Illuminant Estimation Based on von Kries Transformation and Gamut Comparison

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Abstract

Due to the strong connections between research on illuminant estimation problems and chromatic adaptation phenomena, it was believed that application of chromatic adaptation models would be helpful in solving the problems of illuminant estimation. This article introduced an illuminant estimation method based on the fundamental chromatic adaptation model, the von Kries Model. Through image transformation and the comparison between image gamuts and reference gamut, the method is designed to simulate the adjustment of visual systems, transforming the image to be as if taken under the reference illuminant. Then, the estimation of scene illuminant was deduced from the transformation coefficients. Gamut comparison was repeated at each intensity level in the three-dimensional (x, y, Y) color space to maintain the three-channel color information of images and to simplify the calculation. Experimental results illustrate the efficiency of this proposed method.

Introduction

Illuminant estimation from images has been a problem studied for a long time, and also has been receiving more attention during recent years because of the demands of many imaging areas, such as digital photography and machine vision. An increasing number of algorithms have been proposed based on various viewpoints to this problem. The most widely known algorithms are Gray World,[1-2] Maximum RGB,[3-4] Maloney-Wandell,[5] and Dichromatic model.[6-7] Since Forsyth proposed the idea of using gamut to estimate scene illuminant,[8] many methods based on gamut-mapping technique have been studied because of its simplicity and accuracy.

On another research front, for more than 100 years the color constancy abilities of human eyes have prompted scientists to study the mechanism of the human visual systems. A series of chromatic adaptation models have been proposed, from the oldest von Kries Model to the recent RLAB and LLAB Models.[9]

The researches on illuminant estimation and chromatic adaptation have their common points, in that both of them concern the illuminant factors in images. While studies in illuminant estimation concentrate on determining the unknown illuminant from image colors, chromatic adaptation research attempts to find out what mechanisms the visual systems uses to discount the effect of illumination change. The application of a chromatic adaptation model is therefore potentially helpful in illuminant estimation problems.

In this article, we will introduce an illuminant estimation method which applies the von Kries Model as an image processing step. von Kries is used because it is simple and still highly effective.[10] A gamut comparison technique follows to detect the best transformation, which reveals the most likely scene illuminant for the original image.

Gamut calculation and comparison is based on the color space where gamuts are described. There are different selections of color space in describing gamuts, for example, (R, G, B) color space,[8] and some two-dimensional color space as (r, g), (R/B, G/B) and (R, B).[11-13] As we know, when gamuts are expressed in three-dimensional space, for example (R, G, B), they are normally described as polyhedrons. And gamut calculation and comparison may involve intensive computation because of the complexities in calculating polyhedron volumes and intersections. On the other hand, when describing gamuts in two-dimensional color space, the original three-channel information of images may not be used thoroughly.

In this method, the color space (x, y, Y) is selected to describe gamuts in order to keep the three-dimensional information of images and to simplify the calculation. The gamut comparison is performed as two-dimensional geometric calculation at each Y level. Another reason for this selection is to avoid the gamut differences caused by different kinds of camera sensors when doing gamut comparison. Besides, in order to avoid null estimation, a outstretch tolerance is introduced to permit transformed gamuts to have some exceeding out of the reference gamut.

The evaluation of this method is divided to the testing of synthetic images and the testing of real images, and the evaluation errors are compared with some other methods.

Method

Application of von Kries Transformation

In 1902, von Kries proposed a simple model of chromatic adaptation, which laid the foundation for all modern chromatic-adaptation models. In his article, he outlined his hypothesis that "the individual components present in the organ of vision are completely independent of one another and each is fatigued or adapted exclusively according to its own function".[9] The interpretation of his hypothesis can be expressed in Equation (1), which is referred as the von Kries Model.

$$\begin{pmatrix} L' \\ M' \\ S' \end{pmatrix} = \begin{pmatrix} k_L & 0 & 0 \\ 0 & k_M & 0 \\ 0 & 0 & k_S \end{pmatrix} \cdot \begin{pmatrix} L \\ M \\ S \end{pmatrix} \tag{1}$$

L, M, S and L', M', S' are the initial and post-adaptation cone signals, while k_L, k_M and k_S are the scaling coefficients.

The original image is transformed with von Kries model to show the effect as if taken under another illuminant, defined as the *transformed illuminant*. The three scaling coefficients k_L, k_M and k_S can be expressed as the ratio between cone responses of white point under the transformed illuminant and those under the original illuminant, that is,

$$\begin{aligned} k_L &= \frac{L_{W_T}}{L_{W_O}} \\ k_M &= \frac{M_{W_T}}{M_{W_O}} \\ k_S &= \frac{S_{W_T}}{S_{W_O}} \end{aligned} \tag{2}$$

The subscript W_T means white point under transformed illuminant and W_O means white point under original illuminant.

In this method, one typical illuminant, for example Illuminant D65, is defined as reference illuminant. With one group of suitable coefficients k_{L_R}, k_{M_R} and k_{S_R}, the transformed image could have the chromaticities of the transformed illuminant the same as those of the reference illuminant. Then the cone responses of white point under the original illuminant can be calculated as:

$$\begin{aligned} L_{W_O} &= \frac{L_{W_R}}{k_{L_R}} \\ M_{W_O} &= \frac{M_{W_R}}{k_{M_R}} \\ S_{W_O} &= \frac{S_{W_R}}{k_{S_R}} \end{aligned} \tag{3}$$

Here L_{W_R}, M_{W_R} and S_{W_R} are L, M, S values of white point under reference illuminant. For the original image, the relationship between L, M, S and the chromatic tristimulus value X, Y, Z can be presented as Equation (4).

$$\begin{pmatrix} L \\ M \\ S \end{pmatrix} = M \cdot \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} \tag{4}$$

where

$$M = \begin{pmatrix} 0.400 & 0.708 & -0.081 \\ -0.226 & 1.165 & 0.046 \\ 0 & 0 & 0.918 \end{pmatrix}$$

After the transformation as Equation (1), the tristimulus values X', Y', Z' of the transformed image can be transformed from L', M', S' as Equation (5).

$$\begin{pmatrix} X' \\ Y' \\ Z' \end{pmatrix} = M^{-1} \cdot \begin{pmatrix} L' \\ M' \\ S' \end{pmatrix} \tag{5}$$

With the above transformation, original images' chromatic tristimulus values can be transformed into cone responses, which are used in von Kries transformation, and the transformed cone responses can be returned back to chromatic tristimulus values.

Gamut Comparison in Color Space (*x*, *y*, *Y*)

From the above analysis, we know that when the transformed illuminant has the chromaticities the same as the reference illuminant, the original illuminant chromaticities can be calculated from Equation (3). But since the chromaticities of both the original illuminant and the transformed illuminant are unknown, there should be some criterion to detect the coincidence of the transformed illuminant and the reference illuminant. The criterion in this article is based on the comparison of the transformed image gamut and the reference gamut, where the reference gamut refers to the possible color ranges under the reference illuminant.

In order to keep the three-channel information of images, it's better to describe gamuts in a three-dimensional color space. But the process in finding the vertices of gamut polyhedrons and the calculation of volume and intersection of gamuts in three-dimensional spaces are normally complex and with intensive computation. Here, gamut comparison is performed in (x, y, Y) space. Three-dimensional gamut calculations are divided into a series of two-dimensional geometric calculation in (x, y) space with spaced Y steps. This color space has the characteristics that the (x, y) ranges with lower Y values are always larger than the (x, y) ranges with higher Y values. Then (x, y) range at each Y step is the convex polygon envelope that covers all the (x, y) values of image pixels with larger Y values. So the calculation could be simplified. Another reason for this color space is to make the gamut comparison process not be affected by the variation in camera sensors. For example, when describing gamut in (R, G, B) space, both the reference gamut and the transformed image gamuts would be changed according to the selection of camera sensors. Figure 1 shows an example of such gamut description. It is the gamut of optimal colors[14-15] under Illuminant D65 with spaced Y step equal to 10.

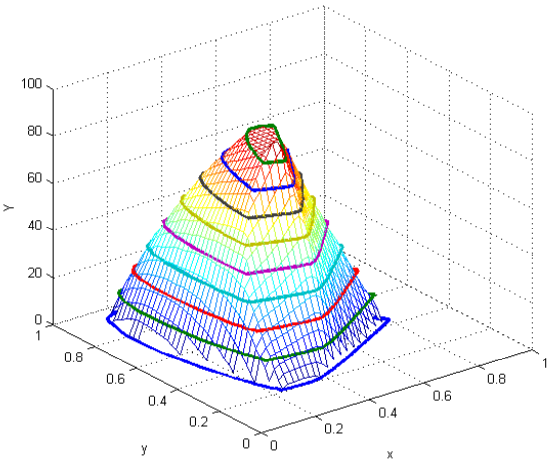

Figure 1. Optimal color gamut under Illuminant D65.

The next step is the comparison of the transformed image gamuts with the reference gamut. Normally, when the transformed illuminant has the same chromaticities as the reference illuminant, the transformed gamut should be inside the reference gamut. But because of the possibility that some object reflectances exceed the range of reference reflectance database, or because of some errors in transformations and due to noise, it is possible for the transformed gamuts to have some parts outstretch the reference gamut even when the transformed illuminant is the same as the reference illuminant. In order to avoid the problem of null estimation resulted from no possible transformation to make the transformed gamut be totally inside the reference gamut, an outstretch tolerance is set to permit a little exceeding of the reference gamut. The tolerance is defined as the area ratio between the gamut intersection part and the transformed image gamut. The tolerance is first set at a high value, for example 0.99, then for those images that still have null estimations, the ratio is decreased finely until one estimation is found.

Since three-dimensional gamut calculation has been simplified as a series of two-dimensional geometry calculations, the intersection of two gamuts can also be treated as the polygon intersection in (x, y) space at each Y step. Figure 2 shows an example of the gamut intersection at one Y step.

The calculation of polygon intersection areas involves two steps: (1) find the vertices of the common region which describes the intersection of the two polygons; and (2) calculate the area of the common region. The vertices of the common region are composed of the line intersecting points of the two polygons and the vertices of one polygon inside the other polygon. The area of the common region can be calculated using Equation (6).

$$S_{polygon} = \frac{1}{2}\left(\begin{vmatrix} x_1 & y_1 \\ x_2 & y_2 \end{vmatrix} + \begin{vmatrix} x_2 & y_2 \\ x_3 & y_3 \end{vmatrix} + \cdots + \begin{vmatrix} x_n & y_n \\ x_1 & y_1 \end{vmatrix} \right) \tag{6}$$

Here (x_1, y_1) to (x_n, y_n) are the coordinate values of the common region vertices. Since gamuts in lower intensity levels have larger areas than those in higher intensity levels, in order to treat each intensity level the same weight, the overlapping degree at each Y step is defined as the ratio between the areas of the common region and the areas of the reference gamut range. Then the overlapping degree for the whole gamut comparison can be expressed as:

$$p = \frac{1}{n}\sum_{i=1}^{n} \frac{S^i_{P_I}}{S^i_{P_R}} \tag{7}$$

Here, n is the number of Y steps, $S^i_{P_I}$ is the intersection polygon area at ith Y step, and $S^i_{P_R}$ is the reference gamut (x, y) polygon area at ith Y step. When the transformed gamut and the reference gamut have the maximum overlapping degree, the transformed illuminant is assumed to have the same chromaticities as the reference illuminant, and the chromaticities of the original illuminant can be deduced from the transformation coefficients k_L, k_M and k_s as Equation (3).

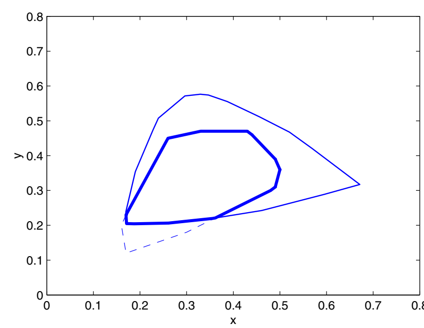

Figure 2. Gamut intersection at each Y step can be calculated as polygon intersection.

Experiments

In this work, the establishment of the reference gamut was based on the database made by 1373 spectral reflectance samples. These include Vrhel database[16] (354 samples), and other objects including patches from the Munsell Color Book, paint samples, flowers and leaves, and additional manmade and natural objects.

The testing of the method is divided in two parts. The first is the testing of synthetic images, and the second is the testing of some real images.

In the testing of synthetic image, four groups of synthetic images were established. Each group contains 1000 images composed of 8, 16, 32, 64 surfaces. The surfaces are randomly selected from the reference spectral reflectance database. The simulated sensor sensitivities are composed of cubic spline functions peaked at 450nm, 550nm and 590nm with half-width 40nm, 60nm and 60nm. Image illuminants are randomly selected from 13 blackbody radiation with color temperature ranging from 2500K to 8500K.

The testing results are compared with Gray World method and Maximum RGB method. In addition, Barnard proposed a new method as three-dimensional color by correlation.[17] Although the method in this article was not inspired or referred from Barnard's new method, the two have some main common points, such as doing gamut comparison at different intensity levels. One main difference between the two methods is the selection of color space, where three-dimensional color by correlation is performed in (r, g, L) color space. In order to see the effect of this difference, the method was also tested in (r, g, L) color space, where $L=R+G+B$, and $r=R/L$, $g=G/L$. And the image transformation is also performed on (R, G, B) sensor output values as

$$\begin{pmatrix} R' \\ G' \\ B' \end{pmatrix} = \begin{pmatrix} k_R & 0 & 0 \\ 0 & k_G & 0 \\ 0 & 0 & k_B \end{pmatrix} \cdot \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{8}$$

The error metric is defined as the Euclidean distance of the chromaticity of estimated illuminant and real illuminant in (r, g) space. The comparison results of minimum, mean and maximum errors for different methods for each synthetic image group are shown in Table 1. And Figure 3 shows the mean estimation errors for each method.

Table 1. Estimation error comparison of different methods for synthetic images with different surface number.

	Minimum	Mean	Maximum
	8 surfaces		
Gray World	0.003	0.072	0.27
Max RGB	0	0.061	0.29
Proposed method	0	0.063	0.25
In (r,g,L) space	0	0.059	0.25
	16 surfaces		
Gray World	0.003	0.064	0.21
Max RGB	0.001	0.043	0.20
Proposed method	0	0.041	0.21
In (r,g,L) space	0	0.040	0.21
	32 surfaces		
Gray World	0.002	0.063	0.16
Max RGB	0	0.027	0.14
Proposed method	0	0.020	0.13
In (r,g,L) space	0	0.019	0.15
	64 surfaces		
Gray World	0.001	0.061	0.12
Max RGB	0	0.018	0.082
Proposed method	0	0.012	0.074
In (r,g,L) space	0	0.012	0.11

The results show that for synthetic images, normally the proposed method has better performance than Gray World and Maximum RGB, except that Maximum RGB works a little better when surface number is 8. On the other hand, when gamuts are described in (r, g, L) space, and the transformation is on (R, G, B), the performance is a little better than those in (x, y, Y) space, especially when surface number is lower. That is partly because there are less transformations when doing transformation on (R, G, B), and also because the (L, M, S) response curves are normally wider than sensor sensitivity curves.

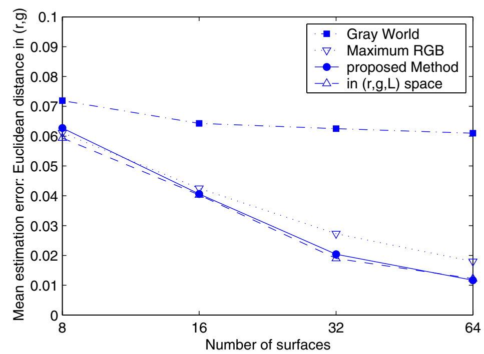

Figure 3. Mean estimation errors of different methods for each surface number.

For testing real images, the experimental images were taken by Sony DTS-ST5 digital camera. Their properties were determined through the measurement of color patches with known spectral reflectance. The initial camera output data were linearized and transferred into tristimulus values (X, Y, Z). The original illuminants included light sources in light booth and in photo studio, and also some natural daylights. Their spectral power distributions were measured at the same time with PhotoResearch PR650 spectro-radiometer. The experimental images included 5 scenes of the GretagMacbeth ColorChecker rendition chart, fruits and vegetables, groups of small objects, doll and painting. Each scene was taken under 9 illuminants ranging from 2300K to 8000K, altogether 45 images. The testing results are compared with the method of Gray World and Maximum RGB. The estimation error results are shown as Table 2.

Table 2. Estimation error comparison of different methods for real images.

	Minimum	Mean	Maximum
Gray World	0.035	0.102	0.136
Max RGB	0.059	0.130	0.293
Proposed method	0.010	0.058	0.128

The results show that the method in this article obviously outperforms Gray World and Maximum RGB methods for real images. Here, Maximum RGB method was not as efficiency as Gray World method as for synthetic images because of the existence of saturated highlights in real images. Besides, the estimation efficiencies are also affected by image scenes. The scenes with colorful surfaces or objects, for example the Macbeth ColorChecker has more accurate illuminant estimations than those with dull colors.

Conclusions

The article has introduced an illuminant estimation method based on von Kries transformation and gamut comparison. By simulating the color constancy abilities of the visual system, the method applied the von Kries model to transform the chromaticities of the original image, simulating the effect of being taken under a reference illuminant. The method used the three-dimensional color space (x, y, Y) to describe gamuts, which keeps the three-channel information of images and simplified the computations of gamut volumes and intersections as a series of two-dimensional geometric calculations. And the method used only one illuminant reference gamut. Through the comparison between transformed image gamuts and the reference gamut, the method detected the coincidence of the transformed illuminant and the reference illuminant. The original scene illuminant was deduced through the transformation coefficients. The performance of this method was tested through both synthetic and real images, and the estimation errors were compared with some other methods. The experimental results illustrated the efficiency of this proposed method.

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