Colorimetric and Spectral Properties of Natural Colorants Used in Handmade Traditional Persian Carpets

Mansoureh Ghanbar Afjeh, Sarvenaz Ghanean and Firozmeher Mazaheri

***Abstract*—The colorimetric specifications and the dimensional properties of the spectral reflectance of natural dyes, which are used in the traditional handmade Persian carpet, are investigated. Different natural dyes are employed on woolen yarns to provide a collection of 286 colored samples. The colorimetric expansion and the spectral behaviors of samples are compared with Munsell color-matt finish collection.**

The principal component analysis technique as well as the non-negative matrix factorization method is employed for the spectral evaluation of datasets. Although the natural dyes present smaller color gamut in comparison to the Munsell dataset, the dimensional properties of the reflectance spectra of both datasets provide very close cumulative percentage of variances. The results are reconfirmed by the calculation of the mean root square errors between the original and the reconstructed spectra of samples from reduced spaces employing different numbers of positive-negative and all positive bases as well as the CIELAB color difference values under D65 and A illuminants and 1964 standard observer.

Key words: Color, handmade Persian carpet, non-negative matrix factorization, principal component analysis, spectral dimension.

I. INTRODUCTION

HANDMADE Persian carpet is known worldwide due to its matchless designs, artistic structure and unique raw materials. This ingeniously artwork is weaved knot by knot by the artistic hands of the traditional weavers in a very long production period. In colorimetric point of view, a wide range of colors are mysteriously produced on woolen yarns in the hank form by traditional dyeing process using different natural colorants as dyes and a variety of natural salts as mordants. Strangely, different tones (mostly unrepeatable) are achieved by identical materials while traditional dyers use their own secretively matchless techniques and/or tricks. Finally, millions of fine knots, hundreds of colors and the art of the weavers create the precious artwork named Persian carpet.

A variety of natural dyestuffs are used on woolen yarn to prepare a broad range of colors. To improve the fastness of naturally dyed yarns and extend the resultant color gamut, different natural materials such as metallic salts (mostly in their raw and unpurified mineral forms) are employed. The employed natural dyes have both plant and animal sources while dyes with plant origin are more popular. Footrest, pomegranate peel, matric aria, henna, mignonette and hundreds of plants in the form of root, stem and leaf are usually used as natural colorants while alums, lyes and vitriols as well as other natural salts are utilized as mordants. In rural areas, some particular aftertreatment techniques such as washing the dyed yarns in a given spring water, which probably contains specific metallic salts, provide the desired fastness, shade and vividness.

In spite of the great artistic and economic importance of Persian carpet, the color gamut and the dimensional property of the spectral reflectances of such valuable skillful product have not been investigated, yet. In this paper, the colorimetric specifications of samples are presented in the xy chromaticity diagram of CIEXYZ color system and the principal component analysis (PCA) technique is employed to determine the actual dimensional sizes of the reflectance spectra of the colored woolen yarns that are used in traditional Persian carpets. To make the results more sensible, the analysis is also extended to Munsell color chips and the dimensional properties of the sets, i.e. natural colorants and Munsell samples, are compared with each other. Finally, the PCA technique and the non-negative matrix factorization (NNMF) method are employed for the compression and the reconstruction of the spectral data of two datasets and the results are spectrally and colorimetrically evaluated.

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II. MATHEMATICA BACKGROUND

Principal component analysis is widely used for determination of the principal directions of scattered data as spectral behaviors of objects and light sources [1]. The method reduces the dimensionality of dataset by capturing the variance in a dataset and highlights the most important directions. The extracted bases that are called principal components are in fact a set of variables, which encapsulates the maximum variation in the desired dataset. The technique was practically used in spectral data processing. The extraction of the principal directions of spectral data could help to represent the samples in reduced spectral spaces. A reflectance spectrum of N wavelengths could be defined by Eq. (1):

$$r(\lambda) = [r(\lambda_1), r(\lambda_2), \ldots, r(\lambda_N)]^T = [r_1, r_2, \ldots, r_N]^T \qquad (1)$$

Then, an estimator for the covariance matrix A is defined by Eq. (2).

$$A = \frac{1}{P}\sum_{i=1}^{P}(x_i - x_m)(x_i - x_m)^T = \frac{1}{P}(R - R_m)(R - R_m)^T \quad (2)$$

where, R consists of P random column vectors carrying the reflectance spectra of P samples and subscript m shows the mean spectrum. Since the covariance matrix A is a $N \times N$ matrix, N eigenvectors and eigenvalues could be obtained from Eq. (3).

$$AV = VD \quad (3)$$

where the columns of the matrix V are the eigenvectors and the diagonal elements $d_i, i = 1, 2, ..., N$ of the matrix D are the eigenvalues. Reordering the eigenvlaues as $d_1 \geq d_2 \geq ... \geq d_N$ and subsequently the corresponding eigenvectors arranges the principal directions according to their variances. Simply, the database could be represented in lower dimensional space e.g. M ($M \leq N$) by this statistical analysis. Equation (4) shows the percentage of the information which is carried by the first M eigenvectors.

$$p\% = \frac{\sum_{i=1}^{M} d_i}{\sum_{i=1}^{N} d_i} \times 100 \quad (4)$$

Consequently, the original dataset could be recovered by the first M bases as shown by Eq. (5).

$$\hat{R} = V.V^T.R = V.C \quad (5)$$

where $\hat{R}$ and C respectively show the reconstructed spectrum and the specifications of sample in the reduced space.

The method was employed for analyzing of different spectral datasets. Depending to the type of spectral data, the reflectance spectra of standard color charts such as Munsell or Swedish Natural Color System (NCS) have been presented in low dimensional spaces such as 5 to 9 dimensions with the particular accuracies [2-6].

While the PCA is the most popular non-psychophysical dimensionality reduction technique in the spectral data processing, the extracted positive-negative bases make the method somewhat insensible. Although the bases were introduced as statistical colorants[7], the negative behaviors of them could not assemble the actual performances of the real primaries. Hence, the colorimetric behaviors of such bases have been mostly interpreted rather than being computed [8]. The bases that provide all positive entries were introduced by Lee and Seung [9] and have been employed in spectral data processing [8, 10-11].

Different forms of NNMF have been introduced which differ in the employed divergence functions and/or regulations of bases and weights. However, the Lee and Seung's algorithm is more welcomed method due to its easiness and the convergence guaranty. For a non-negative matrix R, the non-negative matrix factors W and H could be obtained by:

$$R_{N \times P} = W_{N \times S}.H_{S \times P} \quad (6)$$

while $(N + P) \times S \langle N \times P$. The multiplicative update rules whose goals are to minimize $\|R - W.H\|$ and provide $W, H \geq 0$ make the NNMF method very attractive in some types of applications. In the case of spectral data, the extracted bases exhibit more similar behaviors to reflectance spectra of real primaries than those obtained by PCA. In fact, similar to real primaries, the colors of non-negative bases which make more sense than negative bases could be simply calculated under a certain set of illuminant-observer viewing condition.

III. EXPERIMENTAL

The colored samples were prepared by dyeing of woolen yarns with different natural colorants. The footrest, pomegranate peel, gross, sumac leaf, henna, madder, henna leaf, walnut leaf, cochineal, indigo, sappanwood were used as natural colorants while, the alum, lye, vitriol, tin and sodium dichromate were employed as mordants. To prepare more complete package of colored specimens of the Persian carpets, some samples were also collected from the domestic traditional dyeing workshops of the famous regions of the carpet production provinces, e.g. Tabriz, Shiraz, Kashan, Isfahan and Qom. Totally, 286 colored samples in the form of woolen yarn were prepared or collected. Due to the nature of the traditional dyeing process, it is no doubt that the colors practically change with the origin of the natural colorants such as the season of the harvest of plant and/or the type of farm. Hence, the selected colored yarn wool could be considered as a representative of the colors which are used in Persian carpets; however, the authors do not claim to collect the full pallet of colors in the Persian carpets which seems an impossible task.

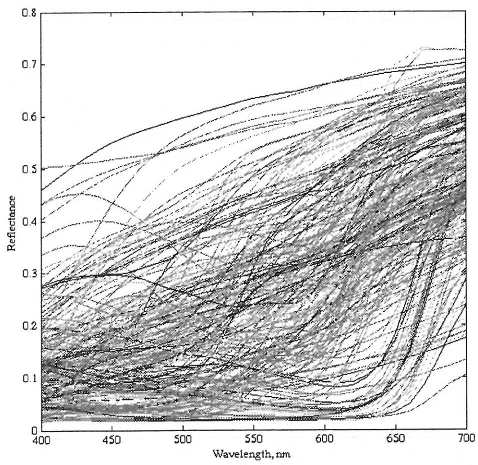
A ColorEye 7000A spectrophotometer was used for the reflectance measurements. The specular component of reflectance was excluded. Woolen yarns were wounded over a 2cm×4cm cards with suitable thickness. Samples were measured from 360 to 730 nm at 10 nm intervals. In order to minimize the sample presentation effects, the reflectance of each sample was measured at four different rotational positions and the average of four measurements was thought to be true reflectance. Finally, the spectral range of measured spectra was narrowed to 400 to 700 nm for further mathematical and computational operations.

To compare the results of spectral behavior of natural dyed samples with standard samples, the reflectance spectra of 1269 colored chips of Munsell Book of Color–Matt Finish Collection were downloaded from the website of color group of University of Joensuu [12]. The original spectra were measured with Perkin Elmer Lambda 18 spectrophotometer and the wavelength range was from 380 nm to 800 nm with 1 nm interval. However, the reflectance data were fixed between 400 nm to 700 nm at 10 nm intervals in this work.

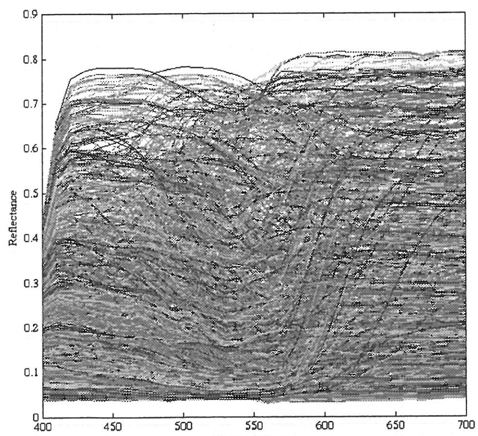
The colors of samples were computed under 1964 standard observer and D65 and A illuminants. The CIELAB color difference formula was used for determination of the colorimetric differences of samples while the root mean square error (RMS) was employed for demonstration of the spectral dissimilarity of the samples. Matlab, the mathematical software from Mathworks, was operated for all computational calculations [13].

IV. Results and Discussion

The spectral reflectances of the natural dataset and the Munsell color chips are shown in Figure 1. The colorimetric specifications of both datasets are also computed under D65 and 1964 standard observer and demonstrated in Figure 2 in CIExy chromaticity diagram. To make the comparison easier, Figure 2(b) shows both datasets in the expanded plot of Figure 2(a). As the figures show, the natural samples scatter over a limited region of CIExy chromaticity diagram and totally have lower purities in comparison to Munsell samples. However some purples could be found in the natural package which exhibit greater purities than Munsell samples. Totally, the spectral reflectances of the naturally dyed samples confirm the lack of bright samples in this dataset.



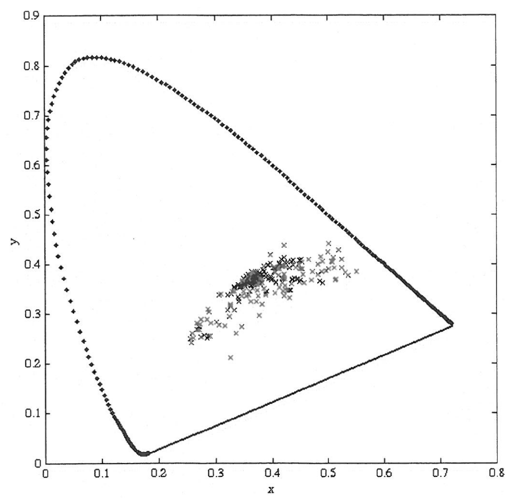
(a)



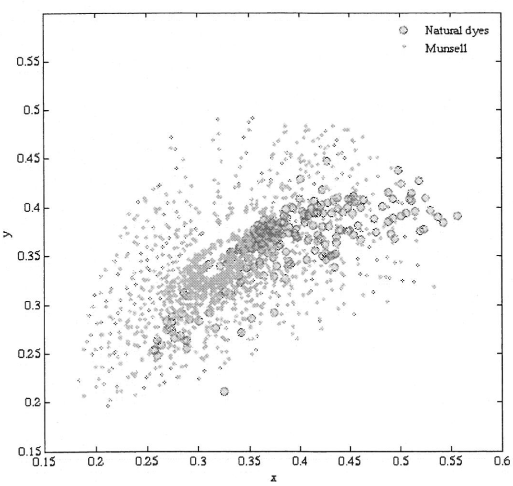
(b)

Fig. 1. The spectral reflectances of naturally dyed woolen yarns used in Persian carpets (a) and the reflectance spectra of Munsell color chips (b).

The first six most important directions of the reflectance spectra of natural dataset as well as the Munsell samples were extracted by using the classical PCA method. Figure 3 shows the extracted bases which show dipole responses, i.e. illustrate both positive and negative spectral values. To demonstrate the spectral characteristics of the bases more clearly, the principals are plotted in two different sets, i.e. the first three and the second three bases. As the figure shows, the smooth behaviors of the first three bases of both datasets confirm their roles as the basic statistical primaries, while the spectral behaviors of the second sets are less smooth. However, the second sets of bases, i.e. the fourth to sixth eigenvectors of two datasets, are not still too sharp and may be considered as the tuning virtual colorants in spectral reconstruction.



(a)



(b)

Fig. 2. The chromaticities of woolen yarns dyed with natural colorants in CIxy diagram under D65 illuminant and 1964 standard observer are shown in plot (a). Plot (b) shows the Munsell samples along with the dyed woolen yarns in magnified scale under mentioned conditions.

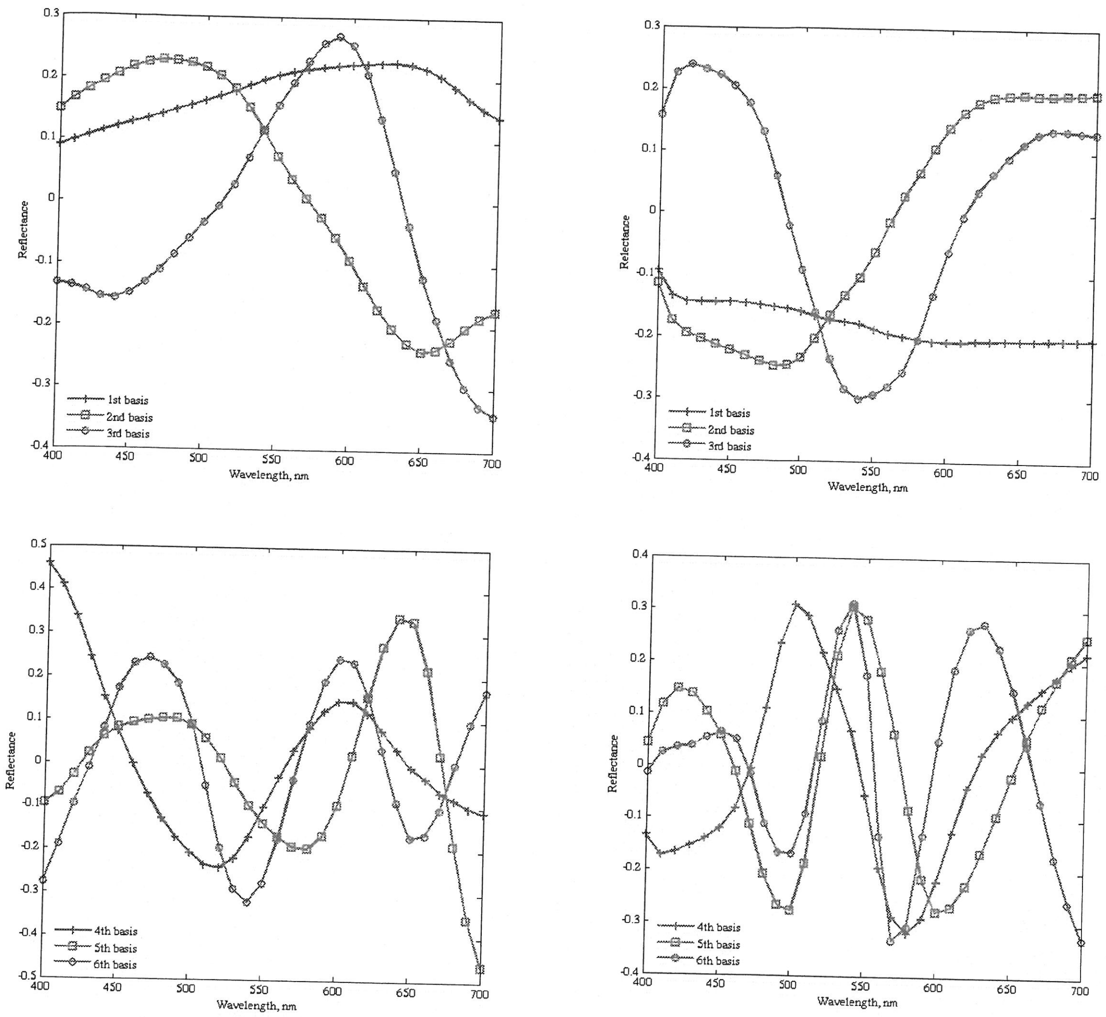


Fig. 3. The first six eigenvectors of the reflectance spectra of the natural colorants and Munsell datasets. Left plots show the natural colorants and the right demonstrate the Munsell samples. The upper and the lower plots show the first three and the fourth to sixth bases, respectively.

TABLE I
THE CUMULATIVE PERCENTAGE OF VARIANCES OF THE FIRST SIX EIGENVECTORS

Dataset	Cumulative percentage variance					
	1	2	3	4	5	6
Natural	80.47	92.36	97.35	98.81	99.70	99.86
Munsell	76.77	92.60	98.56	99.32	99.68	99.80

The cumulative percentage variances of the reduced spaces were also calculated for both databases and are shown in Table I. As expected, the values of cumulative index reasonably increase with the increasing of the numbers of spectral dimensions. Besides, while the cumulative percentage variance of the first eigenvector is greater for natural colorants, the values for this group of samples are smaller when up to four eigenvectors are employed. Reasonably, the values converge to 100 for both sets by increasing the numbers of principal directions and consequently, the differences between the reduced spaces become negligible in such condition.

Three to six non-negative bases of both datasets were also extracted by using NNMF method and the results are shown in Figure 4. To make the bases more sensible, they are normalized between zero to one and the figure shows the normalized spectra. Opposed to PCA, the spectral behaviors of the non-negative bases are not constants and change with the selected dimensions. For example, the spectral behaviors of the primaries in a three dimensional space are completely different from those obtained in four, five or six dimensional spaces.

To assess the efficiency of the reduced spaces, the reflectance spectra of samples of two datasets were compressed and consequently reconstructed and the values of the lost data were spectrally and colorimetrically evaluated. Both sets of bases, i.e. the positive-negative and all positive series were employed in the compression and reconstruction trials. The colorimetric evaluations were

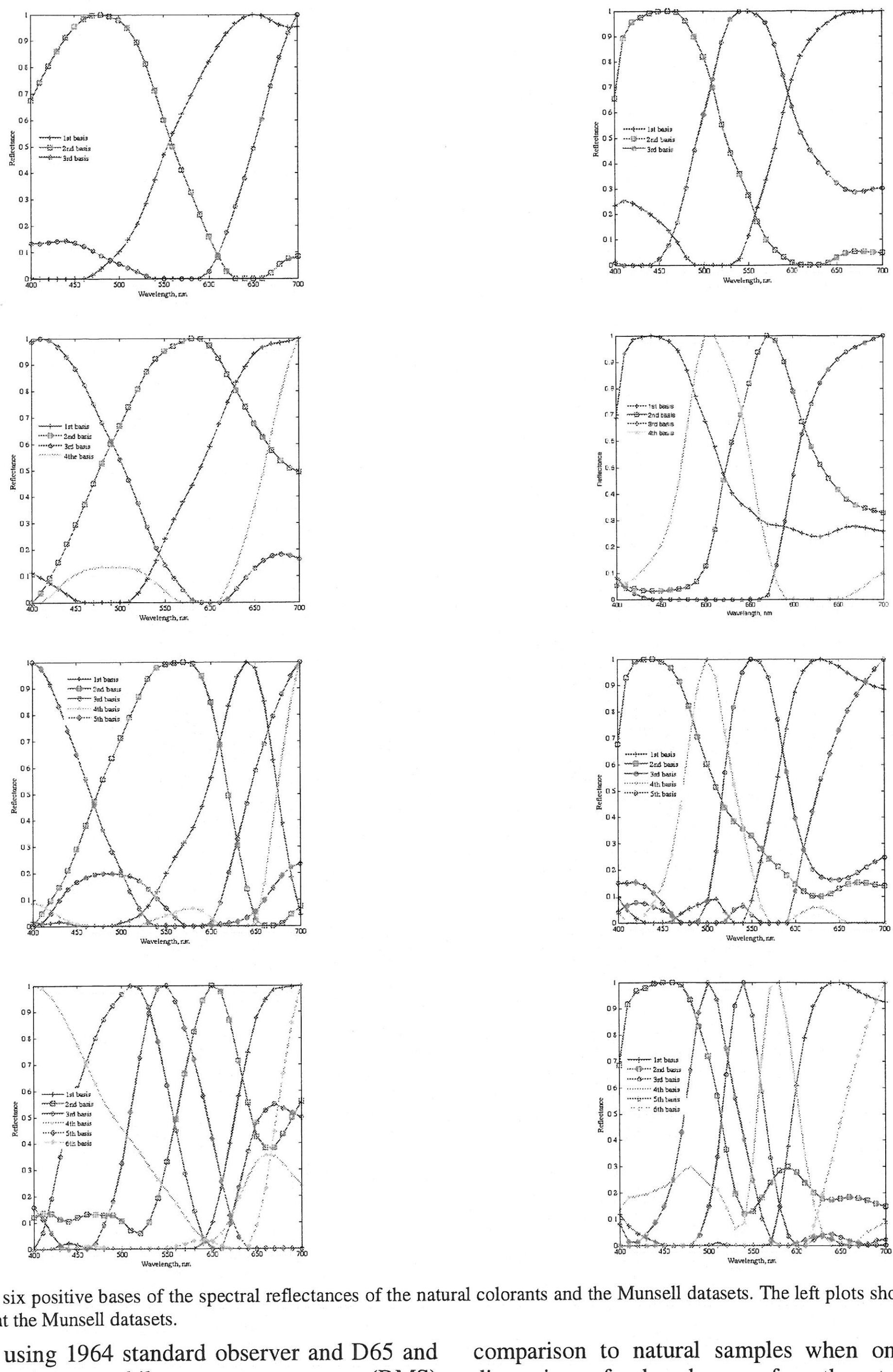


Fig. 4. Three to six positive bases of the spectral reflectances of the natural colorants and the Munsell datasets. The left plots show the natural and the rights present the Munsell datasets.

carried out by using 1964 standard observer and D65 and A standard illuminants, while root mean square (RMS) errors between the actual and the reconstructed spectra were considered as criteria for spectrophotometric accuracies. Figure 5 compares the RMS errors for both sets of data obtained from PCA and NNMF methods using different dimensions

According to Figure 5(a), the RMS error for natural dataset is greater than Munsell when a three dimensional space was employed and the values of errors become close when the numbers of employed bases approach to six. In fact as data in Table I shows, the relative importances of different principal directions are smaller for Munsell set in comparison to natural samples when one increases the dimensions of reduced spaces from three to six.

Results of spectrally compression and reconstruction trial in all positive spaces are demonstrated in Figure 5(b). As the plot shows, both datasets provide smaller RMS errors in comparison to positive-negative spaces. The unexpected behavior of Munsell set in six dimensional space relates to the nature of NNMF method. In fact, the method uses an iterative method starting with random initial vectors. The algorithm could trap in local minima points and converges to a solution of lower rank which may indicate that the result is not optimal [13].

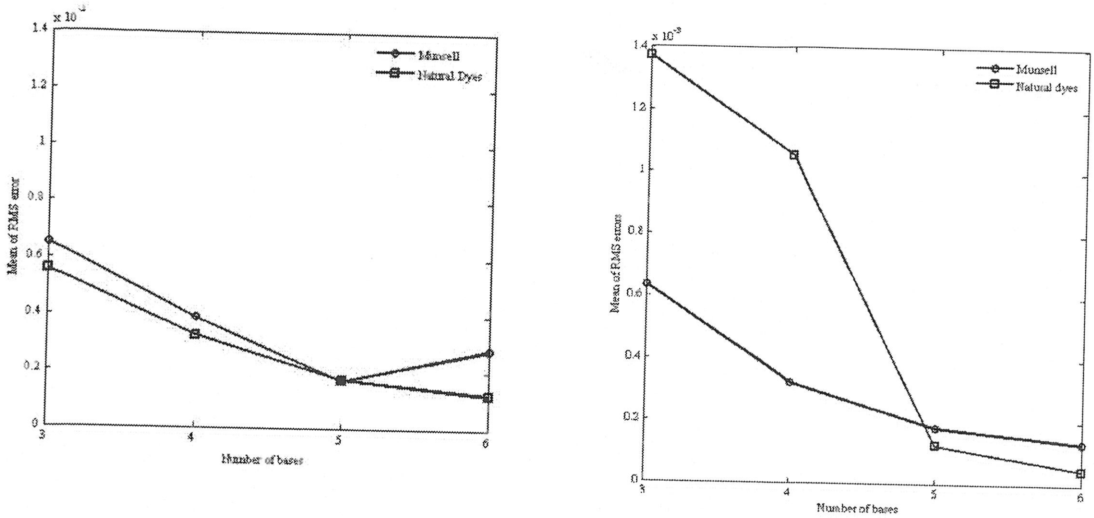
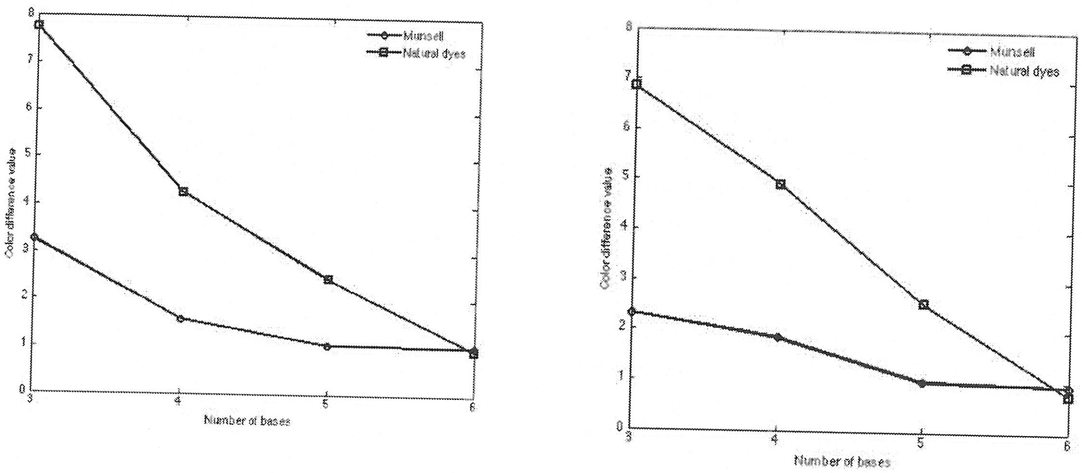
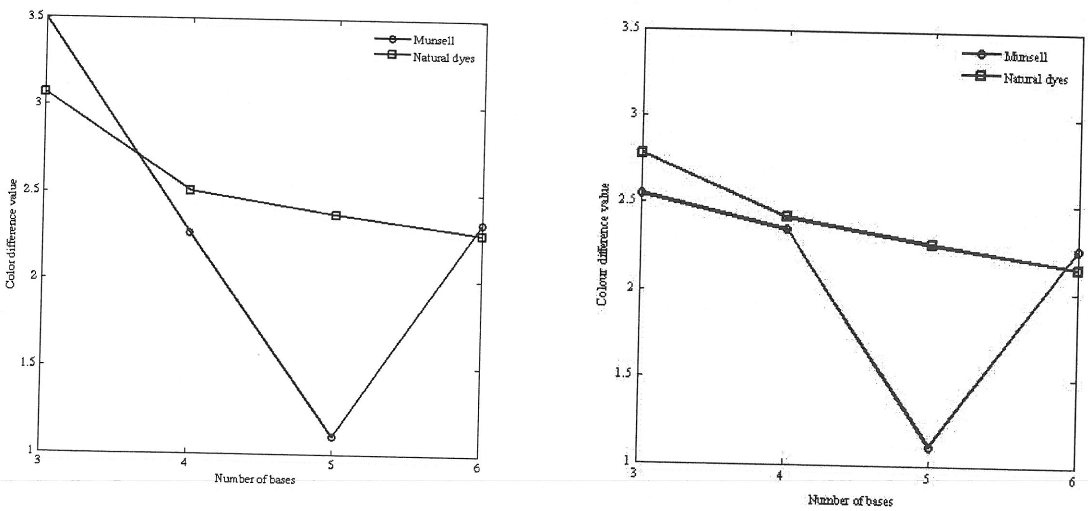


Fig. 5. The RMS errors between the actual and the reconstructed reflectance spectra using different dimensions. (a) shows the results of employing positive-negative bases while (b) demonstrates the results for all positive bases.



(a) (b)

Fig. 6. The color difference values between the actual and the reconstructed reflectance spectra by using different dimensions obtained from PCA method under D65 (a) and A (b) illuminants.



(a) (b)

Fig. 7. The color difference values between the actual and the reconstructed reflectance spectra by using different dimensions obtained from NNMF method under D65 (a) and A (b) illuminants.

The CIELAB color differences between the actual and the reconstructed spectra from PCA method are respectively shown in Figure 6(a) and 7(a) for D65 and A illuminants, while, the 1964 standard observer was used in all colorimetric computations. The figures again confirm the previous finding and show the smaller color difference values of Munsell set in lower dimensional spaces. As the plots show, the colorimetric errors are completely comparable when the numbers of bases increase to six. The values of color differences confirm that both datasets could be compressed in the six dimensional spaces with negligible colorimetric errors.

V. CONCLUSION

The colorimetric behaviors and the dimensional properties of the spectral reflectances of handmade Persian carpet were studied. A set of woolen yarns which were dyed with natural colorants and used in the traditional Persian carpets were prepared and the reflectance spectra and the related colorimetric behaviors were measured and compared with Munsell dataset as a standard package. The colorimetric specifications of the two sets were compared by plotting the chromaticities of samples in the CIExy diagram. Besides, the dimensional properties of reflectance spectra of packages were evaluated by computation of cumulative percentage of variances of different numbers of eigenvectors. Finally, two types of projection spaces i.e. positive-negative and all positive bases were extracted and used for the compression and the reconstruction of spectral data.

While the natural dyes showed smaller color gamut in comparison to Munsell dataset, the dimensional properties of the spectral reflectances of both sets approximately exhibited very close cumulative percentage of variances. The results were approved by the calculation of the mean root square errors as well as the color difference values under D65 and A illuminants between the original and the reconstructed spectra of samples with different numbers of bases. In spite of the smaller colorimetric gamut of the naturally dyed yarns of Persian carpet, the actual spectral dimensions of the package were found comparable with Munsell set.

REFERENCES

[1] D. Y. Tzeng and R. S. Berns, "A review of principal component analysis and its applications to color technology", *Color Res Appl.*, vol. 30, no. 2, pp. 84-98, 2005.

[2] J. B. Cohen, "Dependency of the spectral reflectance curves of the Munsell color chips", *Psychon Sci.*, vol. 1, no. 12, pp. 369-370, 1964.

[3] L. T. Maloney, "Evaluation of linear models of surface spectral reflectance with small number of parameters", *J Opt Soc Am A.*, vol. 3, no. 10, pp. 29-33, 1986.

[4] J. Parkkinen, J. Halikainen and T. Jaaskelainen, "Characteristic spectra of Munsell colors", *J Opt Soc Am A.*, vol. 6, no. 2, pp. 318-322, 1989.

[5] T. Jaaskelainen, J. Parkkinen and S. Toyooka, "Vector-subspace model for color representation", *J Opt Soc Am A.*, vol. 7, no. 4, pp. 725-730, 1990.

[6] A. Garcis-Beltran, J. L. Nieves, J Hernandez-Andres and J. Romero, "Linear bases for spectral reflectance functions of acrylic paints", *Color Res Appl.*, vol. 23, no. 1, pp. 39-45, 1998.

[7] R. S. Berns, "The proper use of indices of metamerism", *Color Res Appl.*, vol. 33, no. 6, pp. 509-512, 2008.

[8] R. Ramanath, R.G. Kuehni, W.E. Snyder and D. Hinks, "Spectral spaces and color spaces", *Color Res Appl.* vol. 29, no. 1, pp. 29-37, 2003.

[9] D. D. Lee and H. S Seung, "Learning the parts of objects by non-negative matrix factorization", *Nature,* vol. 401, no. 21, pp. 788-791, 1999.

[10] G. Sharma, H. J. Trussell and M. J. Vrhel, "Optimal non-negative color scanning filters", *IEEE Trans Image Proc.*, vol. 7, no. 1, pp. 129-133, 1998.

[11] S. H. Amirshahi and S. A. Amirshahi, "Adaptive non-negative bases for reconstruction of spectral data from colorimetric information", *Opt. Rev.*, vol. 17, no. 6, pp. 562-569, 2010.

[12] University of Joensuu Color Group. Spectral Database. Available, http://cs.joensuu.fi/~spectral/databases/download/munsell_spec_mat.htm

[13] MATLAB (2009), The MathWorkInc, Version 7.8.