

# Reflectance reconstruction for multispectral imaging by adaptive Wiener estimation

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**Abstract:** In multispectral imaging, Wiener estimation is widely adopted for the reconstruction of spectral reflectance. We propose an improved reflectance reconstruction method by adaptively selecting training samples for the autocorrelation matrix calculation in Wiener estimation, without a prior knowledge of the spectral information of the samples being imaged. The performance of the proposed adaptive Wiener estimation and the traditional method are compared in the cases of different channel numbers and noise levels. Experimental results show that the proposed method outperforms the traditional method in terms of both spectral and colorimetric prediction errors when the imaging channel number is 7 or less. When the imaging system consists of 11 or more channels, the color accuracy of the proposed method is slightly better than or becomes close to that of the traditional method.

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## 1. Introduction

Recently, multispectral imaging has been widely studied in the reconstruction of the spectral information of the samples being imaged and the recovery of the spectrums of illuminants [1-10]. In a multispectral imaging system, usually more than three imaging channels are used. There are also attempts to recover spectral reflectance using traditional 3-channel digital camera or color scanner [11-13].

In the literature of color imaging, several reflectance reconstruction techniques, such as Wiener estimation [2-4, 8-10], pseudoinverse method [1, 7, 11, 12], and finite-dimensional modeling [4, 11], have been proposed. Among these techniques, Wiener estimation is among the most widely adopted ones, which involves three matrixes, i.e., spectral responsivity, autocorrelation matrix of reflectance, and imaging noise. Shimano proposed a method for reflectance recovery using Wiener estimation without a prior knowledge of the spectral reflectance and system noise [2]. Murakami et al. proposed a nonlinear reflectance estimation method based on Gaussian mixture distribution and Wiener estimation [8]. Shen, *et al.*, found that the color accuracy of the reflectance reconstruction can be improved by combining three different techniques [4].

For a real imaging system, its behavior sometimes departs from the theoretic imaging process, and therefore the special selection of training samples has obvious impact on the color accuracy of the reflectance reconstruction [8, 9, 12, 13]. To cope with this problem, Haneishi et al. proposed to divide the sensor space into several sub-blocks to improve Wiener estimation [9]. Currently, Shen and Xin introduced an optimized estimation method for spectral reflectance reconstruction [12]. Their method consists of three main steps: (1) select a subset of training samples whose responses are close to that of the test sample, (2) calculate the weighting of each training sample, and (3) calculate the transform matrix for the test sample. DiCarlo and Wandell also proposed a method to recover high-dimensional reflectance from low-dimensional response by selecting training samples adaptively [13].

In this study, we propose a method to reconstruct spectral reflectance by using a modified Wiener estimation method, without a prior knowledge of the spectral characteristics of the samples being imaged. We investigate whether the accuracy of reflectance estimation can be improved if the training samples for calculating the reflectance characteristics are adaptively selected and appropriately weighted. The novelty of the proposed method is mainly in the manner of training sample selection and autocorrelation matrix construction. The performance of the proposed adaptive Wiener estimation and the traditional methods are compared in cases of different channel numbers and different noise levels.

## 2. Formulation of multispectral imaging

In this study the multispectral imaging system consists of a monochrome digital camera and several narrowband filters, and the response of the camera is proportional to the intensity of light entering the sensor. Let  $I(\lambda)$  be the spectral power distribution of the imaging illuminant,  $r(\lambda)$  be the spectral reflectance of the sample being imaged,  $f_c(\lambda)$  be the spectral transmittance of the  $c$ th ( $1 \leq c \leq C$ ) channel, and  $s(\lambda)$  be the spectral sensitivity of the monochrome camera, then the response  $v_c$  of the  $c$ th channel can be represented as

$$\begin{aligned} v_c &= \int I(\lambda)r(\lambda)f_c(\lambda)s(\lambda)d\lambda + b_c + n_c, \\ &= \int m_c(\lambda)r(\lambda)d\lambda + b_c + n_c \end{aligned} \quad (1)$$

where  $b_c$  is the bias response caused by dark current, and  $n_c$  is the zero-mean imaging noise. As  $I(\lambda)$ ,  $f_c(\lambda)$  and  $s(\lambda)$  are unknown a priori, they are merged into a single term  $m_c(\lambda)$ , which is referred as spectral responsivity. In practical computation, the continuous functions can be replaced by their sampled counterparts so that the integral can be written as summation. If  $N$  uniformly spaced samples are used over the visible spectrum, Eq. (1) can be written in vector and matrix notation as

$$\mathbf{v} = \mathbf{M}\mathbf{r} + \mathbf{b} + \mathbf{n}, \quad (2)$$

where  $\mathbf{v}$  is the  $C \times 1$  vector of response,  $\mathbf{M}$  is the  $C \times N$  matrix of spectral responsivity,  $\mathbf{r}$  is the  $N \times 1$  vector of reflectance,  $\mathbf{b}$  is the  $C \times 1$  vector of dark current response, and  $\mathbf{n}$  is the  $C \times 1$  vector of imaging noise. In the mathematical recovery of spectral responsivity  $\mathbf{M}$ , two constraints, i.e., non-negativeness and smoothness, are usually imposed [12, 14]. As the filters used in this study are of narrowband, only the non-negativeness constraint for  $\mathbf{M}$  is needed:

$$m_{ij} \geq 0 \quad (3)$$

where  $1 \leq i \leq C$  and  $1 \leq j \leq N$ . For the detailed solution of  $\mathbf{M}$ , interested readers are referred to Ref. 14. If let  $\mathbf{u} = \mathbf{v} - \mathbf{b}$ , Eq. (2) becomes

$$\mathbf{u} = \mathbf{M}\mathbf{r} + \mathbf{n}. \quad (4)$$

### 3. Wiener estimation

The estimation of reflectance is to find an  $N \times C$  matrix  $\mathbf{W}$  that can transform the response  $\mathbf{u}$  into the estimated reflectance  $\hat{\mathbf{r}}$ ,

$$\hat{\mathbf{r}} = \mathbf{W}\mathbf{u}, \quad (5)$$

such that the mean square error between the actual and predicted reflectance is minimized. In Wiener estimation, the transform matrix is

$$\mathbf{W}_{\text{WE}} = \mathbf{K}_r \mathbf{M}^T (\mathbf{M} \mathbf{K}_r \mathbf{M}^T + \mathbf{K}_n)^{-1}, \quad (6)$$

where  $\mathbf{K}_r$  and  $\mathbf{K}_n$  are the autocorrelation matrices of reflectance and noise, respectively:

$$\mathbf{K}_r = E\{\mathbf{r}\mathbf{r}^T\}, \quad (7)$$

$$\mathbf{K}_n = \text{diag}\{\sigma_1^2, \sigma_2^2, \dots, \sigma_C^2\}. \quad (8)$$

In this study the noises of different channels are assumed to be independent, and hence  $\mathbf{K}_n$  is a diagonal matrix. In an actual imaging system, the noise variance of the  $c$ th channel is estimated as

$$\hat{\sigma}_c^2 = E\{\|u_c - \mathbf{m}_c \mathbf{r}\|^2\}, \quad (9)$$

where  $\|\mathbf{x}\|$  denotes Frobenius norm of vector  $\mathbf{x}$ ,  $u_c$  is the response of the  $c$ th channel, and  $\mathbf{m}_c$  is the spectral responsivity of the  $c$ th channel.

### 4. The proposed method

From Eq. (6), it is noticed that the transform matrix  $\mathbf{W}_{\text{WE}}$  in Wiener estimation is decided by 3 matrixes, i.e.,  $\mathbf{M}$ ,  $\mathbf{K}_r$ , and  $\mathbf{K}_n$ .  $\mathbf{M}$  and  $\mathbf{K}_n$  are fixed for a given imaging system, while  $\mathbf{K}_r$  contains the correlation characteristics of the reflectances of the training samples. In traditional Wiener estimation,  $\mathbf{K}_r$  is usually calculated from all the available training samples when it is not easy to get the ensemble of the candidate sample (test sample) in some practical applications. However, it is reasonable to argue that, if the training samples for calculating  $\mathbf{K}_r$  are close to the candidate sample, the transform matrix  $\mathbf{W}$  should contain more meaningful characteristics to the candidate sample. Based on this consideration, we propose a new method for reflectance construction, which is referred as adaptive Wiener estimation in this study.

Suppose the response of the candidate sample is  $\mathbf{u}$ , and then its corresponding reflectance  $\hat{\mathbf{r}}$  can be calculated according to the traditional Wiener estimation in Eq. (6). The training samples with reflectance  $\mathbf{r}_i$  for calculating  $\mathbf{K}_r$  can then be selected according to their spectral similarity to  $\hat{\mathbf{r}}$ . In the calculation of spectral similarity, the reflectance is normalized so that its summation is equal to 1. The reason for normalization is that statistical information of the

reflectance is mainly decided by its shape, not magnitude. The spectral similarity consists of two terms, i.e., mean spectral distance and maximum spectral distance:

$$d_i = \alpha \text{mean} \left\{ \left| \frac{\mathbf{r}_i}{\|\mathbf{r}_i\|} - \frac{\hat{\mathbf{r}}}{\|\hat{\mathbf{r}}\|} \right| \right\} + (1 - \alpha) \max \left\{ \left| \frac{\mathbf{r}_i}{\|\mathbf{r}_i\|} - \frac{\hat{\mathbf{r}}}{\|\hat{\mathbf{r}}\|} \right| \right\}, \quad (10)$$

where  $\alpha$  is a scaling factor,  $|\mathbf{x}|$  denotes the absolute values of the elements of vector  $\mathbf{x}$ . In this study, we let  $\alpha=0.5$ . For two reflectances with similar shapes, both of the mean and maximum distances should not be large. When  $\mathbf{r}_i$  is very similar to  $\hat{\mathbf{r}}$ ,  $d_i$  is close to 0.

We select  $L$  training samples according to their spectral similarities, and sort  $\mathbf{r}_i$  ( $1 \leq i \leq L$ ) in ascending order, or more specifically,  $d_1 \leq d_2 \leq \dots \leq d_L$ . Among the selected  $L$  training samples, it is reasonable to assume that the spectral characteristic of the more similar  $\mathbf{r}_i$  ( $1 \leq i \leq L$ ) should be more close to that of the candidate sample. Therefore, the  $L$  training samples are not equally treated in the calculation of  $\mathbf{K}_r$ . Or equivalently, the closer training samples should contribute more in the  $\mathbf{K}_r$  calculation.

Let  $\Omega$  be the set of training samples,  $\mathbf{r}_i$  is repeated  $k_i$  times:

$$\Omega = \left\{ \underbrace{\mathbf{r}_1 \cdots \mathbf{r}_1}_{k_1 \text{ times}}, \dots, \underbrace{\mathbf{r}_i \cdots \mathbf{r}_i}_{k_i \text{ times}}, \dots, \underbrace{\mathbf{r}_L}_{1 \text{ time}} \right\}, \quad (11)$$

where the repeat time  $k_i$  for the  $i$ th ( $1 \leq i \leq L$ ) selected training sample is calculated as

$$k_i = \lfloor (d_L / d_i)^\gamma + 0.5 \rfloor, \quad (12)$$

where the operator  $\lfloor x \rfloor$  rounds  $x$  to the nearest integer towards zero,  $\gamma$  is the exponential factor. In this study, we let  $\gamma=1$ . As the  $\mathbf{r}_L$  is the most dissimilar training sample to  $\hat{\mathbf{r}}$ ,  $k_L=1$ .

By this way, the number of training samples in set  $\Omega$  is usually larger than  $L$ . Then the transform matrix of the adaptive Wiener estimation becomes

$$\mathbf{W}_{\text{AWE}} = \mathbf{K}_{r,\Omega} \mathbf{M}^T (\mathbf{M} \mathbf{K}_{r,\Omega} \mathbf{M}^T + \mathbf{K}_n)^{-1}, \quad (13)$$

where  $\mathbf{K}_{r,\Omega}$  is the autocorrelation matrix of the reflectances in the training set  $\Omega$ , and  $\mathbf{K}_n$  is the same as Eq. (8). By substituting Eq. (13) into Eq. (5), the spectral reflectance of the candidate sample with response  $\mathbf{u}$  can be reconstructed.

It is noted that the matrix  $\mathbf{W}_{\text{AWE}}$  need to be calculated per pixel in a multispectral image and thus the proposed method is computationally expensive than traditional Wiener estimation. This is actually the common shortcoming for almost all adaptive methods. Nevertheless, it is worthwhile to adopt the adaptive method when the color accuracy is very important.

## 5. Experimental results

In the experiment, the multispectral imaging system includes a QImaging monochrome digital camera model Retiga-EXi, and a liquid crystal tunable filter (LCTF) made by Cambridge Research and Instrument Co. The LCTF can tune the center wavelengths of the narrowband filters electronically. The color target was GretagMacBeth Color Checker DC (CDC), and the reflectances of the color patches on the CDC were measured using a GretagMacBeth spectrophotometer 7000A with an interval of 10 nm. The multispectral images of the CDC were acquired under an approximate D65 lighting condition, and the spatial non-uniformity of the light field was corrected using a white paper. Totally 198 color patches on the CDC were used for reflectance construction, excluding the glossy ones and the duplicated darkest ones. The inherent characteristics of the imaging system, i.e., the spectral responsivity  $\mathbf{M}$  and the noise variances in Eq. (9), were estimated using the CDC. Figure 1 shows the 31-channel spectral responsivity  $\mathbf{M}$ . In the experiment of spectral reflectance estimation, the CDC served as the test target. The reflectances of 1269 Munsell color chips, which were obtained from the

website <http://spectral.joensuu.fi>, were used as training samples. For the sake of data consistency with the measured CDC reflectances, the reflectances of the Munsell chips were also re-sampled at 10 nm interval. The whole collection of the Munsell reflectances is shown in Fig. 2. It is noted that the multispectral images of the Munsell chips are not needed in this study. The autocorrelation matrix  $\mathbf{K}_r$  for the traditional Wiener estimation is calculated from all the 1269 reflectances of the Munsell chips, while the matrix  $\mathbf{K}_{r,\Omega}$  for the proposed adaptive method is calculated from the subset of the selected training reflectances specified in Eq. (11).

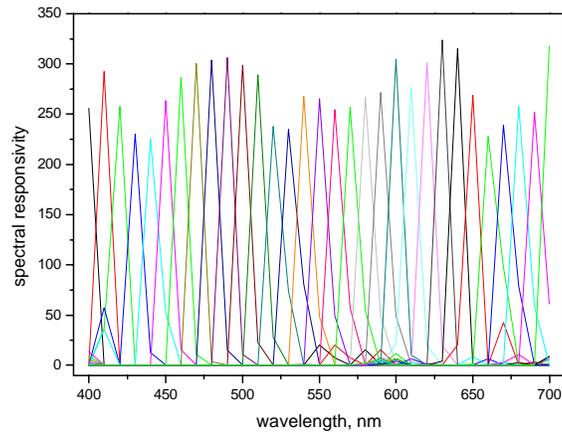


Fig. 1. The spectral responsivities of the 31 channels of the multispectral imaging system.

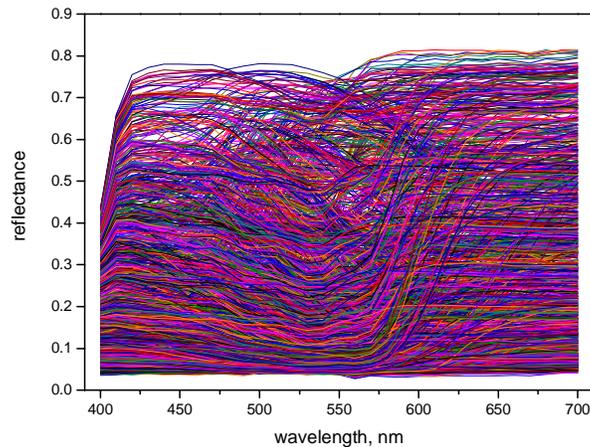


Fig. 2. Reflectances of the 1296 Munsell color chips.

To evaluate the color accuracy of the reflectance reconstruction methods in detail, the experiment was conducted on two data sets, one was synthetic data and the other was real data. In the synthetic data part, the influences of the different combinations of channel number  $C$  and noise level were investigated; in the real data part, only the influences of  $C$  were studied as the noise level was decided by the actual imaging system. The values of channel number  $C$  are 6, 7, 11, or 16. The reason for choosing these  $C$  values is because when the channel sequences are uniformly selected, both of the 1st and 31st channels can be included. Table 1 lists the corresponding channel sequences in each case.

Table 2. The corresponding channel sequences of different channel number  $C$

channel number $C$	channel sequences
6	1,7,13,19,25,31
7	1,6,11,16,21,26,31
11	1,4,7,10,13,16,19,22,25,28,31
16	1,3,5,7,9,11,13,15,17,19,21,23,25,27,29,31

The performance of the proposed method is compared with the traditional Wiener estimation and the optimization method [12]. The comparison between the proposed method and the traditional Wiener estimation was carried out on both synthetic and real data. As the optimization method requires the responses of training samples, its comparison with the proposed method was conducted only on the synthetic data.

The color accuracy of the reflectance reconstruction is evaluated in terms of both spectral and colorimetric error. The spectral rms error between the actual reflectance  $\mathbf{r}$  and its estimate  $\hat{\mathbf{r}}$  is calculated as

$$\text{rms} = \left( \frac{(\mathbf{r} - \hat{\mathbf{r}})^T (\mathbf{r} - \hat{\mathbf{r}})}{N} \right)^{1/2}. \quad (14)$$

The colorimetric error, denoted as  $\Delta E_{00}^*$ , is calculated according to the CIEDE2000 color difference formula [15] under several standard illuminants such as D65 and F2.

### 5.1. Synthetic data

The objective of this part is to comprehensively evaluate the performance of the proposed method under various noise levels and different channel numbers. The spectral responsivity  $\mathbf{M}$  is supposed to be known a priori, and the response  $\mathbf{u}_{\text{syn}}$  of the multispectral imaging system is synthesized as

$$\mathbf{u}_{\text{syn}} = \mathbf{M}\mathbf{r} + \mathbf{n}_{\sigma}, \quad (15)$$

where  $\mathbf{n}_{\sigma}$  denotes additive Gaussian noise with zero-mean and variance  $\sigma^2$ . The noise variance is related to the signal-to-noise ratio (SNR):

$$\text{SNR} = 10 \log \left( \frac{\text{Tr}(\mathbf{M}\mathbf{K}_r\mathbf{M}^T)}{\sigma^2} \right), \quad (16)$$

where the term  $\text{Tr}(\mathbf{M}\mathbf{K}_r\mathbf{M}^T)$  is the average signal power captured by the multispectral imaging system. In this experiment, we investigated the color accuracy of reflectance reconstruction under three SNRs, i.e.,  $\infty$ , 50, and 40.  $\text{SNR}=\infty$  means there is no noise in the imaging system. The noise variance  $\sigma^2$  of the corresponding SNR can be obtained by transforming Eq. (16).

It is noted that the response  $\mathbf{u}_{\text{syn}}$  in Eq. (15) is simulated for each candidate sample on the CDC chart. The responses of the Munsell chips are not simulated for the proposed adaptive Wiener estimation as the selection of training samples is carried out in the reflectance space. For the optimization method, however, the responses of the Munsell samples are also synthesized as its training sample selection is conducted in the response space [12].

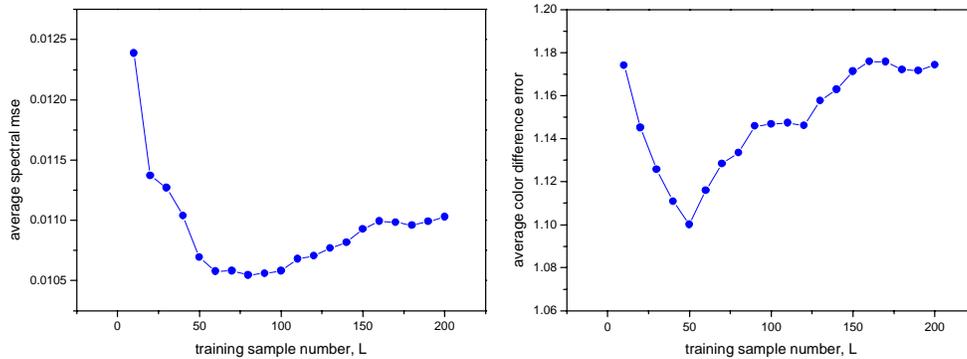


Fig. 3. The distribution of average reflectance rms error (left) and average color difference error (right) with respect to the training sample number  $L$ . Channel number  $C=6$  and  $SNR=50$ .

It is of interest to investigate the influence of training sample number  $L$  on the accuracy of reflectance reconstruction. Figure 3 shows the distributions of average spectral error and colorimetric error with respect to  $L$  when  $C=6$  and  $SNR=50$ , indicating  $L=50$  is appropriate. In the experiment we found that the distribution trends were different when  $C$  and  $SNR$  changed, but the variation of color accuracy was not large. Therefore we simply use  $L=50$  in the following experiments.

Figure 4 shows the selected training sets  $\Omega$  for the given candidates. As expected, the shapes of the training samples are similar to those of the candidate samples.

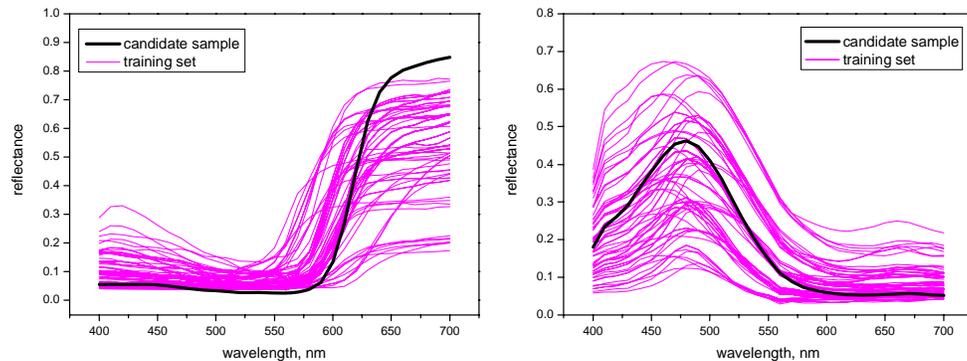


Fig. 4. Two typical examples of the training sets for the given candidate samples. Channel number  $C=6$  and  $SNR=50$ .

Table 2 compares the color accuracy of the proposed adaptive Wiener estimation with the tradition Wiener estimation and the optimization method. In the experiment, the three-dimensional response space of the original optimization method [12] is extended to 6-, 7-, 11-, and 16-dimensional, respectively. It is found that the color errors of the optimization method are generally higher than those of the Wiener estimation and the proposed method, especially when  $SNR$  is low. This indicates that the optimization method doesn't offer good performance for the multispectral imaging system in this study. In the following, we compare the color accuracy of the proposed method and the Wiener estimation method in detail.

Table 2. Comparison of the spectral and colorimetric errors of the proposed adaptive Wiener estimation (AWE), the traditional Wiener estimation (WE), and the optimized method (Opt.) [12] when using synthetic data.

channel number $C$	SNR	method	spectral rms			$\Delta E_{00}^*$ under D65			$\Delta E_{00}^*$ under F2			
			mean	std.	max	mean	std.	max	mean	std.	max	
6	$\infty$	AWE	0.0108	0.0117	0.0978	0.82	1.00	7.17	0.84	1.26	10.86	
		WE	0.0157	0.0113	0.0642	1.17	0.98	5.45	1.44	1.27	6.72	
		Opt.	0.0144	0.0133	0.1190	1.34	1.08	8.82	1.23	1.38	15.87	
	50	AWE	0.0107	0.0103	0.0751	1.10	1.01	6.21	1.11	1.19	8.88	
		WE	0.0160	0.0111	0.0636	1.41	1.08	7.10	1.65	1.33	7.66	
		Opt.	0.0148	0.0136	0.1182	1.49	1.21	8.98	1.38	1.51	16.07	
	40	AWE	0.0126	0.0073	0.0485	1.99	1.86	13.85	1.97	1.90	15.45	
		WE	0.0180	0.0103	0.0625	2.28	1.88	11.57	2.40	1.97	13.04	
		Opt.	0.0191	0.0130	0.1168	2.38	1.96	11.42	2.28	2.31	16.42	
	7	$\infty$	AWE	0.0090	0.0118	0.0991	0.75	0.92	7.73	0.77	1.36	10.94
			WE	0.0112	0.0077	0.0391	0.95	0.63	3.07	0.99	1.05	9.37
			Opt.	0.0114	0.0107	0.0875	1.08	0.92	6.09	1.02	1.13	10.38
50		AWE	0.0087	0.0085	0.0657	0.92	0.88	5.46	0.93	1.13	7.96	
		WE	0.0116	0.0074	0.0386	1.11	0.80	5.96	1.16	1.08	8.79	
		Opt.	0.0117	0.0097	0.0916	1.27	1.00	6.52	1.21	1.19	11.00	
40		AWE	0.0111	0.0054	0.0446	1.75	1.79	15.74	1.73	1.77	15.80	
		WE	0.0146	0.0067	0.0342	1.98	1.85	14.61	2.03	1.83	14.01	
		Opt.	0.0164	0.0131	0.1501	2.16	1.97	13.45	2.19	2.19	16.55	
11		$\infty$	AWE	0.0049	0.0039	0.0267	0.19	0.21	2.29	0.20	0.27	3.02
			WE	0.0060	0.0048	0.0245	0.14	0.08	0.47	0.16	0.14	1.19
			Opt.	0.0049	0.0039	0.0315	0.24	0.18	1.37	0.23	0.21	2.13
	50	AWE	0.0061	0.0038	0.0303	0.61	0.54	3.55	0.60	0.51	2.92	
		WE	0.0064	0.0025	0.0166	0.58	0.57	3.30	0.58	0.55	3.68	
		Opt.	0.0069	0.0046	0.0489	0.64	0.55	3.20	0.64	0.54	4.00	
	40	AWE	0.0105	0.0045	0.0393	1.64	1.62	11.56	1.62	1.55	9.95	
		WE	0.0125	0.0044	0.0257	1.76	1.74	10.83	1.73	1.67	9.24	
		Opt.	0.0144	0.0048	0.0392	1.82	1.75	10.95	1.79	1.75	13.82	
	16	$\infty$	AWE	0.0038	0.0029	0.0172	0.10	0.16	1.84	0.11	0.14	1.73
			WE	0.0038	0.0046	0.0220	0.04	0.02	0.19	0.08	0.04	0.33
			Opt.	0.0030	0.0026	0.0218	0.12	0.10	0.67	0.13	0.11	1.04
50		AWE	0.0056	0.0032	0.0253	0.58	0.47	3.20	0.59	0.46	3.29	
		WE	0.0054	0.0019	0.0137	0.53	0.47	3.55	0.59	0.51	3.58	
		Opt.	0.0060	0.0021	0.0234	0.58	0.55	4.34	0.64	0.64	4.44	
40		AWE	0.0103	0.0044	0.0401	1.51	1.25	9.04	1.50	1.25	9.20	
		WE	0.0123	0.0046	0.0270	1.59	1.28	8.51	1.68	1.38	9.51	
		Opt.	0.0165	0.0045	0.0332	1.75	1.61	10.98	1.97	1.93	13.79	

In the case of 6 and 7 channels, the proposed method outperforms the Wiener estimation in terms of both spectral rms error and color difference error, at a significant level of  $p=0.01$ . In the case of 11 channels, the spectral rms error of the proposed method is lower than that of the Wiener estimation, but the color difference error is slightly larger when  $\text{SNR}=\infty$  and  $\text{SNR}=50$ . This seeming contradiction is due to the nonlinear transform between reflectance and CIELAB space, and also the nonlinear operation involved in the color difference formula calculation. In the case of 16 channels, the spectral errors of proposed method are similar to or even slightly larger than those of the Wiener estimation. The maximum spectral rms errors and color difference errors of the proposed method are usually larger than those of the Wiener estimation for different channel numbers and noise levels. It is interesting to observe that in the case of 11 and 16 channels, both of the spectral and colorimetric errors are lower than those of the Wiener estimation when  $\text{SNR}=40$ . As a whole, it can be conclude from Table 2 that the superiority of proposed method is obvious when the channel response information is not very complete or degraded by noise, or more specifically, when channel number is small or SNR is low.

### 5.2. Real data

In the experiment of real data, the actual responses of the imaging system were used. The color accuracies of the proposed method and the traditional Wiener estimation were investigated using different channel numbers. The noise variances were estimated according to Eq. (9). The spectral rms errors and color difference errors are listed in Table 3. It is observed that the proposed method outperforms Wiener estimation in the cases of 6 and 7 channels. For the case of 11 and 16 channels, the color accuracies of the proposed method are close to those of the Wiener estimation. This finding is consistent with that in synthetic data experiment part. Figure 5 shows typical reconstructed reflectances using the proposed method and the Wiener estimation when channel number  $C=7$ . It is found that the reflectances reconstructed by the proposed adaptive Wiener estimation are more accurate than those of the traditional Wiener estimation.

Table 3. Comparison of the spectral and colorimetric errors of the proposed adaptive Wiener estimation (AWE) and the traditional Wiener estimation (WE) when using real data.

channel number $C$	method	spectral rms			$\Delta E_{00}^*$ under D65			$\Delta E_{00}^*$ under F2		
		mean	std.	max	mean	std.	max	mean	std.	max
6	AWE	0.0144	0.0090	0.0488	1.38	0.91	4.79	1.37	0.94	4.68
	WE	0.0186	0.0124	0.0642	1.55	1.15	7.48	1.77	1.33	8.05
7	AWE	0.0124	0.0080	0.0451	1.05	0.59	3.37	1.13	0.68	4.52
	WE	0.0148	0.0094	0.0433	1.25	0.70	3.52	1.33	0.95	5.82
11	AWE	0.0112	0.0072	0.0379	0.86	0.45	2.67	0.90	0.47	2.64
	WE	0.0112	0.0069	0.0328	0.85	0.50	3.43	0.89	0.51	2.99
16	AWE	0.0106	0.0069	0.0356	0.82	0.44	2.74	0.84	0.45	2.70
	WE	0.0100	0.0064	0.0321	0.79	0.48	3.31	0.83	0.47	2.96

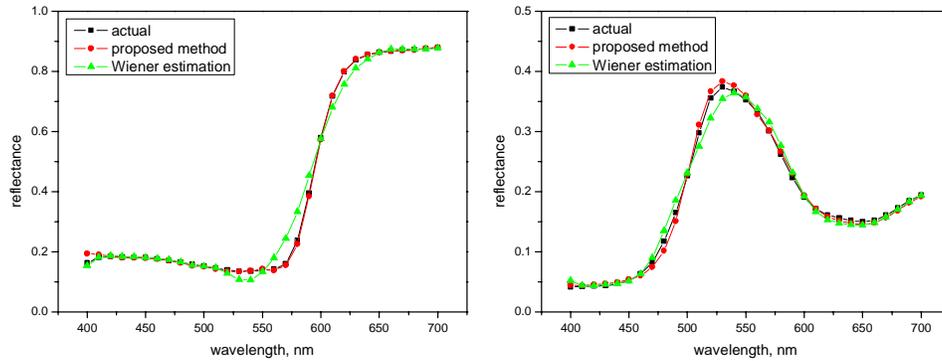


Fig. 5. Reflectance reconstruction of the proposed adaptive Wiener estimation and traditional Wiener estimation when using real data. Channel number  $C=7$ .

## 6. Conclusion

This paper proposes an improved Wiener estimation method for the reconstruction of spectral reflectances without a prior knowledge of the samples being imaged, by the adaptive selection of training samples. The performance of the proposed adaptive Wiener estimation is investigated for the different channel numbers and SNR levels. Experimental results indicate that the proposed method is significantly better than the Wiener estimation when the channel number is not large (for example, 6 or 7), while is slightly better than or close to the traditional Wiener estimation when channel number 11 or more. The proposed method is of potential applications in textile, printing, and other industries.

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