System design for accurately estimating spectral reflectance of art paintings

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ABSTRACT

In order to accurately estimate the spectral reflectance of art paintings from low-dimensional multichannel images, both image acquisition hardware with appropriate spectral characteristics and appropriate estimation software applied to the captured multichannel image are essential. In this study, a system incorporating both factors is designed and developed based on the minimum mean squares error criterion. The accuracy of spectral estimation using the developed system is evaluated and its high performance is demonstrated.

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1. Introduction

In recent years, a system for accurate digital archiving of fine art paintings has been increasingly desired. If such a system is established, digital image data can be easily exchanged through the computer network, and consequently, people may appreciate a variety of paintings at any viewing site, for instance, their local museum. Recording the current state of paintings as accurately as possible is also important for preserving them for the future in a digital form. Research and development of such a system is in progress, conducted by several groups [1-7]. We are also developing a digital archiving system to obtain the two-dimensional spectral reflectance of oil paintings with high spatial resolution[8-10].

In accurate digital archiving of fine art paintings, the accurate recording of color information and high spatial resolution are the most important factors. Therefore, a system design that takes into account both factors is required. In this paper, however, we focus on the recording of accurate color information. Spatial resolution is discussed elsewhere [10].

Conventional color images with red (R), green (G), and blue (B) channels are strongly dependent on the characteristics of the imaging system including the illuminant for image acquisition. On the other hand, spectral reflectance is the most accurate representation of the color of an object and is completely independent of the characteristics of the imaging system. Such color information allows us to reproduce the image of the object under an arbitrary illuminant. This means that, under any illumination condition, appropriate color reproduction considering the color appearance characteristics of the human visual system is possible. Furthermore, we believe that such spectral representation of invaluable fine arts is necessary for research purposes.

A conventional technique of recording two-dimensional spectral reflectance has been the use of many narrow-band filters, such as an interference filter, in image acquisition. However, as described in the previous papers and as shown in detail in the following sections, the statistical analysis of reflectance spectra of paint samples suggests that a relatively small number of channel images is sufficient to estimate the spectral reflectance because of smooth spectral characteristics [11-13]. Therefore, an imaging system such as that shown in Fig. 1, which incorporates both hardware for multichannel image acquisition with several broad-band filters and software for spectral estimation from the obtained multichannel images is promising.

In order to accurately estimate the spectral reflectance of art paintings from low-dimensional multichannel images, a system including both hardware for image capturing and software for spectral estimation should be designed based on the minimum mean squares error (MMSE) criterion. The factors necessary to achieve accurate reconstruction of spectral reflectance under such a criterion are as follows:

1) accurate estimation of statistical properties of target object and noise,

2) optimization of imaging system.

We will address these two issues in this paper. For the former issue, we statistically analyze the reflectance spectra of color patch sets of oil and water paintings and measure the noise characteristics of the CCD cameras used. For the latter issue, we propose to determine the optimal spectral transmittance characteristics of the color filters in the multichannel imaging system.

This paper is organized as follows. In section 2, we first formulate the reconstruction of spectral reflectance from a multichannel image based on the MMSE criterion. In section 3, we present the results of statistical analysis for the reflectance spectra of the color patches and the measurement of noise properties of the CCD cameras used. In section 4, we evaluate the estimation accuracy in the case that the statistical properties of target objects and noise are taken into account. In section 5, we describe the filter optimization, where the best selection from commercially available filters and the optimum design of the spectral transmittance of filters are both examined. In section 6, the estimation technique of spectral reflectance and the method for filter optimization presented here are compared with other methods. Finally, concluding remarks are presented in section 7.

2. Formulation of Spectral Reflectance Estimation

We will first formulate the spectral reflectance estimation based on the MMSE criterion. In this paper we call this estimation method simply the Wiener estimation method. The response $\mathbf{g}$ at position (x, y) of the CCD camera with the ith color filter is expressed as

$$\mathbf{g}_i(x, y) = \int t_i(\lambda) E(\lambda) S(\lambda) f(x, y; \lambda) d\lambda + n_i(x, y), \qquad i = 1, \ldots, m., \quad (1)$$

where $t_i(\lambda)$, $E(\lambda)$, $S(\lambda)$ and $f(x, y; \lambda)$ are the spectral transmittance of the ith filter, the spectral radiance of the illuminant, the spectral sensitivity of the camera and the spectral reflectance of a painting, respectively. $n_i(x, y)$ denotes additive noise in the ith channel image. m denotes the total number of channels.

For mathematical convenience, we sample each spectral characteristic with l wavelengths and express it as a vector or a matrix. Using vector-matrix notation, Eq. (1) can be expressed as

$$\mathbf{g}(x, y) = \mathbf{T}^t \mathbf{E} \mathbf{S} \cdot \mathbf{f}(x, y) + \mathbf{n}(x, y), \qquad (2)$$

where $[\cdot]^t$ denotes the transposition. The size and meaning of each vector or matrix are listed below.

- $\mathbf{g}$: $m \times 1$ column vector representing the camera response
- $\mathbf{f}$: $l \times 1$ column vector representing the spectral reflectance of painting

- $\mathbf{T} = [\mathbf{t}_1, \mathbf{t}_2, ..., \mathbf{t}_m]$: $l \times m$ matrix in which each column, $\mathbf{t}_i$, represents the transmittance of the *i*th filter
- $\mathbf{E}$ and $\mathbf{S}$: $l \times l$ diagonal matrices corresponding to the spectral radiance of the illuminant and the spectral sensitivity of the CCD camera, respectively.

Hereafter we will omit (x, y) from $\mathbf{g}$ and $\mathbf{f}$ for simplicity. Equation (2) is rewritten as an overall, linear system matrix $\mathbf{H} \equiv \mathbf{T}^t\mathbf{ES}$ with $m \times l$ elements:

$$\mathbf{g} = \mathbf{Hf} + \mathbf{n}. \tag{3}$$

The goal here is to solve Eq. (3) on the basis of the MMSE criterion. The Wiener estimation is achieved by operating a matrix to the observed data $\mathbf{g}$ as

$$\hat{\mathbf{f}} = \mathbf{Wg}. \tag{4}$$

Here the operator, $\mathbf{W}$, in the Wiener estimation is determined so that it minimizes the ensemble average of the square error between the original and estimated spectral reflectance:

$$\left\langle \left\| \mathbf{f} - \hat{\mathbf{f}} \right\|^2 \right\rangle = \left\langle \left\| \mathbf{f} - \mathbf{Wg} \right\|^2 \right\rangle \to \min. \tag{5}$$

Here, $\langle \;\; \rangle$ denotes the ensemble average. The explicit form of the Wiener estimation matrix is given by [14]

$$\mathbf{W} = \mathbf{R}_{ff}\mathbf{H}^t(\mathbf{HR}_{ff}\mathbf{H}^t + \mathbf{R}_{nn})^{-1}, \tag{6}$$

where $\mathbf{R}_{ff}$ and $\mathbf{R}_{nn}$ denote correlation matrices respectively given by

$$\mathbf{R}_{ff} = \left\langle \mathbf{ff}^t \right\rangle, \quad \mathbf{R}_{nn} = \left\langle \mathbf{nn}^t \right\rangle.$$

Namely, the Wiener estimation requires the second-order statistics with respect to the original spectral reflectance and noise, in addition to the system matrix. Since the accuracy of estimation of the spectral reflectance depends on the system matrix $\mathbf{H}$, and the correlation matrices $\mathbf{R}_{ff}$ and $\mathbf{R}_{nn}$ we must estimate the correlation matrices accurately and design the system optimally.

We address both issues in this paper. The correlation matrix of object reflectance, $\mathbf{R}_{ff}$, is estimated from a patch set of oil paints. On the other hand, the correlation matrix of noise, $\mathbf{R}_{nn}$, is estimated by measuring the noise properties of the CCD cameras actually used. For system design, we determine color filters, $\mathbf{T}$, for the multichannel camera in two ways: 1) selection from 22 commercially available dye filters, 2) optimum design of spectral centroid and bandwidth of band-pass color filters by using an optimization algorithm.

3. Statistical Properties of Reflectance Spectra and Noise

3.1 Statistical Analysis of Reflectance Spectra of Paint Samples

For statistical analysis of the spectral reflectance of paintings, we used three sets of color patches of oil or water color paint, as listed below.

Set A: 145 patches of oil paint

Set B: 90 patches of oil paint

Set C: 57 patches of water color paint.

Set A was provided by Holbein Inc. and the reflectance spectra were measured over the range of 380 – 780nm. Sets B and C were extracted from the standard object color spectral data base (SOCS) constructed by the Spectral Characteristics Database Construction Working Group [15, 16]. These two sets have the spectral range of 380 – 730 nm. Figure 2 shows all reflectance spectra in each set. In set A, only the spectral range of 380 – 730 nm is displayed for comparison with sets B and C

The principal component analysis (PCA) for these data was carried out. The common spectral range, 380-730nm, was used for this analysis. Figure 3 and Table 1 show the first six principal components (PCs) and the cumulative contribution ratio, respectively. As shown in Fig. 3, the PCs of the three data sets are similar to each other. This similarity suggests that one of the three sets, e.g., set A, may be used for the estimation of the correlation matrix of reflectance spectra. Thus we decided to use set A for the calculation of the correlation matrix, and sets B and C for accuracy evaluation of the spectral estimation in order to check the robustness of the estimated correlation matrix. The result will be presented in subsection 4.2.

Statistical analysis of the reflectance spectra of these data sets reveals another characteristic. The data in Table 1 indicate that original reflectance spectra can be synthesized with high accuracy using a weighted linear combination of the lower order PCs shown in Fig. 2. For instance, in the case of set A, the original spectral reflectance can be expressed with 98.8% accuracy using only five PCs. Regarding the characteristics of spectral shape, the first PC is the smoothest and the higher order PCs tend to oscillate more rapidly. Nonetheless, the shape of these PCs is rather smooth. Considering the smooth shape of lower order principal components and the high cumulative contribution ratio, it is expected that five or six filters will be sufficient for the reconstruction of spectral reflectance with high accuracy.

Expression of spectral reflectance with fewer numbers of components is possible by an appropriate modeling of colorant mixing. In fact, Tzeng and Berns, based on Kubelka-Munk turbid media theory, presented a linear model of colorant vectors that are obtained by nonlinear transform from spectral reflectance [17]. As this model represents physical properties of colorant mixing appropriately, in the principal component analysis it shows good compactness of data representation (99.98% with first six eigen vectors). On the other hand, since we modeled linearly with basis vectors of spectral reflectance, the compactness is worse (99.3-99.5% with the first six eigen vectors). In the multi-channel imaging with broadband filters, however, an approach as Tzeng did is not available because spectral intensity is integrated before performing the nonlinear transform at each wavelength. Even with our model, we believe that high accuracy in spectral estimation can be achieved by five or six channels.

3.2 Measurement of Noise Properties

A. Noise Model

There are many noise sources in a CCD camera, including dark current N_{DC} and read noise N_R which are both signal-independent, and shot noise N_S which is signal-dependent [18]. We assume that the other noise sources can be ignored. In Eq. (1), noise of the *i*th channel, n_i, is expressed as

$$n_i = N_{DC} + N_R + N_S \,. \tag{7}$$

It is known that dark current noise has a positive mean and fluctuates around it, while read noise and shot noise have zero mean. Representing the dark current noise by a positive mean $\overline{N}_{DC}$ plus fluctuation n_{DC}:

$$N_{DC} = \overline{N}_{DC} + n_{DC} \,, \tag{8}$$

Eq. (7) can be rewritten as

$$n_i = \overline{N}_{DC} + N_C + N_S \,, \tag{9}$$

where we put $N_C = n_{DC} + N_R$.

$\overline{N}_{DC}$ can be estimated at the calibration stage, and subtracted from the obtained image as part of preprocessing. The remainder consists of signal-independent noise N_C and signal-dependent noise N_S. The variance of the noise, σ_n^2, can be expressed as a simple sum of variances of each noise term because the occurrence of each noise is independent of other noise:

$$\sigma_n^2 = \sigma_C^2 + \sigma_S^2, \tag{10}$$

where σ_C^2 and σ_S^2 represent the variances of signal-independent noise and signal-dependent noise, respectively.

B. Measurement

We measured and analyzed noise properties of two types of CCD cameras in hand by the method presented by Healey and Kondepudy [18]. The cameras used are Mutoh CV-04 and KODAK DCS420. CV-04 has 512x480 pixels and outputs 16 bits/pixel. DCS420 has 1542x1012 pixels and outputs 8 bits/pixel in our configuration.

Dark current images were captured simply by placing a cap over the lens. The mean of dark current noise was 448.5 in CV-04 and 20.6 in DCS420 (Table 2). The mean of dark current noise in CV-04 is equivalent to 448.5x256/65536 = 1.75 in the case of 8 bits. This means that DCS420 has a much larger bias caused by dark current than CV-04.

Figure 4 shows the variance of pixel values against average pixel value. The variance was calculated from the difference between repeatedly captured images of a uniform object. Average pixel values were changed using several neutral density filters. Measurement was performed for three different shutter speeds in each camera: 0.1s, 0.3s and 0.5s for CV-04, 1/5s, 1/30s, and 1/150s for DCS420. Based on the results, the following common properties were revealed.

- The variance increases monotonically with average pixel value.
- The y sections of the graphs that provide the variance of signal-independent noise are negligibly small. This suggests that the noise of the cameras used is dominated by signal-dependent noise.
- The plots for the three different shutter speeds are similar to each other.

The first property means that the noise correlation matrix in Eq. (6) should be signal-dependent rather than a fixed matrix. However, from the third property, it seems to depend on only the input signal. In the next section, we show how to incorporate the noise properties into the estimation method and validate its effect through computer simulations.

4. Evaluation of Estimation Accuracy When Considering Statistical Properties

In the previous section, statistical properties of reflectance spectra of paint patches and noise of CCD cameras were measured. In this section, we describe the estimation accuracy of spectral reflectance when these statistical properties are considered. First, we develop an estimation method by taking noise properties into account, and validate its effect. Next, using patch sets B and C, we evaluate the estimation performance of the Wiener estimation matrix obtained using patch set A.

4.1 Improvement of Estimation Accuracy by Taking into Account Noise Properties

A. Method

Although the Wiener estimation matrix should be signal-dependent, it is not practical to prepare the Wiener estimation matrix for all combinations of digital sensor responses. Thus we divide the sensor response space (e.g., a five-dimensional space for a five-channel imaging system) into a small number of sub-blocks and prepare a Wiener estimation matrix for each sub-block. Namely, each pixel of a multichannel image obtained is processed by the Wiener estimation matrix corresponding to the sub-block in which the pixel value falls. Figure 5 shows the schematic illustration of the division into sub-blocks for a three-dimensional case.

B. Validation of the Estimation Method

To validate our method, we examined the estimation accuracy of spectral reflectance through computer simulations based on the measured noise properties. Patch set A was used for both calibration (derivation of Wiener estimation matrix) and evaluation. Five commercially available color filters were selected so as to cover the visible spectral range. These filters are not the optimized ones at this stage. The estimation accuracy was evaluated by both the mean spectral color difference and mean colorimetric color difference. The spectral color difference for each color patch is defined by

$$\Delta E_{spec} \equiv \frac{1}{l}\left\|\hat{\mathbf{f}} - \mathbf{f}\right\|^2 , \tag{11}$$

where l is the number of samples with respect to wavelength, as defined in section 2. Note that the notation for spectral color difference, ΔE_{spec}, is used only for this paper and not a standard one.

The colorimetric color difference is evaluated by the color difference under the D65 standard illuminant measured in CIE-LUV color space, ΔE^*_{uv}, as

$$\Delta E^*_{uv} \equiv [(\hat{L}^* - L^*)^2 + (\hat{u}^* - u^*)^2 + (\hat{v}^* - v^*)^2]^{1/2} , \tag{12}$$

where (L^*, v^*, v^*) and $(\hat{L}^*, \hat{u}^*, \hat{v}^*)$ represent CIE-LUV values corresponding to $\mathbf{f}$ and $\hat{\mathbf{f}}$ under the D65 standard illuminant, respectively.

In order to investigate the effects of dark current subtraction and Wiener estimation incorporating signal-dependent noise properties, we examined the following four cases.

Case 1: Assuming that image capturing is noise free, the estimation accuracy is calculated.

Case 2: It is assumed that recorded data have only positive bias caused by the dark current as a noise component. The estimation accuracy of two cases is compared: (i) without bias subtraction operation, and (ii) with bias subtraction operation.

Case 3: It is assumed that recorded data have only signal-dependent, zero-mean noise with the properties shown in Fig. 4. The estimation accuracy with three types of Wiener estimation matrices are compared: (i) a matrix neglecting noise, (ii) a matrix with a fixed noise correlation matrix with average noise variance, and (iii) 243 matrices which correspond to $3^5 = 243$ sub-blocks in the five-dimensional space of sensor responses where each channel is divided into three levels.

Case 4: It is assumed that recorded data have all the noise properties presented in the previous section. The estimation accuracy of the following cases is compared: (i) the operation without considering any noise properties, and (ii) the operation including both bias subtraction and 243 sub-block Wiener estimation.

Table 3 lists the results. The result for Case 2 clearly shows that dark current subtraction is effective, particularly for DCS420. This is because the dark current level of DCS420 is very high, as mentioned in the previous section. From the result for Case 3, it is obvious that the signal-dependent Wiener estimation is also effective. By introducing the division into sub-blocks, ΔE^*_{uv} improves to around one or less. From the result for Case 4, it was confirmed that the estimation taking all noise properties into account improves the accuracy compared with the estimation without considering any noise properties.

There was no notable difference between the noise properties of the two cameras, except for the dark current level; therefore the estimation method could be applied to both cameras. The tested two cameras do not have high spatial resolution very much. We don't think, however, that the noise properties mentioned above are different in high resolution cameras if those are CCD cameras based on basically the same principles as ones tested this time. Namely, it is expected that the proposed method can be applied to general CCD cameras including high resolution CCD camera.

4.2 Robustness Evaluation of the Estimation Matrix

Using the Wiener estimation matrix obtained with patch set A, the estimation accuracy for the other two patch sets, B and C, was investigated. The assumed filters and noise condition are the same as described in the previous subsection. The color difference was calculated using the range of 380-780nm for set A and 380-730 nm for sets B and C. The result is summarized in Table 4. The accuracy was again evaluated by the two measures used above. As shown in this table, the estimation accuracies for sets B and C are fairly good. This result supports that set A can be used for calibration.

5. Filter Design

The selection of optimum filters from commercially available ones would be a practical and reasonable approach if it provides a sufficiently high accuracy of spectral estimation. On the other hand, we are still interested in how better estimation accuracy can be achieved if the filters would be designed more flexibly. We therefore investigated the best filters and the estimation performance using them.

5.1 Selection of Best Filter Set from Commercially Available Filters

The estimation accuracy for all combinations of 22 color filters in hand was calculated. The range of number of filters assumed is three to six. The filters tested are Fuji Photo film, tri acetyl cellulose base dye filter. Figure 6 shows transmittance spectra of these filters. The mean spectral color difference and mean colorimetric color difference were again used for the evaluation, as described in the previous section. Color sample set A was used again. DCS420 was assumed to be a CCD camera and its noise properties were considered. The result of selection is shown in 5.3 together with optimally designed filters.

5.2 Filter Optimization Using Simulated Annealing

We carried out the optimization of the spectral transmittance of filters. In our optimization, from a practical point of view, single-Gaussian band-pass filters were assumed and its spectral centroid and bandwidth were determined.

Figure 7 illustrates the procedure for filter design. As for the best filter selection mentioned above, color patch set A was used for filter optimization, and the CCD camera DCS420 was assumed. Using the spectral characteristics of the acquisition system, the camera responses corresponding to 145 color patches were first calculated. Next, two correlation matrices, $\mathbf{R}_{ff}$ and $\mathbf{R}_{nn}$, and the acquisition system matrix, $\mathbf{H}$, were used to obtain the Wiener estimation matrix, $\mathbf{W}$. Then the reflectance spectra were estimated using Eq. (4) and the differences between the original and the estimate are calculated. The mean spectral color difference, $\langle \Delta E_{spec} \rangle$, and mean colorimetric color difference, $\langle \Delta E^*_{uv} \rangle$, under CIE D65 standard illuminant were used again as a cost function in optimization.

Minimization of the cost function was done by simulated annealing algorithm [19]. This algorithm is an analogy of the annealing process for making a pure crystal. Annealing, or, reducing temperature slowly as keeping thermal equilibrium makes liquids be crystallized or be at the state of minimum energy. Simulated annealing accepts the update of parameter that increases the cost function or energy, with the probability,

$$p = \exp(-\Delta E / T),$$

where ΔE is the change of cost function due to the update, and T is temperature. The update decreasing the cost function is accepted with probability of 1. Thermal equilibrium is reached by repeating the update of parameters at each T. Starting with high temperature T, we gradually reduce the temperature and repeat the above procedure until temperature becomes low enough and any updates no longer take place. This is a brief outline of simulated annealing. Simulated annealing code in C language is described in [20].

5.3 Result

Table 5(a) and 5(b) list the estimation accuracy achieved with the optimally selected, commercially available filters (called CAFs) and the optimally designed filters (called ODFs) for each number of filters, respectively. The mean values in Table 5 are also plotted in Figure 8. Figures 9 and 10 show the transmittance spectra of the five CAFs and five ODFs that yield the minimum value in each measure, respectively.

For all graphs of Fig. 8, the accuracy improves as the number of filters increases. But the degree of improvement becomes small as the number of filters increases. $\Delta E^*_{uv} \leq 1$ in average may be achieved with six CAFs and with four or more CDFs.

In Figures 9 and 10, filter combinations and shapes for each measure are considerably different. As a general feature, while optimum filter sets under the spectral measure distribute widely in the spectral region, those under the colorimetric measure concentrate in the inside region. This result is explained as follows. The spectral color difference is calculated with equal importance for each wavelength, while the colorimetric color difference is calculated with small weights near both ends of the visible spectral range through the color-matching functions. Under the colorimetric measure, therefore, spectral reflectance in the wavelength range to which human vision is sensitive is more important, and color filters concentrated in this range are selected to achieve good estimation.

In figure 8, while CAFs and ODFs' performance are similar under the spectral measure, CAFs' performance is clearly worse than ODF's under the colorimetric measure. This result seems to have relation to the above mentioned property and transmittance features of CAFs. Many CAFs with a transmittance peak in short wavelength region have high transmittance again in long wavelength region. Any combination of those filters cannot be close to the CDFs shown in Fig. 10(b). On the other hand, CAFs under the spectral measure can be close to the CDFs shown in Fig.

10(a) which are distributed widely in the spectral range. In fact, we assumed to attach an IR filter reducing the transmittance in the long wavelength region and recalculated CAFs. As a result we confirmed that the accuracy of CAFs under the colorimetric measure improved in some degree. However, those CAFs conversely degraded the accuracy under the spectral measure because of the poor performance in representing the long wavelength region.

Figure 11 shows four examples of spectral reflectance estimation obtained with five ODFs based on the spectral measure. The first two examples are moderate accuracy estimation and the others are a best estimation and a worst estimation. In the first two examples, the estimated spectra exhibit slight oscillations compared with the smooth shape of the original spectra. This is because the Wiener estimation matrix in this case has five columns to represent the spectral pattern and the weighted mixture of these columns generates such oscillations. Nonetheless, the estimated profiles achieve an acceptable accuracy on the whole. In the worst estimation example, the estimated reflectance fails to fit the curve in the long wavelength region of the original reflectance. This is again because any Wiener estimation bases do not have such a shape in this region.

6. Discussion

6.1 Comparison with other estimation techniques

In the spectral estimation, we needed an inversion of the system matrix, $\mathbf{H}$, and decided to adopt the Wiener estimation matrix. The other possible techniques include a method using a generalized pseudo inverse and a method using principal components of statistical distribution of the reflectance spectra [21].

Since the problem estimating the spectral reflectance from a limited number of data is underdetermined, the generalized pseudo inverse is given by [22],

$$\mathbf{H}^{-} = \mathbf{H}^{T}(\mathbf{H}\mathbf{H}^{T})^{-1} \quad .$$

Clearly it does not include the statistical information of object and noise as Wiener estimation does. This matrix reconstructs only the components that the system matrix transfers. If we do not have any information about the object and noise, this estimation would be the most reasonable technique. However, we have sure knowledge about the statistics of the object and noise.

The second method makes use of the statistics of the object as well as the Wiener estimation does. This method solves the problem by approximating the spectral reflectance by a linear combination of a small number of PCs. However, this is not the optimum technique in a sense of minimum mean square error unless the subspace spanned by sensor vectors perfectly matches to that spanned by the principal components.

6.2 Comparison with other filer design methods

A series of papers on mathematically sophisticated filter optimization has been published [23]-[27]. These papers' points similar to and different from ours are discussed here. Vrhel and Trussell have proposed a method to determine color filters using a set of color samples and several viewing illuminants [23], and further discussed on the accuracy in the presence of noise [24]. Their methods for designing filters are based on the MMSE criterion as well as ours. They restricted viewing illuminants to several, commonly used ones. This is a practical approach, in particular, in the case that the target is a commercial product. On the other hand, we do not restrict the viewing illuminant. This is not only to offer maximum flexibility in viewing condition but also to meet the needs of archiving the spectrally correct information of invaluable fine arts.

Both their papers and ours take the measurement noise into account. However, there are some differences in assumption. They modeled basically that the measurement noise is signal-independent though several SNR's were investigated. On the other hand, based on the close measurement of camera noise property, we modeled that the noise is signal-dependent and introduced a technique corresponding to such a noise property. We believe that this approach is effective especially when imaging a wide dynamic range of light intensity.

Vrhel and Trussell introduced the constraint on signal power when optimizing the filter in the presence of noise[24][25]. Considering the limited time or limited light intensity in image acquisition, this is reasonable for general scanning situation. On the other hand, we did not introduce such constraint. We assumed that enough time or light intensity can be allowed for image acquisition of a limited number of fine art painting.

Filter optimization by Vola and Trussell is based on “the mean square error of spectra that are independent and identically distributed at each wavelength” [26]. This method is data independent and different from Vrhel’s and ours at this point. In the modeling of filter, however, they introduced a parametric filter design technique using a mixed Gaussian model as we do except that our model is a single Gaussian. They also investigated on the optimum selection from existing filters.

As optimization algorithm, they used Nelder-Mead simplex method or gradient based method. On the other hand, we adopted simulated annealing algorithm. This method takes very long time to converge. This method, however, has a advantage that it provides not local optimum but a global optimum and therefore does not require repeated optimization.

Next, let us compare our results with theirs. Vrhel’s paper says that more filters do not necessarily improve the accuracy. At SNR’s greater than 40 dB, using four-color filters provides a significant improvement over the three optimal filters. But at 50 dB, using more than four filters provides little to no improvement. Sharma et al later modified the Vrhel’s method [27]. The modified method showed that improvement can be achieved as a whole and that “going from three to four filters offers the most significant improvement and the improvement obtained upon using more than four filters is incremental”. Our results show that more filters provide better accuracy though the degree of improvement decreases as the number increases. As mentioned above, we did not introduce a constraint on signal power even for increased number of filter. We consider that this assumption lead to the above result.

7. Conclusions

We have proposed a system for accurately estimating the spectral reflectance of art paintings. Statistical properties of reflectance spectra of paint patches and noise properties of two CCD cameras were analyzed. The results of these analyses were incorporated into the Wiener estimation matrix. Optimum filters used in the multichannel acquisition system were also designed. Through computer simulations, we confirmed that the estimation technique incorporating the noise properties improves the estimation accuracy and that the optimized set of filters can achieve a very high accuracy of spectral estimation. Comparison of our approach with the other methods was also discussed.

In this work, we consistently used two measures of estimation accuracy: spectral color difference and colorimetric color difference. We believe that there is no absolute superiority of one over the other. The former measure is better for exactly archiving the spectral reflectance itself. On the other hand, the latter measure is better for evaluating the appearance by human observers under a specific illuminant. An alternative and practical measure that we did not adopt in this paper would be the average colorimetric color difference under not a specific illuminant but several, commonly used ones as Vrhel et al. did. The selection among these measures should be made according to the application.

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Figure captions

Figure 1 Multichannel imaging system.

Figure 2 Reflectance spectra of three sets of paint patches. Sets A and B: oil paint; Set C: water color paint.

Figure 3 First six principal components of three sets of paint patches.

Figure 4 Noise characteristics against average pixel value. (a) CV-04 (b) DCS420. The pixel value of CV-04 is converted from 16 bits to 8 bits for the purpose of comparison with DCS420.

Figure 5 Schematic illustration of dividing the sensor response space into sub-blocks for signal-dependent Wiener estimation.

Figure 6 Transmittance spectra of 22 color filters commercially available.

Figure 7 Color filter optimization procedure.

Figure 8 Estimation accuracy of spectral reflectance. (a) Spectral color difference ΔE_{spec}, (b) colorimetric color difference ΔE^*_{uv}.

Figure 9 Best combination of five filters among 22 commercially available filters. (a) Spectral measure, (b) colorimetric measure.

Figure 10 Five optimally designed color filters. (a) Spectral measure, (b) colorimetric measure.

Figure 11 Typical examples of spectral reflectance estimation.(a) and (b) moderate accuracy, (c) best accuracy, (d) worst accuracy.

Table 1. Cumulative contribution ratio.

Number of PCs	Set A	Set B	Set C
1	0.701	0.698	0.619
2	0.874	0.909	0.860
3	0.953	0.967	0.956
4	0.976	0.984	0.979
5	0.988	0.991	0.992
6	0.993	0.995	0.995

Table 2. Dark current noise.

CCD camera	Mean
CV-04	448.48 (1.75 *1)
DCS420	20.57

*1 normalized to 8-bit value for the purpose of comparison with DCS420.

Table 3. Estimation accuracy with noise effect

Case 1: Noise free

Case 2: Assuming recorded data have only positive bias caused by dark current with small fluctuation as noise, check the effectiveness of bias subtraction.

Case 3: Assuming recorded data have only signal-dependent, zero-mean noise according to the properties shown in Fig. 4, check the effectiveness of Wiener estimation matrix considering the noise properties.

Case 4: Assuming recorded data have both noise properties mentioned above, check the effectiveness of proposed estimation method.

Camera		CV-04		DCS420	
Color difference measure		$\langle \Delta E_{spec} \rangle$	$\langle \Delta E^*_{uv} \rangle$	$\langle \Delta E_{spec} \rangle$	$\langle \Delta E^*_{uv} \rangle$
Case 1		0.141	1.88	0.167	1.81
Case 2	(i) No subtraction	0.145	2.85	0.792	15.90
	(ii) Subtraction	0.141	1.88	0.168	2.02
Case 3	(i) Neglect noise	0.243	3.18	0.256	3.52
	(ii) 1 block	0.206	3.07	0.219	2.91
	(iii) 243 blocks	0.142	2.17	0.169	1.91
Case 4	(i) No noise operation	0.261	3.68	0.797	16.89
	(ii) All operations	0.143	2.18	0.171	1.95

Table 4. Robustness evaluation of the Wiener estimation.

CCD camera	Patch set	$\langle \Delta E_{spec} \rangle$ (x 10^{-2})	$\langle \Delta E^*_{uv} \rangle$
CV-04	Set A	0.143	2.18
	Set B	0.105	1.70
	Set C	0.140	2.16
DCS420	Set A	0.171	1.95
	Set B	0.155	1.71
	Set C	0.193	1.92

Table 5. Estimation accuracy achieved with (a) the best combination of commercially available filters and (b) the optimally designed filters.

(a)

	ΔE_{spec}			ΔE^*_{uv}		
Number of filters	mean (x 10^{-2})	min (x 10^{-4})	max (x 10^{-2})	mean	min	max
3	0.495	0.79	2.66	3.42	0.06	12.79
4	0.196	0.54	1.66	2.17	0.15	8.76
5	0.114	0.41	1.13	1.24	0.06	5.46
6	0.074	0.42	0.60	0.99	0.05	2.51

(b)

	ΔE_{spec}			ΔE^*_{uv}		
Number of filters	mean (x 10^{-2})	min (x 10^{-4})	max (x 10^{-2})	mean	min	max
3	0.441	0.74	2.33	1.87	0.09	15.26
4	0.179	0.46	1.05	0.71	0.01	4.20
5	0.098	0.32	0.74	0.53	0.02	1.88
6	0.060	0.31	0.19	0.44	0.05	1.59