Scanner color management model based on improved back-propagation neural network

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Scanner color management is one of the key techniques for color reproduction in information optics. A new scanner color management model is presented based on analyzing rendering principle of scanning objects. In this model, a standard color target is taken as experimental sample. Color blocks in color shade area are used to substitute complete color space to solve the difficulties in selecting experimental color blocks. Immune genetic algorithm is used to correct back-propagation neural network (BPNN) to speed up the convergence of the model. Experimental results show that the model can improve the accuracy of scanner color management.

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In computer and multimedia technology, scanner is one of the main input equipments to input image information and a conversion tool of digital image reconstruction. Generally, color scanner is to produce three images corresponding to three color primaries of red (R), green (G) and blue (B) initially and then synthesize them to complete the color image scanning. The color space that represents the color characteristics of scanner is the RGB space that follows the rendering principle of additive process, while the one that represents the color characteristics of scanning object is the YMC (yellow, magenta and cyan) space that follows the rendering principle of subtractive process. Both RGB space and YMC space depend on their respective equipment materials, and it is difficult to perform the direct transform between them. Consequently, the quality control of image color becomes one of the most difficult pivotal technologies as well as one of the research hotspots. The major task of color management is to transform images among different color spaces with the minimized image color distortion during the whole duplication process. The basic approach includes three steps: firstly, a referentials color space independent of equipments is selected; secondly, the equipment is characterized; finally, a relationship between the color space of each equipment and the referential color space is established to provide a definite approach for data files when they converse among different equipments. The main focus here is to study the realization of precise conversion between RGB space that is dependent on equipments and the XYZ space that is independent through the means of scanner color management[1].

The current ways of color management include parameter method, interpolation method, and machine learning method. Optical parameter method is to construct a mathematic conversion model of RGB and XYZ with the parameters provided by the equipments or materials involved in the conversion[2]. A case in point is to construct a color reproduction curve through the analysis of the photographic features of photographic materials. Because there are various nonlinear elements in the optical indicatrices such as lighting spectrum curve, RGB color filter, characteristic curve of photographic transmission of photographic component involved in the scanner equipment, parameter method holds great difficulty when applied to the scanner. Interpolation method only undergoes the processes of analysis and fitting control to the input and output color values of a certain number of standard color blocks. Then, with the help of space relationship, they are interpolated for conversion formula of other blocks. Neugebauer equation method, one-dimensional nonlinear function method, linear or matrix conversion method, multi-dimensional table conversion method and polynomial-fitting algorithm all fall into this category[3−5]. However, the conversion relation between the color blocks is not absolutely linear, its precision has to depend on the selection of trial color blocks, and the improper color block selection results in great error easily and also depends on the quantity of color blocks. So, the conversion precision of interpolation method is not high enough. Machine learning method is mainly based on back-propagation neural network (BPNN) algorithm[6−8], which is fairly good in accuracy but leaves behind the question of slow convergence speed of BPNN so that it is hard to be put into effect in practice.

In this paper, immune genetic algorithm is taken to correct and modify BPNN model to improve the convergence speed of BPNN. At the same time, the simplicity of the model structure and the transformation accuracy are ensured. In this way, a new color management model of scanning image is advanced.

In addition, the selection of color block samples plays a very important or even decisive role in the subsequent color error correction. As for the selection of color samples to be scanned, the prevalent practice can be divided into two kinds. The first one is to take color target for experimental color blocks, in which the number of color blocks to be calculated is too large and algorithm efficiency is too low. The second one is to compile a program in which different kinds of color blocks are generated according to the progression of brightness and difference, and the blocks are mixed to form different colors. In this course, blocks are scanned after other ones have already been generated by the image system itself,

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which is totally in disagreement with the actual image processing procedures. Thus, errors are produced artificially and the ultimate model may produce relatively great errors in real applications. Based on the rendering principle of scanning image, the standard color target is taken as experimental sample and color blocks in color shade district are used to substitute complete color space here to indicate standard color space. Thus the scanner does not have avoid to correct color error produced by itself.

A colortron is used as color measuring equipment. An Epson 3170 scanner with 3200×6400 dpi resolution is used as tested scanner.

The standard test calibration target for scanner used in this experiment LT8/2 calibration target, was made by AgFa Corp. in 2006 with the serial number of 6x7c60103xx. Its color rendering material was qualified for ISO12641 standard reflective color calibration target. Among its color scale area, three columns (columns $13-15$) of color blocks three subtractive primary colors of yellow (Y), magenta (M) and cyan (C) extending from light to dark, three columns (columns $17-19$) for red (R), green (G) and blue (B) extending from light to dark, and still one column (column 16) indicates neutral color with increasing gray value. Columns $17-19$ are mixtures of two of Y, M, and C subtractive primary colors, while column 16 is the mixture of Y, M, and C colors.

The measured results of both calibration target and color values on the photograph images are recorded to reduce various errors resulting from impersonal measuring conditions.

Firstly, using the scanner with default setting, the picture of the whole calibration target is taken to measure its RGB and XYZ values. RGB value adoption range is $0-255$, while the value adoption range of all the input values in BPNN is $0-1$. As a result, all element values in RGB database are normalized, i.e. database values are R/255, G/255, and B/255.

Secondly, the RGB values of color blocks in the color scale area of the calibration target are measured using the colortron equipment with default setting. After normalization, a conversion RGB value database is built up for intermediate conversion to derive the color management model. Then, the RGB values of all the color blocks on the calibration target are measured, and after normalization, the verification database is established for model accuracy verification.

Finally, the XYZ values of color blocks in the color scale area of the calibration target are measured to build up a conversion XYZ value database for intermediate conversion. Then, the XYZ values of all the color blocks on the calibration target are measured to build up the verification XYZ value database for model accuracy verification.

It is indicated that there were similarities among the quality of weight value initialization of BPNN, the quality of antibody instruction system initialization in the immune system and the quality of immune response. A simultaneous analysis and design called SAND algorithm was advanced to solve the problem regarding the weight value initialization in BPNN[9]. In SAND algorithm, each antibody corresponds to a weight value vector of neuron given in one of several layers of neural networks, its length is l, and the affinity $\mathrm{aff}(x_i, x_j)$ between antibody x_i and antibody x_j is shown by their derivative of Euclidean distance function $D(x_i, x_j)$ as

$$\mathrm{aff}(x_i, x_j) = \frac{1}{D(x_i, x_j) + \varepsilon}, \tag{1}$$

where ε is a positive value which is always assigned to 0.001. The Euclidean distance function $D(x_i, x_j)$ is defined as[9]

$$D(x_i, x_j) = \sqrt{\sum_{k=1}^{l} (x_{ik} - x_{jk})^2}. \tag{2}$$

SAND algorithm aims to reduce the similarities between the antibodies and produce the antibody repertoire to cover the entire form space, so the energy function

$$E = \sum_{i=1}^{N} \sum_{j=i+1}^{N} D(x_i, x_j) \tag{3}$$

is maximized.

In the method of Euclidean form space, the energy function is not represented as percentage. Considering the diversity of the vector, SAND algorithm has to define a stop condition. Given vector x_i, $i = 1, 2, \cdots, N$, its standardization is unit vector I_i, $i = 1, 2, \cdots, N$, $\bar{I}$ is used to calculate the average vector. The diversity of unit vector and the stop condition of SAND algorithm are

$$\left\|\bar{I}\right\| = (I^{\mathrm{T}} I)^{1/2}, \tag{4}$$

$$U = 100 \times (1 - \left\|\bar{I}\right\|), \tag{5}$$

where $\left\|\bar{I}\right\|$ means the average vector distance from the origin of coordinate, U is the stop condition of SAND algorithm.

According to the actual application, providing that both the input and output numbers of nodes and the input and output values in BPNN have been confirmed, activation function adopts S-type function. The following steps show the BPNN design based on immune genetic algorithm.

1) Every layer of BPNN adopts the weight value initialization separately by SAND algorithm.

2) Antibody coding. The initial weight value derived by SAND algorithm constructs the structures of BPNN. Each antibody corresponds to a structure of BPNN. The number of hidden nodes and network weight value adopt mixture real number to code. The antibody clusters are shown in Fig. 1.

3) Fitness function design. Fitness function $f(x_i)$ is defined as the mean value function of squared error of neural network,

$$f(x_i) = \frac{1}{E(x_i) + \xi}, \tag{6}$$

where

number of hidden nodes N	W_1	W_2	$\cdots$	W_N

Fig. 1. Antibody coding. W_i represents the weight value corresponding to the ith hidden node.

$$E(x_i) = \frac{1}{2p} \sum_{N=1}^{p} \sum_{j=1}^{o} (T_j^n - Y_j^n)^2, \quad (7)$$

where p is the number of total training samples, o is the number of nodes of output layer, T_j^n and Y_j^n are the expected output and actual output of the nth training sample in the j output node separately, and ξ is a constant larger than zero.

4) Genetic operation. The model adopts the Gaussian compiling method to perform genetic operation so that each antibody decoding is the corresponding network structure, and the network weight value is changed as

$$x_i^m = x_i + \partial \exp(-f(x_i)) \times \mu(0,1), \quad (8)$$

where x_i and x_i^m are the antibodies before and after the variation, $\mu(0,1)$ shows that the average value is zero and squared error l is a random variable of normal distribution, and $\partial \in (-1,1)$ is the individual variation rate. It is seen in Eq. (8) that the variation degree varies inversely as the fitness does, i.e. the lower the fitness is (the less the fitness value of objective function is), the higher the individual variation rate is, or *vice versa*. After the variation, all the hidden nodes and weight value components constitute a new antibody again.

5) Group renewal based on density. In order to guarantee the antibody diversity and improve the entire searching ability of the algorithm, the model adopts the Euclidean distance and the fitness based on the antibodies to calculate the similarity and density of the antibody. Providing that there are x_i and x_j antibodies, and $\eta > 0$ and $t > 0$ are given constants, if

$$\begin{cases} D(x_i, x_j) \le \eta \\ |f(x_i) - f(x_j)| \le t \end{cases} \quad (9)$$

is satisfied, then x_i and x_j antibodies are similar, the number of antibodies similar to the antibody x_i is the density of x_i marked by C_i. The probability of selecting antibody x_i is

$$p(x_i) = \alpha C_i \left[1 - \frac{f(x_i)}{M(x)}\right] + \beta \frac{f(x_i)}{M(x)}, \quad (10)$$

where α and β are adjustable parameters between $(0,1)$, and $M(x)$ is the maximum fitness value of all the antibodies. It is seen in Eq. (10) that while the antibody density is high, the probability of selecting the antibody with high fitness is low, and conversely high. Therefore, excellent individual is not only retained, but the probability of selecting similar antibodies is reduced, and the individual diversity is guaranteed.

The proposed modification model is realized with C language. According to the scanner's rendering principle in the detailed realization, the BPNN structure adopts the three-layer structure of three inputs and outputs, and the hidden node adopts 84 color blocks in the color scale area to represent the color management model in the cycling training of the whole color space. RGB value and XYZ measurement value are the input and output values of the model separately, the values of stop condition U of SAND algorithm, ∂, α, and β are adopted as 99, 0.1, 0.5, respectively[9].

Table 1. Verification Data of Gray Scale with the Modification Model for Twelve Color Blocks

No.	X_b	Y_b	Z_b	X_q	Y_q	Z_q	ΔE
0	73.42	75.90	62.93	71.49	72.64	61.88	3.93
1	60.86	63.58	52.35	59.99	62.17	51.19	1.83
2	46.76	48.58	39.40	49.99	50.16	42.61	4.82
3	34.70	36.05	29.19	35.65	33.83	33.19	5.01
4	25.74	26.86	21.49	28.19	28.18	23.44	3.40
5	19.30	20.28	16.12	22.43	22.11	18.63	4.01
6	13.24	13.88	10.94	15.35	14.97	13.01	3.07
7	7.85	8.24	6.44	8.95	9.98	8.19	2.70
8	4.46	4.69	5.66	5.94	6.30	4.61	2.43
9	2.72	2.88	2.20	3.41	2.67	2.02	1.12
10	1.12	1.17	0.97	0.78	0.36	0.22	1.56
11	0.77	0.57	0.72	0	0	0	1.40

X_b, Y_b, Z_b, X_q, Y_q, and Z_q are the standard values and computed values of the color blocks; $\Delta E = \sqrt{(X_b - X_q)^2 + (Y_b - Y_q)^2 + (Z_b - Z_q)^2}$.

Table 2. Conversion Accuracy for the Algorithm in this Paper, Polynomial Fitting Algorithm, and BPNN Algorithm

Algorithm	This Paper	Polynomial Fitting	BPNN
Average Error	3.59	9.78	7.48
Maximum Error	6.19	275.85	12.83
Number of Color Blocks with $\Delta E > 5$ NBS	5	35	24

Tables 1 and 2 show the color block verification results of 12 blocks in the neutral gray scale area of three-color mixture in the IT8/2 calibration target. Since this area is mixture of three primitive colors, the errors always are the greatest. X_b, Y_b, Z_b, X_q, Y_q, Z_q stand respectively for the standard values of X, Y, and Z, the values of X, Y, and Z computed by the management model, and ΔE is the difference between them ($\Delta E = \sqrt{(X_b - X_q)^2 + (Y_b - Y_q)^2 + (Z_b - Z_q)^2}$). Table 2 provides the conversion accuracy statistics for all the 288 color blocks in the calibration target through the algorithm of this paper, the polynomial fitting algorithm[9] which is widely used and has its relatively high conversion accuracy, and the BPNN algorithm[5]. The difference unit is the National Bureau of Standards (USA) unit, NBS. According to the research results of colorimetry, the color can be accepted as visual equivalency when $\Delta E < 5$ NBS. From Table 2, it is shown that the model of this paper offers satisfactory color conversion accuracy and can be used to manage the scanner colors with regard to different situations.

In conclusion, through fully applying the advantages of genetic neural network such as simple structure, quick convergence, and good accuracy, a new model for scanner color management is put forward in combination with IT8/2 calibration target. The experimental results show that the new model cannot only solve the problem of convergence speed of BPNN, but also improve the conversion accuracy.

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