The use of fundamental color stimulus to improve the performance of artificial neural network color match prediction systems

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ABSTRACT

Attempts were made for the first time to use the fundamental color stimulus as the input for a fixed optimized neural network match prediction system. Four sets of data having different origins were used to train and test the performance of the network. The results showed that the use of fundamental color stimulus greatly reduces the errors and improves the performance of the neural network prediction system.

1. INTRODUCTION

In recent years there have been tendencies to use artificial neural network systems in order to attain color recipes more intelligently.[1,2] However it must be noted that techniques based on neural networks have their own shortcomings which can be subdivided into inherent neural networks shortcomings and valued coloristic shortcomings. It is usual practice to use measured reflectance as input for the neural network in order to predict concentrations of a set of colorants (although some prefer the reverse process).The use of measured R as input would imply the achievement of a spectral (non-metameric) match. However according to Wyszecki's hypothesis[3], the measured reflectance is composed of two components, a basic fundamental color stimulus component (R_{FCS}) and a second metameric black component(R_{MB}) having tristimulus values of zero.Cohen and Kappauf[4] provided the means by which to split the measured reflectance R into its components (i.e. R_{FCS} and R_{MB}).

Based on the above mentioned premise the present investigation was carried out in order to minimize some of the shortcomings of the artificial neural network technique of color match prediction, hopefully giving advantages such as: 1-Achievement of true spectral matches, 2-Provisions for vastly reduced training samples, 3-Negligible effect of variants such as substrates sets of colorants and dyeing procedures on the predictions, 4-Acheivement of a more intelligent neural network.

2. METHOD

Four different sets of data depicted in Table 1 were utilized in the present work. As can be seen from Table 1 the origins of the data are completely different. The Texflash spectrophotometer from the Datacolor Company was used for the reflectance measurements of all samples. In this way four sets of data were at hand, the origins of which were completely different and were made to create color centers covering as far as possible the gamut of available colors for the given set of colorants. These data were utilized to test the effect of different substrates, different colorants and different methods of dyeing on the predictions of an artificial neural network color match prediction system.

Data set 35-1 comprising of 35 color centers was extracted from data set 1 and was not used in the training. A second data set 35-234 comprising nearly the same color centers as data set 35-1 was selected from the whole of data set 2, data set 3 and data set 4. Therefore data set 35-1 and data set 35-234 formed 35 metameric near (but not exact) matches having parameric differences of less than 1.7 $\Delta ECIE_{1994}$ units under the reference conditions (i.e. illuminant D65 /CIE 1964 Supplementary Standard Colorimetric Observer). 348 polyester samples being extracted from data set 1 dyed by the thermosol process were used to train an optimized artificial neural network. Data set 35-

1 was used to test the neural network. MSE (mean square error) and $\Delta Cn = [\sum_{i=1}^{35} |Cnai - Cnpi|]/35$ where n is the number of colorants, i is the number of metameric matches and Cnai and Cnpi are the respective actual and predicted concentrations, were used as measures of error determination. The average concentration differences, $\Delta Cave = [\sum_{n=1}^{6} \Delta Cn]/6$ of these colorants are also given. Additionally, the summation of the mean concentration differences divided by their respective actual concentrations multiplied by hundred gave indication of the percentage errors involved for the number of colorants and metameric matches considered.

Table 1: Data sets preparations

Variable	**Data set 1**	**Data set 2**	**Data set 3**	**Data set 4**
Colorants	Terasil*(Yellow 6G,Red R, Blue BG, Blue GN, Violet BL, Brown 3R)	Lanaset* (Yellow 2R ,Blue 2R , Bordeaux B, Green B)	Lanaset* (Yellow 4GN ,Blue 5G ,Red 2B ,Violet B, Green B)	Terasil*(Yellow GWL,Red F B, Blue 3RL)
Number of samples	383	107	183	142
Substrate	Polyester	Wool serge	Wool serge	Polyester
Dyeing method	Thermosol	Exhaustion	Exhaustion	High temperature
Type of colorants	Disperse	Reactive-metal complex 2:1	Reactive-metal complex 2:1	Disperse

*Ciba Specialty Chemicals

3. RESULTS

MATLAB 6.5 [5] was used as a tool for obtaining color recipes predicted on a fixed optimized 16×24×16×6 neural network architecture. The input layer consisted of the measured surface spectral reflectance (or one of its four transformations mentioned below) of the target color centers at 16 wavelengths of 20 nm intervals throughout the visible range of the spectrum between 400-700 nm. The output layer corresponded to the concentrations of the mentioned colorants and two hidden layers of 24 and 16 nodes respectively completed the architecture. The network was trained using the Scaled Conjugate Gradient Back Propagation algorithm. [6] A positive linear activation function was used in the output layer whilst the logsig function was used in the hidden layers. Training was made to continue over 100000 epochs. Each network was made to run three times and the network with the least mean square error (MSE) was selected for further analysis.

Networks were trained separately as follows:

1-Trained with the untransformed original measured spectral reflectance (i.e. R)

2-Trained with a transformation based on a weighted cube root coordinates [7]

$$R_{CRC} = [\Sigma\{\bar{u} \times L\}^2 + \Sigma\{\bar{v} \times L\}^2 + \Sigma\{\bar{w} \times L\}^2]^{1/2} \quad ; \quad \text{where } L = 25(R)^{1/3} - 17 \tag{1}$$

3-Trained with a transformation based on the Munsell value polynomial transformation [8]

$$R_{MVP} = 1.2219 \times R - 0.23111 \times R^2 + 0.23951 \times R^3 - 0.021009 \times R^4 + 0.0008404 \times R^5) \tag{2}$$

4-Trained with an exponential transformation $\quad R_{EX} = \exp(R) \quad$ (3)

5-Trained with the fundamental color stimulus transformation (i.e. R_{FCS}).

The five just mentioned inputs produced five artificial neural networks trained by 348 and 383 samples as mentioned previously. These trained networks were first tested by data set 35-1 and were then subsequently tested by the second selected 35 samples of data set 35-234. The performance of the five input functions were expressed as the MSE depicted in Figures 1 and 2 (given only for R and R_{FCS}. Average concentration difference between the actual and predicted concentration of individual colorants (i.e. ΔC_1, ΔC_2,…ΔC_6),as well as the average concentration difference of the recipe for all colorants (i.e. ΔCave) are illustrated in Table 2. The standard deviation of average concentration differences (Std(ΔCave)) obtained when the network was run three times are also given in Table 2. As can be seen from Figures 1 and 2, training with 348 samples of data set 1 and testing with data set 35-1, i.e. the data set of the same origin leads to small MSE for the training and test data and the MSE of the test data almost superimpose on the MSE of the train data being always a little bit higher than the training data irrespective of the input functions. This trend also holds good for concentration differences between the actual and predicted concentrations as is illustrated in Table 2. This is indicative of a well-trained artificial neural network giving a maximum average concentration difference of 0.026(i.e. default of the network's architecture) irrespective of the input function. However, the situation dramatically changes when the training is carried out by data set 1 and tested with data set 35-234, i.e. the data set of completely different origins. As can be seen from the right hand side graphs of Figures 1 and 2, except for R_{FCS}, the MSE of the test data for all the other input functions(only R being given here) diverge from the MSE of the training data; the deviation being maximum for the untransformed function R. Table 3 clearly shows the same trend in terms of MSE-test and percentage error in concentration difference for all the samples in data set 35-234. Again, R gives the worst and R_{FCS} the best results in terms of these parameters.

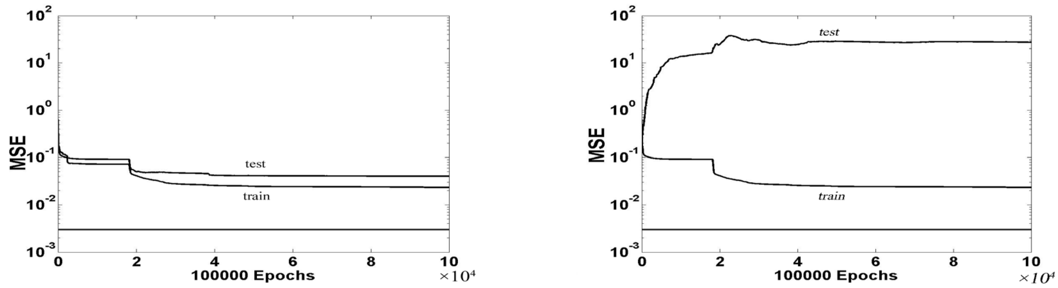

Figure 1: Train and test results for untransformed measured reflectance(R), Left: for data set 35-1, Right: for data set 35-234

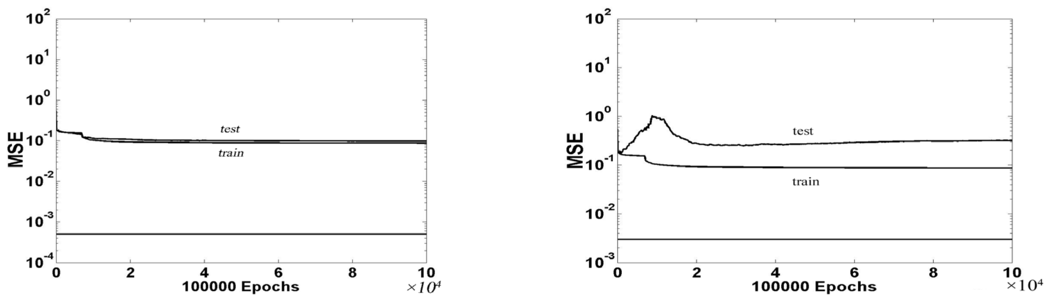

Figure 2: Train and test results for R_{FCS}, Left: for data set 35-1, Right: for data set 35-234

Table 2: Colorant concentration error for various reflection functions

Data type	Function	ΔC_1	ΔC_2	ΔC_3	ΔC_4	ΔC_5	ΔC_6	ΔC_{ave}	Std(ΔC_{ave})
Trained with 348 samples of data set 1 and tested with data set 35-1	R	0.003	0.027	0.015	0.021	0.005	0.025	0.016	0.003
	R_{CRC}	0.004	0.034	0.003	0.023	0.063	0.025	0.025	0.003
	R_{MVP}	0.002	0.034	0.014	0.019	0.031	0.025	0.021	0.015
	R_{EX}	0.016	0.016	0.009	0.016	0.043	0.025	0.021	0.014
	R_{FCS}	0.018	0.018	0.015	0.016	0.063	0.025	0.026	0.002
Trained with data set 1 and tested with data set 35-234	R	0.617	0.036	0.030	2.014	0.590	0.025	0.552	0.074
	R_{CRC}	0.306	0.034	0.030	0.736	0.973	0.025	0.351	0.033
	R_{MVP}	0.914	0.034	0.030	1.032	0.352	0.025	0.398	0.020
	R_{EX}	0.444	0.035	0.036	0.398	0.731	0.045	0.281	0.022
	R_{FCS}	0.048	0.028	0.025	0.085	0.088	0.025	0.050	0.004

Table 3: Colorant concentration errors, when trained with data set 1 and tested with data set 35-234

Function	MSE-test	ΔC_{ave}	Error %
R	27.55	0.552	99.8
R_{CRC}	4.05	0.351	68.9
R_{MVP}	14.15	0.398	90.1
R_{EX}	8.68	0.281	58.6
R_{FCS}	0.32	0.050	13.2

Similar previous work [9,10] also picked R_{FCS} as the best candidate for more limited intentions. The preliminary trends in all the results favor the utilization of R_{FCS} as the input function for artificial neural network match prediction procedures. It seems that R_{FCS} might be able to enhance the capability of neural network systems through increased generalization of the relationships, giving rise to less variables and hence more intelligence.

4. CONCLUSIONS

The aim of the present investigation was to use a series of transformation of measured reflectance in order to enable an optimized artificial neural network system of color match prediction to predict the concentrations of a given set of colorants of one data set whilst the network was trained by a data set of a completely different origin. The preliminary results demonstrate that R_{FCS} shows promise for the goals sough after. Should the trend hold true for other sets of data and the visual implications of the percentage errors in concentration differences be acceptable, then vast reduction of training samples can be visualized. The idea could be extended into visualizing that substrates, sets of colorants and coloration procedures would have no or vastly reduced effects on the predictions.

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