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Spectral Estimation of Printed Colors Using a Scanner, Conventional Color Filters and Applying Backpropagation Neural Network

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ABSTRACT

Reconstructing the spectral data of color samples using conventional color devices such as a digital camera or scanner is always of interest. Nowadays, multispectral imaging has introduced a feasible method to estimate the spectral reflectance of the images utilizing more than three-channel imaging. The goal of this study is to spectrally characterize a color scanner using a set of conventional color filters. To this end, a 1355 chart was generated and printed; the images of the printed charts were scanned putting a translucent color filter in front of each page during scanning process. Each page was scanned with 4 color filters, including gray, blue, green and yellow ones. A feed-forward Back-Propagation neural network with 12 input neurons of camera responses, one hidden layer containing 20 neurons, and an output layer of 31 neurons of spectral reflectance values was applied. It was shown that it is accurately possible to estimate the spectral data of printed samples from the scanner responses using conventional color filters and the proposed NN with an average GFC value of 0.999. The mean of color difference error was about 0.612 CIEDE2000 (1:1:1) unit or 0.987 CIELAB unit. Prog. Color Colorants Coat. 4(2011), 39-49.

1. Introduction

A digital scanner or camera gives the device-dependent characteristics (RGB). Also, the spectral sensitivity of most of these digital imaging devices is not practically a linear transformation of CIE color matching functions, device metamerism may usually exist [1]. To be able to have the device-independent color information it is necessary to characterize color devices. Characterization is to find the relation or transforming functions between a device-dependent color space (such as RGB) and a device-independent one. Generally there are two kinds of characterization; colorimetric characterization in which destination space would be a trichromatic standard space such as CIE XYZ, and spectral characterization which its goal is to achieve spectral data.

During the last two decades, a lot of researches have been published in the field of color device characterization [1-10].

Reconstruction the spectral data from the device-dependent values such as RGB values of a digital scanner are so important not only for device characterization but also having a low-cost and simple method to estimate the spectral data without using expensive instruments such as a spectrophotometer. In addition, however, spectro-photometer is an excellent choice for measuring the spectral data of single colors it cannot give the spectral information of color images correctly [11]. If accurate spectral recovery from image data is available, color

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reproduction of the images under any illuminating and viewing conditions would be possible. Multispectral image analysis brings the chance to achieve spectral data of color images. The aim of multispectral imaging is to recover the spectral information of the samples being images using multi channel (more than three) imaging [11-22]. In this way, the scanner or camera is being a spectrophotometer and can give the spectral information of an image pixel by pixel. It can be possible because the spectral data of most color samples are almost smooth functions of wavelengths. This technique has been also recommended and applied for spectral color device characterization approach to reach the device-independent information [23-26].

Several linear and non-linear methods have been suggested for spectral recovery of images from the device-dependent results. Some of these mathematical models include Wiener inverse, pseudoinverse, Principal component analysis, spline interpolation, neural network, genetic algorithm and, etc. [11-26]. Techniques such as wiener estimation need the spectral sensitivity of the device to instrumentally be measured or mathematically calculated. Some other methods like pseudoinverse do not need the physical information of the instrument and computes the transformation function between device response and reflectance of the samples applying a suitable known data set. Multi-channel color devices' responses might be applied as inputs of a mathematical model like those mentioned, the outputs would be the corresponding spectral data.

The aim of the present study is to spectral reconstruction of printed samples from scanners by applying a set of conventional color filters and employing back-propagation neural network.

Recovery spectral data from RGB digital devices

If the scanner response is linear the response data of a color scanner for a uniform surface with spectral reflectance (R) and under a specified illuminant (E) is given by equation 1:

$$O_i = \sum_{\lambda} S_i(\lambda)\, E(\lambda)\, R(\lambda) \tag{1}$$

Where S_i indicates the spectral sensitivity of the ith channel and λ is a symbol for wavelength. A commercial digital scanner has three Red, Green and Blue channels so equation 1 can be rewritten as follows:

$$\begin{aligned} R &= \sum_{\lambda} S_R(\lambda)\, E(\lambda)\, R(\lambda) \\ G &= \sum_{\lambda} S_G(\lambda)\, E(\lambda)\, R(\lambda) \\ B &= \sum_{\lambda} S_B(\lambda)\, E(\lambda)\, R(\lambda) \end{aligned} \tag{2}$$

Assuming that the spectral data is represented at 31 wavelengths from 400nm to 700nm with 10nm intervals, equation 2 can be written in matrix notation as follows:

$$O_{3\times n} = A_{3\times 31} \cdot R_{31\times n} \tag{3}$$

Where O is the scanner response for n samples, A is a 3×31 transform matrix contains spectral sensitivity of the scanner multiplied by the spectral radiance of the illuminating source and R stands for the spectral reflectance of the n samples.

As mentioned, in multispectral imaging for reducing metamerism effect and obtaining more accurate recovery of spectral data, more than three channels (m>3) is implemented, for example, using some color filters. In this case, equation 3 can be generalized as:

$$O_{m\times n} = A_{m\times 31} \cdot R_{31\times n} \tag{4}$$

To reconstruct the spectral data from equation 4, it needs to solve an underdetermined system (usually m<31). In general the reconstruction equation can be expressed as follows:

$$R = T \,.\, f(O) \tag{5}$$

f(O) is a linear or non-linear function of O and T indicates the transform function. In the case of linear equation, T can be easily determined by a mathematical method such as pseudoinverse technique. If f(O) is assumed as a nonlinear function of O different methods would be used. For example, as a 2 order polynomial function (R, G, B, R^2, G^2, B^2), using least-square can be applied to predict the coefficient matrix. As an alternative approach for a nonlinear situation, neural network may be used to predict the mapping function from input to output data.

2. Experimental

To be able to spectrally characterize a scanner, at first it is necessary to produce proper samples. For this purpose, a wide gamut color chart was generated via Eye-One GretagMacbeth professional maker.

The chart was printed by a Hp Photosmart Pro B8850 photo printer. This printer had an eight ink set comprising cyan, yellow, magenta, light cyan, light magenta, gray, and both a matte black and photo black. The spectral reflectances of the printer's inks are shown in Figure 1. The color chart was printed on Premium Silky Photo Paper and prepared on 6 separated A4 papers.

The spectral reflectances of the printed colors were measured using a GretagMacbeth Eye-One spectrophotometer in the range between 380nm and 730nm with 10nm intervals. In all the experiments only the data between 400nm and 700nm (31 wavelengths) were applied.

The original chart has 2250 samples. After printing and measuring the spectral data, a set of 1355 samples was selected in a way that the minimum spectral RMS difference between each two samples was at least 0.01.

To measure the repeatability of the printer a one-page chart counting of 459 patches was printed four times. The color differences between the first try assumed as the standard one, and the second, the third and the fourth tries were computed. The statistical values are shown in Table 1. As illustrated, the used photo printer has an acceptable repeatability.

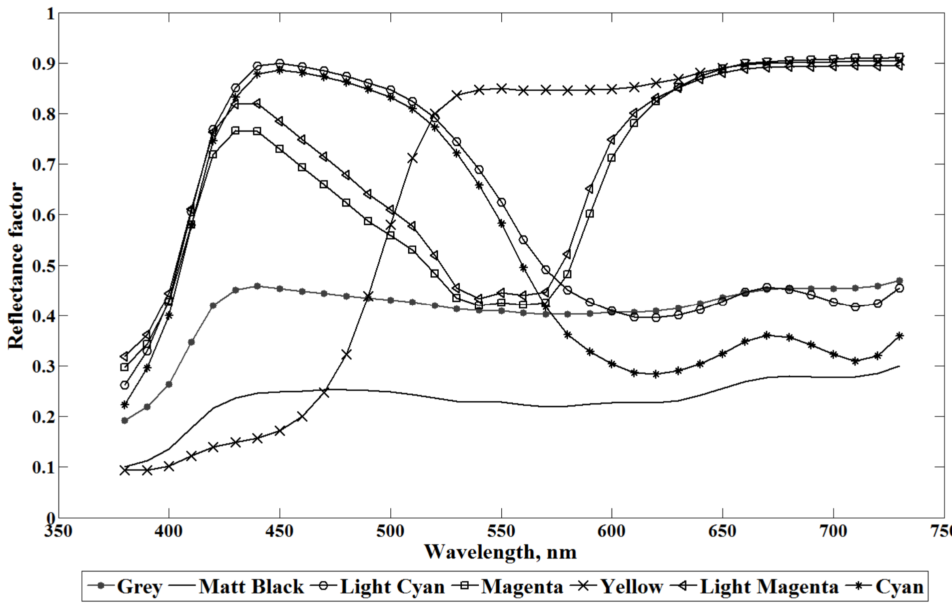

Figure 1: Spectral reflectance of the Hp Photosmart Pro B8850 printer's inks.

Table 1: The results of the printer repeatability based on the color difference values between the first try as the standard and the other three tries.

	CIEDE2000 (1:1:1) D65				CIELAB D65			
	Mean	std	Min	Max	Mean	std	Min	Max
Try2	0.5965	0.4088	0.0484	2.3263	1.0384	0.6804	0.0734	3.4493
Try3	0.3939	0.3205	0.0290	2.0170	0.6252	0.4581	0.0425	2.9925
Try4	0.4052	0.2670	0.0248	1.5303	0.6618	0.4107	0.0356	2.2940

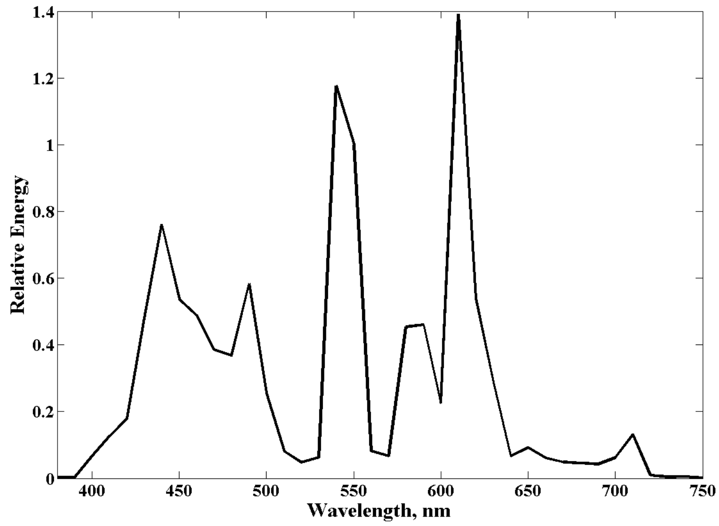

Figure 2: The spectral power distribution of the light source of the scanner.

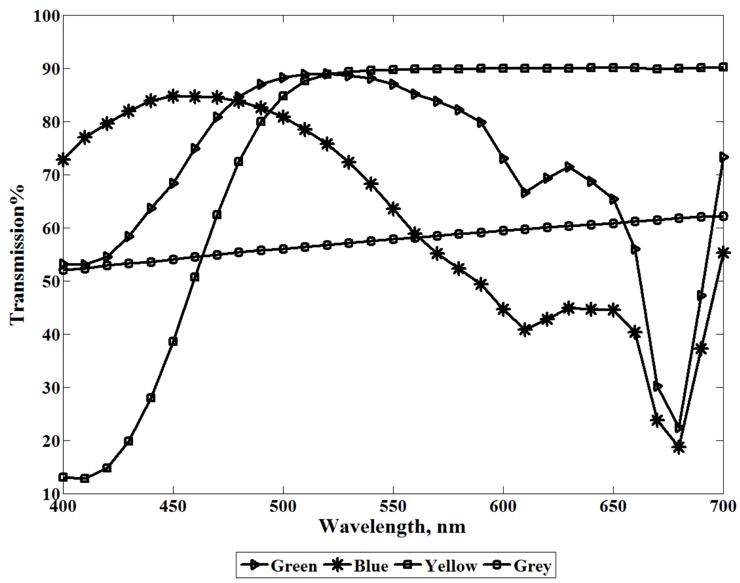

Figure 3: The spectral transmissions of the applied filters.

A V700 EpsonPro color scanner was employed. The spectral power distributions of the light source of the scanner measured by a Xrite LIGHTSPEX spectro-radiometer is shown in Figure 2. Each page was scanned by putting a color filter in front of the page. Considering the use of four color filters; gray, blue, yellow and green, plus one more time without using any filter, each page was scanned five times. The scanning resolution was set as 150 dpi and the images were saved with TIFF format. Before scanning, all automatic color correction was turned off.

The applied color filters were conventional translucent sheets in A4 size. The spectral transmissions of the filters, measured with Color-Eye 7000A spectro-photometer, are shown in Figure 3.

Moreover, the contrast ratio of the filters was given in Table 2. Contrast ratio tends towards unity for opaque materials and towards zero for transparent materials. The applied filters should not affect the color of the samples significantly in the way that the color of the filter conquests the color of the samples. So they should be completely translucent and have a small contrast ratio.

The uniformity of the scanning window was evaluated by scanning a white and a gray A4 paper. The scanning window was divided to 32 equal sections. For each section, the mean of RGB values was considered as its total color signal. The percentage of error between each two sections was computed using equation 6. The obtained results are given in Table 3. As indicated the scanning window of the applied scanner has an acceptable uniformity. The color uniformity of each filter was measured similarly. Each filter was scanned while the uniform white page of the scanner door made it to be opaque. The results are given in Table 5.

$$Normal\ Error = \left(\frac{|R_i - R_j|}{R_i} + \frac{|G_i - G_j|}{G_i} + \frac{|B_i - B_j|}{B_i} \right) \times 100 \quad (6)$$

Where, i and j denote ith and jth sections.

Table 2: The contrast ration of the used filters.

Filter	Contrast ratio (%)
Green	16.31
Blue	20.98
Yellow	15.73
Gray	23.90

Table 3: The results of the uniformity of scanner scanning window based on equation 6.

	Mean	std	Min	Max
White	3.3428	2.9223	0.2564	9.7459
Gray	1.7288	1.1602	0.1611	4.3774

Table 4: The results of the color uniformity of the filters based on equation 6.

	Mean	std	Min	Max
Green	3.6309	2.3309	0.7407	7.9624
Blue	3.6425	2.4331	0.1535	8.9095
Yellow	5.4981	2.7403	0.6127	11.3769
Gray	3.3385	1.7922	0.5537	8.0295

Table 5: The results of the scanner repeatability based on equation6. The errors were computed between the first try as the standard and the other three tries.

	Mean	std	Min	Max
Try2	7.4444	8.3655	0.4736	38.7195
Try3	3.9054	3.8871	0.1831	19.4324
Try4	4.3768	4.4622	0.1833	23.4854

Repeatability of the scanner was evaluated by scanning a one-page chart, including of 459 patches four times. The first try was assumed as the standard one; the scanning difference between the other three tries with the standard one was computed using equation 6. The statistical values are shown in Table 5. It can be seen that, the used scanner has acceptable repeatability with an average error lower than 8 percentages.

For each patch, the average RGB values were calculated and utilized as its specified color. Moreover, 20% of the boundary pixels were left out to eliminate boundary error and 80% of the central pixels were employed.

Furthermore, Median filter was applied on each of the three channels (R, G and B) of the images for reducing the probable noise. Median filter is a kind of Order-Statistics filters. It replaces the value of a pixel by the median of the pixel values in its neighborhood and for some types of random noise provides excellent noise reduction with the least blurring effect [27].

To find a model for estimating the spectral data of the scanned images from scanner responses of four color filters, a fully connected feed-forward back-propagation network was applied. The inputs had 12 neurons included the RGB values of the scanner responses applying 4 color filters (3RGB×4filters) and the outputs were 31-dimension of spectral reflectances.

Moreover, another experiment was carried out while the scanned images without any filter were substituted for gray-filtered images. In the other way, the 12D input data consisted of 3RGB of filtered-free scanned image together with the three blue, green and yellow filtered-images.

After several trials of different architectures, it was found that one hidden layer of 20 neurons was appropriate. The tan-sigmoid transfer function was applied as activation functions in the hidden and the linear transfer function was used for output neuron layers.

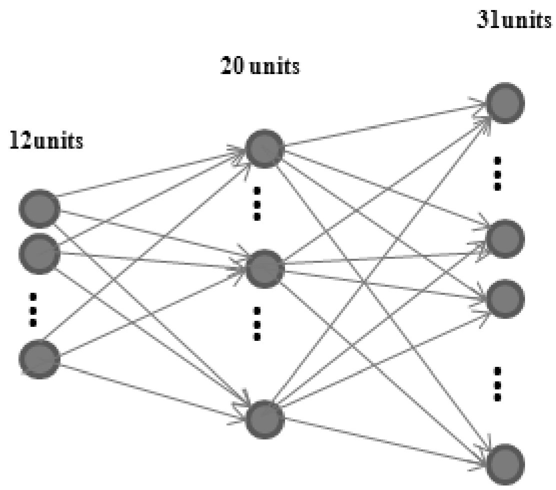

Figure 4: Schematic diagram of the used neural network structure.

Figure 4 shows a schematic form of the used neural network.

There were totally 1355 color patches in the chart. 60% of the samples (813) were randomly selected as training set, and 40% (542) were applied as test samples. The color coordinates of the training and test samples in CIEL*a*b* color space are shown in Figure 5.

The performance of the reconstruction method was evaluated using the average color difference values computed by CIELAB and CIEDE2000 (1:1:1) [28] color difference formulae, Root Mean Square Error (RMS) of spectral reflectance and Goodness-of- Fit Coefficient (GFC) [29]. GFC metric was calculated by the following equation, where R and $\hat{R}$ are the original (the measured data by spectrophotometer) and reconstructed spectral reflectance respectively. In should be mentioned that for all the computations, the 1931 CIE standard observer was applied.

$$GFC = \frac{\left|\sum_{\lambda} R_{\lambda}\, \hat{R}_{\lambda}\right|}{\sqrt{\left|\sum_{\lambda} {R_{\lambda}}^{2}\right|}\ \sqrt{\left|\sum_{\lambda} {\hat{R}_{\lambda}}^{2}\right|}} \qquad (7)$$

3. Results and discussion

Figure 6 shows and reconstructed spectral data from scanner responses applying the proposed method together with the original data. The RMS and GFC values of spectral reconstruction from muti-filtering scanner responses by the proposed method are shown in Table 6. The results of this table show that the spectral reflectance of the printed samples can be accurately estimated by the suggested method with an average of the 0.999 GFC and 0.007 RMS values. It can be seen that the obtained errors for the test samples are also acceptable and be closed to the training ones, so the applied neural network was well trained.

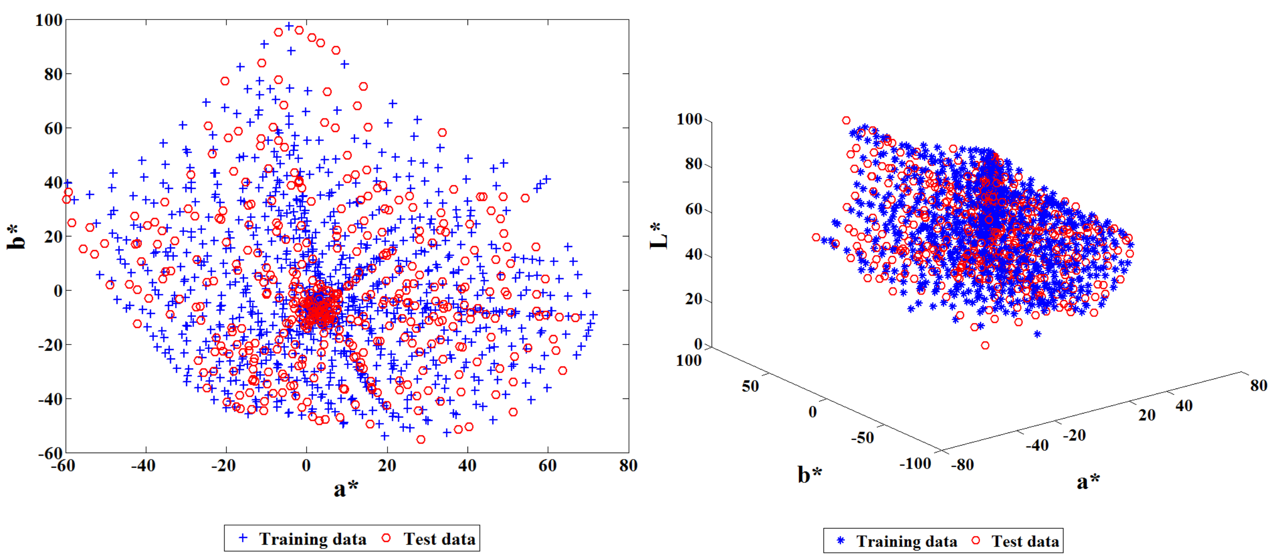

Figure 5: The color coordinates of the training and test samples in CIEL*a*b* diagram under illuminant D65 and 1931 CIE standard observer.

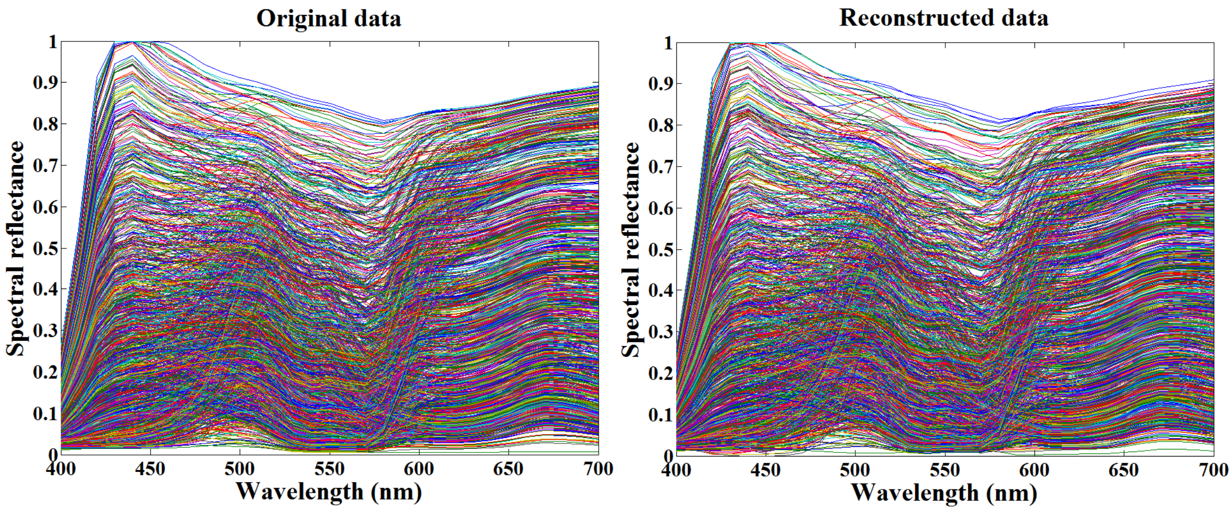

Figure 6: The original and reconstructed spectral reflectance data.

Table 6: RMS and GFC values of spectral estimation by the proposed neural network.

	RMS		GFC	
	Mean	std	Mean	std
Training	0.0058	0.0040	0.9999	0.0004
Test	0.0080	0.0082	0.9996	0.0051
Total	0.0067	0.0061	0.9998	0.0033

Table 7: Average color difference of spectral estimation by the proposed neural network.

	CIEDE2000 (1:1:1)						CIELAB					
	D65 illuminant			A illuminant			D65 illuminant			A illuminant		
	Mean	std	No>3	Mean	std	No>3	Mean	std	No>5	Mean	std	No>5
Training	0.5678	0.3442	0	0.5402	0.3264	1	0.8991	0.7652	4	0.8494	0.6536	2
Test	0.6774	0.4641	3	0.6680	0.5156	3	1.1197	0.9139	4	1.0702	0.8491	2
Total	0.6116	0.4000	3	0.5913	0.4171	4	0.9873	0.8346	8	0.9377	0.7456	4

Table 7 gives the corresponding colorimetric errors of Table 6. This table shows the color difference errors of spectral recovery under two illuminants applying two color difference formulae. As indicated, the proposed NN method can reconstruct spectral data of the printed chart with the mean value of 0.612 CIEDE2000 (1:1:1) color difference unit or 0.987 CIELAB unit. The number of samples with a color difference more than 3 CIEDE2000 (1:1:1) unit and 5 CIELAB unit is also given. As illustrated there are a few samples with large color difference error, and they seem as the noise of the system. In view of the spectral power distribution of the scanner's light source, it might be one of the reasons of this error. For more clarification, the histogram of the color difference errors is illustrated in Figure 7.

In addition, it can be seen that, the mean of color difference error under A illuminant is almost lesser than the color difference under D65 which indicates approximately acceptable metamerism index and suitable reconstruction. For more surveys, the estimated spectral reflectances of 9 samples were chosen randomly and demonstrated in Figure 8.

As mentioned, another experiment was applied while the input data was the RGB data of filtered-free scanned image and the three blue, green and yellow filtered-images. Table 8 and 9 show the corresponding results. In comparison to Table 6 and 7, it can be seen that applying four color filters included gray one can give almost better results however it might be dependent on the light source of the used scanner. Consequently, it seems that the filtered-free scanned images with three color filters would be also an alternative solution.

Moreover, the capability of the proposed neural network for spectral recovery of EyeOne ScanerTaget 1.4 test chart as an instance of non-printed sample was tested. The obtained results show that this trained network could not be suitable for other charts. However while the neural network is trained with the same samples it gives appropriate results.

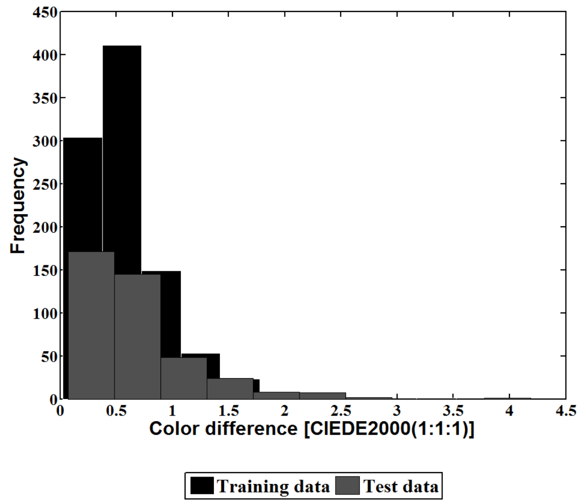

Figure 7: The histogram of color difference errors computed by CIEDE2000 (1:1:1).

Table 8: RMS and GFC values of spectral estimation by the proposed neural network (filtered-free and 3 color filtered images).

	RMS		GFC	
	Mean	std	Mean	std
Training	0.0065	0.0047	0.9998	0.0019
Test	0.0081	0.0078	0.9999	0.0002
total	0.0071	0.0062	0.9998	0.0014

Table 9: Average color difference of spectral estimation by the proposed neural network (filtered-free and 3 color filtered images).

	CIEDE2000 (1:1:1)						CIELAB					
	D65 illuminant			A illuminant			D65 illuminant			A illuminant		
	Mean	std	No>3	Mean	std	No>3	Mean	std	No>5	Mean	std	No>5
Training	0.6591	0.5519	3	0.6255	0.4438	2	1.0313	0.9557	5	0.9635	0.7832	3
Test	0.7406	0.5090	4	0.7157	0.4761	1	1.1478	0.8911	5	1.1025	0.8183	2
Total	0.6917	0.5365	8	0.6616	0.4590	3	1.0779	0.9318	10	1.0191	0.8000	5

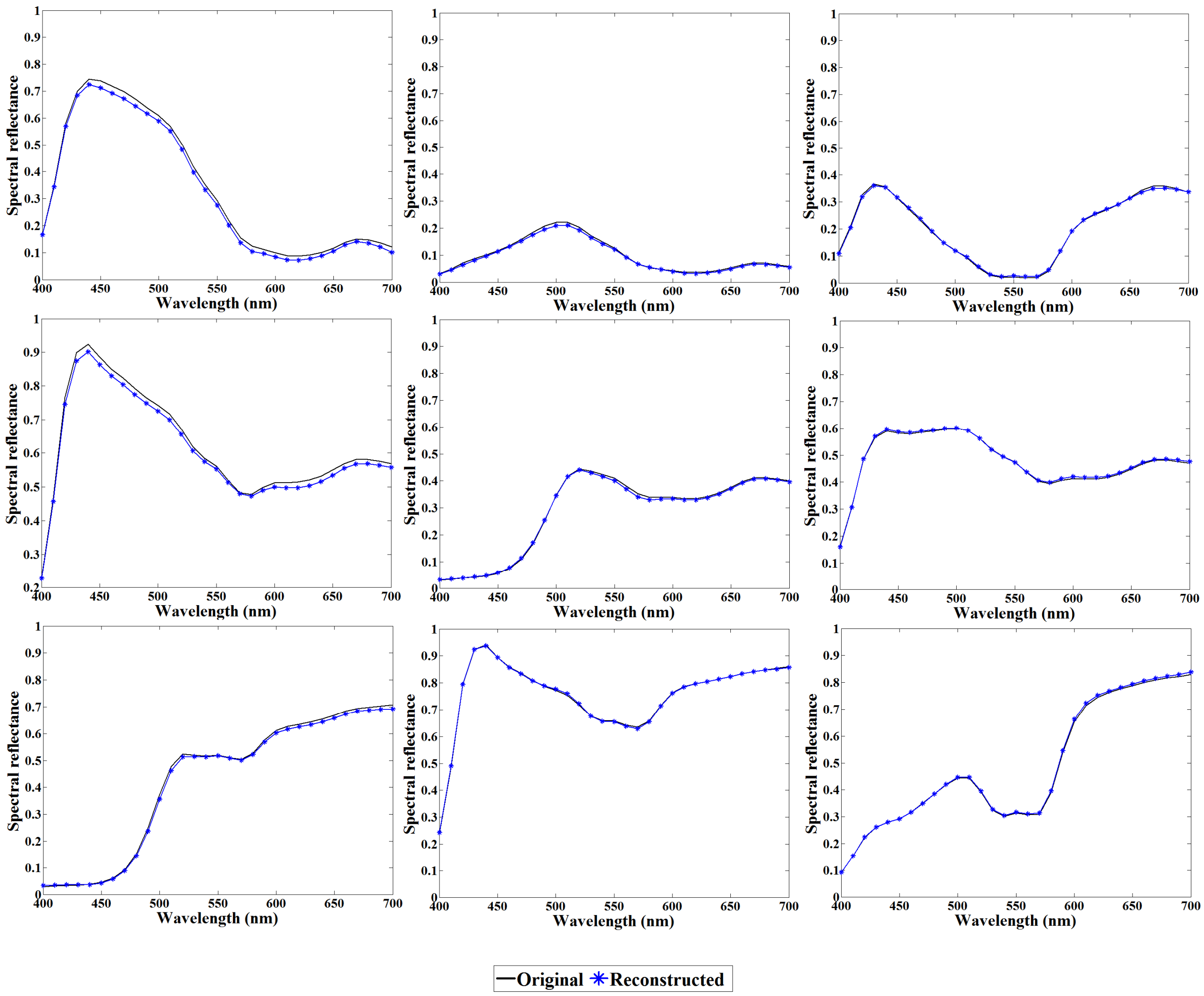

Figure 8: Comparison of original and predicted spectral reflectance values of 9 samples.

4. Conclusions

Spectral characterization of digital color devices has been recently more considered especially in multispectral imaging. Recovery of spectral data from a digital color scanner or camera, which is based on three responses, results in a metameric pair of the original sample. Multispectral imaging gives the possibility to reconstruct the spectral data by capturing images with more than three channels. Several mathematical models have been proposed to transform the camera outputs to spectral information.

The goal of this study was to introduce a feasible method for spectral reconstruction of printed colors using a color scanner and conventional color filters. The back-propagation neural network was applied as mathematical transforming model. To this end, an appropriate color chart with a wide gamut was printed. Each page was scanned four times, each time by putting one of the four color filters in front of it. A feed-forward back-propagation neural network with 1 hidden layer consisted of 20 neurons was applied. It was shown that the spectral reflectance values can be accurately estimated based on GFC, RMS and color difference values between the original and reconstructed samples. In addition it is possible to substitute scanned image without any filtering for gray filtered images.

Consequently, it was shown that it is accurately possible to estimate the spectral data of the printed samples from the scanned images applying suitable color filters in front of the scanner scanning window. A back-propagation neural network can be employed to model the transforming function between the camera responses and spectral data.

In further research, optimizing the color filters and testing the method for different printers would be considered.

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