Wiener Estimation Method in Estimating of Spectral Reflectance from RGB Images[1]

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Abstract—Color is one of the most important features in digital images. The representation of color in digital form with a three-component image (RGB) is not very accurate, hence the use of a multiple-component spectral image is justified. At the moment, acquiring a spectral image is not as easy and as fast as acquiring a conventional three-component image. One answer to this problem is to use a regular digital RGB camera and estimate its RGB image into a spectral image by the *Wiener estimation* method, which is based on the use of a priori knowledge. In this paper, the *Wiener estimation* method is used to estimate the spectra of icons. The experimental results of the spectral estimation are presented.

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1. INTRODUCTION

The aim of this study is to use the Wiener estimation [4] method in spectral image estimation from RGB images. A spectral image is an image which has tens of components, whereas a conventional RGB image has three. The spectrum of visible light (380–780 nm) is sampled with a suitable wavelength interval. This leads to more accurate reproduction of colors in digital form [1].

At the moment, the acquisition of spectral images with a spectral camera is slow, and the mobility of the equipment is poor. These reasons lead us to the estimation of spectral images from the RGB image acquired by a digital RGB camera. With this method, collecting spectral data of pictures, for example, in museums and art exhibitions, is easier because of the RGB camera's good mobility and fast image acquiring time [3].

The estimation of the spectral image is done using the Wiener estimation method, which is based on the use of a priori knowledge [4]. In our research, we used a Gretag Macbeth standard color checker with 24 color pads as a priori samples. We measured the spectra of the color pads with a radiometer and acquired RGB images with a digital SLR camera.

[1] The text was submitted by the authors in English.

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2. WIENER ESTIMATION

The purpose of the Wiener estimation is to make estimations from low-dimensional data into high-dimensional data, for example, from three-filter camera responses into reflectance spectra. The wiener estimation is one of the conventional estimation methods which is quite simple and provides accurate estimates [1].

The response of a digital camera $v_i(x, y)$ in spatial coordinates (x, y) with ith color filter can be calculated with Eq. (1),

$$v_i(x, y) = \int t_i(\lambda)E(\lambda)S(\lambda)r(x, y; \lambda)d\lambda, \quad i = 1, \dots, m, \tag{1}$$

where $t_i(\lambda)$ is the permeability of the ith filter, $E(\lambda)$ is the spectrum of the illuminant, $S(\lambda)$ is the sensitivity of the camera, and $r(x, y; \lambda)$ is the reflectance spectrum in spatial coordinates (x, y). In practice, there are only three filters in a digital camera with filters R, G, and B, so in this study m is three.

It is useful to present Equation 1 as vectors and matrices. In this form, the equation is

$$v = Fr, \tag{2}$$

where v is an m element column vector and r is a k element column vector which corresponds to the reflectance spectrum of one pixel of an image. In Eq. (2), the r and v vectors are related to each other

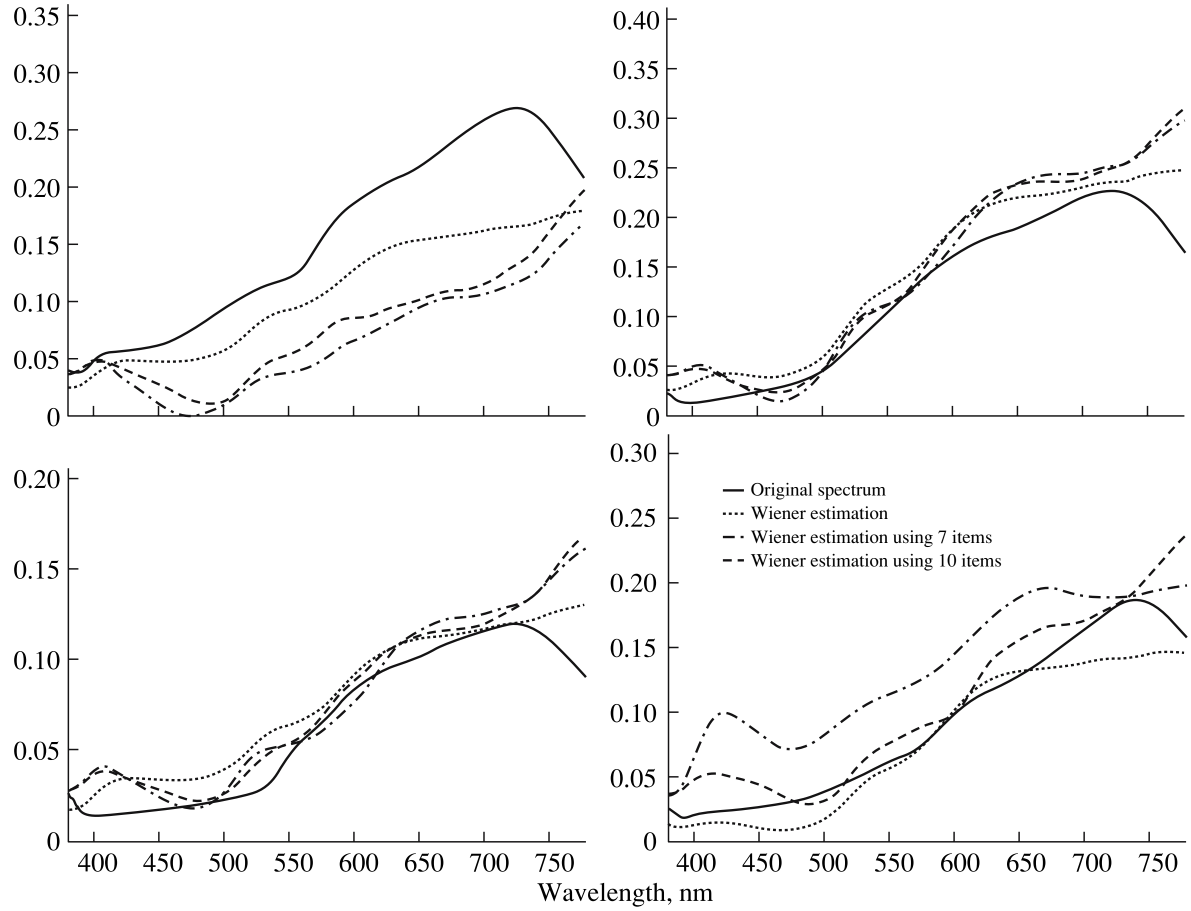

Fig. 1. Estimated average spectra of the icons 1–4. The continuous line represents the original spectrum; also given are the estimated spectra with three terms (dotted), seven terms (dashed–dotted), and ten terms (dashed).

by a linear ($m \times k$) matrix F. Matrix F is represented as follows:

$$F = UES, \tag{3}$$

where

$$U = [u_1, u_2, u_3]^t. \tag{4}$$

Column vector u_i represents the response of the ith filter (in our case, the number of filters was three, which comes from RGB), and $[\,]^t$ is a transpose. In Eq. (3), matrices E (spectrum of the illuminant) and S (sensitivity of the camera) are ($k \times k$) diagonal matrices.

The solution to Eq. (2) can be found using the linear Wiener estimation method,

$$r_{\mathrm{est}} = Gv, \tag{5}$$

where v is the RGB response vector and G is the estimation matrix. The purpose of the estimation matrix G is to minimize the minimum square error between original r and estimated r_{est}

$$e = \langle |r - r_{\mathrm{est}}| \rangle \longrightarrow \min. \tag{6}$$

In Eq. (6), signs $\langle\ \rangle$ mean that the error e is normalized by the amount of used reflectance spectra. Estimation matrix G is explicitly represented as follows:

$$G = R_{rv} R_{vv}^{-1}, \tag{7}$$

where R_{rv} and R_{vv} are correlation matrices. R_{rv} and R_{vv} are defined as

$$R_{rv} = \langle r v^t \rangle, \quad R_{vv} = \langle v v^t \rangle. \tag{8}$$

In Eq. (8), R_{rv} is the cross-correlation matrix between vectors r and v. Matrix R_{vv} is the autocorrelation matrix of vector v [1, 2].

The spectral image data $f(x, y, \lambda)$ are calculated from vector v, which is the RGB response, or with vector v including higher order pixel values. In the digital image $f(x, y)$, the matrix G is used as follows:

$$f(x, y, \lambda) = Gv, \tag{9}$$

where G is the estimation matrix. Usage of higher order terms means that instead of using only RGB values, we

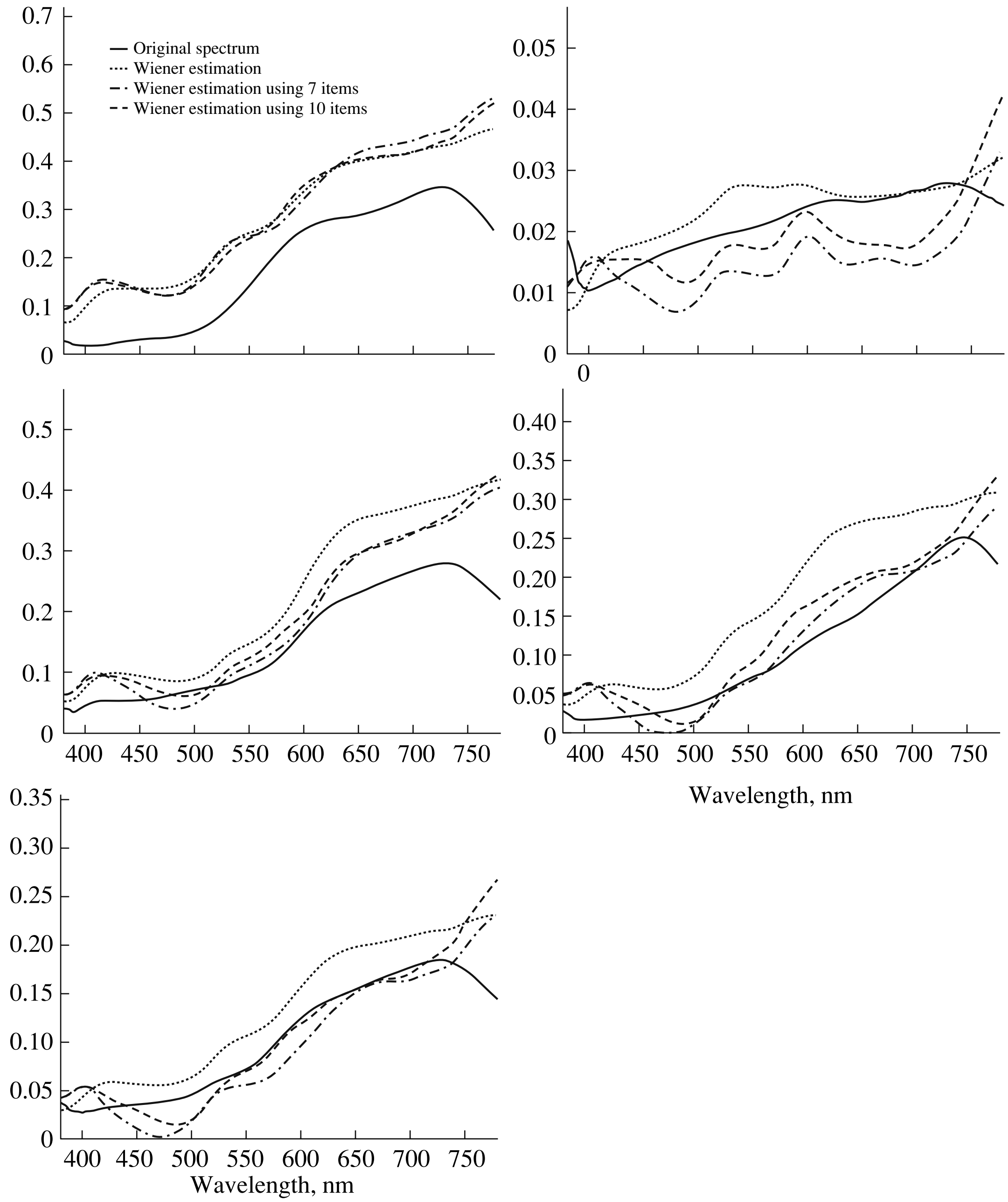

Fig. 2. Estimated average spectra of the icons 5–9. The original spectrum is the continuous line and the estimated spectra are given with three terms (dotted), seven terms (dashed–dotted), and ten terms (dashed).

also use [$R * G$, $R * G$, $G * B$, R^2, G^2, B^2] and a constant value 1 [3]. We also wanted to test third-order polynomials to reproduce color. This idea came from Jon Hardeberg's thesis, where he uses third-order polynomials in the linear regression step of colorimetric scanner characterization. Third-order polynomials are [$R * G * B$, $R * G * G$, $R * R * G$, $R * R * B$, $B * G * G$, $B * B * G$, $B * B * R$, R^3, G^3 and B^3] [2].

3. ERROR MEASURES

In this study, we used peak-signal-to-noise (PSNR), root-mean-square error (RMSE), $\Delta E_{\mathrm{CIELAB}}$, and $\Delta E_{\mathrm{S\text{-}CIELAB}}$ error measures. The first of these, PSNR, is calculated using the equation

$$\mathrm{PSNR} = 10\log\left(\frac{2^{\mathrm{bpp}}-1}{\mathrm{RMSE}}\right), \tag{10}$$

Fig. 3. On the left, an icon acquired with a spectral camera and transformed into sRGB color space. On the right, the same icon acquired with a digital RGB camera, estimated into spectra image with the Wiener estimation method and then transformed into sRGB color space.

where RMSE is calculated with Eq. (11) and bpp is the amount of bits per pixel. The unit of PSNR is dB.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \Delta x_i^2}{n}}. \qquad (11)$$

In Eq. (11), n is the number of spectral channels and x is the spectral reflectance vector of one pixel. Δx_i^2 is the squared difference of the ith channel values of two spectra.

The color difference was calculated using Eq. (12), where ΔL^{*2}, Δa^{*2}, and Δb^{*2} are the squared differences of the $L^*a^*b^*$ transforms of two spectra.

Table 1. Error measures of the icons. Wiener estimated spectral images from RGB images compared to original spectral images of the icons. Three, seven, and ten terms used in estimation

	3 terms				7 terms				10 terms			
	RMSE	PSNR	$\Delta E_{\mathrm{CIELAB}}$	$\Delta E_{\mathrm{S\text{-}CIELAB}}$	RMSE	PSNR	$\Delta E_{\mathrm{CIELAB}}$	$\Delta E_{\mathrm{S\text{-}CIELAB}}$	RMSE	PSNR	$\Delta E_{\mathrm{CIELAB}}$	$\Delta E_{\mathrm{S\text{-}CIELAB}}$
icon 1	0.114	66.984	15.300	10.822	0.096	68.460	26.593	15.756	0.094	68.692	16.652	12.090
icon 2	0.137	65.370	14.905	10.474	0.133	65.660	28.606	17.692	0.128	66.014	15.902	11.493
icon 3	0.067	71.649	20.693	11.050	0.098	68.263	18.852	13.081	0.086	69.488	14.500	9.377
icon 4	0.092	68.825	14.192	8.595	0.089	69.146	28.802	14.416	0.086	69.457	19.112	11.116
icon 5	0.086	69.450	12.899	8.163	0.093	68.792	13.848	8.537	0.092	68.826	13.960	8.751
icon 6	0.182	62.934	28.893	21.487	0.213	61.561	28.006	20.821	0.214	61.532	26.611	19.784
icon 7	0.071	71.130	11.174	7.812	0.113	67.046	27.471	18.200	0.102	67.946	20.292	15.331
icon 8	0.023	80.733	10.685	4.670	0.024	80.709	10.843	5.261	0.023	80.826	9.658	4.736
icon 9	0.093	68.735	20.721	13.272	0.096	68.528	21.017	13.029	0.094	68.640	20.992	13.034
Mean	0.096	69.534	16.607	10.705	0.106	68.685	22.671	14.088	0.102	69.047	17.520	11.746

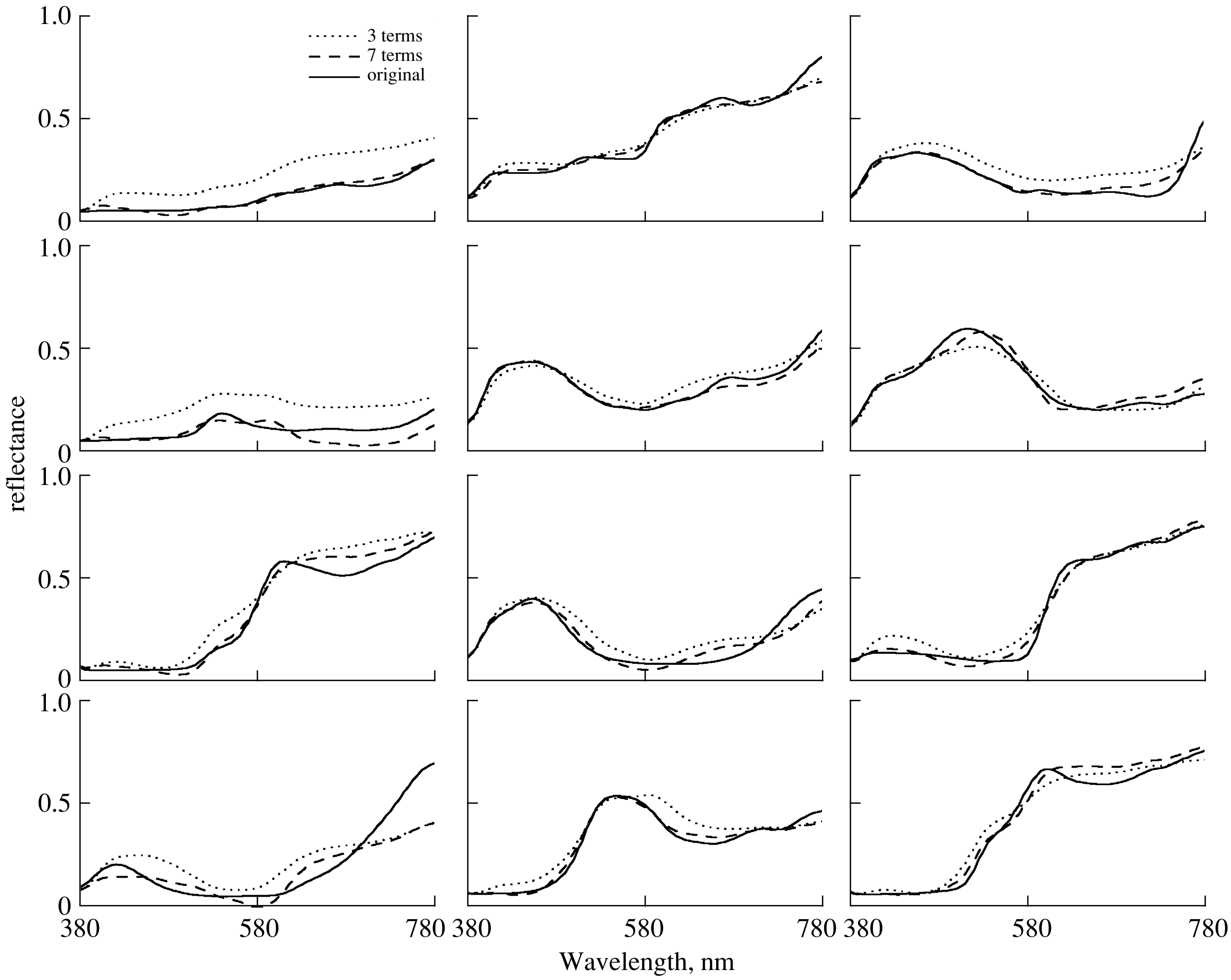

Fig. 4. First 12 Macbeth checker-board pads, their original spectra measured with a radiometer, and Wiener-estimated spectra using three and seven terms.

The error measures were calculated for icons and for the Macbeth color checker. Aside from the Macbeth color checker, we did not use $\Delta E_{\text{S-CIELAB}}$. S-CIELAB color difference also takes into account the spatial properties of the image and it can be calculated using the scielab.m-function. This function is downloadable from the web address http://white.stanford.edu/~brian/scielab/ [5].

$$\Delta E_{\text{CIELAB}} = \sqrt{\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2}} \quad (12)$$

4. TESTING THE ESTIMATION

We used icons and the Macbeth color checker to test the Wiener estimation. The testing was done so that we first acquired spectral images of the icons with an ImSpector spectral camera and then acquired RGB images of both the icons and the color checker with a Fujifilm S1 Pro digital SLR camera.

All the images were taken under D65 standard illumination with 45/0 geometry. We used a standard white to measure the illumination spectrum. The illumination spectrum was used to transform the raw spectral camera data into reflectance spectra. This was done by dividing the spectral camera radiance spectra with the standard illumination spectrum. Also the noise of the camera was taken into account. It was measured with the lens cap on and subtracted from both the spectral radiance data and the standard white spectrum before dividing.

Before starting the calculations, we had to measure the a priori data with a radiometer. This was also done under standard D65 illumination but now with 0/45 geometry. After removing the effect of the light source, we got 24 reflectance spectra from the color checker. The estimated average spectra of the nine icons are presented in Figs. 1 and 2. The original spec-

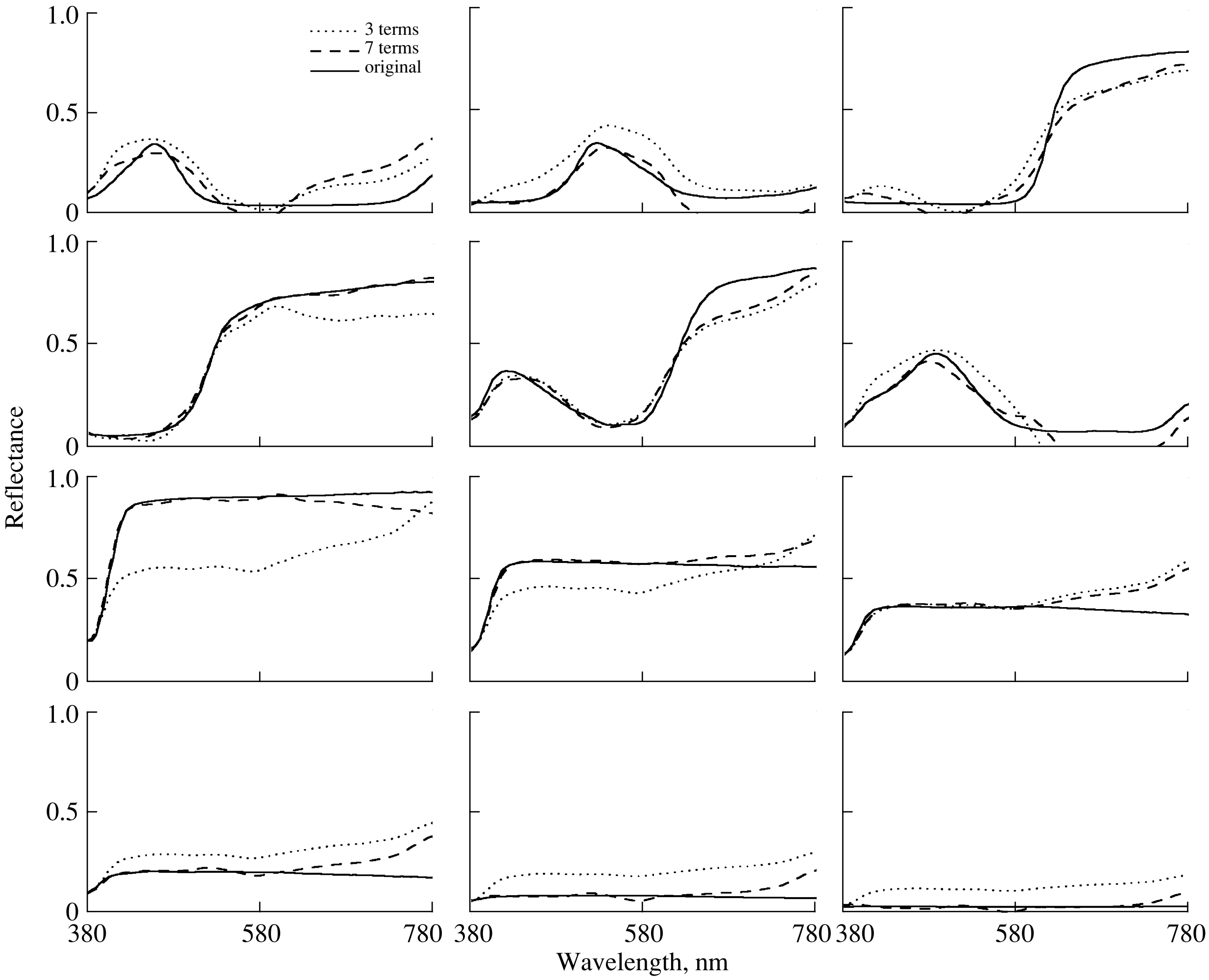

Fig. 5. Last 12 Macbeth checker-board pads, their original spectra measured with a radiometer, and Wiener-estimated spectra using three and seven terms.

tra are the continuous lines and the estimated spectra with three terms (dotted), seven terms (dashed–dotted), and ten terms (dashed).

The icon images were 512 × 640 pixels each. The program we used for data processing was Matlab version 6.5 with 8-byte real values for calculations. The spectral wavelength area was from 380 nm to 780 nm and the wavelength interval was 5 nm, which meant 81 samples for each pixel's spectrum. This means that the icon images took 512 × 640 × 81 × 64 bits (about 210 megabytes) of memory.

The Wiener estimation for icons was made so that first we took images of the icons and the Macbeth checker board, which was placed next to every icon, with RGB camera. The exposure time was chosen suitably for every icon. At the same time, we got images of the Macbeth board with corresponding exposure times for every icon. We used these RGB values of the Macbeth board pads as a priori data.

Then we calculated the Wiener estimation matrix with Eq. (7) for each icon with RGB and spectral values of the Macbeth checker board pads. The spectral values were the same for every icon. When the estimation matrix was ready, we used the RGB pixel vectors of an RGB icon image with Eq. (5), which gave us the estimated spectral reflectance of every pixel of the spectral image.

As a result of the Wiener estimation for the RGB images, we obtained the spectral images. In the Wiener estimation, three, seven, and ten terms were used for all the icons. The three and ten terms were the same as indicated earlier in this paper, and the seven terms were R, G, B, R^2, G^2, B^2, and 1.

In Fig. 3, there are two images of the same icon: on the left is the spectral camera image transformed into sRGB color space and on the right is a Wiener estimated spectral image of a digital camera RGB image transformed into sRGB color space. This is just an example to show what the tested icons look like.

Table 2. Error measures of the Macbeth checker-board pads. Wiener estimated spectral reflectances from RGB images of the Macbeth checker-board pads compared to original spectral reflectances of the pads. Three, seven, ten, and nineteen terms used in estimation

	3 terms			7 terms			10 terms			19 terms		
Macbeth color	PSNR	RMSE	ΔE_{CIELAB}	PSNR	RMSE	ΔE_{CIELAB}	PSNR	RMSE	ΔE_{CIELAB}	PSNR	RMSE	ΔE_{CIELAB}
1 Moderate brown	79.928	0.026	3.469	74.958	0.046	13.293	78.361	0.031	8.614	72.557	0.060	4.535
2 Light reddish brown	73.487	0.054	6.086	69.480	0.086	8.085	72.045	0.064	5.894	79.957	0.026	2.356
3 Moderate blue	71.411	0.069	10.326	79.038	0.028	2.786	78.005	0.032	2.900	81.653	0.021	2.036
4 Moderate olive green	74.333	0.049	9.762	77.058	0.036	7.142	81.469	0.022	3.066	77.848	0.033	5.582
5 Light violet	69.654	0.084	14.096	74.695	0.047	5.402	75.624	0.042	5.477	82.622	0.019	1.410
6 Light bluish green	70.180	0.079	13.817	71.525	0.068	5.869	79.873	0.026	2.066	94.290	0.005	0.436
7 Strong orange	72.139	0.063	14.150	76.575	0.038	10.205	79.630	0.027	1.580	81.704	0.021	3.550
8 Strong purplish blue	70.800	0.074	13.576	70.440	0.077	15.029	78.872	0.029	3.103	76.747	0.037	4.469
9 Moderate red	71.678	0.066	5.846	70.730	0.074	4.594	74.827	0.046	0.664	84.190	0.016	1.697
10 Deep purple	65.019	0.143	10.643	65.314	0.138	18.330	66.539	0.120	4.635	71.990	0.064	0.884
11 Strong yellow green	71.895	0.065	16.352	83.489	0.017	2.798	76.131	0.040	2.855	85.264	0.014	0.543
12 Strong orange yellow	72.810	0.058	11.986	75.906	0.041	6.397	79.414	0.027	5.907	82.245	0.020	7.687
13 Vivid yellowish green	74.055	0.051	12.542	72.374	0.061	15.741	68.159	0.100	14.514	73.678	0.053	4.955
14 Strong yellowish green	71.834	0.065	6.966	72.253	0.062	11.877	84.198	0.016	3.699	86.541	0.012	1.827
15 Strong red	72.005	0.064	12.549	71.695	0.066	32.004	79.351	0.027	2.388	95.353	0.004	1.547
16 Vivid yellow	70.324	0.078	16.488	72.260	0.062	5.418	73.126	0.056	2.620	84.031	0.016	3.165
17 Strong reddish purple	74.206	0.050	4.401	75.187	0.044	2.511	78.621	0.030	4.815	97.761	0.003	0.090
18 Strong greenish blue	72.941	0.057	8.224	75.791	0.041	10.488	76.151	0.040	3.883	94.261	0.005	0.444
19 White	59.834	0.260	14.997	70.882	0.073	2.467	78.507	0.030	1.020	97.337	0.003	0.124
20 Light grey	69.097	0.089	6.328	77.428	0.034	1.299	78.490	0.030	1.607	82.161	0.020	1.252
21 Light medium grey	70.901	0.073	1.383	72.245	0.062	1.906	74.950	0.046	2.117	81.164	0.022	1.394
22 Medium grey	73.323	0.055	5.170	74.745	0.047	4.609	76.099	0.040	4.155	81.674	0.021	0.998
23 Grey	85.760	0.013	3.885	79.127	0.028	6.535	80.341	0.025	4.282	89.302	0.009	1.697
24 Black	87.034	0.011	5.176	83.457	0.017	7.890	85.101	0.014	5.451	87.962	0.010	3.145
Mean	72.694	0.071	9.509	74.444	0.054	8.443	77.245	0.040	4.055	84.262	0.021	2.326

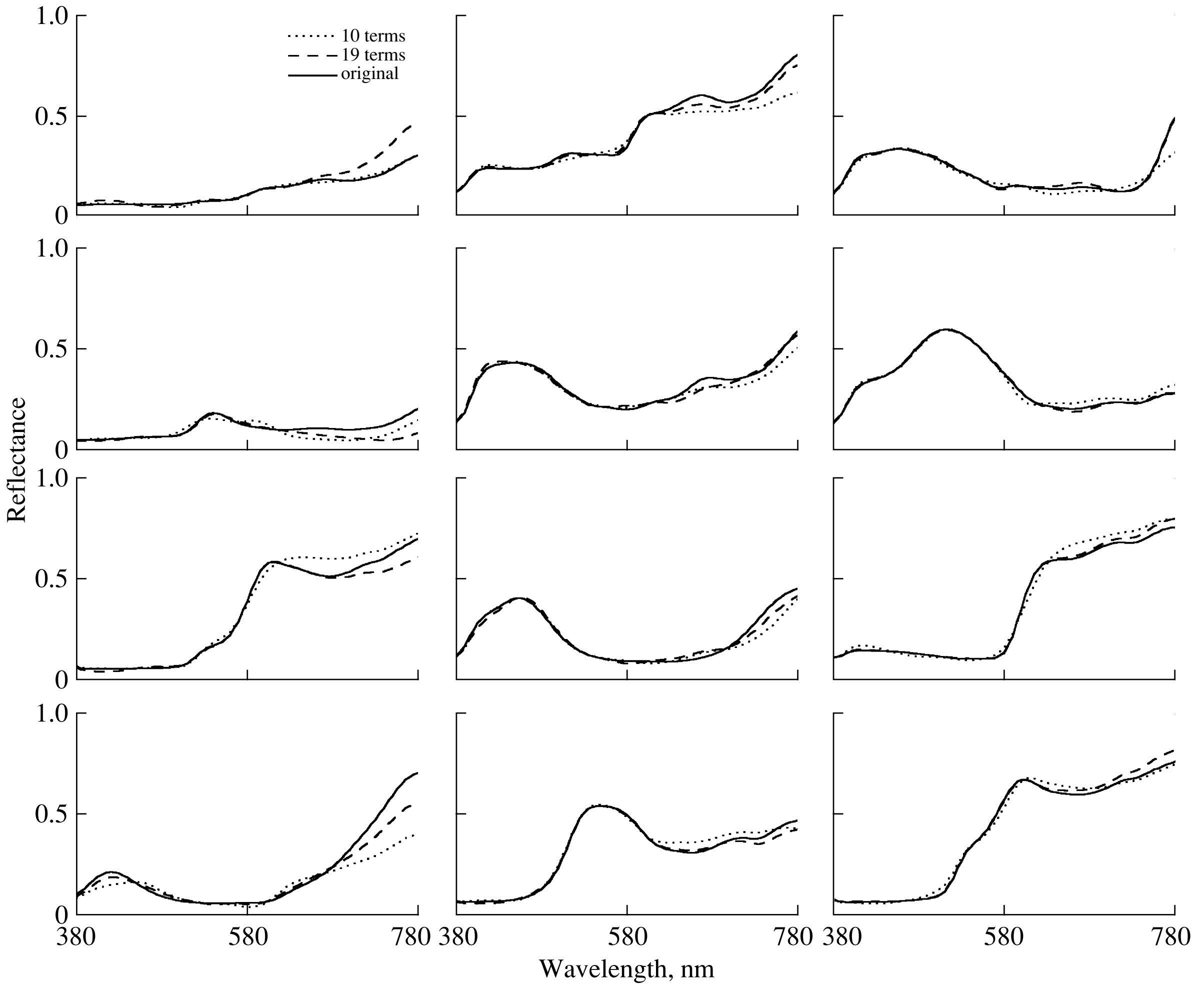

Fig. 6. First 12 Macbeth checker-board pads, their original spectra measured with a radiometer, and Wiener-estimated spectra using 10 and 19 terms.

When examining the images in Fig. 3, one can make conclusions about the differences in color only by the color space ocular in sRGB. We wanted to know how the spectra differ from each other so we calculated error measures. The calculations were done using three different numbers of terms in the Wiener estimation for the icons. The results show quite large color differences when comparing the original spectral images to the Wiener estimated ones. The biggest reason for this is a mirror-like reflection and the form of the surface of the icons. The RGB images taken with the digital SLR camera tend to saturate in some parts of the icon, hence the exposure time is too low for the camera to receive a noiseless or low-noise image from other parts of the icons than the parts that have the mirror-like reflection.

In the icons' case, it can be seen that with three and ten terms we have the best $\Delta E_{\mathrm{CIELAB}}$ and $\Delta E_{\mathrm{S\text{-}CIELAB}}$ values in Table 1. All $\Delta E_{\mathrm{CIELAB}}$ and $\Delta E_{\mathrm{S\text{-}CIELAB}}$ values were calculated using a D65 standard light source and a CIE 1931 standard colorimetric system. We also tested the estimation with 19 terms, but then all of the error values were not acceptable anymore. As mentioned earlier, this is due to the noisy and partly saturated RGB images.

With the Macbeth color checker, we used all amounts of terms when testing the Wiener estimation for all 24 color pads. It shows in Figs. 4–7 that 19 terms works very well, but, for example, 3 terms works poorly with almost all the pads. This can also be seen from Table 2.

5. CONCLUSIONS

The tests conducted with icons and the Macbeth color checker show us that the number of terms in the Wiener estimation affects on the results. In the icons' case, the estimations with 3 and 10 terms gave the best results. In the Macbeth checker-board case, 19 terms gave the best results. One reason for this difference between the best results in the two different test material cases is the RGB camera's noisy and partly satu-

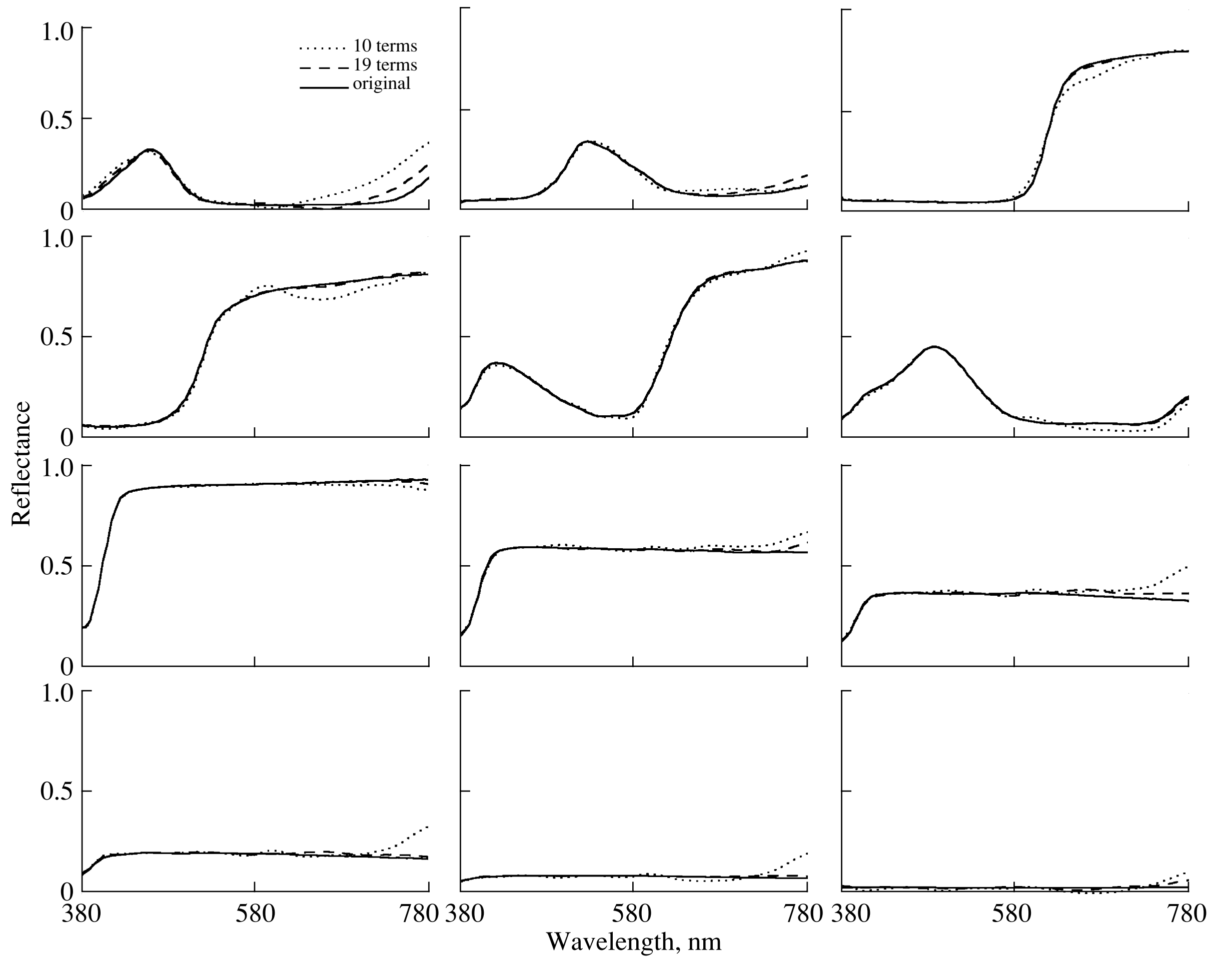

Fig. 7. Last 12 Macbeth checker-board pads, their original spectra measured with a radiometer, and Wiener-estimated spectra using 10 and 19 terms.

rated response of the icons. Another straightforward reason is the choice of a priori data.

We can conclude that with a low noise and unsaturated RGB image, the increasing of terms improves the result in Wiener estimation when the a priori data is, on some suitable scale, similar enough to the material to be estimated.

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