A New Proposal for the Accurate Recovery of Spectral Reflectances of Imaged Objects without Prior Knowledge

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Abstract

Recovery of spectral reflectances of imaged objects is important to reproduce color images under arbitrary illuminations. In this paper, a new method is proposed to recover spectral reflectances accurately through the use of image data without prior knowledge of the imaged objects. It is shown that the Wiener estimation which uses the noise variance estimated by training samples and the features of the recovered spectral reflectances is effective to improve the recovery performance.

Introduction

Digital archive of art paintings and objects is a key technology to record and to leave them as historical heritages for the future. Since the impressions of a painting change extremely by the changes in the illuminations, the reproduction of a color image under a variety of illuminations by taking account of the chromatic adaptation of the visual system is very important[1,2]. The colorimetric values of the pixels of the imaged paintings under arbitrary illuminations are required to use these models. Therefore, the accurate recovery of spectral reflectances of the imaged objects through the use of image data is very important for the purpose.

There have been various studies to recover spectral reflectances of imaged objects[3-8] through the use of image data. Among them the finite dimensional linear mode[4], the Wiener estimation[3,9] and the regression model[5, 10] are widely used. The linear model and the Wiener estimation require the spectral sensitivities of a color imaging device and the spectral power distribution of the illumination used for the image acquisition, on the other hand the regression model does not require the spectral characteristics of them. Although the regression model is easy to use, however the recovery performance is not sufficient when test samples are different from the learning samples. Usually, the recovered spectral reflectances by the linear model are very sensitive to noise and instabilities in the recovery occur in the presence of noise [8]. On the other hand the Wiener estimation is robust to noise, but its recovery performance depends largely on the noise variance used for the estimation.

All these recovery models require the learning process, since prior knowledge of spectral reflectances of the imaged objects such as the art paintings is unknown in the image acquisition. In the learning model, the evaluation of the computational efficiency, robustness and statistical stability are very important. The robustness means that the algorithms must handle noisy data for real applications. The statistical stability means the performance of the algorithms should not be sensitive to the particular training data set.

One of the authors (N.S) already proposed a model to estimate the noise variance of an image acquisition system by using the spectral reflectances of the learning color samples and their corresponding image data, and applied it to recover spectral reflectances by the Wiener estimation without prior knowledge of the spectral reflectances of the imaged objects[3]. The accuracy of the recovered spectral reflectances by this proposal was compared with other recovery models, such as the linear model[4], regression model[5, 10], Imai-Berns model[6] and Shi-Healey model[7], and it is confirmed that the results by this proposal is the most accurate when test samples are different from learning samples[8]. The main reasons of the results are :(1) the regression model, Imai-Berns model and Shi-Healey model do not satisfy the statistical stability, i.e., these model optimized for the training samples and outperform superiorly for training samples but does not perform well for test samples. (2) The liner model does not satisfy the robustness, i.e., it is sensitive to noise.

However the mean square error (MSE) of the spectral reflectances between measured and recovered by this proposal is three times larger than that of the spectral reflectances recovered by the Wiener filter with the autocorrelation matrix calculate by the measured spectral reflectances of the imaged objects [8]. The main reason of the differences in the accuracy is considered to be originated from the differences in the features of the spectral reflectances of the learning samples and test samples (imaged objects). Several experimental results of the regression model showed that selecting the training spectral reflectance similar to that of the test samples is effective to improve the recovery performance. However the color samples except for a test sample in the same color chart were used as a set of training samples[5,10].

In this paper, it is shown that the Wiener estimation which uses the estimated noise variance and features of the recovered spectral reflectances is effective to improve the recovery performance.

Model

A. Wiener Estimation with Estimated Noise Variance

In this section, a brief sketch for the estimation of the noise variance of a color image acquisition system is described. A vector space notation is useful in the problems. In this approach, the visible wavelengths 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 an $N \times 1$ spectral reflectance vector $\mathbf{r}$ can be expressed by

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

where $\mathbf{p}$ is an $M \times 1$ sensor response vector from the M channel sensors, S is an $M \times N$ 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 an $M \times 1$ additive noise vector. The noise $\mathbf{e}$ represents the system noise [3] that includes not only the noise of the CCD but also includes all measurement errors in the spectral characteristics of an image acquisition system. 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

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

where $E\{\bullet\}$ represents the expectation. If the Wiener estimation is used to recover a spectral reflectance $\hat{\mathbf{r}}$, then $\hat{\mathbf{r}}$ is given by

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

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[3]

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

where, λ_i is the eigenvalues of Rss, and b_{ij}, κ_i^v and β represent j-th element in 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.

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))

$$\mathrm{MSE}\left(\sigma_e^2 = 0\right) = \sum_{i=1}^{N} \lambda_i - \sum_{i=1}^{N}\sum_{j=1}^{\beta} \lambda_i b_{ij}^2 + \sum_{i=1}^{N}\sum_{j=1}^{\beta} \frac{\sigma^2}{\kappa_j^{v^2}} \lambda_i b_{ij}^2 \cdot \tag{5}$$

From Eq.(5) the system noise variance $\hat{\sigma}^2$ can be estimated by

$$\hat{\sigma}^2 = \frac{\mathrm{MSE}\left(\sigma_e^2 = 0\right) - \sum_{i=1}^{N} \lambda_i + \sum_{i=1}^{N}\sum_{j=1}^{\beta} \lambda_i b_{ij}^2}{\Sigma_{i=1}^{N} \Sigma_{j=1}^{\beta} \dfrac{\lambda_i b_{ij}^2}{\kappa_j^{v^2}}}. \tag{6}$$

Therefore, the system noise variance σ^2 can be estimated using Eq. (6), since the all terms of the fraction in the right hand side of Eq.(6) except MSE($\sigma_e^2 = 0$) 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) by applying the Wiener filter with $\sigma_e^2 = 0$ to sensor responses. Therefore, Eq. (6) gives a method to estimate the actual noise variance σ^2 [3].

Therefore the noise variance estimated by Eq.(6) can be used to recover the spectral reflectances by the use of Eq.(3).

B. A Recovery Model which uses the Feature of Recovered Spectral Reflectances

Several studies have been performed to improve the recovery performance by the use of pseudoinverse model. In these approaches, the training samples were selected so that these samples are similar to the test samples. In the previous works, the samples except for test samples in the same color chart were used for training samples.

In this study, different color charts were used for training and test samples, e.g., the GretagMacbeth ColorChecker was used for test samples and Kodak Q60 (IT8) was used for training samples, and vice versa.

Fig.1 shows the schematic illustration of the proposal. In the first step, the noise variance is estimated by using training samples as illustrated. In the second step, the estimated noise variance $\hat{\sigma}^2$ and the autocorrelation matrix R_{ss} calculated by using training sample's spectral reflectances were used to recover the spectral reflectances of imaged object (test samples) by the use of the image data $\mathbf{p}$. In the third step, spectral reflectances similar to recovered spectral reflectances in the second step were selected from the data base. In the final step, those selected spectral reflectances $(\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_m)$ and the noise variance $\hat{\sigma}^2$ estimated in the first step were used for the second recoveries.

In the data base, the spectral reflectances of the Munsell color chips were used for the experiments, and if spectral reflectances of the training samples were used for the data base, then the spectral reflectances similar to that of the test samples would be selected from the training samples.

Experimental Procedures and Results

The GretagMacbeth ColorChecker, Kodak Q60 and Munsell Color Chips were used for the experiments. In the Wiener estimation

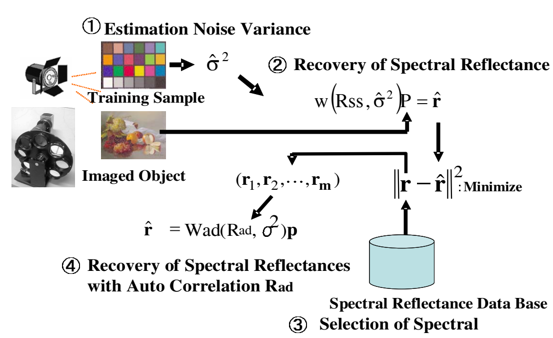

Figure 1. Schematic illustration of the procedures used in the experiments

without the prior knowledge of the imaged objects, the noise variance is estimated by using the spectral reflectances of the training samples and their corresponding image data, and the spectral reflectances of imaged objects are recovered by applying it to the Wiener filter. Three different procedures, which use the recovered spectral reflectances in the second step, were performed. These three procedures were:

(1) The recovered spectral reflectances in the second step were directly used in the second recovery (the fourth step). The autocorrelation matrix calculated by using the recovered spectral reflectances was used for the second recovery, where the noise variance estimated using the training samples in the first step was always used in the second recovery.

(2) The spectral reflectances of the Munsell color chart similar to recovered spectral reflectances in the second step were selected from the database, and those spectral reflectances were used to calculate the autocorrelation matrix in second recovery (the fourth step).

(3) The spectral reflectances similar to recovered spectral reflectances in the second step were selected from the training samples, and those spectral reflectances were used to calculate the autocorrelation matrix for the second recovery.

The selection of the spectral reflectances from the data base was performed so that the square of the Euclid norm of the difference between the recovered spectral reflectance and spectral reflectance in the data base is minimized.

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 sensitivities of the video camera were optimized based on the colorimetric evaluation model proposed by the author (N.S.) [11] and were 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.2. The illuminant that simulates daylight (Seric Solax XC-100AF) was used for the image acquisition. The spectral power distribution of the illuminant was measured by the spectroradiometer (Minolta CS-1000) from 400 to 700nm at 10nm sampling interval and it is presented in Fig.3.

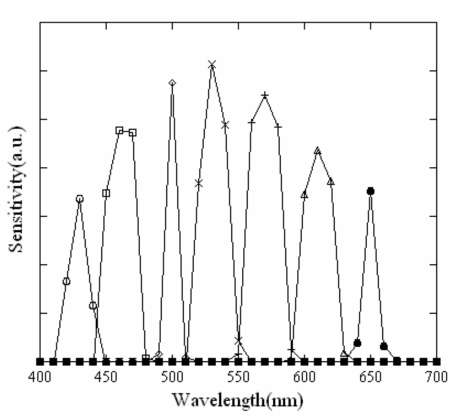

Figure 2. Spectral sensitivities of a multispectral camera

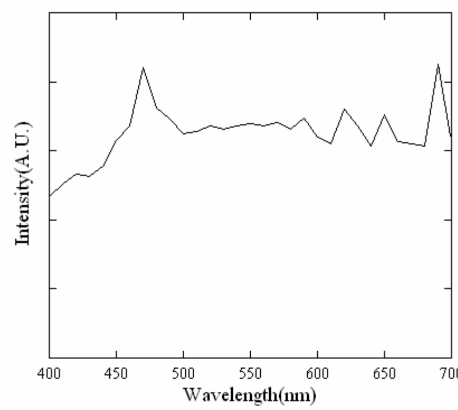

Figure 3. Spectral power distribution of the illumination used for image acquisition

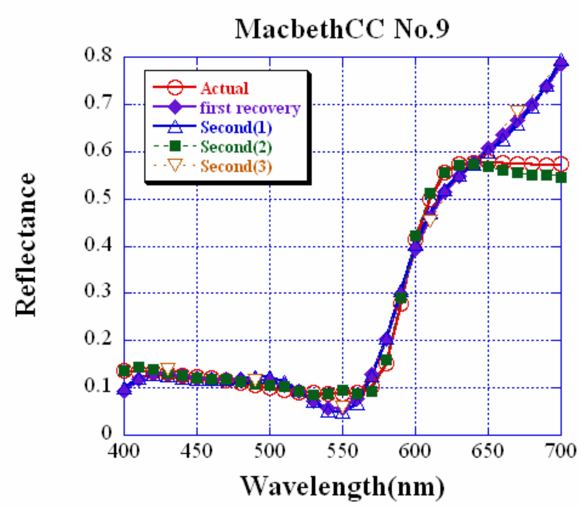

Figure 4. Recovered spectral reflectances with different procedures.

Typical examples of the spectral reflectances recovered by different procedures are shown in Fig.4. From the experimental results, it can be understand that the recovered spectral reflectances by the procedure (2) is most accurate than the others and that the recovery performance by other procedures are almost the same. The MSE and the mean color difference ΔEab^* of the recovered spectral reflectances in the CIELAB uniform color space under the D65 illuminant are summarized in Table 1. The experimental results in the table show typical examples of the recovery performance when the Kodak Q60 and the GretagMacbeth ColorChecker were used for training and test samples, respectively. The left column in the table shows the procedures used for the recovery. The notation of "Macbeth ColorChecker" in this column indicates the recovery performance when the GretagMacbeth ColorChecker was used as samples for both training and test. The notation of "Kodak (First Recovery)" in the column indicates the recovery performance when Kodak Q60 was used for training

Table 1: Comparative spectral recovery performance :Kodak Q60 used as samples for training and GretagMacbeth ColorChecker used as test samples

Procedure	MSE	ΔEab*
Macbeth ColorChecker	0.01216	1.03
Kodak (First Recovery)	0.03981	1.21
Procedure (1)	0.03816	1.15
Procedure (2)	0.01462	1.11
Procedure (3)	0.04195	1.28

samples and the GretagMacbeth ColoChecker was used for test samples in the second step as illustrated in the figure 1.

The experimental results show that the recovery performance of the procedure (2) is superior and that the accuracy of this procedure is close to the results when the GretagMacbeth ColoChecker was used for both test and training. The procedure (1) improves the accuracy slightly from the first recovery in the second step. The procedure (3) degrades the accuracy.

Conclusion

In this paper, we proposed a new model that recovers the spectral reflectances of imaged objects accurately without prior knowledge of the imaged objects. The Wiener estimation which uses the noise variance estimated by training samples and the features of the recovered spectral reflectances is effective to improve the recovery performance..

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