A printer reverse characterization model based on BP neural network

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Abstract

For colour printer, there are very complicated nonlinear relation between its printed colour chromatic values and input digital image pixel values. In the research, data sets of printed colour chromatic values and their digital image pixel values are classified by hue angle range, the data in each hue angle range is taken as learning samples to create BP neural network. With improved combined method of additional momentum factor and variable learning rate, BP neural network of each hue angle range is trained and created. The experiment result shows that, with appropriate structure and classified learning samples, the reverse characterization model based on ten BP neural networks can be trained in relative short time; the colour errors between the experimental printed colour chromatic values and computed printed chromatic values are far less than the threshold of human eyes, i.e. the reverse characterization model achieves rather high accuracy.

Keywords: BP neural network, Hue angle range, Data classification, Colour management

1 Introduction

The working principle of printer is to output colour according to the input drive value [1]. There are two device models to descript the relationship of the input drive values and the printed colour chromatic values of printer. One is from input drive values to printed colour chromatic values, it predicts printed colour chromatic values according to input drive values, and it is characterization model. Another one is from printed colour chromatic values to input drive values, it lookups input drive values according to printed colour chromatic values; it is reverse characterization model [2]. At present, both the models are mainly based on linear fitting method, polynomial regression method and look-up table method etc. These methods have made a certain effect, in spite of their own limitations. Linear fitting method has low conversion accuracy and practicality [3], the coefficients of polynomial regression method are difficult to determine, and the computation is intensive [4], the look-up table method requires a very large amount of data and high system resources occupancy to create model and to attain its higher accuracy [5].

Printers differs in working principle, interior structure, and driver and so on, so a same digital image pixel is inputted, different printers are likely to show different colours. The colour range represented by printer shows different area sizes and shapes as gamuts [6]. A colour management system adopts both the models [7]. In the research, colour chromatic value is described by CIE 1976 $L^*a^*b^*$ chromatic system.

2 Basic principle of BP neural network

The artificial neural network includes mass interconnected simple components, it is built to achieve a certain function on the basis of mathematics knowledge and how human brain works and constitutes.

2.1 NEURON

Neuron is the basic unit of neural network; it is generally nonlinear component with multi-input and single-output. A typical neuron model is showed in Figure 1, containing R input components and an offset b, the output of activation function f is a. The input of the activation function f includes the input components p_j(j=1, 2, 3…, R) and the weight value component w_j(j=1, 2, 3…, R), the net input of the activation function f is $n=Wp+b$. Wherein, W and p are respectively the vector form of the weight value component w_j and the input component p_j.

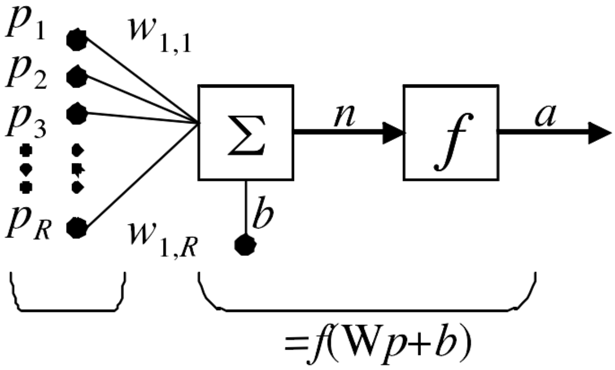

FIGURE 1 Neuron Model

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The vector form of neuron output a is:

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

Typically, the offset b is a fixed constant as 1; it plays an important role in the neural network [8]. In the study, all the BP neural networks contain offset.

2.2 ACTIVATION FUNCTION OF NEURONS

Activation function is the key factor of neurons and neural networks; it controls the activation, conversion and output of neuron input component, and converts infinite input to limited output. It determines the nature and capacity of neurons and neural networks.

Common activation function includes linear function, threshold function, Sigmoid function and hyperbolic tangent function, which can be selected according to the problem to be solved. In the research, nonlinear activation functions are used to convert colour chromatic value to digital image pixel value [9].

2.3 BP NEURAL NETWORK

BP neural network, i.e. back propagation neural network, belongs to feedback neural networks. There is full interconnection between each adjacent layer neurons, but there is no direct connection between neurons of the same layer and between the input and output layers. In its training process, according to the error between the network output and target values, Wildrow-Hoff generalized learning rule is used to modify nonlinear differential function weights repeatedly, until it reaches the set target.

The neurons number of input layer and output layer is determined by specific problems. Besides the input layer and output layer, several hidden layers are introduced to enhance the BP neural network simulation and computing ability. In theory, as long as it has sufficient hidden layers and hidden layers have enough neurons, it can approximate any function or data relationship [10].

3 Experiment

3.1 LEARNING SAMPLE ACQUISITION OF BP NEURAL NETWORK

Based on 24-bit deep BMP format RGB digital image pixel value, colour patches are generated. Pixel values are selected as approximate equal interval of ten points, which are 0, 28, 56, 84, 112, 140, 168, 196, 224 and 255 respectively. By combining the pixel values of the three RGB channels, 1000 patches are shown as Figure 2.

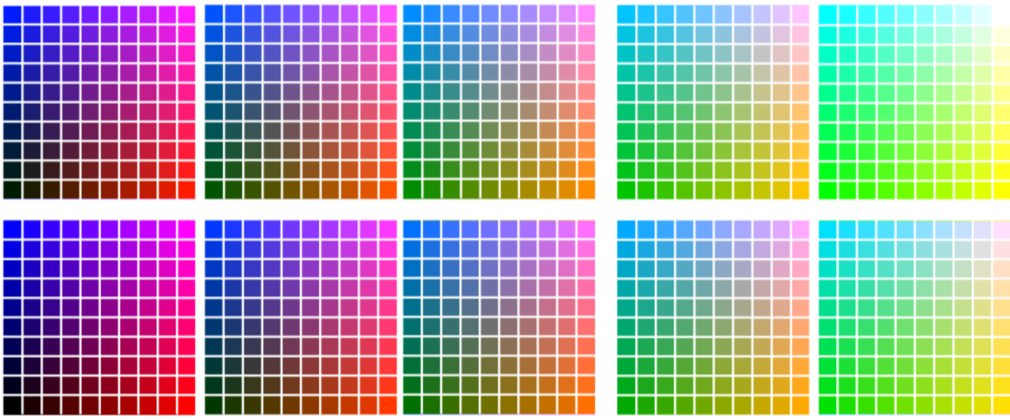


FIGURE 2 Printed Colour Patches

Image with colour patches are printed on photo-printing paper by EPSON Stylus Pro 7600 high-resolution printer, with black, shiny black, magenta, light magenta, green, bright blue, yellow ink, at 720×720dpi resolution. After ink drying, under a D65 illumining 10° visual field, chromatic values of colour patches are measured by X-Rite 528 spectral density meter and recorded as Excel 2003 files.

3.2 DETERMINATION OF BP NEURAL NETWORK STRUCTURE AND TRAINING PARAMETERS

According to BP neural network theory, its simulation and approximation ability are closely related with its hidden layer number and its hidden layer neurons number. In general, the more the hidden layer number and the hidden layer neurons number is, the stronger its data processing and simulation capability is [10]. In the study, BP neural network will convert printed colour patches chromatic values into digital image pixel values. Printed colour patches chromatic values L*a*b* distribute in the range of (0,100), (-120,120) and (-120,120), meanwhile the digital image pixel values RGB distribute in the range of (0,255), (0,255) and (0,255). Both the hidden layer number and the hidden layer neurons number of BP neural network are necessary to be increased appropriately to enhance the simulation and computation ability, to describe the relation between the two data sets with such feature.

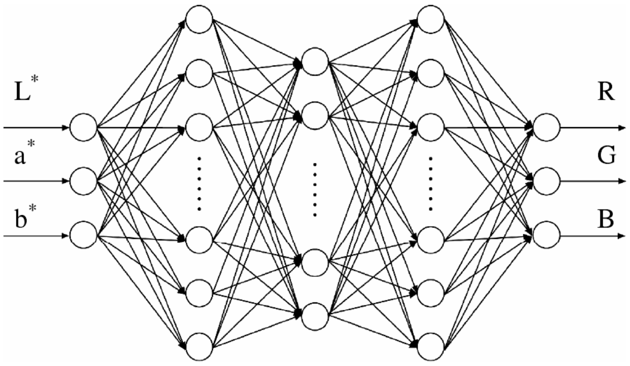


FIGURE 3 BP network structure

In the study, BP neural networks with one hidden layer are not adopted. Referring to the literatures of BP neural network in colour management [11], considering the factors of computing ability and learning sample characteristics, the BP neural network is determined and shown in Figure 3. The neurons of each layers is 3-30-20-30-3. Both the neurons number of input layer and output layer are three, which corresponds to printed colour chromatic value $L^*a^*b^*$ and digital image pixel value RGB respectively. BP neural networks are created by MatLab 12.0 neural network tools, its parameters are shown in Table 1.

TABLE 1 Parameters of BP neural network

Items of BP Neural Network		Parameters
Structure	Input Layer Data	L^* a^* b^*
	Input Neuron Number	3
	Output Layer Data	R G B
	Output Neuron Number	3
Functions	Hidden Layer1	Tansig
	Hidden Layer2	Tansig
	Hidden Layer3	Tansig
	Output Layer	Purelin
Learning Process	LearningFcn	Traingdx
	performFcn	MSE function
	trainParam.lr	0.05
	trainParam.lr_inc	1.05
	trainParam.lr_dec	0.7
	trainParam.max_fail	5
	trainParam.max_perf_inc	1.04
	trainParam.mc	0.9
	trainParam.min_grad	1e-10
	trainParam.epochs	1000000
	trainParam.goal	0.0005
	trainParam.time	Inf
	show	10

3.3 CLASSIFICATION OF LEARNING SAMPLE AND TRAINING OF BP NEURAL NETWORK

3.3.1 Preliminary training and analysis of BP neural network

Under the supervision of learning sample data, the BP neural network is trained by all learning sample in Matlab 12.0. In the training, the objective function error converged slowly for a long time or even stagnated, so that the BP neural network cannot be trained successfully. According to neural network theory and practical experience [12], the BP neural network has stronger capability; but the amount of learning sample is too large to train the network successfully. In addition, how learning samples distribute in three-dimensional space can also explain the reason of training failure. The distribution of printed colour patches chromatic values and pixel values in the three-dimensional space are shown in Figure 4a and Figure 4b respectively. It can be seen from Figure 4, the digital image pixel values distribute in the space of a cube evenly, but printed colour patches chromatic values distribute in the specification space unevenly.

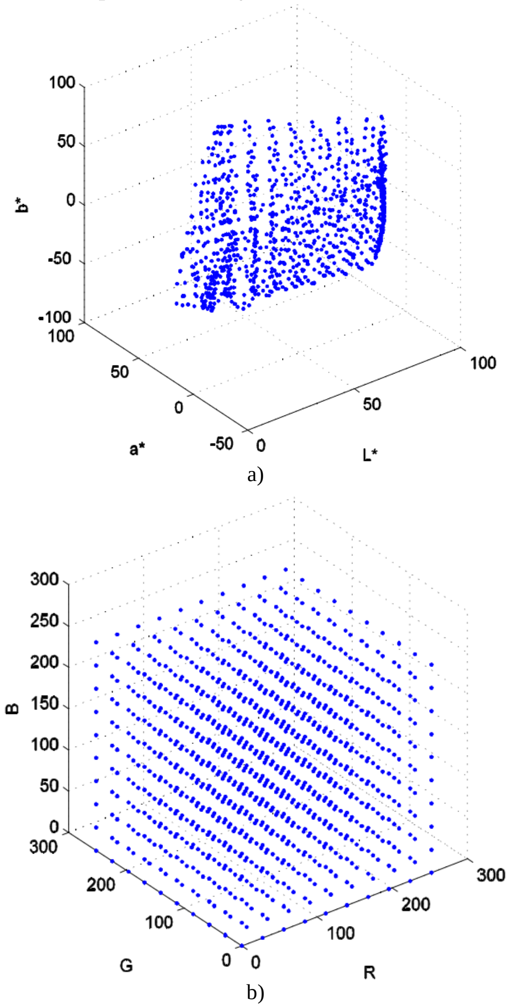


FIGURE 4 Distribution of learning samples in three dimension space: a) Printed colour patches chromatic values; b) Digital image pixel values

Printer reverse characterization model converts printed colour patch chromatic value into pixel value. As can be seen from Figure 4, if a single BP neural network is used to convert unevenly distributed data into evenly distributed data, both the hidden layer number and hidden layer neurons number should be increased. Even if the BP neural network is trained successfully, the neural network training time will increase and the operating efficiency will reduce when the model works.

3.3.2 Learning samples classification by hue angle range

In order to improve the training success rate and shorten the training time, referring to the learning sample classification method by lightness [13], all the learning samples are classified by chromatic value of printed colour patches. Hue angle of learning sample is calculated as formula:

$$\alpha=\tan^{-1}(b^*/a^*). \quad (2)$$

Take L^* axis as centre, for instance, CIE 1976 $L^*a^*b^*$ colour space is divided into 8 equal parts according to hue angle range. The view on the positive direction of the L^* axis is shown in Figure 5, wherein the hatched line portion represents a hue angle range.

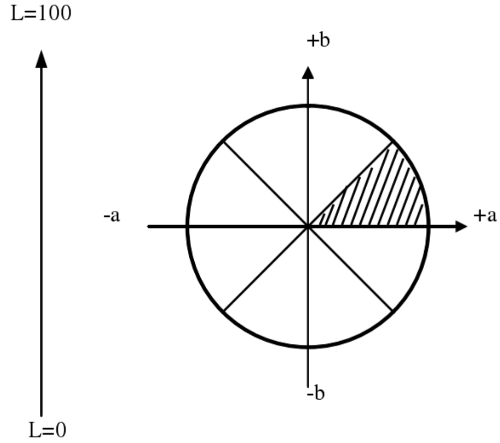


FIGURE 5 Hue angle range

In the study, CIE 1976 $L^*a^*b^*$ colour space is divided into 10 equal parts; each part is taken as the main part of a hue angle range. The hue angle range radian of No. i(i=2, 3, 4 ... 9) is:

$$[2\pi((i-1)/10)-TFactor,\ 2\pi(i)/10)+TFactor], \quad (3)$$

where TFactor is the redundancy factor. It is taken as one tenth of a single hue angle range, i.e. $(1/100)*2\pi$. For instance, the radian of 6th hue angle range is:

$$[2\pi(5/10)-0.02\pi,\ 2\pi(6/10)+0.02\pi]. \quad (4)$$

Meanwhile, the radians of 1st and 10th hue angle range are respectively:

$$[2\pi-0.02\pi,\ 2\pi]\cup[0,\ 2\pi(1/10)+0.02\pi], \quad (5)$$

$$[2\pi(9/10)-0.02\pi,\ 2\pi]\cup[0,\ 0.02\pi]. \quad (6)$$

The redundancy factor is introduced to train network in a relative wider range, and the BP neural network works in relative narrower range, in order to improve neural network accuracy [13].

The learning sample is classified into ten sets, as learning samples of the BP neural networks within each hue angle respectively. Thus, the printer reverse characterization model consists of ten sub-models. When the reverse characterized model is implemented, hue angle is obtained according to formula (2) to determine the hue angle range where printed colour patches chromatic values locates, and then digital image pixels values is calculated by the sub-model which corresponds to the hue angle range.

How the learning samples distribute in the ten hue angle ranges of CIE 1976 $L^*a^*b^*$ colour space is shown in Table 2.

TABLE 2 Distribution of learning samples in each hue angle range

No. of hue angle range	Hue angle range (*Unit: radian*)	Learning samples number
1	$(6.220,2\pi)\cup(0,0.691)$	**75**
2	(0.565,1.319)	**101**
3	(1.193,1.948)	**132**
4	(1.822,2.576)	**232**
5	(2.450,3.204)	**98**
6	(3.078,3.832)	**58**
7	(3.707,4.461)	**53**
8	(4.335,5.089)	**88**
9	(4.964,5.718)	**217**
10	$(0,0.062)\cup(5.592,2\pi)$	**135**

It can be seen from Table 2, due to the introduction of redundancy factor, learning sample amount in all hue angle ranges is 1189, which is more than the learning samples amount 1000. It is because part data is in the hue angle range edged, which belongs to two adjacent hue angle ranges at the same time.

3.3.3 Distribution of classified learning sample in three-dimensional space

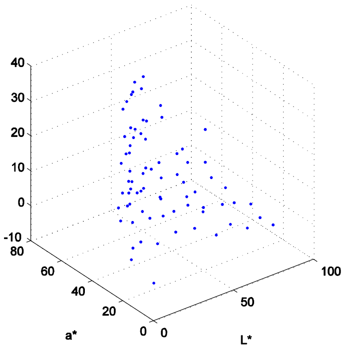
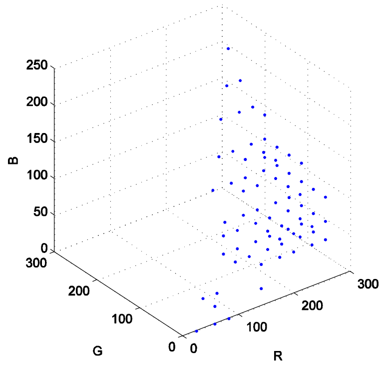
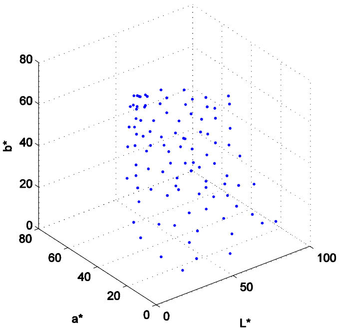
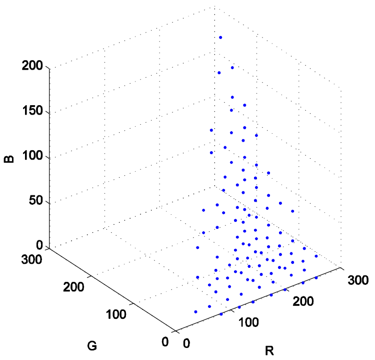
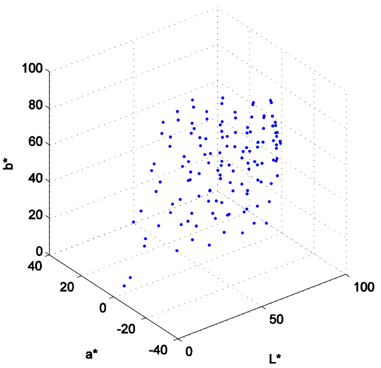
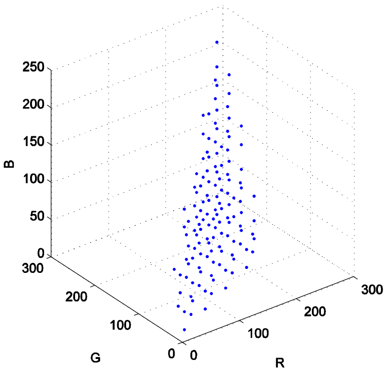
How the 10 sets of learning sample data distribute in three-dimensional space is shown in Table 3. On the view of learning samples distribution in three-dimensional space, the relation of all learning samples is converted into the relation of learning samples in each hue angle range.

4 Experimental results and analysis

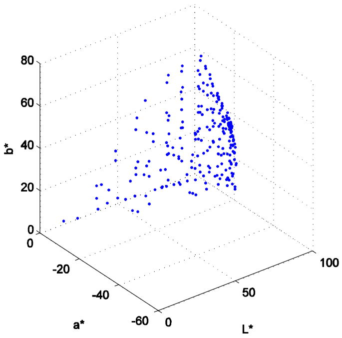
4.1 TRAINING PROCESS EVALUATION OF BP NEURAL NETWORK IN EACH HUE ANGLE

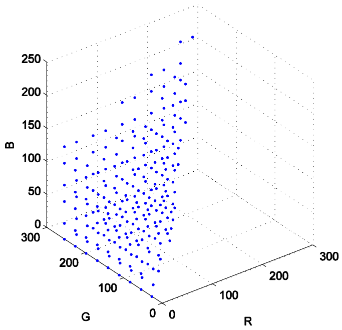
In order to improve the BP neural networks training speed, learning samples in each hue angle range are normalized to the range (-1,1) [13], combined training method of additional momentum factor and variable learning rate are adopted. The training process parameters and training process features of the ten BP neural networks are shown as Table 4 and Table 5.

TABLE 3 Learning Samples distribution in three-dimensional space in each hue angle range

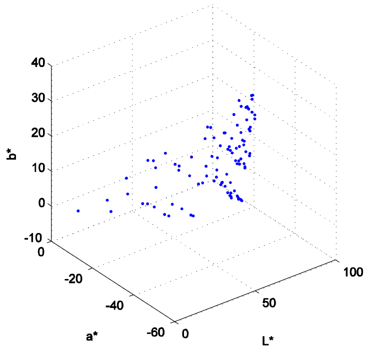
Hue angle range No.	Printed Patches $L^*a^*b^*$ Values	Digital Image Pixel RGB Values
1		
2		
3		

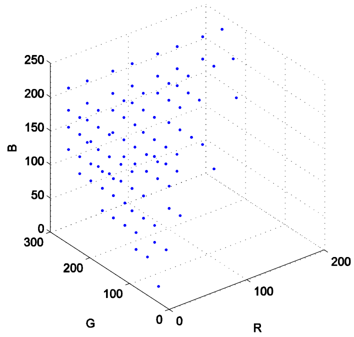
4


b*
0
20
40
60
80
a*
0
-20
-40
-60
L*
0
50
100


B
0
50
100
150
200
250
G
300
200
100
0
R
0
100
200
300

5


b*
-10
0
10
20
30
40
a*
0
-20
-40
-60
L*
0
50
100


B
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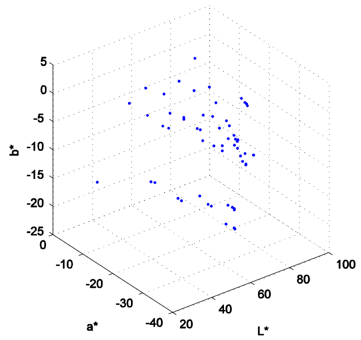
6


b*
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a*
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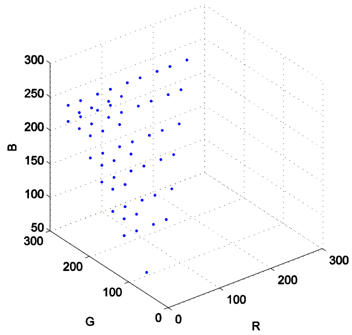
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R
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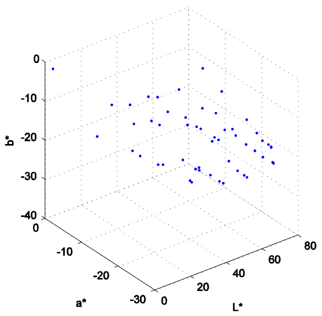
7


b*
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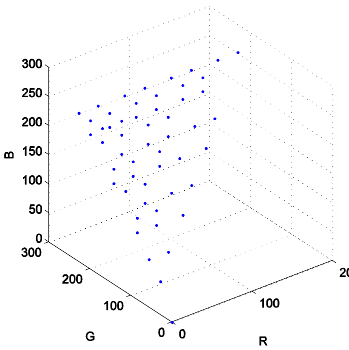
-20
-10
0
a*
0
-10
-20
-30
L*
0
20
40
60
80


B
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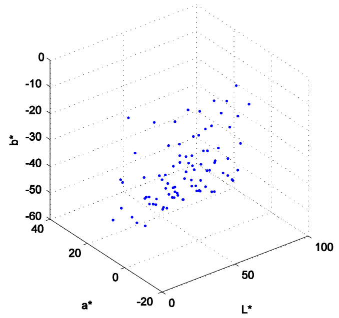
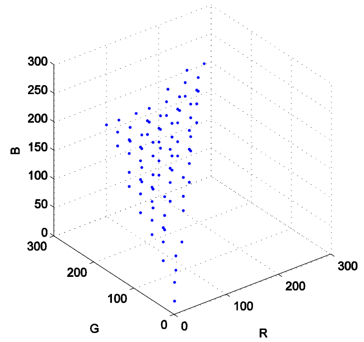
300
G
300
200
100
0
R
0
100
200

8





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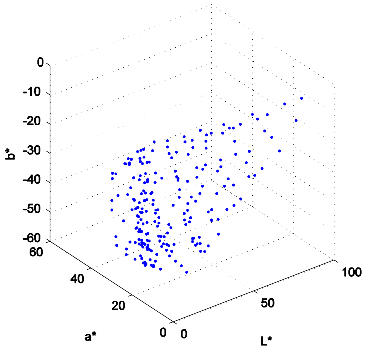

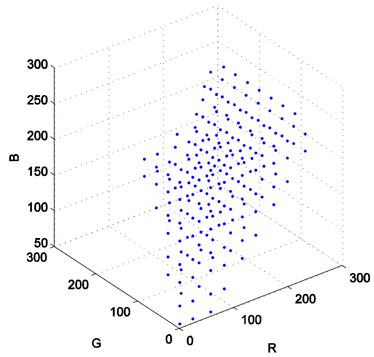

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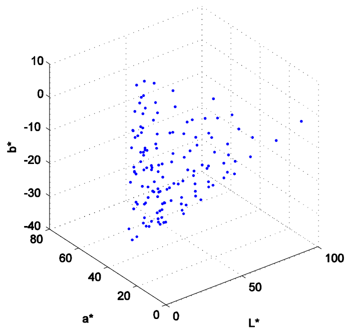


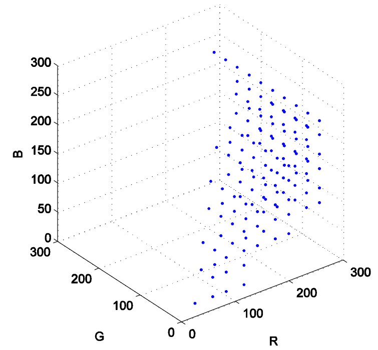
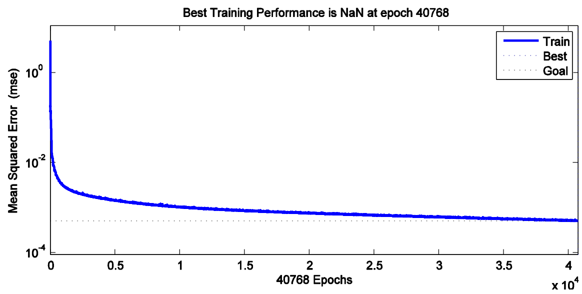
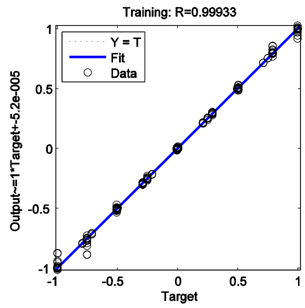
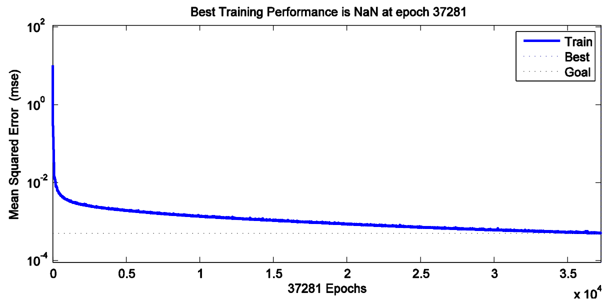
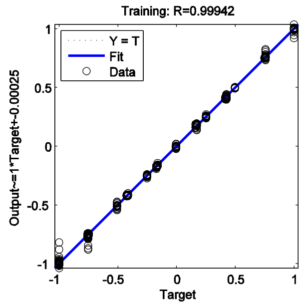
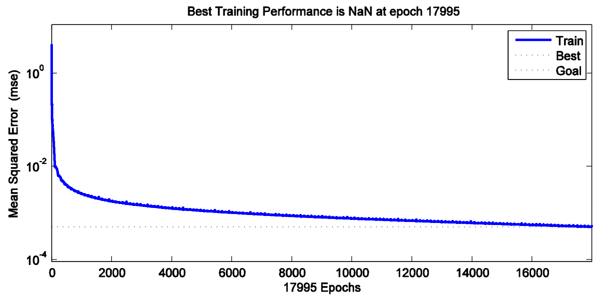
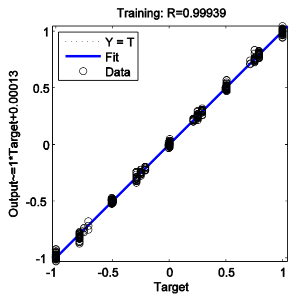
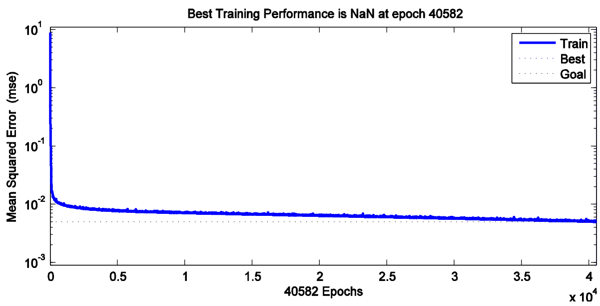
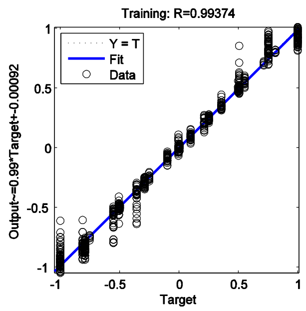


TABLE 4 Training process parameters of the BP neural network of each hue angle range

Hue angle range No.	Epoch number	Training time	MSE function performance
1	40768	0:05:24	5.08
2	37281	0:05:12	10.4
3	17995	0:02:22	4.17
4	40582	0:06:45	8.90
5	39391	0:05:05	8.80
6	70701	0:11:24	4.28
7	19516	0:02:07	5.99
8	41481	0:07:08	3.49
9	143060	0:47:03	5.46
10	224598	1:12:10	4.95

As can be seen from Table 4, all the ten BP neural networks trained successfully, and their training time distribute in the range (0:02:07, 1:12:10). In general, the learning sample amount affects the training time of the neural network directly, so does how the learning samples distribute in three-dimensional space. Take the neural network with shortest and longest training time as example, their training time is 0:02:07 and 1:12:10, their neural network corresponds to the hue angle rang of 7 and 10 respectively. The learning sample amount of the neural network of the shortest training time is indeed the least, it is 53. Meanwhile, the learning sample amount of the neural network of the longest training time is not the most; it is 135, which is far less than that of hue angle range 4. Though the learning sample amount of hue angle range 4 is the most, its training time of is only 0:06:45. So that, how the learning samples distribute in three-dimensional space affects the training time more than the learning sample amount does. Thus, qualitative relationship between the training time and the learning sample distribution in the three-dimensional space can be concluded from Table 4.

TABLE 5 Training process characteristic of the BP neural networks of each hue angle range

Hue angle range No.	MSEREG of the network during learning	Correlation coefficient of target data and output data
1		
2		
3		
4		

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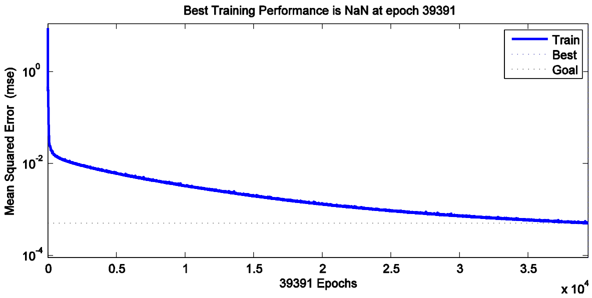
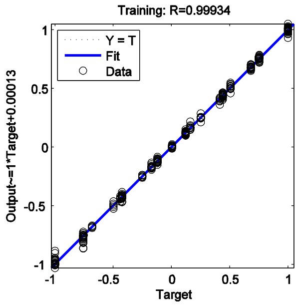
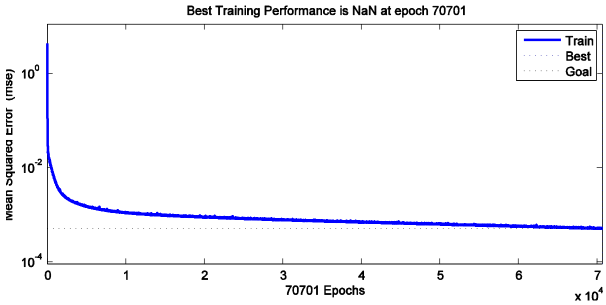
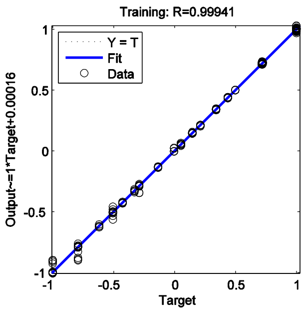

Best Training Performance is NaN at epoch 39391
Train
Best
Goal
Mean Squared Error (mse)
39391 Epochs
x 10^4

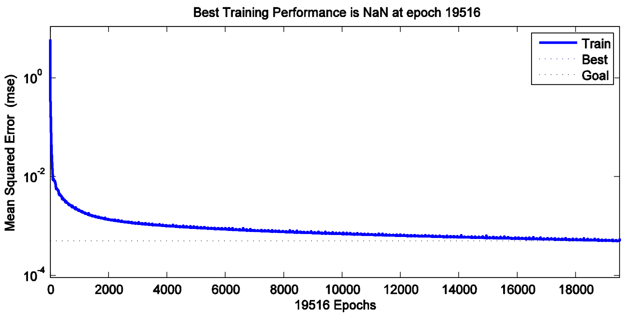

Training: R=0.99934
Y = T
Fit
Data
Output~=1*Target+0.00013
Target

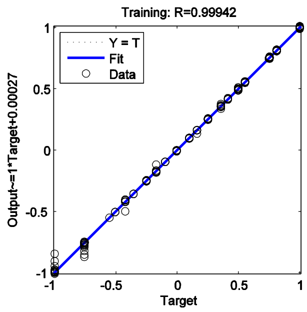
6


Best Training Performance is NaN at epoch 70701
Train
Best
Goal
70701 Epochs
x 10^4

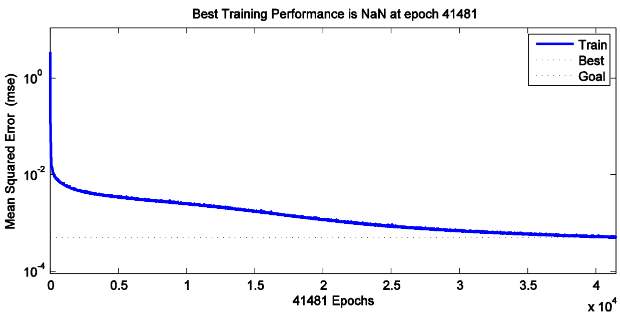

Training: R=0.99941
Y = T
Fit
Data
Output~=1*Target+0.00016
Target

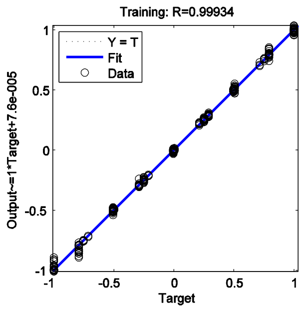
7

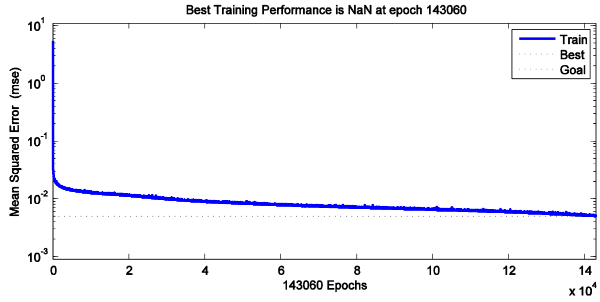
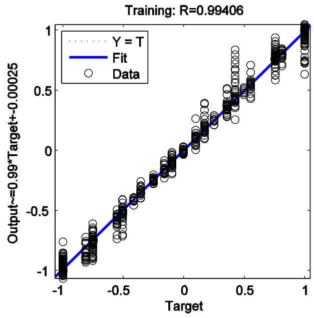
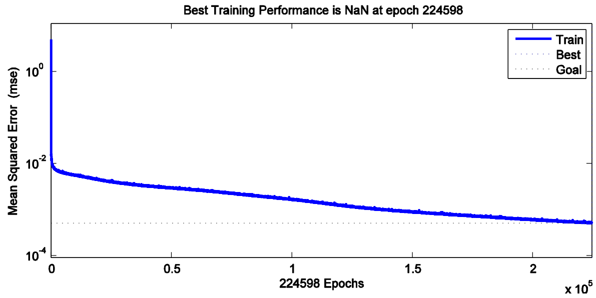
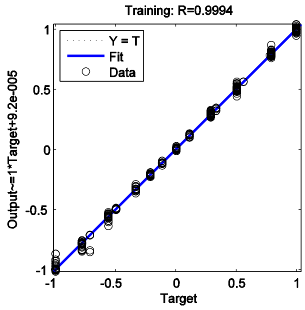

Best Training Performance is NaN at epoch 19516
Train
Best
Goal
Mean Squared Error (mse)
19516 Epochs


Training: R=0.99942
Y = T
Fit
Data
Output~=1*Target+0.00027
Target

8


Best Training Performance is NaN at epoch 41481
Train
Best
Goal
Mean Squared Error (mse)
41481 Epochs
x 10^4


Training: R=0.99934
Y = T
Fit
Data
Output~=1*Target+7.6e-005
Target

9		
10		

As can be seen from Table 4 and Table 5, the learning samples of the networks with shorter training time distribute more concentrated and has a more consistent distribution characteristics. While the learning samples of the networks with longer training time distribute more dispersed, and the distribution characteristics is less consistently, which is the root cause that result in different training time. It is also shown in the MSE functions, i.e. generally, the larger the performance values are and the smaller the learning samples amount are, the shorter the training time is, and vice versa. The more important factor that affects the training time is the distribution characteristics in three-dimensional space of the learning sample.

In addition, from Table 5, to the fitting diagram of BP neural network output value and output learning sample, in spite of all neural network with the same parameters and structure, the processing power of learning samples of different numbers is closely related to the learning samples amount. Limited by the same neural network structure, the training data of BP neural network of hue angle range 4 and 9 with maximum learning sample amount is most dispersed, their fitting is the worst of all the ten BP neural networks, and vice versa, the less the learning sample amount is, the closer the neural network output value and the output learning samples are, i.e. the better the fitting is.

The gradient decline curve of MSE function reflects the complex relationship of the number of iterations epochs, training time and MSE function performance. The smoother the curves are, the shorter the training time is. MSE function also shows relatively good performance, such as the networks in hue angle range 3 and 7, and vice versa, the longer the training time is, such as the networks in hue angle range 9 and 10. The MSE function curves could be used to determine whether training process should be terminated timely and re-started, without spending unnecessary time waiting for the training failure.

4.2 EVALUATION OF PRINTER REVERSE CHARACTERIZATION MODEL

81 sets of chromatic values are selected from the printer gamut randomly, and input into printer reverse characterization model. Colour patches contain calculated pixel values are printed and their chromatic values are measured. The colour errors between colour patches to be printed and the printed colour patches are calculated and shown as Figure 6 according to their colour patches No.. The maximum colour error, minimum colour error and average colour error are 5.126, 0.576 and 2.137 respectively. As can be seen from Figure 6, the colour patches number whose colour error less than 4 is 76, and most of them concentrate within 3. Considering the printer repeatability, printer reverse characterization model shows rather high conversion accuracy.

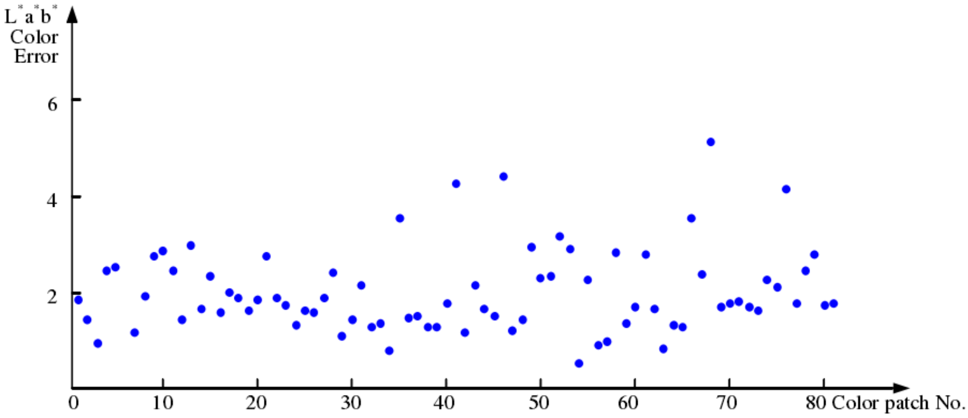


FIGURE 6 Colour error between the colour patches to be printed and the printed colour patches

5 Conclusions

In the study, according to the distribution characteristics of the learning samples in three-dimensional space, the reason why a single BP neural network cannot be trained successfully is analysed. With improved combined training methods of additional momentum factor and variable learning rate, a printer reverse characterization model based on ten BP neural networks is proposed, whose learning samples are classified by hue angle range. The learning sample classified method not only solves the problem of training failure, but also shortens the training time. Due to the good nonlinear approximation characteristics of BP neural network, the reverse characterization model reaches a high accuracy, and the average colour error between the experimental measurement values and the model calculated values is far less than the threshold that the human eye can perceive.

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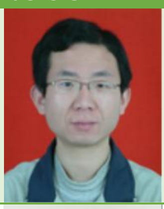

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