

Camera Spectral Sensitivity Estimation from a Single Image under Unknown Illumination by using Fluorescence

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Abstract

Camera spectral sensitivity plays an important role for various color-based computer vision tasks. Although several methods have been proposed to estimate it, their applicability is severely restricted by the requirement for a known illumination spectrum. In this work, we present a single-image estimation method using fluorescence with no requirement for a known illumination spectrum. Under different illuminations, the spectral distributions of fluorescence emitted from the same material remain unchanged up to a certain scale. Thus, a camera's response to the fluorescence would have the same chromaticity. Making use of this chromaticity invariance, the camera spectral sensitivity can be estimated under an arbitrary illumination whose spectrum is unknown. Through extensive experiments, we proved that our method is accurate under different illuminations. Moreover, we show how to recover the spectra of daylight from the estimated results. Finally, we use the estimated camera spectral sensitivities and daylight spectra to solve color correction problems.

1. Introduction

Light spans a wide range of wavelengths. With a digital color camera, the scene radiance is recorded as RGB values via color filters that specify light in different wavelength ranges to be observed. Therefore, the recorded RGB values are dependent on the spectral sensitivity of color filters (or sensors), *i.e.*, different sensors yield different RGB outputs for the same scene. Camera spectral sensitivity plays an important role for a lot of computer vision tasks that use color information, such as spectral reflectance recovery [17, 10], color correction [16] and color constancy [8, 9]. That means estimation of camera spectral sensitivity is necessary to guarantee various color-based methods work well.

A standard technique for estimating camera spectral sensitivity is to take pictures of monochromatic light whose bandwidth is narrow [2]. The spectral sensitivity of the camera can be reliably estimated from recorded observations and known spectral distributions of monochromatic light. Although it gives accurate estimates, the method requires expensive hardware to generate and measure a series of monochromatic light, thus its use has been limited to well-equipped laboratories only. In addition, the whole procedure is laborious because of the need for multiple observations of different light.

To simplify the procedure, methods using calibration targets whose reflectance is known have been proposed [7, 21, 15]. These methods estimate the camera spectral sensitivity by recording a calibration target, *e.g.*, IT8 Target, under illumination with a known spectral distribution. These approaches reduce the effort needed for measurement. However, their requirement for a known illumination spectrum limits their practicability due to the need for a spectrometer or a specific light source with known illumination.

In this paper, we propose a new method for estimating the camera spectral sensitivity from a single image captured under an *unknown* illumination. The key idea is to use fluorescence: a physical phenomenon whereby the substance emits specific wavelengths of light by absorbing radiation of different wavelength. Its physical property of a fixed emission spectrum is particularly useful for the camera spectral sensitivity estimations because the spectral profile of the fluorescence remains unchanged up to a certain scale under arbitrary illumination. To make a single image estimate, we use a chart of fluorescent materials whose emission spectra are pre-determined. Then, from the emission spectra of these fluorescent materials, we derive an analytic solution for determining the camera spectral sensitivity.

There are three key properties about the proposed method. First, it does not require the illumination spectrum to be known. The estimate can be made under unknown lighting conditions, *e.g.*, outdoors under sunlight, under a skylight, or indoors under a fluorescent lamp, without hav-

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ing to measure any spectrum. Second, the estimation requires only a single shot of a scene with the calibration target. This reduces the cost of data acquisition. Third, the fluorescent chart used in this work is made from fluorescent paint, which is inexpensive and readily available at stationery stores. These properties will make the camera spectral sensitivity estimation more widely available.

2. Related Works

Camera spectral sensitivity can be estimated by establishing a relationship between incident narrow-band light with different wavelengths across the visible wavelength range and the camera’s outputs. To achieve this goal, the standard technique uses a monochromator or narrow-band filters to generate a series of monochromatic light. Each monochromatic light is cast on a standard white board, and the reflected light is observed by the target camera. At the same time, the spectral distributions of the monochromatic light are measured by a spectrometer. The camera spectral sensitivity can then be calculated using the captured images and measured spectra [2]. Because measurements are independent of each other, this method is accurate. However, it requires expensive optical equipments and a dark room. Moreover, capturing dozens of images and spectral distributions makes the whole procedure time-consuming.

To make measurement more practical, methods using calibration targets are proposed. These calibration targets, *e.g.*, the IT8 target or Macbeth ColorChecker, contain several patches whose spectral reflectance is known. Under illumination with known spectrum, spectra of reflected light from these patches can be computed. The camera spectral sensitivity can also be estimated from the RGB values of these patches in captured images [7, 4, 6, 21]. However, these methods require controlled lighting conditions, which means the light should be spatially uniform and its spectral distribution is known. These requirements can be satisfied only in laboratories. To extend the scope of these methods out of the lab, Rump *et al.* [15] devised an imaging model accounting for specularly and spatially varying illumination. By using this model, measurements can be conducted in an environment where specularly or shadows exist. However, it still needs a known illumination spectrum.

To avoid the requirement for a known illumination spectrum, we make use of fluorescence. Fluorescence has been receiving more and more attention recently. In [13, 12], methods describing how to model and render fluorescent materials are presented. Modified color constancy methods to deal with fluorescent surfaces are shown in [3]. In [11], fluorescence is used to sample the geometry of transparent objects that cannot be sampled with traditional methods. In this work, we explore the spectral properties of fluorescence and use them to estimate the camera spectral sensitivity.

3. Fluorescence

Fluorescence is a common phenomenon that has been used for a variety of purposes, such as in lamps, stationery, safety vests, *etc.* Fluorescence is the emission of light by a substance that has absorbed light of different (generally shorter) wavelengths. In this absorption and re-emission process, two terms about fluorescence are involved, *i.e.*, absorption (or excitation) spectrum and emission spectrum. The absorption spectrum represents how strongly the fluorescent material absorbs fluorescence-exciting light as a function of its wavelength. The emission spectrum describes the spectral profile of fluorescence emitted from the fluorescent material. Both of the absorption spectrum and emission spectrum are determined by the properties of the fluorescent material itself.

The emitted fluorescence from the p -th fluorescent material, $f_p(\lambda)$ ($p = 1, 2, 3, \dots, P$), is described as

$$f_p(\lambda) = \left(\int a_p(\lambda') l(\lambda') d\lambda' \right) e_p(\lambda), \quad (1)$$

where λ' and λ are the wavelengths of the incoming light and the outgoing fluorescence, $a_p(\lambda')$ and $e_p(\lambda)$ are the absorption and emission spectra of the p -th fluorescent material, $l(\lambda')$ is the spectral distribution of the incoming light.

We can see that the integral part in Eq. (1) is determined by the absorption spectrum and the spectrum of the incoming light. Therefore, it is independent from the spectrum of the outgoing fluorescence. Replacing that part by a scale factor k_p , we can rewrite Eq. (1) as

$$f_p(\lambda) = k_p e_p(\lambda). \quad (2)$$

Eq. (2) means that the emitted fluorescence from a certain fluorescent material under different illuminations remains unchanged up to a certain scale.

To verify this unique property of fluorescence, we measured the fluorescence emitted from a patch smeared with fluorescent paint under different monochromatic light. The measured spectral distributions are shown in Fig. 1. As expected from Eq. (2), all these distributions are different only in scales.

When the emitted fluorescence from the p -th fluorescent material is observed with an RGB camera, the relationship between the pixel intensity $(R_p^f, G_p^f, B_p^f)^T$ and the emitted fluorescence is represented by¹

$$R_p^f = \int f_p(\lambda) c_R(\lambda) d\lambda. \quad (3)$$

Here, $c_R(\lambda)$ ($c_G(\lambda)$ and $c_B(\lambda)$) is the spectral sensitivity of the red (green and blue) channel. G_p^f and B_p^f can be

¹We assume the camera has a linear intensity response function. Without loss of generality, geometric factors is omitted here.

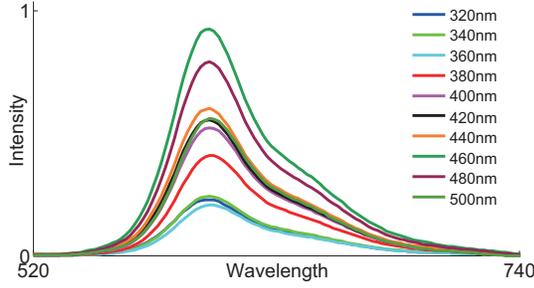


Figure 1. Spectral distributions of emitted fluorescence from the same material under different monochromatic light remain unchanged up to a certain scale.

represented in a similar manner. For the sake of simplicity, we hereafter derive equations for red channel and omit those for green and blue channels if they are trivial.

Substituting Eq. (2) into Eq. (3), we obtain

$$R_p^f = k_p \int e_p(\lambda) c_R(\lambda) d\lambda. \quad (4)$$

Note that the scale factor k_p is the same for all three channels. Thus, the chromaticity $(r_p^f, g_p^f, b_p^f)^T$ of the emitted fluorescence is described as

$$\begin{aligned} r_p^f &= \frac{R_p^f}{R_p^f + G_p^f + B_p^f} \\ &= \frac{\int e_p(\lambda) c_R(\lambda) d\lambda}{\int e_p(\lambda) (c_R(\lambda) + c_G(\lambda) + c_B(\lambda)) d\lambda}. \end{aligned} \quad (5)$$

The other two components g_p^f and b_p^f can be described in a similar manner. Clearly, the scale factor k_p is eliminated. As a result, the chromaticity of the emitted fluorescence is invariant with respect to the spectrum of the incoming light.

Using the chromaticity invariance of emitted fluorescence is the key idea of our method. It enables us to estimate the spectral sensitivity of a camera without having to know the illumination spectrum.

4. Separating Fluorescent and Reflective Components

As discussed in Sec. 3, the chromaticity of emitted fluorescence is invariant with respect to changes in illumination. Unfortunately, however, fluorescent materials often not only emit fluorescence but also reflect incident light. Thus, the observed pixel intensity of the p -th fluorescent material, $(R_p, G_p, B_p)^T$, contains a fluorescent component $(R_p^f, G_p^f, B_p^f)^T$ as well as a reflective component $(R_p^r, G_p^r, B_p^r)^T$:

$$R_p = R_p^f + R_p^r. \quad (6)$$

Therefore, we need to separate these two components in order to make use of the chromaticity invariance of the fluorescent component.

Recently, Zhang and Sato [23] proposed a method for separating fluorescent and reflective components by using independent component analysis, but their method requires at least two images captured under different illuminations. In this section, we show how to separate the fluorescent and reflective components from a single image. The key idea is to use non-fluorescent materials with known spectral reflectance as a reference (Fig. 2).

We first estimate the reflective components of fluorescent materials under an unknown illumination. It can be described as

$$R_p^r = \int s_p(\lambda) c_R(\lambda) l(\lambda) d\lambda, \quad (7)$$

where $s_p(\lambda)$ is the spectral reflectance of the p -th fluorescent material. G_p^r and B_p^r can be described in a similar manner. According to a previous study [18], the spectral reflectance of various materials can be approximately represented by a linear combination of a small number of basis functions. Thus, we have

$$s_p(\lambda) = \sum_{n=1}^N \alpha_{p,n} b_n^r(\lambda), \quad (8)$$

where $b_n^r(\lambda)$ ($n = 1, 2, 3, \dots, N$) are the basis functions for spectral reflectance that are available in [18], $\alpha_{p,n}$ are the corresponding coefficients. Substituting Eq. (8) into Eq. (7), we obtain

$$R_p^r = \sum_{n=1}^N \alpha_{p,n} \int b_n^r(\lambda) c_R(\lambda) l(\lambda) d\lambda. \quad (9)$$

To compute R_p^r , we just need to know $\alpha_{p,n}$ and $\int b_n^r(\lambda) c_R(\lambda) l(\lambda) d\lambda$. Because our objective is to design a calibration target, corresponding $s_p(\lambda)$ can be measured once in advance. Then, coefficients can be computed as $\alpha_{p,n} = \int s_p(\lambda) b_n^r(\lambda) d\lambda$ since the basis functions are known and orthogonal to each other. Hence, the remaining problem is how to get $\int b_n^r(\lambda) c_R(\lambda) l(\lambda) d\lambda$. To solve this problem, a reference containing a number of non-fluorescent materials with known spectral reflectance is used.

As shown in Fig. 2, we put the reference as well as the fluorescent chart together. Under the same illumination, the observed pixel intensity of the q -th reference material, $(R_q, G_q, B_q)^T$ ($q = 1, 2, 3, \dots, Q$), is represented by

$$R_q = \sum_{n=1}^N \alpha_{q,n} \int b_n^r(\lambda) c_R(\lambda) l(\lambda) d\lambda. \quad (10)$$

Here, $\alpha_{q,n}$ are known and $\int b_n^r(\lambda) c_R(\lambda) l(\lambda) d\lambda$ are unknown. For all materials on the reference, we obtain a set of linear equations that are similar to Eq. (10). The number of

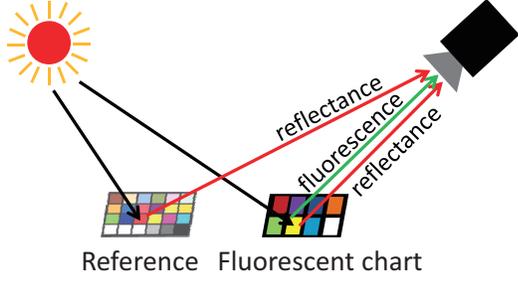


Figure 2. Under spatial uniformly distributed illumination, a reference containing a number of non-fluorescent patches with known spectral reflectance is used to help separating the fluorescent component from the reflective component of the captured images of the fluorescent chart.

equations is Q (reference materials) \times 3 (channels), and the number of unknowns is N (basis functions) \times 3 (channels). When $Q \geq N$, the unknown integral $\int b_n^r(\lambda)c_R(\lambda)l(\lambda)d\lambda$ can be estimated. Because we set $N = 8$ according to the previous study [18], the reference chart should contain at least eight materials whose spectral reflectance is linearly independent.

Once we obtain the value of the integral in Eq. (10), the reflective components of the fluorescent materials can be calculated by Eq. (9). Finally, the fluorescent components $(R_p^f, G_p^f, B_p^f)^T$ are computed by subtracting the calculated reflective components from the observed pixel intensities as

$$R_p^f = R_p - R_p^r. \quad (11)$$

5. Estimating Camera Spectral Sensitivity

In the previous sections, we described that the chromaticity of fluorescence is invariant under different illuminations and that the fluorescent components can be extracted by using non-fluorescent materials as a reference even under an unknown illumination. In this section, we show how to use the illumination-invariant chromaticity of the fluorescent components for estimating the camera spectral sensitivity.

Although different cameras have different spectral sensitivities, their spectral sensitivities should not deviate a lot from each other. Thus, it becomes possible to use a limited number of parameters or basis functions to express camera spectral sensitivity [7, 20]. To estimate spectral sensitivity, we just need to estimate the parameters or corresponding coefficients. To guarantee the general applicability of our method, we adopt Fourier basis functions². Accordingly, the spectral sensitivity $(c_R, c_G, c_B)^T$ can be decomposed

²Assuming the range of spectral sensitivity is $[\lambda^l, \lambda^u]$, the first few Fourier basis functions are $b_1^c(\lambda) = 1$, $b_2^c(\lambda) = \sin[2\pi(\lambda - \lambda^l)/(\lambda^u - \lambda^l)]$, $b_3^c(\lambda) = \cos[2\pi(\lambda - \lambda^l)/(\lambda^u - \lambda^l)]$, and *etc.* We could also use eigenvectors computed from a set of camera spectral sensitivities as basis functions if such data are available.

into a sum of sines and cosines as

$$c_R(\lambda) = \sum_{m=1}^M \beta_{R,m} b_m^c(\lambda), \quad (12)$$

where $b_m^c(\lambda)$ are the m -th Fourier bases for representing the camera spectral sensitivity. $\beta_{R,m}$ are the corresponding coefficients for the red channel. The spectral sensitivities of the green and blue channels, c_G and c_B , can be decomposed in a similar manner.

Substituting Eq. (12) into Eq. (5), we obtain

$$r_p^f = \frac{\sum_m \beta_{R,m} \int e_p(\lambda) b_m^c(\lambda) d\lambda}{\sum_m (\beta_{R,m} + \beta_{G,m} + \beta_{B,m}) \int e_p(\lambda) b_m^c(\lambda) d\lambda}. \quad (13)$$

Denoting the integral $\int e_p(\lambda) b_m^c(\lambda) d\lambda$ by $t_{p,m}$, we can rewrite Eq. (13) as

$$\begin{bmatrix} (r_p^f - 1)t_p & r_p^f t_p & r_p^f t_p \end{bmatrix} \begin{bmatrix} \beta_R \\ \beta_G \\ \beta_B \end{bmatrix} = 0, \quad (14)$$

where $t_p = (t_{p,1}, \dots, t_{p,M})$ is a $1 \times M$ row vector, $\beta_R = (\beta_{R,1}, \dots, \beta_{R,M})^T$ is a $M \times 1$ column vector, β_G and β_B are defined in a similar manner. Similar equations can be obtained for the green and blue channels. Since there are P fluorescent materials, we have P (fluorescent materials) \times 3 (channels) equations in total:

$$\begin{bmatrix} (r_1^f - 1)t_1 & r_1^f t_1 & r_1^f t_1 \\ g_1^f t_1 & (g_1^f - 1)t_1 & g_1^f t_1 \\ b_1^f t_1 & b_1^f t_1 & (b_1^f - 1)t_1 \\ \vdots & \vdots & \vdots \\ (r_P^f - 1)t_P & r_P^f t_P & r_P^f t_P \\ g_P^f t_P & (g_P^f - 1)t_P & g_P^f t_P \\ b_P^f t_P & b_P^f t_P & (b_P^f - 1)t_P \end{bmatrix} \begin{bmatrix} \beta_R \\ \beta_G \\ \beta_B \end{bmatrix} = \mathbf{0}. \quad (15)$$

Eq. (15) can be expressed in the form of $\mathbf{A}\mathbf{X} = \mathbf{0}$, where \mathbf{A} is a $3P \times 3M$ matrix and \mathbf{X} is a $3M \times 1$ vector. A nonzero solution of this linear equation is found as the eigenvector of the square matrix $\mathbf{A}^T \mathbf{A}$ corresponding to the smallest eigenvalue.

In experiments, we found that the estimated coefficients $(\beta_R, \beta_G, \beta_B)^T$ are sometimes sensitive to noise. Therefore, to make the computation more stable, we incorporate a smoothness constraint on spectral sensitivity. Here, the second derivative of spectral sensitivity with respect to wavelength is used. As a result, we obtain

$$\begin{bmatrix} \mathbf{A} & \mathbf{0} & \mathbf{0} \\ w_R \phi & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & w_G \phi & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & w_B \phi \end{bmatrix} \mathbf{X} = \mathbf{0}, \quad (16)$$

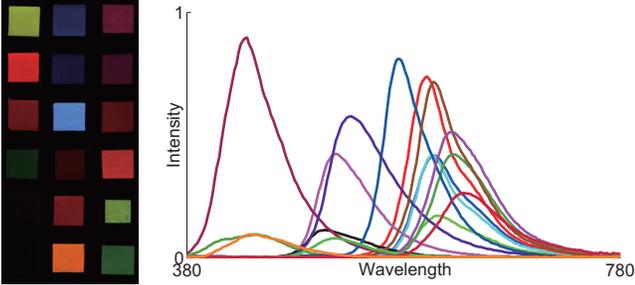


Figure 3. Left: fluorescent chart used in this work. Right: spectral distributions of fluorescence emitted from its 16 patches.

where $(w_R, w_G, w_B)^T$ is the weight of the smoothness term and $\phi = (d^2 b_1^c(\lambda)/d\lambda^2, \dots, d^2 b_M^c(\lambda)/d\lambda^2)$. Substituting the solution of Eq. (16) into Eq. (12), camera spectral sensitivity can be obtained up to a scale.

The steps for camera spectral sensitivity is summarized as (1) take a picture of the fluorescent chart and the reference; (2) separate the fluorescent and the reflective components of the fluorescent chart in the captured image; (3) compute the chromaticity of the fluorescent component; (4) estimate the camera spectral sensitivity as described in this section; (5) normalize the estimated camera spectral sensitivity, by which the largest absolute value of the estimated results in RGB channels is set to one.

6. Experiments

In this section, we show experimental results to evaluate our method for estimating camera spectral sensitivity and two applications, namely, daylight spectrum estimation and color correction.

A chart containing 16 patches, shown in Fig. 3, was used in our experiments. Those patches were made by smearing 16 different types of fluorescent paint ($P = 16$) on a black board. To measure the emission spectra of these fluorescent patches, they were lit by 320nm UV light generated by a monochromator (SHIMADZUTM SPG-120) one by one, and the spectral distributions of light from these patches were measured by a spectrometer (PhotoResearchTM PR-670). Because no light in the visible wavelength range was emitted from the monochromator, the measured results (Fig. 3) are the spectral distributions of fluorescence $f_p(\lambda)$.

As stated in Sec. 4, a non-fluorescent reference is used for separating fluorescent and reflective components. In our experiments, we used a Macbeth ColorChecker with 24 patches whose spectral reflectance is publicly available [1]. For the spectral reflectance of fluorescent patches, we use the method proposed in [5]. To each fluorescent patch, we build its bispectral radiance factor matrix (Donaldson matrix). Spectral reflectance of the fluorescent patch can be represented by the diagonal elements of the matrix.

6.1. Result of spectral sensitivity estimation

We estimated the spectral sensitivities of three different cameras by taking pictures under four common illuminations, sun, blue sky, cloudy sky, and fluorescent-lamp. The spectral distributions of these illuminations were unknown. Based on the previous study [7], 9 Fourier basis functions are used for representing camera spectral sensitivity. The weight of the smoothness term is set to $(8, 8, 3)$. The Estimated results using our method are shown as continuous curves in Fig. 4. The Results by using monochromatic lights are shown as dotted curves. To evaluate the difference between them, for each estimated result, we computed the average value of the root mean square errors (RMSE) of RGB 3 channels. The numbers are also shown in Fig. 4. These results show the accuracy of our method even without knowing the illumination spectra.

Observing the estimated results of our method, we can see that the results under sunlight have a little bigger errors than those under the other illuminations. The reason behind this is the fact that fluorescent materials absorb light with higher energy than their emitted fluorescence. As shown in Fig. 5, to light from the blue sky or the cloudy sky, its intensity in the shorter wavelength range (higher energy) is stronger than that in the longer wavelength range (lower energy). On the contrary, sunlight is stronger in the longer wavelength range. Hence, the fluorescent component of the fluorescent chart under the sunlight is darker than those under the other illuminations. This results in that the estimated results under sunlight by our method are more easily affected by noise and errors. Therefore, when using our method, illuminations which are strong in high energy wavelength range, *e.g.*, skylight, are recommended.

Another observation about the estimated camera spectral sensitivities is that results of the blue channel show larger deviations when compared with those of the green or red channel. Our explanation is that fluorescent materials which emit blue fluorescence require stronger UV light and absorb less visible light, thus their fluorescent components always appears darker than the other patches under common illuminations. Our estimate for the blue channel are thus more easily affected by noise or errors than the other two channels.

6.2. Daylight spectrum estimation

Daylight includes all direct and indirect sunlight during the daytime. The spectrum of daylight is important for dealing with various imaging problems, such as color correction and color constancy in outdoor environments. In this subsection we show how to estimate the spectrum of daylight by the camera spectral sensitivity.

According to the previous studies [14, 22, 19], daylight spectrum can be well approximated with a small number of basis functions. To reconstruct daylight, we need to esti-

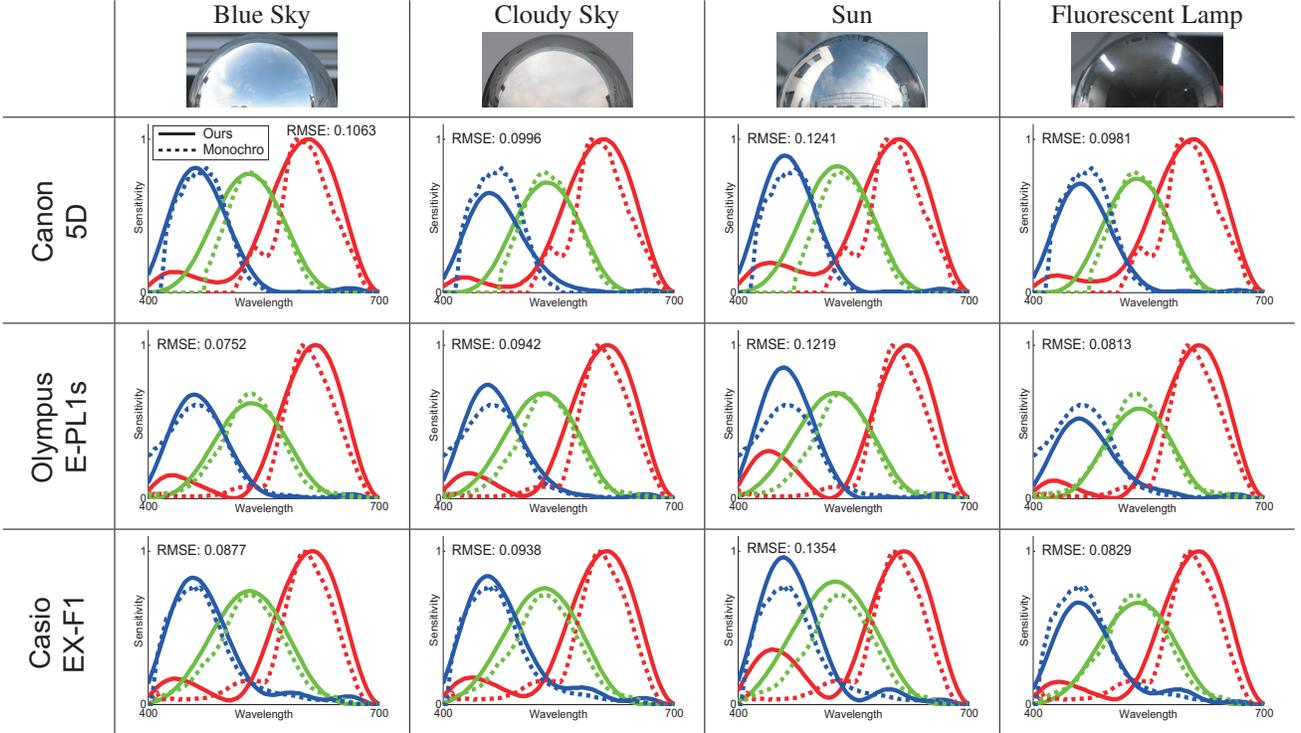


Figure 4. Estimated spectral sensitivities of cameras under different illuminations whose spectra are unknown. Results of our method are similar to those using monochromatic light, but ours have less high frequency because of the use of Fourier bases and the smooth constraint.

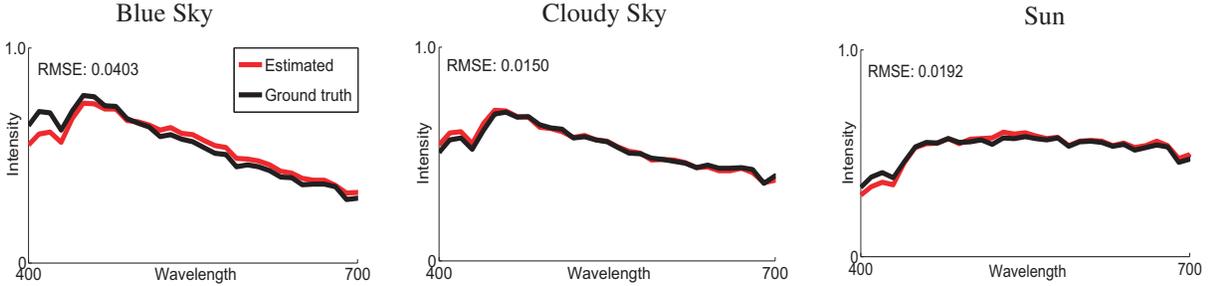


Figure 5. The spectral distributions of daylight can be accurately estimated from the estimated camera spectral sensitivity of a Canon 5D and the appearance of the Macbeth ColorChecker in the captured images. Note that each spectrum is normalized to ensure the area of the region below the corresponding curve is a constant. Thus, the intensities are relative values for the two distributions in the same figure.

mate its corresponding coefficients. Here, we adopt a widely used three-basis model [22]:

$$l(\lambda) = \sum_{j=1}^3 \gamma_j b_j^l(\lambda), \quad (17)$$

where $b_j^l(\lambda)$ is the j -th basis for daylight that is available in [22], and γ_j is the corresponding coefficient. Recall that we used the Macbeth ColorChecker as the reference for separating the fluorescent component in Sec. 4, the appearance of its q -th patch under daylight, $(R_q, G_q, B_q)^T$ ($q = 1, \dots, 24$), can be represented as

$$R_q = \int s_q(\lambda) c_R(\lambda) l(\lambda) d\lambda. \quad (18)$$

Substituting Eq. (17) into Eq. (18), we obtain

$$R_q = \sum_{j=1}^3 \gamma_j \int s_q(\lambda) c_R(\lambda) b_j^l(\lambda) d\lambda. \quad (19)$$

Three factors in the integral of Eq. (19) are known, and only γ_j are unknown. For all 24 patches on the ColorChecker, we have $24(\text{patch number}) \times 3$ (channels), *i.e.*, 72, linear equations that are similar to Eq. (19). The three unknown coefficients γ_j can be calculated in terms of the least-squares error. With the calculated results, the spectrum of daylight can be estimated by Eq. (17).

The estimates for different daylight conditions are shown in Fig. 5. The estimated spectra are indicated by red curves, and ground truths measured by the spectrometer are indicated by black curves. We can see that they are very similar to



Figure 6. A synthetic image of a postcard composed from three real captured images. Cameras and illuminations are shown in parentheses.



Figure 7. The calibration targets are placed in the scene.

each other. The root mean square errors (RMSE) of the estimated results are very small. Through these comparisons, we can see that the spectra of daylight can be accurately estimated by the camera spectral sensitivity.

Based on the above discussion, it is apparent that we are capable of estimating not only camera spectral sensitivity but also the daylight spectrum from a single captured image.

6.3. Color correction

It is well known that the appearance of the same scene varies a lot under different illuminations or using different cameras. One example is shown in Fig. 6. This difference can be seen as multiplying albedo of scene points with different scales in the RGB channels. The scales can be calculated by multiplying the obtained camera spectral sensitivities and daylight spectra in the spectral domain, *i.e.*, $\int c_R(\lambda)l(\lambda)d\lambda$. By making use of these scales, the color of captured images under different illuminations or by different cameras can be corrected.

Let us suppose that the spectral sensitivity of a camera is $(c_R(\lambda), c_G(\lambda), c_B(\lambda))^T$, daylight is $l(\lambda)$, and the observed intensity of a scene point is $(R, G, B)^T$. For a different camera $(\overline{c_R}(\lambda), \overline{c_G}(\lambda), \overline{c_B}(\lambda))^T$ or under different daylight $\overline{l}(\lambda)$, the observed intensity of the same scene point is $(\overline{R}, \overline{G}, \overline{B})^T$. The relationship between these two observations can be described as

$$\overline{R} = \frac{\int \overline{c_R}(\lambda)l(\lambda)d\lambda}{\int c_R(\lambda)l(\lambda)d\lambda} R, \quad (20)$$

for the red channel. The relationship for the blue and green channels can be described in a similar manner.

As discussed in previous sections, appearance of the fluorescent chart and the Macbeth ColorChecker is required



Figure 9. Difference between two Macbeth ColorChecker images captured under sunlight and blue sky conditions by the Canon 5D. Left: Macbeth ColorChecker. Middle: difference ($\times 5$) before correction. Right: difference ($\times 5$) after correction.

for estimating camera spectral sensitivity and daylight spectrum. If they can be placed in the scene, a single image can capture their appearance as well as the scene (as shown in Fig. 7). Otherwise, two images need to be taken, *i.e.*, one of the calibration targets, and another one of the scene.

Once the corresponding camera spectral sensitivities and the daylight spectra are obtained, the color of a scene's appearance can be corrected using Eq. (20). Here, we took images about 2 scenes under different daylights with different cameras, a building and a postcard. These images are framed in blue in Fig. 8. With the estimated camera spectral sensitivities and daylight spectra, we calculated the scenes' appearances under different daylight conditions with different cameras by Eq. (20). The calculated results are framed in red. Each column shows a real captured image and a color corrected image. We can see that, although the corrected results are not identical to the real captured images, the difference is significantly decreased, by which the effectiveness of our method can be demonstrated.

To evaluate how well our method works on different colors, we captured two Macbeth ColorChecker images using a Canon 5D under the sun and blue sky conditions. The differences between these images before and after correction are shown in Fig. 9. The darker the patches are, the smaller the differences are. From the middle image, we can see that because sunlight is more reddish than light from the blue sky, for patches which have high reflectivity to red light, their differences in the red channel are obvious before color correction. After color correction, as shown in the right image, those obvious differences are greatly reduced.

7. Conclusions

In this work, we proposed an estimation method for camera spectral sensitivity under unknown illumination. Making use of chromaticity invariance of fluorescence, our method is capable of estimating camera spectral sensitivity from a single image of a calibration chart made with fluorescent paint and a Macbeth ColorChecker taken under unknown illumination. The effectiveness of the proposed method was successfully demonstrated with experiments using real images taken under various illumination conditions. In addition, two applications of our method were in-

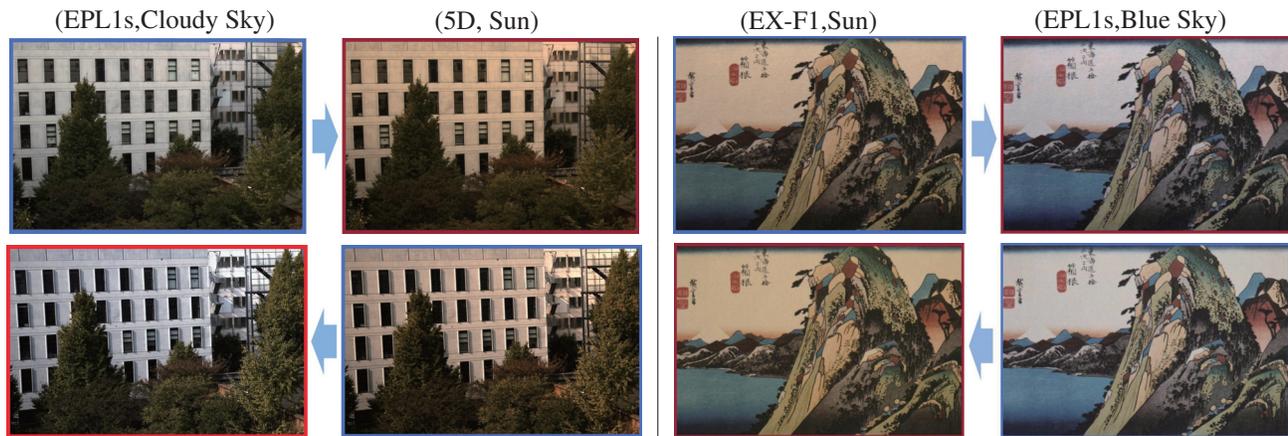


Figure 8. The color in the captured images can be corrected to match other images captured under different illuminations or by different cameras with estimated camera spectral sensitivities and daylight spectra. Here, we show two scenes, buildings (left) and a postcard (right). Cameras and illuminations are shown in parentheses.

roduced: daylight spectrum estimation and color correction for outdoor images. In the future, we are planning to work on how to select a set of fluorescent paint to achieve better estimation accuracy under a wide range of illumination conditions.

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