Approximating the CIECAM02 color appearance model by means of neural networks

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An artificial neural network used to realize the approximating problem of the color appearance model (CAM) CIECAM02 in color management is demonstrated. GretagMacbeth ColorChecker Charts, which now are widely used in calibration of digital camera, are chosen as samples to implement the forward and reverse color appearance models. When the predictive results are evaluated, for forward model, the output color appearance space is converted to the uniform color space based on CAM and is evaluated, while for reverse model, because the prediction precision is insufficient, we try to convert the color appearance space, which is the cylinder space, to the cube space similar to the red, green, and blue (RGB) space, and the results show that the precision is obviously improved.

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With the progress of the color desktop publishing system (DTP), color management techniques have increasingly become important. Color management is the progress of reproducing accurate, consistent color among a variety of input and output devices. A color management system (CMS) maps color between devices (such as scanners, monitors, and printers), transforms colors from one color space to another (for example, RGB (red, green, and blue) to CMYK (cyan (blue), magenta (red), yellow, and black)), and provides accurate on-screen or print previews.

Recently, interest in color appearance model (CAM) has been greatly stimulated by the need of color reproduction. Some articles about the CAM have been reported[1−7] in the last few years. Especially, in cross-media color reproduction, CAM is important to be able to predict the appearance of colors under a wide range of viewing conditions such as various illuminants, luminance levels, backgrounds, and media[1,3].

CAM plays an important role in color conversion. The color appearance attributes are used as an intermediate color representation, they can be transformed to any place through internet and the color images can be faithfully reproduced. However, CAM is consisted of a series of complex mathematic formulae and nonlinear transforms, so in this paper a multi-layered neural network is utilized to implement the operation of forward and reverse CAMs CIECAM02[8].

In the following section, we introduce the selection of training sample for neural networks and the architecture of the network.

The Gretagmacbeth ColorChecker chart was used to perform neural network as training sample, the ColorChecker is a unique test pattern scientifically designed to help determine the true color balance of any color rendition system. It can be applied in many fields such as photography (checking films, lights etc.), electronic publishing (checking scanners, monitors, and proofing devices), and television (checking cameras and monitors). Furthermore, the ColorChecker chart provides an easy way to recognize and evaluate many factors that can affect color reproduction, and to simply compare the chart's color image (photograph, television picture, computer monitor or printed sample) with the actual ColorChecker. This comparison may be made visually or through optical density measurements.

The ColorChecker is a checkerboard array of 24 scientifically prepared colored squares in a wide range of colors. Many of these squares represent natural objects of special interest, such as human skin, foliage, and blue sky. These squares are not only the same color as their counterparts, but also reflect light in the same way in all parts of the visible spectra. Because of this unique feature, the squares will match the colors of natural objects under any illumination and with any color reproduction process.

Because the chart is based on the Munsell system, our testing sample also is selected from the Munsell system[9,10]. For training data, in terms of the spectral reflectance of the Munsell charts, we choose these spectral reflectance curves of 24 ColorChecker charts, then conversed the spectral reflectance data to x, y, and Y values under the standard illuminant D65 for the CIE1931 standard colorimetric observer (2°). During the course of training, two ways were chosen, a way is colorimetric coordinate (x, y, Y); another way is tristimulus value (X, Y, Z). The testing samples are 40 groups and are uniformly distributed in the whole color gamut. Normally the Munsell system totally has ten hue names, and every hue includes 4 color samples. Their value and chroma also are selected in respective range.

We adopted a multi-player feedforward neural network model to perform the prediction of forward and reverse CAMs. The error backed-propagation (BP) algorithm was applied in the training of the neural network. Usually a multiplayer perceptrons is made of three layers, that is, input layer, hidden layer, and output layer. The neurons between the two layers are connected by weights.

In multiplayers with any of a wide variety of continuous nonlinear hidden layer activation functions, one hidden layer with an arbitrarily large number of units suffices for the "universal approximation" property. But at present there is as yet no theory that can tell us how many hidden units are needed to approximate any given function. Since there are no theoretical results to help in the choice of the architecture, that is usually determined either on the basis of previous experience with a given problem domain, or experimentally by a time-consuming activity of training and the testing precision. By experience and practice, we generally adopt 2—3 hidden layers; each layer approximately has 10 neurons[7,11].

To obtain the appropriate structure of the network, we evaluated the ability of the neural network to generalize with the test by changing the number of the hidden units and started our experiment with a "3-10-10-10-3" network architecture (one input layer with three neurons, three hidden layers with ten neurons each, and one output layer with three neurons). Because of the global error of network was minimum when the hidden unit is 20 for forward and reverse CAM, we decided that the appropriate number of the hidden units is 20, thus the structure of network is 3-20-20-20-3. Figure 1 shows the neural network structure and the input-output color space used for training.

Before the training processing, the learning rate α and the momentum factor η were respectively selected. The learning strategy was started from an initial value 0.7 (learning rate) and 0.9 (momentum factor). We reduced the learning rate and the momentum factor by a step of 0.2 every 1000 epochs until the learning rate and the momentum factor reached 0.1 and 0.3, respectively. From the whole process, we found that the conversion from the tristimulus value (X, Y, Z) to color appearance attributes (J, C, H) more precise for forward CAM, than from (J, C, H) to (X, Y, Z) for reverse model.

For forward model, the output values are lightness (J), chroma (C) and hue (H). The color appearance space JCH is not uniform color space, so we cannot simply use the Euclidean distance between the original data and

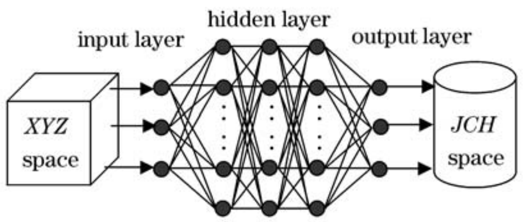

Fig. 1. The architecture of the BP neural network (forward).

the reproduced data. In order to accurately evaluate the accuracy, we adopt the uniform color space based on CIECAM97s[12], that is $J'a'_1b'_1$ color space, it is built on the Jab space (color appearance attributes a and b denoting redness-greenness and yellowness-blueness, respectively) which was brought forward by the professor Luo in Derby University. In the uniform $J'a'_1b'_1$ color space we can use Euclidean color difference formula to evaluate[12]

$$\Delta E_{\mathrm{CAM}} = [(\Delta J')^2 + (\Delta a'_1)^2 + (\Delta b'_1)^2]^{1/2}.$$

It is the color difference expression in orthogonal coordinates. Then the expression in cylindrical coordinates is given

$$\Delta E_{\mathrm{CAM}} = [(\Delta J/S_J)^2 + (\Delta C_1/S_{C1})^2 + (\Delta H_1/S_{H1})^2]^{1/2},$$

where the linear relation between the lightness difference and lightness is expressed as $S_J = 0.0144J + 0.5419$, the linear relation between the chroma difference and chroma is expressed as $S_{C1} = 0.0375C_1 + 1.1389$, the linear relation between the hue difference and chroma is expressed as $S_{H1} = 0.0146C_1 + 1.1119$. ΔJ, ΔC_1, and ΔH_1 denote respectively the difference of lightness, chroma, and hue in Ja_1b_1 color space.

For reverse model, the output values are tristimulus values XYZ, thus we can use the color difference formula in CIEL*a*b* color space to estimate the accuracy. Table 1 shows the detailed training errors and testing errors for forward and reverse prediction. From Table 1 we can see that these mean color differences of training data are very small for both forward and reverse models. However, the mean testing error of reverse prediction is slightly bigger than that of forward prediction.

Based on the above circumstance, we thought that it is the cause of the incompletely mapping from the cylindrical coordinates to the cube coordinates. According to the conversion of color model in color image process, we tried to convert the cylinder to the cube similar to RGB space by dividing the hue into three parts (0°−120°), (120°−240°) and (240°−360°), the input and output data are in similar cube color space, and the sample was trained as the tristimulus way (X, Y, Z). Then the mean color difference of the training is 1.004, which is basically same as former training results, but for the testing, the mean color difference is 4.150, and the prediction accuracy has obvious improvement compared with the former testing results.

Table 1. Prediction Accuracy for Forward and Reverse Operation

Input Way	Forward Prediction		Reverse Prediction	
	Training	Testing	Training	Testing
	ΔE_{CAM} ($\Delta E_{\max}, \Delta E_{\min}$)	ΔE_{CAM} ($\Delta E_{\max}, \Delta E_{\min}$)	ΔE_{LAB} ($\Delta E_{\max}, \Delta E_{\min}$)	ΔE_{LAB} ($\Delta E_{\max}, \Delta E_{\min}$)
(X, Y, Z)	0.292	4.049	0.983	8.825
	(0.810, 0.045)	(12.95, 0.131)	(3.337, 0.045)	(16.14, 0.770)
(x, y, Y)	0.287	5.481	1.406	9.221
	(0.043, 0.812)	(15.36, 0.611)	(4.994, 0.032)	(18.68, 0.496)

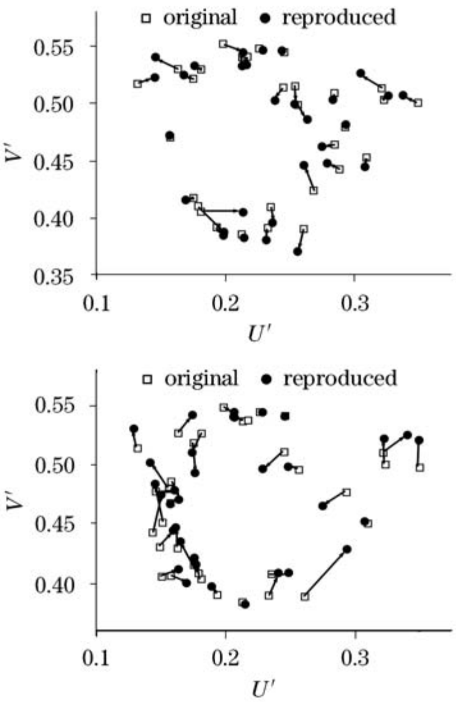

Fig. 2. The colorimetric values of the original and reproduced colors for inverse prediction. The input-output space is (a) cube to cube, (b) cylinder to cube.

Figure 2 shows the accuracy comparison for testing results in these two color spaces for reverse CAM. Color difference between the original and reproduced color chips were plotted on the u' v' chromaticity diagram. Squares and dots indicate the original and reproduced colors, respectively, and the distance between these symbols represents the color difference visually. The result again shows that the conversion way from the cylindrical coordinates to the cube coordinates brings the ameliorative effect. So the neural network can learn the reverse CAM with sufficient accuracy basically.

In conclusion, a five-layered neural network can be a powerful tool for not only the forward but reverse CAM. Because of the parallel running way (high speed) of the neural network, the result can be conveniently applied in the real-time image process and color reproduction faithfully. However, because the prediction for CAM is the conversion between the cube space and the cylinder space, it is inevitable that some data are completely mapped from the one space to another especially for reverse model. The neural network approach, as demonstrated in this paper, is a very effective way for performing CAM. Now there is an increasing awareness of the complicated problems related to the color image quality, such as the preferable color reproduction[13,14] or the color gamut mapping[15,16]. The neural networks have been also applied to solve these problems.

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