RECONSTRUCTION OF HYPERSPECTRAL IMAGE BASED ON REGRESSION ANALYSIS

Optimum Regression Model and Channel Selection

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Abstract: The purpose of this study is to develop an efficient appraoch for producing hyperspectral images by using reconstructed spectral reflectance from multispectral images. In this study, an indirect reconstruction based on regression analysis was employed because of its stability to noise and its practicality. In this approach however, the regression model selection and channel selection when acquiring the multispectral images play important roles, which consequently affects the efficiency and accuracy of reconstruction. The optimum regression model and channel selection were investigated using the Akaike information criterion (AIC). By comparing the model based on the AIC model based on the pseudoinverse method (the pseudinverse method is a widely used reconstruction technique), RMSE could be reduced by fifty percent. In addition, it was shown that AIC-based model has good stability to noise.

1 INTRODUCTION

Hyperspectral imaging technology, which records detailed spectral reflectance of each pixel of a digital image, is continuously attracting increasing attention. It has a wide range of applications in various fields such as remote sensing, medicine, archiving of cultural heritage, and others (Y. Miyake et.al, 2005; P. Cotte et.al, 2005).

There are two ways to obtain a hyperspectral image. One is to measure the spectral reflectance directly on every point of an image.(Pezzati L. et.al, 2006) The other is to reconstruct it from the image with lower dimensional spectral information, such as RGB image or multispectral image (Berns R. S. et.al, 1996).

A considerable number of studies have been conducted on the second approach, especially in the field of archiving of cultural heritage (i.e. from multispectral image). This is done in order to minimize the radiation on the target and record the image in high resolution (Konig, 1999; Shimano, 2007). There is strict restriction in the amount of radiation on the cultural heritage, therefore the development of an efficient multispectral image acquisition system and a mathematical approach that requires fewer channels and therefore enables reconstruction of more accurate spectral reflectance is imperative.

Several methods are used to reconstruct spectral reflectance from multispectral image namely, direct reconstruction, indirect reconstruction, and interpolation reconstruction. Direct reconstruction is based on a transfer function that is obtained from the spectral characteristics of the image acquisition system such as spectral radiance of the light source and spectral sensitivity of the sensor. Theoretically, this approach enables the user obtain the most accurate results. However, this procedure is complex and unstable because of the difficulty in measuring the necessary spectral characteristics of the system accurately. Indirect reconstruction is based on a transfer function obtained from the spectral information and the multispectral image of a learning sample using statistical analysis. Once the spectral reflectance of the learning sample is measured accurately, this approach is the most practical. Finally, interpolation reconstruction only focuses on the sensor response and requires only a white reference, but this approach requires more spectral channels compared to the other methods.

The final goal of this study is to apply hyperspectral imaging technology into digital

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archiving of cultural heritage with corresponding material analysis. For this purpose, the image acquisition system should be stable and safe for the target. In this study, the indirect method was selected since it is the most practical approach especially in the analysis of cultural heritage. Regression analysis was used in obtaining the transfer functions. The target used was a color chart made of pigments commonly used in classical Japanese painted arts.

There has been no study that tried to investigate the optimum regression model for a spectral reflectance reconstruction. Adopting Akaike's information criterion (AIC) as the criterion of model selection, the optimum regression model was investigated. In addition, a new statistical approach for determining the number of channels and selecting the optimum combination were also explored.

2 LINEAR TRANSFER MODEL FOR RECONSTRUCTION OF SPECTRAL REFLECTANCE

2.1 General Model to Reconstruct Spectral Reflectance

The relationship between the response of the camera sensor from each channel which is defined as the sensor which has certain spectral sensitivity band, and spectral reflectance of the target is generally expressed as

$$\mathbf{p} = \int \mathbf{C}(\lambda) L(\lambda) r(\lambda) \mathrm{d}\lambda + \mathbf{e} \qquad (1)$$

where $\mathbf{p}$ is an $M \times 1$ vector consisting of the response from the M-channel sensor, $\mathbf{C}(\lambda)$ is an $M \times 1$ vector of spectral sensitivity of the sensor, $L(\lambda)$ is the spectral radiance of the illumination, $r(\lambda)$ is the spectral reflectance of the target, and $\mathbf{e}$ is an $M \times 1$ additive noise vector. For mathematical convenience, equation (1) can be expressed with a vector space notation as follows:

$$\mathbf{p} = \mathbf{CLr} + \mathbf{e} \qquad (2)$$

where $\mathbf{C}$ is an $M \times N$ matrix of spectral sensitivity of the sensor, $\mathbf{L}$ is an $N \times N$ diagonal matrix of spectral radiance of the illumination, and $\mathbf{r}$ is an $N \times 1$ spectral reflectance vector of the target. This expression shows that there is a linear relationship between the sensor response and spectral reflectance of the target. Therefore the transfer function from the sensor response to the spectral reflectance can be expressed as a matrix. Indirect reconstruction approach is required for solving this inverse problem.

2.2 Regression Model for Spectral Reflectance Reconstruction

There are several methods available in obtaining the transfer function for indirect reconstruction. In this paper a method for constructing the optimum regression model is proposed. Furthermore the result is compared with the pseudoinverse method (R. S. Bern, 2005), which is a widely used approach, in order to reconstruct the spectral reflectance based on regression analysis. In the new approach suggested,, Akaike's information criterion was adopted as the criterion of model selection and this method is described as "AIC-based method".

2.2.1 Model based on Pseudoinverse Method

Let $\mathbf{p}_i$ be a sensor response vector that is obtained from the ith learning sample in learning chart with known spectral reflectance $\mathbf{r}_i$. Let $\mathbf{P}$ be an $M \times k$ matrix and let $\mathbf{R}$ be an $N \times k$ matrix as following.

$$\begin{aligned} \mathbf{P} &= [\mathbf{p}_1 \quad \mathbf{p}_2 \quad \cdots \quad \mathbf{p}_k] \\ \mathbf{R} &= [\mathbf{r}_1 \quad \mathbf{r}_2 \quad \cdots \quad \mathbf{r}_k] \end{aligned} \qquad (3)$$

Then the transfer function matrix $\mathbf{W}$ is determined to minimize $\|\mathbf{R} - \mathbf{WP}\|$. The matrix $\mathbf{W}$ is given by

$$\mathbf{W} = \mathbf{RP}^{+} = \mathbf{RP}^{t}(\mathbf{PP}^{t})^{-} \qquad (4)$$

where $\mathbf{P}^{+}$ is the pseudoinverse matrix of $\mathbf{P}$. By applying a matrix $\mathbf{W}$ to a sensor response vector, spectral reflectance of the target is reconstructed as follows:

$$\hat{\mathbf{r}} = \mathbf{Wp} \qquad (5)$$

2.2.2 Model based on AIC

In the pseudoinverse model, responses of every channel are used to reconstruct the reflectance at each wavelength, though some of them should have almost no information at that wavelength. In this case, the sensor responses which have no information will act as noise and the model will generally become unstable. In order to solve this problem, optimum regression model is constructed in following approach.

First, the following linear multiple regression model is assumed.

$$r_i = \sum \beta_k p_k + e \tag{6}$$

where r_i is the reflectance at ith wavelength, p_k is the sensor response of kth channel, and e is a constant. β_k which minimizes $\|\hat{r}_i - r_i\|$ is to be obtained by multiple regression analysis.

Next, in order to determine whether the kth explaining variable should be added or removed from the model, the model should be evaluated based on adequate criterion. In this paper, AIC was adopted for model selection.

In the evaluation of multiple regression models, AIC is described as follows,

$$\mathrm{AIC} = n\ln\left(\frac{S_e}{n}\right) + 2(k+2) + n(\ln(2\pi)+1) \tag{7}$$

where n is the number of data, S_e is the residual sum of squares, and k is the number of explaining variables. The model which minimize AIC should be selected. Omitting the constant terms in Equation 7, Equation 7 can be simplified as following.

$$\mathrm{AIC} = n\ln\left(\frac{S_e}{n}\right) + 2k \tag{8}$$

Given that number of channel is m, the number of possible models is 2^m. In this paper after optimum channel selection, which is described in next subsection, AIC was calculated for all possible models and the model with the minimum AIC was selected for every wavelength.

2.2.3 Optimum Channel Selection

In order to reconstruct the spectral reflectance accurately, the channels that have high sensitivity at a given wavelength should be selected (Hardeberg, 2003). Based on this idea, the correlation coefficient R^2 between reflectance at a wavelength and sensor response is adopted as the selection criterion. The channel with the highest R^2 value was selected for each wavelength. By taking the R^2 values into account, the channel which has low AIC was removed to minimize the number of channels.

3 EXPERIMENTAL PROCEDURE

3.1 Image Acquisition

Multispectral images were obtained using a multispectral imaging scanner developed in Kyoto University. This scanner was designed especially for scanning of cultural assets. It consists of a monochromatic line CMOS camera unit, a flat-bed frame structure and an illumination unit, which focuses the illumination at the region of interest using a cylindrical lens. A mixed light source a metal halide lamp and a halogen lamp was used as illumination. The spectral sensitivity of the line CMOS camera is shown in Figure 1. A total of 18 filters, which determine the spectral characteristics of each channel, were used to acquire the images. The transmittance of these filters is shown in Figure 2. All 18 multispectral images were taken at a resolution of 600dpi (an approximate pixel size of 40 μm).

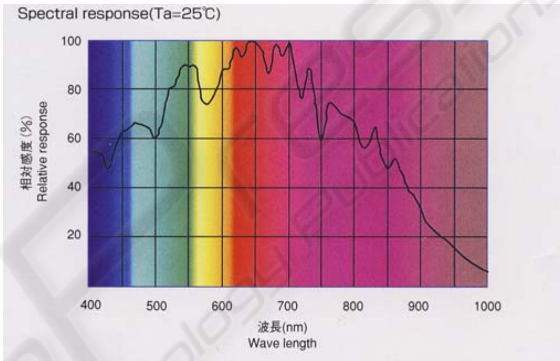

Figure 1: Spectral sensitivity of line CMOS camera.

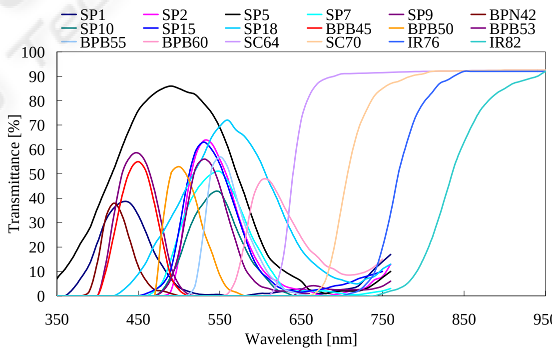

Figure 2: Transmittance of filters.

A learning chart consisting of major pigments and colorants used in Japanese classic paintings was developed and employed for experiments (shown in Figure 3). They are derived from natural mineral pigments, dyes (organic compounds that are originated from plants), artificial mineral pigments, and metal powders. In this paper our interest is limited in the visible and near infrared (NIR) region; therefore the spectral reflectance of the pigment chart was measured from 400 nm to 850 nm.

Figure 3: Pigment chart consisting of major Japanese pigments used in classical art works.

3.2 Test of Linear Regression Model

In order to test the adequacy of the linear regression model, a scatter chart of sensor response from a channel and reflectance on the pigment chart was created. A representative chart is shown in Figure 4.

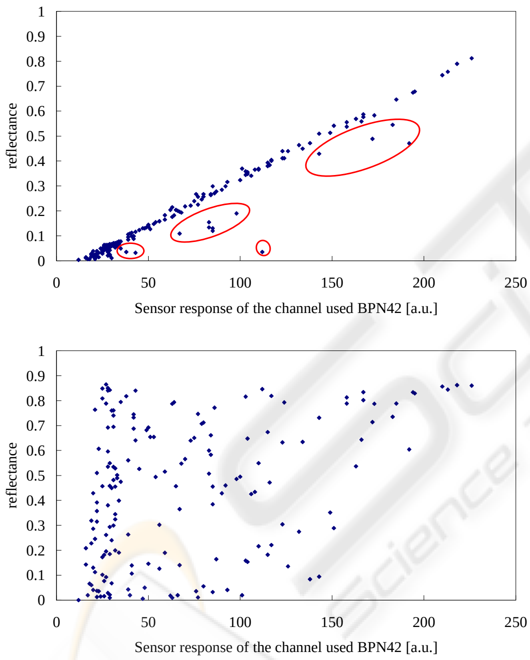

Figure 4: Scatter chart of sensor response of the channel which used BPN42 filter and reflectance (a) Reflectance at 440 nm. The data points that deviated from linear correlation are circled. (b) Reflectance at 700 nm.

Figure 4(a) shows the linear correlation between the sensor response and reflectance in the range when the channel has enough sensitivity. On the other hand, Figure 4(b) shows no correlation between sensor response and reflectance, which is due to the lack of useful information transmitted to the channel. In Figure 4(a), there are several data points, which deviated from the linear correlation. These data points originated from the glossy pigment, such as metal powder, and this phenomenon can be attributed to strong specular reflections. In order to stabilize the regression model, these data point was removed from the data for subsequent analysis.

3.3 Channel selection

First, single regression analysis was conducted and the correlation coefficient between the sensor response and reflectance was calculated for each wavelength. In the next step the channel with the highest correlation coefficient was selected as the most informative channel for regression model at that wavelength. At this stage 13 channels were selected. In order to minimize the number of channels, the channels with low AIC values were removed and the changes in the correlation coefficient were carefully monitored. This process is shown in Figure 5.

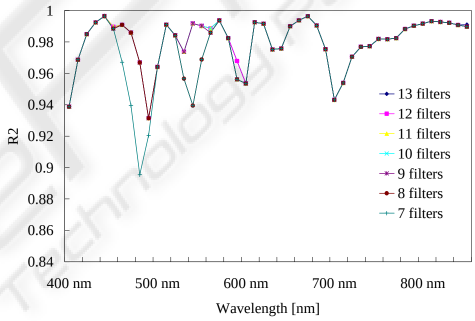

Figure 5: Shift of correlation coefficient.

The number of channels was reduced gradually from a total of 13 channels until there were only seven channels. However, when there were only 7 channels, the correlation coefficient dropped drastically especially between 450-500nm. Therefore 8 channels were selected following the selection criteria. The transmittance of the filters used for the selected channel is shown in Figure 6.

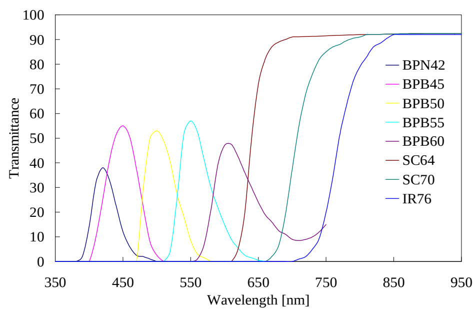

Figure 6: Transmittance of selected filter.

3.4 Model Construction

The transfer function was calculated based on both the AIC-based method and the pseudoinverse method using the channels selected in the previous section. However, when employing the AIC-based method, it is sometimes enough to obtain the necessary information for reconstruction using fewer channels (i.e. 4-5 channels on the average). This condition is dependent on the sensitivity of the channel as a function of wavelength.

4 RESULTS AND DISCUSSION

In this section, the result of spectral reflectance reconstruction is discussed in detail.

First, the result of spectral reflectance reconstruction of malachite and azurite is shown in Figure 7 as representatives. It shows that the spectral reflectance of malachite is reconstructed accurately using both methods. On the other hand, reconstructed spectral reflectance of azurite has quite a large error especially when using the pseudoinverse method. These results indicate that the reconstruction using PIM is unstable in some cases.

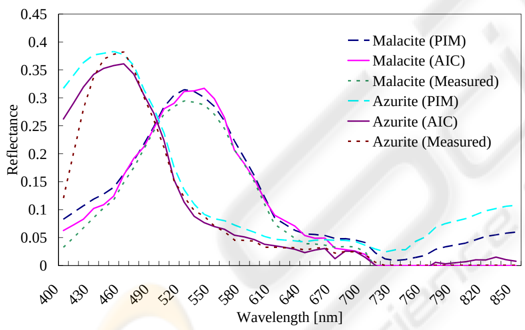

Figure 7: Representative result of spectral reflectance reconstruction.

Next, the root mean square error (RMSE) between the measured spectral reflectance and reconstructed spectral reflectance was derived in order to evaluate the accuracy of the reconstruction. RMSE is calculated as follows,

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\left(\mathbf{R}-\hat{\mathbf{R}}\right)\cdot\left(\mathbf{R}-\hat{\mathbf{R}}\right)^t} \tag{9}$$

where N is the number of data. The result is shown in Table 1.

Table 1: Comparison between pseudoinverse method and AIC-based method.

	RMSE	Maximum error
Pseudoinverse method	0.0317	0.1424
AIC-based method	0.0196	0.1155

This result shows that model based on AIC is a more accurate model for spectral reflectance reconstruction based on to the calculated error.

A comparison of the residual sum of squares in the wavelength region is shown in Figure 8. In this figure, every square error between measured spectral reflectance and reconstructed spectral reflectance was summed up. This result shows that the model based on pseudoinverse method has relatively large errors in the near infrared region. This phenomenon might be due to the S/N ratio of sensor response in NIR region. In NIR region, the sensitivity of the sensor is quite low so the S/N ratio of the sensor response was expected to be lower. This resulted to an upward shift of the residual noise in the NIR region. This was further aggravated because the Pseudoinverse does not have a constant term. Given that this hypothesis is correct, the result implies that AIC-based method is relatively more stable.

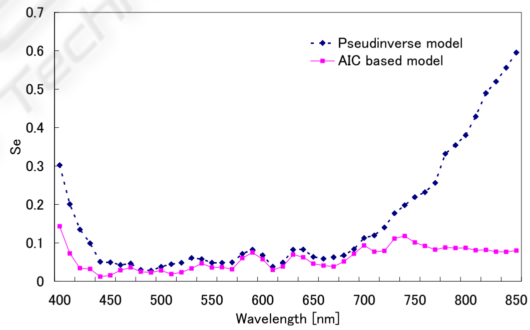

Figure 8: Residual sum of squares in wavelength region.

Finally, the spectral reflectance of glossy samples removed from the dataset for model construction was reconstructed. A representative result is shown in Figure 9. The result shows that neither the pseudoinverse method nor the AIC method are able to reconstruct the spectral reflectance of the glossy sample accurately. The spectral reflectance of the glossy sample is strongly dependent on the illuminance and measuring condition due to specular reflection. In order to solve this problem, the conditions in measuring the spectral reflectance and capturing the multispectral images should be accounted for.

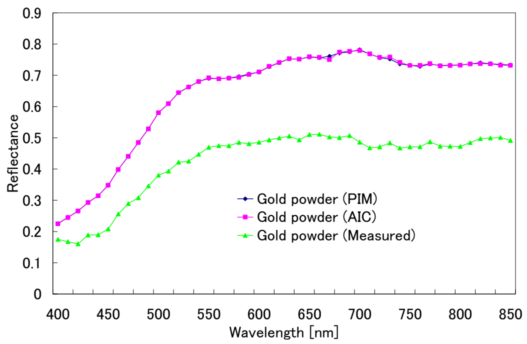

Figure 9: Spectral reflectance reconstruction of glossy target.

5 SUMMARY AND CONCLUSIONS

In this study the optimum regression model and channel selection for hyperspectral image reconstruction from multispectral image was investigated. Adopting Akaike's information criterion (AIC) as the selection model, the optimum regression model was explored. In addition, a new statistical approach for determining the number of channels and selecting the best combination of channels was presented.

The optimum regression model was successfully constructed based on AIC. AIC-based method was evaluated by comparing it with pseudoinverse method which is a widely used technique for spectral reflectance reconstruction from multispectral images. The results show that the model based on AIC is more accurate than the model based on pseudoinverse method and indicate that the AIC-based method is stable even with noise.

The results also show that it is quite difficult to reconstruct the spectral reflectance of a target with strong specular reflection. This is due to the lighting condition and measuring condition. In order to obtain the hyperspectral image of glossy samples, further investigation on the image acquisition system and the mathematical approach of spectral reflectance reconstruction is required.

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