Evaluating the Noise Variance of an Image Acquisition System with Various Reconstruction Matrices

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Abstract

Estimation of the noise variance of image acquisition systems is very important to solve the inverse problems such as the recovery of spectral reflectances through the use of image data or to get a clear image from a blurred image, etc. In the color imaging community, the acquisition of accurate spectral reflectances of objects at the resolution of pixels is important to reproduce realistic color images under a variety of viewing illuminants. The accuracy of recovered spectral reflectances is usually evaluated by the mean square errors (MSE) between the measured and the recovered reflectances. The MSE is dependent on the noise present in an image acquisition system, which is called as the system noise below, and estimating the noise level is important to increase the estimation accuracies. In the evaluation of the influence of the noise, dividing the MSE into two terms, i.e., the noise independent MSE (MSEfree) and noise dependent MSE (MSEnoise), is essential to estimate the noise variance and to analyze the influence of the noise on the MSE. A model separating the MSE into the two terms and estimating the noise variance was already proposed based on the Wiener estimation by one of the authors. Later the model was modified to a comprehensive model based on an arbitrary reflectance reconstruction matrix and was also applied to the noise estimates by two spectral estimation models such as the Wiener and the linear model.

In the previous paper, it was not possible to apply the comprehensive model to the regression model or the Imai-Berns model, which are the models to estimate spectral reflectances, because their reconstruction matrices are derived from the sensor responses which include the system noise in it.

In this paper, a new method is proposed to extend the comprehensive model to four reconstruction models (Wiener, linear, regression and Imai-Berns models), since it is very interesting whether the influence of the noise on the recovery performance is dependent on the model used or not. By defining the theoretical estimates of the sensor responses and by estimating the reconstruction matrices without the system noise for the regression model and the Imai-Berns model, it is shown that the increasing in the MSE by the noise present in an image acquisition system can be evaluated by a simple formulation for the four models. From the experimental results it is shown that the comprehensive model analyzes the effect of the system noise on the increase in the MSE on the reflectance recovery.

INTRODUCTION

A single picture of a scene only tells of what it looks like under a given illuminant. Color appearances of a picture may vary under varying illuminant. Thus, the acquisition of accurate spectral reflectances of objects is very important to record the property of the object and to reproduce accurate color images under a variety of viewing illuminants. The accuracy of the recovered spectral reflectances depends on the number of sensors and their spectral sensitivities, the objects being imaged, the recording illuminants, the noise present in a device and a model used for the recovery. Several models have been proposed to evaluate a colorimetric performance of a set of color sensors [1]-[4], and the optimization of a set of sensors has been performed based on the evaluation models [5],[6].

Evaluating the noise present in the image acquisition devices and analyzing the effect of the noise are required for the accurate estimating colorimetric or spectral information of the objects being viewed. Reference [7] proposed a model to estimate the noise variance of an image acquisition system and applied it to the proposed colorimetric evaluation model and a spectral evaluation model, and confirmed that the evaluation model agrees quite well with the experimental results by multispectral cameras [8]-[12]. The evaluation model was based on the least squares filtering (or Wiener) model and later we modified it to the comprehensive model [13] to make it possible to evaluate the noise estimated by a variety of spectral reflectance estimation models. In the previous paper [13], the comprehensive model was applied to the Wiener and the linear model but it didn't fit for the regression nor the Imai-Berns model due to the noise included in the reconstruction matrices. Thus, we extended the comprehensive model and applied it to the regression and the Imai-Berns model to estimate the noise variance in our latest proposal [14].

In this paper, the previously proposed model is refined and is applied to the four recovery models, such as the Wiener, the linear, the regression and the Imai-Berns model. With these four recovery models, the effect of the system noise variance to the image acquisition was analyzed. It was confirmed by experiments that the increase in the MSE with the estimated noise variance agrees quite well with the proposed model.

MODELS

In this section, the previous models used for the experiments are briefly reviewed.

Previous model to separate the MSE based on the Wiener estimation

A vector space notation for a color reproduction is useful in the problems. In this approach, 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 an $N \times 1$ spectral reflectance vector 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. In this work, the noise $\mathbf{e}$ is defined to include all the sensor response errors resulting not only from a CCD itself but also from the measurement in the spectral characteristics of sensitivities, an illumination and reflectances, and quantization and it is termed as the system noise [7] 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

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

where $E\{\bullet\}$ represents the expectation. If $\hat{\mathbf{r}}$ is given by $\hat{\mathbf{r}} = W_W(\sigma_e^2)\mathbf{p}$, the Wiener estimation matrix which minimizes the MSE is given by

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

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) and letting $\sigma_e^2 = \sigma^2$ leads to [7]

$$\mathrm{MSE}(\sigma^2) = \sum_{i=1}^{N} \lambda_i - \sum_{i=1}^{N}\sum_{j=1}^{\beta} \lambda_i b_{ij}^2 + \sum_{i=1}^{N}\sum_{j=1}^{\beta} \frac{\sigma^2}{\kappa_j^{v2} + \sigma^2} \lambda_i b_{ij}^2, \tag{4}$$

where, λ_i is the eigenvalues of R_{SS}, b_{ij}, κ_i^v and β represent i-th row of the j-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. The first and second terms of the Eq.(4) represent the MSE of the noiseless case (MSEfree) and the third term represents the increase in the MSE by the noise (MSEnoise). The MSE of the reflectance recovered by the Wiener matrix $W_W(0)$ in the experiment (MSE_0 ,i.e., $\mathrm{MSE}_0 = E\left\{\|\mathbf{r} - W_W(0)\mathbf{p}\|^2\right\}$) gives the estimated system noise variance $\hat{\sigma}^2$ by [7]

$$\hat{\sigma}^2 = \frac{\mathrm{MSE}_0 - \mathrm{MSE}_{free}}{\sum_{i=1}^{N}\sum_{j=1}^{\beta} \frac{\lambda_i b_{ij}^2}{\kappa_j^{v2}}}. \tag{5}$$

Multiple regression analysis

Let $\mathbf{p}_i$ be an $M \times 1$ sensor response vector that is obtained by the image acquisition of a known spectral reflectance $\mathbf{r}_i$ of the i-th object. Let P be an $M \times k$ matrix that contains the sensor responses $\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_k$, and let R be an $N \times k$ matrix that contains the corresponding spectral reflectances $\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_k$, where k is the number of the learning samples. The pseudoinverse model is to find a matrix W_R which minimizes $\|R - W_R P\|$, where notation $\|\bullet\|$ represents the Frobenius norm [15]. The matrix W_R is given by.

$$W_R = RP^+, \tag{6}$$

where P^+ represents the pseudo inverse matrix of the matrix P. By applying a matrix W_R to a sensor response vector $\mathbf{p}$, i.e., $\hat{\mathbf{r}} = W_R \mathbf{p}$, a spectral reflectance is estimated [16].

Linear model

Assuming the spectral reflectances $\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_k$ are smooth over the visible wavelengths, the spectral reflectance $\mathbf{r}$ can be written by

$$\mathbf{r} = V\boldsymbol{\varphi} \tag{7}$$

with the basis matrix V and the column vector of the weights $\boldsymbol{\varphi}$. By letting the system noise $\mathbf{e}$ in Eq.(1) equals 0, the sensor response can be written as

$$\mathbf{p} = S_L \mathbf{r}. \tag{8}$$

Thus the reconstruction matrix W_L, which gives $\hat{\mathbf{r}} = W_L \mathbf{p}$ for the linear model is given by

$$W_L = V(S_L V)^+. \tag{9}$$

Imai-Berns model

Let Σ be a $d \times k$ matrix that contains the column vectors of the weights $\boldsymbol{\varphi}_1, \boldsymbol{\varphi}_2, \cdots, \boldsymbol{\varphi}_k$ to represent the k known spectral reflectances $\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_k$ and let P be an $M \times k$ matrix that contains corresponding sensor response vectors $\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_k$ of those reflectances, where d is a number of the weights to represent the spectral reflectances. The multiple regression analysis between these matrices is expressed as $\|\Sigma - BP\|$. A matrix B that minimizes the Frobenius norm is given by

$$B = \Sigma P^+. \tag{10}$$

Since a weight column vector $\boldsymbol{\varphi}$ for a sensor response vector $\mathbf{p}$ is estimated by $\hat{\boldsymbol{\varphi}} = B\mathbf{p}$, the estimated spectral reflectance vector is derived from $\hat{\mathbf{r}} = \mathbf{V}\hat{\boldsymbol{\varphi}}$, where a matrix V is the basis matrix that contains first d orthonormal basis vectors of spectral reflectances. Thus the reconstruction matrix W_I, that gives $\hat{\mathbf{r}} = W_I \mathbf{p}$ for the Imai-Berns model [17] is given by

$$W_I = VB. \tag{11}$$

PROPOSED MODEL

Let W be a reconstruction matrix, then $\hat{\mathbf{r}} = W(S_L \mathbf{r} + \mathbf{e})$ and the MSE of the reconstruction by the matrix W is given by

$$\mathrm{MSE}(W) = \mathrm{Tr}\left[E\left\{(\mathbf{r} - \hat{\mathbf{r}}) \cdot (\mathbf{r} - \hat{\mathbf{r}})^T\right\}\right] \tag{12}$$

$$= \mathrm{Tr}\left[E\left\{((I_N - WS_L)\mathbf{r} - W\mathbf{e}) \cdot \left(\mathbf{r}^T (I_N - WS_L)^T - \mathbf{e}^T W^T\right)\right\}\right] \tag{13}$$

where I_N is an $N \times N$ identity matrix. We assume that the reflectance $\mathbf{r}$ and the error $\mathbf{e}$ has no correlation, thus $E\{\mathbf{r}\mathbf{e}^T\} = 0$ and $E\{\mathbf{e}\mathbf{r}^T\} = 0$, and let $E(\mathbf{e}\mathbf{e}^T) = \sigma^2 I_M$ where I_M is an $M \times M$ identity matrix, then the $\mathrm{MSE}(W)$ is given as

$$\mathrm{MSE}(W) = \mathrm{Tr}\left\{(I_N - WS_L) E\{\mathbf{r}\mathbf{r}^T\} (I_N - WS_L)^T\right\} + \sigma^2 \mathrm{Tr}(WW^T). \tag{14}$$

We denote the first term of the Eq.(14) as MSEfree(W) (the noise independent MSE by the matrix W) and the second term as MSEnoise(W) (the noise dependent MSE by the matrix W). Thus,

$$\mathrm{MSE}_{free}(W) = \mathrm{Tr}\left\{(I_N - WS_L) E\{\mathbf{r}\mathbf{r}^T\} (I_N - WS_L)^T\right\}, \tag{15}$$

$$\mathrm{MSE}_{noise}(W) = \sigma^2 \mathrm{Tr}(WW^T). \tag{16}$$

Also the MSEnoise(W) can be denoted as

$$\mathrm{MSE}_{noise}(W) = \sigma^2 \sum_{i=1}^{R} \kappa_i^2, \tag{17}$$

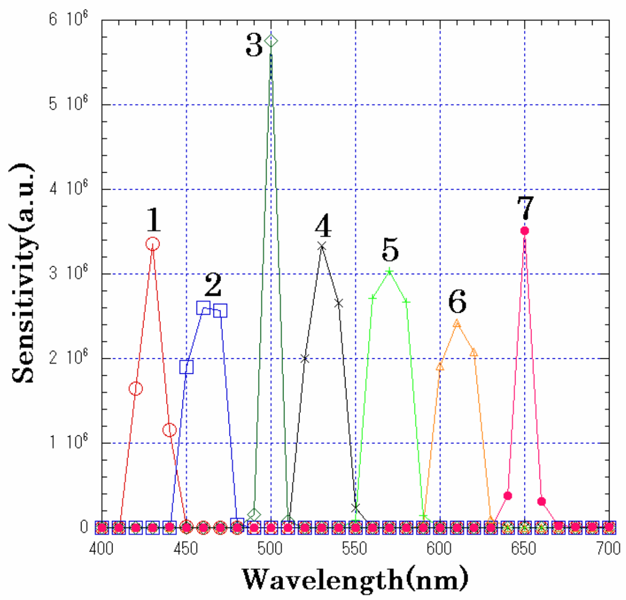

Fig. 1. (a)Spectral sensitivities of the camera in arbitrary unit.

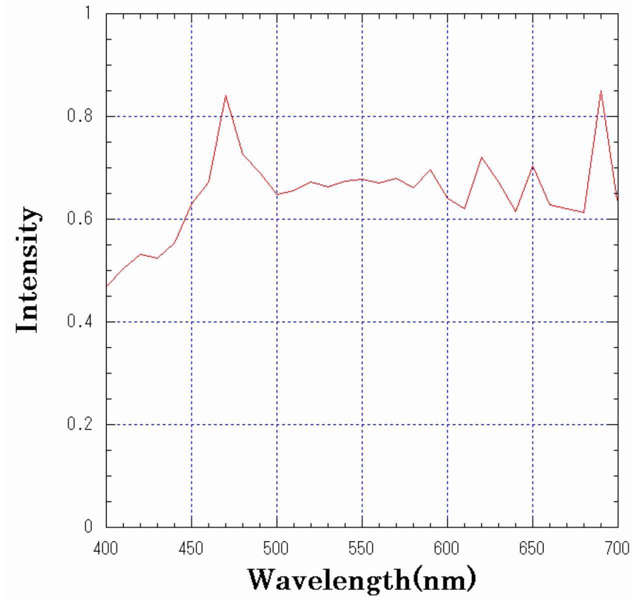

Fig. 1. (b)Spectral power distribution of the recording illumination.

where the SVD of the matrix W as $W = \sum_{i=1}^{R} \kappa_i \mathbf{w}_i \mathbf{u}_i^{\,t}$ is used. κ_i, $\mathbf{w}_i$ and $\mathbf{u}_i$ are the i-th singular value, the i-th left and right singular vector of the matrix W, respectively.

Thus the estimated system noise variance $\hat{\sigma}_W^2$ with a reconstruction matrix W is given by

$$\hat{\sigma}_W^2 = \left(MSE(W) - MSE_{free}(W)\right) / \sum_{i=1}^{R} \kappa_i^{\,2} \,. \tag{18}$$

In the previous paper [13], only the Wiener estimation matrix $W_W(0)$ (by letting $\sigma_e^2 = 0$ in Eq.(3)) and the matrix W_L in the linear model were used as the matrix W since the matrix W should not contain the system noise to make the MSEfree(W) free from the noise. The reconstruction matrix of the regression and the Imai-Berns model contain the noise because they include the sensor response vector $\mathbf{p} = SL\mathbf{r} + \mathbf{e}$, thus it is impossible to apply them to the proposed model. In order to exclude the noise from the reconstruction matrix W, the matrix W should be calculated only from S_L and $\mathbf{r}$. Now, by defining the noiseless sensor response as $\hat{\mathbf{p}} = SL\mathbf{r}$, it is possible to apply the reconstruction matrix derived from the noiseless sensor responses to the proposed model. Thus, the two reconstruction matrices W of the regression (W_R) and the Imai-Berns model (W_I) can be used to calculate the MSEfree(W) and can be defined as a function of the noiseless sensor response $\hat{\mathbf{p}}$ respectively using Eqs. (6) and (11), as

$$W_R(\hat{\mathbf{p}}) \equiv R\hat{P}^{+} \,, \tag{19}$$

$$W_I(\hat{\mathbf{p}}) \equiv V\Sigma\hat{P}^{+} \,. \tag{20}$$

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 8-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(a).

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.1(b).

The GretagMacbeth ColorChecker (24 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 GretagMacbeth ColorChecker was used as both the learning and the test sample. Further detailed experimental procedures are described in the previous paper [7].

RESULTS AND DISCUSSIONS

ΔMSE and MSEnoise(W) for each model

To analyze the influence of the system noise on the recovered spectral reflectances, a measure for the increase in the MSE by the system noise is required to compare the theoretical prediction with the MSEnoise(W). As described above, the matrix W in the MSEfree(W) should not include the system noise, thus we define the reconstruction matrix free from the system noise as W_0, which is $W_W(0)$ for the Wiener model, W_L for the linear model, $W_R(\hat{\mathbf{p}})$ for the regression model, and $W_I(\hat{\mathbf{p}})$ for the Imai-Berns model. By using the matrix W_0, we define the ΔMSE (the increase in the MSE by the system noise for each reconstruction matrix W), which is obtained by the experiment, as

$$\Delta MSE = MSE(W) - MSE_{free}(W_0) \,. \tag{21}$$

Fig.2 shows the ΔMSE as a function of MSEnoise(W) for various combinations of sensors from three to seven. The MSEfree(W_0) and the MSEnoise(W) were obtained by the proposed model and the MSE(W) was obtained by the experiment with the reconstruction matrices W= $W_W(\hat{\sigma}^2)$ as Eq.(3), W_L as Eq.(9), W_R as Eq.(6) or W_I as Eq.(11) for each reconstruction model. Though some plots by the Wiener model deviate from the theoretical predictions, the ΔMSE and the MSEnoise(W) agrees well with the prediction of the proposed model.

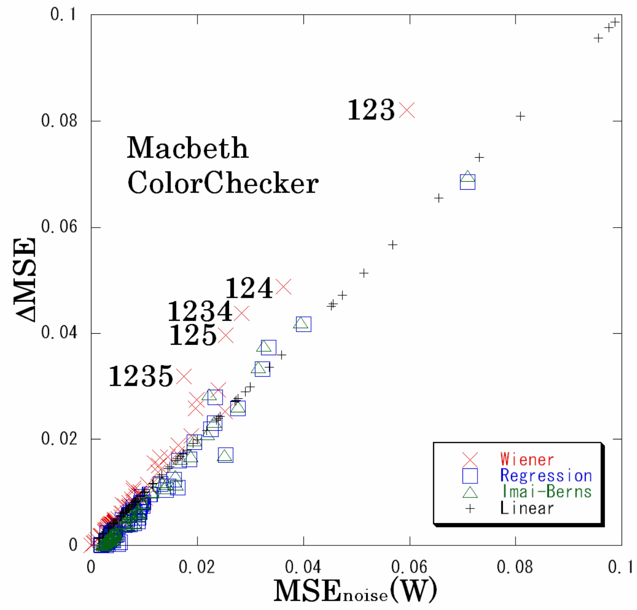

Fig. 2. The relation between the increase in the MSE by the system noise (ΔMSE) and MSEnoise(W) by the Wiener, regression, Imai-Berns and linear model for the GretagMacbeth ColorChecker. The combinations of the sensors are shown to the left of the deviating plots.

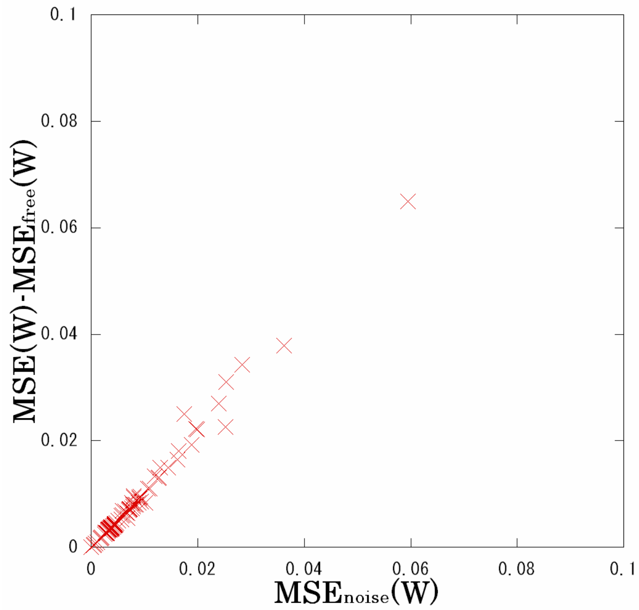

Fig. 3. The relation between MSE(W)-MSEfree(W) and the estimate of the MSEnoise(W) for the Wiener model. The estimate of the MSEnoise(W) is the same as the MSEnoise(W) in Fig.2.

Discussion about deviating plots

In Fig.2, some of the plots deviate from the prediction, especially some plots by the Wiener model deviate largely. The deviation is mainly caused by the approximation of the sensor response as $\hat{\mathbf{p}} = \mathrm{SL}\mathbf{r}$ by neglecting the system noise in the image acquisition system. As seen from Eqs.(14), (15) and (16), the MSE of the reconstruction by the matrix W is given by

$$\mathrm{MSE}(\mathrm{W}) = \mathrm{MSE}_{\mathrm{free}}(\mathrm{W}) + \mathrm{MSE}_{\mathrm{noise}}(\mathrm{W}). \quad (22)$$

Thus, the theoretical MSEnoise(W) equals to MSE(W)-MSEfree(W). But as mentioned above, the matrix W of the MSEfree(W) should not contain the system noise to make the MSEfree(W) free from the noise. Otherwise, the MSEfree(W) increases with the increase in the system noise. Table 1 shows the MSEfree by the previous model, the MSEfree(W_0) and the MSEfree(W) by the proposed model when $\mathrm{W}_0 = \mathrm{W}_\mathrm{W}(0)$ and $\mathrm{W} = \mathrm{W}_\mathrm{W}(\hat{\sigma}^2)$ for six and seven sensor sets and the deviating sensor sets in Fig.2. It was mathematically proved in the previous paper [13] that the proposed model is equivalent to the previous model when the reconstruction matrix $\mathrm{W} = \mathrm{W}_\mathrm{W}(0)$ for the Wiener estimation. Thus, the MSEfree(W_0) equals to the MSEfree while the MSEfree(W) is slightly larger than the MSEfree(W_0). To calculate the increase in the MSE by the system noise, the proposed model uses MSEfree(W_0) instead of the MSEfree(W). Thus, the difference between MSEfree(W_0) and the MSEfree(W) is one of the cause of the deviation. The difference between MSEfree(W_0) and MSEfree(W) for the deviating sensor sets is larger than the rest of the sensor sets.

On the other hand, we estimate the MSEnoise(W) by the multiple of the $\mathrm{Tr}(\mathrm{W}\mathrm{W}^\mathrm{T})$ and the system noise variance $\hat{\sigma}_\mathrm{W}^2$ estimated with the reconstruction matrix W_0. Fig.3 shows the relation between MSE(W)-MSEfree(W) and the estimate of the MSEnoise(W) for the Wiener model.

Table 1.The MSEfree by the previous model and the MSEfree($\mathbf{W_0}$) and MSEfree(W) by the proposed model for the six and seven sensor sets and the deviating sensor sets. The Wiener reconstruction matrices are $\mathbf{W_0=W_W(0)}$ and $\mathbf{W=W_W(\hat{\sigma}^2)}$, respectively.

Sensor Set	Previous model	Proposed model (Wiener model)	
	MSEfree	MSEfree(W_0)	MSEfree(W)
1234567	1.03E-02	1.03E-02	1.06E-02
123456	3.61E-02	3.61E-02	3.70E-02
123457	1.42E-02	1.43E-02	1.45E-02
123467	1.26E-02	1.26E-02	1.28E-02
123567	1.24E-02	1.24E-02	1.27E-02
124567	1.27E-02	1.27E-02	1.30E-02
134567	1.23E-02	1.23E-02	1.25E-02
234567	1.41E-02	1.41E-02	1.43E-02
123	8.25E-01	8.25E-01	8.42E-01
124	5.70E-01	5.70E-01	5.81E-01
125	4.13E-01	4.13E-01	4.21E-01
1234	5.51E-01	5.51E-01	5.61E-01
1235	3.94E-01	3.94E-01	4.01E-01

If this estimate of the MSEnoise(W) is precise, then the MSE(W)-MSEfree(W) and the estimate of the MSEnoise(W) should deviate downwards by the increase in the MSEfree(W), i.e. the MSEfree(W) is larger than the MSEfree(W_0) due to the increase by the system noise. Though, the plots deviate less than those in Fig.2, the plots still deviate and some are deviating upwards. This means that the further analysis for the estimation of the MSEnoise(W) is required.

For the analysis of the Wiener model, the previous model derived from the Wiener estimation gives the better correlation between the MSE-MSEfree and the MSEnoise. The relation between the MSE-MSEfree and the MSEnoise is shown in Fig.4.

Table 2.The estimated system noise variance for seven and six sensors.

Sensor Set	Optimum	Previous model	Proposed model			
			Wiener	Linear	Regression	Imai-Berns
1234567	1.15E-04	8.39E-05	8.39E-05	1.42E-04	8.39E-05	8.19E-05
123456	1.45E-04	1.32E-04	1.32E-04	6.54E-05	1.32E-04	1.38E-04
123457	1.14E-04	1.05E-04	1.05E-04	7.06E-05	1.05E-04	1.11E-04
123467	1.79E-04	1.22E-04	1.22E-04	6.78E-05	1.22E-04	1.38E-04
123567	1.60E-04	1.17E-04	1.17E-04	6.99E-05	1.17E-04	1.37E-04
124567	1.31E-04	1.17E-04	1.17E-04	1.26E-04	1.17E-04	1.31E-04
134567	2.09E-04	1.20E-04	1.20E-04	2.10E-04	1.20E-04	1.27E-04
234567	1.63E-04	9.21E-05	9.21E-05	1.83E-04	9.21E-05	9.80E-05

Table 3.The MSE of the recovered spectral reflectances by the Wiener estimation (Eq.(3)) with each estimated noise variance in Table 2 for six and seven sensors. (MSEs larger than the optimum are shown in bold.)

Sensor Set	Optimum	Previous model	Proposed model			
			Wiener	Linear	Regression	Imai-Berns
1234567	1.33E-02	1.33E-02	1.33E-02	1.33E-02	1.33E-02	1.33E-02
123456	4.41E-02	4.41E-02	4.41E-02	**4.44E-02**	4.41E-02	4.41E-02
123457	1.78E-02	1.78E-02	1.78E-02	**1.79E-02**	1.78E-02	1.78E-02
123467	1.63E-02	1.63E-02	1.63E-02	**1.64E-02**	1.63E-02	1.63E-02
123567	1.60E-02	1.60E-02	1.60E-02	**1.61E-02**	1.60E-02	1.60E-02
124567	1.67E-02	1.67E-02	1.67E-02	1.67E-02	1.67E-02	1.67E-02
134567	1.58E-02	**1.59E-02**	**1.59E-02**	1.58E-02	**1.59E-02**	**1.59E-02**
234567	1.68E-02	1.68E-02	1.68E-02	1.68E-02	1.68E-02	1.68E-02

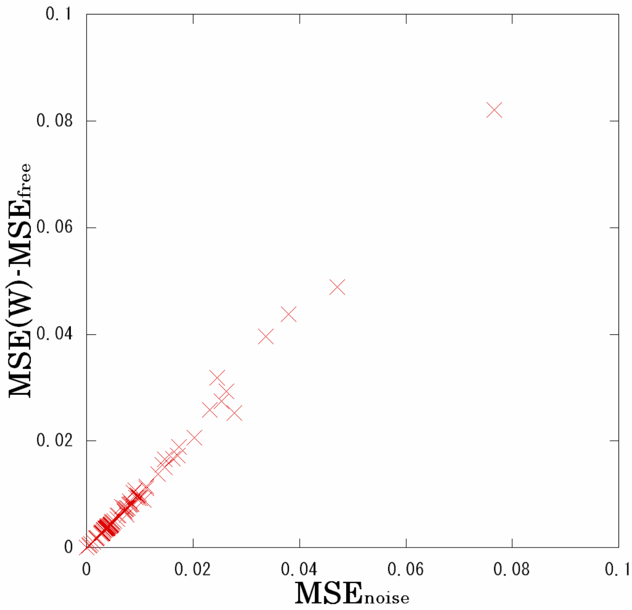

Fig. 4. The relation between the MSE(W)-MSEfree and the MSEnoise by the previous model.

The estimated system noise variance and the MSE by the Wiener model

Table.2 shows the optimum noise variances that make the MSE minimum using the Wiener estimation by Eq.(3), which are searched by the brute force method, and the estimated system noise variances by the proposed model with each reconstruction matrix W_0 are shown. The previous model and the regression model (W_R) gives the same estimate of the system noise variance as the Wiener model. The noise variance estimated by each model is almost the same except for the linear model.

It is very easy to evaluate whether the noise variances are correctly estimated by the proposal or not, since the MSE of the spectral reflectances recovered by the Wiener estimation is minimized when the noise variance σ_e^2 equals to the actual system noise variance in Eq.(3) [7]. In the experiments, it is important to remember that the actual system noise variance is unknown and we only know that the estimated noise variance gives the minimum MSE in the Wiener estimation in a given precision. Thus, a broad range of the estimates minimize the MSE in the Wiener estimation.

The noise variance estimated by various reconstruction matrices are substituted into Eq.(3) and the MSEs by Eq.(3) with each estimated noise variance are shown in Table.3. The MSEs except for the linear model are almost the same as those of the optimum which correspond to the MSE at actual noise variance. Only the MSEs by the linear model scatter a little, since the linear model is not regularized.

CONCLUSIONS

For the Wiener, linear, regression and the Imai-Berns model, the comprehensive evaluation model was refined to analyze the increase in the MSE on the reflectance recovery by the system noise. The experimental results by multispectral cameras agree quite well with the proposed model. From this result, it is concluded that the proposed model is appropriately formulated and that the separation of the MSE into MSEfree and the MSEnoise is essential for estimating the noise variance and for evaluating the influence of the system noise on the image acquisition system. From the experimental results the noise variance is correctly estimated by the proposal.

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