An Empirical Approach for Spectral Color Printers Characterization

Raimondo Schettini, Daniela Bianucci, Giancarlo Mauri, and Silvia Zuffi°
DISCo, Università degli Studi di Milano Bicocca, Milano, Italy
°ITC-CNR, Milano, Italy

Abstract

The spectral-based characterization of inkjet printers is often based on a physical description of the printing process. The objective of our work is to see whether an approach based on the use of neural networks is an effective strategy for spectral printer characterization without requiring a deep knowledge of the printing process. In our experiments, we treat the printers as RGB devices, and exploit finite-dimensional linear models to reduce the amount of information required to characterize them. To select a good architecture, we compared the behavior of 15 different networks to compute reflectance spectra from RGB digital counts. To test our characterization procedure we consider an Epson 890 inkjet printer using photo quality paper.

1. Introduction

The spectral-based characterization of inkjet printers is often based on a physical description of the printing process, but our experience tells us that often we are unable to fit a mathematical model to a given printer. Many methods have been proposed for the spectral-based characterization of printers, most of them based on the Neugebauer equation.[1-4] Clearly, the Neugebauer model alone cannot foresee with enough accuracy the reflectance spectrum of a printed color, as the effects of interaction of inks with paper and of interaction among inks are not accounted for. Many authors have suggested strategies to model mechanical and optical dot-gain, some of them trying to understand how the physical placement of each ink determines its contribution to the final reflectance.[5] In these methods the printer driver plays a rule.

In our work we take an empirical approach, summarized as follows:

- we make no assumption concerning the printer model and the printer is treated as an RGB device (the printer-driver operations are implicitly included in our model);
- we exploit properly designed and trained neural networks as a strategy to approach the complex problem of printer spectral modeling;
- we exploit finite-dimensional linear models to reduce the amount of information required to characterize the printer spectral behavior.

The feasibility of our approach is proved on an Epson 890 inkjet printer using photo quality paper.

The adopted neural networks and reflectance function representation are briefly described in Section 2 and 3, while Section 4 illustrates the experiments performed.

2. The Adopted Neural Networks

The printer model has been approximated by means of a feed-forward neural network trained with back-propagation.[6-8] Multiple-layer feed-forward neural networks consist of several distinct layers of neurons. The first, or input layer, serves as a holding site for the values to be processed; the last, or output layer, is the point at which the final state of the network can be read. Connections can only go from neurons of one layer to the neurons of the next layer. During the training phase, back-propagation provides the prescription for changing the weights of any feed-forward network so that it can learn to compute a function from a set of input-output data pairs (training set). Standard back-propagation is a gradient descent technique designed to reduce the error between the actual and the desired output of the network.

Of course the interest does not lie in learning a particular training set, but in building networks that can generalize, that is that behave correctly in new cases. Properly defined networks with biases, an hidden layer with sigmoid activation function, and a linear output layer are capable of approximating any function with a finite number of discontinuities. To improve generalization, usually the input data are divided into a training and a validation set. In the training procedure, following each epoch, the performance of the network is evaluated on both the training and validation sets. As long as the network performance improves on both the data sets the learning is continued, when the error on the training set still decreases but the network shows poorer performance on the validation set the learning phase is stopped in order to avoid network overfitting of the training data.

3. Reflectance Function Representation

It has been shown that surface spectral reflectances can be expressed as a weighted sum of *n* linearly independent basis functions.[9]

$$R(\lambda)=c_1F_1(\lambda)+c_2F_2(\lambda)+\ldots+c_nF_n(\lambda) \qquad (1)$$

where $F_i(\lambda)$ are the basis functions and c_i the coefficients. The number of basis elements, n, represents the degrees of freedom of the linear model. If n is big enough, any surface reflectance function can be expressed by the linear model. When the applicative domain is well defined, the basis functions necessary to represent reflectance spectra can be obtained by Principal Component Analysis of a set of measured color samples. PCA basis set corresponds to directions having maximum variance, the idea being that the direction in which the measured data has most variance is accounted for. Using PCA, an assumption of Gaussian form on the distribution of the data is implicitly forced.

Given **R**, a matrix where the columns are reflectance vectors, consider **X**, a translation of R centered around the reflectances mean values. If N is the number of wavelength samples, the PCA identifies a set of Ñ vectors $\mathbf{u}_j$ corresponding to the direction, in N-dimensional space, where reflectance vectors exhibit maximum variance: these vectors define an orthogonal basis of a sub-space of dimension Ñ.

The basis set vectors are computed as the first Ñ eigenvectors of

$$S = XX^T \tag{2}$$

and correspond to the first Ñ largest eigenvalues of S.

The number of components necessary to accurately represent a set of reflectance spectra depends on the characteristics of the data set.

4. Experiments and Results

We tested our approach using an Epson 890 inkjet printer. We adopted a driver that employs Floyd Steinberg dithering and used Epson Photo Quality paper.

The training and validation sets consisted respectively of 729 and 125 colors uniformly distributed in the RGB color space (Figures 1, 2). The test set consisted of 777 samples obtained by regular sampling the HSV color space (Figure 3).

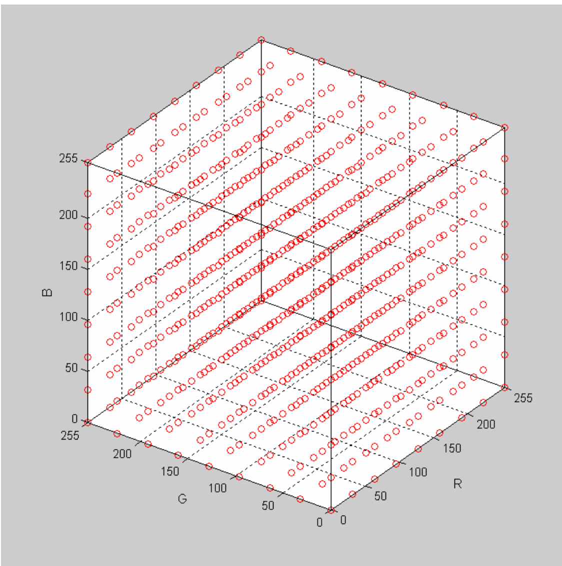

Figure 1. Training set in the RGB color space

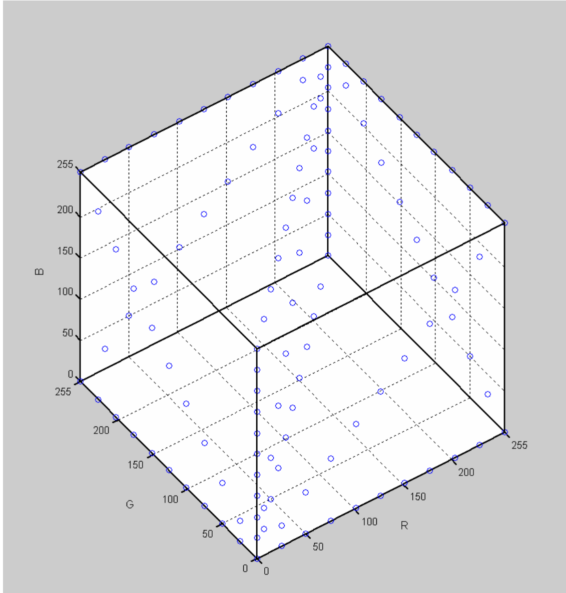

Figure 2. Validation set in the RGB color space

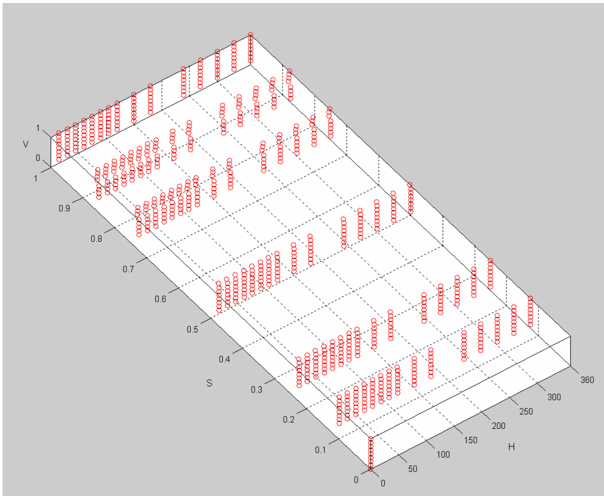

Figure 3. Test set in the HSV color space

Spectral measurements have been executed with a Gretag Spectrolino, considering values in the wavelength range from 400 to 700 nm with a step of 10 nm. Reflectances are therefore vectors of 31 elements, in the range [0,100].

The reflectance space dimension has been reduced from 31 to 9 throughout PCA. Hardeberg[9] considers the effective dimension of a PCA basis as the number of singular values required to achieve a certain accumulated energy. If the required energy is fixed at 99%, for a set of reflectance databases, among which the Munsell dataset, a number of basis components ranging from 10 to 23 can be obtained. In the context of our work, a compromise need to be done between the potential accuracy of the reflectance representation computed by modeling the spectra with the linear combination of PCA basis, and the dimension of the problem domain. As the number of components grows, the dimension of the solution space to be spanned from the neural network increases, therefore it is not appropriate, for our task, to consider a large number of basis. Here, a basis of 9 reflectance functions is obtained by Principal Component Analysis on the training set, with a required energy of 99%.

We designed a neural network to implement the direct transform from printer input digital counts to the reflectance functions basis coefficients, and a second neural network to implement the inverse transform (Figure 4).

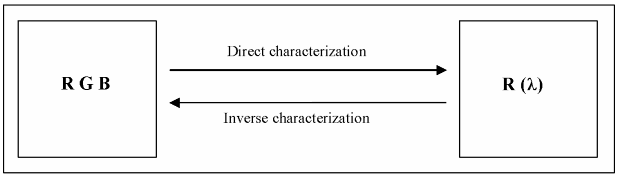

Figure 4. Printer characterization: direct and inverse transforms.

To select a good architecture, we compared the behavior of 15 different networks in learning the direct printer transform. All these networks had 3 input and 9 output neurons, while the number of hidden layers and of units in each layer was varied so that there were about 400 to 1500 weights to be learned.

In all the trained networks, the weights associated with the network links were initialized randomly with values in the interval of [-1,1], and the neuron transition function was the logistic mapping on [-1,1], that is,

$$\sigma(x)=[2/(1+e^{-2x})]-1. \tag{3}$$

For back-propagation we applied a network training function that updates the weight and bias values according to the Levenberg-Marquardt optimization and minimizes a combination of squared errors and weights to produce a network which generalizes well (Bayesian regularization).[10-12]

The direct characterization neural network is composed by an input layer of 3 neurons corresponding to an RGB triple, two hidden layers, each composed by 25 sigmoid neurons, and an output layer of 9 linear neurons corresponding to the coefficients of the linear model. The inverse characterization neural network is composed by an input layer of 9 neurons corresponding to the coefficients of the linear model, two hidden layers, each composed by 25 sigmoid neurons, and an output layer of 3 pseudo sigmoid neurons corresponding to a RGB triple. We used the Matlab Neural Network Toolbox to implement the neural networks.[13]

Performance results are reported in terms of color difference in CIELAB ΔE^*_{ab} under three different illuminants (D65, A and TL84), and root mean square error. In Figure 5 (a, b) is shown the diagram for computing the performance of the neural networks; error statistics for the direct and inverse characterization are reported in Table 1 (a, b and c) and Table 2, respectively.

Table 1a. Direct characterization: statistics of color distances and spectra differences for the training set (m= mean, M= maximum, sdv= standard deviation).

	m	M	sdv
ΔE^*_{ab} A	1.42	5.07	0.84
ΔE^*_{ab} TL84	1.55	5.47	0.87
ΔE^*_{ab} D65	1.42	4.78	0.80
RMS	0.45	1.83	0.24

Table 1b. Direct characterization: statistics of color distances and spectra differences for the validation set.

	m	M	sdv
ΔE^*_{ab} A	1.57	5.47	0.90
ΔE^*_{ab} TL84	1.58	5.47	0.91
ΔE^*_{ab} D65	1.63	4.77	1.05
RMS	0.62	1.68	0.28

Table 1c. Direct characterization: statistics of color distances and spectra differences for the test set.

	m	M	sdv
ΔE^*_{ab} A	1.55	5.47	0.84
ΔE^*_{ab} TL84	1.81	5.51	0.97
ΔE^*_{ab} D65	1.62	5.05	0.91
RMS	0.52	2.21	0.34

Table 2. Inverse characterization: statistics of color distances and spectra differences for the test set.

	m	M	sdv
ΔE^*_{ab} A	1.40	7.01	0.92
ΔE^*_{ab} TL84	1.48	8.97	1.04
ΔE^*_{ab} D65	1.41	8.46	0.99
RMS	0.62	3.31	0.49

Our experimental results permit us to think that this learning method will work for different devices and media. This means that, in absence of a satisfactory model, neural networks could constitute an efficient way of realizing the desired transformation.

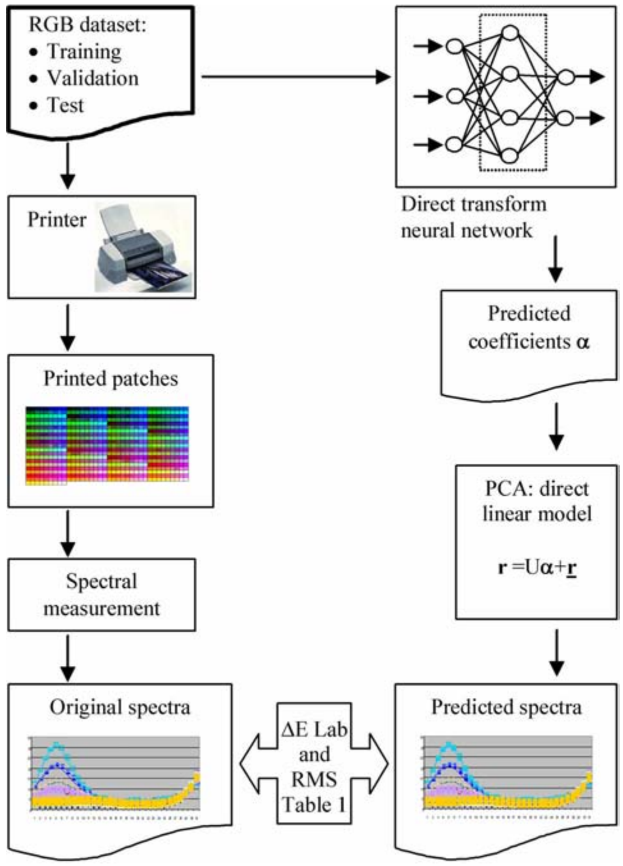

Figure 5a: Diagram for the direct transform performance estimation.

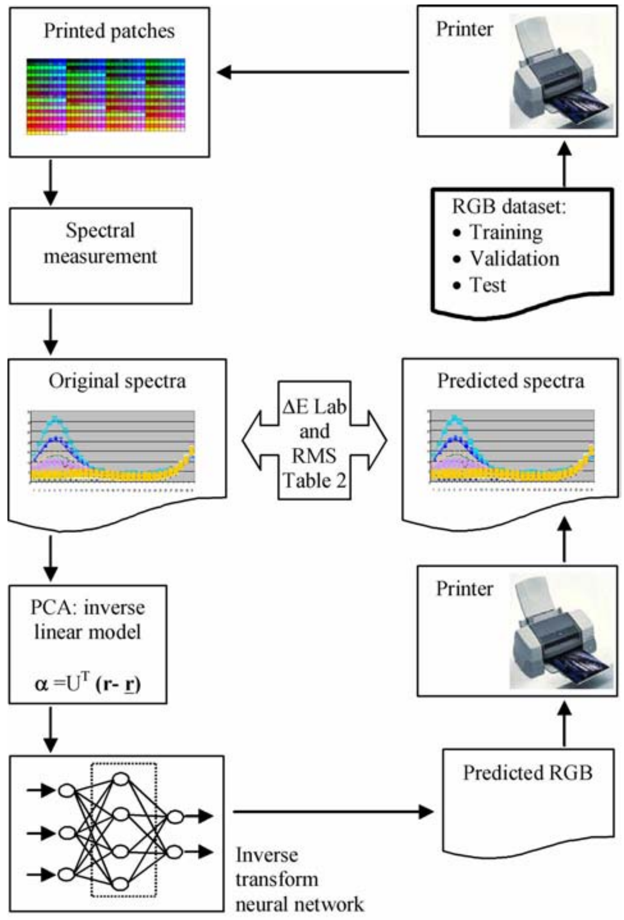

Figure 5b: Diagram for the inverse transform performance estimation.

5. Conclusions

We have defined a method for faithfully approximating the printer spectral behavior by means of feed-forward neural networks trained with back-propagation. The reflectance spectra of most natural occurring objects are smooth functions of wavelength; the same is true for spectra produced using photography, printing or paints. Consequently we exploit finite-dimensional linear models to reduce the amount of information required to characterize the printer spectral behavior.

We have presented experimental evidence that the designed method is capable of learning quite satisfactorily the mapping between printer digital counts and corresponding printed colors reflectance spectra. Finding the proper network architecture has been a time consuming matter, while the learning procedures, depending on the number of epochs, have in general required 2 hours of processing on a AMD Athlon XP 1700+, 1.47 GHz, 256 MB of RAM. However, in operation only a few simple arithmetic operations are required to produce the color mapping.

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Biography

Raimondo Schettini is Associate Professor at DISCo, University of Milano Bicocca, where he is in charge of the Imaging and Vision Lab. He has been team leader in several research projects and published more than 140 refereed papers on image processing, analysis and reproduction, and on image content-based indexing and retrieval. He was General Co-Chairman of the First European Conference on Color in Graphics, Imaging and Vision, and of the EI Internet Imaging Conferences (2000-2004). He was guest editor of the special issue Color Image Processing and Analysis (Pattern Recognition Letters, 2003).