Spectral reflectance curves for multispectral imaging, combining different techniques and a neural network

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In this paper, we present an alternative procedure for the digital reconstruction of spectral reflectanc curves of oil painting on canvas using multispectral imaging. The technique is based on a combination of the results obtained by pseudo-inverse, principal component analysis and interpolation; these results are the input to a feed-forward back propagation neural network fittin the values of the curves to a target obtained using a spectrophotometer *Shimadzu UV2401*. Goodness-of-Fit Coefficien (*GFC*), absolute mean error (*ABE*) and spectral Root Mean Squared error (*RMS*) are the metrics used to evaluate the performance of the procedure proposed.

Keywords: Artificia neural network; spectral reflectanc curves; multispectral imaging; curve fitting

Se presenta un procedimiento alternativo para la reconstrucción numérica de curvas de reflectanci espectral de pinturas de óleo sobre lienzo. La técnica se basa en la combinación no lineal de los espectros de reflectanci reconstruidos por procedimientos lineales, tales como: pseudoinversa, análisis en componentes principales e interpolación. Estos espectros constituyen la entrada a una red neuronal artificia entrenada mediante el algoritmo *backpropagation*. La red neuronal ajusta sus pesos y umbrales de acuerdo a los espectros patrones, obtenidos mediante un espectrofotómetro *Shimadzu UV2401*. Para evaluar el desempeño del procedimiento se utilizaron las métricas: cálculo del error espectral cuadrático medio, el coeficient de buen ajuste y el error medio absoluto.

Descriptores: Espectros de reflectancia ajuste de curvas; imágenes multiespectrales; redes neuronales artificiales

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1. Introduction

The multi-channel nature of multi-spectral images permits the numerical reconstruction of spectral reflectanc curves, which are suitable elements for several tasks, including computational color reproduction, restoration and digital archiving of art painting and historical documents [1-2]. Obtaining reflectanc spectral curves, either through a spectrophotometer or by numerical techniques, is an essential step towards the full colorimetric characterization of color objects. In addition, the enormous quantity and quality of information minimizes the *metamerism* and reduces ambiguity in the verifi cation of color patterns [3-4].

Fitting the reflectanc of an object using multispectral imaging is essentially a process of sampling and quantization in spectral bands [3]. This sampling requires the proper selection of illuminating and optical filters The information recorded by imaging devices is the input for different linear numerical procedures, such as pseudoinverse, Principal Component Analysis (PCA) or finit dimensional model, and cubic spline interpolation. Moreover, non-linear processes such as neural networks and genetic algorithms have been reported [5]. Any procedure for digital reconstruction of spectral reflectanc requires definin the objects of interest, in our case, oil painting on canvas, a database of spectral reflectanc curves of these objects, and a system of multispectral imaging acquisition according to *CIE (Commission International d'Eclairage)*.

Recently, an algorithm for digital reconstruction of spectral reflectanc curves, combining the spectral curves obtained using several linear techniques, was proposed [6]. This procedure uses quadratic programming to minimize the spectral error (standard deviation or variance of the root mean squared) and the colorimetric error. Based on this idea, we propose to estimate a spectral reflectanc curve, combining two or more very well known linear techniques and a neural network.

In this study, an artificia neural network (ANN), trained properly, and where inputs are the reflectanc spectra reconstructed using linear techniques, pseudoinverse, PCA and interpolation, has been used to predict a spectral curve, in order to obtain better performance than the curve obtained by the techniques mentioned above.

1.1. Theoretical framework

For computation, the spectral quantities are substituted by their sampled version, that is,

$$c_k = \sum_{h=0}^{N-1} r(\lambda_h) W(\lambda_h) \Delta\lambda \qquad (1)$$

with $W(\lambda_h) = i(\lambda_h) o(\lambda_h) s(\lambda_h) F_k(\lambda_h)$, which is called spectral sensitivity of k-th channel and where $i(\lambda_h)$, $o(\lambda_h)$, $s(\lambda_h)$, $F_k(\lambda_h)$ and $r(\lambda_h)$ are the radiant spectral flu of the illuminant, the dispersion of the optical imaging system, the spectral response of the sensor, the spectral transmittance of

k-th filte and the reflectanc of the sample in the range of wavelengths$[\lambda_0, \lambda_{N-1}]$, respectively [7]. In Eq. (1) , λ_h are uniformly spaced wavelengths covering the visible region of the spectrum, $\lambda_h = \lambda_0 + h\Delta\lambda$, with $\Delta\lambda$ as the wavelength sampling interval. n_k, is the additive noise of k-th channel, with temporal and spatial characteristics (dark current, lack of uniformity in lighting, etc.). Setting $\Delta\lambda = 1$, Eq. (1) can be written as a dot product [1],

$$c_k = \mathbf{r}^t \mathbf{W}_k + n_k \tag{2}$$

In Eq. (2) the superscript t denotes transpose. For work conditions with short time acquisition, the temporary noise is diminished by using an average of multiple acquisitions. On the other hand, the spatial noise is attenuated by subtracting the background of the image. This makes it possible to neglect n_k in Eq. (2), giving

$$c_k = \mathbf{r}^t \mathbf{W}_k \tag{3}$$

Considering k filters Eq. (3) can be written in matrix-vector notation,

$$\mathbf{c}_{K \times 1} = \mathbf{\Theta}_{K \times N} \, \mathbf{r}_{N \times 1} \tag{4}$$

where $\mathbf{\Theta}_{K \times N}$, is a matrix with rows are formed by $\mathbf{W}_k$ vector.

Thus digital reconstruction of spectral reflectanc curves can be seen as determining an operator $\mathbf{Q}_{N \times K}$, which applied to the responses of the imaging sensor produces the reflectance

$$\mathbf{r}_{N \times 1} = \mathbf{Q}_{N \times K} \, \mathbf{c}_{K \times 1}. \tag{5}$$

There are many techniques for estimating the $\mathbf{Q}$ operator. One of these would be to calculate the pseudoinverse, pinv of $\mathbf{C}_{K \times p}$ matrix (Eq. 6), whose columns are p reflectanc spectra, measured previously from patches of oil painting on canvas, with similar characteristics to the spectral reflectanc curves which are tried to reconstruct

$$\mathbf{Q}_{N \times K} = \mathbf{R}_{N \times p} \, \text{pinv} \, (\mathbf{C})_{p \times K} \tag{6}$$

$R_{N \times p}$ is a matrix with columns formed by p reflectanc spectra recorded by means of a spectrophotometer. Once $\mathbf{Q}_{N x K}$ operator, has been obtained $\mathbf{r}_{N \times 1}$ is calculated using Eq. (5).

Another procedure for reconstructing the spectral reflectanc curves requires an orthogonal basis obtained by *PCA* using singular value decomposition (*SVD*) of data matrix $\mathbf{R}$. Thus, spectral reflectanc can be expressed as a linear combination of $m \leq N$ orthogonal vectors $\mathbf{v}_i$, with N components [8-11].

$$\mathbf{r} = \sum_{i=1}^{m} \alpha_i \mathbf{v}_i \tag{7}$$

The scalar coefficient α_i in Eq. (7) are unknown. They are the components of vector $\mathbf{r}_{N \times 1}$ in the orthogonal basis $\mathbf{V}_{N \times p}$. In order to determine α_i, it is necessary for the number of channels K and the number of vectors p to be the same.

Coefficient for each channel, $\alpha_{K \times 1} = [\alpha_1, \alpha_2, \cdots \alpha_K]^t$ can be obtained using Eq. (10):

$$\alpha_{K \times 1} = \mathbf{V}_{K \times K}^{-1} \mathbf{c}_{K \times 1} \tag{8}$$

where the vectorial basis $\mathbf{V}_{K \times K}^{-1}$, is formed by sampling $\mathbf{v}_i$ vectors at K wavelengths corresponding to each channel. $\mathbf{c}_{K \times 1}$ is the corresponding system reconstruction response, and thus spectral reflectance $\mathbf{r}_{N \times 1}$, is obtained by substitution in Eq. (7).

Another approach for the reconstruction of spectral reflectanc curves is based on interpolation techniques [12]. Amongst the best known and most generally used is cubic-spline interpolation.

1.2. Feed-forward back-propagation neural network: a brief description

An Artificia Neural Network (*ANN*) is a general mathematical computing paradigm that models the operations of biological neural systems [13]. In this work, we use a feed-forward back propagation neural network. This architecture is very well known and is widely used. Developed in 1974 by Werber, Parker and Rumelhart, it exhibits characteristics such as robustness and easy learning, although the computational cost during its training is relatively high.

This *ANN* type, applies to models with more than two layers of neurons. Thus it can have one input layer with L neurons, an output layer with M neurons and at least one hidden layer with Q neurons [14].

Learning in a feed-forward *BNN* involves two steps: in the firs one, the pattern is introduced to the input layer of *ANN* and it is propagated through each upper layer until an output is generated. By comparison of the output pattern with the desired output, an error signal is computed for each output. In the second step, error signals are transmitted backward from the output layer to each node in the hidden layers that contributes directly to the output. However, each neuron in the hidden layers receives only a portion of the total error signal, based approximately on the relative contribution the neuron made to the original output. Training is done by repeating this process, layer by layer, until each node in the network has received an error signal that describes its relative contribution to the total error. Based on the error signal received, connection weights and bias are then updated by each neuron in order for the network to converge toward a state that allows all the training patterns to be encoded [15-16].

1.3. The proposed method

Recently, reconstruction of spectral reflectanc curves has been proposed, by means of a weighted sum of the results from different linear techniques, namely, Wiener estimation, pseudoinverse and *PCA*. The weightings of these techniques have been calculated by minimizing the combined standard deviation of both spectral errors and colorimetric errors [6].
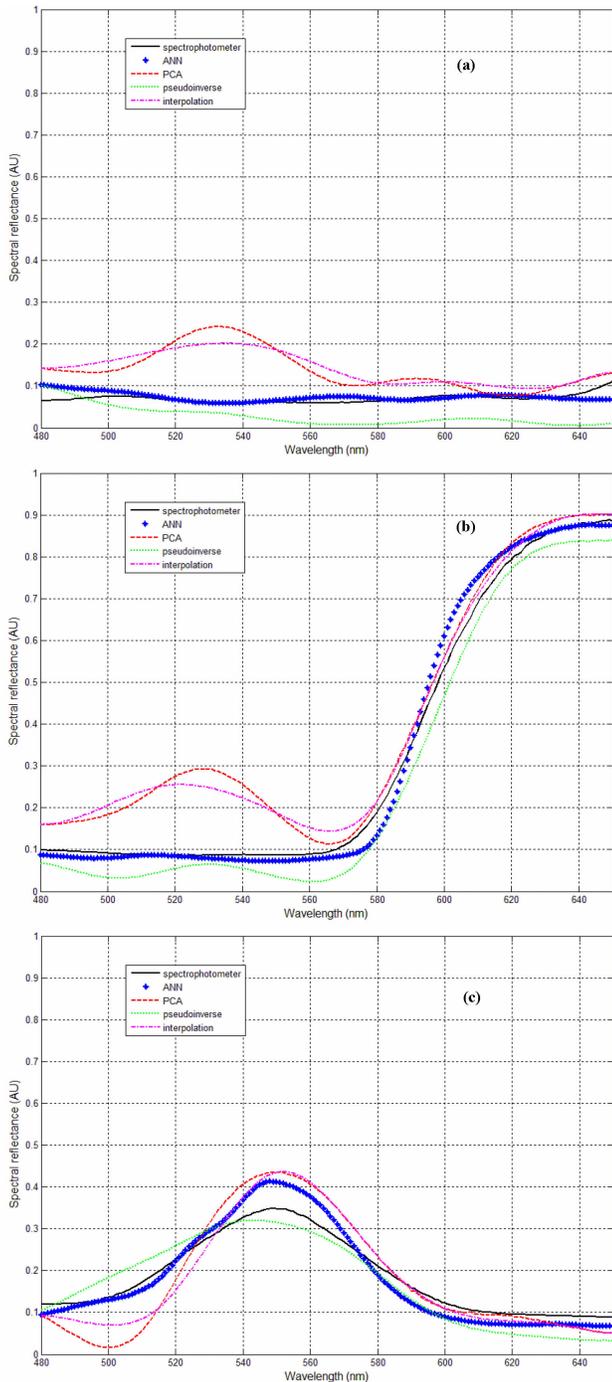
FIGURE 1. Reconstruction of spectral reflectanc curves according to proposed method; (a), (b) and (c) show the best results. In order to compare, curves obtained by pseudoinverse, PCA and interpolation are displayed.

TABLE I. Results of performance metrics for reconstruction by proposed method.

Curve	RMS	ABE	GFC
a	0.0002	0.0097	0.9842
b	0.0009	0.0213	0.9982
c	0.0009	0.0260	0.9909

TABLE II. Results by principal component analysis.

Curve	RMS	ABE	GFC
a	0.0072	0.0682	0.9113
b	0.0082	0.0674	0.9862
c	0.0036	0.0466	0.9638

TABLE III. Results by pseudoinverse.

Curve	RMS	ABE	GFC
a	0.0031	0.0483	0.7046
b	0.0024	0.0461	0.9969
c	0.0015	0.0356	0.9820

TABLE IV. Results by interpolation

Curve	RMS	ABE	GFC
a	0.0068	0.0714	0.9201
b	0.0071	0.0661	0.9877
c	0.0023	0.0403	0.9749

Based on this idea, we proposed training a feed-forward back-propagation neural network. After a systematic scan on several architectures, we implemented the network with the following characteristics: the input pattern to the *ANN* is a $3 \times N$ matrix, whose rows are results obtained by *PCA,* pseudoinverse and interpolation, no strict order is required. The network used is 3-85-1, which means three (3) input neurons with linear transfer function, 85 neurons in the hidden layer using Radial Basis Neuron and one (1) output neuron with a linear transfer function. Once the weights and biases have been initialized, the training is carried out, using the Levenberg-Marquardt algorithm for optimization [14]. One hundred thirteen reflectanc curves were used: ninety-eight as a training set and the other fiftee as a testing set. The criterion to stop the training of ANN is supported by calculating the RMS spectral error between the output desired and output calculated. Thus RMS error is fi ed at one small, arbitrary value, stopping the training when it is reached.

2. Experimental

Conforming matrix $\mathbf{R}_{N \times p}$ in Eq. (6), p spectral reflectanc curves from patches of oil painting on canvas were obtained, using the spectrophotometer (*Shimadzu UV-2401*) with the integrating sphere attached. The sample (patch) is compared with a BaSO4 white standard, and spectrally scanned between 450 and 800 with scanning step 1 ± 0.1 [nm]. The spectrophotometer light source is a halogen lamp of 50 [W].

In order to obtain the multispectral images, the patches of oil painting on canvas were illuminated according to the standard *CIE* viewing geometry, 45°/0°, using two halogen lamps. The light reflecte by the patches is transmit-

ted through seven narrow-band interferential filter with central wavelength at: 480, 515, 550, 580, 600, 636 and 650 nm. The full width half maximum of the filter (FWHM) is 10 ± 2 nm.

Filters were placed in front of a monochrome CCD camera that records the corresponding response to each filte. The acquired image is digitized by means of a video card (*Matrox*^{TM}*Meteor II*). Image size is 640×480 pixels with an 8-bit deep resolution. In order to reduce the noise, the camera recording is the average of 20 captures. In addition, we did processing to improve the uniformity of the illumination.

Once $\mathbf{R}_{N \times p}$ and $\mathbf{C}_{K \times p}$ arrays are obtained, the numerical treatment to reconstruct the spectral reflectanc curves is carried out using software *Matlab*^{TM} [17-20].

3. Results and discussion

Figure 1 shows the best results in the reconstruction of spectral reflectanc curves according to the proposed method, from the testing set of curves; these curves correspond to three different patches. The reconstructed curve is compared to the spectrophotometer response and the reconstructed curves using PCA, pseudoinverse and interpolation. From Tables I to IV, performance of the metrics is shown. In order to evaluate the performance of the reconstruction, three metrics are used. The firs is the root mean square error, define as:

$$RMS = \frac{1}{N} \sum_{i=1}^{N} \|r_m(\lambda_i) - r_e(\lambda_i)\|^2 \qquad (9)$$

Other metrics used are: the absolute mean error,

$$ABE = \frac{1}{N} \sum_{i=1}^{N} |r_m(\lambda_i) - r_e(\lambda_i)| \qquad (10)$$

and goodness-of-fi coefficien described by

$$GFC = \frac{\left| \sum_{i=1}^{N} r_m(\lambda_i) r_e(\lambda_i) \right|}{\sqrt{\left| \sum_{i=1}^{N} [r_m(\lambda_i)]^2 \right|} \sqrt{\left| \sum_{i=1}^{N} [r_e(\lambda_i)]^2 \right|}} \qquad (11)$$

where in Eqs. (9)-(11), the N-vectors, $r_m(\lambda_i)$ y $r_e(\lambda_i)$ are the spectral reflectanc measured by the spectrophotometer and estimated by the neural network (and any other technique), respectively.

Table I in comparison with Tables II, III and IV, exhibits best performance in agree ment with that displayed in Fig. 1. In Table I, GFC results are satisfactory because they exceeded the benchmark of 0.9. However, values greater than 0.999 are desirable [1]. On the other hand, *RMS* spectral error of the proposed method is two orders less than other metrics.

4. Conclusion

According to the results, we fin an alternative procedure for digital reconstruction of spectral reflectanc curves with satisfactory performance. This procedure is supported by the results obtained using very well-known linear techniques. Even though the digital spectral reconstruction, based on linear techniques, has good reports in the literature, the robustness of neural networks and the possibility of fixin its limit of learning make it possible to surpass the linear methods in the task of spectral prediction.

The training of the *ANN* is the key to the method; it requires the testing of several architectures and evaluates the performance with the appropriate metrics. In order to improve the results, a supervised learning is recommended. That means, during the training, curves with important spectral contents in different bands could be introduced into the network.

Although the technique was used for the numerical spectral reconstruction of oil painting on canvas, it can be generalized to any other situation in different fields Moreover, the spectral window, 480-650 nm, can be extended to the entire visible range.

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