A Model to Evaluate Color Image Acquisition Systems Aimed at the Reconstruction of Spectral Reflectances

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Abstract

The recovery of spectral reflectances of objects being imaged from the color image data is very important in reproducing a color image under a variety of viewing illuminants. Accurate recovery of spectral reflectances is important for the color reproduction and the accuracy depends on the spectral sensitivities of a set of sensors, an illumination, spectral reflectances of objects, the noise present in an image acquisition system and a model used for the recovery. In our previous work, we derived a formula to evaluate the quality (Qr) of an image acquisition system aimed at recovery of spectral reflectances based on the Wiener estimation model and we applied it to multispectral image acquisition systems[1,2]. It is confirmed that the experimental results agree quite well with the theoretical predictions of the model and that the model is appropriately formulated.

In this paper the evaluation model was applied to the multiple regression analysis[3] and Imai-Berns model[4], which are usually used for the recovery of spectral reflectances, i.e., the relation of the mean square errors (MSE) of the recovered spectral reflectances by the two models and the Qr was examined by using the multispectral cameras. The experimental results agree quite well with the theoretical predictions by the evaluation model. It is shown that the proposed model is appropriately formulated and is able to be used for the evaluation of color image acquisition systems.

1. Introduction

There are two aspects in the color image acquisition, one is the acquisition of the colorimetric information and the other is the acquisition of the spectral information of the objects being imaged. The main aim of the former approach is considered as the acquisition of accurate colorimetric values of objects through the use of sensor responses. Several models have been proposed to evaluate a colorimetric performance of a set of color sensors[5-9], and the optimization of a set of sensors has been performed based on the evaluation models[10,11]. The colorimetric quality[7-9] and the accuracy of the estimated tristimulus values[12-14] depend not only on the spectral sensitivities of the sensors but also on the noise present in the devices. However, the application of the evaluation models to real color image acquisition devices such as digital cameras and color scanners has not appeared because of the difficulty in estimating noise levels. Recently one of the authors (N.S.) proposed a new model to estimate the noise variance of an image acquisition system[2] and applied it to the proposed colorimetric evaluation model, and confirmed that the evaluation model quite agrees well with the experimental results by multispectral cameras[15].

The purpose of the latter approach is the acquisition of the spectral reflectances of objects being imaged through the use of sensor responses. The accuracy of the recovered spectral reflectances depends on the number of sensors, their spectral sensitivities, the objects being imaged, the recording illuminants, the noise present in a device and a model used for the recovery. Therefore the evaluation of a camera aimed at the recovery of spectral reflectances is important for the optimization of an image acquisition system and to get an intuitive understanding about the acquisition of the spectral information. The author (N.S.) already derived the evaluation model based on the Wiener estimation[1]. The proposed model is formulated by $\mathrm{MSE} = E_{max}(1 - Q_r)$, where MSE is the mean square errors of the recovered spectral reflectances, Emax represents a constant which is determined by spectral reflectances of objects and Qr is the quality of the image acquisition system aimed at recovery of spectral reflectances. The model was applied to the multispectral cameras and it was confirmed that the model agrees quite well with the experimental results, i.e., the MSE of the recovered spectral reflectances by the Wiener estimation as a function of the quality Qr of a set of sensors by taking account of the noise shows the straight line. It is very important to confirm whether the model can be applied to other recovery models since the quality Qr is useful not only for the evaluation of an image acquisition device but also for the optimization of a set of sensors aimed at recovery of spectral reflectances.

In this paper, it is shown that the proposed model can be applied to the multiple regression analysis and Imai-Berns model which are usually used for the recovery of spectral reflectances and that the Qr is appropriately formulated for these models.

2. Model

2.1 Wiener Estimation Using Estimated Noise Variance

In this section, a brief sketch for a derivation of the quality Qr to evaluate the color image acquisition system is described. A vector space notation for color reproduction is useful in the problems. In this approach, the visible wavelengths from 400 to 700 nm are sampled at 10-nm intervals and the number of the samples is denoted as N. A sensor response vector from a set of color sensors for an object with a $N \times 1$ spectral reflectance vector $\mathbf{r}$ can be expressed by

$$\mathbf{p} = \mathrm{SL}\mathbf{r} + \mathbf{e}, \qquad (1)$$

where $\mathbf{p}$ is a $M \times 1$ sensor response vector from the M channel sensors, S is a $M \times N$ matrix of the spectral sensitivities of sensors in which a row vector represents a spectral sensitivity, L is an $N \times N$ diagonal matrix with samples of the spectral power distribution of an illuminant along the diagonal, and $\mathbf{e}$ is a $M \times 1$ additive noise vector. The noise $\mathbf{e}$ is defined to include all the sensor response errors such as the measurement errors in the spectral characteristics of sensitivities, an illumination and reflectances, and quantization errors in this work and it is termed as the system noise[2] below. The system noise is assumed to be signal independent, zero mean and uncorrelated to itself. For abbreviation, let $S_L = SL$. The MSE of the recovered spectral reflectances $\hat{\mathbf{r}}$ is given by

$$\mathrm{MSE} = E\left\{\left\|\mathbf{r} - \hat{\mathbf{r}}\right\|^2\right\}, \qquad (2)$$

where $E\{\bullet\}$ represents the expectation. If the Wiener estimation is used for $\hat{\mathbf{r}}$, then $\hat{\mathbf{r}}$ is given by

$$\hat{\mathbf{r}} = \mathrm{Rss} S_L^T \left(S_L R_{SS} S_L^T + \sigma_e^2 I\right)^{-1} \mathbf{p}, \qquad (3)$$

where T represents the transpose of a matrix, R_{SS} is an autocorrelation matrix of the spectral reflectances of samples that will be captured by a device, and σ_e^2 is the noise variance used for the estimation. Substitution of Eq.(3) into Eq.(2) leads to[2]

$$\mathrm{MSE} = \sum_{i=1}^{N} \lambda_i - \sum_{i=1}^{N} \sum_{j=1}^{\beta} \lambda_i b_{ij}^2 + \sum_{i=1}^{N} \sum_{j=1}^{\beta} \frac{\sigma_e^4 + \kappa_j^{v^2} \sigma^2}{\left(\kappa_j^{v^2} + \sigma_e^2\right)^2} \lambda_i b_{ij}^2, \qquad (4)$$

where, λ_i is the eigenvalues of Rss, b_{ij}, κ_i^v and β represent j-th row of the i-th right singular vector, singular value and a rank of a matrix $S_L V \Lambda^{1/2}$, respectively, σ^2 is the actual system noise variance, V is a basis matrix and Λ is an $N \times N$ diagonal matrix with positive eigenvalues λ_i along the diagonal in decreasing order. It is easily seen that the MSE is minimized when $\sigma_e^2 = \sigma^2$, and the MSE is given by

$$\mathrm{MSE} = \sum_{i=1}^{N} \lambda_i - \sum_{i=1}^{N}\sum_{j=1}^{\beta} \lambda_i b_{ij}^2 + \sum_{i=1}^{N}\sum_{j=1}^{\beta} \frac{\sigma^2}{\kappa_j^{v^2} + \sigma^2} \lambda_i b_{ij}^2 . \quad (5)$$

Equation (5) can be rewritten as

$$\mathrm{MSE} = \sum_{i=1}^{N} \lambda_i \left(1 - \frac{\Sigma_{i=1}^{N}\Sigma_{j=1}^{\beta} \lambda_i b_{ij}^2 - \Sigma_{i=1}^{N}\Sigma_{j=1}^{\beta} \frac{\sigma^2}{\kappa_j^{v^2} + \sigma^2} \lambda_i b_{ij}^2}{\Sigma_{i=1}^{N} \lambda_i} \right) . \quad (6)$$

Therefore the quality of a set of color sensors in the presence of noise is formulated as

$$Q_r = \frac{\Sigma_{i=1}^{N}\Sigma_{j=1}^{\beta} \lambda_i b_{ij}^2 - \Sigma_{i=1}^{N}\Sigma_{j=1}^{\beta} \frac{\sigma^2}{\kappa_j^{v^2} + \sigma^2} \lambda_i b_{ij}^2}{\Sigma_{i=1}^{N} \lambda_i} . \quad (7)$$

Hence, the MSE is expressed as

$$\mathrm{MSE} = E_{max}(1 - Q_r), \quad (8)$$

where $E_{max} = \Sigma_{i=1}^{N} \lambda_i$. This equation shows that the MSE has a linear relation to Qr and the slope of the line is $\Sigma_{i=1}^{N} \lambda_i$. The values of $\Sigma_{i=1}^{N} \lambda_i$ are dependent only on the surface spectral reflectance of the objects being captured. The MSE decreases as the Qr increases to one.

If we let the noise variance $\sigma_e^2 = 0$ for the Wiener filter in Eq. (3), then the MSE($\sigma_e^2 = 0$) is derived as (by letting $\sigma_e^2 = 0$ in Eq. (4))

$$\mathrm{MSE}(\sigma_e^2 = 0) = \sum_{i=1}^{N} \lambda_i - \sum_{i=1}^{N}\sum_{j=1}^{\beta} \lambda_i b_{ij}^2 + \sum_{i=1}^{N}\sum_{j=1}^{\beta} \frac{\sigma^2}{\kappa_j^{v^2}} \lambda_i b_{ij}^2 . \quad (9)$$

The first and second terms on the right-hand side of Eq. (9) represent the MSE at a noiseless case. We denote this MSE as MSE_{free}, then the estimated system noise variance $\hat{\sigma}^2$ can be represented by

$$\hat{\sigma}^2 = \frac{\mathrm{MSE}(\sigma_e^2 = 0) - \mathrm{MSE}_{free}}{\Sigma_{i=1}^{N}\Sigma_{j=1}^{\beta} \frac{\lambda_i b_{ij}^2}{\kappa_j^{v^2}}}, \quad (10)$$

where MSE_{free} is given by

$$\mathrm{MSE}_{free} = \sum_{i=1}^{N} \lambda_i - \sum_{i=1}^{N}\sum_{j=1}^{\beta} \lambda_i b_{ij}^2 . \quad (11)$$

Therefore, the system noise variance σ^2 can be estimated using Eq. (10), since the MSE_{free} and the denominator of Eq. (10) can be computed if the surface reflectance spectra of objects, the spectral sensitivities of sensors and the spectral power distribution of an illuminant are known. The MSE($\sigma_e^2 = 0$) can also be obtained by the experiment using Eqs. (2) and (3) applying the Wiener filter with $\sigma_e^2 = 0$ to sensor responses. Therefore, Eq. (10) gives a method to estimate the actual noise variance σ^2.[2]

The quality Qr and MSE can be computed by substituting the estimated noise variance in Eq.(7) and Eq.(3) , respectively.

2.2 Multiple Regression Analysis

Let $\mathbf{p}_i$ be a sensor response vector which is obtained by the image acquisition of a known spectral reflectance $\mathbf{r}_i$ of the i-th object, where i represents a number. Let P be a matrix which contains the sensor responses $\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_k$, and let R be a matrix which contains the corresponding spectral reflectances $\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_k$, where k is the number of learning samples. The pseudoinverse model is to find a matrix W which minimizes $\|R - WP\|$, where notation $\|\bullet\|$ represents the Frobenius norm[16]. The matrix W is given by.

$$W = RP^{+}, \quad (12)$$

where, P^{+} represents the pseudo inverse matrix of the matrix P. By applying a matrix W to a sensor response vector $\mathbf{p}$, i.e., $\hat{\mathbf{r}} = \mathrm{W}\mathbf{p}$, a spectral reflectance is estimated. Therefore this model does not use the spectral sensitivities of sensors or the spectral power distribution of an illumination, but it uses only the spectral reflectances of learning samples.

2.3 Imai-Berns Model

Imai-Berns model is considered as the modification of the linear model by using the regression analysis between the weight column vectors for basis vectors to represent the known spectral reflectances and corresponding sensor response vectors.

Let Σ be a d×k matrix which contains the column vectors of the weights to represent the k known spectral reflectances $\boldsymbol{\sigma}_1, \boldsymbol{\sigma}_2, \cdots, \boldsymbol{\sigma}_k$ and let P be a M×k matrix which contains corresponding sensor response vectors of those reflectances $\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_k$. The regression analysis between these matrixes is expressed as $\|\Sigma - \mathrm{BP}\|$. A matrix B which minimize the Frobenius norm is given by

$$\mathrm{B} = \Sigma \mathrm{P}^{+} . \tag{13}$$

Since a weight column vectors $\boldsymbol{\sigma}$ for a sensor response vector $\mathbf{p}$ is estimated by $\hat{\boldsymbol{\sigma}} = \mathrm{B}\mathbf{p}$, the estimated spectral reflectance vector is derived from $\hat{\mathbf{r}} = \mathbf{V}\hat{\boldsymbol{\sigma}}$, where a matrix V is the basis matrix which contains first d orthonormal basis vectors of spectral reflectances. This model does not use the spectral characteristics of sensors or an illumination.

3. Experimental Procedures

A multispectral color image acquisition system was assembled by using seven interference filters (Asahi Spectral Corporation) in conjunction with a monochrome video camera (Kodak KAI-4021M). Image data from the video camera were converted to 16-bit-depth digital data by an AD converter. The spectral sensitivity of the video camera was measured over wavelength from 400 to 700 nm at 10-nm intervals. The spectral sensitivities of the camera with each filter are shown in Fig.1. The illuminant used for image capture was the illuminant which simulates daylight (Seric Solax XC-100AF). The spectral power distribution of the illuminant measured by the spectroradiometer (Minolta CS-1000) is presented in Fig.2.

The Macbeth ColorChecker DC (164 colors) was illuminated from the direction of about 45 degree to the surface normal, and the images were captured by the camera from the normal direction. The image data were corrected to uniform the nonuniformity in illumination and sensitivities of the pixels of a CCD. The computed responses from a camera to a color by using the measured spectral sensitivities of the sensors, the illuminant and the surface reflectance of the color dose not equal to the actual sensor responses since the absolute spectral sensitivities of a camera depend on the camera gain. Therefore, the sensitivities were calibrated using an achromatic color in the charts. In this work, the constraint is imposed on the signal power as given by $\rho = \mathrm{Tr}\left(\mathrm{S_L R_{SS} S_L^T}\right)$, where relation of $\rho = 1$ was used so that the estimated system noise variance can be compared for different sensor sets.

By using various combinations of sensors from the three to seven in Fig.1, the system noise variance was estimated by the methods described above for each combination of sensors. Then the estimated noise variance was used to recover the spectral reflectances by the Wiener estimation, and then the MSE of the recovered spectral reflectances was computed. The spectral reflectances were also recovered by multiple regression model and Imai-Berns model. By using the estimated noise variance, the quality Qr for each combination of sensors was computed using Eq.(7).

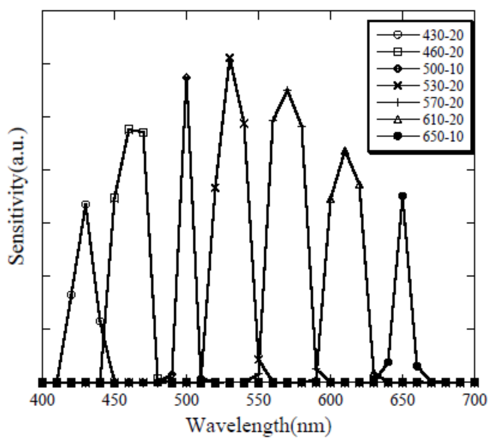

Figure . 1. Spectral sensitivities of the camera. The name of the filter shows peak wavelength and half-value width.

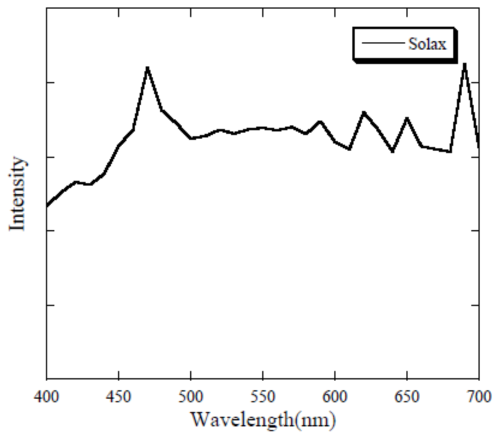

Figure . 2. Spectral power distribution of the illumination.

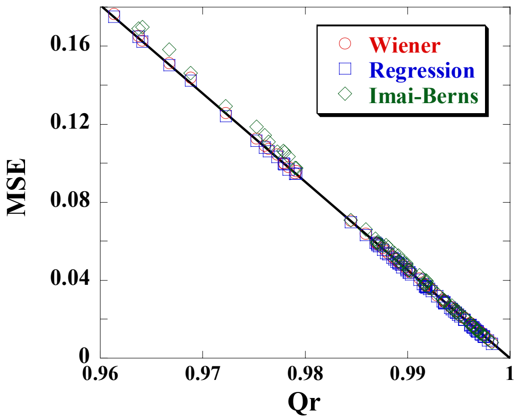

Figure 3. The MSEs of the recovered spectral reflectances by Wiener, Regression, and Imai-Berns method for Macbeth ColorChecker DC are plotted as a function of Qr.

4. Results

The values of the MSE as a function of Qr were plotted for the 80 sets of sensors in Fig.3. The line in the figure indicates the theoretical relation between the MSE and Qr, as given by Eq. (8), where $E_{max} = \sum_{i=1}^{N} \lambda_i$ was used for the determination of the slopes of the line. The results show that each MSE of the recovered spectral reflectances by multiple regression analysis and Imai-Berns method has linear relation to Qr as well as Wiener estimation. This result means that the formulation of the Qr is appropriate and that Qr is able to be used with multiple regression analysis and Imai-Berns model since these two models are equivalent to the Wiener estimation, i.e., the matrixes W in Eq.(12) and B in Eq. (13) are equivalent to the Wiener filter in Eq.(3) and which can be proved by the mathematical analysis.

5. Conclusion

The evaluation of an image acquisition system aimed at recovery of spectral reflectances, which is derived based on the Wiener estimation, was applied to the multiple regression analysis and Imai-Berns method. The experimental results by multispectral cameras agree quite well with the proposed model. From this result, it is concluded that the proposed evaluation model is appropriately formulated and that the estimation of the noise variance of an image acquisition system is essential to evaluate the quality Qr. The quality Qr is useful not only to evaluate a set of sensors aimed at recovery of spectral reflectances but also useful to optimize the sensors and to get intuitive understanding of the spectral information acquisition.

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