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Control Scheme For Printers Using More Than Three Color Inks

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ABSTRACT

A method is described for realizing an exact color reproduction on a printer using more than three color inks. The CIE-L*a*b* color system is used as the device-independent color space. The mapping from the L*a*b* color space to the printer color space is constructed using a neural network. This mapping does not use such techniques as UCR and GCR. The problem in four-color printing is considered as the problem of controlling an unknown system with four inputs and three outputs. We present a two-phase procedure for solving this control problem. The first phase determines a printer model, and the second phase determines the combined network system of a printer model and a controller so as to provide the identity mapping. This technique is applied to the color control of a six-color printer using CMYK plus light Cyan and light Magenta.

Key Words: Color Reproduction, Neural Networks, Color Control, Color Printers, Mapping, Learning

1. INTRODUCTION

Color reproduction requires color conversion between the color signals, depending on the device used, and the standard color coordinates, representing color appearance like the CIE-L*a*b* color system[1-3]. Color reproduction on a CRT monitor is based on an additive mixture of three primaries. On the other hand, the color reproduction of print is based on the subtractive mixture of the three primaries Cyan (C), Magenta (M) and Yellow (Y), or four primaries with the addition of Black (K). It is usually difficult to predict from the knowledge of the amounts of ink for these primaries what color stimulus will be generated on paper. In other words, it is difficult to control the CMYK color signals to produce the desired L*a*b* values on a printer. Moreover recent color printers use many such color inks as CMYK plus light Cyan and light Magenta.

There are several methods for producing a desired color stimulus on a printer. These are (1) an analytical method using the Neugebaouer equations, (2) matrix transformation, (3) use of a look-up table and three-dimensional interpolation[4-5], and (4) a neural network method[6-7]. In (2)-(4), a color printer is regarded as a black box. Method (4) models the mapping between the printer color signals and the output color stimulus values by means of neural networks.

The present paper describes a neural network method for solving the mapping problem from the three-dimensional color space of color stimuli to the higher dimensional color space of printer signals. The mapping from the L*a*b* color space to the printer color space is constructed using a neural network. This mapping does not use such techniques as undercolor removal (UCR) and gray component replacement (GCR). The problem in four-color printing is considered as the problem of controlling an unknown printing system with four inputs and three outputs. A controller finds the CMYK signals necessary to produce the desired L*a*b* values from a printer. Our solution for this control problem is based on a two-phase procedure. The first phase determines a neural network for modeling the printer, and the second phase determines the combined neural network system of a printer model and a controller so as to provide the identity mapping. Moreover, this technique is applied to the color control of a six-color printer using CMYK plus light Cyan and light Magenta.

In the following Section 2 reviews the basic principle of the control problem[8]. The practical algorithms are presented in Section 3 for realizing the mapping from the L*a*b* color space to the printer CMYK space. In Section 4 we consider a color control problem for a six-color printer using CMYK plus light cyan and light magenta. Experimental results are shown using a six-color ink jet printer.

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2. PRINCIPLES OF COLOR CONTROL

Let us consider the color reproduction problem in four-color printing. This problem is treated as the problem of controlling a system with unknown characteristics as shown in Figure 1. The color printer is an unknown physical system with four inputs and three outputs. A controller, which is constructed with a neural network, tries to realize the inverse mapping of the system, i.e., the controller transforms the target L*a*b* values into the CMYK values, which are then transformed into the actual L*a*b* values by the unknown printing system. Therefore, the controller must determine the printer ink signals in such a way that the color stimulus errors between the targets and the printed colors are minimized in the L*a*b* color space. In this process, a model is used for the physical printer. The printer model is constructed as a neural network with the same input-output relationship as the physical printer. The following two-phase procedure provides a solution for this control problem[8-9].

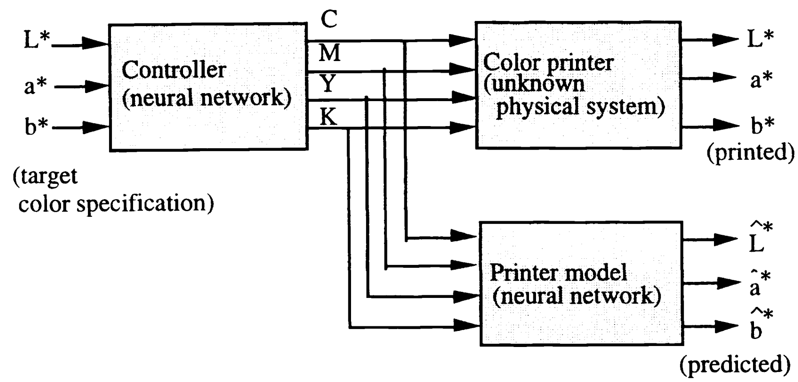

Figure 1 Color control of a printer by neural networks.

The first phase is identification of the unknown printer system. The printer system is modeled by a neural network, that is, the neural network is trained to act like a printer. The printer model is determined by a learning procedure which is based on minimizing the color difference between the target L*a*b* values in the training data and the corresponding L*a*b* values ($\hat{L}^*\hat{a}^*\hat{b}^*$) predicted by the network.

The second phase is devoted to the determination of a combined neural network system (combined NN system) including the controller and the printer model. Once the printer system has been learned in the first phase, the control system for mapping a color specification vector into an ink vector can be determined using a neural network. We adopt an indirect approach for doing this. Let us consider the combined NN system. From a global point of view, this combined system represents a mapping from the target L*a*b* values to the predicted L*a*b* values describing the printer outputs. It should be noted that this mapping is always required to produce the same color values as the input color values. Therefore, the combined NN system is trained to realize a one-to-one mapping. In this training, the network structure of the printer model and its network parameters are fixed, while the network parameters of the controller are being adjusted to minimize the error.

When the combined NN system completes the one-to-one mapping in the second phase, the network of the controller part must realize an inverse mapping of the printer model that is equivalent to the physical printer. Thus the controller can be used to determine the CMYK signals so that the desired L*a*b* color specifications are produced by the printer.

3. PRACTICAL ALGORITHMS

3.1 Determination of the printer model

Figure 2 depicts the network structure used for modeling a printer. The mapping from the input space of the four ink signals CMYK to the output L*a*b* space is implemented as a four-layered neural network. Each of the two hidden layers has 10 units. The network size was determined by empirically selecting the most effective numbers of hidden layers and units. In Figure 2, each unit receives its input signals from the prior layer, computes their weighted sum, and outputs the unit's level of activation by weighting this sum with a nonlinear function.

Let o_i be the output of the i-th unit in the prior layer, w_{ji} be the weighting coefficient for the connection from the i-th unit to the j-th (target) unit, and b_j be the bias term of the unit. The input to the j-th unit is then described as the sum of the weighted outputs from the prior layer

$$\mathrm{net}_j = \sum_i w_{ji} o_i + b_j. \quad (1)$$

The nonlinear output of the j-th unit is given by

$$o_j = f(\mathrm{net}_j), \quad (2)$$

where f is the sigmoidal activation function

$$f(\mathrm{net}_j) = 1/\{1 + \exp(-4\alpha\ \mathrm{net}_j)\}. \quad (3)$$

This function takes any real number in the interval [0, 1], and the positive constant α represents the slope of f at net=0. The operations of (1)-(2) are executed at all units except the input layer.

All input/output signals of the network are normalized. First, the CMYK values, which lie in the region of 0 to 255, are scaled to the range [0, 1]. Concerning the output signals, we assume that the ranges for three quantities L*, a*, and b* are given as [0, 100], [-100, 100], and [-100, 100], respectively. The color gamut of the physical printer is contained within the rectangular prism delimited by these ranges. All of these ranges are then normalized into the range [0, 1] to form a cube.

Modeling a printer by such a 4-10-10-3 type network (Figure 2) requires 170 weighting coefficients and 23 biases, or a total of 193 parameters, to be adjusted. This set of parameters is determined through a learning procedure based on the measurement data. We adopt error backpropagation as the learning rule.

Now let us define the p-th vector of the normalized L*a*b* values in the training data set as $\mathbf{t}_p \equiv [t_{p1},\ t_{p2},\ t_{p3}]$ and define the corresponding output vector of the network as $\mathbf{o}_p \equiv [o_{p1},\ o_{p2},\ o_{p3}]$. All the weights and biases in the network are then adjusted such as to minimize the squared error between the target $\mathbf{t}_p$ and the actual output $\mathbf{o}_p$, $E_p = \|\mathbf{t}_p - \mathbf{o}_p\|^2$. The change Δw_{ji} in the weight w_{ji} is computed by the following recursive algorithm including a momentum term:

$$\Delta w_{ji}(n+1) = \eta \delta_{pj} o_{pi} + \beta \Delta w_{ji}(n), \quad (4)$$

where n indicates the n-th learning step. The notation $\Delta w_{ji}(n)$ represents the amount of correction in the weight from the i-th unit to the j-th unit in the next layer at the n-th step. δ_{pj} is an error term in the j-th unit, which is calculated recursively from the output layer by using the equations of error backpropagation. η and β are positive constants called the "learning constant" and "momentum constant", respectively. The change Δb_j in the bias b_j is computed in the same manner as the other weights. One period of presenting the entire training data to the network is defined as an epoch, and the mean squared error E_p over the data set is evaluated as the system error. Corrections of all the parameters are repeated for as many epochs as are necessary to decrease the system error to an acceptable level.

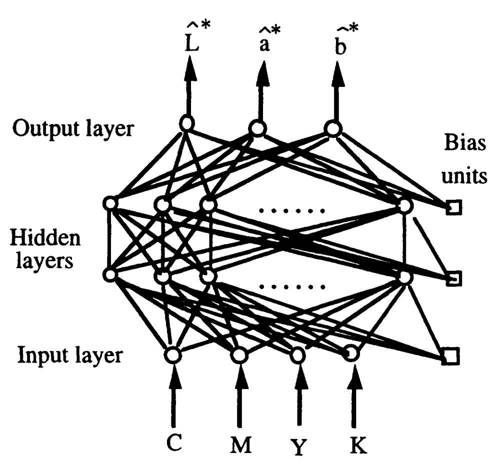

Figure 2 Network structure of the printer model.

3.2 Determination of the controller

The network structure of the controller is assumed to have the same complexity as the printer model, because it should be modeling the inverse system of the printer. As shown in Figure 3, the controller is constructed with a four layered network of the 3-10-10-4 type with 3 units in the input and 4 units in the output.

First, the printer model and the controller network are combined into a single large network as shown in Figure 3. This combined NN network is an eight-layered network, consisting of the input/output layers and six hidden layers. Note that the 3rd and 4-th hidden layers are double, since the same signals are copied simply from the lower layer to the upper one. Therefore, only five hidden layers are effective for the complete mapping. Both the input and output signals of the combined network are the normalized L*a*b* values in the range [0, 1], compressed from the color specifications in the regions of $0 \leq L^* \leq 100$, $-100 \leq a^* \leq 100$, and $-100 \leq b^* \leq 100$.

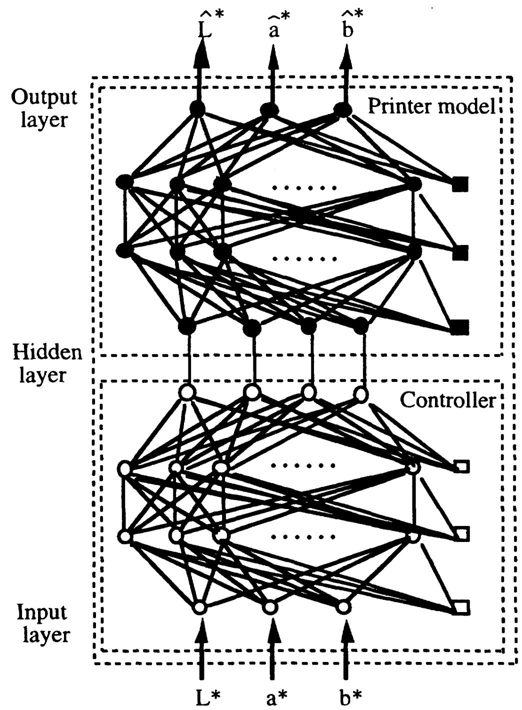

Figure 3 Network structure for determining the identity mapping and the controller.

The above neural network is trained to realize an identity mapping from the L*a*b* color space to the L*a*b* color space. The computations in each unit are coincident with Eqs. (1)-(3). The network learning is performed according to the following procedure.

(1) Because of the one-to-one mapping, the same L*a*b* values are presented to both the input and output layers. CMYK values are not used as training data. Moreover, the L*a*b* values are not necessarily selected from the measured data set, but any L*a*b* values sampled in the color gamut can be used.

(2) The combined NN system is trained based on the error-backpropagation rule. At the same time, the weights and biases in the printer model part are kept fixed as previously estimated according to section **3.1**; they never change as $w_{ij}(n)=w_{ij}(0)$ and $b_j(n)=b_j(0)$. Thus, the parameters to be newly determined in the combined NN system are limited to a total of 194 parameters (170 weights and 24 biases). In Figure 3, the filled circles and squares (●, ■) indicate, respectively, the fixed units and biases, while the units and biases indicated by (○, □) are determined by training the combined network, starting from a random number set.

(3) The error is propagated backward through the combined network from the output layer to the input layer. The upper half of the network does not change its network parameters, and the error passes only through the hidden layers. On the

other hand, the lower half corrects its parameters due to the recursive computations, accompanied by the error backpropagation.

The above learning procedure is repeated for the entire gamut in the L*a*b* color space. When the system error of the combined network becomes sufficiently small, the squared error

$$\| L^* - \hat{L}^* \|^2 + 4 \| a^* - \hat{a}^* \|^2 + 4 \| b^* - \hat{b}^* \|^2 \tag{5}$$

between the target L*a*b* values of color specifications and the $\hat{L}^*\hat{a}^*\hat{b}^*$ values predicted by the network is minimized. Because of the error minimization over the entire region, the combined network realizes the identity mapping of the L*a*b* color space.

With respect to the structure of the completed total network, we note that the printer model part in the upper half remains unchanged, while the controller part in the lower half is newly trained. Because the upper half represents the mapping from the CMYK space to the L*a*b* space, and moreover the combined NN system performs the one-to-one mapping, the lower half must realize the inverse mapping of the printer model part, i.e., the mapping from the L*a*b* space to the CMYK space. In other words, the desired controller of the printer is obtained by utilizing the lower half of the combined network. This controller can determine the four ink signals necessary to generate any target L*a*b* color specifications on the printer.

4. APPLICATION TO A SIX-COLOR PRINTER

The proposed principles of the neural network approach are applied to the color control of printers using many color inks more than three. We use an ink jet printer which prints six colors of cyan (C), magenta (M), yellow (Y), black (K), light cyan (Lt_C), and light magenta (Lt_M) at the resolution of 720 dots per inch. The color gamut of this printer is larger than that of the four-color printer. Each of the six color printer primaries is expressed in 256 levels (8-bits).

We have a mapping problem from the three-dimensional color space of L*a*b* to the six-dimensional color space of printer signals C, M, Y, Y, Lt_C, and Lt_M. In other words the color reproduction problem is to determine the six input control color signals such that the printer outputs the desired L*a*b* values. If we apply the above network method directly to the present problem, then the printer is modeled by a neural network with six inputs and three outputs, and the controller is constructed with a neural network with three inputs and six outputs. For example, the 6-10-10-3 type and 3-10-10-6 type networks might be used for the printer model and the controller network, respectively. However it should be noted that the combined neural network has a large network size, so that the learning procedure for determining the network parameters is complicated and time-consuming.

4.1 Spectral reflectance functions of inks

We propose an effective method for solving this high dimensional neural network problem. First, the color characteristics of the printer were investigated in six-color printing. Many color patches were made with papers printed by changing each value of the six color signals in the range [0, 255]. The surface-spectral reflectances of these color patches were measured by a spectro-meter. The shape of the measured spectral reflectance curves changes uniformly with the digital value in [0, 255]. We made a comparison between two sets of spectra for M and Lt_M primaries.

Then it is found that the two sets of spectral curves can be merged into a single set of 256 spectral curves, which change uniformly over the wide range between the darkest magenta (M=0) and the lightest magenta (Lt_M=255). That is, the M and Lt_M signals are combined into the extended magenta signal. Figure 4 indicates the surface-spectral reflectances of this extended magenta. Moreover Figure 5 depicts a lookup table to determine the relationship between the extended magenta and the original two primaries. The content of the table consists of the re-sampled digital values from the dark part of M and the most light part of Lt_M. In the same way, we made the extended cyan signal by merging the original C and Lt_C because the same properties exist between those primaries.

Therefore the six-dimensional color control problem can be reduced to the four-dimensional problem, so that the same neural network algorithms as the ones developed for four-color printing are used for the present printer.

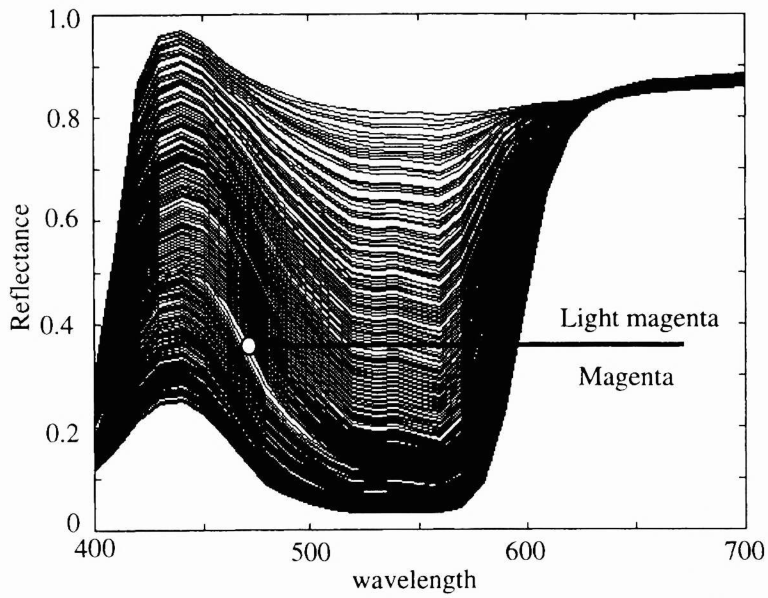

Figure 4 Surface-spectral reflectances of the extended magenta signal.

magenta

M		M	Lt_M
0		0	0
1		0	2
2		0	3
•		•	•
•		•	•
•		•	•
146		0	248
147	⇔	0	251
148		0	255
149		108	0
150		112	0
151		115	0
•		•	•
•		•	•
•		•	•
253		253	0
254		254	0
255		255	0

cyan

C		C	Lt_C
0		0	0
1		0	1
2		0	2
•		•	•
•		•	•
•		•	•
154		0	233
155	⇔	0	237
156		0	239
157		108	0
158		112	0
159		115	0
•		•	•
•		•	•
•		•	•
253		253	0
254		254	0
255		255	0

Figure 5 Lookup table for merging two primary signals.

4.2 Experimental results

We have conducted experiments with the above ink jet printer. A digital halftoning technique for the ink jet printer was developed based on the error diffusion algorithm[11]. The original printer-input signals of six inks C, M, Y, Y, Lt_C, and Lt_M are transformed into the summarized set of four ink signals, which consists of the extended C and M inks as shown in **4.1** and the original Y and K inks.

(A) Printer model

First, we have constructed a training data set from the measurements of many color patches printed in the four inks of the extended CMYK The accuracy of color reproduction is evaluated based on color difference between the reproduced color and the target color in the L*a*b* color space. In order to improve this accuracy, the color patches are printed so that color samples are taken uniformly in equal steps of each scale in the L*a*b* coordinate system. We have 4603 color samples in all within the color gamut. These measured color samples were specified in the L*a*b* color space under the CIE illuminant D_{65}. The color specifications are plotted almost uniformly in the color space. Thus the training data set consists of 4603 pairs of the input ink signals and their corresponding printer-output L*a*b* color values.

The networks were simulated on a work station. The initial values of the weights $w_{ij}(0)$ and the biases $b_j(0)$ were set to random numbers. The training data were selected based on uniformly random sampling so that every data pair was selected only once in random order in each epoch. After 40000 epochs of the iterative learning process, the total system error reached a small value of 0.292. This error corresponds to the average system error of 6.34×10^{-5} per one normalized data item. Moreover, it is equivalent to the average color difference of $\Delta E^*_{ab}=0.87$.

(B) Controller

The controller was constructed by training the total eight-layered network according to the procedure in **3.2**. For realizing the identity mapping, the same L*a*b* values were presented to both the input and output layers, which were identical with the 4603 L*a*b* values of the training data used for modeling the printers. The training constants in the iterative process were set in the same manner as shown for the printer model. During training, the squared error of the combined network converges at around 40000 iterations, with the total system error, the average system error, and the equivalent color difference being 0.161, 3.50×10^{-5}, and 0.648, respectively. Since the system errors became sufficiently small, the controller parts from each combined NN system could be utilized.

(C) Accuracy test

The accuracy of color reproduction achieved by the controller obtained was examined as follows: First we tested color samples from the printer outputs. These color samples consisted of 263 color patches, which were produced using such extended CMYK values that the test color samples were sampled uniformly in the L*a*b* color space. The color specifications of the measured color patches are shown in Figure 6, where the ○ symbols represent each coordinate point of the test data. Secondly, the L*a*b* color specifications of the target colors were fed into the controller for determining the ink amounts of the extended CMYK primaries. Thirdly, color patches were reproduced from these CMYK signals with the real printers. The accuracy was examined by comparing the reproduced color specifications and the target color specifications in the L*a*b* space. The *-symbols in Figure 6 represent the reproduced color coordinate points. The color differences between the targets ○ and the reproduced colors * represent the overall error of color reproduction. The average color difference is 2.20 as Euclidean distance ΔE^*_{ab} (RMS Delta E).

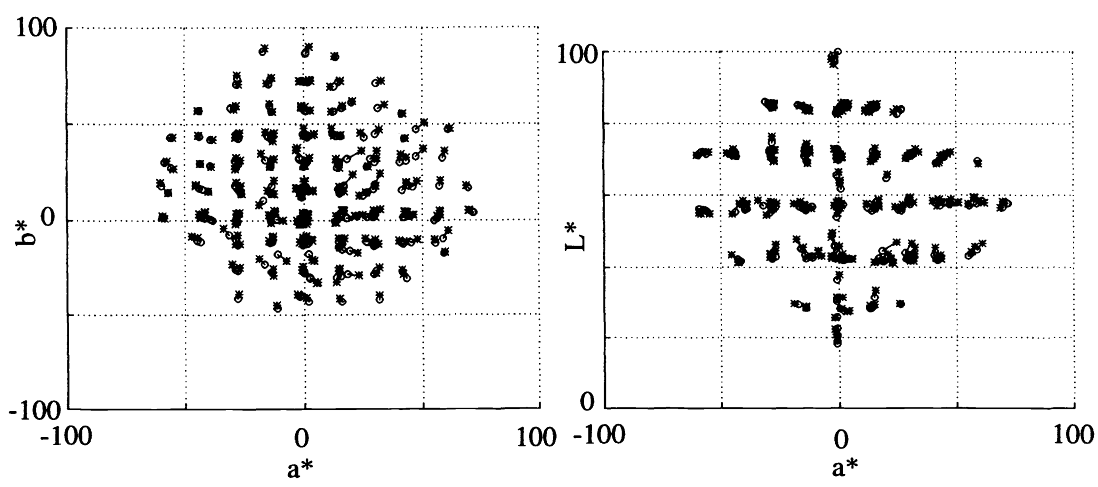

Figure 6 Test results of color reproduction for the ink jet printer using six colors.

5. CONCLUSION

The present paper has described a method for realizing an exact color reproduction on a printer using more than three color inks. The mapping from the L*a*b* color space to the printer color space is constructed using a neural network. This mapping does not use such techniques as UCR and GCR. The problem in four-color printing is considered as the problem of controlling an unknown system with four inputs and three outputs. We present a two-phase procedure for solving this control problem. The first phase determines a printer model, and the second phase determines the combined network system of a printer model and a controller so as to provide the identity mapping.

The proposed principles of the neural network approach were applied to the color control of an ink jet printer which prints six colors of C, M, Y, Y, Lt_C, and Lt_M. Then we have the high dimensional color control problem of mapping from the L*a*b* color space to the six-dimensional color printer space. The examination of spectral-reflectance functions of inks has suggested that the two sets of spectral curves for M and Lt_M (also C and Lt_C) can be merged into a single set of spectral curves, and the M and Lt_M signals are combined into the extended magenta signal. As a result the six-dimensional color control problem can be reduced to the four-dimensional color control. The experimental results suggest that the controller achieves a good color reproduction accuracy.

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