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Measuring Reflectance Spectra of Textile Fabrics by Scanner

A. Shams-Nateri*

Textile Engineering Department, University of Guilan, Rasht, Iran

Abstract

This study presents a practical approach for estimation reflectance spectra by means of scanner. New methods were based on polynomial regression, neural network, neuro-fuzzy and principal component analysis techniques. Obtained results indicate that the recovery error decreases with increase number of principal component and number of terms in a polynomial. Also, application of principal component increase accuracy of reflectance measurement. The best estimation is obtained by principal component analysis and artificial neural network (PCA- ANNET) with 0.0297 RMS and 6.14 ΔE*ab error.

Keywords: Scanner; Reflectance estimation; Principal component analysis; Polynomial regression; Neural network; Neuro-fuzzy

Introduction

A calibration procedure is unavoidable for high quality color reproduction by low-cost color devices such as digital color cameras, scanner etc. Each device has a different gamut and its own color space defined by the relationship between the input colors and the corresponding RGB codes used to represent them. A simple method of converting scanner or digital camera RGB responses to estimates of object tristimulus coordinates is to apply a linear transformation to the RGB values. The transformation parameters are selected subject to minimization of some significant error measure. The basic idea of color target-based characterization is to use a reference target that contains a certain number of color samples. Typical methods like least squares polynomial modeling tristimulus, neural networks and three-dimensional lookup tables with interpolation and extrapolation can be used to derive a transformation between RGB values and XYZ values [1-8].

Estimation spectral information from digital color image has become a field of much interest and practical importance during the last few years. The color reproduction based on trichromatic data is often insufficient to obtain the device independent color, e.g. XYZ. In addition, an accurate illumination correction is impossible from trichromatic data, which is required when the color image is reproduced under different illuminations from the one used in the recording. Conversely, the spectral reflectance of an object is its intrinsic characteristic, which can be obtained by recording a spectral reflectance image. The device independent color under the any illumination light can be calculated from spectral reflectance. Various kinds of multi-band cameras have been developed for the purpose of spectral reflectance image achievement. A considerable number of studies have been also conducted on the spectrum estimation method from multi-band image data. A practical problem in the estimation of spectral reflectance images is that spectrum estimation depends on the spectral properties of the camera and the light illuminating the object. In order to obtain their properties, a spectral measurement device, such as spectrophotometer, is generally used [3,4,7-11].

The spectral characterization consists in approximating the different spectral characteristics of the sensor. A multispectral image is an image where each pixel contains information about the spectral reflectance of the imaged scene. Multispectral images carry information about a number of spectral bands: from three components per pixel for RGB color images to several hundreds of bands for hyperspectral images. Multispectral imaging is relevant to several domains of application, such as remote sensing, astronomy, medical imaging, and analysis of museological objects, cosmetics, medicine, high-accuracy color printing, or computer graphics. Multispectral scanners are mostly based on a point-scan scheme and are thus too slow and expensive [12,13].

Principal component analysis is a basis of new statistical method for data analysis. This has been used in data analysis and compression. Principal component analysis is a basis of latest data analysis, which has been called one of the most important results from applied linear algebra. PCA is used abundantly in all forms of analysis such as neuroscience and image processing. It is a simple, non-parametric method of extracting relevant information from confusing data sets. Principal components analysis generates a new set of variables, called principal components. Each principal component is a linear combination of the original variables and all the principal components are orthogonal to each other. There are numerous ways to construct an orthogonal basis for a set of spectral data. The first principal component accounts for as much of the variability in the data as possible, and each subsequent component accounts for as much of the remaining variability as possible. By grading the eigenvectors for descending eigenvalues, so that largest is first, one can create an ordered orthogonal method with the first eigenvector having the direction of largest variance of the data. In this way, we can find directions in which the data set has the most significant amounts of energy and variation [13-19].

In color science, principal component analysis has been used mainly for data compression and defines the principal directions that a set of data orient. A number of researchers have since investigated to estimation spectral information from tristimulus and application of principal components analysis in the recovering spectral information. The colorimetric data can be easily calculated from spectral data, but the computation of spectral data from colorimetric values is not

***Corresponding author:** A. Shams-Nateri, Textile Engineering Department, University of Guilan, Rasht, Iran, E-mail: a_shams@guilan.ac.ir

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similarly possible. The three-dimensional color data such as tristimulus value is insufficient for accurate estimation of reflectance spectra of the material. Several papers have been published attempting to solve this problem in extract the reflectance data from the corresponding tristimulus values. Several mathematical techniques such as simulated annealing method, application of ideal subtractive or additive Gaussian primaries, simplex method have been used for the reconstruction of reflectance spectra of samples from their corresponding tristimulus. Among them, the principal component analysis has been widely used for the reconstruction reflectance spectra. The recovery performance of the method mostly depends on the number of principal components, which have been chosen for estimation reflectance spectra [17-20].

Neural network

Recently, many researches have utilized a parallel processing structure that has a large number of simple processing with many interconnections between them. The use of these processors is much simpler and faster than one central processing unit. Because of recent advantages in technology, the neural network has emerged as a new technology and has found wide application in many areas. In this work, the multi-layer perceptron was used to process data by using the modified back-propagation algorithm. This algorithm attempt to minimize an error function by modification of network connection weights and bias. In each iteration, an input vector is presented to the network and propagated forward to determine the output signal. The output vector is then compared with the target vector resulting an error signal, which is backed propagated through the network in order to adjust the weights and bias. This learning process is repeated until the network respond for each input vector with an output vector that is sufficiently close to the desired one [21-24].

Neuro-fuzzy

The fuzzy inference system (FIS) is a computing system based on the concepts of fuzzy set theory, fuzzy IF/THEN rule and fuzzy reasoning to make relationship between an input space into an output space. The basis for fuzzy logic is the basis for human communication. Fuzzy reasoning contains very simple mathematical concepts. The fuzzy system can match any set of input-output data. This process is made particularly easy by adaptive techniques like adaptive neuro-fuzzy inference systems. ANFIS is about taking a fuzzy inference system and training it with a backpropagation algorithm, well known in the artificial neural network (ANN) theory, based on some collection of input/output data. The basic structure of fuzzy inference system consists of three conceptual components: A rule base, database or dictionary which defines the membership functions used in the fuzzy rules, and reasoning mechanism which performs the inference procedure upon the rule and a given condition to derive a reasonable output or conclusion [25-27].

The present study describes a new technique based on principal component analysis, polynomial regression, neural network and neuro-fuzzy techniques that attempts to reconstruction reflectance spectra from the scanner RGB values.

Materials and Methods

The Benq 5550T color scanner was used for scanning and imaging the colored fabrics. The fabrics were scanned under the condition of 600 pixels/inch and 24 bit /pixel. The reflectance spectra of dyed fabrics were measured by using Texflash spectrophotometer of Datacolor Corporation. The colored fabrics were consisting of polyester fabrics dyed with disperse dyestuff in varieties of colors. The chromaticity of fabrics is shown in Figure 1 under condition of 10 degree standard observer and D65 illuminant. A set of 141 patches of fabrics were used as training data and 41 patches were kept for testing. The lightness of training and testing samples are shown in Figures 2 and 3, respectively. All computations were performed by using MATLAB software.

sRGB method

In this method, the relationship between the reflectance spectra and scanner RGB values was obtained by using sRGB equation. The experimental procedure is outlined below:

- Scan fabrics by scanner and obtain the scanner RGB responses from colored fabrics images.
- Then RGB value of scanner was converted to CIEXYZ by follow:

$$\begin{cases} R = \dfrac{R}{255} \\ G = \dfrac{G}{255} \\ B = \dfrac{B}{255} \end{cases} \tag{1}$$

$$r = \begin{cases} \dfrac{R}{12.92} R \le 0.04045 \\ \left(\dfrac{R+0.055}{1.055}\right)^{2.4} R > 0.04045 \end{cases} \quad 2)$$

$$g = \begin{cases} \dfrac{G}{12.92} G \le 0.04045 \\ \left(\dfrac{G+0.055}{1.055}\right)^{2.4} G > 0.04045 \end{cases} \tag{3}$$

$$b = \begin{cases} \dfrac{B}{12.92} B \le 0.04045 \\ \left(\dfrac{B+0.055}{1.055}\right)^{2.4} B > 0.04045 \end{cases} \tag{4}$$

$$\begin{cases} \bar{R} = 100 \times r \\ \bar{G} = 100 \times g \\ \bar{B} = 100 \times b \end{cases} \tag{5}$$

$$\begin{cases} X = 0.4124 \times \bar{R} + 0.3576 \times \bar{G} + 0.1805 \times \bar{B} \\ X = 0.2126 \times \bar{R} + 0.7152 \times \bar{G} + 0.0722 \times \bar{B} \\ Z = 0.0193 \times \bar{R} + 0.1192 \times \bar{G} + 0.9505 \times \bar{B} \end{cases} \tag{6}$$

- Measuring the reflectance spectra of training samples by spectrophotometer.
- Calculating principal components of reflectance spectra.
- Calculating the tristimulus of principal components (XYZ_{PC}):

$$X_i = \frac{100}{K} \sum_{\lambda} E_{\lambda} \times PC_{\lambda,i} \times \bar{x}_{\lambda} \tag{7}$$

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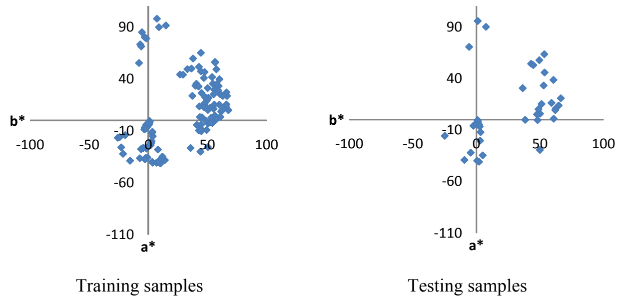

Figure 1: Chromaticity distribution of training and testing samples.

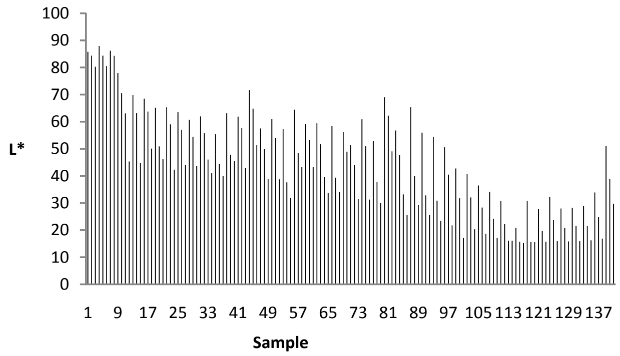

Figure 2: The lightness of training samples.

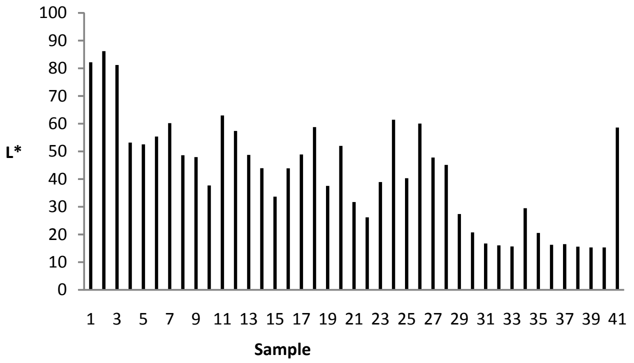

Figure 3: The lightness of testing samples.

$$Y_i = \frac{100}{K}\sum_{\lambda} E_{\lambda} \times PC_{\lambda,i} \times \bar{y}_{\lambda} \quad (8)$$

$$Z_i = \frac{100}{K}\sum_{\lambda} E_{\lambda} \times PC_{\lambda,i} \times \bar{z}_{\lambda} \quad (9)$$

where $K = \sum_{\lambda} E_{\lambda} \times \bar{y}_{\lambda}$, i =1, …, n and n is number of principal components

- Calculating the transformation matrix by Equation 4:

$$M = XYZ \times (XYZ_{pc})^{-1} \quad (10)$$

where M is transformation matrix (principal component weighting), XYZ are tristimulus values of testing samples which is evaluated in previous stage. XYZ_{PC} is tristimulus of principal components with highest eigenvalue.

- Application: calculating reflectance spectra by using principal component weighting (transformation matrix) in Equation 11.

$$R = m_1 \times PC_1 + m_2 \times PC_2 + \ldots\ldots\ldots\ldots m_n \times PC_n \quad (11)$$

XYZ-polynomial regression method

In this method, the relationship between the reflectance spectra and scanner RGB values was obtained by means of polynomial regression technique. The experimental procedure is outlined below:

- Scan fabrics by scanner and obtain the scanner RGB responses from colored fabrics images.
- Measure the reflectance spectra and CIEXYZ values of colored fabrics by spectrophotometer.
- Derive a transfer matrix that matches scanner RGB to CIEXYZ values of color fabrics by multiple polynomial regression by Equation 12. The polynomial functions are shown in Table 1.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = M \times h(m,R,G,B) \quad (12)$$

- Measuring the reflectance spectra and the tristimulus values (XYZ) of training samples by spectrophotometer.
- Calculating principal components of reflectance spectra.
- Calculating the tristimulus of principal components (XYZ_{PC}) by equations 7, 8 and 9.
- Calculating the transformation matrix (principal component weighting) by Equation 10.
- Application: calculating reflectance spectra by using principal component weighting (transformation matrix) in Equation 11.

PCA-polynomial regression method

The relationship between the reflectance spectra and scanner RGB values was achieved by means of polynomial regression and principal component analysis techniques. The procedure of calibration is outlined below:

- Scan samples by scanner and obtain the scanner RGB responses from their image.
- Measure the reflectance spectra of samples by spectrophotometer.
- Calculating principal components of reflectance spectra of training dataset.
- Calculating principal component weighting.
- Obtain the conversion polynomial function (A) between scanner polynomial function (h(n, R, G, B)) and principal component weighting (M_n):

$$A_n = M_n \times pinv(h(n,R,G,B)) \quad (13)$$

where M_n is weighting of n principal components and A_n is a n×n

matrix of coefficients, h(n, R, G, B) is a vector of scanner output signals polynomial function, where n is the number of terms in a polynomial and number of principal components at each model. Various polynomial transform functions were applied as detailed in Table 2.

- Application: convert scanner RGB into transformation matrix by obtained function in Equation 14.

$$\begin{bmatrix} m_1 \\ m_2 \\ . \\ . \\ . \\ . \\ . \\ . \\ . \\ m_n \end{bmatrix} = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,n} \\ a_{2,2} & a_{2,2} & a_{2,n} \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \\ . & . & . \\ a_{n,1} & a_{n,2} & a_{n,n} \end{bmatrix} \times h(n,R,G,B) \qquad (14)$$

Calculate reflectance spectra by using principal component weighting and average of training samples reflectance spectra in Equation 15.

$$R = R_m + m_1 \times PC_1 + m_2 \times PC_2 + ...m_n \times PC_n \qquad (15)$$

ANNET method

In this method, the relationship between the reflectance spectra and scanner RGB values was obtained by means of artificial neural network. The experimental procedure is outlined below:

No.	Number of terms	Polynomial terms ($h(m,R,G,B)$)
1	3	R G B
2	4	R G B 1
3	7	R G B R^2 G^2 B^2 1
4	8	R G B R×G R×B G×B R^2 G^2 B^2 1
5	14	R G B R×G×B R×G R×B G×B R^2 G^2 B^2 R^3 G^3 B^3 1

Table 1: Polynomial regression function.

No.	Number of PCA	number of terms	Polynomial terms ($h(m,R,G,B)$)
1	3	3	R G B
2	3	4	R G B 1
3	3	7	R G B R^2 G^2 B^2 1
4	3	8	R G B R×G R×B G×B R^2 G^2 B^2 1
5	3	14	R G B R×G×B R×G R×B G×B R^2 G^2 B^2 R^3 G^3 B^3 1
6	4	7	R G B R^2 G^2 B^2 1
7	4	8	R G B R×G R×B G×B R^2 G^2 B^2 1
8	4	14	R G B R×G×B R×G R×B G×B R^2 G^2 B^2 R^3 G^3 B^3 1
9	5	7	R G B R^2 G^2 B^2 1
10	5	8	R G B R×G R×B G×B R^2 G^2 B^2 1
11	5	14	R G B R×G×B R×G R×B G×B R^2 G^2 B^2 R^3 G^3 B^3 1

Table 2: Polynomial regression function.

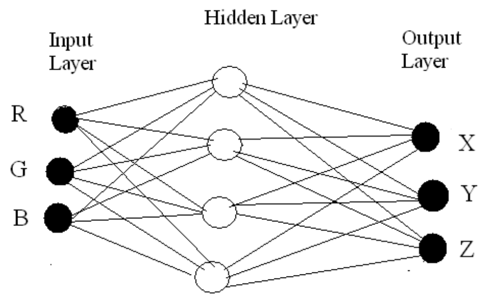

Figure 4: Structure of neural network with three output.

No.	Number of terms	mean	max	min	SD
1	3	0.0899	0.1675	0.0413	0.0343
2	4	0.0806	0.1647	0.0236	0.0387
3	7	0.0865	0.2740	0.0199	0.0601
4	8	0.0852	0.2555	0.0133	0.0599
5	14	0.0820	0.2001	0.0083	0.0549

Table 3: The spectrophotometric accuracy of polynomial regression (RMS).

- Scan fabrics by scanner and obtain the scanner RGB responses from colored fabrics images.
- Measure the reflectance spectra values of training samples by spectrophotometer.
- Calculating principal components of reflectance spectra.
- The used multilayer perceptrons neural networks contain three inputs as scanner RGB responses, and three outputs as CIEXYZ values. Figure 4 shows the structure of neural network with three inputs, three outputs and one hidden layer, which contain 4 nodes. The topologies details of neural networks are shown in Table 3.
- The neural network was trained with backpropagation algorithm, which was continued over 500 epochs. The trained neural networks were used to evaluate the CIEXYZ values of testing samples from their RGB values.
- Measuring the reflectance spectra of training samples by spectrophotometer
- Calculating principal components of reflectance spectra.
- Calculating the tristimulus for principal components by Equations 7, 8 and 9.
- Calculating the transformation matrix (principal component weighting) by Equation 10:
- Application: calculating reflectance spectra by using principal component weighting (transformation matrix) in Equation 11.

PCA-ANNET method

In this section, neural network and principal component analysis were used for construction relationship between the reflectance spectra and scanner RGB values. The experimental procedure is outlined below:

- Scan samples by scanner and obtain the scanner RGB responses from their image.
- Measure the reflectance spectra of samples by spectrophotometer.
- Calculating principal components of reflectance spectra.
- Calculating principal component weighting.
- Neural networks with multi-layer perceptron configuration applied to conversion scanner RGB values to principal component weighting. The neural network has 3 inputs as scanner RGB values and three to five outputs as coefficients first principal components (Figure 5). Several topologies were tested to make relation between principal component weighting and scanner RGB values. The neural network was trained with backpropagation algorithm. The error goal was 0.0001 and neural network training was continued over 1000 epochs by back propagation algorithm.
- Application: convert scanner RGB into principal component weighting by trained neural network and calculate reflectance spectra by means of principal component weighting (Equation 15).

Neuro-Fuzzy method

In this method, the relationship between the reflectance spectra and scanner RGB values was obtained by means of neuro-fuzzy. The experimental procedure is outlined below:

- Scan fabrics by scanner and obtain the scanner RGB responses from colored fabrics images.
- Measure the reflectance spectra and CIEXYZ values of training samples by spectrophotometer.
- Three ANFIS systems have been used. Each system has three input nods referred to the scanner RGB values and one output referred to one of the tristimulus values (Figure 6). Several membership functions such as gbellmf (Generalized bell-shaped built-in membership function), gauss2mf (Gaussian combination membership function), gaussmf (Gaussian curve built-in membership function) and dsigmf (Built-in membership function composed of the difference between two sigmoidal membership functions) were used for input nodes. Different numbers of membership functions have been also used for each input node. The neuro-fuzzy system has been trained by a hybrid method consisting of back propagation for the parameters associated with the input membership functions, and the least squares estimation for the parameters associated with the output membership functions.

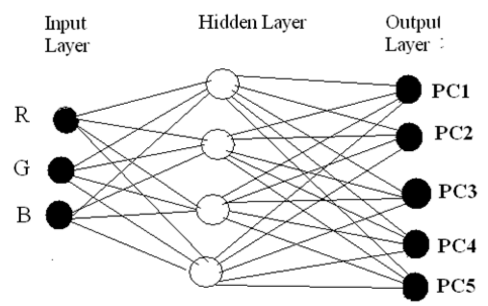

Figure 5: Structure of neural network with five principal components.

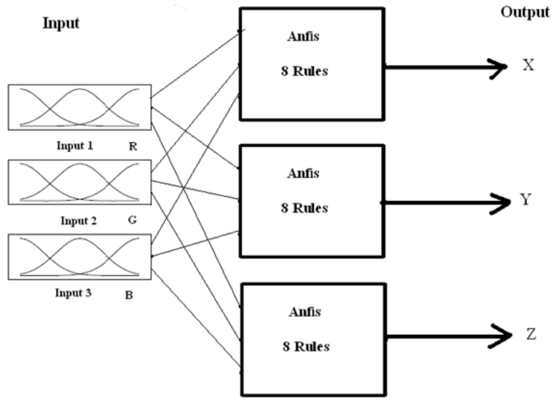

Figure 6: Three ANFIS system with three inputs, and one output.

The trained neuro fuzzy were used to evaluate the CIEXYZ values of testing samples from their RGB values.

- Calculating principal components of reflectance spectra.
- Calculating the tristimulus for principal components by Equations 7, 8 and 9.
- Calculating the transformation (principal component weighting) matrix by Equation 10.
- Application: calculating reflectance spectra by using principal component weighting (transformation matrix) in Equation 11.

PCA-Neuro fuzzy method

In this method, the relationship between the reflectance spectra and scanner RGB values was obtained by means of neuro fuzzy and principal component analysis techniques. The experimental procedure is outlined below:

- Scan fabrics by scanner and obtain the scanner RGB responses from colored fabrics images.
- Measure the reflectance spectra and CIEXYZ values of training samples by spectrophotometer.
- Calculating principal components of reflectance spectra.
- Three, four and five ANFIS systems have been used. Each system has three input nods referred to the scanner RGB values and one output referred to one of principal component (Figure 7). gbellmf (Generalized bell-shaped built-in membership function), gauss2mf (Gaussian combination membership function), gaussmf (Gaussian curve built-in membership function) and dsigmf (Built-in membership function composed of the difference between two sigmoidal membership functions) were used for input nodes. Different numbers of membership functions was also used for each input node. The neuro-fuzzy system was trained by a hybrid method consisting of back propagation for the parameters associated with the input membership functions, and the least square estimation for the parameters associated with the output membership functions.
- The trained neuro-fuzzy was used to evaluate the weight of principal components of testing samples with highest

eigenvalue from their RGB values.

- Application: principal components can be converted into reflectance spectral by means of transformation matrix and mean reflectance Equation 15.

Results and Discussion

The principal component analysis was applied on 141 reflectance spectra of training databases for extraction principal component and understanding the statistical nature of reflectance spectra. The principal components were calculated and their eigenvector are shown in Figure 8. The eigenvalues of principal components are also shown in Figure 9. From this figure, three initial principal components have highest and significant value and others are insignificant.

We tried to estimate the textile fabrics color by using scanner. The characterization was done by several methods such as sRGB, polynomial regression, PCA-polynomial regression, neural network, PCA-neural network, neuro-fuzzy and PCA-neuro fuzzy. The recovery performance was evaluated by spectrophotometric and colorimetric method. The spectrophotometric accuracy was calculated by the root mean square (RMS) error of the spectral fit. Colorimetric accuracy was evaluated by using CIELAB color difference equation under illuminant D65 and 1964 standard observer.

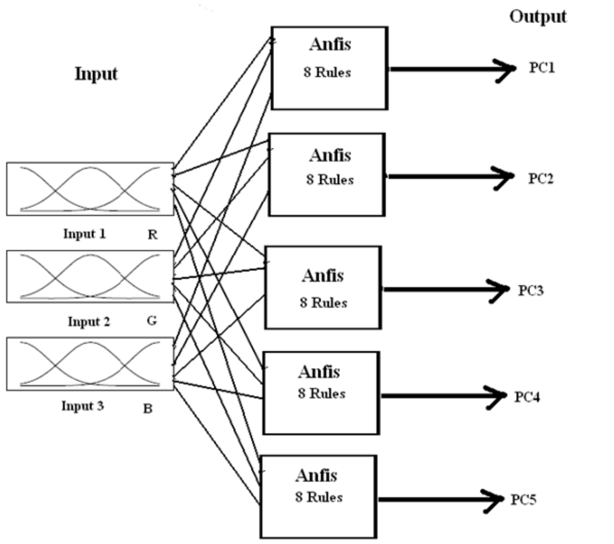

Figure 7: Five ANFIS system with three inputs and one output.

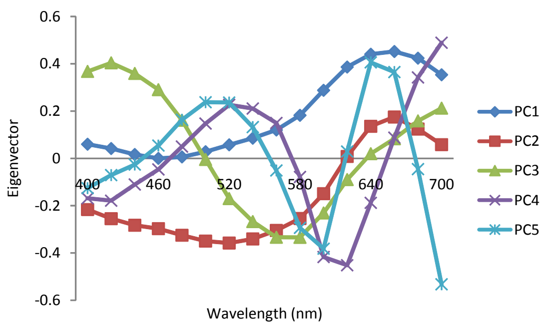

Figure 8: Eigenvector of principal components.

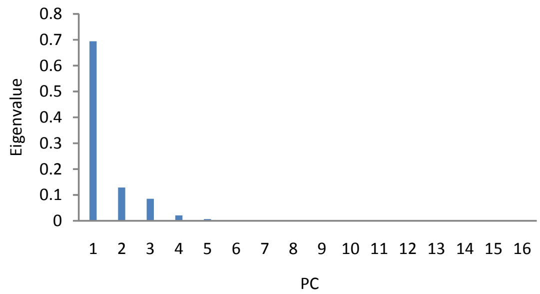

Figure 9: Eigenvalues of principal components.

No.	Number of terms	mean	max	min	SD
1	3	18.55	41.11	5.52	8.53
2	4	21.19	44.07	5.57	10.60
3	7	10.87	34.09	1.82	7.40
4	8	7.47	32.43	0.53	5.68
5	14	5.79	31.38	0.46	5.04

Table 4: The colorimetric accuracy of polynomial regression (ΔE*ab).

No.	Number of PC	number of terms	mean	max	min	SD
1	3	3	0.1484	0.2921	0.0239	0.0834
2	3	4	0.0553	0.1723	0.0113	0.0308
3	3	7	0.0493	0.1750	0.0104	0.0301
4	3	8	0.0479	0.1692	0.0102	0.0292
5	3	14	0.0476	0.1631	0.0121	0.0285
6	4	7	0.0397	0.1851	0.0072	0.0292
7	4	8	0.0365	0.1763	0.0076	0.0275
8	4	14	0.0353	0.1699	0.0091	0.0271
9	5	7	0.0376	0.1851	0.0066	0.0298
10	5	8	0.0337	0.1765	0.0087	0.0281
11	5	14	0.0317	0.1701	0.0093	0.0279

Table 5: The accuracy of PCA-polynomial regression (RMS).

The results of polynomial regression method are shown in Tables 3 and 4 as spectrophotometric accuracy and colorimetric accuracy, respectively. As illustrated in these tables, the spectrophotometric recovery error changed from 0.0097 to 0.0899 RMS and 5.79 to 21.19 ΔE*ab. It is recognized that high order polynomials will fit the experimental data better. From the mathematical point of analysis, as with series increase, a better approximation is obtained by adding additional terms to an equation. The best reflectance estimation is obtained by polynomial with 14 terms with 0.0820 RMS and 5.79 ΔE*ab.

The results of PCA-polynomial regression method are shown in Tables 5 and 6 as spectrophotometric accuracy and colorimetric accuracy, respectively. As illustrated in these tables, the spectrophotometric recovery error changed from 0.0317 to 0.1484 RMS and 6.71 to 23.46 ΔE*ab. It is recognized that high order polynomials will fit the experimental data better. In addition, the accuracy of estimation increased with increasing number of principal components. From the mathematical point of analysis, as with series increase, a better approximation is obtained by adding additional terms to an equation. The best reflectance estimation is obtained by polynomial with 14 terms and five first principal component with 0.0317 RMS and 6.71 ΔE*ab.

No.	Number of PC	number of terms	mean	max	min	SD
1	3	3	23.46	43.61	5.36	12.14
2	3	4	20.84	43.46	5.68	10.27
3	3	7	15.90	40.18	2.61	11.82
4	3	8	15.60	39.25	1.08	11.77
5	3	14	15.41	38.39	1.32	10.81
6	4	7	10.07	33.86	2.11	7.46
7	4	8	8.03	33.20	1.34	6.14
8	4	14	8.38	32.35	0.55	5.66
9	5	7	11.40	33.57	0.70	9.47
10	5	8	7.66	32.11	1.10	5.61
11	5	14	6.71	31.21	0.33	5.32

Table 6: The accuracy of PCA-polynomial regression (ΔE*ab).

No.	Term	RMS	ΔE*ab
1	mean	0.1173	14.99
2	max	0.3107	47.4
3	min	0.0103	5.8
4	SD	0.0697	7.38

Table 7: The accuracy of SRGB method.

No.	Number of layers	Number of nods per layer	mean	max	min	SD
1	3	3 3 3	0.0853	0.3182	0.0091	0.0632
2	3	3 5 3	0.0835	0.2124	0.0094	0.0554
3	3	3 7 3	0.0817	0.2122	0.0083	0.0556
4	3	3 9 3	0.1079	1.0090	0.0083	0.1547
5	3	3 11 3	0.0895	0.2300	0.0067	0.0606
6	4	3 3 3 3	0.0846	0.2686	0.0082	0.0586
7	4	3 3 5 3	0.0874	0.1944	0.0096	0.0580
8	4	3 5 3 3	0.0852	0.2201	0.0087	0.0585
9	4	3 5 5 3	0.0850	0.1997	0.0064	0.0559
10	4	3 3 7 3	0.0961	0.3477	0.0078	0.0739
11	4	3 7 3 3	0.1104	0.2481	0.0067	0.0716
12	4	3 5 7 3	0.1027	0.3446	0.0080	0.0818
13	4	3 7 5 3	0.0917	0.2076	0.0062	0.0569
14	4	3 2 2 3	0.0827	0.2100	0.0097	0.0546
15	4	3 4 2 3	0.0842	0.2169	0.0069	0.0563
16	4	3 2 5 3	0.0853	0.2198	0.0083	0.0571

Table 8: the accuracy of ANNET with 5 pc (RMS).

No.	Number of layers	Number of nods per layer	mean	max	min	SD
1	3	3 3 3	7.24	63.73	0.69	10.47
2	3	3 5 3	5.54	30.98	0.49	5.42
3	3	3 7 3	4.14	31.85	0.41	5.28
4	3	3 9 3	8.40	122.31	0.66	19.07
5	3	3 11 3	6.62	31.73	1.08	6.36
6	4	3 3 3 3	6.09	31.74	0.86	5.69
7	4	3 3 5 3	8.44	33.23	1.42	6.64
8	4	3 5 3 3	4.61	30.97	0.70	4.90
9	4	3 5 5 3	5.19	32.28	0.75	5.13
10	4	3 3 7 3	9.41	43.37	1.14	8.82
11	4	3 7 3 3	9.58	67.74	0.57	12.52
12	4	3 5 7 3	9.47	44.28	1.24	10.15
13	4	3 7 5 3	6.11	33.36	0.11	6.18
14	4	3 2 2 3	6.02	31.64	0.98	5.75
15	4	3 4 2 3	4.23	31.69	0.37	4.99
16	4	3 2 5 3	5.04	30.66	0.47	5.11

Table 9: The accuracy of ANNET with 5 pc (ΔE*ab).

No.	Number of layers	Number of nods per layer	mean	max	min	SD
1	3	3 3 3	0.0544	0.2174	0.0129	0.0387
2	3	3 5 3	0.0526	0.2119	0.0100	0.0360
3	3	3 7 3	0.0543	0.2065	0.0109	0.0416
4	3	3 9 3	0.0526	0.2257	0.0094	0.0375
5	3	3 11 3	0.0794	0.4853	0.0097	0.0922
6	4	3 3 3 3	0.0548	0.2266	0.0098	0.0380
7	4	3 3 5 3	0.0655	0.3592	0.0096	0.0638
8	4	3 5 3 3	0.0566	0.3034	0.0109	0.0524
9	4	3 5 5 3	0.0667	0.5129	0.0104	0.0804
10	4	3 3 7 3	0.0561	0.2301	0.0101	0.0393
11	4	3 7 3 3	0.1668	1.7011	0.0106	0.3709
12	4	3 5 7 3	0.0685	0.2670	0.0097	0.0616
13	4	3 7 5 3	0.1112	1.3480	0.0107	0.2095
14	4	3 2 2 3	0.0554	0.2208	0.0112	0.0390
15	4	3 4 2 3	0.0553	0.2251	0.0102	0.0400
16	4	3 2 5 3	0.0536	0.2283	0.0098	0.0358

Table 10: The accuracy of PCA-ANNET with 3 pc (RMS).

The accuracy of reflectance spectra by sRGB method are shown in Table 7 as spectrophotometric accuracy and colorimetric accuracy. As shown in this Table, the spectrophotometric and colorimetric recovery error are 0.117313 RMS and 14.99 ΔE*ab.

The results of artificial neural network (ANNET) method are shown in Tables 8 and 9 as spectrophotometric accuracy and colorimetric accuracy, respectively. As illustrated in these tables, the spectrophotometric recovery error changed from 0.0817 to 0.1104 RMS and 4.14 to 9.58 ΔE*ab. The best reflectance estimation is obtained by neural network with one hidden layers and 7 nods with 14 terms with 0.0817 RMS and 4.14 ΔE*ab.

The results of principal component analysis and artificial neural network (PCA-ANNET) method are shown in Tables 10, 12 and 14 as spectrophotometric accuracy and Tables 11, 13 and 15 as colorimetric accuracy. As illustrated in these tables, the spectrophotometric recovery error changed from 0.0297 to 0.1668RMS and 6.14 to 22.12 ΔE*ab. The best reflectance estimation is obtained by neural network with two hidden layers, respectively with 2 and 5 nods, and five principal components with 0.0297 RMS and 6.14 ΔE*ab.

No.	Number of layers	Number of nods per layer	mean	max	min	SD
1	3	3 3 3	16.03	36.85	1.07	9.23
2	3	3 5 3	16.20	36.70	1.35	10.47
3	3	3 7 3	16.18	35.19	1.42	10.28
4	3	3 9 3	15.92	35.83	2.20	10.00
5	3	3 11 3	19.39	92.55	2.77	17.42
6	4	3 3 3 3	16.60	37.21	2.32	10.53
7	4	3 3 5 3	16.70	47.62	1.46	11.67
8	4	3 5 3 3	17.08	72.39	1.27	13.30
9	4	3 5 5 3	16.88	45.16	2.65	10.68
10	4	3 3 7 3	16.51	36.01	1.39	9.68
11	4	3 7 3 3	22.12	94.05	1.21	20.89
12	4	3 5 7 3	18.28	44.57	2.18	11.57
13	4	3 7 5 3	23.53	118.74	2.84	19.13
14	4	3 2 2 3	14.58	35.85	1.46	9.27
15	4	3 4 2 3	15.28	35.37	2.38	9.55
16	4	3 2 5 3	16.64	38.28	1.49	10.49

Table 11: The accuracy of PCA-ANNET with 3 pc (ΔE*ab).

No.	Number of layers	Number of nods per layer	mean	max	min	SD
1	3	3 3 4	0.0360	0.1734	0.0081	0.0271
2	3	3 5 4	0.0394	0.1854	0.0081	0.0317
3	3	3 7 4	0.0396	0.2110	0.0075	0.0348
4	3	3 9 4	0.0505	0.2897	0.0076	0.0590
5	3	3 11 4	0.0530	0.2260	0.0060	0.0501
6	4	3 3 3 4	0.0444	0.2037	0.0091	0.0409
7	4	3 3 5 4	0.0453	0.2277	0.0066	0.0406
8	4	3 5 3 4	0.0457	0.2201	0.0054	0.0483
9	4	3 5 5 4	0.0426	0.2208	0.0051	0.0377
10	4	3 3 7 4	0.0566	0.3237	0.0061	0.0632
11	4	3 7 3 4	0.0553	0.3240	0.0079	0.0644
12	4	3 5 7 4	0.0614	0.3805	0.0090	0.0762
13	4	3 7 5 4	0.0697	0.4677	0.0084	0.0861
14	4	3 2 2 4	0.0379	0.1869	0.0065	0.0313
15	4	3 4 2 4	0.0361	0.1795	0.0078	0.0291
16	4	3 2 5 4	0.0460	0.2199	0.0078	0.0415

Table 12: The accuracy of PCA-ANNET with 4 pc (RMS).

No.	Number of layers	Number of nods per layer	mean	max	min	SD
1	3	3 3 4	8.65	32.44	2.07	5.66
2	3	3 5 4	8.57	32.85	2.31	6.61
3	3	3 7 4	7.68	33.22	1.05	5.52
4	3	3 9 4	9.88	55.60	1.48	9.96
5	3	3 11 4	9.00	37.08	0.67	7.66
6	4	3 3 3 4	8.06	30.37	0.24	5.55
7	4	3 3 5 4	10.75	34.91	2.08	7.51
8	4	3 5 3 4	9.44	36.45	2.06	6.50
9	4	3 5 5 4	9.76	61.14	1.63	9.78
10	4	3 3 7 4	7.26	35.44	1.20	5.49
11	4	3 7 3 4	10.57	89.06	0.80	14.73
12	4	3 5 7 4	9.14	43.64	0.99	8.32
13	4	3 7 5 4	12.65	50.84	2.24	11.78
14	4	3 2 2 4	12.74	55.46	1.45	12.39
15	4	3 4 2 4	7.81	31.73	2.05	5.26
16	4	3 2 5 4	9.25	39.44	1.87	7.71

Table 13: The accuracy of PCA-ANNET with 4 pc (ΔE*ab).

No.	Number of layers	Number of nods per layer	mean	max	min	SD
1	3	3 3 5	0.0340	0.1767	0.0063	0.0305
2	3	3 5 5	0.0319	0.1712	0.0058	0.0299
3	3	3 7 5	0.0335	0.2099	0.0066	0.0363
4	3	3 9 5	0.0385	0.2341	0.0061	0.0470
5	3	3 11 5	0.0398	0.2142	0.0056	0.0397
6	4	3 3 3 5	0.0341	0.1713	0.0054	0.0290
7	4	3 3 5 5	0.0351	0.2002	0.0054	0.0338
8	4	3 5 3 5	0.0437	0.2306	0.0067	0.0424
9	4	3 5 5 5	0.0480	0.3465	0.0084	0.0607
10	4	3 3 7 5	0.0548	0.4766	0.0062	0.0805
11	4	3 7 3 5	0.0471	0.3205	0.0066	0.0614
12	4	3 5 7 5	0.0471	0.3205	0.0066	0.0614
13	4	3 7 5 5	0.0613	0.5755	0.0049	0.0984
14	4	3 2 2 5	0.0500	0.2786	0.0062	0.0543
15	4	3 4 2 5	0.0318	0.1721	0.0066	0.0307
16	4	3 2 5 5	0.0297	0.1780	0.0053	0.0290

Table 14: The accuracy of PCA-ANNET with 5 pc (RMS).

In neuro-fuzzy method, several membership function such as Generalized bell-shaped built-in membership function, Gaussian combination membership function, Gaussian curve built-in membership function and Built-in membership function composed of the product of two sigmoidally-shaped membership functions were used for input nodes. The results of neuro-fuzzy method are shown in Tables 16 and 17 as spectrophotometric accuracy and colorimetric

No.	Number of layers	Number of nods per layer	mean	max	min	SD
1	3	3 3 5	7.38	33.20	1.31	6.20
2	3	3 5 5	5.78	30.43	0.61	4.94
3	3	3 7 5	7.82	32.61	1.09	6.30
4	3	3 9 5	7.59	34.43	1.10	5.93
5	3	3 11 5	7.52	38.96	0.80	8.94
6	4	3 3 3 5	6.61	31.70	0.65	5.41
7	4	3 3 5 5	8.90	36.74	0.89	7.30
8	4	3 5 3 5	7.75	34.08	0.58	6.60
9	4	3 5 5 5	10.12	85.09	0.71	14.52
10	4	3 3 7 5	7.15	34.34	0.68	6.08
11	4	3 7 3 5	7.15	34.34	0.68	6.08
12	4	3 5 7 5	9.74	50.63	1.50	9.69
13	4	3 7 5 5	6.51	35.53	1.07	6.19
14	4	3 2 2 5	6.02	29.37	0.58	4.99
15	4	3 4 2 5	5.76	32.07	1.16	5.31
16	4	3 2 5 5	6.14	32.32	1.16	5.46

Table 15: The accuracy of PCA-ANNET with 5 pc (ΔE*ab).

No.	Membership function	Number of Membership function	mean	max	min	SD
1	gaussmf	2 2 2	0.0839	0.2202	0.0080	0.0580
2	gaussmf	2 2 3	0.1073	0.4393	0.0070	0.0998
3	gaussmf	3 2 2	0.0899	0.2407	0.0075	0.0624
4	gaussmf	2 3 2	0.0849	0.2471	0.0064	0.0607
5	gaussmf	3 3 2	0.0962	0.5696	0.0072	0.0942
6	gaussmf	3 2 3	0.1115	0.4275	0.0093	0.0935
7	gaussmf	2 3 3	0.1486	2.6040	0.0074	0.3974
8	gaussmf	3 3 3	0.2310	2.1700	0.0116	0.4183
9	gbellmf	2 2 2	0.0825	0.2038	0.0063	0.0551
10	gbellmf	2 2 3	0.1063	0.7220	0.0088	0.1203
11	gbellmf	3 2 2	0.0957	0.4165	0.0095	0.0817
12	gbellmf	2 3 2	0.0853	0.2423	0.0063	0.0583
13	gbellmf	3 3 2	0.1247	0.9908	0.0087	0.1710
14	gbellmf	3 2 3	0.1059	0.5289	0.0065	0.1083
15	gbellmf	2 3 3	0.1006	0.2477	0.0067	0.0695
16	gbellmf	3 3 3	0.1119	0.7296	0.0063	0.1194
17	dsigmf	2 2 2	0.0815	0.2043	0.0068	0.0541
18	dsigmf	2 2 3	0.0993	0.2998	0.0068	0.0706
19	dsigmf	3 2 2	0.1033	0.5026	0.0080	0.0911
20	dsigmf	2 3 2	0.0839	0.2679	0.0073	0.0629
21	dsigmf	3 3 2	0.0835	0.2014	0.0083	0.0565
22	dsigmf	3 2 3	0.1443	1.2095	0.0065	0.2334
23	dsigmf	2 3 3	0.1464	0.7324	0.0065	0.1643
24	dsigmf	3 3 3	0.1571	2.1900	0.0069	0.3401
25	gauss2mf	2 2 2	0.0848	0.2590	0.0066	0.0603
26	gauss2mf	2 2 3	0.0914	0.3835	0.0064	0.0759
27	gauss2mf	3 2 2	0.1219	0.9454	0.0072	0.1591
28	gauss2mf	2 3 2	0.1244	1.5596	0.0071	0.2410
29	gauss2mf	3 3 2	0.1459	1.4051	0.0075	0.2360
30	gauss2mf	3 2 3	0.1328	1.1786	0.0074	0.2009
31	gauss2mf	2 3 3	0.1457	1.5360	0.0070	0.2469
32	gauss2mf	3 3 3	0.1082	0.4665	0.0066	0.0995

Table 16: The accuracy of Neuro-Fuzzy (RMS).

No.	Membership function	Number of Membership function	mean	max	min	SD
1	gaussmf	2 2 2	4.36	32.07	0.52	5.06
2	gaussmf	2 2 3	7.01	50.18	0.47	11.41
3	gaussmf	3 2 2	5.46	33.22	0.40	6.71
4	gaussmf	2 3 2	6.54	35.54	0.40	8.14
5	gaussmf	3 3 2	8.85	107.14	0.30	17.05
6	gaussmf	3 2 3	10.01	73.56	0.40	14.84
7	gaussmf	2 3 3	8.57	119.76	0.39	19.00
8	gaussmf	3 3 3	24.23	190.95	0.25	46.59
9	gbellmf	2 2 2	4.47	32.58	0.70	5.04
10	gbellmf	2 2 3	6.84	53.21	0.45	11.68
11	gbellmf	3 2 2	7.83	92.58	0.51	17.41
12	gbellmf	2 3 2	6.15	32.72	0.47	7.47
13	gbellmf	3 3 2	12.37	155.12	0.47	27.53
14	gbellmf	3 2 3	10.89	92.18	0.80	19.03
15	gbellmf	2 3 3	10.07	39.91	0.59	11.11
16	gbellmf	3 3 3	8.83	48.39	0.29	11.58
17	dsigmf	2 2 2	5.93	32.92	0.25	5.68
18	dsigmf	2 2 3	7.95	43.90	0.82	9.12
19	dsigmf	3 2 2	11.02	149.15	0.30	25.32
20	dsigmf	2 3 2	6.45	39.53	0.43	8.56
21	dsigmf	3 3 2	8.13	34.45	0.70	9.17
22	dsigmf	3 2 3	12.50	129.92	0.72	23.71
23	dsigmf	2 3 3	17.70	129.24	0.54	28.94
24	dsigmf	3 3 3	11.50	114.19	0.75	19.93

25	gauss2mf	2 2 2	4.70	32.97	0.50	6.18
26	gauss2mf	2 2 3	6.10	50.84	0.79	8.87
27	gauss2mf	3 2 2	12.05	128.72	0.37	25.69
28	gauss2mf	2 3 2	9.72	142.86	0.56	23.15
29	gauss2mf	3 3 2	12.68	122.72	0.50	24.54
30	gauss2mf	3 2 3	11.26	108.69	0.56	23.67
31	gauss2mf	2 3 3	12.02	93.06	0.35	22.12
32	gauss2mf	3 3 3	12.29	116.50	0.67	20.93

Table 17: The accuracy of neuro-fuzzy (∆E*ab).

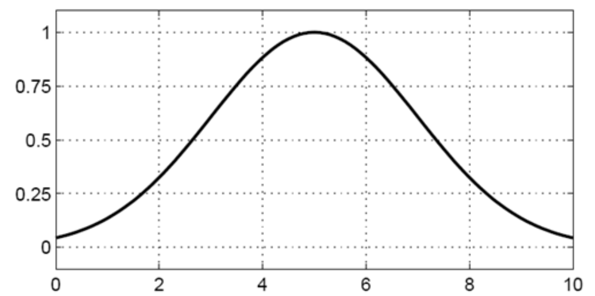

Figure 10: Gaussmf membership function.

No.	Membership function	Number of Membership function	mean	max	min	SD
1	gaussmf	2 2 2	0.0496	0.1854	0.0107	0.0327
2	gaussmf	2 2 3	0.0619	0.5768	0.0106	0.0886
3	gaussmf	3 2 2	0.0544	0.2038	0.0094	0.0371
4	gaussmf	2 3 2	0.0518	0.1903	0.0105	0.0342
5	gaussmf	3 3 2	0.0655	0.4169	0.0104	0.0692
6	gaussmf	3 2 3	0.0585	0.2173	0.0092	0.0415
7	gaussmf	2 3 3	0.0666	0.4873	0.0100	0.0804
8	gaussmf	3 3 3	0.0877	0.4719	0.0099	0.0904
9	gbellmf	2 2 2	0.0502	0.1831	0.0098	0.0335
10	gbellmf	2 2 3	0.0608	0.4239	0.0095	0.0680
11	gbellmf	3 2 2	0.0705	0.5397	0.0098	0.0897
12	gbellmf	2 3 2	0.0530	0.1977	0.0097	0.0373
13	gbellmf	3 3 2	0.0630	0.4152	0.0111	0.0667
14	gbellmf	3 2 3	0.0535	0.2203	0.0095	0.0362
15	gbellmf	2 3 3	0.0814	0.7554	0.0094	0.1301
16	gbellmf	3 3 3	0.1183	1.2679	0.0099	0.2083
17	dsigmf	2 2 2	0.0523	0.1781	0.0095	0.0354
18	dsigmf	2 2 3	0.0625	0.3163	0.0099	0.0636
19	dsigmf	3 2 2	0.0608	0.2650	0.0110	0.0500
20	dsigmf	2 3 2	0.0511	0.1789	0.0101	0.0319
21	dsigmf	3 3 2	0.0763	0.3951	0.0104	0.0840
22	dsigmf	3 2 3	0.0790	0.4673	0.0108	0.0998
23	dsigmf	2 3 3	0.0561	0.1961	0.0122	0.0428
24	dsigmf	3 3 3	0.0766	0.4218	0.0096	0.0861
25	gauss2mf	2 2 2	0.0522	0.1852	0.0094	0.0374
26	gauss2mf	2 2 3	0.0520	0.1817	0.0104	0.0360
27	gauss2mf	3 2 2	0.0697	0.3968	0.0101	0.0822
28	gauss2mf	2 3 2	0.0534	0.1966	0.0099	0.0375
29	gauss2mf	3 3 2	0.0672	0.4074	0.0098	0.0693
30	gauss2mf	3 2 3	0.0676	0.3372	0.0105	0.0711
31	gauss2mf	2 3 3	0.0621	0.2683	0.0096	0.0555
32	gauss2mf	3 3 3	0.0746	0.3869	0.0097	0.0796

Table 18: The accuracy of PCA-Neuro-Fuzzy with 3 pc (RMS).

No.	Membership function	Number of Membership function	mean	max	min	SD
1	gaussmf	2 2 2	15.62	34.24	1.68	9.86
2	gaussmf	2 2 3	16.23	76.86	1.88	14.03
3	gaussmf	3 2 2	16.32	36.72	2.19	10.07
4	gaussmf	2 3 2	16.73	36.30	0.89	10.15
5	gaussmf	3 3 2	18.03	45.23	3.27	10.75
6	gaussmf	3 2 3	16.92	54.03	1.60	11.85
7	gaussmf	2 3 3	19.06	88.43	1.97	15.31
8	gaussmf	3 3 3	22.97	114.97	1.76	21.67
9	gbellmf	2 2 2	15.51	34.18	1.65	10.03
10	gbellmf	2 2 3	18.51	147.44	1.82	22.95
11	gbellmf	3 2 2	18.28	47.29	2.65	12.06
12	gbellmf	2 3 2	17.05	44.24	1.64	11.41
13	gbellmf	3 3 2	18.15	58.24	3.37	12.56
14	gbellmf	3 2 3	16.36	38.30	1.33	10.51
15	gbellmf	2 3 3	19.05	73.92	1.95	14.99
16	gbellmf	3 3 3	24.27	99.10	2.88	21.08
17	dsigmf	2 2 2	16.00	37.42	2.67	10.04
18	dsigmf	2 2 3	17.26	60.81	2.17	13.96
19	dsigmf	3 2 2	16.81	67.60	3.36	13.05
20	dsigmf	2 3 2	16.22	34.33	2.57	10.00
21	dsigmf	3 3 2	20.15	52.40	3.62	12.73
22	dsigmf	3 2 3	21.61	128.18	2.97	22.42
23	dsigmf	2 3 3	16.65	41.02	1.28	10.94
24	dsigmf	3 3 3	19.54	79.81	2.32	14.42
25	gauss2mf	2 2 2	15.98	33.64	2.30	10.17
26	gauss2mf	2 2 3	15.39	36.61	1.05	9.87
27	gauss2mf	3 2 2	17.10	46.53	1.67	11.94
28	gauss2mf	2 3 2	15.99	34.59	1.76	10.08
29	gauss2mf	3 3 2	18.65	53.71	3.64	11.66
30	gauss2mf	3 2 3	18.37	77.29	1.28	14.04

31	gauss2mf	2 3 3	17.35	43.23	1.29	12.41
32	gauss2mf	3 3 3	19.81	71.49	2.81	14.66

Table 19: the accuracy of PCA-Neuro-Fuzzy with 3 pc (ΔE*ab).

No.	Membership function	Number of Membership function	mean	max	min	SD
1	gaussmf	2 2 2	0.0373	0.1898	0.0077	0.0315
2	gaussmf	2 2 3	0.0510	0.5749	0.0083	0.0895
3	gaussmf	3 2 2	0.0471	0.2092	0.0067	0.0453
4	gaussmf	2 3 2	0.0429	0.1908	0.0077	0.0399
5	gaussmf	3 3 2	0.0577	0.4172	0.0068	0.0781
6	gaussmf	3 2 3	0.0485	0.2175	0.0058	0.0434
7	gaussmf	2 3 3	0.0570	0.4935	0.0057	0.0849
8	gaussmf	3 3 3	0.0971	0.4820	0.0064	0.1234
9	gbellmf	2 2 2	0.0390	0.1878	0.0074	0.0350
10	gbellmf	2 2 3	0.0505	0.4180	0.0050	0.0706
11	gbellmf	3 2 2	0.0611	0.5394	0.0071	0.0924
12	gbellmf	2 3 2	0.0490	0.2982	0.0070	0.0544
13	gbellmf	3 3 2	0.0611	0.4324	0.0075	0.0793
14	gbellmf	3 2 3	0.0450	0.2194	0.0046	0.0373
15	gbellmf	2 3 3	0.0927	0.7553	0.0057	0.1440
16	gbellmf	3 3 3	0.1093	1.2668	0.0056	0.2116
17	dsigmf	2 2 2	0.0413	0.1803	0.0072	0.0361
18	dsigmf	2 2 3	0.0528	0.3157	0.0055	0.0668
19	dsigmf	3 2 2	0.0506	0.2714	0.0073	0.0521
20	dsigmf	2 3 2	0.0463	0.1881	0.0073	0.0450
21	dsigmf	3 3 2	0.0721	0.6065	0.0074	0.1104
22	dsigmf	3 2 3	0.0715	0.4695	0.0072	0.1044
23	dsigmf	2 3 3	0.0469	0.2245	0.0098	0.0498
24	dsigmf	3 3 3	0.0713	0.4075	0.0049	0.0848
25	gauss2mf	2 2 2	0.0433	0.2109	0.0076	0.0453
26	gauss2mf	2 2 3	0.0402	0.1869	0.0079	0.0359
27	gauss2mf	3 2 2	0.0591	0.3974	0.0067	0.0856
28	gauss2mf	2 3 2	0.0639	0.8142	0.0056	0.1276
29	gauss2mf	3 3 2	0.0671	0.5155	0.0058	0.1009
30	gauss2mf	3 2 3	0.0620	0.3246	0.0074	0.0804
31	gauss2mf	2 3 3	0.0580	0.3399	0.0059	0.0729
32	gauss2mf	3 3 3	0.0672	0.3917	0.0055	0.0811

Table 20: The accuracy of PCA-Neuro-Fuzzy with 4 pc (RMS).

No.	Membership function	Number of Membership function	mean	max	min	SD
1	gaussmf	2 2 2	7.80	33.74	1.06	6.13
2	gaussmf	2 2 3	9.37	78.73	2.14	12.27
3	gaussmf	3 2 2	10.78	51.23	0.79	9.68
4	gaussmf	2 3 2	10.15	36.33	1.41	8.82
5	gaussmf	3 3 2	11.49	46.56	0.64	10.13
6	gaussmf	3 2 3	10.22	59.38	2.04	10.30
7	gaussmf	2 3 3	10.34	82.43	1.35	13.36
8	gaussmf	3 3 3	17.95	118.35	1.65	23.68
9	gbellmf	2 2 2	8.07	31.25	1.83	5.83
10	gbellmf	2 2 3	12.47	147.07	2.32	22.71
11	gbellmf	3 2 2	12.27	48.41	1.02	11.05
12	gbellmf	2 3 2	11.36	39.60	1.52	9.98
13	gbellmf	3 3 2	14.14	65.57	1.67	14.90
14	gbellmf	3 2 3	9.37	38.24	2.64	6.65
15	gbellmf	2 3 3	14.25	73.96	0.61	17.34
16	gbellmf	3 3 3	16.70	96.41	1.03	21.13
17	dsigmf	2 2 2	9.83	30.28	2.95	6.35
18	dsigmf	2 2 3	11.44	80.73	1.73	15.76
19	dsigmf	3 2 2	10.85	79.29	1.28	12.86
20	dsigmf	2 3 2	10.41	39.18	1.10	8.56
21	dsigmf	3 3 2	14.76	84.23	1.32	15.56
22	dsigmf	3 2 3	16.45	128.37	0.96	23.90
23	dsigmf	2 3 3	9.81	36.57	1.91	7.73
24	dsigmf	3 3 3	13.87	85.98	1.94	14.23
25	gauss2mf	2 2 2	9.46	32.61	1.81	7.08
26	gauss2mf	2 2 3	9.33	37.90	2.21	7.97
27	gauss2mf	3 2 2	12.36	63.68	0.49	13.68
28	gauss2mf	2 3 2	12.90	128.67	0.80	20.13
29	gauss2mf	3 3 2	14.64	95.00	0.78	19.43
30	gauss2mf	3 2 3	11.90	88.75	1.76	14.96
31	gauss2mf	2 3 3	10.42	39.03	0.97	7.96
32	gauss2mf	3 3 3	13.21	49.98	1.03	10.71

Table 21: the accuracy of PCA-Neuro-Fuzzy with 4 pc (ΔE*ab).

No.	Membership function	Number of Membership function	mean	max	min	SD
1	gaussmf	2 2 2	0.0328	0.1899	0.0061	0.0322
2	gaussmf	2 2 3	0.0478	0.5838	0.0069	0.0919
3	gaussmf	3 2 2	0.0447	0.2377	0.0053	0.0503
4	gaussmf	2 3 2	0.0406	0.1995	0.0054	0.0442
5	gaussmf	3 3 2	0.0551	0.4170	0.0052	0.0799
6	gaussmf	3 2 3	0.0500	0.3437	0.0051	0.0633
7	gaussmf	2 3 3	0.0570	0.5828	0.0050	0.0997
8	gaussmf	3 3 3	0.0953	0.4855	0.0060	0.1252
9	gbellmf	2 2 2	0.0349	0.1880	0.0054	0.0366
10	gbellmf	2 2 3	0.0473	0.4183	0.0044	0.0717

11	gbellmf	3 2 2	0.0591	0.5538	0.0060	0.0959
12	gbellmf	2 3 2	0.0473	0.3180	0.0063	0.0593
13	gbellmf	3 3 2	0.0583	0.4403	0.0055	0.0809
14	gbellmf	3 2 3	0.0420	0.2222	0.0045	0.0396
15	gbellmf	2 3 3	0.0919	0.8236	0.0051	0.1536
16	gbellmf	3 3 3	0.1067	1.2668	0.0049	0.2131
17	dsigmf	2 2 2	0.0386	0.2147	0.0069	0.0435
18	dsigmf	2 2 3	0.0502	0.3321	0.0053	0.0695
19	dsigmf	3 2 2	0.0482	0.2974	0.0048	0.0571
20	dsigmf	2 3 2	0.0516	0.3358	0.0059	0.0677
21	dsigmf	3 3 2	0.0690	0.6069	0.0054	0.1087
22	dsigmf	3 2 3	0.0722	0.4776	0.0051	0.1096
23	dsigmf	2 3 3	0.0507	0.2789	0.0082	0.0605
24	dsigmf	3 3 3	0.0688	0.4061	0.0041	0.0865
25	gauss2mf	2 2 2	0.0391	0.2067	0.0062	0.0458
26	gauss2mf	2 2 3	0.0368	0.1874	0.0069	0.0402
27	gauss2mf	3 2 2	0.0622	0.5753	0.0059	0.1086
28	gauss2mf	2 3 2	0.0601	0.7787	0.0048	0.1235
29	gauss2mf	3 3 2	0.0655	0.5060	0.0065	0.1005
30	gauss2mf	3 2 3	0.0602	0.3395	0.0056	0.0837
31	gauss2mf	2 3 3	0.0556	0.3402	0.0056	0.0776
32	gauss2mf	3 3 3	0.0640	0.3569	0.0050	0.0792

Table 22: The accuracy of PCA-Neuro-Fuzzy with 5 pc (RMS).

No.	Membership function	Number of Membership function	mean	max	min	SD
1	gaussmf	2 2 2	6.42	32.54	1.75	5.58
2	gaussmf	2 2 3	8.59	73.39	1.48	11.64
3	gaussmf	3 2 2	9.17	35.90	1.23	7.95
4	gaussmf	2 3 2	8.98	36.79	0.64	9.59
5	gaussmf	3 3 2	10.24	48.38	0.43	11.04
6	gaussmf	3 2 3	9.50	74.58	1.10	12.74
7	gaussmf	2 3 3	8.93	88.18	0.98	14.01
8	gaussmf	3 3 3	17.26	110.00	0.89	23.15
9	gbellmf	2 2 2	7.21	30.02	0.89	6.01
10	gbellmf	2 2 3	11.46	142.50	1.02	22.40
11	gbellmf	3 2 2	11.07	46.93	0.98	11.41
12	gbellmf	2 3 2	9.76	33.37	1.48	10.00
13	gbellmf	3 3 2	11.97	59.68	0.53	14.21
14	gbellmf	3 2 3	8.73	34.76	1.12	6.29
15	gbellmf	2 3 3	14.55	79.43	1.93	17.45
16	gbellmf	3 3 3	15.39	96.85	1.43	21.36
17	dsigmf	2 2 2	8.54	29.02	1.93	6.68
18	dsigmf	2 2 3	11.33	79.88	1.88	15.26
19	dsigmf	3 2 2	9.47	82.16	0.65	13.36
20	dsigmf	2 3 2	6.81	30.58	1.24	6.39
21	dsigmf	3 3 2	13.24	86.24	1.12	16.18
22	dsigmf	3 2 3	16.14	132.24	0.89	26.81
23	dsigmf	2 3 3	9.95	43.43	1.29	9.00
24	dsigmf	3 3 3	12.80	92.64	1.38	15.27
25	gauss2mf	2 2 2	8.23	31.30	1.72	6.85
26	gauss2mf	2 2 3	8.03	41.15	0.83	7.88
27	gauss2mf	3 2 2	11.07	77.86	0.67	15.11
28	gauss2mf	2 3 2	11.57	128.39	0.75	20.18
29	gauss2mf	3 3 2	12.97	92.11	0.64	17.16
30	gauss2mf	3 2 3	10.88	79.31	1.22	13.85
31	gauss2mf	2 3 3	9.22	35.75	0.84	7.49
32	gauss2mf	3 3 3	11.71	50.03	1.11	11.54

Table 23: The accuracy of PCA-Neuro-Fuzzy with 5 pc (ΔE*ab).

accuracy, respectively. As illustrated in these Tables, the reflectance recovery error changed from 0.0815 to 0.2310 RMS and 4.36 to 24.23 ΔE*ab. The best reflectance estimation is obtained by neuro-fuzzy with Gaussian curve built-in membership function (gaussmf) (Figure 10) with 14 terms with 0.0839 RMS and 4.36 ΔE*ab.

In PCA-neuro-fuzzy method, several membership function such as Generalized bell-shaped built-in membership function, Gaussian combination membership function, Gaussian curve built-in membership function and Built-in membership function composed of the product of two sigmoidally-shaped membership functions were used for input nodes. The results of neuro-fuzzy method are shown in Tables 18, 20 and 22 as spectrophotometric accuracy and Tables 19, 21 and 23 as colorimetric accuracy. As illustrated in these tables, the reflectance recovery error changed from 0.0328 to 0.1183 RMS and 6.42 to 24.27ΔE*ab. The best reflectance estimation is obtained by neuro-fuzzy with 2 Gaussian curve built-in membership function (gaussmf) for each input and 5 principal components with 0.0328 RMS and 6.42 ΔE*ab.

Conclusions

This article explained a numerical method based on principal component analysis, polynomial regression, neural network and neuro-fuzzy techniques to measure the reflectance spectra by scanner.

In polynomial method, estimation error is 0.0820 RMS and 5.79 ΔE*ab. The reflectance estimation error in PCA-polynomial method is 0.0317 RMS and 6.71 ΔE*ab. In sRGB method, the estimation error is 0.1173 RMS and 14.99 ΔE*ab. The reflectance estimation error of neural network method is 0.0817 RMS and 4.14 ΔE*ab. In PCA-ANNET method, the estimation error is 0.0297 RMS and 6.14 ΔE*ab. The reflectance estimation error of neuro-fuzzy method is 0.0839 RMS and 4.36 ΔE*ab. In PCA-neuro-fuzzy method error is 0.0328 RMS and 6.42 ΔE*ab. Obtained results indicate that the recovery error decreases with increase number of principal component and number of terms in a polynomial. Also, application of principal component increase accuracy of reflectance measurement. The reflectance estimation performance of PCA- ANNET method is better than others.

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