Colorimetric Evaluation of a Set of Spectral Sensitivities

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Abstract

A colorimetric evaluation of an image acquisition device is important for evaluating and optimizing a set of sensors. We have already proposed a colorimetric evaluation model [J. Imaging Sci. Technol. 49(6), 588-593 (2005)] based on the Wiener estimation. The mean square errors (MSE) between the estimated and the actual fundamental vectors by the Wiener filter agrees quite well with the proposed model and we have shown that the estimation of the noise variance of the image acquisition system is essential to the evaluation model. We also have confirmed that the proposed model can be applied to two different reflectance recovery models and that the proposed colorimetric quality (Qc) can be estimated by applying these models without a prior knowledge of the spectral characteristics of the sensors, the recording illuminant and the noise present in the image acquisition device, which are required for the estimation by the Wiener model.

In this paper, the effects of the sampling intervals of the spectral reflectance and the quantization error to the evaluation model are studied and it is confirmed from the experimental results that at least 8-bit depth of the image data and 20-nm sampling intervals are required to apply the evaluation model accurately.

Introduction

There are two approaches to evaluate a color acquisition device, one is the spectral evaluation and the other is the colorimetric evaluation. In the spectral evaluation, the main purpose of the image acquisition device is to obtain the accurate spectral reflectances of objects being imaged in reproducing a color image under a variety of viewing illuminants [**1**]. To obtain the spectral reflectances of the imaged objects through the use of sensor responses, several models, such as the Wiener model [2], the multiple regression model [3][4], the Imai-Berns model [5] and the Shi-Healey model [6], have been studied. The optimizations of spectral sensitivities for the acquisition of accurate spectral information of objects are also reported [2][7][8].

On the other hand in colorimetric evaluation, the main purpose of the image acquisition device is to estimate the accurate colorimetric values of the pixels of objects being imaged. Neugebauer proposed a quality factor for the evaluation of a single sensor [9] and Vora and Trussell developed a model to evaluate a set of sensors for the first time [10]. However, the Vora-Trussell model used a random variable assumption of a surface reflectance. Since a surface spectral reflectance is smooth over the visual wavelength and falls into a subspace spanned by a small set of basis vectors, their assumption was not adequate. Later, Sharma and Trussell reported a comprehensive analysis to establish the colorimetric quality of an image acquisition device by taking the noise effects into account and statistical propertied of spectral reflectance of samples in the tristimulus values, the orthogonal color space and the linearized CIELAB color space [11]. However, the formula by Sharma and Trussell was too complicated to give an intuitive insight into the influence of the noise on color correction and to predict new phenomena. One of the authors, Shimano proposed a simple formula to evaluate colorimetric quality of a set of color sensors by considering the statistical properties of spectral reflectance of samples [12]. However, the application of the evaluation models to real color image acquisition devices has not appeared because of the difficulty in estimating noise levels. Recently Shimano proposed a new model to estimate the noise variance of an image acquisition system [13] and applied it to the proposed colorimetric evaluation model [12][14] and spectral evaluation model [15], and confirmed that both evaluation models agree quite well with the experimental results by multispectral cameras.

For a colorimetric evaluation, color stimuli can be divided into two parts, the fundamental and the residual [16]. The fundamental is a projection of a color stimulus onto the human visual subspace (HVSS) and evokes color sensation to human visual system. The residual is an orthogonal part of the color stimulus and evokes no sensation. In the proposed colorimetric evaluation model, the colorimetric quality is related with the difference between the estimated and measured fundamental vectors that are the reflectance vectors projected onto the HVSS. The proposed colorimetric evaluation model is formulated by $\mathrm{MSE}(\sigma^2) = E_{max}\left(1 - Q_c(\sigma^2)\right)$, where $\mathrm{MSE}(\sigma^2)$ is the mean square errors between the recovered and measured fundamental vectors with the estimated noise variance σ^2, E_{max} represents a constant that is determined by the viewing illuminant, the CIE color matching functions and the spectral reflectances of objects and $\mathrm{Qc}(\sigma^2)$ is the colorimetric quality of the image acquisition system with the estimated noise variance σ^2. It was shown that $\mathrm{Qc}(\sigma^2)$ is determined by the spectral sensitivities of the sensors, the spectral power distribution of the recording and viewing illuminants, the noise variance of the image acquisition device and the spectral reflectances of the imaged objects. The model was applied to the multispectral cameras and it was confirmed that the model agrees quite well with the experimental results. As $\mathrm{Qc}(\sigma^2)$ is derived from Wiener estimation, it is very important to confirm whether the model can be applied to other recovery models since the colorimetric quality $\mathrm{Qc}(\sigma^2)$ is useful not only for the colorimetric evaluation of an image acquisition device but also for the colorimetric optimization of a set of sensors.

In our recent study, we have shown that the colorimetric quality $\mathrm{Qc}(\sigma^2)$ can be applied to three different reflectance recovery models [17], such as the Wiener model, the multiple regression model, the Imai-Berns model. It was confirmed that the $\mathrm{Qc}(\sigma^2)$ can be estimated without the prior knowledge of the spectral characteristics of the sensors and a recording illuminant, and the noise variance, and this relation provides us an easier way for the colorimetric evaluation of a real existing image acquisition system. We have also shown that the spectral quality of a set of sensors aimed at recovery of spectral reflectances proposed by us [13] can be applied to three different reflectance recovery models [18] [19].

Although, it is possible to estimate the colorimetric quality $\mathrm{Qc}(\sigma^2)$ easily by the use of the multiple regression model or the Imai-Berns model, however the influence of the quantization errors and of the sampling intervals on the accuracy of the quality estimation in these two models is not known.

In this paper, the effects of the sampling intervals and the quantization error of the image data are examined. From the experimental results, it is shown that even in the low signal-to-noise ratio (SNR), the colorimetric evaluation model still holds for the fundamental vectors recovered by the multiple regression analysis and the Imai-Berns model. It is confirmed that 8-bit image data and 20-nm sampling intervals of the reflectance is good enough for the accurate estimation of the colorimetric quality Qc (σ^2) by these two models.

This article is organized as follows. The outline of the colorimetric evaluation model and the method to estimate the noise variance are briefly reviewed. In the following sections, the experimental procedures and the results to demonstrate the trustworthiness of the proposal are described. The final section presents the conclusions.

Models for the colorimetric evaluation

In this section, the derivation of the colorimetric quality Qc (σ^2) to evaluate a color image acquisition system and the models used for the experiments are briefly reviewed.

Wiener Estimation Using Estimated Noise Variance

The visible wavelengths from 400 to 700 nm are sampled at constant 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

$$\mathbf{p} = SL_o\mathbf{r} + \mathbf{e}\ , \tag{1}$$

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_o is a $N \times N$ diagonal matrix with samples of the spectral power distribution of a recording 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 [13] below. The system noise is assumed to be signal independent, zero mean and uncorrelated to itself. For abbreviation, let $S_L = SL_o$. Denote the projection matrix onto the HVSS as P_V which is represented by $P_V = \sum_{i=1}^{\alpha} \mathbf{a}_i \mathbf{a}_i^T$, where $\mathbf{a}_i$ is the i-th orthonormal basis vector which spans HVSS and $\alpha = \mathrm{Rank}(TL_V)$. $\{\mathbf{a}_i\}_{i=1,\ldots,\alpha}$ are the right singular vectors determined by the singular value decomposition (SVD) of the matrix TL_V, where T is the $3 \times N$ matrix of CIE color matching functions and L_V is a $N \times N$ diagonal matrix with samples of the spectral power distribution of a viewing illuminant along the diagonal,. The projected vector $P_V\mathbf{r}$ is termed a fundamental vector [12][14][16]. If $\hat{\mathbf{r}}$ represents the recovered spectral reflectance, the mean square errors (MSE) between the actual fundamental vector $P_V\mathbf{r}$ and the recovered fundamental vector $P_V\hat{\mathbf{r}}$ is given by

$$\mathrm{MSE} = E\left\{\left\|P_V\mathbf{r} - P_V\hat{\mathbf{r}}\right\|^2\right\}, \tag{2}$$

where $E\{\bullet\}$ represents the expectation. If the $\hat{\mathbf{r}}$ is estimated by $\hat{\mathbf{r}} = W_0\mathbf{p}$, then the matrix W_0 which minimizes the Eq.(2) is given by

$$W_0 = RssS_L^T\left(S_L R_{SS} S_L^T + \sigma_e^2 I\right)^{-1}, \tag{3}$$

where superscripted T represents the transpose of a matrix, R_{SS} is an autocorrelation matrix of the spectral reflectance 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 [12][14][13]

$$\mathrm{MSE}(\sigma_e^2) = \sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^v\right\|^2 - \sum_{i=1}^{\alpha}\left\|P_{CV}\mathbf{a}_i^v\right\|^2 + \sum_{i=1}^{\alpha}\sum_{j=1}^{\beta}\frac{\sigma_e^4 + \kappa_j^{v2}\sigma^2}{\left(\kappa_j^{v2} + \sigma_e^2\right)^2}\left(\mathbf{b}_j^{vT}\mathbf{a}_i^v\right)^2, \tag{4}$$

where $\mathbf{b}_i^v$, κ_i^v and β represent the i-th right singular vector, i-th singular value and a rank of a matrix $S_L V \Lambda^{1/2}$, respectively. The expression σ^2 represents the actual system noise variance. The column vector $\mathbf{a}_i^v$ is given by $\mathbf{a}_i^v = \Lambda^{1/2}V^T\mathbf{a}_i$, R_{SS} is represented as $R_{SS} = V\Lambda V^T$ where V is a basis matrix and Λ is a $N \times N$ diagonal matrix with positive eigenvalues λ_i along the diagonal in decreasing order, P_{CV} is the projection matrix onto the subspace spanned by a set of basis vectors $\{\mathbf{b}_i^v\}_{i=1,\ldots,\beta}$ and represented by $P_{CV} = \sum_{i=1}^{\alpha}\mathbf{b}_i^v\mathbf{b}_i^{vT}$.

It is easily seen that the MSE is minimized when $\sigma_e^2 = \sigma^2$ by differentiating Eq.(4) with σ_e^2, and the MSE (σ^2) is given by

$$\mathrm{MSE}(\sigma^2) = \sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^v\right\|^2 - \sum_{i=1}^{\alpha}\left\|P_{CV}\mathbf{a}_i^v\right\|^2 + \sum_{i=1}^{\alpha}\sum_{j=1}^{\beta}\frac{\sigma^2}{\kappa_j^{v2} + \sigma^2}\left(\mathbf{b}_j^{vT}\mathbf{a}_i^v\right)^2. \tag{5}$$

The first and second terms on the right-hand side of the Eq.(5) represent the MSE for the noiseless case and the third term corresponds to the increase in the MSE due to the presence of the noise.

Equation (5) can be rewritten as

$$\mathrm{MSE}(\sigma^2) = \sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^v\right\|^2\left(1 - \frac{\sum_{i=1}^{\alpha}\left\|P_{CV}\mathbf{a}_i^v\right\|^2 - \sum_{i=1}^{\alpha}\sum_{j=1}^{\beta}\frac{\sigma^2}{\kappa_j^{v2} + \sigma^2}\left(\mathbf{b}_j^{vT}\mathbf{a}_i^v\right)^2}{\sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^v\right\|^2}\right). \tag{6}$$

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

$$Q_c(\sigma^2) = \frac{\sum_{i=1}^{\alpha}\left\|P_{CV}\mathbf{a}_i^v\right\|^2 - \sum_{i=1}^{\alpha}\sum_{j=1}^{\beta}\frac{\sigma^2}{\kappa_j^{v2} + \sigma^2}\left(\mathbf{b}_j^{vT}\mathbf{a}_i^v\right)^2}{\sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^v\right\|^2}. \tag{7}$$

Hence, the MSE (σ^2) is expressed as

$$\mathrm{MSE}(\sigma^2) = E_{max}\left(1 - Q_c(\sigma^2)\right), \tag{8}$$

where $E_{max} = \sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^v\right\|^2$. This equation shows that the MSE (σ^2) has a linear relation to Qc (σ^2) and the slope of the line is $\sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^v\right\|^2$. The values of $\sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^v\right\|^2$ are dependent only on the viewing illuminant, the CIE color matching functions and the surface spectral reflectance of the objects being captured. The MSE (σ^2) decreases as the Qc (σ^2) increases to one.

The first term on the right-hand side of the Eq.(5) is considered to represent the statistical mean energy of color stimuli which is incident on the cones (SMECS). The second term on the right-hand side of the Eq.(5) represents the energy of the SMECS captured by a set of color sensors. And the third term of it corresponds to the increase in the MSE due to the presence of the noise [12]. Therefore, the colorimetric quality Qc (σ^2) in Eq.(7) can be interpreted as the ratio of the energy of a set of sensors capture to that of the SMECS.

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

$$\mathrm{MSE}(0)=\sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^{v}\right\|^2-\sum_{i=1}^{\alpha}\left\|\mathrm{P}_{CV}\mathbf{a}_i^{v}\right\|^2+\sum_{i=1}^{\alpha}\sum_{j=1}^{\beta}\frac{\sigma^2}{\kappa_j^{v^2}}\left(\mathbf{b}_j^{vT}\mathbf{a}_i^{v}\right)^2 . \qquad (9)$$

The first and second terms on the right-hand side of Eq.(9) represent the MSE (0) at a noiseless case. We denote this MSE as MSE_{free}, and then the estimated system noise variance $\hat{\sigma}^2$ can be represented by

$$\hat{\sigma}^2=\frac{\mathrm{MSE}(0)-\mathrm{MSE}_{free}}{\sum_{i=1}^{\alpha}\sum_{j=1}^{\beta}\frac{\left(\mathbf{b}_j^{vT}\mathbf{a}_i^{v}\right)^2}{\kappa_j^{v^2}}}, \qquad (10)$$

where MSE_{free} is given by

$$\mathrm{MSE}_{free}=\sum_{i=1}^{\alpha}\left\|\mathbf{a}_i^{v}\right\|^2-\sum_{i=1}^{\alpha}\left\|\mathrm{P}_{CV}\mathbf{a}_i^{v}\right\|^2 . \qquad (11)$$

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 the recording and viewing illuminants are known. The MSE (0) can also be obtained by the experiment using Eqs. (2) and (3) by 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. [12][14]

The colorimetric quality Qc (σ^2) and MSE (σ^2) can be computed by substituting the estimated noise variance in Eq.(7) and Eq.(3) , respectively.

Application of the Multiple Regression Analysis to Fundamental Vector Evaluation

To achieve the colorimetric evaluation, the multiple regression model is used to recover the fundamental vectors. Let $\mathbf{p}_i$ be a $M\times 1$ sensor response vector which is obtained by the image acquisition of a known spectral reflectance $\mathbf{r}_i$ of the i-th object. Let P be a $M\times k$ matrix which contains the sensor responses $\mathbf{p}_1,\mathbf{p}_2,\cdots,\mathbf{p}_k$, and let F be a $N\times k$ matrix which contains the corresponding fundamental vectors $\mathbf{f}_1,\mathbf{f}_2,\cdots,\mathbf{f}_k$, where $\mathbf{f}_i=\mathrm{P}_V\mathbf{r}_i$ and k is the number of the learning samples. The matrix W which minimizes $\|F-WP\|$, where notation $\|\bullet\|$ represents the Frobenius norm[20] is given by.

$$W=FP^{+}, \qquad (12)$$

where, P^{+} represents the pseudo inverse matrix of the matrix P. The estimated fundamental vector $\hat{\mathbf{f}}_i$ is given by $\hat{\mathbf{f}}_i=W\mathbf{p}_i$. Therefore this model does not use the spectral sensitivities of sensors or the spectral power distribution of an illumination, but it uses only the fundamental vectors of the learning samples.

Application of the Imai-Berns Model to Fundamental Vector Evaluation

To achieve the colorimetric evaluation, the Imai-Berns model is applied to estimate the weight matrix in the HVSS and used to recover the fundamental vectors. Let Σ be a $d\times k$ matrix which contains the column vectors of the weights $\boldsymbol{\sigma}_1,\boldsymbol{\sigma}_2,\cdots,\boldsymbol{\sigma}_k$ to represent the k known fundamental vectors $\mathbf{f}_1,\mathbf{f}_2,\cdots,\mathbf{f}_k$ where d is a number of the weights and let $\mathbf{r}_1,\mathbf{r}_2,\cdots,\mathbf{r}_k$ be the spectral reflectance, where $\mathbf{f}_i=\mathrm{P}_V\mathbf{r}_i$ and let P be a $M\times k$ matrix which contains corresponding sensor response vectors $\mathbf{p}_1,\mathbf{p}_2,\cdots,\mathbf{p}_k$ .The multiple regression analysis between Σ and P is expressed as $\|\Sigma-BP\|$. A matrix B which minimize the Frobenius norm is given by

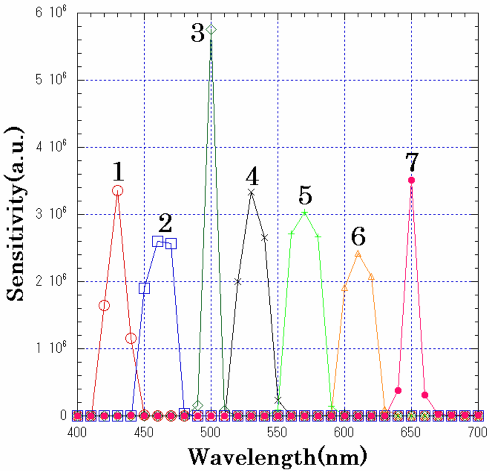

Figure 1. Spectral sensitivities of the sensors of the camera.

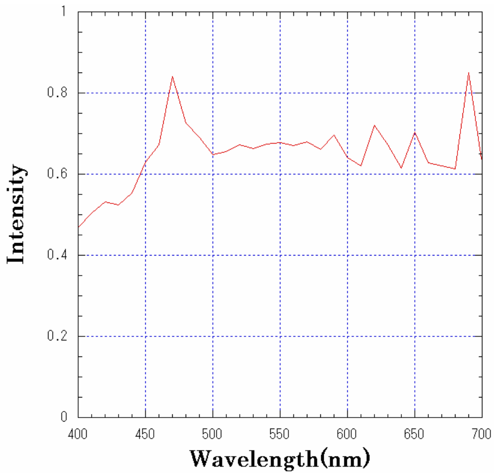

Figure 2. Spectral power distribution of the illumination.

$$B=\Sigma P^{+}. \qquad (13)$$

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

Experimental Procedures

Experiment 1

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 measured 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).

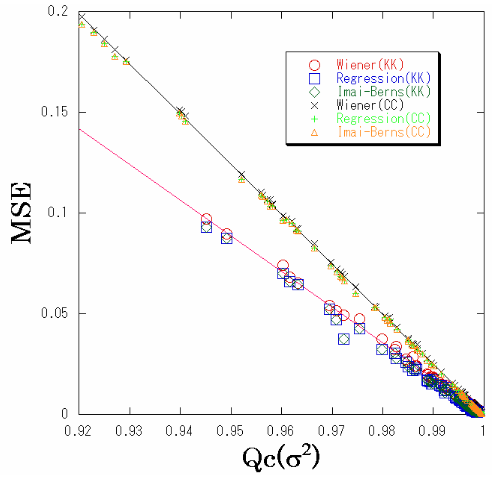

Figure 3. The MSEs of the recovered fundamental vectors by the Wiener, Regression, and Imai-Berns model for the GretagMacbeth ColorChecker (CC) and the Kodak Q60R1 (KK) are plotted as a function of Qc (σ^2)

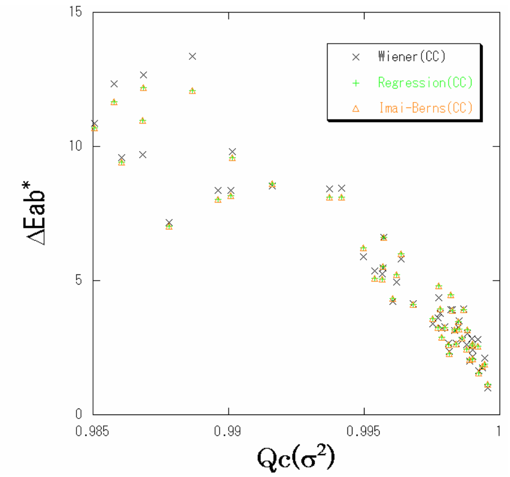

Figure 4. The color difference ΔEab between the actual and the recovered fundamental vectors by the Wiener, Regression, and Imai-Berns model for the GretagMacbeth ColorChecker (CC) are plotted as a function of Qc* (σ^2) .

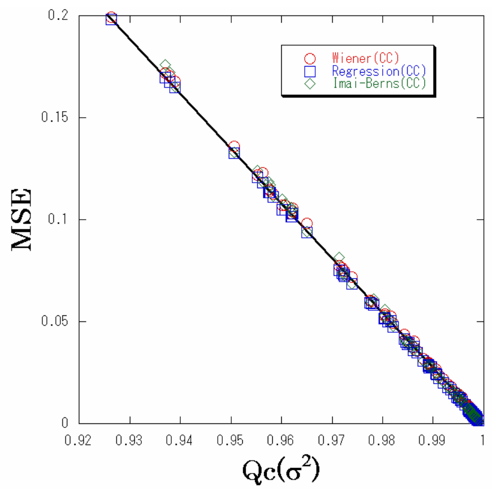

Figure 5. The MSEs of the recovered fundamental vectors by the Wiener, Regression, and Imai-Berns model for another GretagMacbeth ColorChecker (CC) are plotted as a function of Qc (σ^2) *with 8-bit image and 10-nm sampling intervals.*

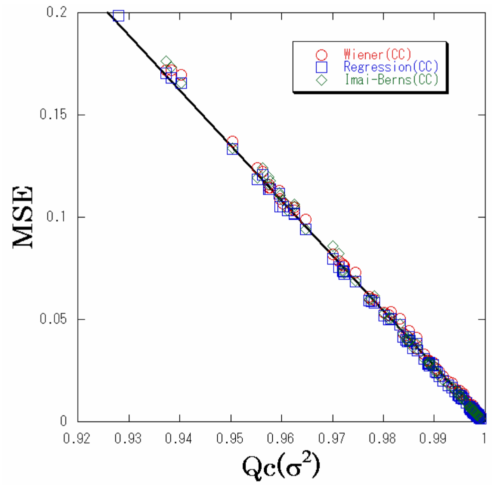

Figure 6. The MSEs of the recovered fundamental vectors by the Wiener, Regression, and Imai-Berns model for another GretagMacbeth ColorChecker (CC) are plotted as a function of Qc (σ^2) *with 8-bit image and 20-nm sampling intervals.*

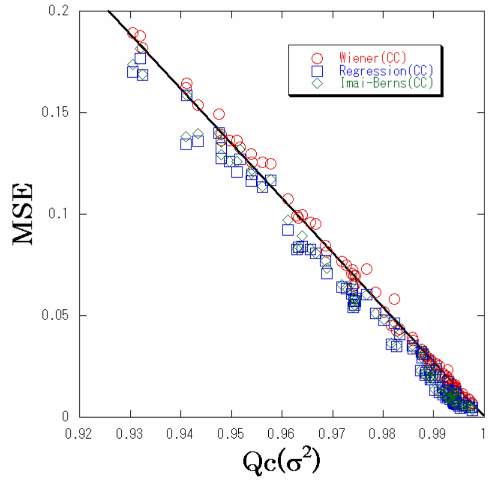

Figure 7. The MSEs of the recovered fundamental vectors by the Wiener, Regression, and Imai-Berns model for another GretagMacbeth ColorChecker (CC) are plotted as a function of Qc (σ^2) *with 6-bit image and 10-nm sampling intervals.*

The spectral power distribution of the illuminant measured by the spectroradiometer (Minolta CS-1000) is presented in Fig.2.

The GretagMacbeth ColorChecker (24 colors) and the Kodak Q60R1 (228 Colors), let us denote them CC and KK respectively for abbreviation below, were 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 $\rho = \mathrm{Tr}(S_L R_{ss} S_L^T)$, 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 fundamental vectors by the Wiener estimation, and then the $\mathrm{MSE}(\sigma^2)$ of the recovered fundamental vectors was computed by averaging the difference between actual and recovered fundamental vectors over colors. The fundamental vectors were also recovered by the multiple regression model and the Imai-Berns model and MSE of the recovered fundamental vectors by theses models were computed. By using the estimated noise variance, the colorimetric quality $\mathrm{Qc}(\sigma^2)$ for each combination of sensors was computed using Eq.(7).

Experiment 2

The images of a different Macbeth ColorChecker were captured in the same way as the experiment 1 and the spectral reflectances of the Macbeth ColorChecker were measured at 1-nm sampling intervals by using spectrophotometer (Shimadzu UV-3100PC) and the least significant bits of the measured 16-bit image data are taken away to simulate various quantization errors.

Results and discussions

The plots of the $\mathrm{MSE}(\sigma^2)$ of the CC and KK as a function of $\mathrm{Qc}(\sigma^2)$ with 16-bit image and 10-nm sampling intervals for the reflectance (16bit-10nm) in the experiment 1 are shown in Fig.3. The lines in the figure show the theoretical relation between the $\mathrm{MSE}(\sigma^2)$ and $\mathrm{Qc}(\sigma^2)$ as given by Eq.(8), where the equation $E_{max} = \sum_{i=1}^{\alpha} \|\mathbf{a}_i^v\|^2$ determines the slopes of the line for each color chart. The experimental results of the MSE as a function of $\mathrm{Qc}(\sigma^2)$ by the multiple regression analysis and the Imai-Berns model agree well with the theoretical lines. Also the relation between $\mathrm{Qc}(\sigma^2)$ and ΔEab* for CC is shown in Fig.4 [17] [19] .

In Fig.5, the $\mathrm{MSE}(\sigma^2)$ of CC as a function of $\mathrm{Qc}(\sigma^2)$ with 8bit-10nm in the experiment 2 are shown, and those with 8bit-20nm and 6bit-10nm are shown in Fig.6 and Fig.7, respectively. In the experiment 2, the slope of the theoretical line is different from that of experiment 1 because the measured color chart is not the same as the one in the experiment 1.

In Fig.6, although the plots for 8bit-20nm scatter slightly compared to those for 8bit-10nm, the results agree fairly well with the theoretical line. In Fig.7, the plots for 6bit-10nm still are along the theoretical line but they scatter largely compared to those for 8bit-10nm.

Let $\mathrm{Qc}(0)$ be the value of $\mathrm{Qc}(\sigma^2)$ when the noise variance $\sigma^2 = 0$, i.e.,

$$Q_c(0) = \frac{\sum_{i=1}^{\alpha} \|P_{CV}\mathbf{a}_i^v\|^2}{\sum_{i=1}^{\alpha} \|\mathbf{a}_i^v\|^2} . \qquad (14)$$

The experimental results on the relation between $\mathrm{Qc}(0)$ and $\mathrm{MSE}(0)$ correspond to the case where the noise present in the image acquisition device is not taken into account, which are shown with 8bit-10nm and 6bit-10nm in Fig.8 and Fig.9, respectively. The $\mathrm{MSE}(0)$ can be obtained by the experiment using Eqs. (2) and (3) applying the Wiener filter with $\sigma_e^2 = 0$ .In Fig.8, the plots scatter slightly above the theoretical line and in Fig.9, the plots scatter largely far above the theoretical line because the image data with 6bit-10nm has more quantization error than that with 8bit-10nm. Therefore, this result shows the importance of the estimation of the noise variance in the evaluation model.

From the experiments, it is confirmed that the colorimetric quality $\mathrm{Qc}(\sigma^2)$ can be estimated by the multiple regression model or the Imai-Berns model without prior knowledge of the spectral sensitivities of the set of sensors, spectral power distribution of an illumination and the noise present in the image acquisition system, since the point (which represents the MSE estimated by these models) on the theoretical line gives us the estimate of the colorimetric quality $\mathrm{Qc}(\sigma^2)$. Therefore, the quality can be easily estimated without the difficult computations. However, the 6-bit image gives the estimates of the quality with the low accuracy but the 8-bit image data gives the estimates with high accuracy. The experiments also showed that at least 8-bit image data and 20-nm sampling intervals of the spectral reflectance are required to estimate the colorimetric quality $\mathrm{Qc}(\sigma^2)$ accurately by these models.

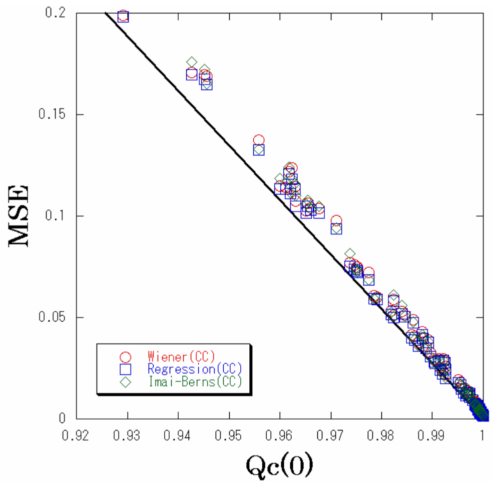

Figure 8. The MSEs of the recovered fundamental vectors by the Wiener, Regression, and Imai-Berns model for another GretagMacbeth ColorChecker (CC) are plotted as a function of Qc (0) *with 8-bit image and 10-nm sampling intervals.*

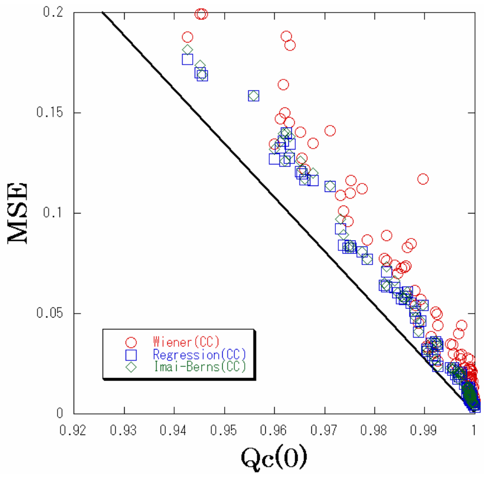

Figure 9. The MSEs of the recovered fundamental vectors by the Wiener, Regression, and Imai-Berns model for another GretagMacbeth ColorChecker (CC) are plotted as a function of Qc (0) *with 6-bit image and 10-nm sampling intervals.*

Conclusion

The colorimetric evaluation model derived from the Wiener estimation was applied to the multiple regression analysis and the Imai-Berns model and the influence of the quantization errors and sampling intervals of an image acquisition system on the evaluation was studied. The experimental results showed that the evaluation model can be applied to these estimation models.

Experimental results show that the 6-bit image gives the estimates of the quality with the low accuracy but the 8-bit image data gives the estimates with high accuracy. The experiments also showed that at least 8-bit image data and 20-nm sampling intervals of the spectral reflectance are required to estimate the colorimetric quality $Qc(\sigma^2)$ accurately by these models.

The experimental results under the low SNR show that the inaccuracy of the estimated colorimetric quality by the multiple regression model or the Imai-Berns model. Thus, the further improvement of the evaluation model will be required to overcome this difficulty.

References

1. Y. Miyake and Y. Yokoyama, "Obtaining and Reproduction of Accurate Color Images Based on Human Perception", Proc. SPIE **3300**, 190-197(1998).
2. H. Haneishi, T. Hasegawa, N. A. Hosoi, Y. Yokoyama, N. Tsumura and Y. Miyake, "System design for accurately estimating the spectral reflectance of art paintings", Appl. Optics, 39,6621-6632(2000).
3. Y. Zhao, L.A. Taplin, M. Nezamabadi and R.S. Berns, "Using the Matrix R Method for Spectral Image Archives", The 10th Congress of the International Color Association (AIC'5), (Granada, Spain), pp.469-472 (2005).
4. J. L. Nieves, E. M. Valero, S. M. C. Nascimento, J. H. Andrés, and J. Romero, "Multispectral synthesis of daylight using a commercial digital CCD camera", Appl. Optics, 44, 5696-5703(2005).
5. F.H. Imai and R.S. Berns, "Spectral Estimation Using Trichromatic Digital Cameras", Proc. Int. Symposium on Multispectral Imaging and Color Reproduction for Digital Archives, Chiba, Japan. 42-49, (1999).
6. M. Shi and G. Healey, "Using reflectance models for color scanner calibration", J. Opt. Soc. Am. A 19(4), 645-656 (2002).
7. R. Piché, "Nonnegative color spectrum analysis filters from principal component analysis characteristic spectra," J. Opt. Soc. Am. A 19, 1946-1950 (2002)
8. M. Mahy, P. Wambacq, L. Van Eycken, and A. Oosterlinck, "Optimal filters for the reconstruction and discrimination of reflectance curves," Proc. IS&T/SID's 2nd Color Imaging Conf., pp. 140–143 (1994).
9. H.E.J. Neugebauer "Quality factor for filters whose spectral transmittances are different from color mixture curves, and its application to color photography." J. Opt. Soc. Am. 46(10),821-824 (1956)
10. P.L. Vora and H.J. Trussell, "Measure of goodness of a set of color-scanning filters," J. Opt. Soc. Am. A 10(7), 1499-1508 (1993).
11. G. Sharma and H.J. Trussell, "Figure of merit for color scanners," IEEE Trans. Image Process. 6(7), 990-1001 (1997).
12. N. Shimano, "Suppression of noise effect in color corrections by spectral sensitivities of image sensors," Opt. Rev. 9(2), 81-88 (2002).
13. N. Shimano, "Recovery of Spectral Reflectances of Objects Being Imaged Without Prior Knowledge" IEEE Trans. Image Process. vol. 15, no.7, pp. 1848-1856, Jul. (2006).
14. N. Shimano, "Application of a Colorimetric Evaluation Model to Multispectral Color Image Acquisition Systems" J. Imaging Sci. Technol. 49(6), 588-593 (2005).
15. N. Shimano, "Evaluation of a multispectral image acquisition system aimed at reconstruction of spectral reflectances", Optical Engineering, vol.44, pp.107115-1-6, (2005).
16. J. B. Cohen, "Color and color mixture: Scalar and vector fundamentals," Color Res. Appl., vol. 13, (1), pp. 5-39, (1988).
17. M. Hironaga, N. Shimano, "Applying colorimetric evaluation model to image acquisition devices with different characterization models" (Submitting to J. Electron. Imaging).
18. M. Hironaga, K. Terai and N. Shimano, "A model to evaluate color image acquisition systems aimed at the reconstruction of spectral reflectances", Proc. Ninth International Symposium on Multispectral Color Science and Application, Taipei, R.O.C. 23-28, (2007).
19. M. Hironaga, N. Shimano, "Evaluating a quality of an image acquisition device aimed at the reconstruction of spectral reflectances by the use of the recovery models" J. Imaging Sci. Technol. (2008). (To be published)
20. G.H. Golub and C.F.V. Loan, "Matrix Computations", 3rd ed. (The Johns Hopkins Univ. Press, 1996), p.55.

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