A Method of Transformation from CIE L*a*b* to CMY Value by a Three-Layered Neural Network

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Introduction

The color reproduction systems, such as a color copier and/or a color printer, are widely used to visualize any graphical information as recent progress in electrophotographic technique. However, some kinds of problems have occurred because the color reproduction theories for these systems are based on the densitometric color value that depend on the difference of physical characteristics of color reproduction systems and/or chemical characteristics of the color materials; the difference of the reproduced color between each color reproduction system. Therefore, it is necessary to adopt CIE L*a*b* value or other colorimetric values as a device-independent representation to reproduce color accurately. Furthermore, we require a method of transformation between device-dependent color representation and independent color representations. Recently, Irie et al.[1] and Funahashi[2] have mathematically proven that the three-layered artificial neural network can approximately realize the continuous mapping with any accuracy unless the number of unit in hidden layer of the network is limited.

In this study, we propose the transformation method which realizes the nonlinear mapping from CIE L*a*b* value to CMY dot area size by using a multilayered artificial neural network with a back propagation (BP) learning algorithm[3]. The transformation accuracy of the proposed method was evaluated in terms of the color difference between original color chips and the reproduced color chips which correspond to the output of the trained artificial neural network. We show that the ability of the nonlinear mapping of the neural network can provide a practical and an efficient transformation method for color representation.

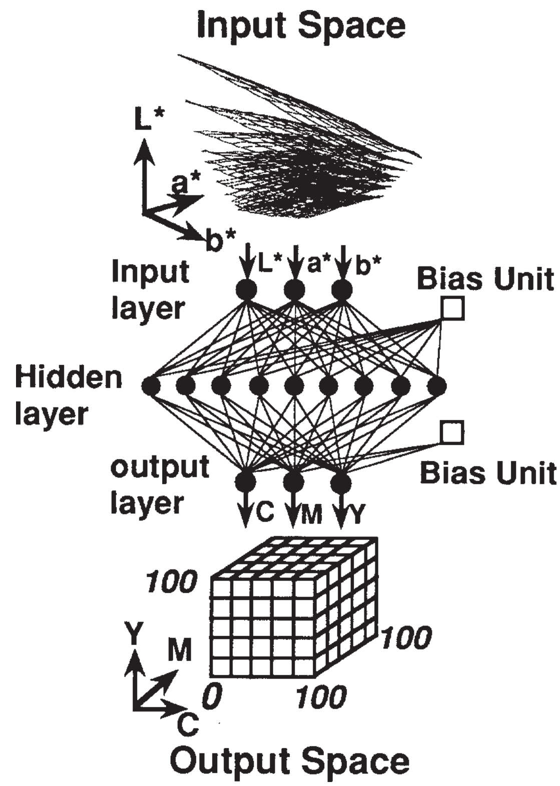

*Figure 1. Structure of three—layered artificial neural network. The layers consist of 3, 9 and 3 units, respectively. The input of the neural network is the CIE L*a*b* coordinates for 9261 color chips and output of the neural network is the CMY dot area size coordinates for 9261 color chips. The network was learned to transform CIE L*a*b* value to CMY dot area size with back propagation learning algorithm.[3]*

Method

The structure of the three-layered neural network

Figure 1 shows the structure of the constructed three-layered neural network, which consists of 3 units for the input layer with linear function, 9 units for the hidden layer with sigmoid function and 3 units for the output layer with sigmoid function respectively, and also show the input and teaching data for the neural network learning. We will discuss the statistical analysis to determine the network structure, especially the optimal number of hidden unit, in the next section.

We printed 9261 color chips with a 4-color (Cyan, Magenta, Yellow and Black: CMYK) printing machine by changing each CMY dot area size from 0% to 100% at 5% interval to produce the trained data set of the neural network. Note the Black (K) was not used in this study. For the input data set, we measured spectral reflectance under the standard light source D65 for individual chips and these spectral reflectance data were converted to CIE L*a*b* values at 2 degrees. For the teaching data set, we used the CMY dot area size of indivisual chips.

Selection of the training data sets

In order to examine the efficient number of training data, we selected 8, 27 and 125 chips from 9261 chips for the training data set as shown in Figure 2. Each data set was generated by changing CMY dot area size from 0% to 100% at 100%, 50% and 25% interval respectively.

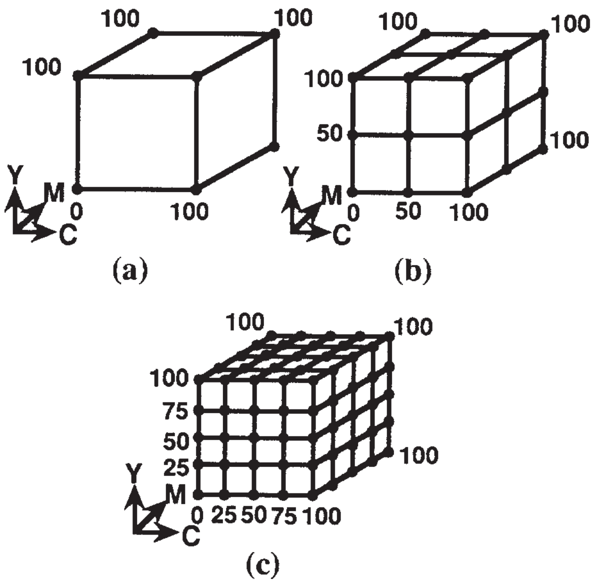

Figure 2. Selection of the training data sets. 8, 27 and 125 training chips were selected from 9261 chips to examine the efficient number of data sets for network learning. (a) sampling interval is 100%, (b) sampling interval is 50%, (c) sampling interval is 25%.

Network learning

We used the set learning of the modified back propagation algorithm for adjusting the connection weights of the network, which has been added a momentum term to original back propagation algorithm[3] for the 8 and 27 data sets. Besides, we also used a modified back propagation algorithm with additional step to train the network using 125 data sets. This step is as follows:

Step 1: Train the network, using-16 chips randomly selected from the training data set.

Step 2: After the network has learned sufficiently well, add another randomly selected set of training chips of equal size and train the network with this doubled set.

Step 3: Repeat step 2 until all the data in the training data set have been used.

The change in the mean square error (MSE) between the teaching data and the output of the network during BP learning process using 125 data sets is shown in Fig. 3; the MSE is defined as:

$$\mathrm{MSE} = \frac{1}{mn}\sqrt{\sum_{i=1}^{m}\left\|\mathrm{T}_i - \mathrm{O}_i\right\|^2} \quad (1)$$

where n is the number of patterns, m is the number of unit in the output layer, $\boldsymbol{T}_i$ is the teacher vector of the ith output unit (teaching data), $\boldsymbol{O}_i$ is the vector of the output value (output of the network) for the ith output unit and the symbol $\|.\|$ indicates the norm operation to the vector. The MSE value increases when the training set size is doubled during the learning process. The convergence condition of the network learning for each data set is used until the MSE reaches less than 2% in the output dot area size.

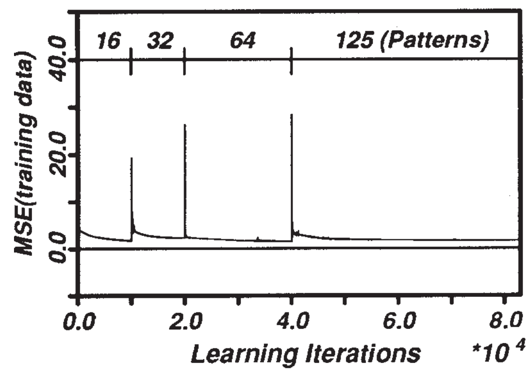

Figure 3. Changing in the MSE during the back propagation learning. The MSE value increases when the training set size is doubled.

Determination of the optimal number of unit of the hidden layer

It is necessary to determine the optimal structure of the network in order to acquire the best transformation accuracy not only for the training data set but also for the test data set. Therefore, because the transformation accuracy with respect to the test data depends on the number of hidden layer unit, we evaluated the ability of network to generalize with test chips to determine the optimal number of hidden layer unit by changing from 3 to 16 units after learning phase. We used 125 training data set for each neural network learning and used 9136 test data set which were not used at learning phase. Figure 4 shows the averaged MSE which is averaged value of the MSE with changing the initial value of the weights for the each neural network at 5 times.

By this criterion, although the averaged MSE tend to decrease while the number of unit is 3 to 9, the averaged MSE tend to increase slightly while the number of unit 9 to 16. This suggests that the optimal number of unit for hidden layer is 9.

Evaluation of the transformation accuracy

For the test data set, we randomly selected 360 test data from 9136 data. After the networks with 9 units in hidden layer were trained sufficiently using 8, 27 and 125 data set, we transformed the 360 test data from CIE L*a*b* to CMY dot area size by each neural network to evaluate the accuracy of transformation, and printed 360 color chips with respect to the output of each neural network. Furthermore, we measured the spectral reflectance under the standard light source D65 for individual chips, and calculated a mean color difference value ΔE between the original 360 data and the outputs of each neural network. The mean color difference was defined as follows:

$$\overline{\Delta \mathbf{E}} = \frac{1}{N}\sum_{i=1}^{N} \Delta \mathbf{E}_i \quad (N = 360) \tag{2}$$

where ΔE_i is the color difference for *i*th color chips. Figure 5 shows the relationship between the number of training data set and the accuracy of the transformation by using a color difference. Figure 6 shows the comparison of original color and the reproduced color with regard to the output of each network on the *u'v'* chromaticity diagram of the CIE LUV color space. In this figure, 25 plotted data were randomly sampled from 360 testing data, and the oblique line above each diagram represents the spectral locus. Figure 7 show the color difference histogram for each network.

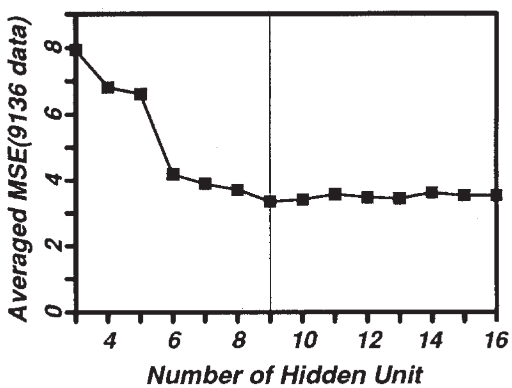

Figure 4: Relationship between number of hidden unit and the averaged MSE. Although the averaged MSE tend to decrease while the number of unit is 3 to 9, the averaged MSE tend to increase slightly while the number of unit 9 to 16. According to this criterion, the optimal number of unit for hidden layer is 9.

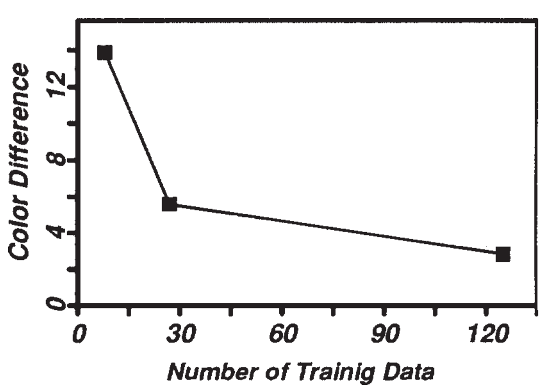

*Figure 5. Comparison of accuracy of transformation by each neural network using a color difference. The neural network acquire the nonlinear mapping from CIE L*a*b* to CMY dot area size for color information with enough accuracy by using a fairly small number of data, such as 27 to 125 examples.*

This results show that the trained neural network using 125 data sets realized the transformation accuracy corresponding to the mean color difference :ΔE = 2.91 and the maximum color difference :ΔE_{max} = 13.4. Table 1 show the actual color difference of the data which correspond to 25 plotted data for each neural network in Figure 6. As the results of these evaluation, the neural network acquire the nonlinear mapping from CIE L*a*b* to CMY dot area size for color information with enough accuracy by using a relatively small number of data set (125 data).

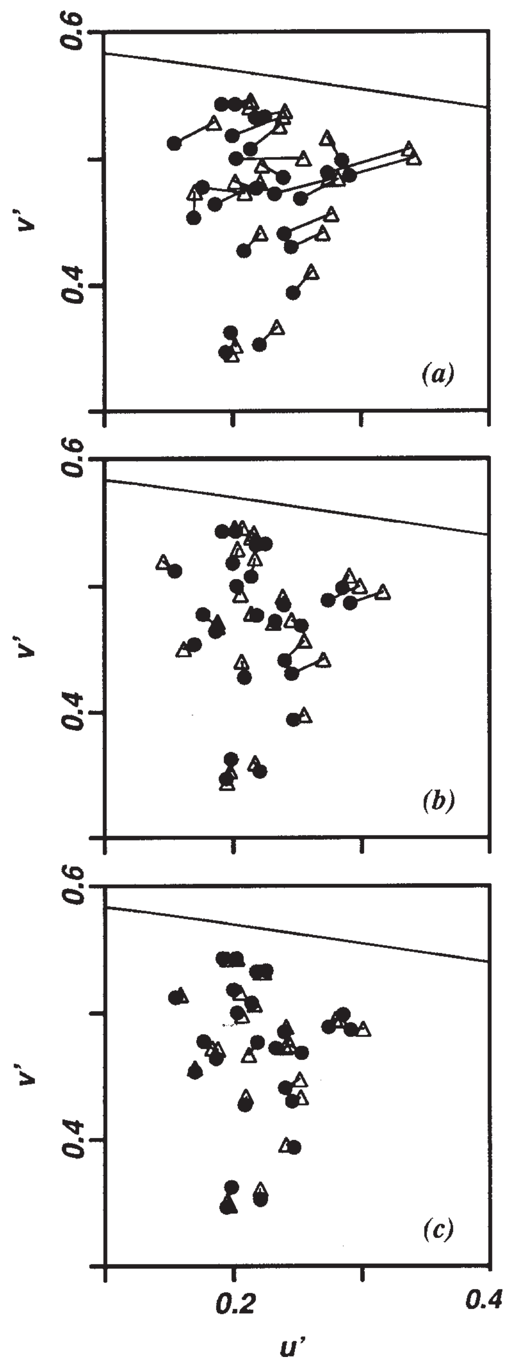

Figure 6: Comparison of accuracy of the transformation by each neural network on u'v' *chromaticity diagram. Symbol Δ indicates the reproduced color, and Symbol ● indicates original color. The oblique line above each figure indicates the spectral locus. (a) 8 patterns, (b) 27 patterns, (c) 125 patterns.*

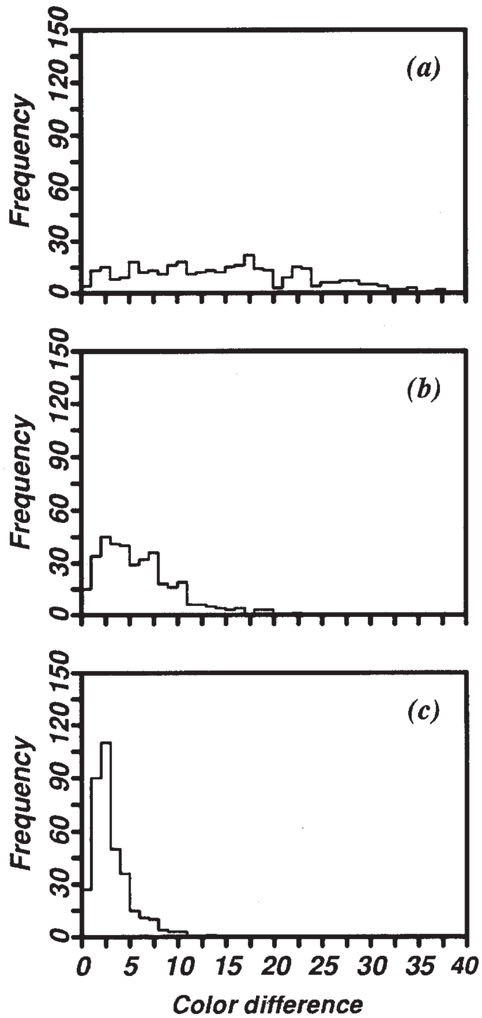

Figure 7: Histogram for color difference between original color and reproduced color by each neural network. The maximum color difference of neural network by using 125 data set was ΔE_{max} = 13.4. (a) 8 patterns, (b) 27 patterns, (c) 125 patterns.

Table 1

	Color Difference : ΔE								
8 pattern	22.390	12.572	28.396	5.203	28.211	13.847	16.749	17.257	2.243
27 pattern	10.057	7.924	12.713	5.719	9.562	8.353	16.018	6.093	1.303
125pattern	3.556	1.492	2.360	2.793	3.514	4.520	2.338	2.924	0.986
8 pattern	13.852	14.545	14.781	23.195	34.341	5.746	9.884	15.380	16.623
27 pattern	3.896	7.007	1.240	9.115	13.150	3.126	3.608	10.081	4.269
125pattern	2.970	4.143	2.509	2.793	3.780	4.727	2.876	2.592	8.253
8 pattern	22.797	12.234	21.368	6.221	22.175	17.139	16.119	—	—
27 pattern	6.009	3.389	13.892	3.037	9.924	7.753	4.155	—	—
125pattern	2.529	4.285	1.853	2.636	2.875	3.221	2.411	—	—

Discussion

The artificial neural network described above may provide a new method for the transformation of color information. Laihanen[4] has attempted to establish a transformation method by using classical Neugebauer equations[5] and the modified Neugebauer equations. It was suggested that these equations cannot be used for practical applications because of the problems such as accuracy of the transformation and/or calculation cost. On the other hand, a Look-up-table (LUT) is well known as the accurate and quick transformation method, which is not practical method for the transformation of color information because it requires the huge number of data, such as more than 1000 data set, to acquire the sufficient transformation accuracy.

The three-layered artificial neural network is the useful and convenient for the transformation of the color information from engineering point of view of that Funashi's theory ensure that the three-layered neural network realizes a nonlinear mapping with any accuracy.

Conclusion

We have constructed a three-layered artificial neural network to realize a nonlinear mapping for the color representation and have shown that the neural network acquired the nonlinear mapping from CIE L*a*b* value to CMY dot area size for 9261 data with considerably well accuracy by using a relatively small number of data (125 data), that is, the error of the transformation realized by the neural network is less than the mean color difference :$\Delta E < 3$ and maximum color difference :ΔE_{max} = 13.4. Besides, we have determined an optimal number of unit for hidden layer by a statistical analysis of the ability of the network to generalize and have found that the optimal number of hidden unit is 9.

The accuracy of the transformation achieved by the network is better than not only Neugebauer equation but also LUT from point of view of the calculation cost and the number of data used for network learning. This result suggests that the three-layered artificial neural network is a practical and efficient method for the transformation between device-dependent color representation and device-independent color representation, and the learning ability of the network provides a useful and powerful method to calibrate the changes in the physical characteristics of a color reproduction systems and/or the chemical characteristics of a color materials.

Acknowledgment

We thank to Dr. S. Nakauchi of Toyohashi University of Technology in Japan for his helpful and important discussions.

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