Recovery of Spectral Reflectances of an Art Painting without Prior Knowledge of Objects Being Imaged

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ABSTRACT

The recovery of spectral reflectances of pixels of objects being imaged is very important in reproducing color images of art paintings under a variety of viewing illuminants. The accuracy of the recovery depends not only on the spectral sensitivities of a set of sensors but also on the noise present in a color image acquisition system. The Wiener filter is usually used for the recovery. However, prior knowledge of the noise and the spectral reflectances of an art painting are required for the use of the filter. In this manuscript, a new model for the estimation of the noise variance of a multispectral color image acquisition system is proposed and it was applied to the recovery of spectral reflectances of pixels of an image of an art painting without prior knowledge.

1. INTRODUCTION

The recovery of spectral reflectances of pixels of objects being imaged is very important in reproducing color images of art paintings under a variety of viewing illuminants by using color appearance models[1,2]. The accuracy of the recovery depends not only on the spectral sensitivities of a set of sensors but also on the noise present in a color image acquisition system. The Wiener filter is usually used for the recovery[3]. However, prior knowledge of the noise and the spectral reflectances of an art painting are required to use the Wiener filter[4]. Therefore, spectral reflectances are previously measured about the plural points of an art painting or the pigments used for the painting, and then the optimum noise variance which minimizes the mean square errors (MSE) of the recovered spectral reflectances by the Wiener filter is estimated. The estimated optimum noise variance is used for the recovery of all pixels of the image of the painting. Hence the previous methods are difficult to use for valuable art paintings, since the measurement may cause damage to the objects. In this manuscript, a new model for the estimation of the noise variance of a multispectral color image acquisition system is proposed and it was applied to the recovery of spectral reflectances of pixels of an image of an art painting without prior knowledge.

2. A METHOD TO ESTIMATE THE NOISE VARIANCE

The model for the estimation of the noise variance is discussed briefly below. 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

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

where $\mathbf{p}$ is a sensor response vector from the M channel sensors, S is a $M \times N$ matrix of the spectral sensitivities of sensors, L is a $N \times N$ diagonal matrix with samples of the spectral power distribution of an illuminant along the diagonal, $\mathbf{e}$ is a $M \times 1$ additive noise vector and N represents the number of the sampling points over the visible wavelengths from 400 to 700nm. The noise vector $\mathbf{e}$ is defined to include all sensor response errors that are originated not only from a CCD itself but also from all measurement errors about spectral characteristics of sensors, illuminants and reflectances, etc and this noise is termed as the system noise in this manuscript. For abbreviation, let $S_L = SL$ below. The difference between the recovered surface reflectance vector $\hat{\mathbf{r}}$ by the Wiener estimation and the actual reflectance $\mathbf{r}$ is given by,

$$\Delta\mathbf{r} = \mathbf{r} - R_{SS}S_L^T(S_L R_{SS} S_L^T + \sigma^2 I)^{-1}\mathbf{p} \tag{2}$$

where T represents the transpose of a matrix and R_{SS} is an autocorrelation matrix of the spectral reflectances of objects. If the system noise is assumed as uncorrelated random variables, then the correlation matrix of the noise can be represented by $\sigma^2 I$, where σ^2 and I represent the system noise variance and an identity matrix, respectively.

Usually, the system noise variance is unknown. Since the autocorrelation matrix Rss is symmetrical, it is represented by a set of eigenvectors and eigenvalues of the matrix as $R_{SS} = V\Lambda V^T$, where V represents a basis matrix and Λ is a $N \times N$ diagonal matrix with positive eigenvalues of the matrix Rss along the diagonal in decreasing order. Let $S_L^V = S_L V \Lambda^{1/2}$.

To estimate the system noise variance, if the Wiener filter with the noise variance σ^2=0 is applied to sensor responses and the values of $\|\Delta \mathbf{r}\|^2$ are averaged over the colors, then the MSE(σ^2 =0) for the recovered spectral reflectances is given by

$$\mathrm{MSE}\left(\sigma^2 = 0\right) = \sum_{i=1}^{N} \lambda_i - \sum_{i=1}^{N}\sum_{j=1}^{\beta} \lambda_i b_{ij}^2 + \sum_{i=1}^{N}\sum_{j=1}^{\beta} \frac{\sigma^2}{\kappa_j^{v\,2}} \lambda_i b_{ij}^2 \tag{3}$$

where, λ_i, κ_j^v and b_{ij} represent the eigenvalue of the Rss, j-th singular value and the i-th element of the j-th right singular vector of $S_L^V = S_L V \Lambda^{1/2}$ by the singular value decomposition[5], respectively. Therefore, the estimated system noise variance $\hat{\sigma}^2$ can be formulated as

$$\hat{\sigma}^2 = \frac{\mathrm{MSE}\left(\sigma^2 = 0\right) - \mathrm{MSE}_{\mathrm{free}}}{\sum_{i=1}^{N}\sum_{j=1}^{\beta} \frac{\lambda_i b_{ij}^2}{\kappa_j^{v\,2}}} \tag{4}$$

where $\mathrm{MSE}_{\mathrm{free}}$ represents the noise independent MSE and is given by

$$\mathrm{MSE}_{\mathrm{free}} = \sum_{i=1}^{N} \lambda_i - \sum_{i=1}^{N}\sum_{j=1}^{\beta} \lambda_i b_{ij}^2 \tag{5}$$

The $\mathrm{MSE}_{\mathrm{free}}$ and the denominator of Eq.(4) 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 $\mathrm{MSE}\left(\sigma^2 = 0\right)$ can also be obtained by the application of the Wiener filter with σ^2 = 0 to sensor responses and averaging $\|\Delta \mathbf{r}\|^2$ over color samples. Therefore, the system noise variance $\hat{\sigma}^2$ can be estimated.

3. EXPERIMENTAL RESULTS

3.1 Experimental Procedure

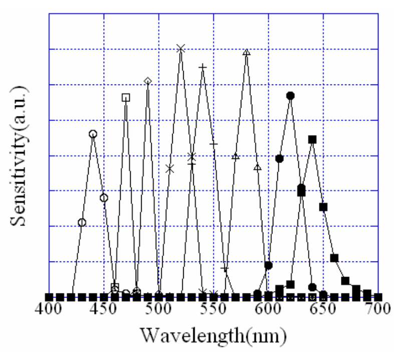

Fig.1: Spectral sensitivities of the camera.

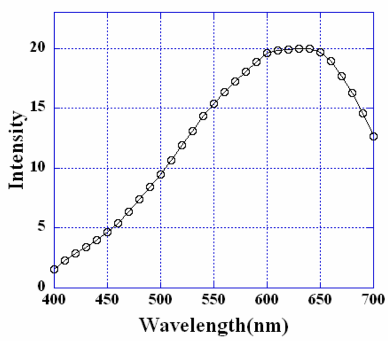

Fig.2: Spectral power distribution of the halogen lamp.

A multispectral color image acquisition system was assembled using eight interference filters (Asahi Spectral Corporation) in conjunction with a monochrome video camera (SONY XC-75) with an optical lens (CANON zoom lens V6$\times$16). Image data from the video camera were converted to 8bit-depth digital data by an AD converter. The spectral sensitivity of the video camera with the optical lens was measured over the wavelengths from 400 to 700nm at 10nm intervals. The multiplication of the sensitivity of the video camera with the measured transmittance of the filters at each sampled wavelength gives the spectral sensitivities of the multispectral color image acquisition device. The measured spectral sensitivities are illustrated in Fig.1. A halogen lamp was used to capture the images and the spectral power distribution of the illuminant is presented in Fig.2.

The Macbeth ColorChecker and an art painting were illuminated from the direction of about 45° to the surface normal, and then the images were captured by the multispectral camera from the normal direction. At first, the system noise variance $\hat{\sigma}^2$ was estimated by the procedure described above using the image data of the Macbeth ColorChecker and the spectral reflectances of it. Then, the estimated system noise variance was used to recover the reflectance spectra of the art painting by the use of the Wiener filter. Several sets of spectral reflectances of color charts, such as the Munsell chips set and the Macbeth ColorChecker were used for an autocorrelation matrix of the filter. The Munsell chips were divided into three groups according to the color saturation, i.e., the high ($40 < C_{ab}^* \le 60$), middle ($20 < C_{ab}^* \le 40$) and low saturation ($0 \le C_{ab}^* \le 20$), by the use of the measure of the metric chroma $Cab^* = \sqrt{a^{*2} + b^{*2}}$, where a^* and b^* represent the coordinates in the CIELAB spece.

3.2 Experimental Results

The art painting used in this experiment is given in Fig.3. To recover the spectral reflectances of the painting without prior knowledge of the reflectance, the spectral reflectances of it were recovered by using the Wiener filter with the estimated system noise variance $\hat{\sigma}^2$ by the Macbeth ColorChecker and the autocorrelation matrix of the spectral reflectances of the Munsell color chips set or the Macbeth ColorChecker. To check the accuracy of the recovery, 21 points were selected in the painting and the spectral reflectances of the points were measured. The typical examples of the

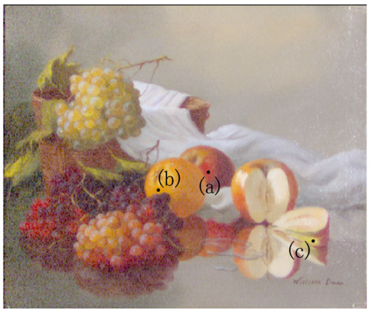

Fig.3: A painting used in the experiment.

Rss	MSE($\sigma^2 = 0$)	MSE($\hat{\sigma}^2$)	MSE($\hat{\sigma}^2_{opt}$)	ΔEab^*
High	0.03444	0.01694	0.01189	2.35
Middle	0.03443	0.01773	0.01699	2.61
Low	0.04546	0.02939	0.01890	3.52
Macbeth	0.03605	0.01534	0.01363	2.39
Painting	0.15079	0.00744	0.00744	1.94

Table 1: Summary of the estimated parameters by the proposal.

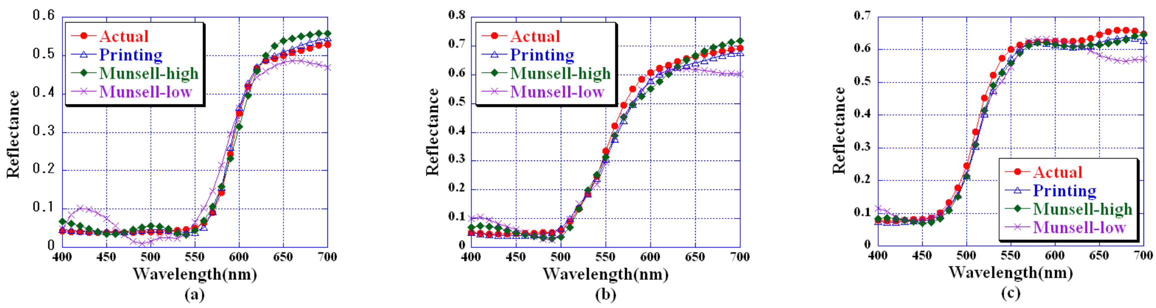

Fig.4: Typical examples of the recovered spectral reflectances.

recovered spectral reflectances corresponding to the three points marked in the picture are represented in Fig.4. The accuracy of the recovered spectral reflectances about the 21 points in the painting by using various sets of spectral reflectances for the Rss is summarized in the Table 1. In this table the values of the $\mathrm{MSE}(\sigma^2 = 0)$, $\mathrm{MSE}(\hat{\sigma}^2)$ and $\mathrm{MSE}(\sigma^2_{opt})$ represent MSE at $\sigma^2 = 0$, $\sigma^2 = \hat{\sigma}^2$ and $\sigma^2 = \hat{\sigma}^2_{opt}$, respectively, where σ^2_{opt} represents the system noise variance which minimizes the MSE of the recovered spectral reflectances of the painting by using various Rss. $\Delta Eab*$ in this table represents the average color differences of the recovered spectral reflectances in CIELAB color space. From the results, it is confirmed that the estimated system noise variance is sufficient to reduce the MSE, i.e., the value of the MSE reduces from the $\mathrm{MSE}(\sigma^2 = 0)$ to that of the $\mathrm{MSE}(\hat{\sigma}^2)$ which is nearly equal to the value of the $\mathrm{MSE}(\sigma^2_{opt})$. A $\Delta Eab*$ error of 2.35 units was obtained by using the autocorrelation matrix of spectral reflectances of the highly saturated Munsell chips set. Therefore the proposed method is useful to recover spectral reflectances of art paintings without prior knowledge of the objects.

4. CONCLUSIONS

A new model for the estimation of the noise variance of a multi spectral image acquisition system is proposed in this manuscript. The estimated noise variance and the autocorrelation matrix of the spectral reflectances of a set of color charts were applied to the Wiener filter to recover the spectral reflectances of an art painting without the prior knowledge of the objects. The estimated noise variance was useful to recover the spectral reflectances accurately and the average $\Delta Eab*$ error of 2.35 units was obtained for the recovered spectral reflectances about the 21 points in the painting. Therefore, it is concluded that the proposed method is useful to recover the spectral reflectances of art paintings without prior knowledge of the objects.

Acknowledgement

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