

Further Research on the Sensor Correlation Method for Scene Illuminant Classification

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Abstract

The present paper extends previous results on the sensor correlation method for illuminant classification[1]. We describe several algorithm modifications that improve classification accuracy and applicability to a variety of scenes. First, we use the reciprocal scale of color temperature, called "mired", in order to obtain perceptually uniform illuminant classification, rather than physical illuminant classification by the original color temperature scale. Second, we introduce a new image normalization operation with an adjustable parameter to adjust overall intensity differences between images and find a good fit to the illuminant gamuts. Third, we calculate a correlation value between an image gamut and the reference illuminant gamut, rather than between the image pixels and the illuminant gamuts. This calculation makes it more reliable to select a unique illuminant gamut as an estimate. Fourth, we develop the 3D classification algorithms using all three-color channels, and compare this with the original 2D algorithms from the viewpoint of accuracy and efficiency. Finally, the improved algorithms incorporating the above four points are evaluated using a real image database.

Introduction

The estimation of scene illumination from image data is important in the field of color science, image understanding, and image processing. Given the inescapable limitations on spectral estimation, it is reasonable to classify the illuminant as belonging to one of several likely types. In a previous paper[1], we built on earlier illuminant classification methods[2] to estimate the illuminant color temperature. Our illuminant classification is to restrict the estimation to a set of blackbody radiators. Color temperature classification provides simple specification of many common light sources. That, which we called sensor correlation, used a scaled version of the red and blue sensor responses to classify scene illuminant by color temperature.

This paper describes several algorithm modifications and experimental results using the sensor correlation method. We improve the algorithms to increase the accuracy and applicability to a variety of scenes.

First, we use the color temperature on a reciprocal scale for the purpose of illuminant classification. By using this scale the classification on the original color temperature corresponds more closely to differences that are relevant to human color perception. The unit on the scale of (10^6K^{-1}) is called "mired," and a given small interval in this scale is equally perceptible, regardless of the color temperature.

Second, we describe a new image scaling operation to adjust for intensity differences between images. The sensor correlation method uses the fact that bright image regions contain much information about the illuminant than dark regions. In our original investigation on an image database every image contains, more or less, white surfaces or bright neutral surfaces. However, suppose that an image consists of only dark chromatic surfaces, the image intensities may be scaled up excessively. A precise scaling operation is needed so that the performance is independent of brightness and colorfulness of the image.

Third, the pixel-based correlation computation provides the correlation values depending on the color distribution of an image. The correlation computation between two gamuts of a given image and the reference illuminant may make it more reliable to select a unique illuminant gamut.

Fourth, the original illuminant classification algorithms use only two of the three color channels of digital camera. This limitation is lifted at the cost of increased computation. We develop the 3D algorithms using the use of all color channels and examine its performance.

Finally, the proposed algorithms are evaluated using a database of image acquired under different types of light sources, including a fluorescent source.

Improved Computational Methods

Illuminant Gamuts

The scene illuminant classification algorithms use a set of illuminant gamuts to define the range of sensor responses. The illuminant gamuts are created using a database of surface-spectral reflectances by Vrhel et al.[3] together with the reflectances of the Macbeth Color Checker. The image data are obtained using a Minolta camera (RD-175). The sensor responses are predicted using

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \int_{400}^{700} S(\lambda) M(\lambda) \begin{bmatrix} r(\lambda) \\ g(\lambda) \\ b(\lambda) \end{bmatrix} d\lambda \,, \qquad (1)$$

where $S(\lambda)$ is the surface-spectral reflectance function and $r(\lambda)$, $g(\lambda)$, and $b(\lambda)$ are the spectral-sensitivity functions and $M(\lambda)$ is the scene illuminant. The scene illuminants for classification are blackbody radiators at color temperatures spanning 2500 to 8500K. Figure 1 shows the spectral power distributions of blackbody by a single parameter of color temperature in K (mired).

For the purpose of illuminant classification, we use the reciprocal scale (10^6/T) of the color temperature T. The unit on this scale is called "microreciprocal degree", in short, "mired" or called "reciprocal megakelvin" denoted by MK^{-1} [4]. The advantage of this scale is that small intervals in reciprocal color temperature are more nearly perceptually equal than small intervals in color temperature. The blackbody radiators are described as a function of reciprocal temperature T' (mired) as

$$M(\lambda) = c_1 \lambda^{-5} \{\exp(c_2 T'/\lambda) - 1\}^{-1} , \qquad (2)$$

where $c_1 = 3.7418 \times 10^{-16}$ Watts-m^2 and $c_2 = 1.4388 \times 10^4$ Watts/mired.

The illuminant gamuts are defined on the RB plane. The (R, B) sensor plane is a reasonable choice for the blackbody radiators because their illuminant gamuts differ mainly with respect to this plane. The key point is that using sensor space, rather than chromaticity coordinates, preserves relative intensity information that is helpful. The boundary of the illuminant gamut is obtained from the convex hull of the set of (R, B) points.

Figure 2 shows the illuminant gamuts of the blackbody radiators in the (R, B) plane in two units. In Figure 2(a) gamuts are depicted at the reciprocal color temperatures, spanning from 118 mired (8500K) to 400 mired (2500K) in 23.5 increments. While, in Figure 2(b) gamuts are depicted at the original color temperatures, spanning from 2500K to 8500K in 500K increments. Note that thirteen gamuts are arranged in the same temperature range [2500, 8500K] in both figures. The illuminant gamuts separated by equal reciprocal color temperature steps are better and more equally separated than those separated in equal color temperature steps.

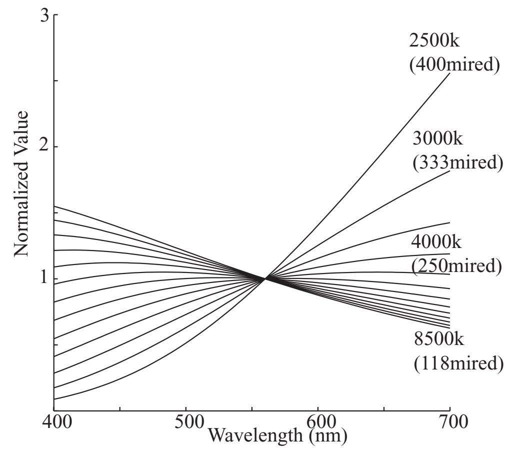
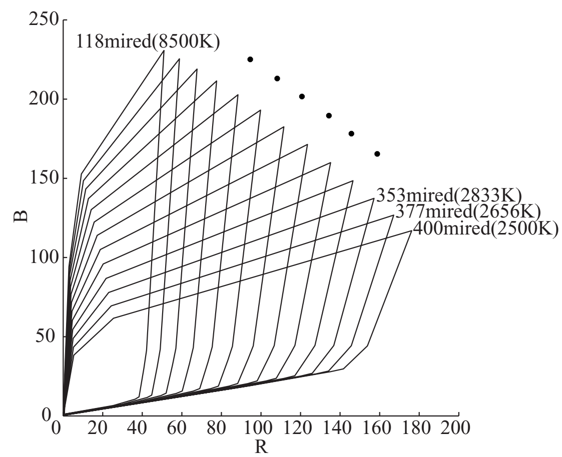
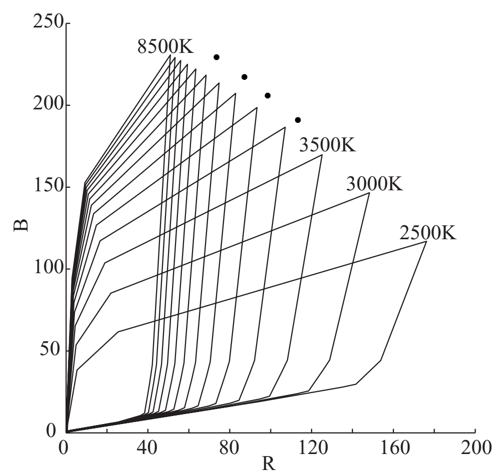


Figure 1 Spectral power distributions of blackbody radiators.



(a) Equal intervals of 23.5 mired



(b) Equal intervals of 500K

Figure 2 Illuminant gamuts for blackbody radiators in the RB sensor space.

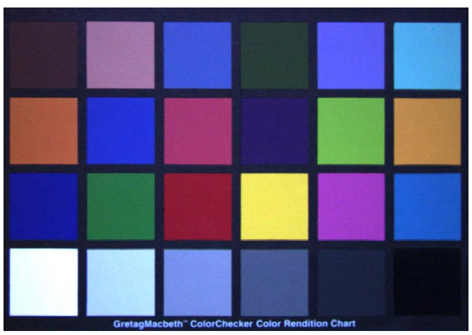
Image Scaling

The main difficulty with using the sensor data is the presence of overall intensity differences between images. The data can be adjusted by a simple scaling operation, equivalent to placing a neutral density filter in the light path or adjusting the exposure duration. Such a scaling operation preserves the shape of the image gamut and the relative intensity information within an image. To scale the data, we define I_i as the i[th] pixel intensity,

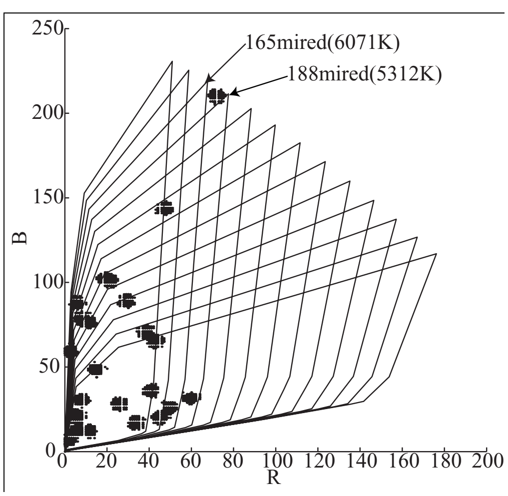
$$I_i = \left(R_i^2 + G_I^2 + B_I^2\right)^{1/2} \qquad (3)$$

and let I_{max} be the maximal value of the intensity over the image. Then to scale the intensity across different images, we divide the sensor RGB values by the maximum intensity,

$$(R,G,B) = (R / I_{\max}, G / I_{\max}, B / I_{\max}).. \qquad (4)$$



(a)



(b)

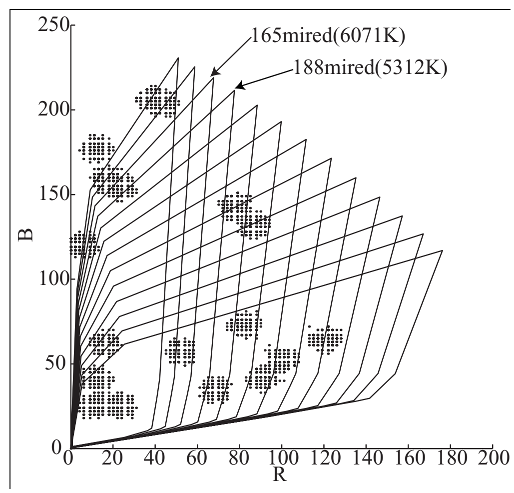
Figure 3 Image scaling for the synthesized image of the Macbeth Color Checker at 5500K. (a) Image; (b) Plot of the scaled (R, B) values with k=1 on the gamuts.

Bright image regions contribute much the illuminant information. This is especially true if white surfaces or bright neutral surfaces appear in a scene. However, if there is no such bright surface, dark surfaces are converted as bright image regions imitatively by the normalization, and the estimation accuracy decreases. Generally dark image regions are less reliable than bright regions for illuminant estimation. We propose a new normalization scheme with an adjustable parameter as

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

where k is a scaling parameter used to adjust the data most properly.

(a)



(b)

Figure 4 Image scaling for the synthesized image of only chromatic color patches at 5500K. (a) Image; (b) Plot of the scaled (R, B) values with k=1 on the gamuts.

Let us demonstrate a simulation experiment using the Macbeth Color Checker. First, we measured the surface-spectral reflectances for 24 color patches of the Macbeth Color Checker. The image data at 5500K were calculated form Eq.(1) with the measured reflectances and the blackbody radiator. Moreover, Gaussian random numbers with the mean of zero and the standard deviation of 1% were added to the RGB values as the observation noises.

Figure 3 shows the image scaling for the synthesized image of the Macbeth Color Checker at 5500K, where (a) is the original image and (b) is the plot of the scaled (R, B) values with k=1 on the gamuts. The bright sensor values fit selectively to the gamut of near 188 mired (5312K).

Next, by assuming the condition without bright patches, we removed a white patch and all achromatic patches from the original image. This synthesized image consists of 18 chromatic patches of the Macbeth Color Checker. Figure 4 shows the image scaling for the synthesized image consisting of only chromatic color patches, where (a) is the image and (b) is the plot of the scaled (R, B) values with k=1. The clusters of dark image regions for chromatic color patches are expanded into different directions on the RB plane, so that a gamut is not uniquely determined.

Thus, if the observed images are always normalized by the fixed scale of k=1, the clusters of dark image regions are expanded excessively on the RB plane. Figure 5 shows the convex hulls of the scaled (R, B) values with different k. The most appropriate value of the parameter k is selected to maximize a correlation between the image gamuts defined by these convex hulls and the illuminant gamuts.

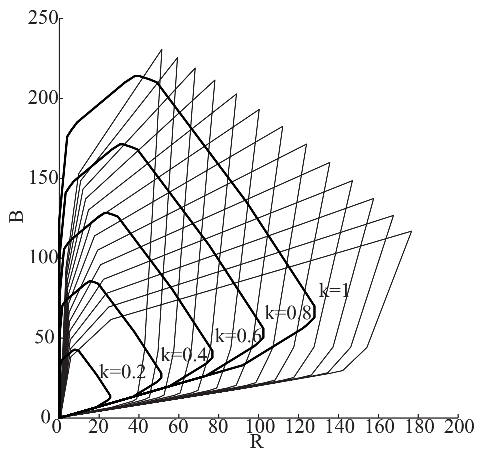


Figure 5 Convex hulls of the scaled (R, B) values with different k for the image of chromatic patches.

Image and Gamut Correlation

To quantify the overlap between image data and illuminant gamuts, we calculate a correlation value. The RB plane is divided into a regular grid (i, j) with 256x256. The illuminant gamuts are represented by setting a g (i, j) value to 1 or 0 depending on whether the cell falls inside the convex hull or not. In the previous paper[1], image data were mapped into the 256x256 array of cells according to whether they contain a corresponding g (i, j) coordinate. A correlation value was then computed between the mapped image pixels and the illuminant gamut. The result of this correlation computation depends greatly on the color elements of the image. Therefore, selection of a unique gamut sometimes fails, especially when bright gray surfaces are not observed and only a small number of chromatic surfaces are observed.

To solve this problem, we propose using the convex hull of an image to determine the image gamut in the RB plane. This image gamut is defined as a binary image on 256x256 pixels, where the binary image array bi (i, j) is 1 or 0 depending on the inside and outside of the convex hull. A correlation value is then computed between the image gamut and the illuminant gamut. It should be noted that the area of an illuminant gamut depends on the color temperature. Therefore a practical correlation value is computed by normalizing the area of gamuts as

$$r_{Ii} = S_{Ii} \Big/ \sqrt{S_I S_i}\ , \tag{6}$$

where S_I and S_i are the areas of an image and the i[th] illuminant gamut, respectively, and S_{Ii} is the area of overlap between the image gamut and the illuminant gamut.

In Figure 5, the convex hulls are calculated by sweeping out the different values of the parameter k. A set of these image gamuts were used to generate the correlation functions shown in Figure 6; each curve shows the function for a different parameter k. To select the appropriate value k for a calculation, we compute all of these gamuts and then chose the peak correlation over all the functions. In this example, the peak correlation occurs for k=0.8 and a reciprocal color temperature of 212 mired (4722K).

We performed a computer experiment using the image consisting of 18 chromatic patches of the Macbeth Color Checker. We generated 61 images under different illuminants by changing color temperatures from 2500K to 8500K in 100 increments. Figure 7 shows the classification results of illuminants by using both of the proposed method and the previous method, where the horizontal axis represents the target color temperature (mired) and the vertical axis represents the estimate. The broken line represents the ideal line of perfect classification without error. A comparison of two results suggests the goodness of the proposed algorithms.

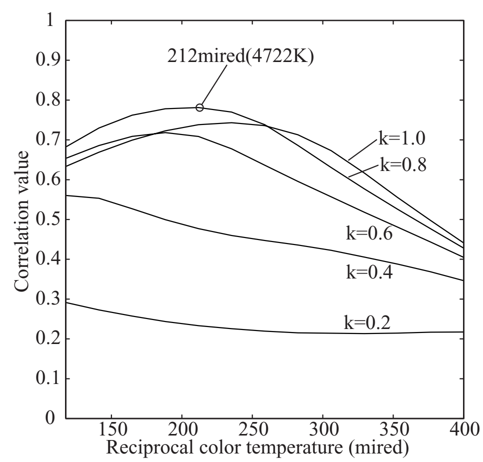


Figure 6 Set of correlation functions as a function of mired with the parameter k.

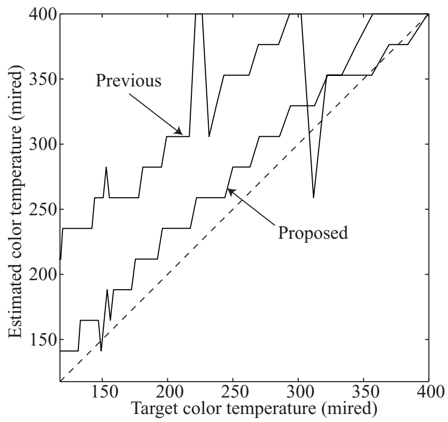


Figure 7 Classification results of illuminants for the synthesized images of 18 chromatic patches.

Use of Three Color Channels

The original calculation uses only two of the three color channels. This limitation can be lifted at the cost of increased computation. Figure 8 shows the three-dimensional illuminant gamuts in the RGB sensor space. The gamuts are obtained as the convex hulls of the RGB data calculated using the reflectance data and the blackbody radiator from 118 mired (8500K) to 400 mired (2500K) in 23.5 increments. It is noted that the illuminant gamuts differ a little with respect to the G axis. Moreover the gamuts move monotonically as R or B increases, but they do not move monotonically as G increases. Mathematically speaking, the gamuts are a type of two-valued function with respect to G.

In order to evaluate the 2D and 3D classification algorithms, a computer experiment was performed using the synthesized images of the Macbeth Color Checker, where the two types of 2D and 3D gamuts were used for estimating the illuminants at different 61 color temperatures from 2500K to 8500K in 100 increments. A comparison between two results suggests that the use of 3D gamuts increases the estimation accuracy a little. However we have decided that the 2D algorithms are effective from a computational point of view.

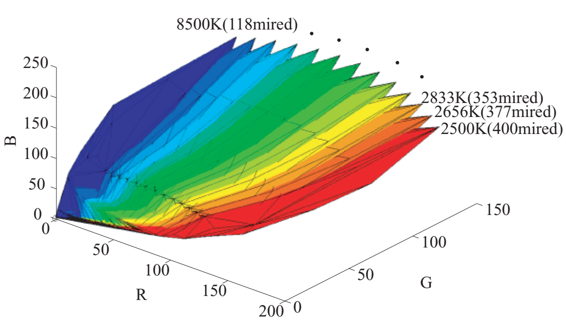


Figure 8 Three-dimensional illuminant gamuts in RGB sensor space.

Application to Real Images

We have evaluated the improved 2D sensor correlation algorithms a database of images acquired under different illuminants. Figure 9 shows a set of images, called Campus, acquired outdoors under daylight. The peak of each correlation function is estimated as the reciprocal color temperature of the scene. The direct measurements of color temperature in outdoor scenes vary over time and also with the viewing direction of the reflectance white placed in the scene to measure the scene illuminant. The measurements for the above scenes ranged from 163 mired (5540K) to 180 mired (6143K). The average error in illuminant classification is about 13 mired. The accuracy is improved, compared with the error of about 11 mired by the previous algorithm.[1]

Figure 9 Image set of Campus.

The present illuminant classification algorithm can be applied to light sources other than blackbody radiators. Figure 10 shows a set of images indoor scenes photographed under a fluorescent lamp. The spectral-power distribution from a fluorescent light source includes strong spikes and essentially differs from the continuous curves of the blackbody radiators shown in Figure 1; the algorithm still works well. The direct measurement of illuminant color temperature was 247 mired (4048K). The estimates range from 259 (3863) to 235 mired (4249K). The average error is about 11 mired, while the average error by the previous algorithms was about 28 mired. Thse performance is improved particularly for dark images 03 and 04 which contain no bright neutral color surfaces at all.

Finally we should note that the illuminants are classified into the interval of 23.5 mired. Increasing the number of illuminant gamuts in a fine interval can reduce the classification error.

Figure 10 Set of images of indoor scenes under fluorescent illumination.

Conclusion

The present paper has described extensions of our research on the sensor correlation method for illuminant classification. We have discussed several methods of improving the algorithms in classification accuracy and applicability to a variety of scenes. First, the reciprocal scale of color temperature, called "mired", should be used for perceptually uniform illuminant classification, rather than for physical illuminant classification by the original color temperature scale. Second, a precise scaling operation was needed to adjust overall intensity differences between images and find a good fit to the illuminant gamuts. We have proposed a new normalization operation with an adjustable parameter. Third, a correlation value should be calculated between an image gamut and the reference illuminant gamut, rather than between the image pixels and the illuminant gamuts. Fourth, the comparison with the original 2D algorithms has suggested that the use of 3D gamuts improves a little the estimation accuracy, and the 2D algorithms are more effective from a computational point of view. Finally, the applicability of the improved algorithms incorporating the above four points was shown using a real image database, including a fluorescent light source.

References

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