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Color texture classification of yarn-dyed woven fabric based on dual-side scanning and co-occurrence matrix

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Abstract

Color texture classification as a part of fabric analysis is significant for textile manufacturing. In this research, a new artificial intelligence method based on a dual-side co-occurrence matrix and a back propagation neural network has been proposed for color texture classification, which could achieve relatively accurate classification results for yarn-dyed woven fabric compared with the traditional co-occurrence matrix for a single-side image. Firstly, a laboratory dual-side imaging system has been established to digitize the upper-side and lower-side images sequentially. Secondly, the dual-side co-occurrence matrix could be generated based on these dual images; four texture features could be extracted for the evaluation of the fabric texture characteristics. Thirdly, a well-trained back propagation neural network was established with the four defined features as the input vectors and the color texture type of yarn-dyed woven fabric as the output vector. The efficiency of two different classification systems based on a dual-side co-occurrence matrix and a single-side co-occurrence matrix has been compared systematically. Our experimental results show that the artificial intelligence system based on a dual-side co-occurrence matrix and back propagation neural network model could achieve a relatively better classification effect, with the high coefficient ratio ($R = 0.9726$) when $d = 0$.

Keywords

color texture, dual-side scanning, dual-side co-occurrence matrix, back propagation neural network, artificial intelligence

Texture, as one of the most important features for the characterization of an image, has been widely applied for image classification and retrieval. However, in some cases grayscale textures cannot provide enough information; color information should be taken into consideration to provide an accurate description of the objects. As a combination of texture information and color information, the color texture could be regarded as a pattern described by the relationship between its chromatic and structural distribution.[1] Among these commonly used approaches, the co-occurrence matrix has been considered to be one of the most popular techniques used to define the texture characteristics of woven fabrics, such as weaving density,[2] fabric defects,[3] fabric appearance,[4] weave pattern,[5] etc.

Some relevant research has been reported for automatic and digital texture analysis. In 2004, Palmer and Wang[6] proposed a new method based on the two-dimensional discrete wavelet transform, which could be used to determine the pilling intensity of fabric images through frequency domain analysis. Kuo and Tsai[7] also proposed a digital approach to identifying the basic weaving pattern of fabrics. It was reported that the wavelet transformation could be used to describe the image texture; the co-occurrence matrix could be applied to evaluate the texture characteristics; and the learning vector quantization networks (LVQN) could be adopted as a classifier to classify the fabric weaving pattern. Zhang et al.[8] used a wavelet transform method to extract texture features of the fiber surface for the purpose of classifying cashmere and superfine

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merino wool fibers. The texture features could be defined to describe the brightness variations caused by the height, shape and interval of cuticular scales. It was reported that the proposed methods were effective for the characterization and classification of different animal fibers. Pan et al.[9] introduced an efficient weave pattern recognition method based on a co-occurrence matrix and back propagation (BP) neural network. A fuzzy C-means (FCM) algorithm was developed to classify the type of yarn floats, and a BP neural network was used to identify woven fabric patterns. It was reported that texture features were defined and extracted based on a white–black co-occurrence matrix and selected as the input variables of the BP neural network used for the determination of weave pattern in their research work.

Although a co-occurrence matrix could describe the essential features of texture in nature, only the image's grayscale information is considered among these methods; therefore, some researchers attempted to extend the study of color texture evaluation, which could be used for both the structural parameters and texture features of colored fabrics. Xin et al.[10] tried to use an active grid model (AGM) to recognize the color pattern of yarn-dyed fabric. In 2010, Pan et al.[11] proposed to use a fuzzy C-means clustering (FCM) algorithm to detect the number of yarn colors and the layout of color yarns in yarn-dyed fabrics. Pan et al.[12] also presented a novel method based on the Hough transform and FCM algorithm to identify the density of the color effect, the layout of color yarns and the woven pattern of yarn-dyed fabric. It was reported that the proposed method was effective for the analysis of the structural parameters of yarn-dyed fabric.

Generally speaking, traditional co-occurrence matrix based methods in previous research has usually studied the characteristics of a single-side image; however, interlaced yarns cannot be observed just from a single side of the surface. Color and texture information extracted from a single-side image of a yarn-dyed woven fabric is not complete and not enough for accurate texture analysis. It is well known that only parts of one single yarn are visible from one side; a reasonable solution is that fabric texture analysis should be based on dual-side images.

In order to improve the accuracy and efficiency of textile analysis for yarn-dyed fabrics, a novel digital method based on dual-side scanning and a co-occurrence matrix has been presented in this paper, for the purpose of color texture classification of yarn-dyed fabrics.

The paper comprises four sections. The first section is the introduction and reference review part; the second section is the methodology part: a laboratory dual-side imaging system is established to capture the upper-side and lower-side images; a newly defined co-occurrence matrix, named the dual-side co-occurrence matrix, describes the characterization of these dual images; a well-trained back propagation neural network model is set up to classify the color texture type of yarn-dyed woven fabric. The third section is the experimental analysis part: the detailed results are reported to illustrate the efficiency of the proposed method, including a comparison between the three-dimensional chart of the dual-side co-occurrence matrix and the single-side co-occurrence matrix. The fourth section is the discussion and conclusion part: some key points are concluded based on the color texture classification results based on the dual-side and single-side co-occurrence matrices.

Methods

Set-up of dual-side image acquisition system

In this research, a new dual-side imaging system used to capture dual-side images of yarn-dyed woven fabric has been established as shown in Figure 1. It has two major functions: (1) one pair of upper-side and lower-side images could then be captured sequentially; (2) image alignment, calibration and matching could then be implemented with accurate location of the reference markers. The presented dual-side imaging system[10] consists of three components: (1) a digital flatbed scanner, which is used to digitalize the dual-side reflective images of yarn-dyed woven fabric sequentially; (2) a sample holder, used to grip the sample with one pair of plates (upper-side and lower-side plates), held in place by four rectangular magnets; four black triangular markers are printed on the surface of each plate, located at each corner of the sampling window; these markers are designed to be reference points for the alignment and calibration of the upper-side and the lower-side images; (3) a personal computer, equipped with self-developed software for image capture and analysis.

A standard workflow for the dual-side imaging process contains the following four steps: (1) put the fabric sample inside the sample holder and flatten it to eliminate internal tensions; (2) align and fasten the sample holder to position the triangular reference points; (3) switch on the flatbed scanner and start image acquisition; (4) flip the sample holder, then repeat steps 1–3.

After the dual-side images are captured using the scanner, the recorded images were transferred to the computer for further processing; the reference markers could then be identified using the following algorithms: (1) the edge of the triangle can be extracted after image segmentation and Sobel edge detection; (2) a Radon

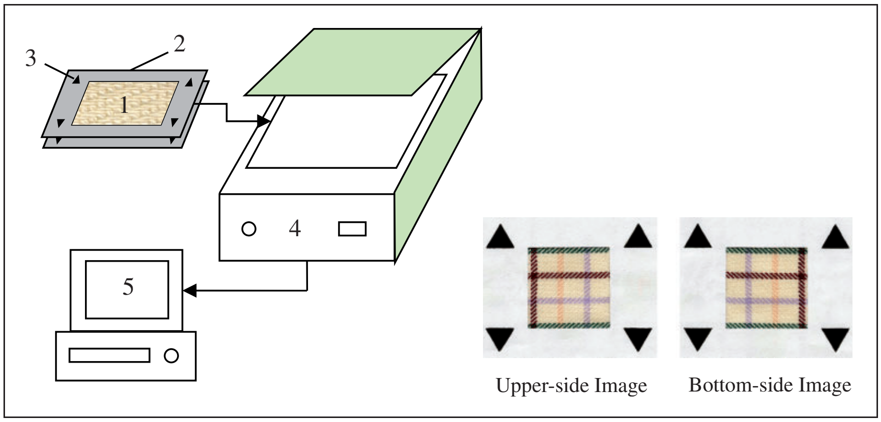

Figure 1. Overview of the dual-side imaging system. 1, Sample; 2, sample holder; 3, reference marker; 4, flat scanner; 5, computer.

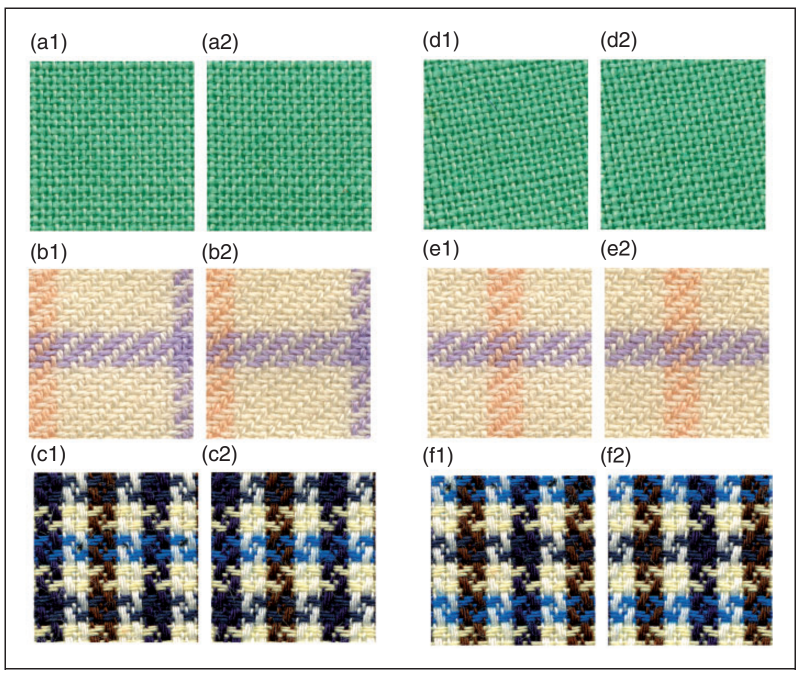

Figure 2. Examples of training and testing color texture pairs. (a1), (a2), (b1), (b2), (c1) and, (c2) are training images; (d1), (d2), (e1), (e2), (f1) and (f2) are test images. (a1) Type1 Upper-side image. (a2) Type1 Lower-side image. (b1) Type2 Upper-side image. (b2) Type2 Lower-side image. (c1) Type3 Upper-side image. (c2) Type3 Lower-side image. (d1) Type1 Upper-side image. (e1) Type2 Upper-side image. (e2) Type2 Lower-side image. (f1) Type3 Upper-side image. (f2) Type3 Lower-side image.

transform was adopted to achieve the equations of three lines $y = kx + b$; (3) the coordinates of the three vertices of the triangle can then be computed; (4) the center of gravity of the triangle can be determined and the location of the reference markers of the dual-side images can be obtained. The upper-side and lower-side images could then be made to accurately correspond with each other using an affine transformation. Ultimately, the images inside the sampling region could then be selected for further color texture classification as shown in Figure 2.

Development of the color texture classification algorithm

Once the upper-side and lower-side images have been aligned and matched at the pixel level, the color texture classification could be carried out using the following procedure (Figure 3). The distance d and the angle θ between two pixels in different images could be set as the parameters to calculate the dual-side co-occurrence matrix. After that, four relevant features, including contrast, correlation, entropy and homogeneity, could

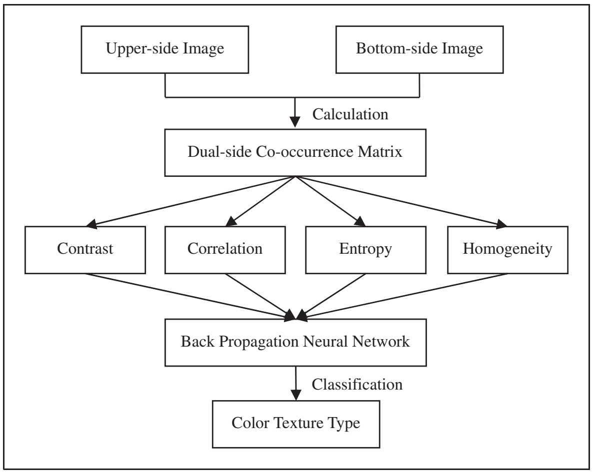

Figure 3. Flowchart of the color texture classification algorithm.

be extracted based on the co-occurrence matrix. The extracted features were input into the back propagation neural network as input vectors and the output vector was the classified color texture type of yarn-dyed woven fabric.

Dual-side co-occurrence matrix. The definition of a traditional co-occurrence matrix usually contains the joint probability of two pixels in a one-side image describing the characterization of the image, which has been considered to be an effective method for texture analysis. Nevertheless, it is impossible to record the texture features of those objects with dual-side surfaces completely through a one-side image. The reason is that only parts of one single yarn can be visible from one-side viewing due to yarn interlacing.[13] In our research, a newly defined co-occurrence matrix, called the dual-side co-occurrence matrix, has been proposed to symbolize the gray level change on the surface of yarn-dyed woven fabric.

Assume that the size of the upper-side image $f(x, y)$ and the lower-side image $g(x, y)$ are both $Nx \times Ny$, and the grayscale is N. Here $f(j, k)$ represents the gray value of the pixel (j, k) in the upper-side image and $g(m, n)$ represents the gray value of the pixel (m, n) in the lower-side image. To identify the pixel-related position, two parameters (θ and d) are defined, where θ is the angle between two pixels, and d is the distance between the two pixels.[14] Considering the warp yarn perpendicular to the weft yarn in the woven fabric, the pixel-related position could be distinguished as the horizontal ($\theta = 0°$), right diagonal ($\theta = 45°$) vertical ($\theta = 90°$) and left diagonal ($\theta = 135°$). These four corresponding positions are defined in equation (1). The co-occurrence matrices are the P functions of the four parameters k, j, d and θ as illustrated in equation (2)

$$\begin{cases} \theta = 0° & R_H(d) : m - j = d,\ n - k = 0 \\ \theta = 45° & R_{RD}(d) : m - j = -d,\ n - k = d \\ \theta = 90° & R_V(d) : m - j = 0,\ n - k = d \\ \theta = 135° & R_{LD}(d) : m - j = d,\ n - k = d \end{cases} \tag{1}$$

$$\begin{cases} P(p,\ q,\ d,\ 0°) = \{R_H(d),\ f(j,\ k) = p,\ g(m,\ n) = q\} \\ P(p,\ q,\ d,\ 45°) = \{R_{RD}(d),\ f(j,\ k) = p,\ g(m,\ n) = q\} \\ P(p,\ q,\ d,\ 90°) = \{R_V(d),\ f(j,\ k) = p,\ g(m,\ n) = q\} \\ P(p,\ q,\ d,\ 135°) = \{R_{LD}(d),\ f(j,\ k) = p,\ g(m,\ n) = q\} \end{cases} \tag{2}$$

Two matrices of the upper-side and lower-side images have been selected as shown in Figure 4(a) and (b). Assume that the size of the image is 4×4 and the grayscale is 8. If $d = 0$, then $m = j$ and $n = k$. When $f(j, k) = 1$, $g(m, n) = 1$, then $P(1, 1) = 4$ and the dual-side co-occurrence matrix can be established as shown in Figure 4(e). If $d = 1$, $\theta = 0°$, then $m = j + 1$ and $n = k$. When $f(j, k) = 2$, $g(m, n) = 2$, then $P(2, 2) = 1$ and the dual-side co-occurrence matrix can be established as described in Figure 4(g). Contrarily, a traditional co-occurrence matrix may be regarded as the single-side co-occurrence matrix corresponding to the joint probability of two pixels in a one-side image, which could be as illustrated in Figure 4(c) and (d) and Figure 4(f) and (h).

The co-occurrence matrix needs to be normalized for the convenience of feature parameter definition.[15] After normalization, the co-occurrence matrix $P(i, j)$ could be defined as equation (3)

$$M(i,\ j) = \frac{P(i,\ j)}{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,\ j)} \tag{3}$$

However, the co-occurrence matrix could not be directly used to describe the image texture characteristics. Four relevant features[16,17] of the co-occurrence matrices have been defined and calculated for the description of texture characteristics. The texture contrast ($I1$) could reflect the diversity of the image texture. A coarse texture shows a lower contrast value than a fine one. The texture correlation ($I2$) could reflect the correlations between textures in different orientations. A coarse texture indicates a higher correlation value than a fine one. The texture entropy ($I3$) could be defined for the description of the texture distribution. A higher entropy value means better regularity in texture. The texture homogeneity ($I4$) could reflect the homogeneity of the image texture. A higher uniformity value indicates a more consistent texture.[4] The specific

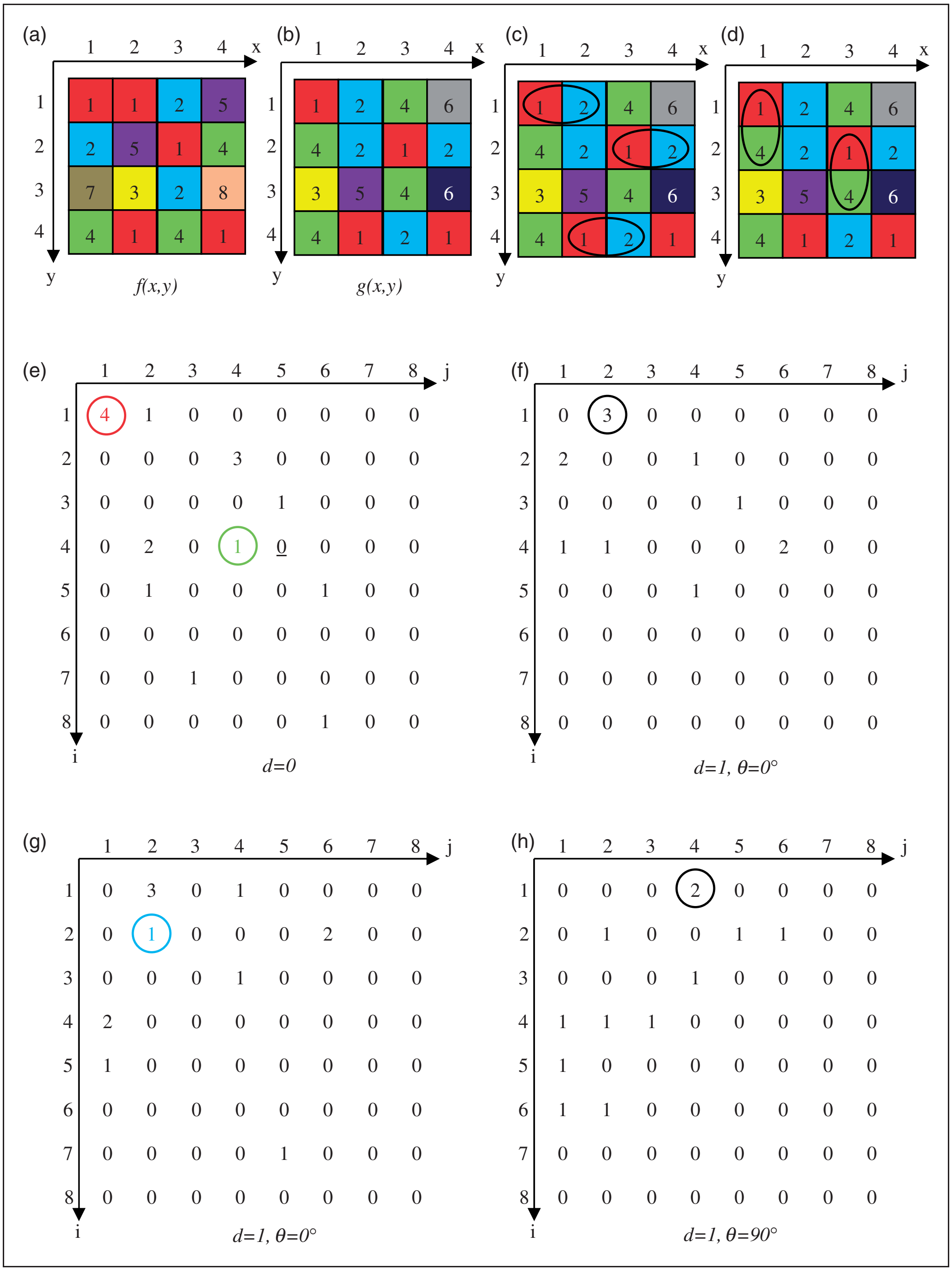

Figure 4. Establishment of the dual-side co-occurrence matrix and the single-side co-occurrence matrix. (a) Upper-side image, $f(x, y)$; (b) lower-side image, $g(x, y)$; (c) single-side image; (d) single-side image; (e) dual-side co-occurrence matrix, $d=0$; (f) single-side co-occurrence matrix, $d=1$, $\theta=0°$; (g) dual-side co-occurrence matrix, $d=1$, $\theta=0°$; (h) single-side co-occurrence matrix $d=1$, $\theta=90°$.

parameters of the dual-side co-occurrence matrix when $d=0$ are shown in Table 1.

BP neural network model. The back propagation neural network (BPNN) is widely used to simulate human judgment behavior, especially for non-linear mappings.[9,18] The typical structure of the BPNN is shown in Figure 5. It can be divided into three layers: input layer, hidden layer and output layer. The basic principle of a BP neural network is to transmit the errors occurring in the output layer back to the hidden layer, and the weighted values in the hidden

Table 1. Values of the parameters for the dual-side co-occurrence matrix

Type	Samples	Contrast $d = 0$	Correlation $d = 0$	Entropy $d = 0$	Homogeneity $d = 0$
1	1	856.01054	0.11676	0.000190261	0.09345
1	2	843.58218	0.12743	0.000191736	0.09620
1	3	776.85190	0.18041	0.000207684	0.09617
1	4	803.20641	0.14704	0.000203125	0.09497
1	5	829.51253	0.09155	0.000210200	0.09525
1	6	777.77284	0.15633	0.000215501	0.09950
1	7	741.69487	0.17488	0.000209474	0.09853
1	8	751.62024	0.16062	0.000210483	0.09785
1	9	781.88533	0.17562	0.000211166	0.09961
1	10	749.57024	0.15692	0.000208343	0.09940
1	11	760.90285	0.15392	0.000207684	0.09819
1	12	773.31302	0.12469	0.000212160	0.09703
1	13	763.35838	0.16165	0.000207753	0.09866
1	14	769.42906	0.14286	0.000207451	0.09779
1	15	782.71686	0.19598	0.000191469	0.09689
2	16	7505.03636	0.36054	0.000751537	0.06295
2	17	4174.48541	0.42595	0.000108952	0.07831
2	18	1027.46103	0.19829	0.000152742	0.08831
2	19	4034.48143	0.43526	0.000110170	0.07464
2	20	1543.38530	0.29370	0.000111627	0.08169
2	21	4092.55641	0.40418	0.000116259	0.07840
2	22	7428.88583	0.34771	0.000800945	0.06235
2	23	4601.26799	0.45027	0.000108740	0.07543
2	24	996.18253	0.20448	0.000154540	0.09180
2	25	4919.13645	0.45620	0.000108974	0.07668
2	26	1500.50214	0.30235	0.000116643	0.08358
2	27	1037.34625	0.16984	0.000149561	0.08862
2	28	1513.54312	0.29775	0.000112353	0.08204
2	29	1504.30060	0.29738	0.000112277	0.08290
2	30	8232.62630	0.43120	0.000582873	0.05945
3	31	4115.90175	0.40762	0.000885455	0.07352
3	32	4247.86191	0.44858	0.000791477	0.06967
3	33	4642.51175	0.43682	0.000902494	0.07290
3	34	4917.89813	0.45844	0.000720659	0.06793
3	35	1352.53358	0.35369	0.000112490	0.08414
3	36	4728.74715	0.45429	0.000853685	0.06940
3	37	4937.71871	0.46195	0.000720658	0.06674
3	38	6877.82799	0.33630	0.000597073	0.05746
3	39	6914.20346	0.33128	0.000592451	0.05932
3	40	6910.36697	0.32940	0.000601287	0.05762
3	41	6945.63864	0.32872	0.000606262	0.05821
3	42	6655.08784	0.37174	0.000481819	0.05438
3	43	7543.13869	0.43628	0.000531660	0.05760
3	44	4075.43782	0.43804	0.000746644	0.06686
3	45	4333.27300	0.43015	0.000602078	0.06280

layer can then be adjusted using the errors. The weighted values of the input layer can then be revised using the errors occurring in the hidden layer.[9]

Following feature characterization, the normalization process is expressed in equation (4). It can be accomplished to eliminate the influence of singular data before data input

$$Q_i = \frac{Q_i - Q_{\min}}{Q_{\max} - Q_{\min}} \tag{4}$$

where Q_i represents the value of the texture feature, $Q_{\max}$ represents the maximum of the selected feature and $Q_{\min}$ represents the minimum of the selected feature.

Subsequently, the BPNN could be established as the total output to the jth neuron of the hidden layer as given by equation (5)

$$\begin{cases} y_j = f(\mathrm{net}_j) & j = 1, 2, \ldots, m \\ \mathrm{net}_j = \sum_{i=0}^{n} v_{ij} x_i & j = 1, 2, \ldots, m \end{cases} \tag{5}$$

where y_j is output of the jth neuron in the hidden layer and v_{ij} is the connection weight between the jth neuron in the hidden layer and the ith neuron in the input layer. The activation function is

$$f(\mathrm{net}_j) = \frac{1}{1 + e^{-\mathrm{net}_j}} \tag{6}$$

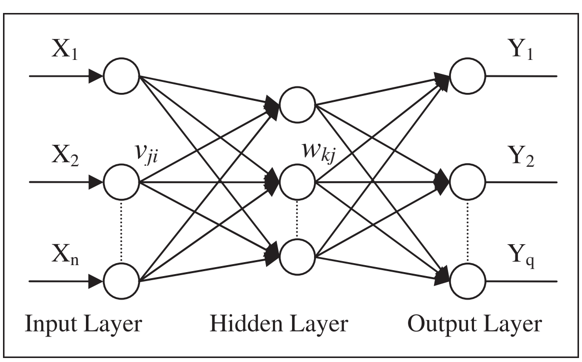

Figure 5. Structure of the BP neural network.

The total output to the kth neuron of the output layer is given by equation (7)

$$\begin{cases} o_k = f(\mathrm{net}_k) & k = 1, 2, \ldots, l \\ \mathrm{net}_k = \sum_{j=0}^{m} w_{jk} y_j & k = 1, 2, \ldots, l \end{cases} \tag{7}$$

where o_k is output of the kth neuron in the output layer and w_{jk} is the connection weight between the kth neuron in the output layer and the jth neuron in the hidden layer. The activation function is

$$f(\mathrm{net}_k) = \mathrm{net}_k \tag{8}$$

The back propagation algorithm was developed to adjust the connection weights in the network in each step, to minimize the mean-square error (MSE) between the predicted value and the actual value of the network,[19] MSE can be defined as the performance function by equation (9)

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (P_i - Y_i)^2 \tag{9}$$

where P_i is a vector of n predictions and Y_i is the vector of the actual values.

On the strength of the co-occurrence matrix analysis, a two-layer BPNN system has been built for classifying the color texture type of yarn-dyed woven fabric as shown in Figure 6, with four neurons in the input layer, four neurons in the hidden layer and one neuron in the output layer. $I1$, $I2$, $I3$ and $I4$ are included as four input variables, and the color texture type of yarn-dyed woven fabric is set to be the output variable. LOGSIG is selected as the activation function of four neurons of the first layer and PURELIN is selected as the activation function of one neuron of the second layer. The network is trained for a maximum of 1000 steps with a learning speed of 0.05. The scaled conjugate gradient is used as the weight learning algorithm and the convergence condition is reached when the error mean square (MSE) is less than 1×10^{-3}.

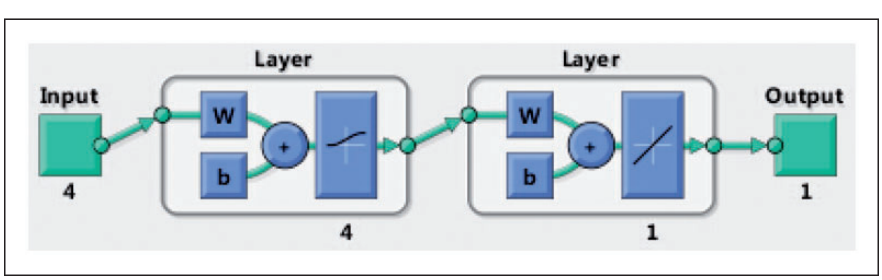

Figure 6. Design of the back propagation neural network.

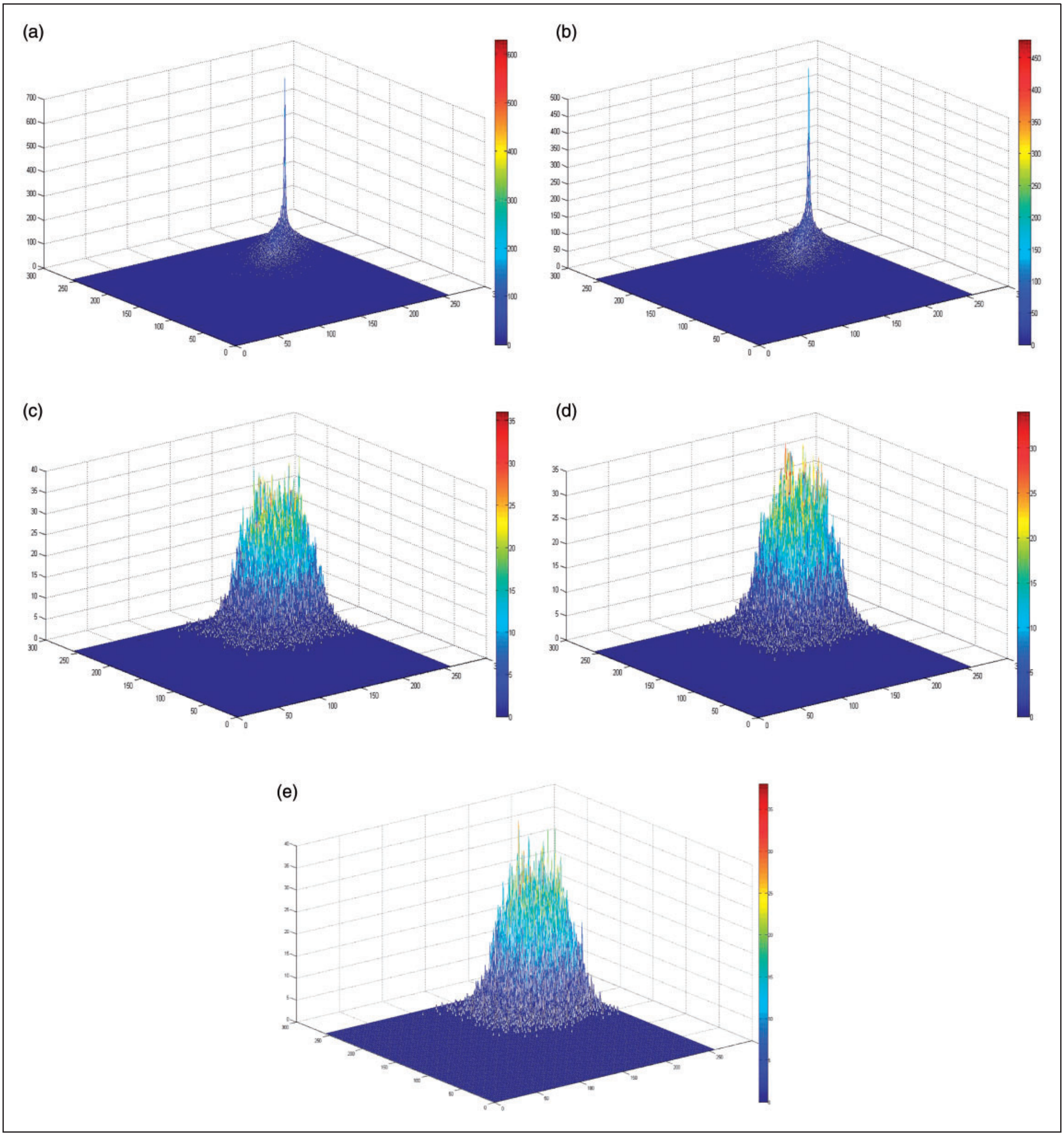

Figure 7. Co-occurrence matrices for type 1. (a) $d = 1$, $\theta = 90^\circ$, single-side co-occurrence matrix; (b) $d = 1$, $\theta = 0^\circ$, single-side co-occurrence matrix; (c) $d = 1$, $\theta = 90^\circ$, dual-side co-occurrence matrix; (d) $d = 1$, $\theta = 0^\circ$, dual-side co-occurrence matrix; (e) $d = 0$, dual-side co-occurrence matrix.

Results

The co-occurrence matrices for the single-side image and the dual-side images can be demonstrated with the aid of a three-dimensional chart as shown in Figures 7–9; the vertical coordinate represents the frequency of occurrence of a grayscale pair. It was found in our research that the co-occurrence matrix for dual-side images contains more information than the co-occurrence matrix for single-side images. It was also found that different color texture types correspond to different shapes of co-occurrence matrices, and the dual-side co-occurrence matrix could be used to classify color textures.

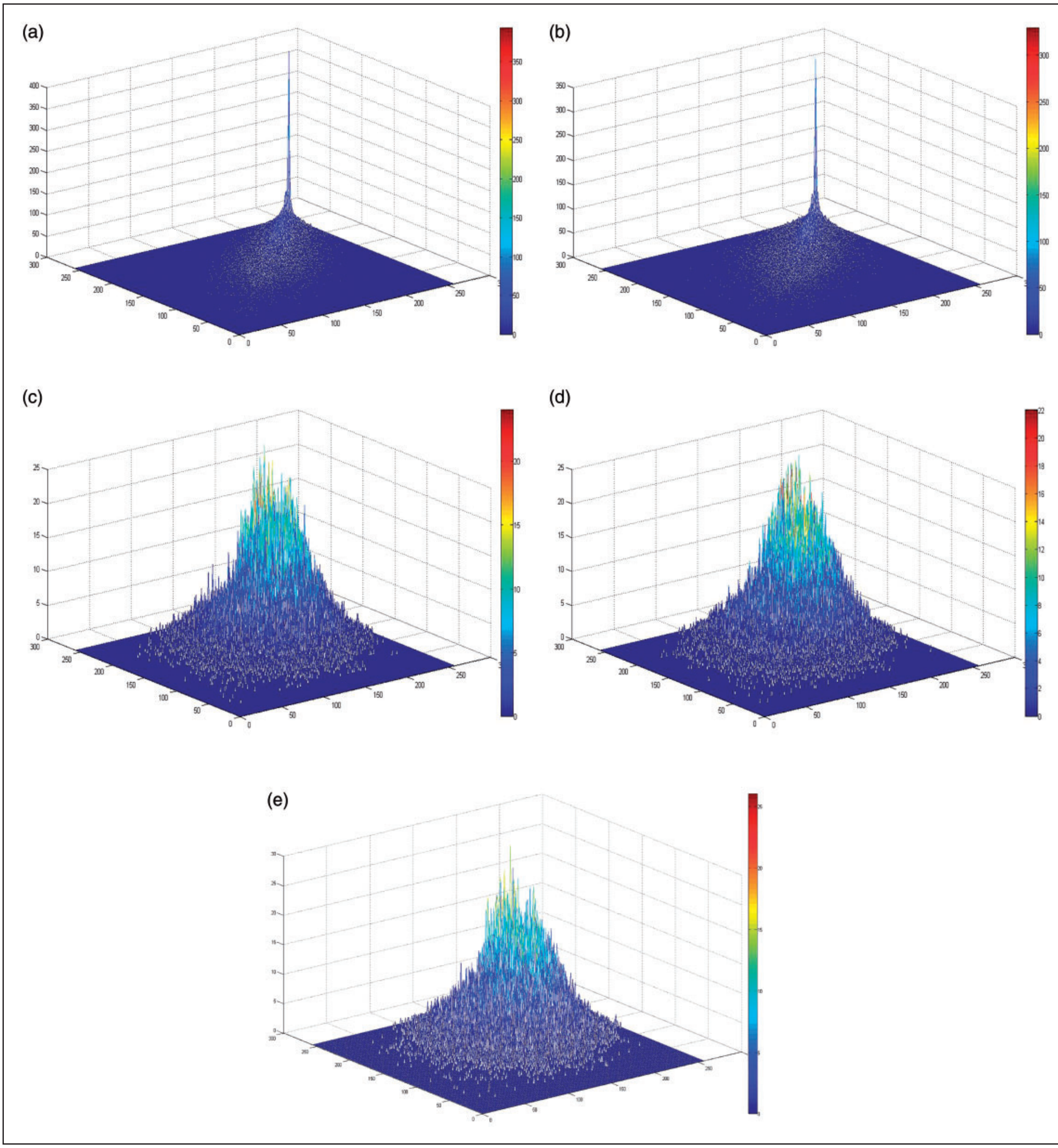

Figure 8. Co-occurrence matrices for type 2. (a) $d = 1$, $\theta = 90^\circ$, single-side co-occurrence matrix; (b) $d = 1$, $\theta = 0^\circ$, single-side co-occurrence matrix; (c) $d = 1$, $\theta = 90^\circ$, dual-side co-occurrence matrix; (d) $d = 1$, $\theta = 0^\circ$, dual-side co-occurrence matrix; (e) $d = 0$, dual-side co-occurrence matrix.

The BPNN model for color texture classification has been trained using a training set including 45 fabric samples, whose color texture types range from type 1 to type 3. Among the training set there are 15 samples classified into type 1, 15 samples classified into type 2 and the other 15 samples classified into type 3. The training process was terminated at a point where all of the training samples could be correctly identified. Since the parameters extracted from the co-occurrence matrix have been input into the neural network model, the training process runs until the MSE approximates the goal set in advance; the performance of the model on the training data set can be seen in Figure 10, and the final MSE is nearly 0.00356. In addition, the

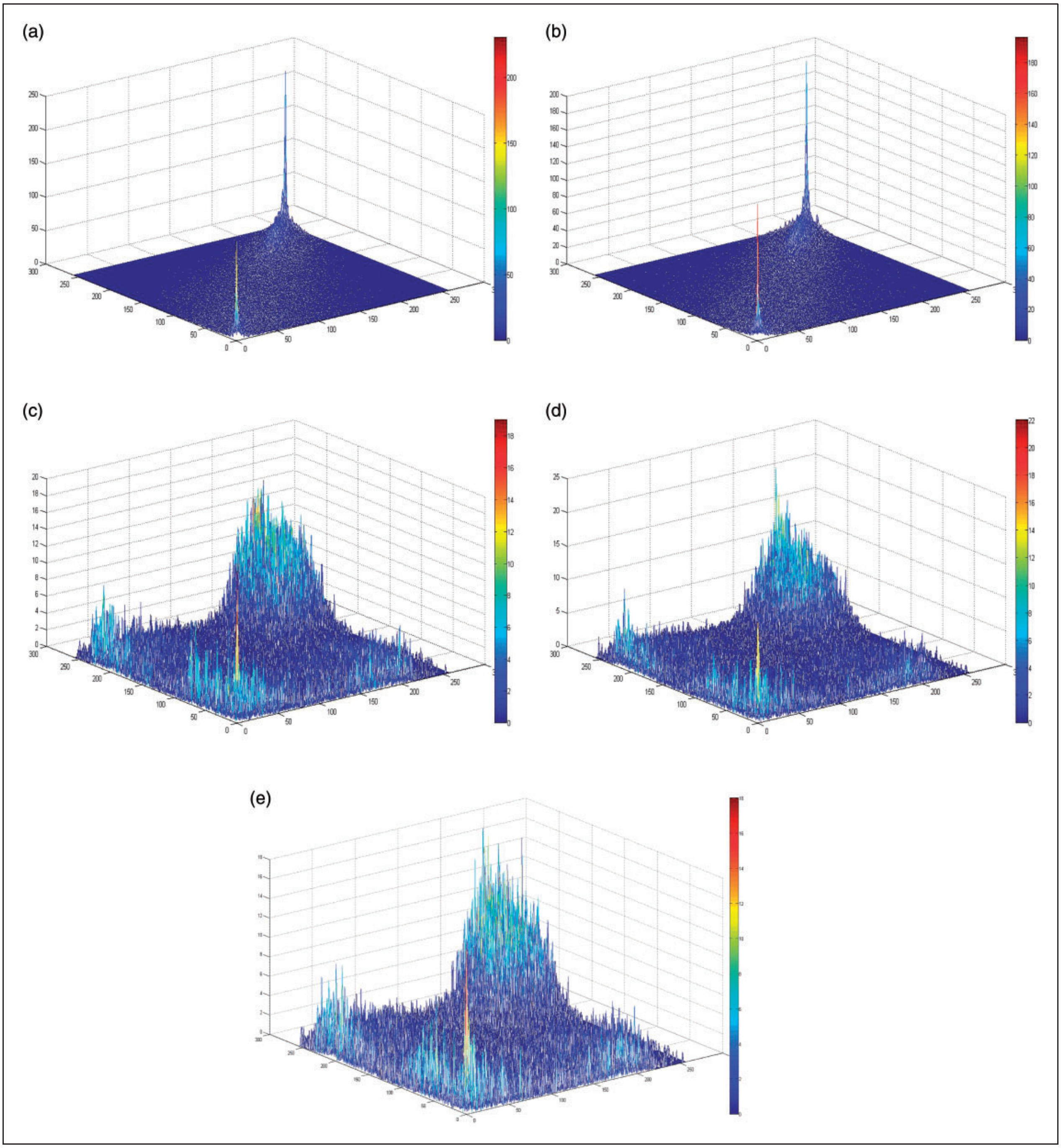

Figure 9. Co-occurrence matrices for type 3. (a) $d = 1$, $\theta = 90^\circ$, single-side co-occurrence matrix; (b) $d = 1$, $\theta = 0^\circ$, single-side co-occurrence matrix; (c) $d = 1$, $\theta = 90^\circ$, dual-side co-occurrence matrix; (d) $d = 1$, $\theta = 0^\circ$, dual-side co-occurrence matrix; (e) $d = 0$, dual-side co-occurrence matrix.

residual values between the predicted outputs of color texture types and the target actual values based on the neural network model are shown in Figure 11, ranging from −0.25 to 0.25.

After the neural network model has been trained, a test data set of another 45 samples has been used to evaluate the performance of the artificial expert system. The experimental results show that the predicted outputs of color texture types exhibit high consistency with the actual values; the established neural network system can achieve good classification results compared with human evaluation; the correlation coefficient between the predicted value and the actual value can be represented by R as well illustrated in Figure 12.

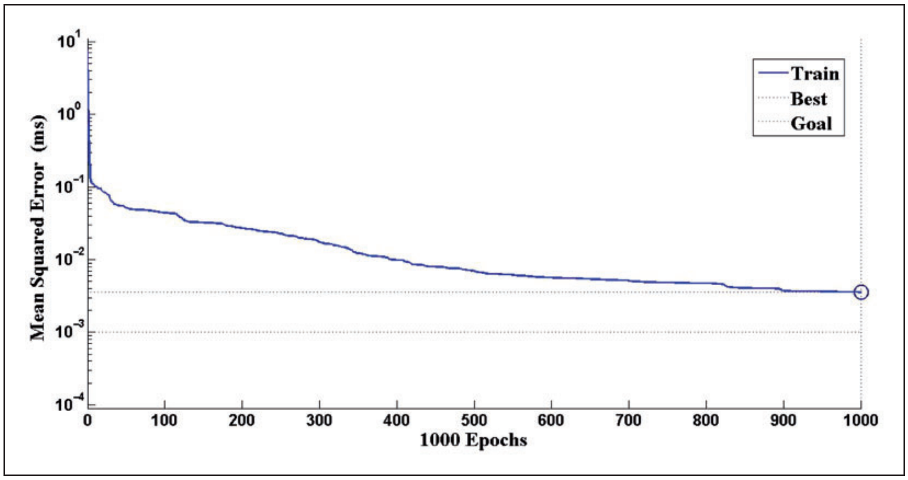

Figure 10. Neural network training processing. Best training performance is 0.0035609 at epoch 1000.

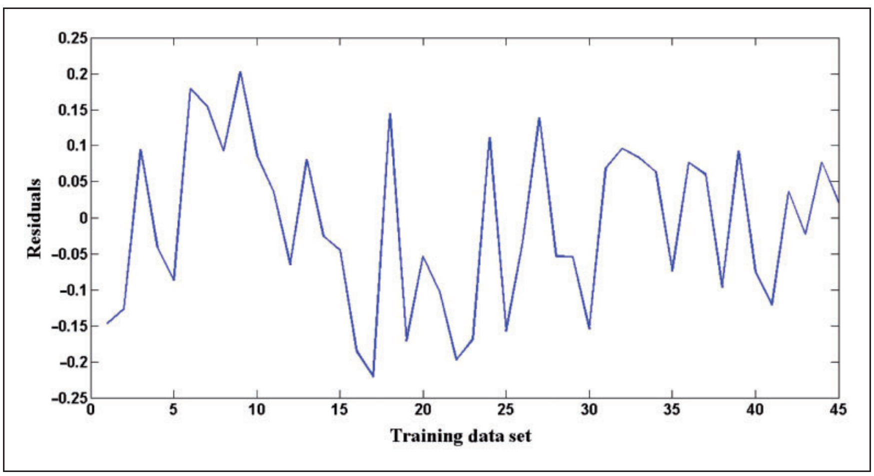

Figure 11. Training performance of the neural network.

Discussion and conclusions

A novel objective and artificial method based on dual-side scanning, a co-occurrence matrix and a neural network has been developed for the classification of color texture. A laboratory dual-side imaging system has been designed to capture upper-side and lower-side images. After that, the dual-side co-occurrence matrix can be calculated. Four relevant features, such as contrast, correlation, entropy and homogeneity, have been extracted so as to describe the image characteristics. To classify the color texture type of the yarn-dyed woven fabric, a well-trained back propagation neural network model has been established with four extracted features as the input vectors and the color texture type as the output vector. The test results for validation show that the predicted values are consistent with the actual values.

According to the correlation coefficient results, it was found that the color texture classification results based on the dual-side co-occurrence matrix works better than a single-side co-occurrence matrix; a co-occurrence matrix with the parameter $\theta = 0^\circ$ achieves a better classification effect than a co-occurrence matrix with the parameter $\theta = 90^\circ$. The artificial intelligence system based on the dual-side co-occurrence matrix and BP neural network model achieves a better classification effect ($R = 0.9726$) when $d = 0$.

Although the dual-side co-occurrence matrix has a better performance than the traditional method for the color texture classification of yarn-dyed fabrics, how to develop an industrial prototype of the robust, reliable and accurate artificial intelligence system to replace the traditional subjective evaluation method based on the human eye is still necessary, and will be the focus of our next research.

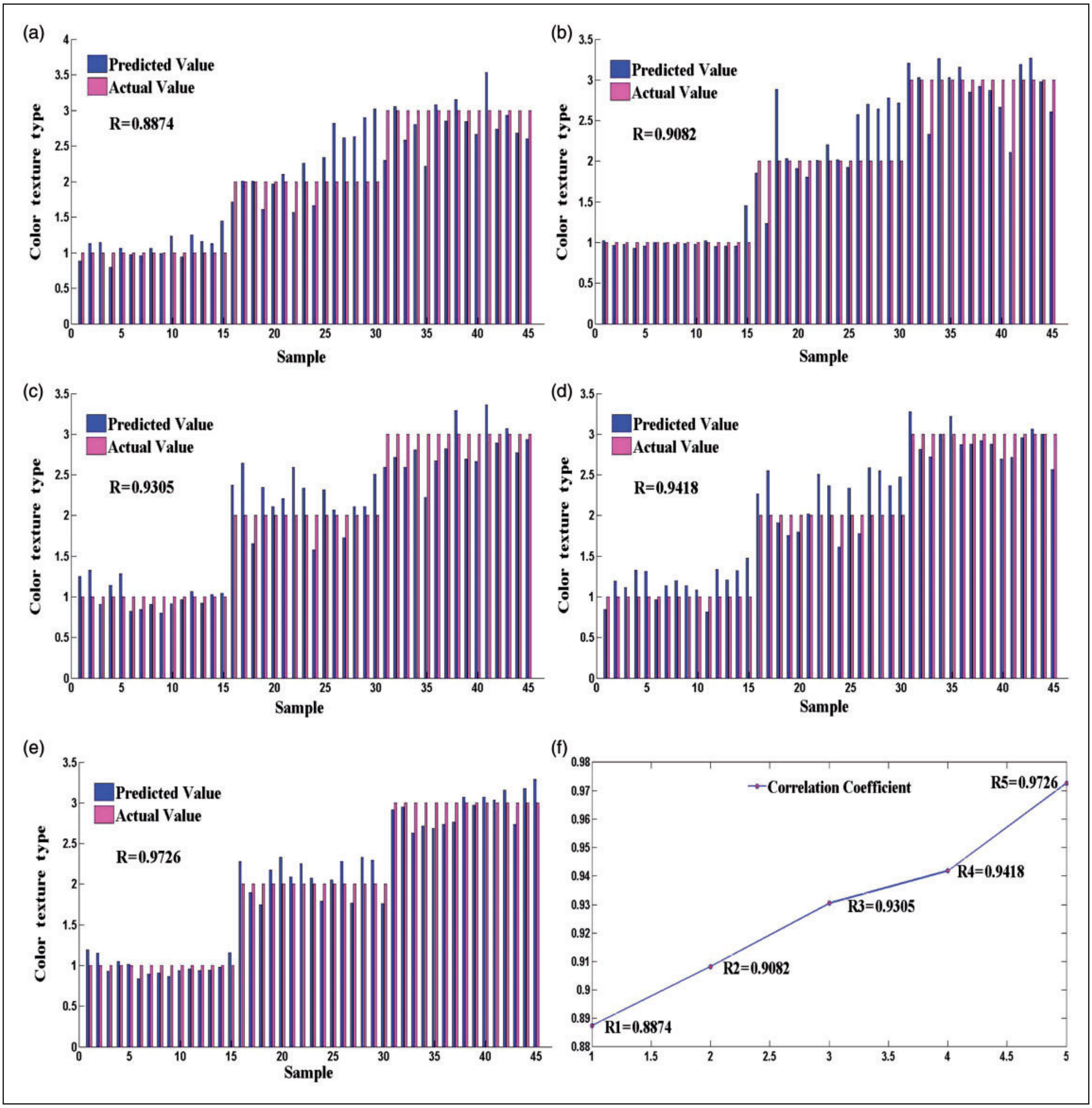

Figure 12. Validation of the neural network model. (a) $d = 1$, $\theta = 90°$, validation of the single-side co-occurrence matrix; (b) $d = 1$, $\theta = 0°$, validation of the single-side co-occurrence matrix; (c) $d = 1$, $\theta = 90°$, validation of the dual-side co-occurrence matrix; (d) $d = 1$, $\theta = 0°$, validation of the dual-side co-occurrence matrix; (e) $d = 0$, validation of the dual-side co-occurrence matrix; (f) correlation coefficient results based on the five validations.

Declaration of conflicting interests

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References

1. Benčo M and Hudec R. Novel method for color textures features extraction based on GLCM. *Radioengineering* 2007; 4: 64–67.

2. Lin JJ. Applying a co-occurrence matrix to automatic inspection of weaving density for woven fabrics. *Text Res J* 2002; 72: 486–490.
3. Kuo CFJ and Su TL. Gray relational analysis for recognizing fabric defects. *Text Res J* 2003; 73: 461–465.
4. Xin BJ, et al. Texture modelling of fabric appearance evaluation based on image analysis. *Fibres Text East Euro* 2012; 20: 48–52.
5. Wang X, Georganas ND and Petriu EM. Fabric texture analysis using computer vision techniques. *Instrum Meas* 2010; 60: 44–56.
6. Palmer S and Wang XG. Evaluating the robustness of objective pilling classification with the two-dimensional discrete wavelet transform. *Text Res J* 2004; 74: 140–145.
7. Kuo CFJ and Tsai CC. Automatic recognition of fabric nature by using the approach of texture analysis. *Text Res J* 2006; 76: 375–382.
8. Zhang JM, Palmer S and Wang XG. Identification of animal fibers with wavelet texture analysis. *World congress on engineering (WCE2010)*. Vol 1, London, UK: America Institute of Physics, 2010, pp.742–747.
9. Pan RR, et al. Automatic recognition of woven fabric pattern based on image processing and BP neural network. *J Text Inst* 2011; 102: 19–30.
10. Xin BJ, et al. Investigation on the classification of weave pattern based on an active grid model. *Text Res J* 2009; 79: 1123–1134.
11. Pan RR, Gao WD, Liu JH, et al. Automatic detection of structure parameters of yarn-dyed fabric. *Text Res J* 2010; 80: 1819–1832.
12. Pan RR, Gao WD, Liu JH, et al. Automatic detection of the layout of color yarns for yarn-dyed fabric via a FCM algorithm. *Text Res J* 2010; 80: 1222–1231.
13. Jing J, et al. Automatic classification of woven fabric structure based on texture feature and PNN. *Fiber Polym* 2014; 15: 1092–1098.
14. Ben Salem Y and Nasri S. Texture classification of woven fabric based on a GLCM method and using multiclass support vector machine. *International Multi-Conference on Systems, Signals and Devices*. Djerba, Tunisia, 23–26 March 2009, pp. 1–8.
15. Kuo CFJ, et al. Application of computer vision in the automatic identification and classification of woven fabric weave patterns. *Text Res J* 2010; 80: 2144–2157.
16. Haralick RM, Shanmugam K and Dinstein IH. Textural features for image classification. *IEEE Trans Syst Man Cybern* 1973; 6: 610–621.
17. Jing J, Wang J, Li P, et al. Automatic classification of woven fabric structure by using learning vector quantization. *Proc Eng* 2011; 15: 5005–5009.
18. Liu JL and Zou BQ. Identification of fabric defects based on discrete wavelet transform and back-propagation neural network. *J Text Inst* 2007; 98: 355–362.
19. Kuo CFJ, Jian BL, Tung CP, et al. Automatic machine embroidery image color analysis system, part II: Application of the genetic algorithm in search of a repetitive pattern image. *Text Res J* 2012; 82: 1099–1106.