



Optimal Color Samples for Camera Spectral Sensitivity Estimation

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Abstract. This study investigated the optimal color samples for camera spectral sensitivity estimation. Principal component analysis (PCA) was performed on a public camera spectral sensitivity database. The eigenvectors were extracted and served as the basis functions, and the coefficients were calculated by a classical least square method. The color samples for spectral sensitivity estimation included a multichannel LED device and a reflective color chart. Three sample selection methods were implemented, which were based on minimizing the condition number, maximizing the minimum distance in the chromaticity plane, and using a simulated imaging system, respectively. It was found all the three methods were able to find the optimal color samples. The spectral sensitivity estimation error decreased and then became stable with the increase of the number of color samples.

Keywords: Camera · Spectral sensitivity · Optimal color samples

1 Introduction

Spectral sensitivity represents the responses of a camera to the lights at different wavelength. This information can be applied in the fields including multispectral imaging, color constancy, filter design, etc. The direct calibration method is to use a monochromator [1]. However, this method requires multiple shots and costly device. Prior studies have been carried out to estimate camera spectral sensitivities by capturing a series of color samples with known spectra information [2–9]. Various algorithms and different color samples have been applied. The algorithms included truncated singular value decomposition [2], basis functions [3], principal component analysis (PCA) [4, 5, 7, 9], regularization [8], etc. In general, the number of color samples affected the camera capture times, and thus determined the measurement efficiency. Therefore, it was necessary to select a few optimal color samples from the total set. Hardeberg et al. [10] presented an algorithm based on the minimization of condition number of reflectance matrix, for the choice of optimal samples with a reduced number in camera spectral sensitivity estimation. While some algorithms were proposed for the selection of representative training samples in spectral reflectance reconstruction [11–13]. However, it

was not clear whether these algorithms could be applied to the field of sample selection in spectral sensitivity estimation. Moreover, it should be noted most of the previous studies on spectral sensitivity estimation used reflective surface color samples. Only a few studies focused on the multichannel LED, but seldom investigated its sample selection problem, or compared different sample selection methods.

In this study, the spectral sensitivities were estimated using a PCA method together with a public spectral sensitivity database. Two types of color samples were utilized, including a multichannel LED device and a reflective color chart. Three sample selection methods were implemented to select different numbers of optimal color samples. The spectral sensitivity estimation accuracy was evaluated by both spectral and colorimetric metrics. It was found the accuracy firstly increased and then became nearly stable with the increase of the number of color samples.

2 Method

The camera spectral sensitivity estimation was usually carried out using the linear camera responses. The camera responses (X) were the integration of the product of the spectral sensitivities of the camera (S) and the spectral radiance of the objects (L) over wavelength. For surface color, the spectral radiance was the product of the spectral reflectance of object and the SPD (spectral power distribution) of light. After sampling the wavelength (400nm to 700nm with a 10nm interval in this study), it can be formulated by Eq. (1).

$$X = LS \quad (1)$$

In general, spectral sensitivity estimation required the known spectral signals L and the corresponding camera responses X . A previous study [7] collected a spectral sensitivity database by combining four public databases [3–5, 14], including 111 cameras in total. After performing PCA on the spectral sensitivities in the database, the eigenvectors can be considered as basis functions to represent the spectral sensitivities as Eq. (2), where B is the eigenvector matrix and a is the coefficients.

$$S = Ba \quad (2)$$

Substituting Eq. (2) into Eq. (1), the least square solution of S can be calculated by Eq. (3). The superscripts T and $^{-1}$ denote the matrix transpose and inverse.

$$\min_a \|LBa - X\|^2$$

$$S = B[(LB)^T(LB)]^{-1}(LB)^TX \quad (3)$$

Different sample selection methods have been proposed. This study implemented and compared three methods, i.e., minimized condition number (minCondNum) [10], MAXMINC [11], and simulated system (simuSys) [13].

The minCondNum method [10] selected the first sample with the maximum root-mean-square value of spectral reflectance (for surface colors) or spectral radiance (for

self-luminance colors). The following samples were selected in turn with the aim of minimizing the condition number (the ratio of the largest to the smallest singular value) of the spectral reflectance or spectral radiance matrix. A set of most significant color samples would be selected following this method.

MAXMINC method [11] selected the first color sample using the same way as the above method. The following samples were selected in turn in order to maximize the minimum distance with the other selected samples in the chromaticity plane. This method confirmed the selected color samples to uniformly span the whole chromaticity plane.

The simuSys method [13] was based on a representative simulation system following Eq. (1). In this study, the spectral sensitivities of the simulated imaging system were randomly selected from the camera database [7]. The optimal color samples were selected to minimize a defined objective function in simulation experiments. In this study, it was the error of spectral sensitivity estimation, i.e., the linear combination of spectral error (SE) [15] and colorimetric error CIEDE2000 (ΔE_{00}^*) [16] as Eq. (4). In this study, it was decided to set $a = 1$ and $b = 0.1$. The selected color samples by the simulated system were tested in practical experiments.

$$obj = a * SE + b * \Delta E_{00}^* \quad (4)$$

3 Experiment

The test camera was a professional DSLR camera Canon 650D. The ground-truth spectral sensitivities were calibrated by a Labsphere QES1000 monochromator. The LED device was a Thouslite 18-channel LED system, and the reflective color sample was an Xrite Macbeth ColorChecker chart (MCCC). The camera was used to capture the images of the multiple LED channel at the light-emitting plane in a dark room, and to capture the color chart under simulated D50, D65, and A illuminants. For the color chart, the spectral sensitivity estimation was carried out under D65, while the estimation accuracy was tested under D50 and A. Figure 1 shows the experimental condition. It was exactly the same as our previous study[7].



a.LED samples b.reflective color chart.

Fig.1. Experimental conditions a) LED samples b) reflective color chart.

The three sample selection methods were applied to the two types of samples, respectively. The spectral sensitivity estimation was conducted using different numbers of color samples. The estimated accuracy was evaluated by four different metrics, spectral error (SE), color difference ΔE_{00}^* , RGB error, and Vora value [7]. Among them, SE and Vora value were spectral metrics indicating the similarity with the ground truth spectral sensitivities measured by the monochromator, and ΔE_{00}^* and RGB error were colorimetric metrics tested by MCCC under D50 and A. The RGB error was calculated between the measured camera responses and those predicted by the estimated spectral sensitivities.

4 Results and Discussion

Figure 2 plots the spectral sensitivity estimation error with different numbers of color samples in terms of the four metrics. It can be seen that with the increase of the number of color samples, the estimated error decreased and then became nearly stable. Due to the presence of camera noise, the results had some small oscillations. The colorimetric metrics had higher speed of convergence compared to the spectral metrics.

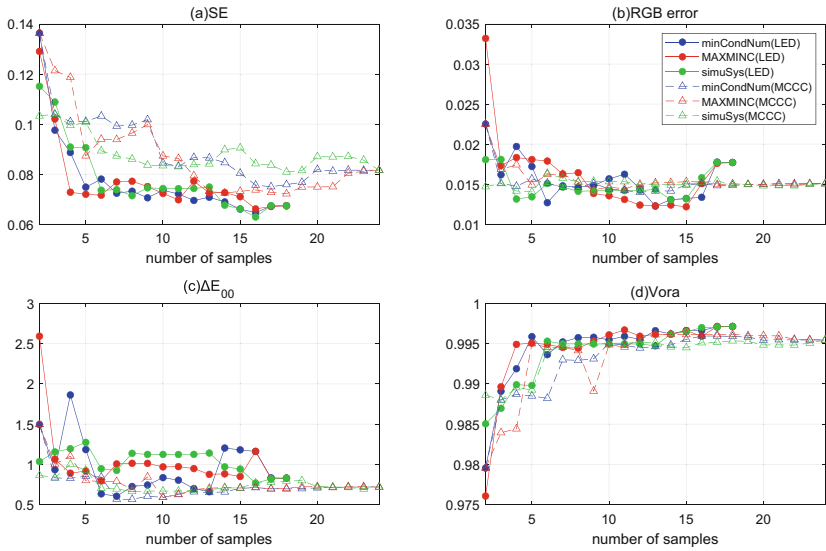


Fig.2. Spectral sensitivity estimation accuracy with different number of color samples. The solid and dashed lines were the results of the LED and MCCC samples, respectively. The error metrics were (a) SE, (b) RGB error, (c) ΔE_{00}^* , and (d) Vora value.

Comparing the two types of color sample, the LED samples achieved higher estimated accuracy in terms of SE and Vora value. The MCCC samples had higher accuracy in terms of ΔE_{00}^* in most cases. While the relationship of RGB error depended on the number of samples. When using MCCC as color samples, the minimized objective of the least square solution was the error of camera responses to the color chart under D65, which could contribute to higher accuracy tested by the same color chart under D50 and

A. Nevertheless, considering the lower colorimetric error but higher spectral error, when using the MCCC samples, the estimated results might be the metamers of the ground truth spectral sensitivities. And it can be observed that the MCCC samples required more numbers of samples (more than 10) than LED samples (about 6) to achieve relatively stable SE values.

Considering the overall tendency of estimated error, it was decided to present the systems with six optimal color samples. Figure 3 plots the spectra and chromaticity of the optimal LED and MCCC color samples selected from different methods. Spectral radiance and spectral reflectance were plotted for the two types of samples, respectively. The chromaticity was both plotted in the CIE 1976 $u'v'$ plane. It can be seen that the samples selected by MAXMINC method were more uniformly distributed in the chromaticity plane. The chromaticity of the LED samples was much more saturated and was close to the spectral locus due to the narrowband feature, so that it was not surprising to result in higher spectral accuracy and serve as more suitable color samples for spectral sensitivity estimation.

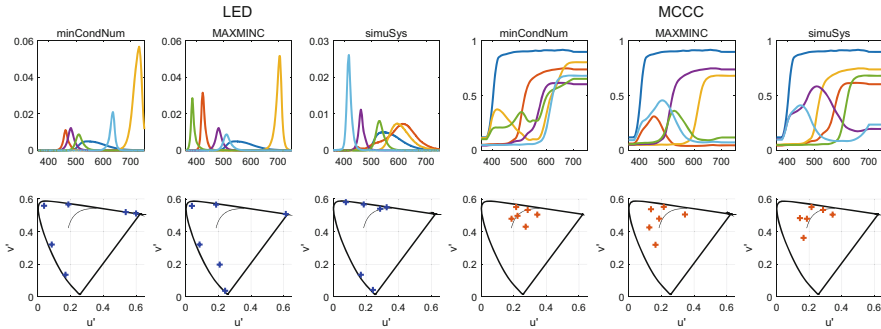


Fig.3. Spectral radiance/reflectance and chromaticity in $u'v'$ plane of the six optimal LED and MCCC color samples selected by the three sample selection methods.

5 Conclusion

In this study, three sample selection methods were implemented for camera spectral sensitivity estimation. The three methods were based on minimizing the condition number, maximizing the minimum distance in the chromaticity plane, and using a simulated imaging system, respectively. Different numbers of optimal color samples were selected. Two types of color samples were used, including a multichannel LED device and a reflective color chart MCCC. It was found with the increase of the number of color samples, the spectral sensitivity estimation error decreased and then became basically stable. Using LED samples resulted in higher spectral accuracy, while MCCC samples led to slightly higher colorimetric accuracy. All the three sample selection methods succeeded to find the optimal color samples. Finally, the systems with six optimal color samples were obtained.

Acknowledgement. This research is supported by National Natural Science Foundation of China (61775190), and Dajiang Innovations Technology Co., Ltd.

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