Spectral characterization of scanner based on PCA and BP ANN

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A novel method for spectral characterization of scanner was proposed in this paper, which combined the principal component analysis (PCA) and back propagation (BP) artificial neural network (ANN). The natural color system (NCS) color patches were adopted as the color targets. The accuracy of this method was evaluated by spectral root mean square (SRMS) error and the CIEDE2000 color difference specification. The experimental results showed that six principal components were appropriate and the spectral characterization accuracy was outstanding when a 3-20-6 BP net structure was used to estimate the scalars from the scanner red/green/blue (RGB) signals.

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The spectral characterization, which recovers the spectral reflectance of a color target from its responses produced by an imaging device, has received considerable attention recently[1−4] for the reasons of high accuracy and not suffering metameric problem. The conventional methods such as least squares based polynomial regression, look-up-table (LUT) with interpolation and extrapolation and artificial neural network (ANN)[4−6] are useful colorimetric approaches for the scanner characterization. However, these are constrained into the specific combination of illuminant and observer functions. When either the illuminant or observer changes, the characterization process has to be carried out again, otherwise, it may result in large color match error. The method of spectral characterization reproduces the spectral reflectance of the color targets from the scanner response signals, and then the tristimulus values under different illuminant and standard observer function can be calculated conveniently.

A novel method, which combined the principal component analysis (PCA) and back propagation (BP) ANN, was proposed to characterize a flatbed panel scanner. The PCA method was significant in color science research[7,8], which was discussed in detail in Ref. [7]. An instance of using PCA method for spectral reflectance recovery based on multispectral imaging was given in Ref. [8]. In this study, it was used to analyze the spectral reflectance of the scanned targets followed by the principal component scalars calculation. The spectral reflectance of a color target can be represented as a function of wavelength. It also can be approximately expressed by a series of discrete values at the sample wavelengths, such as the wavelength range from 400 to 700 nm with 10 nm interval, which are detonated as $\mathbf{R}$ vector

$$\mathbf{R} = \sum_{j=1}^{31} x_j \mathbf{i}_j, \tag{1}$$

where x_j represents the magnitudes of the reflectance at sample wavelength $\mathbf{i}_j$. Therefore, the spectral reflectance of the group of N color targets can be described as vectors $\mathbf{R}_j$ $(j = 1, 2, \cdots, N)$. Assuming a set of orthonormal vectors $\mathbf{e}_j$, there is

$$\begin{cases} \mathbf{e}_1 = l_{11}\mathbf{i}_1 + l_{12}\mathbf{i}_2 + \cdots + l_{13}\mathbf{i}_{31} \\ \mathbf{e}_2 = l_{21}\mathbf{i}_1 + l_{22}\mathbf{i}_2 + \cdots + l_{23}\mathbf{i}_{31} \\ \cdots \\ \mathbf{e}_m = l_{m1}\mathbf{i}_1 + l_{m2}\mathbf{i}_2 + \cdots + l_{m3}\mathbf{i}_{31} \end{cases}, \tag{2}$$

where m is much less than 31 and vectors $\mathbf{R}_j$ can be accurately represented by $\mathbf{e}_1$, $\mathbf{e}_2$, $\cdots$, $\mathbf{e}_m$, so that the high dimension vectors $\mathbf{R}_j$ can be reduced to that in a low dimension space. If the spectral reflectance of N targets is denoted in matrix

$$X = \begin{bmatrix} \mathbf{R}_1 \\ \mathbf{R}_2 \\ \vdots \\ \mathbf{R}_N \end{bmatrix}, \tag{3}$$

then the correlation matrix between each column of X can be calculated. The first m eigenvectors of the correlation matrix are the vectors $\mathbf{e}_1$, $\mathbf{e}_2$, $\cdots$, $\mathbf{e}_m$, which are named principal components; hence PCA is also known as the eigenvector analysis. The scalars of the principal components are calculated according to

$$S = X/E, \tag{4}$$

where X is a $N \times 31$ matrix of the spectral reflectance of the color targets, S is a $N \times m$ matrix of the scalars, and E is a $m \times 31$ matrix of the principal components.

The 320 natural color system (NCS) color patches of 10×10 (mm) square were used as color targets, which were scanned by Epson Perfection 1270 Scanner. Their spectral reflectances were measured by X-Rite SP60 spectral colorimeter. These NCS color patches include all natural colors in 8 different color hues with notations of Y60R, G80Y, G20Y, B70G, B60G, B, R50B, and R20B. Firstly, the number of principal components, $N_{\mathrm{p}} = m$, should be appropriate. A small number of principal components may produce unsatisfied characterization accuracy, while large number of terms may complicate the transformation without performance improved. The cumulative variance contribution of principal components, which represents their significance, can be used to determine the correct component number. The cumulative

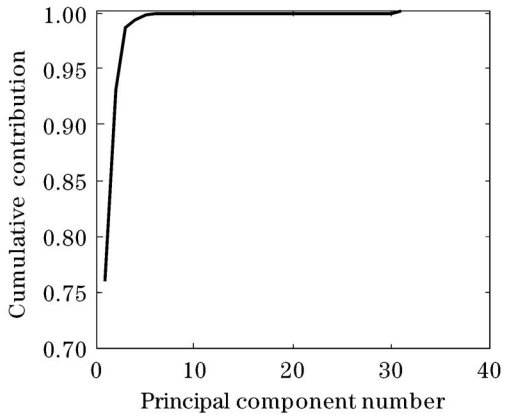

Fig. 1. Cumulative contribution for different principal component number.

Table 1. Cumulative Variance Contribution (CVC), Colorimetric and Spectral Accuracy of Spectral Estimation of NCS Color Patches When Different Number of Principal Components (N_p) Was Used ($\overline{\Delta E_{00}}$: Mean ΔE_{00} (D50, 2°), $\overline{\text{SRMS}}$: Mean SRMS Error (%))

N_p	CVC (%)	$\overline{\Delta E_{00}}$	$\overline{\text{SRMS}}$
6	99.89	0.445	1.07
9	99.98	0.133	0.40
12	100.00	0.024	0.15

contributions for different number of principal components were plotted in Fig. 1. It was found that the plot curve became almost horizontal when N_p was large than 6, which implied the spectral reflectance of all color patches could be defined by the first six principal components in this study. Furthermore, both the color accuracy from the visual point of view and the accuracy of the spectral reflectance estimation were considered. The spectral match was evaluated using spectral root mean square (SRMS) error, which is defined as

$$\text{SRMS} = \left[\frac{(\mathbf{R}_m - \mathbf{R}_e)^T(\mathbf{R}_m - \mathbf{R}_e)}{N}\right]^{1/2}, \quad (5)$$

where, $\mathbf{R}_m$ is the spectral reflectance vector measured, $\mathbf{R}_e$ is the spectral reflectance vector estimated, and N is the wavelength sample number, which is equal to 31 here. The superscript symbol "T" represents the transpose of matrixes. The colorimetric match was evaluated using the latest CIEDE2000 color difference formula[9] in its original form, ΔE_{00}, under the standard illuminant D50 and CIE1931 (2°) observer. These two matrices were also used by Shen *et al.*[1] and Imai *et al.*[2] for the match estimation. The cumulative variance contributions, ΔE_{00} (D50, 2°) values and SRMS errors for the first six, nine, and twelve eigenvectors were shown in Table 1.

As expected, the data in Table 1 that the spectral reflectance was estimated using six principal components were very accurate with the average ΔE_{00} of 0.445 and the average SRMS error of 1.07%, which were similar with the results of Ref. [2]. Therefore, it was considered that the principal component number six is appropriate for the spectral reflectance reconstruction. Herewith the principal component number of six was selected for the spectral characterization in the next experiments of this study. The reflectance spectra of the first six principal components were presented in Fig. 2.

In order to reconstruct the spectral reflectance of targets scanned from corresponding scanner signals, the relationship between scanner signals and the principal component scalars should be first discovered. Unfortunately, this relationship cannot be directly modelled because of the complicated influences in the scan procedure. Since BP ANN has the capability of learning arbitrary nonlinearity and shows great potential in the area of nonlinear transformation research of the imaging device color space, a multilayer BP network was designed in this model. The input layer serves as a holding site for the values to be processed by the network. The output layer is the point at which the final state of the network can be read. The links connect each unit of one layer only to units in the next layer. The activation function of the nodes of the output layer is linear, while that of the hidden layers is tangent sigmoid. The input values, scanner red/green/blue (RGB) signals, were scaled by 255 to the range of [0, 1], and the output values, the principal component scalars, were standard normalized by the mean and the standard deviation. In order to determine the appropriate number of hidden layers and the nodes in each hidden layer for an effective network structure, several networks were trained and tested under different conditions. The 320 NCS color patches were divided uniformly into two groups, one for training and another for testing. Some experimental results were presented in Tables 2 and 3. All the networks in Table 2 were

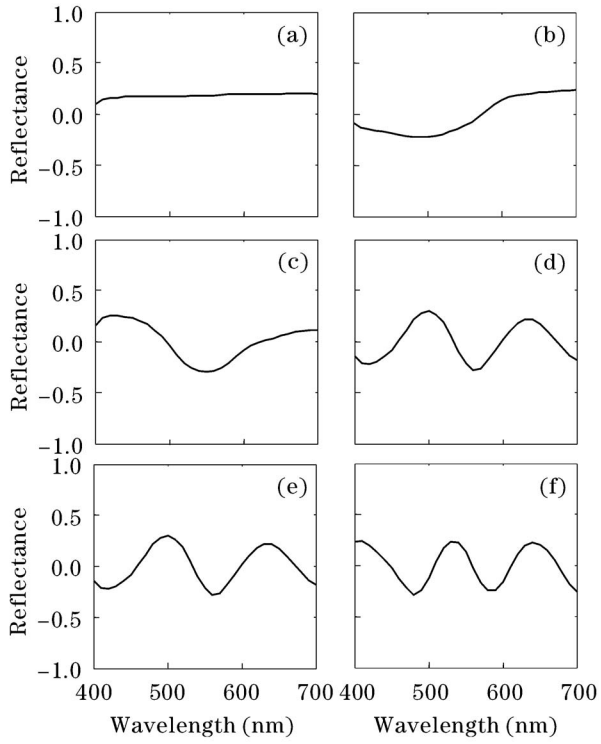

Fig. 2. The reflectance spectra of the first six principal components (PCs). (a) First PC; (b) sencond PC; (c) third PC; (d) fourth PC; (e) fifth PC; (f) sixth PC.

Table 2. Colorimetric and Spectral Accuracy of Scanner Spectral Characterization for NCS Color Patches When Different Network Structures Were Used, All Networks Were Trained for 500 Epochs ($\overline{\Delta E_{00}}/\Delta E_{00}^{\max}$: Mean/Max. ΔE_{00} (D50, 2°))

Network	Training Targets		Testing Targets		All Targets	
Structure	$\overline{\Delta E_{00}}/\Delta E_{00}^{\max}$	$\overline{\text{SRMS}}$	$\overline{\Delta E_{00}}/\Delta E_{00}^{\max}$	$\overline{\text{SRMS}}$	$\overline{\Delta E_{00}}/\Delta E_{00}^{\max}$	$\overline{\text{SRMS}}$
3-10-6	2.223/18.418	2.34	2.347/19.555	2.57	2.285/19.555	2.46
3-20-6	1.816/9.922	1.76	1.883/7.889	2.33	1.850/9.922	2.05
3-30-6	1.364/7.866	1.51	1.898/9.866	2.75	1.631/9.866	2.13
3-40-6	1.071/5.081	1.32	2.173/23.174	3.16	1.622/23.174	2.24
3-50-6	1.011/4.446	1.24	2.132/10.102	4.38	1.572/10.102	2.81
3-60-6	0.780/3.051	1.17	2.498/24.316	4.55	1.639/24.316	2.86
3-10-10-6	2.315/8.983	1.99	3.505/42.969	6.02	2.910/42.969	4.01
3-15-15-6	1.784/7.343	1.82	2.531/13.210	3.57	2.158/13.210	2.70
3-20-20-6	0.803/4.023	1.17	2.892/29.546	5.02	1.848/29.546	3.10

Table 3. Colorimetric and Spectral Accuracy of Scanner Spectral Characterization for NCS Color Patches When Different Network Structures Were Used, All Networks Were Trained for 1000 epochs

Network	Training Targets		Testing Targets		All Targets	
Structure	$\overline{\Delta E_{00}}/\Delta E_{00}^{\max}$	$\overline{\text{SRMS}}$	$\overline{\Delta E_{00}}/\Delta E_{00}^{\max}$	$\overline{\text{SRMS}}$	$\overline{\Delta E_{00}}/\Delta E_{00}^{\max}$	$\overline{\text{SRMS}}$
3-10-6	3.718/31.447	2.93	3.632/30.535	3.08	3.675/31.447	3.01
3-20-6	1.417/6.280	1.65	2.038/12.472	2.88	1.728/12.472	2.27
3-30-6	1.373/4.924	1.60	1.989/7.957	2.74	1.681/7.957	2.17
3-40-6	1.315/9.198	1.43	2.444/24.294	3.43	1.880/24.294	2.43
3-50-6	0.940/2.986	1.25	3.043/29.896	4.37	1.992/29.896	2.81
3-60-6	0.894/3.563	1.18	3.972/27.575	8.99	2.433/27.575	5.09
3-10-10-6	2.080/6.337	2.05	2.747/10.103	3.23	2.414/10.103	2.64
3-15-15-6	1.708/8.416	1.68	3.150/28.082	3.81	2.429/28.082	2.75
3-20-20-6	0.735/3.307	1.17	4.269/21.952	6.69	2.502/21.952	3.93

trained for 500 epochs, while those in Table 3 for 1000 epochs. As can be seen in Tables 2 and 3, when the training epochs increased to two times, the accuracy of colorimetric and spectral match for the same structure network did not get better, furthermore, the performance became slightly worse for some networks. The reason was that the weights and the biases of the same structure network trained in different time were not the same, though the difference was small. The discussion in the following will focus on the data in Table 2.

In Table 2, the performance of networks, including the mean/maximum ΔE_{00} (D50, 2) and the mean SRMS error for training targets, decreased steadily with the increase of the node number in the hidden layer. The experimental results showed that for training targets the accuracy of spectral estimation could be improved at the cost of complexity of BP network structure, which also increased the number of parameters and the computer memory of transformation. In fact, even when the network with 60 nodes in hidden layer was used, the colorimetric accuracy for training targets was yet approximately 2 times larger than that of the theoretic estimation without simulating the scalars from actual scanner RGB signals via BP network. This clearly indicates that the error introduced by BP network is much larger than that of dimensionality reduction, in other words, the choice of six principal components is proved to be effective. For a realistic characterization problem, it would rarely be the case that the candidate sample itself is in the training targets. So it is important to evaluate the characterization accuracy for different targets other than the training colors. The results were also shown in Table 2. There was obvious tendency that the colorimetric and spectral accuracy decreased first and then increased when the number of nodes in hidden layer increased. The 3-10-6 structure of network was the simplest, while its accuracy was unacceptable for either the training targets or the testing targets. The 3-20-6 structure was the best with the mean/maximum colorimetric accuracy of 1.883/7.889 ΔE_{00} (D50, 2°) unit and the mean spectral accuracy of 2.33% SRMS error for testing targets. With the number of nodes increased, the characterization accuracy for testing targets decreased steadily, especially for the 3-40-6 and 3-60-6 structures the maximum color differences reached to 23.174 and 24.316, respectively, which were considered very poor color matches. The networks with two hidden layers, such as 3-10-10-6, 3-15-15-6 and 3-20-20-6, were also tested. The results showed that these structure networks were not suitable for this study. For all targets, the 3-20-6

and 3-30-6 were the best two structures. The former was simpler with comparative accuracy. Therefore, the 3-20-6 structure was the best choice in this study. The mean spectral accuracy of this structure was 1.76% for the same targets and 2.33% for the different targets, which were slightly better than the best experimental results, 1.8% and 2.9%, reported in Ref. [1] using local statistics. The conclusion could be proved again by the data in Table 3.

In conclusion, a new method for spectral characterization of scanner, combining PCA and BP ANN, was proposed and applied using 320 NCS color targets. The theoretic estimation results showed that six was an optimized number of principal components to make a compromise between the spectral accuracy and calculation complexity. The complicated relationship between the scanner response signals and the principal component scalars was modelled by a BP network. Several networks with different layers and different nodes in each hidden layer were compared and analyzed to find an appropriate structure. According to the experimental data, the 3-20-6 structure of network was the optimized with the mean colorimetric accuracy of characterization of 1.816 ΔE_{00} unit for the same targets and of 1.883 ΔE_{00} unit for the different colors, with the corresponding mean spectral accuracies of 1.76% and 2.33% SRMS errors, respectively. In comparison with the techniques presented till now for the spectral characterization of imaging devices such as digital camera and scanner, the proposed method in this study has the advantage of requiring no estimation of the device spectral responsivity, which is difficult for instrumental measurements or accurate mathematical recovery. The accuracy of this method is outstanding, and, in some cases, superior to that reported by other authors in similar experiments. This could make the proposed method a valuable tool in image analysis and image database applications requiring reliable control of the color imaging device.

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