TECHNICAL NOTE

COLOR MATCHING OF BLENDS PREPARED FROM BLACK AND WHITE FIBERS BY NEURAL NETWORKS

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Abstract The color of the blends of pre-colored fibers depends on the ratio of each fiber in the blends. Some theories have been introduced for color matching of blends of pre-colored fibers. Most however, are restricted in scope and accuracy. Kubelka and Munk presented the most applicable theory, which is still used in industry. In this work, the classical Kubelka-Munk method for color prediction of a series of grays, prepared from different ratio of black and white is compared with new technique, which apply neural networks. Thirteen different blends with different ratio of virgin and black fibers were prepared. The reflection of samples was measured and then a two layers network was designed. The modified back-propagation learning strategy was applied. The Sum of Squares Error was calculated for evaluation of methods. Results showed better prediction for networks in comparison to Kubelka-Munk algorithm.

Key Words Color Matching, Pre-colored Fibers, Neural Network, Blend

چکیده رنگ مخلوط الیاف از پیش رنگ شده بستگی به نسبت وجود هر لیف در مخلوط دارد. برای همانندی رنگ مخلوط الیاف از پیش رنگ شده، تئوریهایی ارائه شده است. بیشتر این تئوریها بسبب فراگیر بودن و دقت، دارای محدودیت هستند. قابل استفاده‌ترین تئوری که هنوز در صنعت بکار گرفته می‌شود توسط کیوبلکا و مانک ارائه شده است. در این تحقیق برای پیش بینی رنگهای خاکستری حاصل از مخلوطهای مختلف الیاف سیاه و سفید، روش کیوبلکا- مانک با روش جدید مبتنی بر شبکه عصبی، مقایسه شد. سیزده مخلوط مختلف از الیاف خودرنگ و الیاف سیاه تهیه گردید. بازتاب نمونه‌ها اندازه گرفته شد و یک شبکه عصبی دو لایه‌ای طراحی شد. آموزش شبکه از طریق انتشار خطا به عقب انجام پذیرفت. برای ارزشیابی روش بکارگرفته شده، جمع مربع انحرافات محاسبه شد. نتایج نشان داد که در مقایسه با روش کیوبلکا- مانک، شبکه عصبی بکار رفته از قابلیت پیش‌بینی بهتری برخوردار است.

1. INTRODUCTION

Although computer colorant formulation can considerably reduce trial and error efforts [1], a system has not yet been developed which gives a very high success rate in first-time matches to target. This is especially true for the more complex substrates such as the matching of fluorescent dyes and pigments [2] or blending of pre-colored fibers [3-4]. Obviously a theory, which accurately relates the concentration of individual colorants to the measurable optical factors such as reflectance, is required for computer color formulation. Kubelka and Munk presented a simplest approach for this request. This model, which is commonly used in colorant prediction, is a source of error in color formulation, and leads to very low success if the correction step is not applied consequently.

Amirshahi and Pailthorpe [3-4] discussed the color mixing behavior of blends of pre-colored fibers. They developed and modified some methods on the basis of Kubelka-Munk theory and using them in order to explain and predict the color of blends that were prepared from pre-colored fibers.

On the other hand, the application of neural networks to colorant formulation was discussed by Bishop et al. [5]. They used a synthesized data of three dyes by using different concentrations of single and two mixtures from these primaries, to produce CIELAB color coordinates under D65 Illuminant. A network consisted of two hidden units was applied and the results were theoretically evaluated. In this initial study, they only reported some binary mixtures of dyes and did not investigated any recipe consisting of all primaries. Later, Westland reported that the application of neural networks to color formulation invoke a massive processing power due to the size of network which is required for training [6]. He concluded that this technique is still in its infancy and first steps. Amirshahi et al. [7] recently published a new adaptive method for application of neural networks in recipe prediction in conventional dyeing method. They reported average color difference value of 1.27 for 50 arbitrary targets.

This paper reports the study that is carried out with the aim of the practical application of neural networks to color prediction of blends of pre-colored fibers. As a first attempt, the blends were limited to a series of grays that were prepared from different ratio of black and virgin fibers. In order to evaluate the achievements, results from networks were also compared with the usual Kubelka-Munk algorithm. Besides, in order to speed on the processing time, a modified back-propagation method was applied and compared with normal adaptive back-propagation strategy.

2. NEURAL NETWORKS AND MODIFIED BACK-PROPAGATION ALGORITHM

Recently, many researchers have utilized a parallel processing structure that has a large number of simple processors with many interconnections between them [5-8]. The use of these processors is much simpler and faster than one central processing unit (CPU). Because of recent advances in VLSI technology, the neural network has also emerged as a new technology, and has found wide application in many areas.

In this work, the multi-layer perceptron was used to process data by using the modified back-propagation algorithm. This algorithm attempts to minimize an error function Φ by modification of network connection weights and bias. The parameters of Φ are the weights of the network and its value is an error measure.

In each iteration an input vector is presented to the network and propagated forward to determine the output signal. The output vector is then compared with the target vector resulting an error signal, which is back propagated through the network in order to adjust the weights and bias. This learning process is repeated until the network responds for each input vector with an output vector that is sufficiently close to the desired one. The general formula for the output of each unit in the network (except for the input units) is given by:

$$y_{i,l} = \varphi\left(\sum_{j=1} \omega_{ij,l} \cdot y_{j,l-1} + b_{i,l} \right) \tag{1}$$

where j runs over all nodes of $(l-1)^{th}$ layer and $\omega_{ij,l}$ is the strength of the coupling between unit i in l^{th} layer and unit j in the previous layer, $y_{j,l-1}$ is the activation of j^{th} unit in $(l-1)^{th}$ layer, and $b_{i,l}$ is the bias for unit i in the l^{th} layer. $\varphi(.)$ is the nonlinear activation function which can be log-sigmoid (logistic sigmoid), hardlimiting, etc., but usually the log-sigmoid function is used, $\varphi(s) = 1/(1+e^{-s})$.

At each iteration, the values of the weights are modified in the direction in which the error function should decrease most rapidly. The direction and magnitude of the modification is given by the gradient of the error function with respect to the weight multiplied by a constant of proportionality commonly referred to as the learning rate or step size. The basic formula is, [8]:

$$\omega_{ij}^{n+1} = \omega_{ij}^{n} + \Delta\omega_{ij}^{n}$$
$$\omega_{ij}^{n+1} = \omega_{ij}^{n} - \eta \frac{\partial \Phi^{n}}{\partial \omega_{ij}^{n}} \tag{2}$$

where ω_{ij}^{n} is the interconnection weight between the i^{th} unit in any layer and j^{th} unit in the previous layer in the n^{th} iteration. Φ^n is the error function of network at the n^{th} iteration, and η is the learning rate.

The computation of partial derivatives is described in what follows in some detail. In the general back-propagation method, Φ is defined as the sum of the squared error for all output nodes:

$$\Phi = E_{\Sigma} = \|E\|^2 = \|O - T\|^2 = \sum_{i=1}^{N_o} (o_i - t_i)^2 \tag{3}$$

where N_o is the number of the output nodes. Therefore, the partial derivative of the sum of the squared error, E_Σ, with respect to W is given by:

$$\frac{\partial E_\Sigma}{\partial W} = \frac{\partial E_\Sigma}{\partial O}\cdot\frac{\partial O}{\partial X}\cdot\frac{\partial X}{\partial W} \qquad (4)$$
$$= 2E.O.(1-O).Y'$$

where W is the weights between the last hidden layer and the output layer.

Since, the original Back-Propagation method converges slowly, the new method used to speed convergence. In this method, the new function Φ is designed that is given by [9-10]:

$$\Phi_{new} = (1-T)^m.[\log_e(s) - \log_e(1-s)] + \sum_{j=1}^{p}\left\{\begin{bmatrix}\left(\prod_{i=0}^{j-1}(m-i)\right)\frac{(1-T)^{m-j}}{j!}.(-1)^j. \\ \left[\log_e(s) - \binom{j}{1}s + \binom{j}{2}\frac{s^2}{2} + \ldots \right. \\ \left.(-1)^r\binom{j}{r}\frac{s^r}{r} + \ldots + (-1)^j.\frac{s^j}{j}\right]\end{bmatrix}\right\} \qquad (5)$$
$$\forall\begin{cases} s = O & \text{if } E > 0 \\ s = 2T - O & \text{if } E < 0\end{cases}$$

to minimize where followed to:

$$\frac{\partial \Phi}{\partial W} = \frac{\partial \Phi}{\partial O}\cdot\frac{\partial O}{\partial X}\cdot\frac{\partial X}{\partial W} \qquad (6)$$
$$= \mathrm{sign}(E).|E|^m.Y'$$

The approach of this algorithm is much faster than the other ones designed and provided the better performance.

3. MATERIALS AND METHODS

Acrylic fibers from Polyacryl Iran Fiber Production Company were dyed in a black shade using Maxilon Black T (Ciba, Switzerland). Then, a Shirley analyzer was employed for the preparation of thirteen different binary blends of black and white (virgin) Acrylic fibers. For preparing of randomized blends, each sample was passed through the analyzer at least 8 times. The specifications of blends are shown in Table 1. The reflectance values of blends were measured by a reflection spectrophotometer called Texflash from Datacolor. For the achievement of reproducible packing density, 5 grams of each of the fiber blends were placed in a fiber measurement cell with a glass cover. In order to minimize sample presentation effects, the reflectance was measured at four different rotational positions. The average of the four measurements was taken to be the true reflectance.

A networks consisting of one hidden layer of ten nodes was used. The input layer was included of sixteen nodes, which referred to reflectance values of samples in the ranges of 400 to 700 nm. The output was the percentages of blends' components. The mentioned modified back propagation strategy was used for learning of the nets. The learning rate was within the range:

$$0 < \eta < \frac{1}{\lambda_{max}} \qquad (7)$$

where λ_{max} is the largest eigenvalues of input correlation matrix. The error goal was 0.0001 and training was continued over 13000 epochs by the usual back propagation method that decreased to 8000 by mentioned modified algorithm.

Samples were divided into two groups that was one group for learning and another set for testing of networks. Samples No. 1, 3, 5, 7, 9 and 11 were used for learning and the others for testing.

4. RESULTS AND DISCUSSIONS

Table 2 shows the values of the percentages of each fiber for different blends that were predicted by networks. Networks for all blends included the samples that were used for learning, determined the percentages of black and white fibers. This table also shows the (SSE) for the components of blends.

TABLE 1. Specifications of Binary Blends of Black and White Fibers.

Sample #	%Black	%Virgin
1	0	100
2	5	95
3	10	90
4	20	80
5	30	70
6	40	60
7	50	50
8	60	40
9	70	30
10	80	20
11	90	10
12	95	5
13	100	0

In order to compare the results of networks with usual prediction method, the modified Kubelka-Munk algorithm was also applied for color recipe of desired blends and Table 2 also demonstrates the predicted amounts of fibers for different blends by this method. Again the SSE value was calculated.

As Table 2 shows, results of prediction using neural networks technique leads to smaller value in SSE in comparison with Kubelka-Munk methods. In the other words, the applying of networks for color recipe of blends for a series of black and white fibers leads to more accurate results.

The convergence rate of networks for usual and modified back-propagation algorithm is also demonstrated in Figure 1. Obviously, as Figure 1 shows, the decrease of the SSE against iterations is very rapid for the modified technique in comparison with normal adaptive back-propagation method.

TABLE 2. Prediction of Blends by Neural Networks and Usual Kubelka-Munk Methods.

Sample No.	Predicted by Neural Networks		Predicted by Kubelka-Munk	
	%Black	%Virgin	%Black	%Virgin
1	1	100.2	-2.42	102.42
2	6	93.5	5.01	94.98
3	9.4	89.4	10.18	89.8
4	23.8	76.5	27.15	72.84
5	30	70.5	32.68	67.32
6	39.4	61	41.07	58.92
7	51	49.5	50.90	49.07
8	65.3	34.9	63.74	36.22
9	69	31	67.42	32.56
10	83	16.7	82.08	17.85
11	90.3	9.3	90.50	9.49
12	93.6	5.8	93.90	6
13	97	2.3	98.09	1.51
SSE = $\sum(\Delta C)^2$	6.631	6.072	16.25	15.61

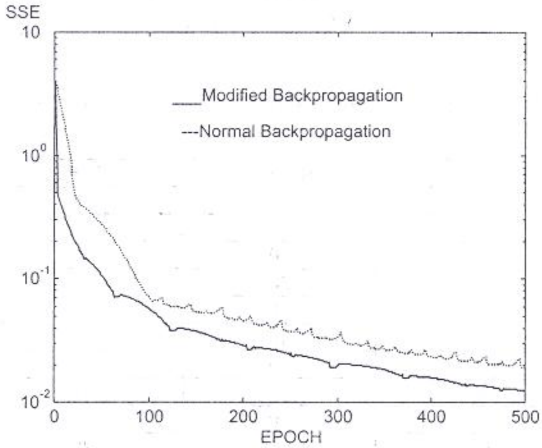

Figure 1. Convergence behavior for the general adaptive back-propagation algorithm and the modified technique.

4. CONCLUSION

The research reported in this paper suggests that the neural networks can be employed in a recipe formulation for a series of grays consisting of different ratio of black and virgin fibers. Results from networks were also compared with usual Kubelka-Munk technique and led to smaller SSE for neural networks.

Although, the color formulation of blends can be considered as an off-line process and the speed is not very critical, but by application of the modified back propagation algorithm, the processing time decrease to a reasonable period. This can help us to apply the technique for more complex blends in future.

REFERENCES

1. Kuehni, R. G., "Computer Colorant Formulation", Lexington Book, Massachusetts, 1975.
2. McDonald R., "Color Physics for Industry", Dyers' Company Publication Trust, Bradford, 1987.
3. Amirshahi S. H. and Pailthorpe M. T., "Applying the Kubelka-Munk Equation to Explain the Color of Blends Prepared From Pre-Colored Fibers", ***Text. Res. J.***, 64, (1994), 357-364.
4. Amirshahi S. H. and Pailthorpe M. T., "An Algorithm for Optimization Color Prediction in Blends", ***Text. Res. J.***, 65, (1995), 632-637.
5. Bishope J. M. Bushnel M. J. and Westland S., "Application of Neural Networks to Computer Recipe Prediction", ***Color Res. Appl. J.***, 16, (1991), 3-9.
6. Westland S., "Advances in Artificial Intelligent for the Color Industry", ***J. Soc. Dyers Color.***, 110, (1994), 370-375.
7. Amirshahi, S. H., Roushan-Zamir, J. M. and Torkamani-Azar, F., "An Attempt to Application of Neural Networks in Recipe Prediction", ***Int. J. Eng. Science***, 11, (2000), 51-59.
8. Rumelhart, G. E., Hilton, G. E. and Williams, R. G., "Learning Internal Representation by Error Propagation, in: Parallel Distributed Processing", Vol. 1, Chp. 8, Cambridge, MA, MIT. Press, (1986).
9. Torkamani-Azar, F., "Comparative Studies of Diffusion Equation Image Recovery Methods with an Improved Neural Network Embedded Technique", PhD Thesis, The University of New South Wales, (Jan. 1995).
10. Torkamani-Azar, F., "A Modified Back Propagation Algorithm", ***Second Annual Computer Society of Iran Conference***, Tehran, (Dec 1996), 217-226.