Bayesian Estimation of Camera Characteristics including Spectral Sensitivities from a Color Chart Image without Manual Parameter Tuning

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Abstract: We proposed a new practical method for identifying characteristics of a color digital camera: spectral sensitivity function, linearization function and noise variance of each color channel. The only input is an image of a color chart acquired by the objective camera with a spectral-content-known illuminant, and the camera characteristics are obtained automatically. The proposed method was developed in the Bayesian statistical framework in order to improve upon previous methods, namely, to eliminate trial-and-error parameter tuning and to identify linearization function as well as spectral sensitivities. The polyline linearization function and the noise variance of a color channel were considered as hyperparameters, and estimated by the marginalized likelihood criterion. Such hyperparameters associated with the smoothness of the sensitivity curves were also estimated similarly. Then the spectral sensitivity of a color channel was obtained as maximum a posteriori solution. In experiments using synthetic data, the proposed method was found to be widely adaptable to the forms of sensitivity curves and the levels of sensor noise.

1 INTRODUCTION

Spectral sensitivities of color channels are one of the most important characteristics of a color imaging devices such as an RGB camera because this characteristic determines the color separation and the colorimetric behavior of the device. Spectral sensitivities are needed to be known for various advanced applications of an imaging device as well as for evaluation of color reproduction and for color calibration (Sharma and Trussell, 1997; Urban and Grigat, 2009), such as spectral reflectance estimation (Shen and Xin, 2006), image deblurring and noise reduction (Urban et al., 2008), and image superresolution (Murayama and Ide-Ektessabi, 2012).

Unfortunately, manufacturers usually don't provide detailed characteristics of their imaging devices including spectral sensitivities. Though we could measure spectral sensitivities by using a monochrometer and a spectroradiometer (Vora et al., 1997), it takes much time and effort for the adjustment and measurement process. The quite high cost of these equipments is also an obstacle.

As a solution, researchers have been developing indirect methods for recovering spectral sensitivities from camera responses for a color chart. This approach has the advantage of practicality because we only have to prepare a color chart with known spectral reflectance, and illuminate it uniformly by using a light source with known spectral power distribution, and then acquire an image of the color chart. The spectral sensitivity of a color channel is obtained by solving a regression problem between the sensor responses and the spectrum reflected from the color chart patches. The early issue in spectral sensitivity recovery is how to stabilize the regression problem because it is a typical ill-conditioned problem, which means a small amount of noise included in the data is dramatically amplified to the regression solution.

Sharma and Trussell (1996) proposed to introduce constraints of spectral sensitivity: non-negativity, smoothness, modality, etc. They calculated a solution which satisfies the all constraints and doesn't make the radial errors of sensor responses over a certain value by applying the computational technique of projections onto convex sets. Finlayson et al. (1998) also used similar constraints, but represented spectral sensitivity through a small number of Fourier basis functions, instead of adopting the constraint of smoothness. They formulate the spectral sensitivity recovery as a constrained minimization problem which can be solved by the quadratic programming. Due to these

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devices, the recovery of spectral sensitivities was enabled in the presence of a relatively high amount of sensor noise.

As an additional issue, Barnard and Funt (2002) pointed out that a nonlinear characteristic of sensor response declined the accuracy of spectral sensitivity recovery, and performed a linearization at the same time of recovering the spectral sensitivity. The linearization of sensor response is necessary in all applications mentioned above. Though the linearization function can be identified from images of same scene captured with different exposures(Grossberg and Nayar, 2006), Barnard and Funt's approach is reasonable because of its possibility of improving accuracy in spectral sensitivity recovery as well of its efficiency. Beside the linearization, they proposed to add a regularization term to the cost function of the regression problem instead of using Fourier basis functions. Regularization is a well-known technique for improving ill-conditioned regression. A regularization term is generally represented by a norm of a variant to be recovered, and they adopted the second derivative norm to smooth the recovered sensitivity.

However, there remains a practical issue of selecting tuning parameters. For example, the smoothness of a recovered spectral sensitivity depends on the threshold value in Sharma and Trussell's method, the total number of Fourier basis functions in Finlayson et al.'s method, and the regularization coefficient in Barnard and Funt's method. These are typical tuning parameters, which need to be selected through trial-and-error process. Besides in Barnard and Funt's method, the linearization function was given parametrically based on the empirical knowledge of their objective camera, and some of the parameters were adjusted with trial and error. Though Carvalho et al. (2004) proposed a scheme to determine all tuning parameters in Finlayson et al.'s method objectively by adopting an extended criterion of cross validation, they didn't deal with the linearization of sensor responses.

This study aims to develop a method for identifying spectral sensitivity functions and linearization functions without manual parameter tuning and with simple implementation. We formalized the problem of spectral sensitivity recovery in the Bayesian statistical framework. A smooth regularization and a nonnegative constraint were adopted, and they were introduced to our Bayesian model as a prior distribution. A polyline function was used for linearization, which achieves a high degree of freedom in calibration regardless of camera choices. The noise variance as well as the spectral sensitivity and the linearization function of a color channel can be identified from a color chart image owing to the modeling in the Bayesian framework. In this study we show the Bayesian formalization, and the implementation of its solution. We also show experiments using synthetic data.

2 PROPOSED METHOD FOR IDENTIFYING CAMERA CHARACTERISTICS

2.1 Outline of Bayesian Estimation

Let $\theta_k(\lambda)$ be the spectral sensitivity of a camera, and $y_k^{(i)}$ its sensor response for the i-th color patch of a color chart ($i = 1, \ldots, N$), where k and λ denote color channel ($k =$R,G,B) and wavelength respectively. The parameter to be obtained is the sensitivity $\theta_k(\lambda)$ and is estimated by a conditional probability $p(\theta_k(\lambda)|\mathbf{y}_k)$ called the posterior, where we denote a set of sensor responses of k-channel by the vector $\mathbf{y}_k = [y_k^{(1)} \cdots y_k^{(N)}]^T$.

The posterior is derived from the likelihood $p(\mathbf{y}_k|\theta_k(\lambda))$ and the prior $p(\theta_k(\lambda))$ by applying the Bayesian theorem on conditional probability:

$$p(\theta_k(\lambda)|\mathbf{y}_k) = \frac{p(\mathbf{y}_k|\theta_k(\lambda))p(\theta_k(\lambda))}{\int p(\mathbf{y}_k|\theta_k(\lambda))p(\theta_k(\lambda))\mathrm{d}\theta_k(\lambda)}. \quad (1)$$

The likelihood represents an input-output model of the camera, and the prior represents the prior knowledge about spectral sensitivity curves which can be utilized to exclude the possibility of inappropriate solutions, and to make the sensitivity recovery stable. The spectral sensitivity of the color channel is obtained as the maximum a posteriori (MAP) estimator, which is the maximum point of the posterior and a common estimator.

In the Bayesian framework, parameters included in the likelihood or the prior can be determined in a data-driven manner. Such parameters are called hyperparameters, and we introduce the camera characteristics except spectral sensitivity as hyperparameters of the Bayesian model. An effective criterion for hyperparameter estimation is the log-marginalized likelihood h defined by

$$h = \ln \int p(\mathbf{y}_k|\theta_k(\lambda))p(\theta_k(\lambda))\mathrm{d}\theta_k(\lambda), \quad (2)$$

where the marginalization by unknown sensitivity $\theta_k(\lambda)$ helps avoid over-fit estimation (Bishop, 2006). The maximization of h can be solved by repeated calculation of the expectation-maximization (EM) algorithm (Bishop, 2006). In E-step, the posterior is calculated using provisional parameters and then the expectation value of the log-likelihood with respect to the provisional posterior is calculated. In M-step, hyperparameters are renewed such that they maximize the expectation value obtained in E-step. These two steps are repeated until convergence.

The proposed method is executed separately in each color channel. Hereafter we omit the color channel index k for easier readability.

2.2 Nonlinear Camera Model and Likelihood

RGB cameras are modeled by the following equation at each pixel (Sharma and Trussell, 1996; Barnard and Funt, 2002):

$$y = \int \theta(\lambda)x(\lambda)\mathrm{d}\lambda + \varepsilon, \tag{3}$$

where $x(\lambda)$ is the input spectra, y and $\theta(\lambda)$ are the sensor response and the spectral sensitivity of a certain color channel, and ε is the sensor noise. The input spectra $x(\lambda)$ can be obtained as the product of spectral power distribution of the illuminant and spectral reflectance of the object at the pixel.

In the case that the sensor has a nonlinear characteristic, Eq.(3) should be applied after converting the real sensor response z to the linearized response y. Let f be a monotonically increasing function for linearizing z with respect to input light intensity. In this study, we normalize z and y to range $[0,1]$ and consider a polyline function at regular intervals as the linearization function f:

$$\begin{aligned} y =& f(z;\{\alpha\}) \\ =& \alpha_i\left(z - \tfrac{i-1}{M-1}\right) + \alpha_{i+1}\left(\tfrac{i}{M-1} - z\right) \\ & \text{for} \quad \tfrac{i-1}{M-1} \le z \le \tfrac{i}{M-1}, \end{aligned} \tag{4}$$

where $\{\alpha\} = \{\alpha_1, \ldots, \alpha_M\}$ are the polyline points, and they are constrained by $0 \le \alpha_1 \le \cdots \le \alpha_M = 1$. Functions of wavelength such as $\theta(\lambda)$ and $x(\lambda)$ are vectorized by wavelength-sampling for the sake of computing. We denote them by vectors θ and $\mathbf{x}$ whose dimensions are the wavelength samplings Λ respectively.

The likelihood is derived by assuming a Gaussian noise and applying the camera model to each color patches of an acquired color chart image as follows:

$$\begin{aligned} p(\mathbf{z}|\theta) &= \prod_{i=1}^{N} \mathcal{N}(y|\theta^T\mathbf{x}^{(i)}, \sigma^2) \\ &= \mathcal{N}(\mathbf{y}|X\theta, \sigma^2 I_N), \end{aligned} \tag{5}$$

where $X = [\mathbf{x}^{(1)} \cdots \mathbf{x}^{(N)}]^T$, $\mathbf{z} = [z^{(1)} \cdots z^{(N)}]^T$ and the superscripts of $\mathbf{x}$ and z indicate the color patch number. $\mathcal{N}(t|\mu,\Sigma)$ denotes the univariate or multivariate Gaussian distribution of t whose mean or mean vector is μ and whose variance or variance matrix is Σ, and I_N denotes the identity matrix of size N.

2.3 Prior Knowledge about Spectral Sensitivity

We introduce a prior reflecting the non-negativity and the smoothness of spectral sensitivity curves as follows:

$$p(\theta) = \begin{cases} a\mathcal{N}(\theta|\mathbf{0}, \omega^2(D_r^T D_r)^{-1}) & \theta \ge \mathbf{0} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where ω is a scale parameter, D_r is a $(\Lambda + r)$-by-Λ matrix representing the r-th degree differential matrix with zero padding, and a is the normalization constant. The i-th column vector of D_r is $[\underbrace{0,\ldots,0}_{i-1}, \underbrace{(-1)^r{}_rC_r, (-1)^{r-1}{}_rC_{r-1}, \ldots, {}_rC_0}_{r+1}, \underbrace{0,\ldots,0}_{\Lambda-i}]^T$, for example,

$$D_2 = \begin{bmatrix} 1 & & & \\ -2 & 1 & & \\ 1 & -2 & \ddots & \\ & 1 & \ddots & 1 \\ & & \ddots & -2 \\ & & & 1 \end{bmatrix},$$

$$D_3 = \begin{bmatrix} -1 & & & \\ 3 & -1 & & \\ -3 & 3 & \ddots & \\ 1 & -3 & \ddots & -1 \\ & 1 & \ddots & 3 \\ & & \ddots & -3 \\ & & & 1 \end{bmatrix}. \tag{7}$$

The first r rows and the last r rows of D_r are added by zero padding to reflect the boundedness, namely that spectral sensitivity closes to zero at both ends of wavelength range. r is related to the smoothness. Figure 1 shows spectral sensitivities sampled from the prior $p(\theta)$. It can be seen how smooth sensitivities are supposed by adopting this prior and that the smoothness increases as increasing r. In Figure 1 ω fixed to 1 but affects the scale of the vertical axis. This prior is equivalent to introducing a regularization term of $\frac{1}{\omega^2}\|D_r\theta\|^2$ in the previous non-Bayesian methods. The 2nd differential matrix without zero padding was used in both Sharma and Trussell's method and Barnard and Funt's method, but we add zero padding and determine the degree r in data-driven manner. In our method, the optimum degree of r is estimated as well as ω. a doesn't need to be calculated.

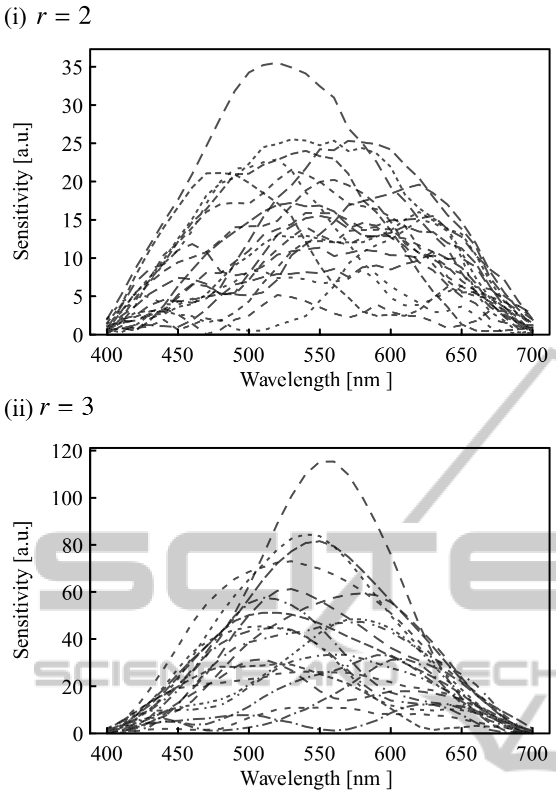

Figure 1: Spectral sensitivities sampled from the prior with different r-values where ω was fixed to be 1.

2.4 Implementation

The posterior is derived from Eqs. (1),(5) and (6) and standard matrix operations as follows:

$$p(\theta|\mathbf{z}) = \begin{cases} b\mathcal{N}(\theta|\mu,\Sigma) & \theta \geq \mathbf{0} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

with

$$\Sigma = \left(\frac{1}{\sigma^2}X^TX + \frac{1}{\omega^2}D_r^TD_r\right)^{-1} \tag{9}$$

$$\mu = \frac{1}{\sigma^2}\Sigma X^T\mathbf{y}, \tag{10}$$

where b is the normalization constant. This posterior is represented as a truncated multivariate Gaussian distribution as well as the prior we introduced, but we employ quadratic approximation in order to avoid high-dimensional numerical integration for obtaining b. The approximated posterior $\tilde{p}(\theta|\mathbf{z})$ is represented as a complete multivariate Gaussian distribution as follows:

$$\tilde{p}(\theta|\mathbf{z}) = \mathcal{N}(\theta|\mu_{\mathrm{MAP}},\Sigma) \tag{11}$$

with

$$\begin{aligned} \mu_{\mathrm{MAP}} &= \arg\max_{\theta}\ p(\theta|\mathbf{y}) \\ &= \arg\min_{\theta\geq\mathbf{0}}\ (\theta-\mu)^T\Sigma^{-1}(\theta-\mu) \\ &= \arg\min_{\theta\geq\mathbf{0}}\left[\theta^T\Sigma^{-1}\theta - \tfrac{2}{\sigma^2}\mathbf{y}^TX\theta\right]. \end{aligned} \tag{12}$$

The EM algorithm is applied to find hyperparameters $\{\{\alpha\},\ \sigma,\ \omega\}$ such that they maximize the marginalized log-likelihood when r is fixed. In our implementation, initially, $\{\alpha\}$ was set so as to represent a simple linear function, and both σ and ω were set to 1. $\{\{\alpha\}^{\mathrm{new}},\sigma^{\mathrm{new}},\omega^{\mathrm{new}}\}$ are set to the initial values, and the EM algorithm is implemented as follows:

E-step

$\left\{\{\alpha\}^{\mathrm{old}},\sigma^{\mathrm{old}},\omega^{\mathrm{old}}\right\} \leftarrow \{\{\alpha\}^{\mathrm{new}},\sigma^{\mathrm{new}},\omega^{\mathrm{new}}\}$,

$\mathbf{y} \leftarrow f(\mathbf{z},\{\alpha\}^{\mathrm{old}})$,

$\Sigma \leftarrow \left(\frac{1}{(\sigma^{\mathrm{old}})^2}X^TX + \frac{1}{(\omega^{\mathrm{old}})^2}D_r^TD_r\right)^{-1}$,

$\mu \leftarrow \frac{1}{(\sigma^{\mathrm{old}})^2}\Sigma X^T\mathbf{y}$, and

$\mu_{\mathrm{MAP}} \leftarrow \arg\min_{\theta\geq\mathbf{0}}\left[\theta^T\Sigma^{-1}\theta - \frac{2}{\sigma^2}\mathbf{y}^TX\theta\right]$.

M-step

$\{\alpha\}^{\mathrm{new}} = \arg\min_{0\leq\alpha^{(1)}\leq\cdots\leq\alpha^{(M)}=1} \|f(\mathbf{z};\{\alpha\}^{\mathrm{old}}) - X\mu\|^2$,

$\mathbf{y} \leftarrow f(\mathbf{z},\{\alpha\}^{\mathrm{new}})$,

$\sigma^{\mathrm{new}} \leftarrow \frac{1}{N}\sqrt{\|\mathbf{y}-X\mu\|^2 + \mathrm{tr}(\Sigma XX^T)}$, and

$\omega^{\mathrm{new}} \leftarrow \frac{1}{\Lambda}\sqrt{\|D_r\mu\|^2 + \mathrm{tr}(\Sigma D_r^TD_r)}$.

These two steps are repeated, where perhaps several tens of times are enough to convergence. Both minimizations to update μ_{MAP} in E-step and $\{\alpha\}$ in M-step can be solved by the quadratic programming (QP) algorithm with low computational cost. The QP algorithm was used in Finlayson et al's method and Barnard and Funt's method. The detailed implementation of the minimization in M-step, which is polyline fitting by the QP method, is described in Aronov et al, 2004 . The spectral sensitivity, polyline points for linearization and noise variance are obtained by the latest values of μ_{MAP}, $\{\alpha\}$ and σ^2 respectively for a certain r. r is chosen as a natural number, such that the marginalized log-likelihood h is minimized. h is derived by applying the same approximation as the posterior as follows:

$$\begin{aligned} h = &\tfrac{1}{2}\ln\det(2\pi\Sigma) - \tfrac{1}{2}\ln\det(2\pi\sigma^2 I_N) \\ &- \tfrac{1}{2}\ln\det(2\pi\omega^2(D_r^TD_r)^{-1}) \\ &- \tfrac{1}{2}\sigma^2\|\mathbf{y}\|^2 - \tfrac{1}{2}\mu_{\mathrm{MAP}}^T\Sigma^{-1}\mu_{\mathrm{MAP}}. \end{aligned} \tag{13}$$

3 RESULTS ON SYNTHETIC DATA

We have tested the proposed method on spectral sen-

Table 1: Comparison of the errors in recovering spectral sensitivities in the case of linear sensor responses. These results correspond to those in Figure 1.

Method	RMSE of spectral sensitivity ($\times 10^{-5}$)					
	Sony DXC-930 camera			Kodak DCS-460 camera		
	R ch.	G ch.	B ch.	R ch.	G ch.	B ch.
Poposed method	8.00	2.24	4.19	5.89	2.00	2.24
Method A	5.15	3.03	12.51	3.72	2.38	3.97
Method B	8.54	1.98	2.05	4.67	2.03	2.91

sitivities of two commercial cameras: Sony DCX-930 and Kodak DCS-200. The former camera has sensitivity curves like Gaussian functions while the latter camera's sensitivities have more complicated forms. The former was used in Barnard and Funt (2004), and the latter was in Finlayson et al. (1998) and Carvalho et al. (2004). The spectral sensitivities of the two cameras were obtained from a spectral sensitivity database (Zhao,). In this experiment, 288 input spectrum were prepared from spectral reflectance of IT8 target, which is a common color chart, and spectral power distribution of D65 standard illuminant. Spectral reflectance of each color patch was measured by ourselves using X-rite SP64 spectrocolorimeter. Both the sensitivities and the spectrum were sampled from 400 nm to 700 nm at 10 nm wavelength intervals. The first experiment (Sec. 3.1) compared our method with two previous methods with only respect to the accuracy of spectral sensitivity recovery. It was performed supposing linear sensor responses because the previous methods don't have the ability of automatic linearization. The second experiment (Sec. 3.2) dealt with linearization of sensor responses under several noise levels, and evaluated the accuracy of the camera characteristics identified by the proposed method. The true values of spectral sensitivities were normalized such that sensor responses become 1 for 100-percent diffuse reflection, namely that perfect white is represented by $y_{\mathrm{R}} = y_{\mathrm{G}} = y_{\mathrm{B}} = 1$.

3.1 Linear Sensor Response

We supposed 1% additive noise and set the standard deviation of sensor noise σ to 0.01 in each color channel. The sensor responses of the two cameras were produced according to Eqs. (3) and (4) where the linearization function f was set to the identity function. Three methods were applied to recover the sensitivities: Our proposed Bayesian method, Finlayson et al.'s method using Fourier basis functions with modality constraints (Method A), and Barnard and Funt's method using smooth regularizations and range constraints (Method B). Method A adopts the squared absolute residue of sensor response as the cost function in the regression while Method B adopts the squared residue divided by sensor response. Nonnegative constraints were adopted in all of the three methods. In this experiment, tuning parameters of Method A and Method B were chosen correctly or optimally. The details are as follows: both the peak wavelength of a sensitivity in Method A and the wavelength range in which a sensitivity is zero in Method B were given based on the true spectral sensitivity, and both the total number of Fourier basis in Method A and the regularization parameter in Method B were selected such that the root-mean-square error (RMSE) of the recovered sensitivity is the minimum. Figure 1 and Table 1 show the results and the RMSEs in spectral sensitivity recovery with respect to methods. Results of the proposed method were resemble to those of Method B, and they achieved high accuracy regardless of the forms and the ranges of spectral sensitivities. Method A provided better recovery in the red channel of Kodak DCS-200 camera, whose sensitivity curve was the most complex in this experiment, but not good recovery in the blue channel of Sony DCX-930 camera. Our method selected hyperparameters automatically but nevertheless it achieved as high accuracy on the whole as the other two methods.

3.2 Nonlinear Sensor Response

A gamma characteristic was supposed as the nonlinearity of sensor responses, which is defined by:

$$z = y^{1/\gamma} \quad \text{or} \quad y = z^{\gamma}. \tag{14}$$

γ was set to 2.2, which approximates the nonlinear characteristic of familiar sRGB-based cameras. We tested our method in three levels of noise: $\sigma = 0.002, 0.01, 0.05$, namely 0.2%, 1% and 5% additive noise. Table 2 shows the RMSEs of the spectral sensitivities recovered by the proposed Bayesian method. Though the recovery accuracy declined as increasing noise level, relatively-high accuracy was achieved in spite of the nonlinearity of sensor responses. Figure 2 shows the identified linearization functions. There occurred small gaps only in the dark range of the red channel and the green channel of the Kodak camera. Table 3 shows the errors of the identified standard deviation of the sensor noises. In all cases the noise

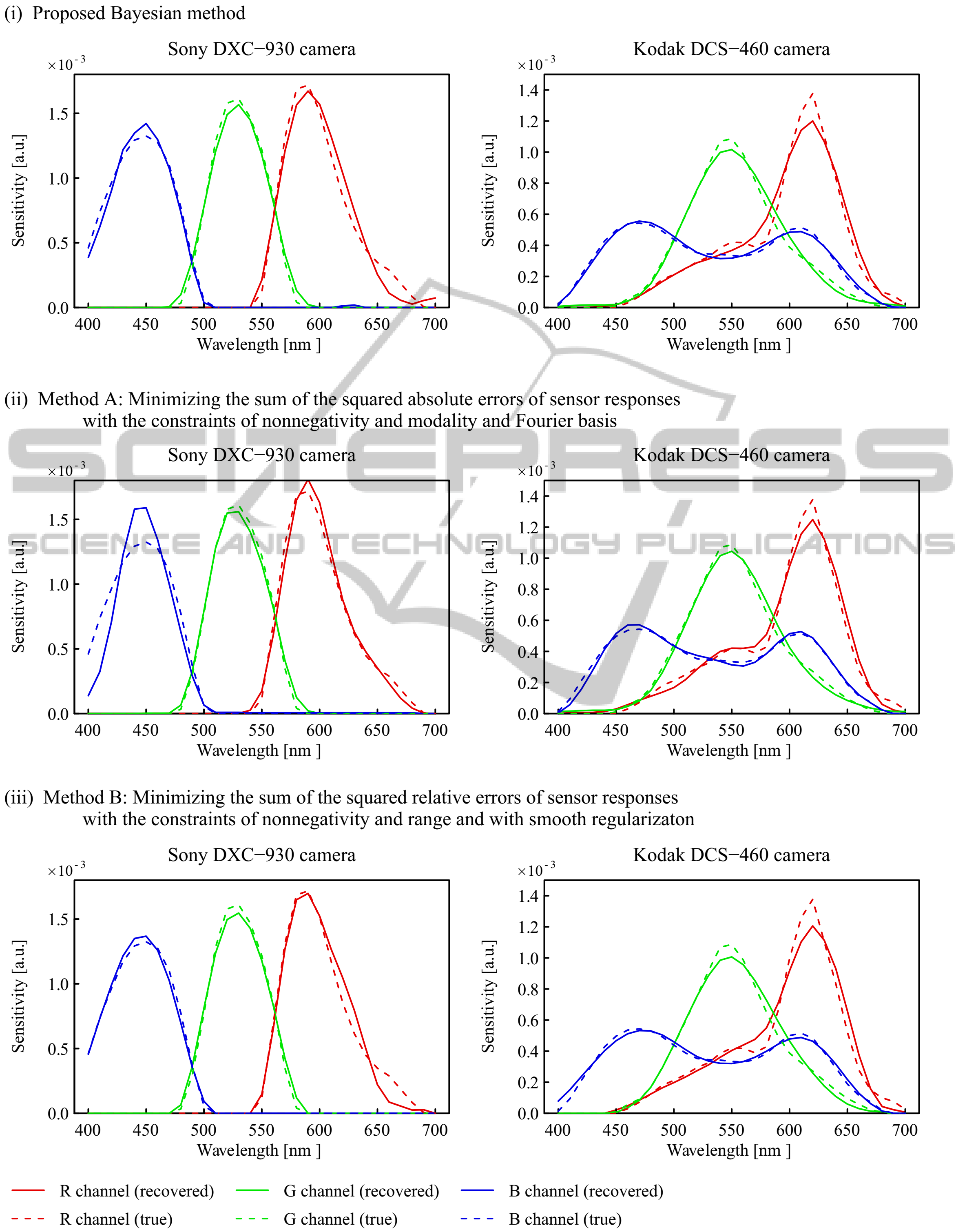

Figure 2: Results of the recovered spectral sensitivities in the case of linear sensor responses. The proposed method and two previous methods were compared using synthetic data on two commercial cameras. 1% noise ($\sigma = 0.01$) was added to the sensor response data.

Table 2: Results of the errors in the spectral sensitivities recovered by the proposed method using synthetic data in the case of nonlinear sensor responses (the gamma characteristic 2.2) under different noise levels.

Noise level	RMSE of spectral sensitivity ($\times 10^{-5}$)					
	Sony DXC-930 camera			Kodak DCS-460 camera		
	R ch.	G ch.	B ch.	R ch.	G ch.	B ch.
0.2% ($\sigma = 0.002$)	8.49	4.82	3.61	9.83	2.95	9.05
1% ($\sigma = 0.01$)	9.02	4.57	7.40	10.30	7.54	10.14
5% ($\sigma = 0.05$)	17.45	4.69	9.14	10.13	12.23	7.68

Table 3: The estimated standard deviation of sensor noise. The settings correspond to those in Table 2.

Noise level	Absolute error of the estimated noise amount σ ($\times 10^{-3}$)					
	Sony DXC-930 camera			Kodak DCS-460 camera		
	R ch.	G ch.	B ch.	R ch.	G ch.	B ch.
0.2% ($\sigma = 0.002$)	1.48	1.50	2.54	1.72	1.36	2.00
1% ($\sigma = 0.01$)	0.50	0.34	0.06	0.75	0.40	0.12
5% ($\sigma = 0.05$)	0.00	1.05	−0.60	−1.70	−0.35	0.20

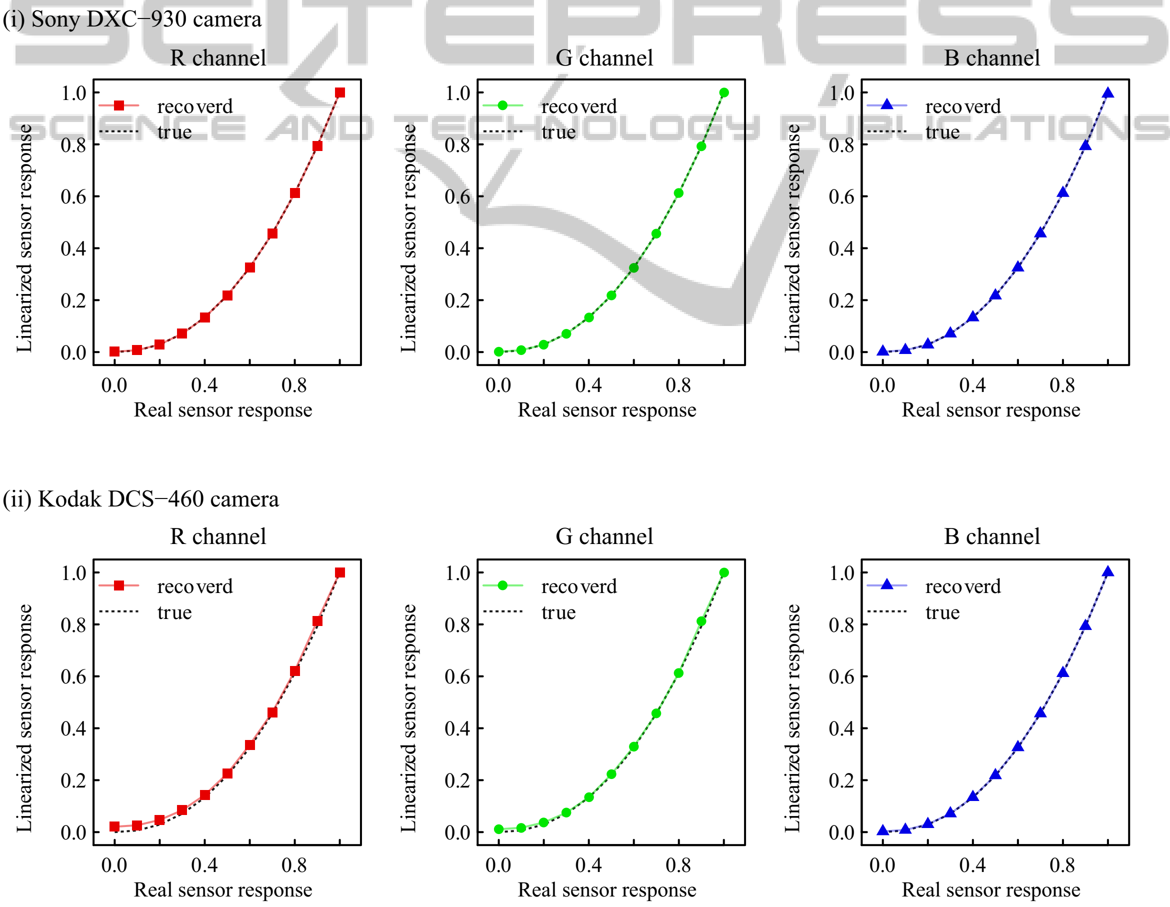

Figure 3: Results of the estimated linearization functions. The settings correspond to those in Table 2.

amounts were in the correct order. At last we show the results of the spectral sensitivities recovered by the proposed method in the presence of 1% sensor noises for reference.

4 CONCLUSIONS

We proposed a Bayesian method for identifying camera characteristics from an acquired image of a color

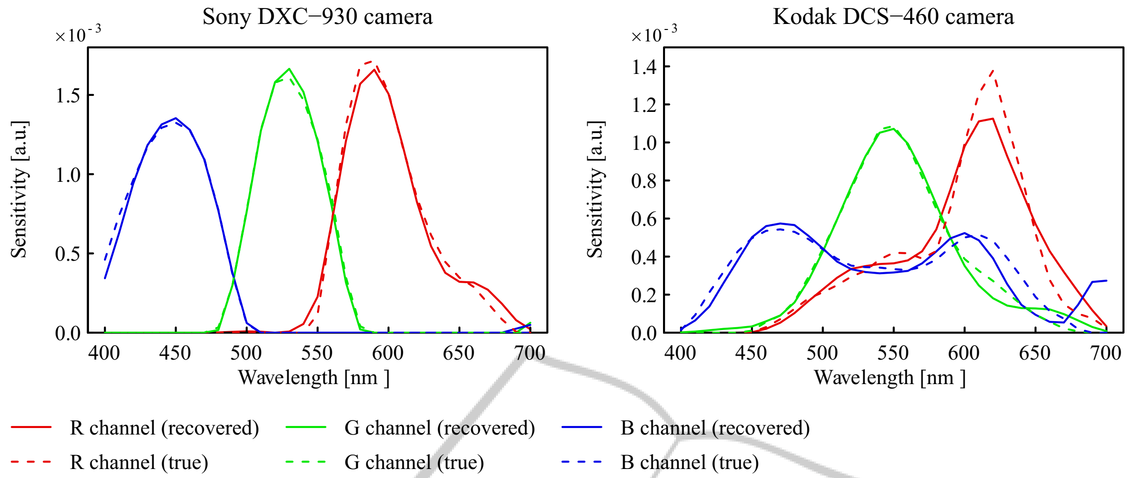

Figure 4: Results of the spectral sensitivities by the proposed method. Nonlinear camera model (the gamma characteristic 2.2) are used and 1% noise ($\sigma = 0.01$) was added to the synthetic sensor response data.

chart. The key features are that it can obtain the linearization function and the noise variance of each color channel as well as the spectral sensitivity function, and never requires any manual tunings of parameters. The experiments using synthetic data demonstrated high accuracy of the proposed method in recovering spectral sensitivities and linearization functions. It was also found that the proposed method was widely adaptable to the forms of sensitivity curves and the levels of sensor noise. Experimental performance tests are the next step of this study.

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