Color Scanner Calibration via a Neural Network

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Abstract

The mathematical formulation of calibrating color scanners is presented. The mapping from scanned values to colorimetric values is inherently nonlinear. Calibration required approximating this nonlinear mapping. Neural networks are particularly suited to this task. Performance using an artificial neural network generated LUT is compared to that achieved by other commonly used methods.

1   Introduction

The proliferation of desktop color scanners and printers has led to an interest in achieving colorimetric accuracy with these devices. A recent special issue of IEEE transactions on image processing was dedicated to the problems of color recording and reproduction [1]. Conveying accurate colorimetric information is of importance to a varied number of applications including product marketing, textile production, the retail catalog industry, and remote sensing to name a few.

In order to reproduce consistent and accurate color with a scanner or printer, a mapping is needed from the device control values to a space that has a one-to-one mapping onto the CIE XYZ color space. This requirement leads to the definitions of device independent and device dependent color spaces.

A *device independent color space* is defined as any space that has a one-to-one mapping onto the CIE XYZ color space. Device independent values describe color for the standard CIE observer.

By definition, a *device dependent color space* cannot have a one-to-one mapping onto the CIE XYZ color space. In the case of a recording device, the device dependent values describe the response of that particular device to color. For a reproduction device, the device dependent values describe only those colors the device can produce.

Scanner calibration is achieved by determining a mapping (if one exists) which maps the device dependent control values to a device independent color space (e.g. CIELAB). These mappings are nonlinear because of the linear characteristics of the actual hardware and, more importantly, because of the nonlinear transformation to the CIELAB space which models the sensitivity of the eye to color differences. It is noted that calibrating printers is even more nonlinear in practice. Typically, these mappings are implemented via a multi-dimensional look-up-table (LUT) in combination with some low order interpolation. The International Color Commission (ICC) has suggested a standard format for the mappings[8].

The neural network is inherently nonlinear when designed with nonlinear neural activation functions. The neural net approach has additional advantages in that it automatically achieves a certain degree of smoothness and does not require special programming on the part of the designer. Here we demonstrate an example of calibrating a color scanner with a neural net generated LUT. The neural net approach is compared to standard methods including global linear and polynomial mappings, and a locally linear approximation method.

2   Color Scanner Calibration

Mathematically, the recording process of a scanner can be expressed as

$$\mathbf{c}_i = \mathcal{H}(\mathbf{M}^T \mathbf{r}_i)$$

where the matrix $\mathbf{M}$ contains the spectral sensitivity (including the scanner illuminant) of the three (or more) bands of the scanner, $\mathbf{r}_i$ is the spectral reflectance at spatial point i, $\mathcal{H}$ models any nonlinearities in the scanner (invertible in the range of interest), and $\mathbf{c}_i$ is the vector of recorded values.

We define *colorimetric scanning* as the process of scanning or recording an image such that the CIE values of the image can be recovered from the recorded data. This means that image reflectances which appear different to a standard observer will be recorded as different device dependent values. Mathematically,

this implies

$$\mathbf{A}^T\mathbf{Lr}_k \neq \mathbf{A}^T\mathbf{Lr}_j \;\Rightarrow\; \mathbf{M}^T\mathbf{r}_k \neq \mathbf{M}^T\mathbf{r}_j$$

for all $\mathbf{r}_k, \mathbf{r}_j \in \Omega_r$ $k \neq j$ where Ω_r is the set of physically realizable reflectance spectra, the columns of matrix $\mathbf{A}$ contain the CIE XYZ color matching functions, and the diagonal matrix $\mathbf{L}$ represents the viewing illumination. In other words, a colorimetric scanner would "see" the image just as a standard observer under illuminant $\mathbf{L}$.

Given such a scanner, the calibration problem is to determine the continuous mapping $\mathcal{F}_{scan}$ which will transform the recorded values to a CIE color space. In other words, determine the function $\mathcal{F}_{scan}$ such that

$$\mathbf{t} = \mathbf{A}^T\mathbf{Lr} = \mathcal{F}_{scan}(\mathbf{c})$$

for all $\mathbf{r} \in \Omega_r$.

Unfortunately, most scanners and especially desktop scanners are not colorimetric, hence the transformation $\mathcal{F}_{scan}$ does not exist. This is caused by physical limitations on the scanner illuminants and filters which prevent them from being within a linear transformation of the CIE color matching functions. Work related to designing optimal approximations is found in [9, 10, 11, 12].

For the non-colorimetric scanner, there will exist spectral reflectances which look different to the standard human observer but when scanned produce the same recorded values. These colors are defined as being metameric to the scanner. Likewise, there will exist spectral reflectances which give different scan values and look the same to the standard human observer. While the latter can be corrected by the transformation $\mathcal{F}_{scan}$, the former cannot.

On the upside, there will always (except for degenerate cases) exist a set of reflectance spectra over which a transformation from scan values to CIE XYZ values will exist.

Printed images, photographs, etc. are all produced with a limited set of colorants. Reflectance spectra from such processes have been well modeled with very few (3-5) principal component vectors [2, 3, 4, 5]. When limited to such data sets it may be possible to determine a transformation $\mathcal{F}_{scan}$ such that

$$\mathbf{t} = \mathbf{A}^T\mathbf{Lr} = \mathcal{F}_{scan}(\mathbf{c})$$

for all $\mathbf{r} \in B_{scan}$ where B_{scan} is the subset of reflectance spectra to be scanned.

Look-up-tables, nonlinear and linear models for $\mathcal{F}_{scan}$ have been used to calibrate color scanners [6, 7, 13, 14]. In all of these approaches, the first step is to select a collection of color patches which span the colors of interest. Since the particular samples selected determine the characteristics of the mapping, the scanner calibration is usually identified with respect to the process which produced the samples. Ideally these colors should not be metameric in terms of the scanner sensitivities or to the standard observer under the illuminant for which the calibration is being produced. This constraint assures a one-to-one mapping between the scan values and the device independent values across these samples. In practice, this constraint is easily obtained. The reflectance spectra of these M_q color patches will be denoted by $\{\mathbf{q}\}_k$ for $1 \leq k \leq M_q$.

These patches are measured using a spectrophotometer or a colorimeter which will provide the device independent values

$$\{\mathbf{t}_k = \mathbf{A}^T\mathbf{q}_k\} \quad \text{for} \quad 1 \leq k \leq M_q.$$

Without loss of generality, $\{\mathbf{t}_k\}$ could replaced with any colorimetric or device independent values, e.g. CIELAB, CIELUV. The patches are also measured with the scanner to be calibrated providing $\{\mathbf{c}_k = \mathcal{H}(\mathbf{M}^T\mathbf{q}_k)\}$ for $1 \leq k \leq M_q$.

Mathematically, the calibration problem is: find a transformation $\mathcal{F}_{scan}$ where

$$\mathcal{F}_{scan} = \arg(\min_{\mathcal{F}} \sum_{i=1}^{M_q} ||\mathcal{F}(\mathbf{c}_i) - \mathcal{L}(\mathbf{t}_i)||^2)$$

where $\mathcal{L}(\cdot)$ is the transformation from CIEXYZ to the appropriate color space and $||.||^2$ is the error metric in the color space.

3 Artificial Neural Net

Because of its embedded nonlinearities, an artificial neural network (ANN) is well suited for the generation of the 3-D LUT in a scanner calibration problem. the mathematical description of the input-output relation for a single hidden layer neural network is given by [15]

$$\mathcal{L}(\mathbf{t}) = \mathbf{W}^1\Phi(\mathbf{W}^0\mathbf{c})$$

where $\Phi(\mathbf{u}) = [\phi_1(u_1), ..., \phi_N(u_N)]^T$, $\mathbf{u} = \mathbf{W}^0\mathbf{c}$, $\phi_i(\cdot)$ represents the neural activation function for the ith hidden neuron, and the bias in the neuron is accounted for by augmenting the vector $\mathbf{c}$. The weights for the input layer are denoted by the superscript 0 and the output layer weights are denoted by the superscript 1. The user selects the number of neurons, N, in the hidden layer and the form of the activation function. Typically, the activation function is the same at each

hidden neuron. The activation function can be considered in some respects as a basis set in which to represent the function $\mathcal{F}_{scan}$.

The training of the network is a process of estimating the optimum weight matrices $\mathbf{W} = [\mathbf{W}^0, \mathbf{W}^1]$ which minimized the error on a given data set. In this case, the vector pairs $\{\mathbf{c}_i, \mathcal{L}(\mathbf{t}_i)\}$ represent the input and output respectively. It is important to test the performance of the neural net after training. This is done by dividing the data into a training set and a testing set. Usually half the data is used to train the network and minimize the error, then the error of the trained network is computed using the testing set. If the errors are of the same order, the user has confidence that the network has not over-fit the training data and will generalize in a robust manner.

Once the network has been trained, the 3-D LUT is generated by evaluating the neural net at the RGB LUT grid points. These points may contain some data samples but since the number of samples is much smaller than the number of grid points, the performance of the LUT depends on the generalizing ability of the mapping obtained from the neural network. To achieve acceptable performance, the LUT must be relatively smooth. The smoothness of the activation function and the number of hidden neurons can assure smoothness to a degree determined by the user. The use of an appropriate basis function in the ANN will insure this requirement. The usual sigmoid function was used in this work but it may be of interest to investigate other functional forms.

Additionally, it must be possible to determine values for grid points in the table which may be outside the range of the scanned target data (i.e. the range of the scanned values $\mathbf{c}_i$ does not cover the entire space of possible scanned values). The neural net can easily be used to extrapolate values for the grid points that are beyond the range of the scanned target values. This is another advantage of the neural net approach. The extrapolation problem is a significant one for methods which reply on nearest neighbor interpolation/extrapolation. Even minor noise can cause large errors for these methods.

4 Example

A color target with 264 samples was measured with a three band (RGB) desktop color scanner. The CIELAB value for each sample was measured for D50 illumination. LUTs of size 32x32x32 which map from the RGB output values to the CIELAB values were generated using four different methods. Linear interpolation was used to determine the values lying off the grid. It is noted that most sample points do not lie on the grid.

In the first method, a global linear fit was obtained between the RGB values and the CIE XYZ values. The fit mapped to CIEXYZ, but minimized the CIELAB ΔE error. Mathematically, this mapping can be described as

$$\mathbf{N}_{scan} = \arg(\min_{\mathbf{N}} \sum_{i=1}^{264} ||\mathcal{L}(\mathbf{N}\mathbf{v}_i) - \mathcal{L}(\mathbf{t}_i)||^2)$$

where $\mathbf{v}_i = \mathcal{H}^{-1}(\mathbf{c}_i)$. The operation $\mathcal{H}^{-1}$ simply linearizes the input data to the fitting function. A nonlinearity still exists in the data due to the transformation to CIELAB.

In the second method, a global nonlinear fit was obtained which incorporated cross-polynomial terms of the scanned RGB data. Again, the fit mapped to CIEXYZ but minimized the CIELAB ΔE error and can be mathematically expressed as

$$\mathbf{P}_{scan} = \arg(\min_{\mathbf{P}} \sum_{i=1}^{264} ||\mathcal{L}(\mathbf{P}\mathbf{z}_i) - \mathcal{L}(\mathbf{t}_i)||^2)$$

where $\mathbf{z}_i = [R, G, B, RG, RB, GB]^T$, $\mathbf{v}_i = [R, G, B]^T$ and RG, RB, GB denote the products of the R, G, and B components.

In the third method, the N closest scanned values to the grid point were used to compute a locally linear fit for that region of RGB space. Mathematically, this mapping can be expressed as

$$\mathbf{Q}_{scan}(\mathbf{u}) = \arg(\min_{\mathbf{Q}} \sum_{i=J_1}^{J_N} ||\mathcal{L}(\mathbf{Q}\mathbf{v}_i) - \mathcal{L}(\mathbf{t}_i)||^2)$$

where $||\mathbf{u} - \mathbf{v}_i|| \leq ||\mathbf{u} - \mathbf{v}_k||$ for all pairs $\{i, j\}$ where $i \in \{J_1, ..., J_N\}$ and $k \notin \{J_1, ..., J_N\}$ (i.e. the indices $\{J_1, ..., J_N\}$ are the N points in $\{\mathbf{v}_i\}_{i=1}^{264}$ which are closest to the point $\mathbf{u}$ in terms of Euclidean distance). For this example, $N=20$ was used.

Finally, for the fourth method, an artificial neural network (ANN) was trained on the 264 samples. A fully connected network with one hidden level was used. The activation function in the hidden level was the sigmoid function. The number of nodes in the hidden level was varied from 5 to 25. The cost function for determining the optimal weights in the network can be expressed as

$$\mathbf{W}_{scan} = \arg(\min_{\mathbf{W}} \sum_{i=1}^{264} ||R_{\mathbf{W}}(\mathbf{v}_i) - \mathcal{L}(\mathbf{t}_i)||^2)$$

where the trained network is represented by $R_{\mathbf{W}_{scan}}$. A Levenberg-Marquardt algorithm was used in optimizing the network weights via back-propagation.

Method	Average ΔE	Max ΔE
Global Linear	4.89	20.70
Global Polynomial	4.08	17.40
Locally Linear	2.80	23.0

Table 1: ΔE results for nonneural methods

Num. Hidden Neurons	Average ΔE	Max ΔE
5	5.96	22.18
10	2.87	13.30
15	2.44	11.59
20	2.20	12.09
25	2.26	10.64

Table 2: ΔE results using ANN

For each method, a 3-D LUT was generated by evaluating the function on the 32x32x32 grid points. The scanned data was then fed into the LUT and the LUT output compared to the known LAB values for those 264 samples. Linear interpolation was performed in the LUT. The results are given in Tables 1 and 2. From these results it is clear that global linear and polynomial methods do not perform as well as the locally linear method or the ANN, and in fact the ANN provides the best results. Further investigation is needed to look into how well each of these transformations generalize.

5 Conclusions

The problem of calibrating color scanners was defined mathematically. Various methods were compared in creating the calibration. From these preliminary results it appears that a neural net approach shows promise for use in generating the 3-D LUT used in processing scanned data.

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