The Faithful Rendition of Color Ranges on Display

R. Schettini
Institute of Cosmic Physics and Related Technologies (IFCTR, CNR)
National Research Council, Milano, Italy

Abstract

Technological developments in recent years have promoted the use of CAD systems in applications, such as textile design, where color is an important factor. A practical approach to the rendering of color ranges on displays integrating colorimetric and interactive methods is proposed here, and the first results of its application are reported.

Introduction

Technological developments in recent years have promoted the use of CAD systems in applications, such as textile design, where color is an important factor. Users of these systems have, however, often been frustrated by the fact that the display does not truly reproduce the appearance of the colors when printed on fabric. This absence of identity, or the laborious business of achieving it, is certainly a major obstacle to the wider use of CAD in the textile industry, and has left many potential users highly diffident towards those who propose or develop such systems.[1]

The fundamental reason for this difficulty is that our knowledge of the mechanisms of vision and the models derived from them have not yet enabled us to completely master the phenomenon of color perception, and deal successfully with all the subjective and environmental factors influencing it.[2]

A practical approach to the reproduction of color ranges in textile CAD, which allow users to view on the monitor colors as almost they are seen on fabric, is presented here. Designers can thus employ a faithful render-ing of the colors of a given firm's color data base, for which the dyeing recipe for a given fabric support is known, in the CAD coloration of new patterns.

The starting point is the observation that the simplest, and perhaps the most effective and common approach in the area of CAD textiles to the reproduction of colors on different devices or supports is to have the user himself define the color combinations interactively on the various devices. The obvious limitations of this approach are the absence of any standardization and the necessity of in-volving highly specialized users in a boring and time consuming activity. The approach proposed here uses a colorimetrically characterized device (the mapping remains valid even when the display is changed, and provides a suitable basis for reproducing the colors on other media), and an artificial neural network to mimic the user's color combining activity, i.e. to model all those factors influencing the evaluation of a color match which colorimetry fails to take into account.

Problem definition and present solutions

Every textile industry usually has several hundred color recipes which, applied to different supports (silk, cotton, etc.), result in many thousands of colors for potential use in design. But at present even sophisticated textile CAD systems do not guarantee fidelity in color reproduction. Colors are only partially or approximately reproduced on the display due to the difficulties of achieving a satisfactory match in their appearance. In practice the number of colors actually used is set not only by the season's fashion trends but also by the designer's limits in keeping in mind the appearance of all the colors available and picturing how these will look when associated in the pattern he is creating.

Typically, palettes restricted to about twenty colors are chosen in advance by specialists are visually reproduced on the screen using a trial and error approach (a procedure which must be performed for each CAD station), and designers are limited to the colors on these palettes in their new patterns.

A different approach to the problem of obtaining colors which look the same on different supports is based on the reproduction of the CIE standard colorimetric tristimulus values. Software systems employing this approach have been tested in the area of CAD textiles. The unquestionable advantage of the colorimetric approach is standardization; its disadvantages lie in the difficulty of accurately characterizing the available hardware colorimetrically, and within the intrinsic limits of colorimetry. In fact, colorimetry enables us to state that the two color stimuli having the same CIE tristimulus values are "per-ceptively" equal only if they are seen in the same con- text, under the same conditions of illumination, by an observer whose perception of the color does not differ from that of the standard CIE colorimetric observer, and whose state of chromatic adaptation is constant. In practice, since the context in which colors are seen on the monitor is very different from the context in which colors are seen once they have been printed on paper or fabric, a perfect colorimetric equivalence can not garantee that the colors will be perceived to be exactly the same.[3,4]

The proposed approach

In the approach proposed here color ranges are reproduced colorimetrically on the display, and the user is given editing tools based on visual interaction with which to match the colors of a suitable training set. An artificial neural network learns the correct response, using the device-independent color description of the mapping interactively defined by the user. The implicit mapping coded in the neural network can then be applied to correct all the colors of the color range to be reproduced on the screen.

Among the several factors not provided for to date and with which the neural network is expected to cope are:

- calibration errors (the monitor black point and ambient light which can not be measured, instrument errors in measuring the phosphors' chromaticity and luminance, small violations of assumptions about monitor performance);
- differences in color appearance caused by the mode of perception, surface properties, surrounding colors, area of the samples, observer's state of adaptation, etc.

Device modeling

Colors on cathode ray tube monitors are usually described by their corresponding RGB values. Since such a description is device-dependent and unstable in time, an appropriate mapping must be established between the RGB and the CIE XYZ tristimulus values. This mapping is based on three assumptions about monitor performance which must be verified: if these were to prove untrue, calibration accuracy would be limited.[5,6]

The first assumption to verify is gun independence, i.e. that each phosphor is excited only by its respective gun. The second is phosphor constancy, i.e. that changing the intensity of the light emitted by a single phosphor does not change the chromaticity of that light. The third is spatial independence, i.e. that the light emitted by the display in a given location depends only on the input values for that location.

If gun independence, phosphor constancy and spatial independence hold, we can, on the basis of some measurements, predict the tristimulus values of any set of input values and vice versa.[7]

The relationship between XYZ and the monitor's input values v_a $(a = R, G, B)$ is expressed by:

$$\ln e_a(v_a) = A_a(\ln(\frac{v_a}{v_{a_{\max}}}))^2 + B_a \ln(\frac{v_a}{v_{a_{\max}}}) + C_a \qquad (1)$$

$$[XYZ] = [N_r N_g N_b]\,[e_r e_g e_b]\begin{bmatrix} x_r & y_r & z_r \\ x_g & y_g & z_g \\ x_b & y_b & z_b \end{bmatrix} \qquad (2)$$

in which e_r, e_g, e_b are the relative excitations of each of the three guns, N_r, N_g, N_b are scale factors (which can be determined by selecting the *RGB* and *XYZ* values for the white point and then solving the system), and *A, B,* and *C* are coefficients determined by a least-squares fit. Alternative approaches to gamma correction are described.[8]

The phosphors' chromaticity and gamma corrections of the guns supplied by the monitor manufacturer are often used in non-critical applications. In applications requiring precise color matching the characteristics of the monitor must be checked. Phosphors' chromaticity should be established by spectroradiometer measurements, and gamma corrections determined by calibrating each gun with a light-meter. Since this equipment is not normally found in a textile industry, the device used in this application has been colorimetrically characterized using a colorimeter.

The monitor black point (the amount by which the monitor gamut has been translated from the origin of the XYZ space) and the ambient light reflected from the screen (that is added, in equal proportion, to all the colors) are not taken into account in the *RGB vs. XYZ* mapping, since they can not be adequately measured. This fact introduces intensity and chromaticity errors, which will be corrected in the next step of processing.

Color specification by visual interaction

The visual interface[9] used to modify the appearance of the colors displayed provides for two operating modes: "color selection" for an approximate match of the color to be reproduced, and "color editing" for further refining the initial proposal.

The dialogue between the user and the system is based on visual interaction, instead of using commands or specifying colors by their numerical coordinates. Various color spaces are made available, since one color space could not meet all application needs or represent all users' ways of experiencing color. These spaces must be considered simply a way of organizing colors that can be produced on a given device, much as the user is accustomed to thinking of them. Each color space can be visually explored following a procedure which produces the color envisaged by gra-dual adjustments from coarse to fine specification. The concept is to allow the user to wander within the preferred color space visualizing two-dimensional sections at different resolutions until the desired color is obtained.

Selecting a color by pointing to samples on display does not permit refinement of the choice beyond the resolution selected. Such refining is essentially an editing operation which can be performed step by step both by acting on the color's numerical coordinates or visually exploring a small volume of the color space around it.

The neural network

Neural networks attempt to emulate some aspects of the nervous system. They consist of a network of highly interconnected processing units. The interconnections are weights which are adaptively updated (exploiting examples or abstracting essential characteristics from inputs) to model data.[10]

A neural network is specified by its basic components: processing units (neurons), connections, activation function, learning rule.

In this application a multilayer feed-forward neural network, consisting of several distinct layers of neurons, has been used. The first, or input, layer serves as a holding site for the values to be processed by the network. The last, or output layer is the point at which the final state of the network can be read. Links connect each unit of one layer only to units in the subsequent layer.

A neural network unit is a simple processor with many different inputs from the units of the previous layer and one output sent to the units of the next layer. Formally, the net input to a unit j in a layer is:

$$net_j = \sum w_{ij} o_i \tag{3}$$

in which o_i and w_{ij} are the current output and the weights of the connection between the *i* unit of the previous layer and the *j* unit, while the output of the unit *j* is given by a sigmoid function, everywhere differentiable, which compresses the range of the *net* value to a range between 0 and 1:

$$o_j = \frac{1}{1 + e^{\frac{-(net_j - \theta_j)}{\theta_o}}} \tag{4}$$

where θ_j is an offset, and θ_o controls the shape of the function.

The back-propagation algorithm gives the prescription for changing the weights of any feed-forward network so it can learn the training set constituted by a set of input-output data. This algorithm is designed to reduce the error between the actual and the desired output of the network in gradient descent. The error measure adopted here, the summed square error *(SSE)*, is defined as:

$$SSE = \frac{1}{2} \sum_p \sum_k (o_{pk} - t_{pk})^2 \tag{5}$$

in which *p* denotes an element of the training set; *k,* the output unit, o_{pk} the output of the unit *k* when the input element is p, and t_{pk}, the corresponding target value. The change at each training iteration the weights Δw_{ij}, that were initialized to small random numbers, is then:

$$\Delta w_{ij} = -k \frac{\partial SSE}{\partial w_{ij}} + m \tag{6}$$

where *k* is the learning rate and *m* the momentum term introduced to reinforce general trends and cancel oscillatory behaviour.

In successful training sessions the network error decreases with successive iterations, and the network converges to a stable set of weights which models the training data. A detailed derivation of the back-propagation algorithm can be found in references 11 and 12.

The complexity of the neural network to be built is determined by the complexity of the function to be mapped.[13] A network with three input and output units, and two hidden layers having 10 units is used. These figures were determined empirically in pilot studies.

Experiment and preliminary results

The first step of this experiment was to obtain suitable training and testing sets for defining and verifying the mapping between the appearance of the samples as seen under given observer conditions and the calibrated dis-play. The test sets had to cover a wide range of chromatici-ties, but be small (since each sample must be carefully edited by the user). In the experiment reported here the Machbeth ColorChecker[14] (T1) and, as fabric support, a set 50 color samples printed on cotton (T2) were used. Two collections of fifty matte (V1) and cotton samples (V2) were used as training sets.

The spectral reflectance function of each color sample of the two data sets was recovered using a spectrophotometer, and the standard formulae were employed to compute the corresponding tristimulus values, taking the standard illuminant D65 as reference illuminant. These sets were then mapped in the RGB color space, and the corresponding color stimuli displayed (unreproducible colors are approximated by projecting them onto the surface of the monitor gamut) and measured. The cathode ray tube used was an IBM 6091/19 driven by a IBM Risc 6000 320H.

The average color difference between the measured and the reproduced colors (lying within the gamut of the display) was about 1.1 CIELUV color-difference units with a standard deviation of 0.4.

A team of experts familiar with color manipulation and matching were selected (AB, MC, LR); they were also required to pass a color vision test.

Before the experimental session began, the experts were given a description of the perceptual task to read, and a training session similar to the experimental one was held to familiarize them with the experiment as well as to gauge their answers.

In an otherwise darkened room, the color monitor was placed to the right of the booth – which provided standard D65 lighting conditions– at approximately eye level, and about 90 cm in front of the subject.

Each expert was asked to position the samples in the light booth and allowed to set the visualization layout of the program interface so that the background colors and geometric properties of the color samples and of their simulations on the display appeared the same to him. Then, using the color editor described in both operation modes (color selection and color editing), he was allowed to modify the appearance of the colors displayed until the best possible match (according to his subjective evaluation) was achieved. The experts spent about forty seconds adjusting the appearance of the reproduced samples. Once a match was obtained, the CIELUV coordinates of the color stimuli were stored for future evaluations. Each observer performed three matches, in different sessions, for each color sample of the training and test sets.

The results showed a high repeatability for individual expert, and significant variance among the different experts. This may confirm the high subjectivity of color matching judgements involving simulations and surface samples.

The mean corrections of training and test sets for each expert are reported in Table 1. This correction is evaluated in terms of the color difference between the CIELUV coordinates of the samples and of the matched colors.

On the whole the experts considered the matches obtained interactively good. It is possible that their involvement in finding the “best” matches have led them to assess the results positively.

Table 1

	T1	T2	V1	V2
AB	7.2	8.8	7.6	8.9
CM	8.4	9.4	8.5	9.2
LR	7.9	7.9	7.5	8.3

Mean color corrections for the training and test sets for each expert.

Table 2 shows the mean color differences between the CIELUV coordinates of the "target" colors of training and testing color sets, and the results of the neural network.

The network is able to learn the training sets correctly, while the corrections proposed for the samples of the test sets are congruent with those of the experts but still not sufficiently accurate for the application addressed.

Attempts to improve network performance by varying the neural network structure (the number of nodes in hidden layers) will be fully documented. However the impression is that the weak point in the experiment is the lack of larger and more complete training sets.

Table 2

	T1	T2	V1	V2
AB	2.1	1.7	5.2	4.6
CM	2.0	1.9	4.7	4.3
LR	1.9	2.0	4.8	4.9

Mean color differences between the color corrections made by the users and the output of the trained neural network.

Conclusion

To be an effective part of a CAD system color range rendering must be accurate, require a minimal low cost equipment, and call for little or no effort on the part of the user. The methodology proposed here seeks to meet these requisites. Satisfactory results in color appearance reproduction can be achieved if the user, starting from a colorimetric match, is allowed to find the "best" results interactively.

The coding, using an artificial neural network, of user's skill in finding solutions must be improved. In-creasing the size of the training set would perhaps improve results. Extensive experiments to this end are being performed in collaboration with textiles industries.

References

1. A. Della Ventura, R. Schettini, Possible solutions to the problem of colour fidelity in computer-aided textile design, *The Canadian Textiles Journal,* **110***: 27-31 (1993).*
2. J. Schanda, Colour and the visual display unit, *The 7th Congress of the International Colour Association*, Budapest, June, 1993 (in press).
3. D. C. Rich, D. L. Alston, L. H. Allen, Psychophysical verification of the accuracy of color and color-difference simulations of surface samples on CRT display, *Color Research and Applications*, **17**: 45-56 (1992).
4. R. Berns, Color tolerance feasibility study comparing CRT-generated stimuli with acrylic laquer coating, *Color Research and Applications*, **16**: 232-242 (1991).
5. W. B. Cowan, N. Rowell, On gun independence and phosphor constancy, *Color Research and Applications*, **11**: S34-S38 (1986).
6. D. H. Brainard, Calibration of computer controlled color monitor, *Color Research and Applications*, **14**: 23-34 (1989).
7. W. B. Cowan, An Inexpensive scheme for calibration of a color monitor in terms of CIE standard coordinates, *Computer Graphics*, **17**: 315-321 (1983).
8. D. L. Post, C.S. Calhoun, An Evaluation of methods for producing desired colors on CRT monitors, *Color Research and Applications*, **14**: 172-186 (1989).
9. R. Schettini, A. Della Ventura, M. T. Artese, Color specification by visual interaction, *The Visual Computer*, **9**: 143-150 (1992).
10. P. D. Wassermann, Neural Computing: theory and practice, Van Nostrand Reinhold, New York, 1989.
11. J. Hertz, A. Krogh, R. G. Palmer, Introduction to the theory of neural computing, Addison-Wesley, New York, 1991, **1**:115-162.
12. D. E. Rumelhart, G. E. Hinton, R. J. Williams, Learning internal representations by error propagation, in *Parallel distributed processing*, D. E. Rumelhart, J. L. McClelland Eds, MIT Press, Cambridge (MA), 1986, **1**: 145-168.
13. H. Hornink, M. Stinchcombe, H. White, Multilayer feedforward networks are universal approximators, *Neural Networks*, **2**: 359-366 (1989).
14. C. S. McCamy, H. Marcus, J. G. Davidson, A color-rendition chart, *J. of Appl. Photo. Eng.* **2**: 95-99 (1976).