Artificial Neural Networks for Recipe Formulation in Leather Dyeing Based on Tristimulus System

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Abstract

Computer color management systems have become increasingly important to the color industry. One of the most important aspects of quality control in manufacturing processes is maintenance of color in the product. This involves selecting a recipe of appropriate dyes which when applied at a specific concentration to the product will render the required color. This process is known as recipe prediction. Color Recipe Prediction is a difficult problem to solve using conventional computer techniques as the Kubelka-Munk (K-M) model that is most widely used theory breaks down under a variety of conditions.

Artificial Neural Networks (ANN) represent a style of computing that is motivated by an understanding of human neural information processes. The use of ANN has become established as a powerful tool in science to tackle non-linear complex problems. The application of Multilayered Perceptrons (MLP) which are types of ANN designed to adapt & acquire knowledge during a period of time to formulate the recipe prediction is discussed. The paper investigates a practical approach for the use of artificial intelligence in finding solutions to traditional and emergent colorimetric problems. The various network structures for mapping the relationships between the sample color parameters and dye concentrations are discussed.

Keywords: Artificial Neural Networks (ANN), Leather Dyeing, Color Recipe Prediction, Color Matching, Tristimulus System, Kubelka-Munk (K-M) theory.

Introduction

Recipe formulation in leather dyeing is an important procedure in leather processing and concerns the prediction of product formulation to meet a desired color specification. The formulation is normally expressed in terms of which dyes to use and at what concentrations. In leather dyeing recipe formulation is traditionally carried out by trained colorists who achieve a color match via a combination of experience and trial and error method. Instrumental recipe formulation was introduced commercially in the allied industry such as textile(Davidson et al. 1963), paint etc., The approaches to instrumental recipe formulations have aimed to develop a parametric model of the relationship between the chemical formulation of product and its color specification(Park et al 1944; Nobbs et al. 1986). Specifically, a traditional colorant formulation systems relies upon being able to predict the reflectance R at a given wavelength λ for a mixture of known colorants. The K-M theory (Alman et al 1987) and variants of it have been used almost exclusively for this purpose. The K-M theory characterizes colorants in terms of radiation absorption and scattering coefficients derived from a small number of calibration samples and have been very successful in providing effective solutions for the allied industries. However the application of the conventional instrumental recipe prediction for leather dyeing do not work well and they are due to the following reasons for failure:

1. The K-M model may not adequately describe the interaction of a colorant with light, either individually or in mixture with other colorants. Leather being a 3-D fiber the interaction of dyes with the substrate plays a very vital role.

2. The K-M model requires the preparation of special samples for use as a calibration database. These samples are prepared mostly in a laboratory scale and there are often systematic and random differences between laboratory and bulk preparations.

3. In leather, the substrate used for dyeing is not white and it is influenced by various tannages.

4. The various unit operations involved in the leather processing impart their own characteristic color to the final leather apart from influencing the dyeing characteristics of the leather

Type 1 errors are fundamental problems with the K-M theory whereas type 2 errors are problems of application of the theory. Type 3 & 4 errors are caused by problems in the coloration process. Recipe formulation in leather dyeing using ANNs to replace the K-M equations promise to alleviate the above errors but cannot be expected to be of assistance if the coloration system is not reproducible.

Neural Networks and Recipe Prediction

The performance of the K-M theory in leather dyeing is such as to warrant an alternative approach. An empirical colorant mixture model has been suggested(Nobbs et al 1986) using high-order polynomial models but the accuracy of such a model will clearly be influenced by the exact choice of polynomial. The trained colorists accumulates experience of the behavior of the dyes and is able to extrapolate and interpolate from this experience to predict recipes for new shades without the use of K-M theory or any other algorithmic model. Neural networks techniques are now beginning to be able to emulate the performance of human operators or experts in many areas of science and engineering and this paper investigates their use on the recipe prediction in leather dyeing.

Neural Network Methods

A neural network is a computational structure modeled on biological processes. It is used to describe the structure and connectivity of the human brain (E Davalo et al 1991). Computer models of neural networks should more accurately be described as artificial neural networks (ANN). There are many different types of ANN(Aleksander et al 1991; L Fausett 1994). Multilayer perceptron (MLPs) are types of ANN designed to adapt and acquire knowledge during a period of time, in order to accomplish a certain task. MLPs consists of layers of simple processing units that process information to the units in the next layer via weighted connections. Each unit in the hidden layer receives data from the input vector, with weights being applied to each input. The same process occurs between the hidden layer and the output vectors(Skapura 1996; Korn 1995; Hertz et al 1991). Units received compute a weighted sum on their input compute and output based on some transfer function on their input. Such networks can effect mappings from input vectors (presented to the first layer of the network) to the output vectors (the output of the final or output layer of units). It has been shown that an MLP with a single hidden layer of units is able to compute any computable transformation to any degree of accuracy(Funahashi 1989).

Before the network can be used to solve a given task it must be trained using known pairs of input and output vectors. Backpropagation is a commonly used procedure applied to carry out the training process of an MLP. It works by leading the network to adjust its synaptic weights through a descendent error minimisation technique(Skapura 1996; Korn 1995; Hertz et al 1991; Funahashi 1989; Blum 1992). The attractiveness of ANNs is based on their ability to adapt to new situations and learn the input-output data relationship of a problem, this being done without inference from an external agent. The application of MLPs to color match prediction was first demonstrated by Westland(Westland et al 1991) and Bishop etal (Bishop et al 1991). They concluded that this technique warranted further investigation, and pointed out that it could be applied to colorimetric systems with complex behaviour, which are difficult to treat using K-M theory.

Experimental

A set of three dyes was used comprising red, blue and yellow. Individual as well as mixtures of these dyes was dyed on the blank substrate. The spectral reflectance factors, at 10nm intervals, of each dyed sample were measured using a sphere-based reflectance spectrophotometer. The number of samples prepared was 335 and these were randomly separated into a training set (300 samples) and a validation set(35 samples).The 300 samples in the training set were used to train an MLP of the type illustrated in Fig.1.

Two different processes are considered for prediction they are color prediction and colorant prediction. Color prediction is the prediction of the ultimate color from a given recipe of colorants. Colorant prediction is the inverse process; given a color a recipe of colorants is predicted. Three approaches were used in the investigation of recipe prediction for leather dyeing using neural networks. Two approaches for color prediction and one for the colorant prediction. In the first, the MLP had three input units, each corresponding to the concentrations of one of the three dyes used in the mixtures. The output layer contained 3 units corresponding to the tristimulus values X,Y,Z. The network was trained using the back-propagation algorithm with different activation functions such as tansig and sigmoid and different combinations were tried for the hidden and output layers. Networks were trained using 2,3,4,5,6, units in the hidden layer and for a total of 10,000 epochs. One epoch is a term used to describe the case where each of the samples in the training set are presented to the network, the errors at the output layer computed, and small changes made to the weights in the network according to the back-propagation algorithm.

Similarly in the second approach, the MLP had three input units, each corresponding to the tristimulus values of the samples and the output layer contained 3 units each corresponding to the concentrations of one of the three dyes used in the mixture.

Results and Discussion

Fig.2&3 shows the learning progress of the XYZ-C and C-XYZ networks over time. It can be observed that there was an initial rapid decrease in the networks' error following the onset of training, after which it became almost constant as the number of epochs was further increased. Interestingly, increasing the number of hidden nodes as well as increasing the network training time, instead of improving its capacity to predict the samples of the testing set more accurately, actually had the reverse effect, especially for the C-XYZ networks. All the networks used in these experiments were trained for a 10000 number of epochs but reached the error goal in 1100 epochs itself which resulted in the good accuracy for the test data.

Performance of networks

After training the XYZ – C, network was used to predict the dye concentration for the samples and the C-XYZ network was also used to predict the color of the samples in the validation set. From figure 4 it can be observed that among these networks, the C-XYZ network presented the best performance whose overall color difference is only 0.45 which is almost negligible when compared to the other network. All the networks predicted with good accuracy and it is important to note that these samples were not used in the training of the network.

Conclusion

The present approach using neural networks has avoided the problems mentioned by the K-M model (see earlier) and led to consistent results. However there are limitations in the use of neural networks for color recipe prediction. An adequate number of samples must be presented for the network to learn the mapping relationship between the input and the output layer. In addition an increase in the number of dyes available if exceeds more than eight will increase the network topology and probably will reduce its performance.

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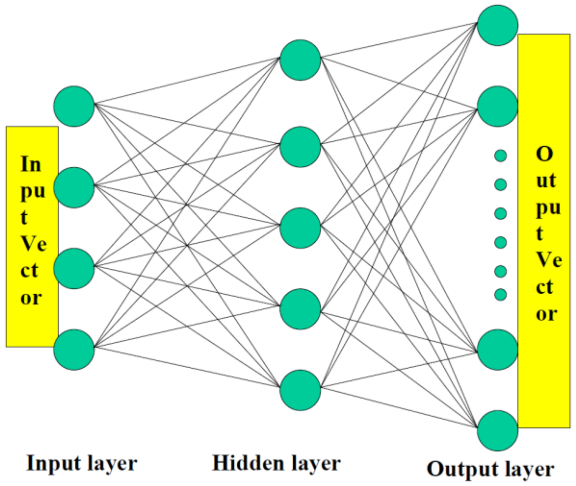

Fig. 1: Schematic diagram of MLP structure.

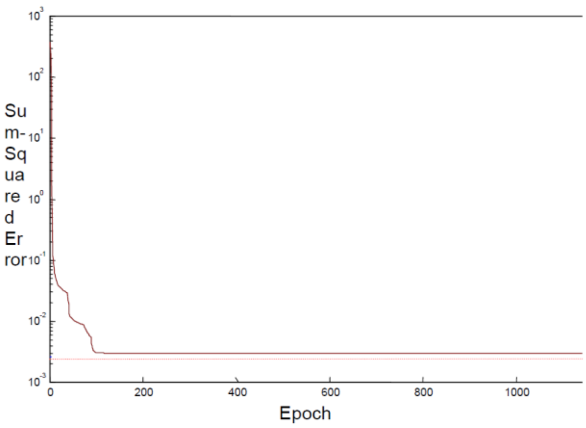

Fig. 2 Sum-Squared Network Error for 1141 Epochs

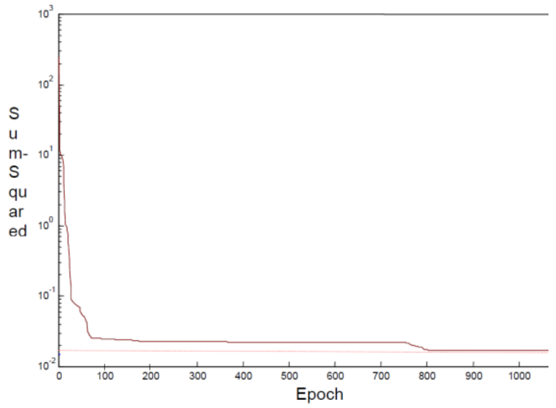

Fig. 3 Sum-Squared Network Error for 1100 Epochs

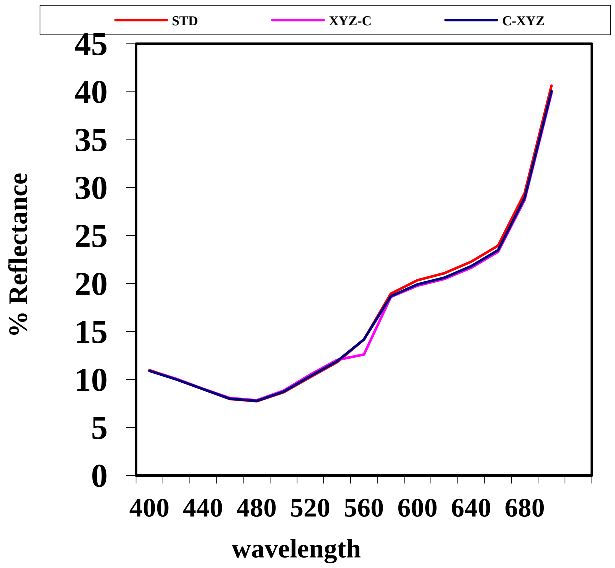

Fig. 4 Reflectance curves of actual sample and the predicted ones by the corresponding networks