

Color Temperature Estimation of Scene Illumination

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Abstract

Knowledge of the full illuminant spectral power distribution is useful for many imaging applications. In most applications, however, accurate estimation is impossible because very few color measurements are made. In many of these cases, however, a great deal is known about the potential set of illuminants. In these cases, classification of scene illumination, rather than estimation of the full spectral power distribution of the illumination, is appropriate and useful. We analyze illuminant classification algorithms designed to group images by illuminant color temperature. To classify the illumination color temperature, a version of the correlation method suggested by Finlayson and colleagues is used. The original algorithm uses chromaticity coordinates, and thus does not use the fact that bright image regions contain more information about the illuminant than dark regions. Using calibrated images with known illuminants, we find that the original correlation method can be improved by using a scaled version of the red and blue sensor responses. When applied to these quantities, the algorithm is more sensitive to differences in illuminant color temperature. Then, we consider an application of the classification algorithm to the problem of rendering a color image acquired under one illumination under a second illuminant, with a different color temperature. This algorithm uses the ratio of R, G, and B sensor responses under different illuminants. The proposed method is applied to an image database of real scene.

Introduction

Estimating the wavelength composition of scene illumination from image data is an important problem in color engineering. Solutions to this problem have applications in image understanding, image processing and computer graphics. Several methods for estimating the full spectral-power distribution have been proposed,[1-6] but all depend on strong physical constraints with respect to the illuminant and often encounter mathematical complexity and robustness difficulties associated with inferring a continuous illuminant spectrum from a small number of color sensor responses.

In recent years, theorists have attempted a useful and simpler form of the estimation problem.[7-8] Rather than numerical estimates of the full spectral power distribution, one tries to classify the wavelength composition of the scene illumination into one of a restricted number of groups. An example of illumination classification is to restrict the estimation to a set of blackbody radiators, say spaced every 500 degrees Kelvin (K). Classification of illuminants by color temperature is useful in many applications, including photography, color imaging, printing, and room lighting. Color temperature classification provides simple specification of many common light sources.[9]

Two related issues are analyzed in this paper. First, we consider the estimation of color temperature of scene illumination from a single image. Second, we consider how a color image acquired under one illumination can be rendered for viewing in an illumination with a different color temperature.

We use a modification of the correlation method suggested by Finlayson et al.[7] In that method, each illuminant is associated with a reference gamut in the chromaticity plane. To estimate the illuminant for a given image, the image pixel chromaticities are compared with the reference gamuts of several different illuminants. The color temperature for the image illumination is estimated by finding the best match between the number of pixels and the reference gamuts.

Using a set of calibrated images with measured spectra, we found that this method provides a poor estimate of the illuminant color temperature. The difficulty rests in the reliance on chromaticity coordinates. By using a scaled version of the red and blue sensor responses, we obtain a better estimate of the illuminant color temperature.

Having estimated the color temperature of the acquired image, it is often desirable to render that image under a simulated illuminant of a different color temperature. When the potential illuminants are restricted to vary only in color temperature, this color correction can be performed in a simple way. The method is described and applied to an image database that includes a variety of real scene.

Reference Data

To determine the basic parameters of the illuminant classification model, we perform calculations using a set of blackbody radiators, a moderately large set of surface reflectance functions, and the properties of our camera. Figure 1 shows the spectral-power distributions of a black body radiator at absolute color temperatures ranging from 1000K to 10,000K in 500K steps.

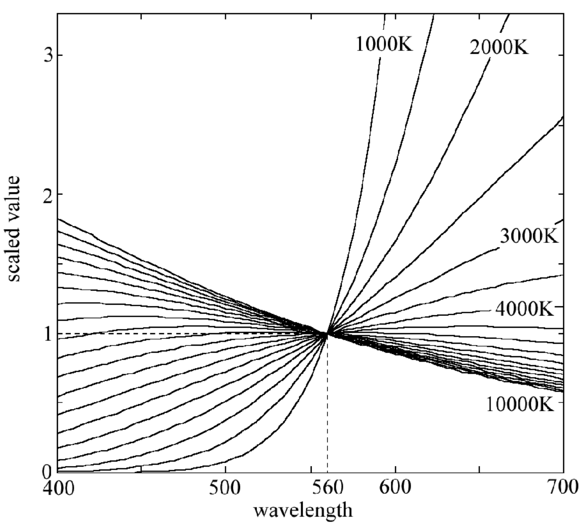


Figure 1. Spectra of a black body radiator.

The spectral radiant power at temperature T (in Kelvin K) is described by an equation of the following form[9]

$$M(\lambda) = c_1 \lambda^5 \{exp(c_2/\lambda T) - 1\}^{-1}, \qquad (1)$$

where c_1 and c_2 are constants. We use the database of surface-spectral reflectances made available by Vrhel et al.[10] The database consists of 354 measured reflectance spectra of different materials collected from Munsell chips, paint chips, and natural products. Finally, reference gamuts are simulated with respect to a three CCD camera in our laboratory. The spectral responsivities of this camera were measured very accurately in separate experiments. The simulated camera sensor responses stimulated in response to test surfaces under illuminant color temperatures ranging from of 2500K to 8500K are used as raw RGB measurements. The convex hull of these measurements, projected into a two-dimensional representation, are used as the reference gamuts. This is the same camera used to acquire natural images in the experiments described below.

Reference Gamut Properties

Consider some desirable properties of a set of reference gamuts. First, one reference gamut must not include another. Otherwise, choosing a unique temperature fails. Second, it is preferable that the gamuts be separated and have minimal overlap. This improves the ability to discriminate between illuminant color temperatures.

We have examined several coordinate systems with these criteria in mind. First consider the sensor chromaticity coordinates (r, b) which are obtained by normalizing the camera outputs RGB for each surface as

$$r = R/(R+G+B),\ b = B/(R+G+B). \qquad (2)$$

Figure 2 shows the reference gamuts with respect to our camera. The gamut for 8500K includes most of the area in the other gamuts. In the presence of even modest amounts of sensor noise, these chromaticity coordinates provide a poor choice for illuminant classification.

Next consider the CIE-xy chromaticity coordinate system. We make a 3x3 matrix for transforming the camera outputs RGB into the tristimulus values XYZ. This matrix is determined by fitting the sensor spectral-sensitivity functions to the CIE color-matching functions. The chromaticity coordinates (x, y) are then obtained by normalizing the tristimulus values XYZ as

$$x = X/(X+Y+Z),\ y = Y/(X+Y+Z). \qquad (3)$$

Figure 3 shows the reference gamuts in the xy chromaticity plane. Again the biggest gamut for 8500K includes most of the area in the other gamuts.

One difficulty in using the chromaticity representation is that the chromaticity projection removes intensity differences. High intensity regions of the image contain more information about the illuminant than dark, shadowed regions. Hence, basing illuminant classification on data that have been normalized by the chromaticity mapping removes an important source of information.

Let us consider classification based on raw sensor data in the RB plane. The raw sensor space does not mix light and dark measurements. It does include absolute intensity differences between images, however, that are undesirable. To calculate reference gamuts in the (R, B) plane, we normalize overall intensity differences between images by scaling each image with a single number. Let I_i be the intensity

$$I_i = \left(R_i^2 + G_i^2 + B_i^2\right)^{1/2} \qquad (4)$$

for an object surface i, and Imax be the maximal value of the intensity over all surfaces. Then the camera outputs RGB are normalized as

$$(R, G, B) = (R/I_{max}, G/I_{max}, B/I_{max}). \qquad (5)$$

Figure 4 shows the reference gamuts in the (R, B) plane at color temperatures intervals of 500K spanning the range (2500K, 8500K). In this space, the reference gamuts are better separated and their positions change smoothly with the color temperature. Figure 5 shows a natural image of one of the outdoor scenes used in this study. The correlated color temperature of this scene is about 6200K. The scaled (R, B) coordinates were calculated for all pixels of this image and they are plotted in the RB plane in Figure 4. The pixel values, particularly for high luminance levels, fits selectively within the gamuts near 6000K - 6500K.

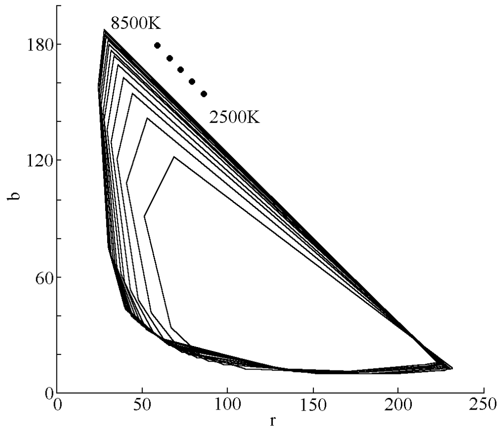


Figure 2. Gamuts in rb chromaticity plane.

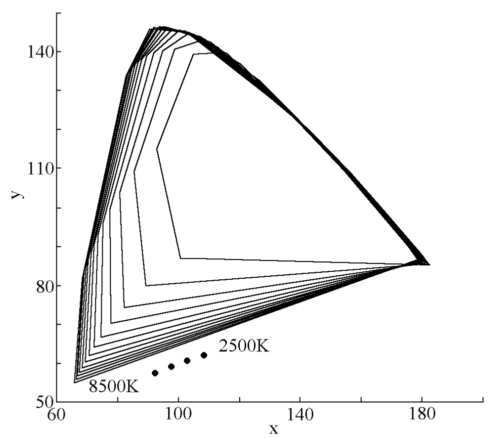


Figure 3. Gamuts in xy chromaticity plane.

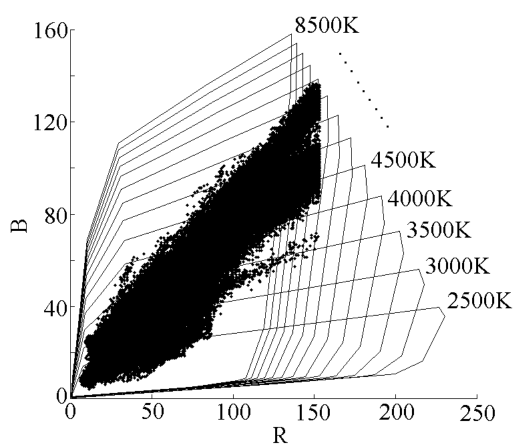


Figure 4. Gamuts in RB sensor plane.

Figure 5. Example of outdoor scene.

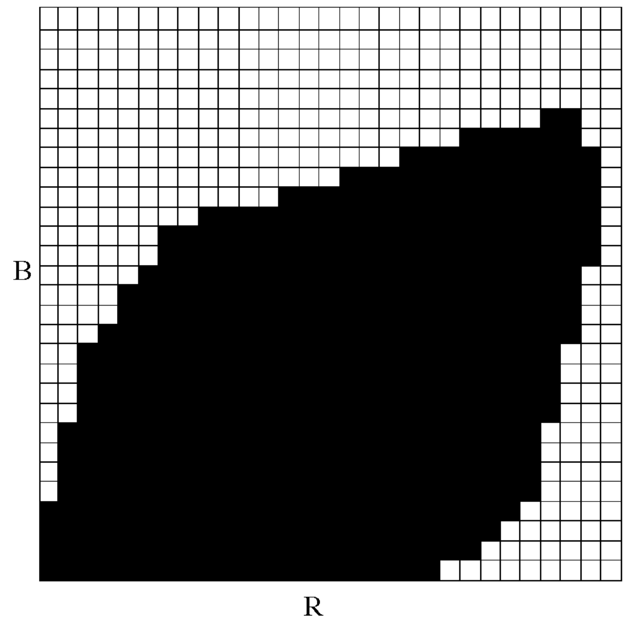
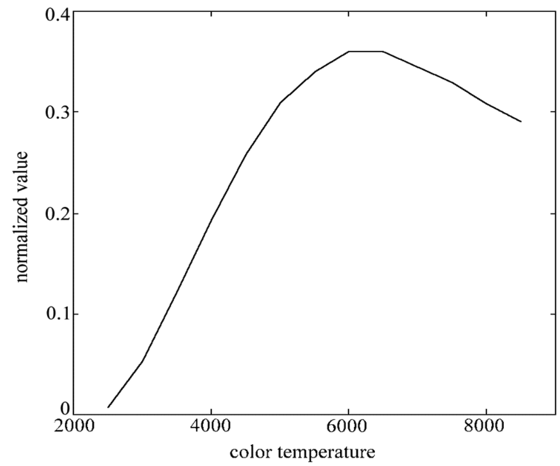


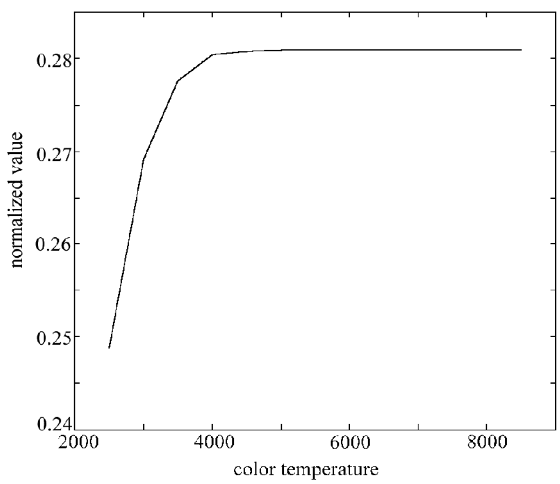
Figure 6. Binary image of gamut.

Color Temperature Estimation

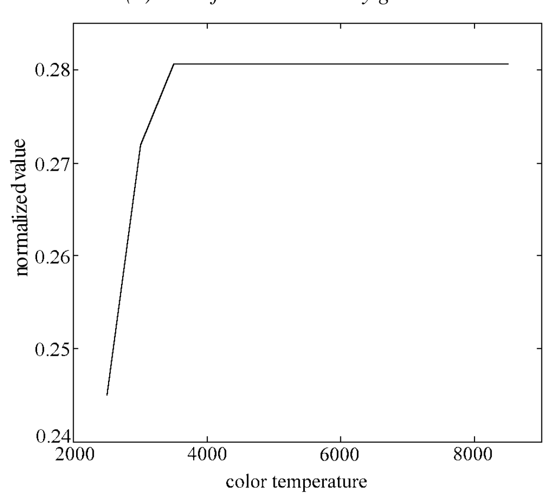
To calculate the overlap between the color gamut for a given image and the reference gamuts, we count the number of pixels whose the (R, B) coordinate points fall in each reference gamut. Following the method described in Finlayson,[7] the RB plane is divided into a regular grid with small even intervals as shown in Figure 6. In practice, the grid is described as an array of 256x256 with fine regular cells. Then we obtain a 256x256 binary image for each reference gamut. In Figure 6, all cells within the gamut are represented by the filled squares, which are set to 1's in the array, and the others are represented by the open squares, which are set to 0's.



(a) Use of RB sensor gamut.



(b) Use of rb chromaticity gamut.



(c) Use of xy chromaticity gamut.

Figure 7. Correlation function for the image in Figure 5.

Next, the RGB data of the CCD camera image are represented in the scaled RB plane. In this case, the original RGB values are normalized with the maximal intensity over all pixels in a given image. The pixel with the maximal intensity should be stable, making the normalization reliable. For this purpose we remove the pixels of isolated highlights as noises. From these data, a binary image of the observations is created. This image has the same size as the reference gamut, when 1's in the cells indicate that pixels with the corresponding (R, B) values appear in the original image. Finally, a correlation value is computed between the binary images of the reference gamut and the image data.

An illuminant color temperature of the given image is estimated as the temperature of a reference gamut providing the largest correlation. We have evaluated the modified algorithm using a database consisting of real images of outdoor scenes taken under sunlight. Figure 7 shows the correlation values as a function of reference gamut color temperature for the image shown in Figure 5. Figure 7 (a) uses the proposed RB sensor gamut shown in Figure 4. The correlation values are calculated from 2500K to 8500K in 500K steps. The color temperature is then estimated as 6000-6500K. Figure 7 (b) and (c) use the rb and xy chromaticity planes, respectively. In both cases, there is no unique peak on the correlation functions, but constant values in a wide range of color temperature. Thus the color temperature estimation using the chromaticity gamuts fails.

Figure 8 demonstrates a set of correlation functions for 16 images of outdoor scenes taken under the same sunlight, each curve indicates the correlation function for one image. The estimated illuminant color temperatures are near 6000k, very close to the direct measurement results. Low estimates of the color temperature occur for some images that contained a small number of dark object colors, such as when we observe a shadow area through zoom lens. High estimates of the color temperature occur for images composed of sky in most part, or when we observe a light source directly.

The estimation error of color temperature is determined as follows: The estimated color temperature T_e is chose as the sampled color temperature at every 500K which provides a maximum of the correlation function. The direct measurement of color temperature was obtained with a reference white standard and a spectro-radiometer. We placed the white plate in the neighborhood of the viewing point and measured the spectral power distribution of the reflected light with the radiometer. The correlated color temperature T_m is determined from the xy chromaticity coordinates of the spectrum. We have T_m = 6264 for these scenes. The estimation error for a set of images is then calculated as the average squared error

$$E = \left(\frac{1}{n} \sum_{i=1}^{n} \left(T_{ei} - T_{mi} \right)^2 \right)^{1/2}, \tag{6}$$

where the symbol n denotes the number of images. We have E=470 for the above images of outdoor scenes under sunlight.

We have performed the same experiment using a variety of natural scenes under different light sources. The proposed algorithms of illuminant color temperature are valid for many light sources including sunlight, incandescent lamps, and fluorescent lamps.

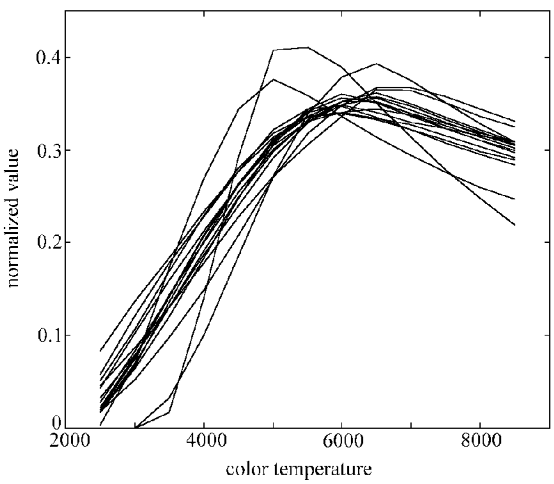


Figure 8. Set of correlation functions for 16 natural images.

Color Correction

Next, we show that once the illuminant color temperature is estimated it is possible to predict the camera sensor responses for the same objects viewed under a different illuminant color temperature. The color correction method is based on summarizing the ratio of R, G, and B sensor responses under different illuminants. One method of calculating these values is illustrated in Figure 9. The camera responses to all 354 surface reflectance functions are calculated for an illuminant at each reference color temperature. These values are used to define two functions of color temperature:

$$k_1(T) = R(T)/G(T)\,,\; k_2(T) = B(T)/G(T). \qquad (7)$$

In this example, the functions are computed using responses from all the surfaces, not just the white point. We have experimented with variations of this formula, including methods that emphasize the white surfaces. Several different methods produce similar results.

The color image acquired at one color temperature can be rendered as an image at another temperature by using k_1 and k_2. Let $(R(T_0), G(T_0), B(T_0))$ be the RGB values for each pixel at estimated color temperature T_0. The RGB values at any temperature T can be estimated as

$$(R, G, B) = (R(T_0)k_1(T)/k_1(T_0),\, G(T_0),\, B(T_0)k_2(T)/k_2(T_0)). \qquad (8)$$

Figure 10 shows an example of converging an acquired image of the Macbeth color checker. Figure 10 (a) shows the original image acquired using an incandescent lamp at a color temperature of 2500K. This color temperature was correctly estimated by the algorithm described in the first part of this paper. Figure 10 (b) shows the image rendered for a 5500K illuminant. This rendering can be compared with the image in Figure 10 (c) that was obtained by direct measurement under a 5500K illuminant. We have found experimentally that the simple rendering algorithm is effective when illuminants are constrained to be blackbody radiators.

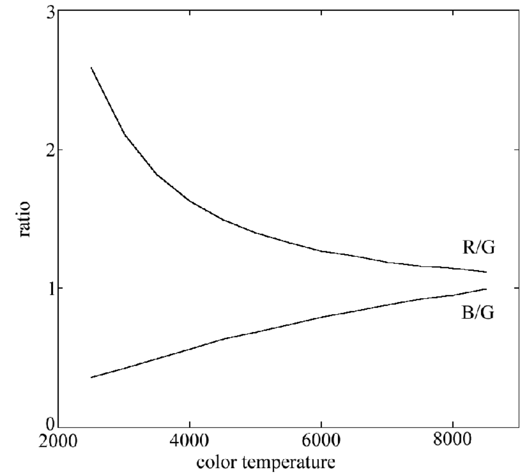
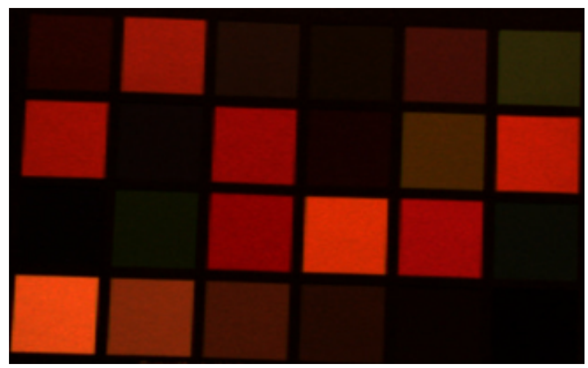
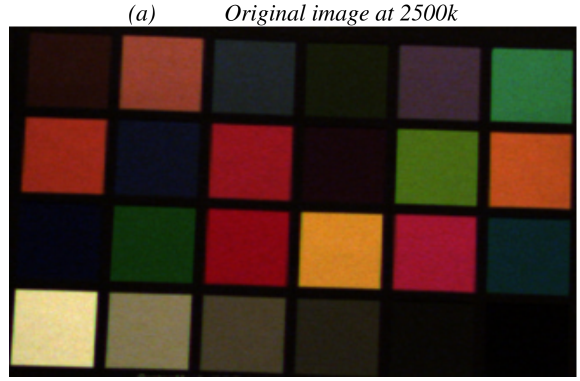


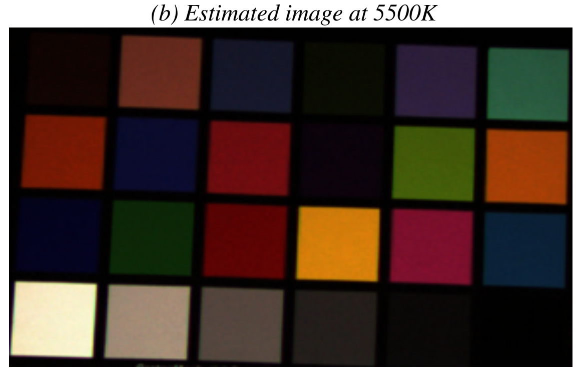
Figure 9. Contents of lookup table.



(a) Original image at 2500k



(b) Estimated image at 5500K



(c) Measured image at 5500K.

Figure 10. Experimental results for Macbeth color checker.

Conclusion

The present paper has analyzed two related issues concerning scene illumination. First, we considered the classification of color temperature from a single image. We have introduced a modification of the correlation method for illuminant estimation. The original correlation method used reference gamuts defined in the chromaticity plane. The estimation performance is improved by using a scaled version of the red and blue sensor responses. The improvement occurs because the best illuminant information is contained in bright regions. The precision of the algorithm was compared using experimental data obtained with a calibrated camera and real images of outdoor scenes.

Second, we have shown that once the illuminant color temperature is estimated it is possible to predict the camera outputs for the same objects viewed under a different illuminant color temperature. The color correction method is based on summarizing the ratio of R, G, and B sensor responses under different illuminants. Two ratios R/G and B/G are defined as a function of color temperature. The color correction can be performed in a simple way using the lookup table. The proposed method can be applied to a variety of real scenes.

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