A ROBUST FRAMEWORK TO ESTIMATE SURFACE COLOR FROM CHANGING ILLUMINATION

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ABSTRACT

Illumination color determines the color appearance of an object. When illumination color changes, the color appearance of the object will change accordingly, causing its appearance to be inconsistent. Many methods have been proposed to solve this problem. However, a few researchers found that despite causing the inconsistency problem, the change of illumination color can produce a crucial constraint that can solve the problem itself. Finlayson et al. [10] proposed a method using this constraint. They showed that, by utilizing two different illuminations, it becomes effective to estimate a consistent surface color. Unfortunately, their method is a pixel-based operation that does not consider the presence of noise, thereby making it less robust for real-world images, particularly for those with insufficient difference of illumination colors. Therefore, in this paper, we propose a more accurate and robust method that is extended from their work. We found that by examining the presence of noise and then eliminating it, we can obtain more accurate and robust results. Our implementation on those two factors using natural images shows the increase in accuracy and robustness

1. INTRODUCTION

Reflected light from an object is the product of surface spectral reflectance and illumination spectral power distribution. As a result, illumination color significantly determines the object's color appearance. When the illumination color changes, the object color appearance changes accordingly. To recover the actual color, which is consistent with the change of illumination, a method to discount the illumination color or usually called color constancy is required.

Color constancy is one important subject in the field of computer vision. Many algorithms in this field, such as color-based object recognition, image retrieval, reflection component separation, real object rendering, etc. require the actual color of objects. Many methods have been proposed to recover object actual color [3, 6, 11, 21, 23, 24, 5, 9, 14, 19, 20, 12, 13, 16, 15, 22]. Based on their input, we can categorize them into dichromatic-based methods and diffuse-based methods. Dichromatic-based methods [5, 9, 14, 19, 20, 12, 13, 22] require the presence of highlighting, while diffuse-based methods [3, 6, 11, 21, 23, 24] require body only reflection.

Most diffuse-based methods use a single input image of objects lit by a uniformly colored surface. While in most situations these methods are practical, usually they require strong constraints in surface colors domain, such as a prior surface color database, and cannot accurately estimate images with few surface colors [12, 21, 23, 24]. A few researchers alternatively introduce color constancy methods based on varying or changing illumination color [4, 10, 2]. They have found that, despite creating the problem of color constancy, the change of illuminations could be a crucial constraint to solve the color constancy problem itself.

D'Zmura [4] proposed a method using approximated linear basis functions to form a closed form equation. One drawback of the method is that it fails to provide robust estimations for natural images. Finlayson et al. [10] introduced a method that uses a single surface color illuminated by two different illumination colors. The main idea of their approach is, if we have two different reflected lights (pixels) produced by the same surface color but different illumination colors; then, by dividing the first pixel with all possible illumination colors (in which the illumination color that illuminated the first pixel exists) and intersecting to the second pixel that is also divided by all possible illumination colors, an intersection point representing the actual surface color is produced. The details of this method will be explained in Section 2.2. Barnard et al. [2] utilized the retinex algorithm [18] to automatically obtain a surface color with different illumination color, and then applied the method of Finlayson et al. [10] to estimate varying illumination colors in a scene.

In this paper, our goal is to estimate surface actual color by changing the color of illuminations. We intend to extend the method of Finlayson et al. [10], and to make the method more robust and accurate, even for natural images with relatively small difference of illumination colors. To accomplish our goal, we include noise in the estimation process. Unlike the method of Finlayson et al., we do not set a fixed value of reference illumination. We compute all intersections by changing the reference illumination, and observe whether the noise effects are significant by examining the intersection angle. If the noise is significant then we eliminate it; otherwise, we ignore the noise.

To estimate the surface actual color successfully, the method requires a number of assumptions: first, the illumination chromaticity forms a straight line in a diagonal matrix component space. Second, the camera sensitivity function is narrowband and known. Third, the output of camera response is linear to the flux of incoming light intensity.

The rest of the paper is organized as follows: in Section 2, we first describe image color formation and the definition of chromaticity ;second, we review the method proposed by Finlayson et al., and third, we explain the Planckian locus, which can substitute Judd et al. daylight illuminations. In Section 3, we introduce our approach to make the estimation more robust and accurate. We provide the implementation of our approach and experimental results for real images in Section 4. Finally in Section 5, we conclude our paper.

2. THEORETICAL BACKGROUND

2.1. Reflection Model

Image Formation An image of a diffuse object taken by a digital color camera can be described as:

$$I_c = \int_\Omega S(\lambda)E(\lambda)q_c(\lambda)d\lambda \tag{1}$$

where I_c is the sensor response (RGB pixel values), $S(\lambda)$ is the surface spectral reflectance and $E(\lambda)$ is the illumination spectral power distribution, q_c is the three-element-vector of sensor sensitivity and index c represents the type of sensors (R, G, and B). The integration is done over the visible spectrum (Ω). In this model we ignore camera noise and gain.

By assuming narrowband sensitivity that follows Dirac delta function, Equation (1) can be written as:

$$I_c = S_c E_c \tag{2}$$

where $S_c = S(\lambda_c)$ and $E_c = E(\lambda_c)$. If camera sensitivity cannot be approximated by Dirac delta function (narrowband sensor), we can apply camera sharpening algorithms proposed by [8, 7, 1].

Chromaticity Following Finlayson et al. [10], in this paper we define chromaticity (or specifically *image* chromaticity) as:

$$\sigma_c = \frac{I_c}{I_B} \tag{3}$$

Index c represents R and G color channels, since image chromaticity is two-dimensional data. We can soon notice that Equation(2) still holds in chromaticity space:

$$\sigma_c = s_c e_c \tag{4}$$

where s_c and e_c corresponds to chromaticities of S_c and E_c which we call surface and illumination chromaticity, respectively. Based on this Equation(4), the transformation from an image chromaticity(σ_c^{inp}) lit by a certain illumination(e^{inp}) to another image chromaticity(σ_c^{ref}) lit by reference illumination(e^{ref}) can be described as:

$$\sigma_c^{ref} = \frac{e_c^{ref}}{e_c^{inp}}\sigma_c^{inp} \tag{5}$$

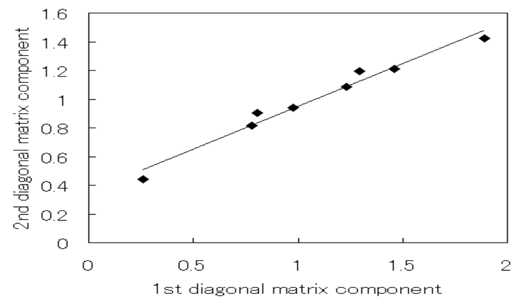

Fig. 1. The straight line approximation of Judd et al' and CIE standard illumination.

since the surface chromaticity does not change in both situations. Therefore, according to Equation (5) we can obtain the chromaticity in reference illumination successfully, with the diagonal mapping whose elements are e_c^{ref}/e_c^{inp}.

2.2. Review of Finlayson's method

The main idea of the method proposed by Finlayson et al. [10] is to use two different reflected lights (pixels) produced by the same surface color but different illumination colors. A brief explanation of their method is as follows.

Let us consider two observed image chromaticities σ^1 and σ^2 under two unknown different illuminations. And let Φ be the set of all diagonal matrices mapping from input image chromaticities (σ^1 and σ^2) to reference chromaticity (σ^{ref}). Here, σ^{ref}'s element equals to $s_c e_c^{ref}$ as we shown in Equation(4). To find a reference chromaticity from given σ^1, σ^2 and Φ is described as:

$$\Phi\sigma^1 \bigcap \Phi\sigma^2 = \sigma^{ref} \tag{6}$$

For the intersection in Equation (6) to exist and be unique, the points of $\Phi\sigma$ must lie on a continuous 1D curve. It requires y in the following equation to be a continuous 1D function of x, where x equals to e_r^{ref}/e_r, and y equals to e_g^{ref}/e_g.

$$\Phi \ni \begin{bmatrix} x & 0 \\ 0 & y \end{bmatrix} \tag{7}$$

To find an intersection, we need to know the function of y, which Finlayson et al. assumed to be a straight line in diagonal matrix space. Figure 1 shows data plots of Judd et al. [17] daylight phases D48, D55, D65, D75 and D100. The data falls roughly on a straight line.

Using analytic derivation, it can be proved that the two lines ($\Phi\sigma^1$ and $\Phi\sigma^2$) always intersect uniquely as long as the straight line formed by Φ does not pass through (0,0). Then the surface chromaticity can always be identified.

Figure 2 shows an example of intersection resulting from two different points that have different illumination color but the same surface color.

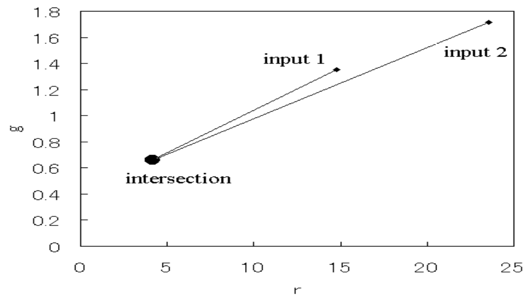

Fig. 2. Example of two intersecting points in diagonal matrix components space

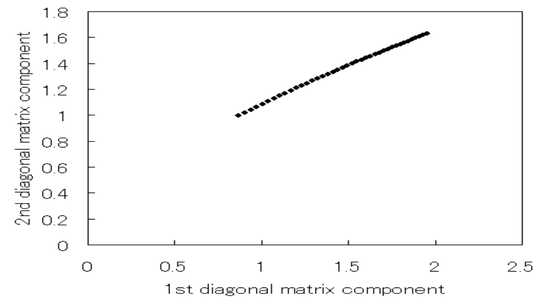

Fig. 3. Planckian locus in diagonal matrix components space

2.3. Planckian Locus

To obtain the function of all possible illuminations, Finlayson et al. use Judd et al.'s daylight illumination phases (D48, D55, D65, D75, D100) and CIE standard illuminations (A, B, C). It is reasonable and supports the whole method well. However, the number of Judd et al.'s daylight phases and CIE standard illuminations are limited (only 8 different illuminations). In general situations, this number is insufficient, because it cannot cover the condition when the difference of illumination color is relatively small. In order to resolve this problem, instead of using Judd et al.'s daylight phases, we use the Planckian locus, which is generated from the Plank formula. In their paper, Judd et al. [17] have already shown that their daylight illuminations can also be approximated by the Planckian locus. Moreover, a number of papers show that the Planck formula is a good representation of almost all natural light sources, including outdoor and indoor illuminants.

The Planck formula is described as:

$$M(\lambda) = c_1 \lambda^{-5} [exp(c_2/\lambda T) - 1]^{-1} \tag{8}$$

where $c_1 = 3.7418 \times 10^{-16}$ Wm^2, $c_2 = 1.4388 \times 10^{-2}$ mK, λ is wavelength (m), and T is temperature in Kelvin. By combining with known sensor sensitivity, we can obtain a camera response of the Planck formula:

$$I_c = \int_\Omega M(\lambda, T) q_c(\lambda) d\lambda \tag{9}$$

Figure 3 shows the Planckian locus in the diagonal matrix components space. The actual shape of the locus in the diagonal matrix components space is a curved line; however, for a certain range of temperatures (4500 K - 8500 K) we can approximate it as a straight line, as shown in Figure 3.

3. A ROBUST FRAMEWORK

The underlying idea of Finlyson et al.'s method that turns the problem of illumination changes into a crucial constraint is significant and applicable for real images. Unfortunately, it still has a few drawbacks, and the main drawback is its sensitivity to noise. Consider that, if the input image chromaticities (σ^1 and σ^2) have noise, which means its location in diagonal-matrix-components space is deviated from their original position, then the intersection of two lines (generated by $\Phi\sigma^1$ and $\Phi\sigma^2$) will be also deviate from the correct location. The matter will be worse if the illumination color difference of the two points is considerably small.

We have conducted an investigation on these problems, and discovered two important causes: intersection angle and noise. We include these two factors in our method, of which the details are as follows.

3.1. Intersection Angle

As already explained in Subsection 2.2, to estimate actual surface color, we need to intersect two straight lines in the diagonal-matrix-component space. This intersection has an angle with the intersection point as a center. In Finlayson et al.'s method, this intersection angle is ignored by setting a fixed reference illumination. In contrast, in our method we consider the intersection angle as crucial information, since it can determine whether the presence of noise is significant.

By changing reference illumination chromaticity (e^{ref}), we can change the location of the intersection (σ^{ref}) made from two input image chromaticities (σ^1 and σ^2). A suface chromaticity under varying illumination makes an upright curved line considering the shape of the Planckian locus. And the two inputs (σ^1 and σ^2) and the intersection (observed surface under reference illumination σ^{ref}) are all on that line, which means to make an intersection from two inputs is to draw a line from the two towards some point on that line. Therefore, we can choose a reference illumination so that an intersection can be located in the middle of the two inputs.

Theoretically, an intersection (σ^{ref}) is located in the middle of two inputs (σ^1 and σ^2), if the angle of the intersection is very wide (Figure 4). In other words, for image chromaticities without noise or less significant noise, we are always able to obtain an intersection with a very wide angle (we set the threshold as more than 90 degrees from our observation) by changing the reference illumination (e^{ref}). However, for real images with significant noise, an intersection with such a wide angle possibly does not exist, even if we use all possible illuminations. Therefore, we can use the

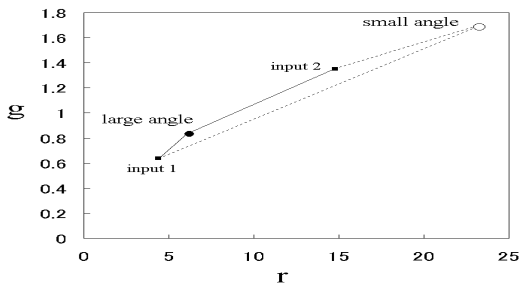

Fig. 4. Example of intersection with a small angle (under 90 degree) and large angle (over 90 degree)

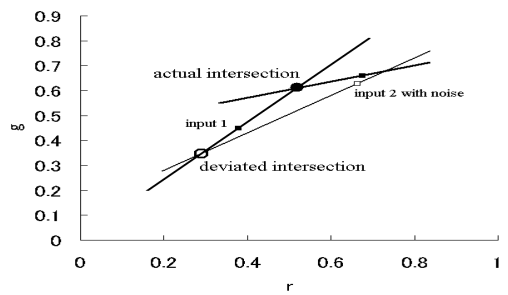

Fig. 5. Illustration of the influence of noise in determining surface color

angle to examine whether the presence of noise is significant. If the noise is significant, then we process it further; otherwise, we ignore the noise.

Although the above angle examination gives a crucial noise detection, it prompts another problem, namely, how if the difference of two image chromaticities (σ^1 and σ^2) is so small that using Judd et al.'s daylight and CIE standard illuminations there is no value of σ^{ref} located in the middle of the two point? Indeed the number of Judd et al.'s daylight and CIE standard illuminations is limited and cannot cover such a condition. Fortunately, Judd et al.'s daylight illuminations can be approximated by the Planckian locus. We can substitute Judd et al.'s illuminations with Planckian locus that has continuous data, making us always able to find σ^{ref} located in the middle of the points.

3.2. Noise

Noise makes the locations of σ^1 and σ^2 deviate from the original ones. If their deviations are significantly large, then the method will produce poor estimation. In the previous subsection, we know that by observing intersection angles, we can determine whether we can ignore the presence of noise.

Figure 5 shows the illustration of noise's influence in determining intersection. If one of the two input image chromaticities suffer from noise, then the actual image chromaticity must be between $\sigma_c^{real} + \delta_{err}$ and $\sigma_c^{real} - \delta_{err}$. Or in other expression, by assuming noise is positive, the input image chromaticity can be described as: $\sigma_c^1 = \sigma_c^{real} + \delta_{err}$. Consequently, based on the analysis of intersection angles, we can decrease the value of σ_c^1 until there is an intersection angle that is more than 90 degrees, which can produce a more accurate estimation of σ_c^{ref}.

The first problem with above noise computation is, it is unknown whether the value of δ_{err} should be decreased or increased, because we do not know whether noise is positive or negative. Fortunately, if there are two image chromaticities with the same surface color but different illumination color, then according to the Planckian locus, both image chromiticities must lie on a horizontal curved line in a two dimensional diagonal-matrix-components space, in which the left point should be lower than the right point. Thus, if oppositely the right point is lower than the left, we should increase its value step by step until we find an intersection angle that is more than 90 degrees.

The second problem is how we can determine which of the two image chromaticities should be changed (by decreasing or increasing). If we change both of them simultaneously, besides it being computationally expensive, we possibly cannot obtain the correct estimation. Thus, to resolve this problem, we approximately choose one of them to be constant, and change the value of another. We consider it as a reasonable approximation, because as long as two points have angle of more than 90 degrees, and their position is not so different horizontally, then even if we wrongly choose image chromaticity to be changed, it does not significantly affect the result of estimation.

Using this kind of increment and decrement noise value can allow us to robustly estimate the surface color even if the noise parameters are unknown. This is one of the advantages of using our framework.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

Implementation In our implementation, we captured two images of a scene from a fixed object and camera position but under different illumination temperatures. From the same pixel location of the two images, we convert the sensor response values into image chromaticity values. By intersecting the lines, we can obtain a value of σ^{ref} and its intersection angles. But instead of using a fixed value of reference illumination, we calculate all intersections from all values of temperature at certain intervals. We check whether there is any intersection that has an angle of more than 90 degrees. If there is an angle with such a degree, then we can obtain the surface color, as we know its reference illumination. On the other hand, if there is no more-than-90-degrees intersection angle, then we choose the righter point to be increased with a small scalar value iteratively until there is at least one angle that is more than 90 degrees. In our experiments, we set the temperature interval value equal to 100, and the noise increment value equal to 0.01.

Experimental Condition We conducted several experiments on real images, taken using a SONY DXC-9000, a progressive 3 CCD digital camera, by setting its gamma correction off. To ensure that the outputs of the camera were linear to the flux of incident light, we used a spectrometer: Photo Research PR-650. We used planar and convex objects to avoid interreflection, and excluded saturated pixels from the computation. For evaluation, we compared the results with the average values of image chromaticity of a white reference image (Photo Research Reflectance Standard model SRS-3), captured by the same camera.

Experimental results Figure 6.a and 6.b show input image chromaticities of pixels taken from an outdoor object illuminated by cloudy sky-light at 15:00 and 18:00. The actual surface color obtain using the standard white reference is shown in 6.c. Figure 6.d shows our surface color estimation, while 6.d is produced by Finlayson et al.'s method with D65 as reference illumination. We have several conditions of experiment with the same object, and our estimation produced consistent results, while the results of Finlayson et al.'s method were so inconsistent that the result could be green or blue, which is far from the ground truth. Figure 7 shows a scene of one of our two input images. This image was taken at 18:05 illuminated by cloudy daylight. Another input (Figure 8) was taken at 15:05 also illuminated by cloudy daylight on the same day. Figure 9 shows our estimation result of the image. To produce this image, we considered only pixels whose intensities are not saturated and above camera dark. We computed the average of the estimated illumination color of image shown in Figure 7, and normalized that image. Note that we excluded the needles of the tower's clock as well as moving leaves from the computation by evaluating the image chromaticity difference. Figure 10 is the result based on the standard white reference which shows that our result is quite good.

Evaluation In our evaluation using the Macbeth color checker illuminated by various condition of outdoor sunlight and skylight, the average error of our estimation in term of CIE chromaticity definition ($\sigma_c = I_c/(\Sigma I_i)$) is 0.063, while that of Finlayson et al.'s method is 0.11. The maximum error of our estimation is 0.16, and Finlayson et al.'s maximum error is 0.32. This error evaluation is mostly done with regard to the red and blue channels. Since, in the green channel, either our method or Finlayson et al.'s method gave considerably accurate results as Planckian-based illumination change is relatively small in this channel.

5. CONCLUSION

We have proposed an extended version of Finlayson et al.'s method [10]; our purpose is to make it more robust and accurate. The underlying idea of our approach is to exploit the possibilities to control the intersection angle and noise. This approach makes the method more applicable in various conditions of natural images. And, the experimental results show the effectiveness of our method.

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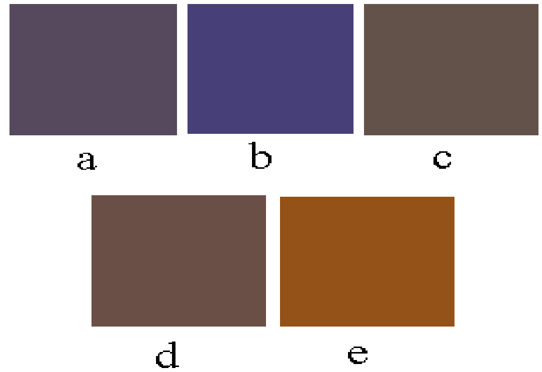

Fig. 6. Comparison results between our proposed method and Finlayson et al.'s method.

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Fig. 7. One of the two input scene, illuminated by cloudy daylight at 18:05.

Fig. 8. The other input, illuminated by cloudy daylight at 15:05.

Fig. 9. The estimated scene actual color of the image shown in Figure 7, computed using our proposed method

Fig. 10. The estimated scene actual color using the standard white reference

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