regardless of lighting conditions. While, the precision rate of the object recognition based on our object color constant image has approached 99.41%. This experiment on object recognition dataset clearly suggests that the color of our object color constant image can serve as a stable feature for object recognition.

5 Conclusion

Approaches for color constancy on a whole image under single light source have made considerable progress. However, color constancy on a whole image under multiple light sources remains an open problem. Different from previous work deriving color constancy for the whole image, this paper settles this problem by focusing on the color constancy for a given object. It can keep the color constancy for a given object under different outdoor lighting conditions, especially for an object under different shadows. This proposed method for object color constancy can be directly applied to some applications such as object recognition and tracking and can improve the performance of these methods.

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