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Study on the Gamut Mapping Method Based on BP Neural Network

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Abstract. For digital color devices, complex relationship exists between their input image pixel values and the output color chromatic values, gamut mapping between them as well. The linear models are difficult to describe this relationship effectively. In the study, based on BP neural network, a gamut mapping model with micro space sections is proposed. The gamut mapping model maps color from monitor gamut to printer gamut. Compared with mature gamut mapping method CARISMA, the experiment shows that, for the perfect nonlinear performance and adaptive ability of BP neural network, the gamut mapping model based on BP neural network decreases the color error between the monitor and the printer significantly and reaches high accuracy.

Keywords: BP neural network, color management, gamut mapping, micro space sections

1 Introduction

The work principle of monitor and printer is to represent color according to the input digital image pixel values [1]. Because monitor and printer differ in their work principle, structure and drive programs, the same input digital image pixel perhaps represents different colors on the two devices. To all the color range that the device represents, it shows as gamut with kinds of area and shape [2]. Color gamut is a range of colors achievable on a given color reproduction medium or present in an image on that medium under a given set of viewing conditions, it is a volume in color space. For subjective accuracy, the aim of gamut mapping can also be stated as desiring “a good correspondence of overall color appearance between the original and the reproduction by compensating for the mismatch in the size, shape and location between the original and reproduction gamuts” [3]. To the ICC organization 3C standard, device calibration, device characterization and gamut mapping are the three essential factors of an effective color management system [4].

Device characterization model transforms input value to color chromatic value, and device reverse characterization model transforms color chromatic value to input value [5]. Gamut mapping model transforms the color from source device gamut into the destination device gamut, and minimizes the chosen desired reproduction property, e.g. preference or subjective accuracy [6], i.e. gamut mapping is a method for assigning colors from the reproduction medium to colors from the original medium or image [7]. There are four kinds of gamut mapping methods; they are perceptual compress, saturation priority, relative colorimetric priority and absolute colorimetric priority respectively. All gamut mapping methods are carried out in color space with normal human eyesight [8].

For the complicated feature of gamut mapping, at present, the gamut mapping is implemented in three-dimensional space. The main algorithms comprise CLLIN, LNLIN, LSLIN, LCLIP, HPMINDE, SGCK, GCUSP, SLMCKS, CARISMA, etc. In CLLIN, LNLIN, LSLIN and LCLIP algorithms, brightness is compressed and then saturation is mapped. In CUSP algorithm, brightness and saturation are compressed simultaneously. In GCUSP, CLLIN and CARISMA algorithms, brightness and saturation are compressed intergratedly [9]. With all the gamut mapping methods above, certain results can be achieved, but their computation in three-dimensional space limits the efficiency [10].

In recent years, new methods based on new theories and other considerations have been introduced in color management, in the device characterization and gamut mapping. Some traditional theories are improved to apply in gamut mapping, such as Laplace transformations, CORDIC iteration, coupled dictionary learning, and baseline method [11-14]. Spatial feature are considered more deeply than that in traditional gamut mapping, cubical gamut mapping with color constancy, and adaptively spatial color gamut mapping algorithm are proposed [15-16]. At the same time, image feature are also emphasized in gamut mapping, gamut mapping using image derivative structures for color constancy, image-individualized gamut mapping algorithms, and hybrid gamut mapping for image reproduction are presented [17-19]. Finally, the factor how the color effects the human vision system are taken into gamut mapping algorithm [20-21]. Among the kinds of new methods, kinds of artificial intelligence are considered to map the color from source device gamut into the destination device gamut, for their self-adaptive ability, perfect approximation, predictive capability and ease of use.

In the study, based on back propagation (BP) neural network, monitor characterization model and printer calibration model are established. Mass number of color samples in printer gamut and relatively small numbers of color samples in monitor gamut are matched; the colors in both printer gamut and monitor gamut with least color errors are found and stored to serves as gamut mapping model neural network supervision samples. With the supervision samples and proper structure of BP neural network, the gamut mapping based on BP neural network is trained. When the training process finishes, the structure and parameters of BP neural network are stored. So the gamut mapping based on BP neural network is established to serve for the gamut mapping. In the study, the color is described by CIE 1976 $L^*a^*b^*$ chromatic system, and the digital image format is 24 bit deep BMP.

2 The basic principle of BP neural network

Artificial neural network is built with mathematic knowledge based on the realization of human neural network. It contains vast number of simple neurons which connects each other.

2.1 Neuron Theory Model

Neuron is the basic unit of neural network, it is usually a many input and one output nonlinear component. Its action can be seen as a step threshold function switch. Its input is affected by both input signal and the factors within itself. A neuron with R input component is showed as Fig.1.

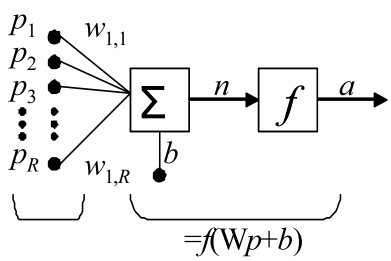


Fig. 1. Neuron model

In Fig.1, input component p_j (j=1, 2, 3-..., R) and their weight value components w_j (j=1, 2, 3-..., R) are multiplied and summed, as the input of activation function f. Another input of activation function f is offset b, so the net input of neuron is $net=Wp+b$. The weights w_j and input p_j matrix can be described as a column vector form by row vectors of W and p. So the neuron output vector is as expression (1) and expression (2).

$$\begin{aligned} W &= [w_1, w_2, \ldots w_r] \\ p &= [p_1, p_2, \ldots p_r] \end{aligned} \tag{1}$$

$$a = f(Wp+b) = f(\sum_{j=1}^{r} w_j p_j + b) \tag{2}$$

The offset b plays an important role in neural network [22]. In the study, offset is contained in all the neural networks to be built.

2.2 The active function of neuron

Activation function is another key factor of neuron. Combined with neural network structure, it determines the ability of neural network. The basic action of active function is to control the action of input to output, and transform input with infinite range into output with definite range.

Common active function includes threshold function, linear function, Sigmoid function and hyperbolic tangent function. The type of function could be selected according to specific situation [23].

2.3 The structure of BP neural network

BP is the abbreviation of back-propagation. Supervised by W-H learning rule, nonlinear differential function adjusts the weights and offsets to build the multi-layer network. To the BP neural network, besides input layer and output layer, hidden layer is introduced. In theory, with enough hidden layers and neurons, it could simulate any function or data corresponding relation [24]. General BP neural network contains three layers, as Fig.2.

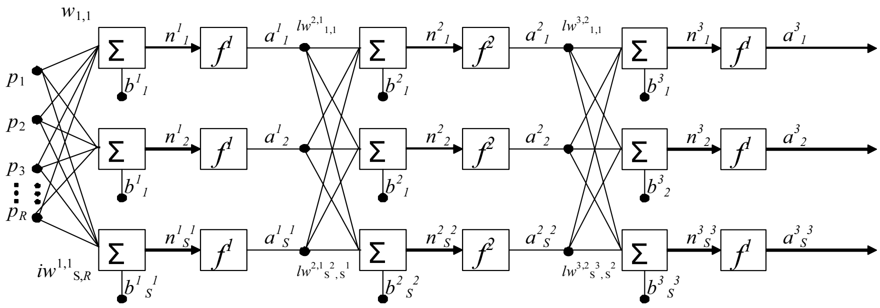


Fig. 2. A BP neural network with three layers

In the BP neural network, there are full interconnections among neurons of adjacent layers. There are no connections in neurons of the same layer. In Fig.2, the neurons numbers of input layer, hidden layer and output layer are s^1, s^2 and s^3 respectively.

2.4 The model of BP neural network

Besides active function model of neurons, BP neural network model includes node output model and self-learning model.

Node Output Model. In BP neural network, neuron output model includes hidden neuron output model and output neuron model; their expressions are as (3) and (4).

$$O_j = f\left(\sum W_{ij} \times X_i - q_i\right) \quad \textbf{(3)}$$

$$Y_k = f\left(\sum T_{jk} \times O_{ji} - q_k\right) \quad \textbf{(4)}$$

In expressions (3) and (4), f is nonlinear interaction function and q is neuron threshold.

Self-Learning Model. In the BP neural network learning process, the weight matrix Wij that connects the neurons in the upper layer and lower layer is corrected to minimize the error between the input and output by interactive algorithm. The self-learning model is as expression (5).

$$\Delta Wi_{j(n+1)} = h \times \phi_i \times O_j + a \times \Delta Wi_{j(n)} \quad \textbf{(5)}$$

In expression (5), h is learning factor; Φ_i is calculating error of output neuron i, O_j is calculating output of output neuron j, and a is momentum factor.

3 Realization of gamut mapping method based on BP neural network

In gamut mapping, BP neural network is about to describe the conversion relationship between the gamut of source device and destination device. In the study, the two devices are monitor and printer. For the gamut mapping method based on BP neural network, its input and output training samples are color samples in monitor gamut and color samples in printer gamut. What is more, these two color samples should be selected in the two gamuts and be matched, so that the gamut mapping model could be built based on these two training samples. In order to achieve the goal, both gamut mapping and BP neural network theory should be combined.

3.1 The learning process of BP neural network

Learning process of BP neural network belongs to supervised learning. BP neural network to be established learns under the guidance of input data and output as learning samples [25]. In the study, take the monitor color as standard, the gamut mapping model map the color in the monitor gamut into the color in the printer gamut. So the chromatic values of monitor color and the chromatic values of printer color are taken as the input learning data and output data of the BP neural network respectively.

BP neural network learning process contains two parts; they are forward propagation and error reflection transmission. In forward propagation, input signal i.e. monitor color chromatic value is processed by input layer, hidden layer and output layer sequentially. The state of each layer of neurons only affects the state of the next layer of neurons. If the output signal, i.e. printer color chromatic value is not qualified, the reflection transmission starts. In the reflection transmission, error signal i.e. the color error between the printer color chromatic value and the color chromatic value calculated by BP neural network is processed by output layer, hidden layer and input layer, the weights and offsets of neurons of each layer are adjusted to decrease error until the output is qualified [26], i.e. the color error between the monitor color and the printer color is matched.

To the sample k, target function is defined as mean square error function as expression (6).

$$E_k = \frac{1}{2}\sum_{j=0}^{N-1}(t_{kj} - a_{kj}')^2 \tag{6}$$

In expression (6), E_k is neural network output error, t_{kj} is the ideal output of the k_{th} neuron when the input is sample k, $a_{kj'}$ is the actual output.

To decrease the target function error, gradient descent algorithm is usually adopted to adjust the weights and offsets. The basic BP neural network learning process is as following.

Step 1: neural network input signal propagates forward.

$$\begin{aligned} &a^0 = p \\ &a^{m+1} = f^{m+1}(w^{m+1}a^m + b^{m+1}), m = 0,1,...,M-1 \\ &a = a^M \end{aligned} \tag{7}$$

Step 2: neural network back propagates sensitive error.

$$\begin{aligned} &s^M = -2F^M(n^M)(t-a) \\ &s^m = F^m(n^m)(W^{m+1})^T s^{m+1}, m = M-1,...,2,1 \end{aligned} \tag{8}$$

At last, approximate steepest descent method is used to update the weights and offsets of neurons.

$$\begin{aligned} &W^m(k+1) = W^m(k) - \alpha s^m (a^{m-1})^T \\ &b^m(k+1) = b^m(k) - \alpha s^m \\ &F^m(n^m) = \begin{bmatrix} f^m(n_1^m) & 0 & \cdots & 0 \\ 0 & f^m(n_1^m) & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & f^m(n_{s^m}^m) \end{bmatrix} \end{aligned} \tag{9}$$

In the expressions (6-9), W, b, s, α, and s^m are weight matrixes, offsets matrixes, sensitive error matrix, output matrix, and learning rate of each layer respectively.

If the output is not qualified, the second iteration starts with the same input until the output meets requirements [27]. The structure, weight matrix and offset matrix of the BP neural network are recorded for its simulation, when the learning process ends.

3.2 Determination of BP neural network structure

According to neural network theory, the simulation ability of network relates to its structure and hidden neuron number. Generally, the more the hidden layer neuron number is, the stronger the network simulation ability is. At the same time, excessive number of hidden layers and its neurons may lead to higher failure rate of BP neural network training and lower executing efficiency. In the study, BP neural network to be built to serve as device characterization and gamut mapping, their learning samples differ in range and attribute. The learning sample data includes digital image pixel value and color chromatic value. The digital image pixel values locate in the range of [0, 255], and the color chromatic values scatter in the ranges of [0,100], [-100, 100] and [-100, 100]. To simulate the relation between the data with such feature, both the layer number and hidden layer neural number should be improved to enhance the network simulation ability. At the same time, the number of sample is 1000, it is relative large.

Considering with simulation and learning time, the BP neural network structure is determined. The hidden layer number is 3. The neuron number of each layer is 3, 30, 20, 30 and 3, from input layer to output layer [28]. Both the input layer and output layer neuron number is 3, which correspond to digital image pixel value or color chromatic value. The action function of hidden layer and output layer are Sigmoid functions, the action function of input layer are linear functions. The action function is as expression (10).

$$\begin{aligned} f(x) &= \frac{1}{1+e^{-x}} \\ f(x) &= x \end{aligned} \tag{10}$$

4 Experiments

4.1 Getting of learning samples for neural network of devices characterization models

The color blocks are generated on the MatLab 12.0 platform, and all the BP neural networks are established by neural network toolbox attached to MatLab. Digital image with color blocks is generated by pixel combinations and the pixel combinations selected by approximately intervals. 9 intervals are gotten, and the step points are 0, 28, 56, 84, 112, 140, 168, 196, 224 and 255. Digital image pixels of color blocks are gotten by combination of three channels of image pixel, and 1000 sets data are gotten for both monitor and printer, the image contained 1000 color blocks is shown as Fig.3.

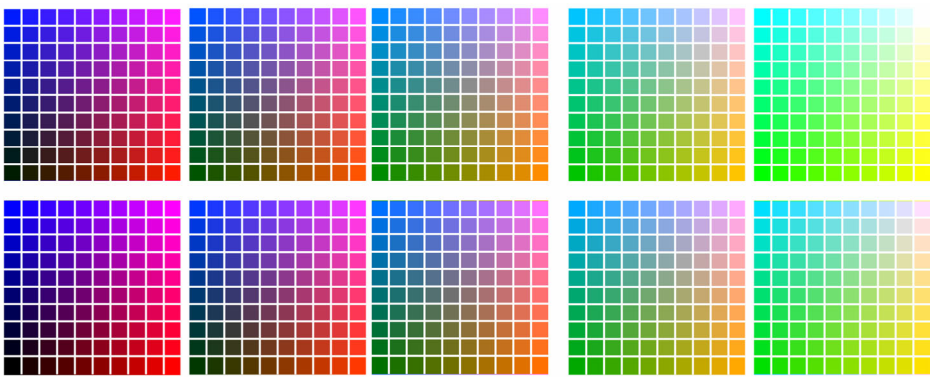


Fig. 3. Color block image for device characterization modeling and gamut mapping modeling

Experiment condition. The monitor is EIZO EDGE CG301W; its color temperature is set as custom mode. The drives values of red, green and blue channel are 75, 70 and 80 respectively, and both lightness and contrast drive value are 50. The monitor is switch on for half hour to achieve stable status. The color chromatic data are measured by X-Rite Monitor Optimizer and recoded by Color Shop as Excel file.

The printer is EPSON Stylus Pro 10600 with high definition. When the ink dried, the chromatic value of each color block was measured by X-Rite 528 spectrometer with D65 light source at 10° eyesight field mode. The experiment data is recorded as Excel file by X-Key.

4.2 Establishing of device characterization models

In spite of the work principle and color represent method of monitor and printer, on the basis premise of stable working status, both monitor and printer could be seen as black boxes, so their input and output relation could be described by black box theory. It is the application basis of BP neural network in the color management. In the study, there are three device models to be built as the basis of gamut mapping. The device models are monitor characterization model, printer characterization model and printer reverse characterization model. By using BP neural network, the device characterization models transform digital image pixel values into chromatic values. At the same time, the device reverse characterization models transform chromatic values into digital image pixel values. Their schematic diagrams are shown as Fig. 4 and Fig.5 respectively.

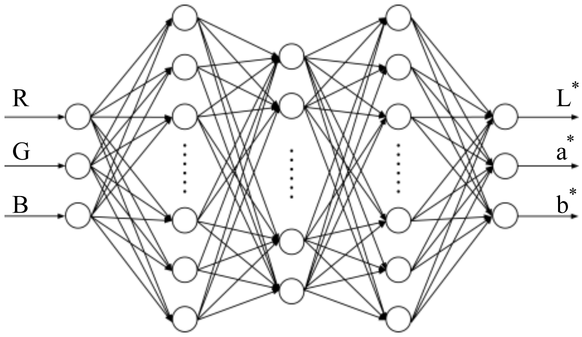


Fig. 4. Device characterization model

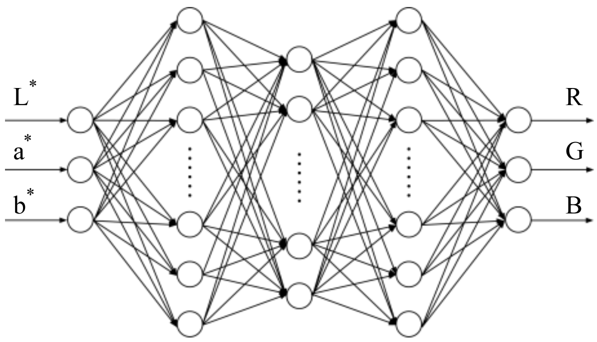


Fig. 5. Device reverse characterization model

In general color management system, monitor characterization and printer reverse characterization model are enough. But in the study, printer characterization model is built to get learning samples for the gamut mapping BP neural network.

The input and output data is normalized to range [0, 1] or [-1, 1] as BP neural network learning samples. The normalization could improve the learning rate and the success likelihood of the neural network.

4.3 Getting of learning samples for gamut mapping BP neural network

The monitor measured experiment data is taken as the gamut mapping BP neural network input learning samples directly. The printer experiment data cannot be taken as the gamut mapping BP neural network out learning samples directly. It should be produced by both printer characterization model and experiment data. By printer characterization model, much more than 1000 set data is gotten in printer gamut.

The vast data is compared with monitor experiment data, the printer gamut data with least color error to monitor gamut data experiment is recorded for the output of the gamut mapping BP neural network.

Color chromatic values as learning samples of printer gamut for gamut mapping BP neural network is gotten based on the pixel value change of 24 bit-deep BMP digital image. Take the interval of 5, all the pixel range is divided into 51 parts. The 52 points at the section edges are 0, 5, 10, 15, …, 250, 255. Thus, 52×52×52=140608 digital image pixel combinations are gotten. Their corresponding chromatic value could be calculated by printer characterization model. Thus, the printer gamut is divided into micro space sections whose color errors are less than normal human eye perceive.

Compared with monitor experiment data and the calculated printer gamut data, both gamut mapping BP neural network input learning samples and output learning samples are gotten.

Taking the gamut mapping model as the core, a prototype color management system could be built. Its workflow is as the following. Firstly, the chromatic value of the color to be displayed on monitor is calculated by monitor characterization model with its corresponding digital image pixel. Secondly, the chromatic value is mapped to its chromatic value to be printed by gamut mapping model. Finally the digital image pixel to be printed on printer is calculated by printer reverse characterization model according to the chromatic value calculated by gamut mapping model. The digital image pixels calculated by printer reverse characterization model are input the printer to represent its corresponding color on paper.

5 Experiment result and analysis

In the study, there are two devices as monitor and printer in the color management prototype system. The gamut mapping model transforms the color in source device gamut into destination device gamut. The mapping effect is evaluated by the following three kinds of data. The data are monitor experiment chromatic value data, printer experiment chromatic value data before gamut mapping and printer experiment chromatic value data after gamut mapping. For the sake of convenience, the three kinds of data are taken as $Data_1$, $Data_2$, $Data_{31BP}$ and $Data_{32}$. What's more, three mature gamut mapping methods CARISMA, GCUSP and CLLIN are introduced to evaluate the gamut mapping model based on BP neural network proposed in the study. The data mapped by CARISMA, GCUSP and CLLIN are defined as $Data_{32CA}$, $Data_{32GC}$ and $Data_{32CL}$.

In order to evaluate the gamut mapping model, another image contained 1000 color blocks is generated. It is the test image, shown as Fig. 6. The pixel values of the test image color blocks are 0, 14, 42, 70, 98, 126, 154, 182, 210 and 255. The pixels locate in the middle point of Fig.3 to evaluate the gamut mapping model more objectively.

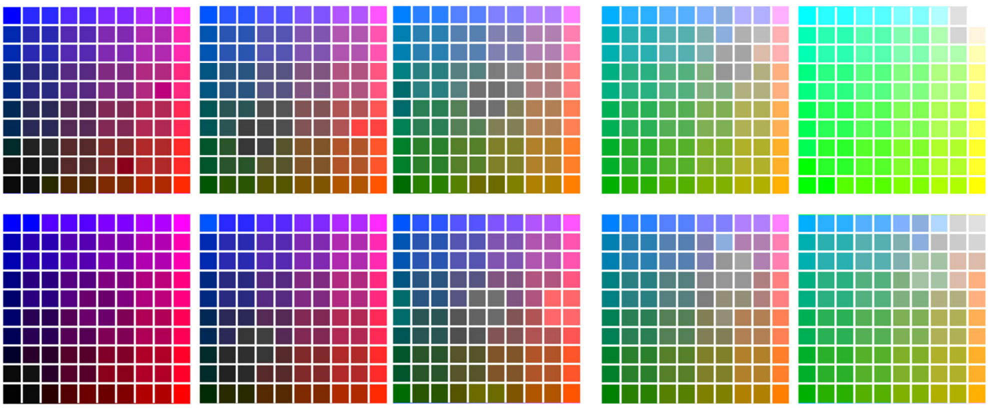


Fig. 6. Test image for gamut mapping model evaluation

In the analysis, first of all, the test images are represented on the monitor and on the printer; the color chromatic of each block is tested and recorded. Then, the test image is input into the gamut mapping model based on BP neural network, CARISMA, GCUSP and CLLIN model, and the images contained color block of processed pixels are gotten. The two images are input into the printer and printed on paper under the same experiment condition. And the color chromatic values of color blocks on the two papers are tested and recorded. In order to facilitate the description, all the chromatic values mentioned above are expressed as the following manners.

The $Data_1$ and $Data_2$ are the chromatic values when the test image represented on the monitor and printer. The $Data_{31BP}$, $Data_{32CA}$, $Data_{32GC}$ and $Data_{32CL}$ are the chromatic values represented on printer with digital image which are generated by the gamut mapping model based on BP neural network, CARISMA, GCUSP and CLLIN respectively, with the cooperation of monitor characterization model, printer characterization model and printer reverse characterization model [29].

5.1 Color error evaluate and analysis

The color errors between $Data_1$ and $Data_2$, $Data_{31}$, $Data_{32}$ are listed in Table 1.

Table 1. The color errors between $Data_1$ and $Data_2$, $Data_{31}$, $Data_{32}$

Color error	$\Delta Data_2$	$\Delta Data_{31BP}$	$\Delta Data_{32CA}$	$\Delta Data_{32GC}$	$\Delta Data_{32CL}$
Max	76.51	88.92	88.44	94.63	85.07
Min	4.41	0.81	0.82	0.71	0.96
Mean	27.03	15.76	15.81	15.72	15.83

How the color error distributes in color error interval is shown in Table 2.

Table 2. The color errors between $Data_1$ and $Data_2$, $Data_{31}$, $Data_{32}$ distribution in color intervals

Color blocks number in each color error interval	$\Delta Data_2$	$\Delta Data_{31BP}$	$\Delta Data_{32CA}$	$\Delta Data_{32GC}$	$\Delta Data_{32CL}$
[0, 4]	0	81	74	79	76
[4, 6]	6	65	69	70	64
[6, 10]	52	140	145	144	146
[10, 20]	383	419	419	421	418
[20, 30]	228	236	234	222	237
[30, 40]	155	43	45	47	42
[40, +∞)	176	16	14	17	17

Between $Data_1$ and $Data_2$, $Data_{31BP}$, $Data_{32CA}$, $Data_{32GC}$, and $Data_{32CL}$, there are mean color errors 27.03, 15.76, 15.81, 15.72 and 15.83; maximum color errors 76.51, 88.92, 88.44, 94.63 and 85.07; and minimum color errors 4.41, 0.81, 0.82, 0.71 and 0.96. The samples numbers whose color error less than 6 are 6, 146, 143, 149 and 150.

By sequential color block number, the color error between $Data_1$ and $Data_2$ is shown as Fig.7. Seen from Fig.5, the color errors are larger on the whole, and the distribution is dispersed. The color errors distribute in the range [4.41, 76.51]. What is more, most of them distribute in the area that more than 10, which could be perceived by normal human eye easily.

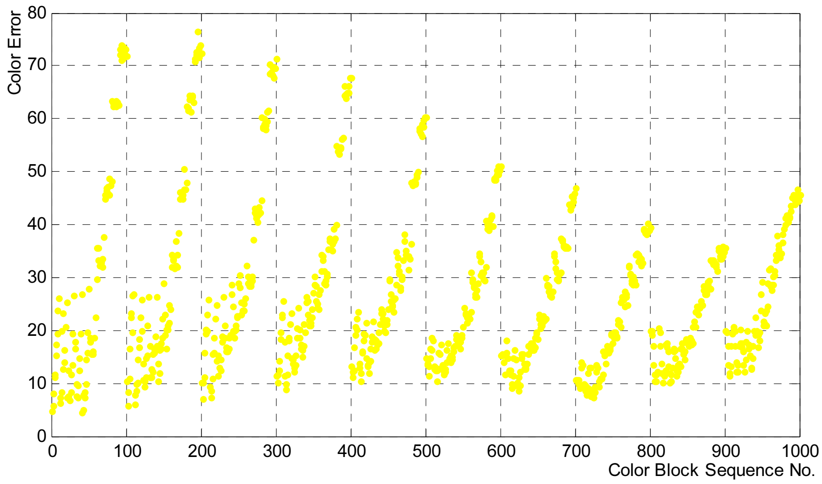


Fig. 7. Color errors between monitor and printer before gamut mapping

To the color of lower lightness, the color errors are smaller. Meanwhile, to the color of higher lightness, the color errors are larger, and the higher the lightness is, the larger the color error is.

Between $Data_1$ and $data_{31BP}$, there is mean color error 15.76, maximum color error 88.92 and minimum color error 0.81. The samples number whose color error less than 6 is 146.

The color error between $Data_1$ and $Data_{31}$ is showed as Fig. 8, with sequential color block number. Seen from Fig.8, on the whole, the color errors are smaller, and the distribution is more centralized. The color errors distribute in the range [0.81, 88.92]. What is more, most of them distribute in the area that less than 6, which could not be perceived by human eye easily. The color error concentration feature is much better than that before gamut mapping, i.e. color error between $data_1$ and $data_2$. The samples number whose color error less than 6 is much more than that before gamut mapping; i.e. there are more color could be represented by printer after gamut mapping and reduce the color error on the whole.

Compared with the two kinds of color errors, color errors of intermediate brightness are smaller, that of the low brightness and high brightness are larger. At the same time, the color errors of the high brightness have also been greatly reduced after the device gamut mapping is carried out.

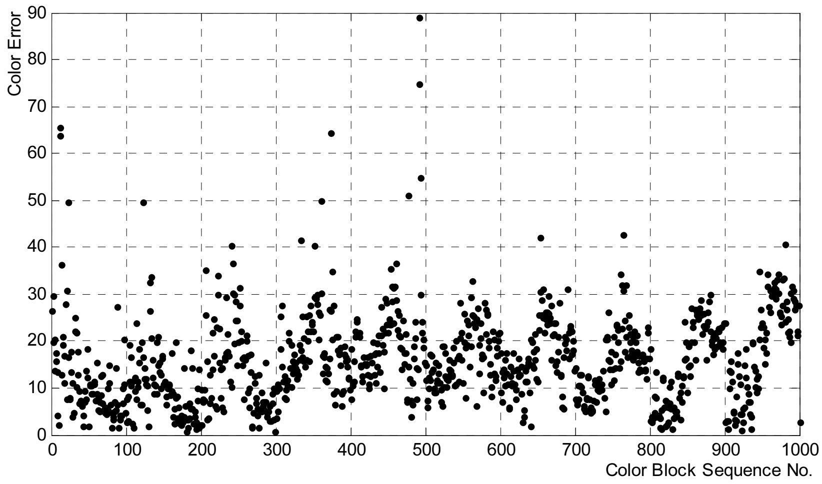


Fig. 8. Color errors between monitor and printer after gamut mapping based on BP Neural Network

Similarly, the color error between $Data_1$ and $Data_{32CA}$, $Data_{32GC}$, $Data_{32CL}$ are showed as Fig.9, Fig.10, and Fig.11. The relation of $Data_1$ and $Data_{32CA}$, $Data_{32GC}$, $Data_{32CL}$ are similar to that of $Data_1$ and $Data_{31BP}$.

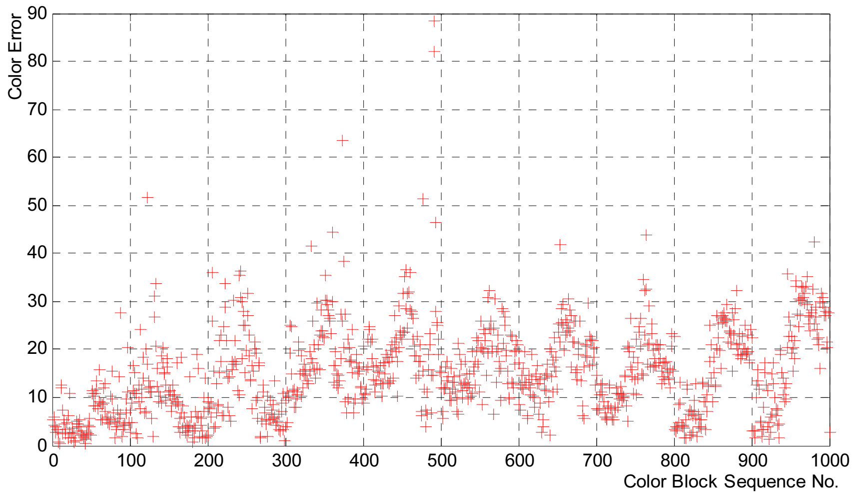


Fig. 9. Color errors between monitor and printer after CARISMA gamut mapping

The color errors between monitor and printer are greatly reduced by the prototype color management system effectively. According to the color error analysis, the gamut mapping effect of gamut mapping method based on BP neural network, CARISMA, GCUSP and CLLIN is similar.

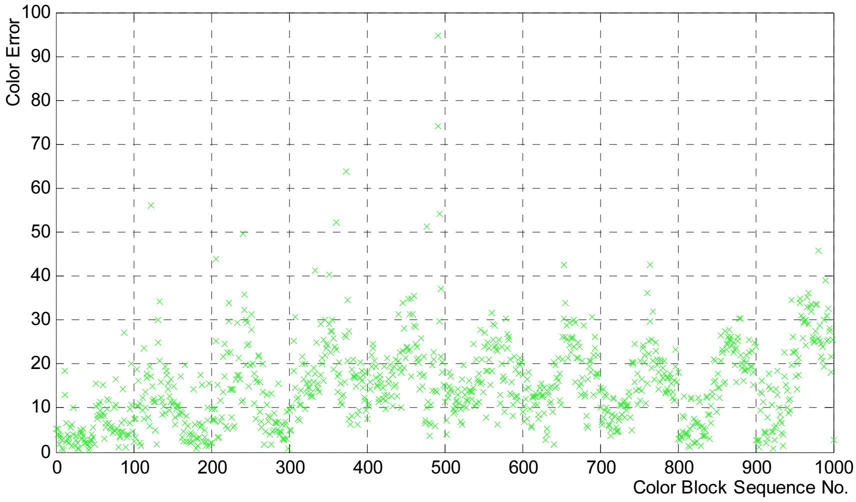


Fig. 10. Color errors between monitor and printer after GCUSP gamut mapping

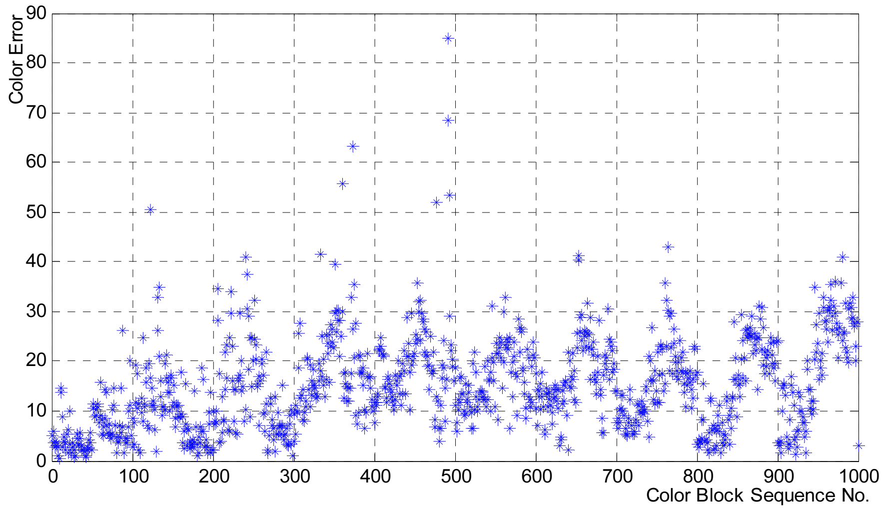


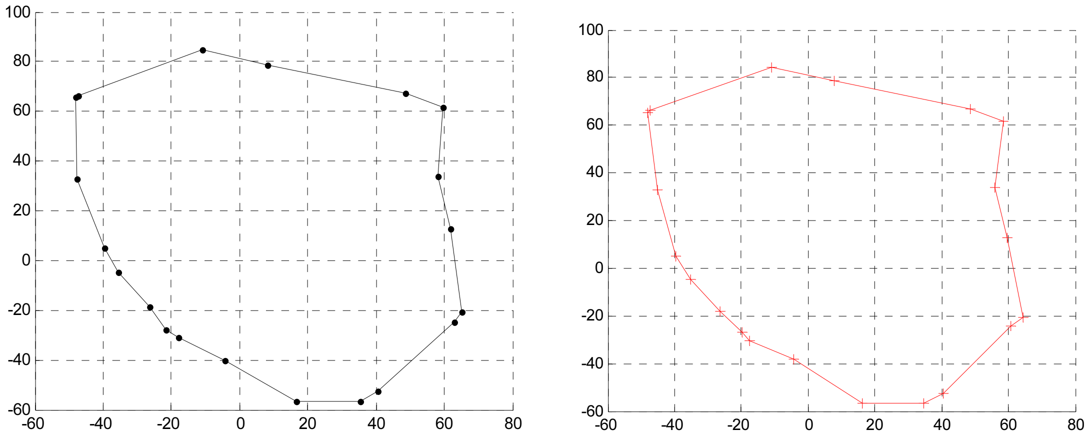
Fig. 11. Color errors between monitor and printer after CLLIN gamut mapping

5.2 Gamut evaluate and analysis

The chromatic values of test image mapped by BP neural network and CARISMA and their gamut are shown in a^*b^* plain. The a^*b^* plain is divided into 20 parts by its origin. In each part, take the color sample with the longest distance to a^*b^* plain origin as the vertex of the gamut polygon. So the gamut of test image data mapped by BP neural network and CARISMA, GCUSP and CLLIN are shown as Fig.12(a), Fig.12(b), Fig.13(a) and Fig.13(b). All of them are the gamut of printer, for that the printer is the destination device in the study.

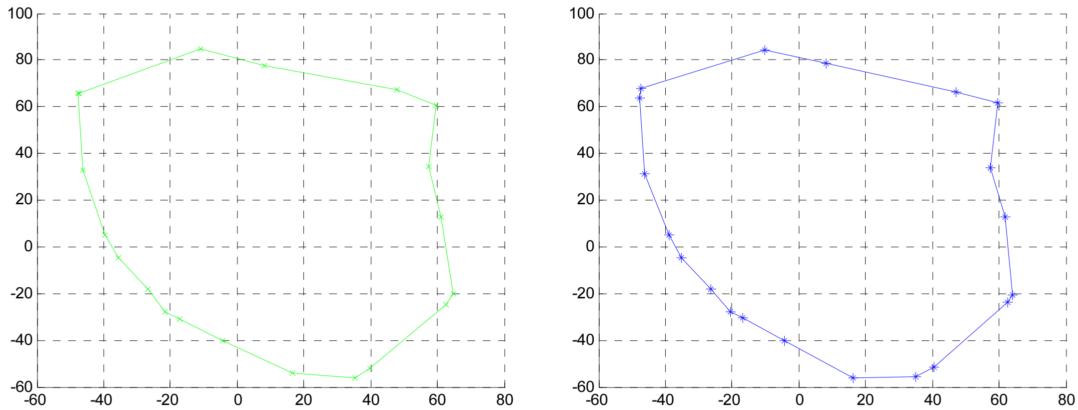
Seen from Fig.12 and Fig.13, under the same device and experiment, the gamut polygon of BP neural network, CARISMA, GCUSP and CLLIN show the approximate shape, vertex position and area, especially in the left part. The attribute shows that the two gamut mapping methods have the similar performance.

In order to compare the two gamut polygon more deeply, they are draw overlapped in a^*b^* plain, as Fig.14. In the Fig.14, most vertexes of the four gamut polygons lay at the same position nearly. Meanwhile, the position of some vertexes of the four gamut polygon differs from the counterpart obviously, such as the vertexes in the left flank and the right flank of the two polygons. The difference of algorithm and precise of the four gamut mapping result in the difference of their gamut polygon shape and vertexes position. On the other hand, in the left flank and right flank, the range of gamut mapped by on BP neural network method is wider than that of the gamut mapped by the other three gamut mapping methods. It shows that the performance of gamut mapping based on BP neural network is better than that of the other three ones.



(a) (b)

Fig. 12. Gamut of polygon of data mapped by BP neural network (a) and CARISMA (b)



(a) (b)

Fig. 13. Gamut polygon of data mapped by GCUSP (a) and CLLIN (b)

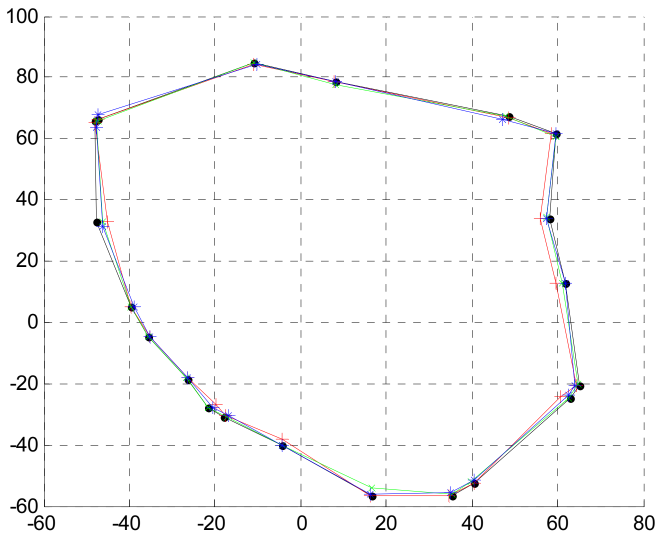


Fig. 14. Gamut polygons of data mapped by BP neural network, CARISMA, GCUSP and CLLIN

6 Conclusions

In the study, based on BP neural network, monitor characterization model, printer characterization model, printer reverse characterization model and gamut mapping model are established. Take the monitor color as standard; a prototype color management system is built to transform the color of monitor gamut to the color of printer gamut. A color management prototype system is built with ICC standard, which includes monitor characterization model, printer reverse characterization model and gamut mapping model, and all the models are built based on BP neural network. For the perfect nonlinear simulation ability of BP neural network, with enough layer neuron number and layer number, the monitor characterization, printer characterization model and printer reverse characterization model reach high accuracy. On the whole, device gamut mapping model based on BP neural network greatly reduced the color error on the monitor and on the printer by adjusting the corresponding digital mage pixel value. Meanwhile, to some color samples, their color errors enlarge after gamut mapping. According to preliminary analysis, it results from the inherent reasons, such as work principle and structure difference between the monitor and printer. How the color errors distribute with continuous tone is not considered, so the gamut mapping model in the research only apply to digital images without continuous tones, and it belongs to relative chromatic priority gamut mapping methods. For the sake that in the research, all the characterization models and gamut mapping model are based on black box theory and BP neural network, in spite of paying attention to how they works within the devices and their work principle, the relation of input data and out data could be built flexibly, so the similar models building method could be used to build characterization model of other devices, such as scanner and digital camera. So does the gamut mapping model between these devices. Compared with mature gamut mapping methods, such as CARISMA, GCUSP and CLLIN, and analyzed by color error and gamut polygon, the gamut mapping method based on BP neural network proposed in the study shows similar performance. It is qualified to taken as the core of a color management system. In the further study, some consideration should be put in the color samples within the low luminance region, for that the color error enlarged after the color samples mapped by the gamut mapping model based on BP neural network. Method such as color samples could be divided into several segments. In each segment, a gamut mapping model based on BP neural network is trained and established, to minimize the color error further.

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References

[1] Liao, N.-F. & Shi, J.-S. (2009). *Digital photo image color management system introduction.* Beijing, China: Beijing Institute of Technology Press.

[2] Liu, W.-H. (2013). *Printing color management*. Beijing, China: Chemical Industry Press.

[3] Zhou, S.-S. (2012). *Printed color science*. Beijing, China: Printing Industry Press.

[4] Li, X.-Z., Chen, G.-X., & Chen, Q.-F. (2010). Study on the color gamut mapping technique in digital printing. *Chinese Printing and Packaging Study, 2*(3), 8-15.

[5] Morovic, J. (2008). *Color gamut mapping*. Chichester, UK: John Wiley & Sons.

[6] Morovic, J., & Luo, M. R. (2001).The fundamentals of gamut mapping: A survey. *Journal of Imaging Science and Technology, 45*(3), 283-290.

[7] Phil, G. (2013). Gamut mapping for the perceptual reference medium gamut. In J. Y. Hardeberg & M. Pedersen (Eds.), *Proceedings of 2013 Colour and Visual Computing Symposium* (pp. 593-597). Red Hook, NY: Curran Associates.

[8] Li, X.-Z. (2012). A framework design of spatial gamut mapping. *Advanced Materials Research, 468-471*, 628-632.

[9] Song, I.-Y., Ha, H.-G., Kyung, W.-J., & Ha, Y.-H. (2012). Spatial gamut mapping for preserving the details of an image. *Proceedings of SPIE—The International Society for Optical Engineering, 8292*, 758-763.

[10] Waqas, Z. S., Javier, V. C., & Marcelo, B. (2014). Gamut mapping in cinematography through perceptually-based contrast modification. *IEEE Journal on Selected Topics in Signal Processing, 8*(3), 490-503.

[11] Eynard, D., Kovnatsky, A., & Bronstein, M. M. (2014). Laplacian colormaps: A framework for structure-preserving color transformations. *Computer Graphics Forum, 33*(2), 215-224.

[12] Deng, Y.-C., Wang,R.-G., Chen, Y., & Zhang, X. (2013). Rapid calculation of LED display color gamut boundary based on CORDIC iteration method. *Chinese Journal of Luminescence, 34*(4), 529-534.

[13] Muhammad, R., Mohsen, A., & Jeffrey, H. (2013). Color de-rendering using coupled dictionary learning. In B. Lovell & D. Suter (Eds.), *Proceedings of IEEE international conference on image processing* (pp. 315-319). Piscataway, NJ: IEEE.

[14] Phil, G. (2015). Baseline gamut mapping method for the perceptual reference medium gamut. *Proceedings of SPIE—The International Society for Optical Engineering, 9395*, 939-950.

[15] Milan, M., & Brian, F. (2010, June). *Cubical gamut mapping colour constancy*. Paper presented at the Proceedings of 5th European Conference on Colour in Graphics, Imaging, and Vision and 12th International Symposium on Multispectral Colour Science, Joensuu, Finland.

[16] Zhang, X.-D., & Xu, H.-S. (2009). An adaptively spatial color gamut mapping algorithm. *Chinese Optics Letters, 7*(9), 873-877.

[17] Gijsenij, A., Gevers T., & Van De Joost, W. (2010). Generalized gamut mapping using image derivative structures for color constancy. *International Journal of Computer Vision, 86*(2-3), 127-139.

[18] Zofia, B., Peter, Z., & Joachim, G. (2010). Image-individualized gamut mapping algorithms. *Journal of Imaging Science and Technology, 54*(3), 0302011-0302017.

[19] Yang, C.-J., & Chen, Y.-F. (2012, November). Hybrid gamut mapping and dithering algorithm for image reproduction. Paper presented at the Proceedings of 12th International Conference on ITS Telecommunications, Taipei, Taiwan.

[20] Lin, M.-H., Luo, Y.-H., & Zhou, S.-S. (2011). Perceived image gamut based on human visual system and wavelet transform. *Advanced Materials Research, 174*, 16-19.

[21] Chen, S. H., & Azeddine, B. (2011). Improve gamut mapping of color management system by perceptual quality-oriented analysis. In ??(Eds.), *Proceedings of 3rd european workshop on visual information processing* (pp. 12-17). Piscataway, NJ: IEEE.

[22] Wu, H.-W., & Wang, F.-Z. (2014). The research of railway coal dispatched volume prediction based on chaos theory. *Journal of Computers (Taiwan), 24*(4), 44-55.

[23] Du, Y. (2013). A novel algorithm based on improved bp neural network and its application in color management. In L. Barolli, I. You, F. Xhafa, F.-Y. Leu, & H.-C. Chen (Eds.), *Proceedings of 7th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing* (pp. 650-653). Piscataway, NJ: IEEE.

[24] Zhi, C., Li, Z.-J., & Shi, Y. (2013). Research on robustness of color device characteristic methods based on artificial intelligence, *Applied Mechanics and Materials, 262*, 65-68.

[25] Wang, Y., & Xu, H. (2005). Spectral characterization of scanner based on PCA and BP ANN. *Chinese Optics Letters, 3*(12), 725-728.

[26] Liao, N.-F., & Yang, W.-P. (2000). CRT chromatic transformation based on multi-layered BP neural network. *China Image and Graphic Letter, 3*, 470-437.

[27] Huang, Q.-M., & Zhao, D.-Z. (2003). Artificial neural network as the printer color space conversion tools. *Optical Technology, 29*(2), 146-148.

[28] Zhou, S.-Q., & Zhao, D.-Z. (2000). BP Neural network-based printer color control technology. *Optical Technology, 32*(1), 49-51.

[29] Zhao L., & Chen, G.-X. (2014). A printer reverse characterization model based on BP neural network, *Computer Modelling & New Technologies, 18*(3), 133-143.