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Self-organizing Map Network for Automatically Recognizing Color Texture Fabric Nature

Chung-Feng Jeffrey Kuo* and Chih-Yuan Kao

Department of Polymer Engineering, National Taiwan University of Science and Technology, Taipei, 106, Taiwan, Republic of China

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Abstract: The method of recognizing color texture brought forth in the present study is to employ unsupervised learning network to automatically recognize the fabric type and the main texture types. Firstly, the color scanner is adopted to extract fabric image which is afterwards saved as the digital image. Secondly, *CIE-Lab* color model is taken to obtain the feature value and wavelet transform is utilized to display the texture of the fabric image. Thirdly, co-occurrence matrix is employed to figure out the feature values of the texture structure such as angular second moment, entropy, homogeneity, contrast. Finally, self-organizing map (SOM) network is used as the classifier. The experiment result shows that the study can automatically and accurately classify the fabric types (including shuttle-woven fabric, jersey fabric and non-woven fabric) and main texture type of the fabric (such as plain weave, twill weave, satin weave, single jersey, double jersey and non-woven fabric).

Keywords: Wavelet transform, Co-occurrence matrix, Self-organizing map (SOM) network

Introduction

With the development and the application of high technology, computers are found in wide application to textile industry in order to reduce cost and improve both capacity and product quality. Therefore image treatment is found in an increased application to the supervision of manufacturing process and quality, as well as the collection of measuring data. As an on-line device for quality control and detection, machine vision system can not only reduce the labor cost but also avoid the careless mistake committed by the workers who have been in service for a long time. Additionally, it can ensure the acquisition of correct detection data within a short period of time, and the swift modification to the production and inspection programs so as to enhance the product quality.

The fabric texture will evolve into the periodical structure indicating the yarn variation on the fabric surface. In analyzing the fabric image, the texture will be formed on the fabric surface as a result of the variation in light reflection. So the texture of the fabric can be analyzed to gain an understanding of the method of weaving fabric and the tissue. The recognizing methods commonly adopted include structural, statistical and spectral method. The statistical method puts an emphasis on extracting texture features and is represented by smoothness, roughness, etc. The texture can be described by the statistics of the same feature, such as mean value, histogram, and variation value or co-occurrence matrices.

Based on the reasons mentioned above, Huang *et al.* [1,2] proposed the idea of nondestructive recognizing of the fabric texture of shuttle-woven fabric by applying the filtering treatment and statistical theory. Jeon *et al.* [3] suggested recognizing the texture of the plain and twill fabric by using back propagation neutral network. Kang *et al.* [4] analyzed the plain texture of the fabric through the equalization of Gauss filtering and histogram. Ravandi [5] proposed using Fourier transform to recognize the fabric texture of shuttle-woven fabric. Salari and Ling [6] proposed using K-mean to separate image texture and multi-layer wavelet transform to separate the different image texture areas. Through the horizontal, perpendicular and diagonal treatment with wavelet transform, the relatively complex texture can be simplified. Kuo *et al.* [7] classified the fabrics into different types by means of wavelet transform and supervised neural network via gray fabric image.

It can be seen from the literature that the fabric texture analysis has been applied to the items related to some fabric types. But only Kuo *et al.* [7] accurately recognized all cloth types and their tissues through supervised learning network. Therefore for all classifiers based upon the supervised learning network, there is a need for obtaining the variables for data input and output, and learning the relationship between output variable and input variable during the training. Usually the learning entails a long period. On the contrary, the unsupervised learning network requires the variable input alone and the clustering rule can be learnt during the training. The learning consumes a short period of time. Therefore, in the present study, the feature value is first obtained through co-occurrence matrices after the adoption of *CIE-Lab* color model and wavelet transform, then unsupervised learning network SOM network is employed to learn and recognize the fabric texture to realize the automatic recognizing of the fabric type and main fabric texture types. It is safe to hail it as a new attempt since there is no research report on the analysis and exploration on automatically recognizing color texture fabric nature through the image treatment and neural network.

*Corresponding author: jeffreykuo@mail.ntust.edu.tw

Research Method

Color Model

When the features of the fabric texture define easy distinction in the recognizing system, it can be distinguished by different colors, which can avoid the mistake in recognizing neural network and promote the recognizing rate. So in the present study 2D of *CIE-XYZ color* model is used to represent the feature of the fabric texture. Between *CIE-XYZ* and *RGB* color model there is a liner transformation relationship which goes as follows:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.607 & 0.174 & 0.200 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 1.116 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

Three color features of *CIE-Lab* are L^*, a^* and b^*, among which L^* refers to lightness. The greater the positive value of a^* is, the closer it gets to the color red, the smaller the negative value of a^* is, the closer it gets to the color green. The greater the positive value of b^* is, the closer it gets to the color yellow, the smaller the negative value of b^* is, the closer it gets to the color blue. What is coming up next is the relationship between *CIE-Lab* and *CIE-XYZ* color model:

$$\begin{aligned} L^* &= 116\left(\frac{Y}{Y_n}\right)^{1/3} - 16 \\ a^* &= 500\left[\left(\frac{X}{X_n}\right)^{1/3} - \left(\frac{Y}{Y_n}\right)^{1/3}\right] \\ b^* &= 200\left[\left(\frac{Y}{Y_n}\right)^{1/3} - \left(\frac{Z}{Z_n}\right)^{1/3}\right] \end{aligned} \tag{2}$$

Where X_n, Y_n, Z_n represents the measurement values of standard white. Let $(R, G, B) = (255, 255, 255)$, X_n, Y_n, Z_n can be figured out through equation (1).

Wavelet Transformation

The fabric texture will evolve into a periodical structure indicating the yarn variation on the fabric surface, which turns the periodic light and shade distribution in the light ray into the unique texture on the fabric surface. However, due to the inconsistency in yarn tension, the yarn arrangement will be distorted and the texture on the fabric surface will be deformed in some areas. In addition, the slight undulation on the fabric itself will result in the different light and shade distribution of the texture. So it is infeasible to incise the texture of the fabric as a whole with the fixed gray threshold. In the present study, after scanning the fabric image, Wavelet transform [8] will be employed to transform the digitized spatial image into the image based on space-frequency. It will integrate the regional and global characteristics and provide more powerful signal treatment function than the traditional Fourier transformation. In the paper Z and R refer to integer set and real number set respectively. $L^2(R)$ represents all measurable quantity. The vector space resulting from the one-dimensional function $f(x)$ whose product can be squared is represented as follows:

$$L^2(R) = \{f(x)\colon R \to R \mid \int |f(x)|^2 dx < \infty\} \tag{3}$$

The method of calculating wavelet transform is shown as:

$$f(t) = \sum_{j \in z} \sum_{k \in z} c(j, k)\, \psi_{j,k}(t)$$

where

$$\langle \psi_{j,k}(t), \psi_{m,n}(t) \rangle = 0, \; j \neq k, \; m \neq n \tag{4}$$

$$c(j, k) = \langle f(t), \psi_{j,k}(t) \rangle \tag{5}$$

where $f(t)$ is the original signal and $c(j, k)$ is coefficient matrices, the jth layer frequency of the Wavelet transform. In terms of orthogonal Wavelet transform, for the Wavelet function at position K, the inner product of any two different substrates is necessarily zero. Therefore the coefficient $c(j, k)$ is the inner product of original signal and the substrate. Developed on the basis of Mallat [8], the Wavelet transform fast algorithm uses low frequency filter and high-frequency filter (derived from the substrate transformation) to decompose the signal into low-frequency signal and high-frequency signal, fix the substrate length, decompose to the lower layer and reserve the down-sampling of the signal, namely, the signal length will be reduced each time when it is decomposed.

The decomposition diagram for two-dimensional Wavelet transform is shown in Figure 1, of which cA indicates the Wavelet coefficient of the low frequency and the number the decomposition layer. cH, cV and cD refer to the horizontal, vertical and diagonal high-frequency signals respectively. In two-dimensional transform, the frequency band filtering structure can be adopted to treat the image in terms of column and line, namely, four one-dimensional filters, g and h constitute the sub-frequency band filtering structure:

$$\begin{aligned} c_j(m, n) &= \{[(c_{j-1}(m, n) * g(m))\downarrow_m^2] * g(n)\}\downarrow_n^2 \\ d_j^V(m, n) &= \{[(c_{j-1}(m, n) * g(m))\downarrow_m^2] * h(n)\}\downarrow_n^2 \\ d_j^H(m, n) &= \{[(c_{j-1}(m, n) * h(m))\downarrow_m^2] * g(n)\}\downarrow_n^2 \\ d_j^D(m, n) &= \{[(c_{j-1}(m, n) * h(m))\downarrow_m^2] * h(n)\}\downarrow_n^2 \end{aligned} \tag{6}$$

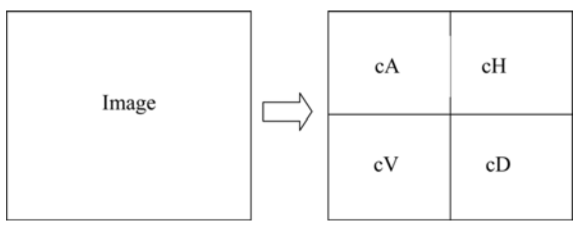

Figure 1. Decomposition diagram for 2D wavelet transform signal.

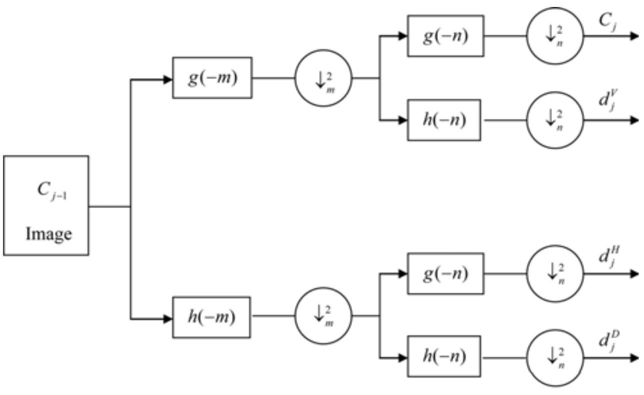

Figure 2. Decomposition flow chart for 2D wavelet transform.

where $\downarrow_m^2$ means down sampling image column by 2 while $\downarrow_n^2$ image line by 2, as is shown in Figure 2.

Co-occurrence Matrices

The change in fabric texture can represent different kinds of fabric texture, so the change in the gray of the texture surface of the image object, the texture analysis is represented by the statistical characteristics of the gray or gradation in the given spatial position. co-occurrence matrices in statistical image space, is the number of the same gray levels of each pixel under the preset conditions. Therefore co-occurrence matrices [9] take probability to simulate texture and the texture is the representation of the correlativity of the gray levels of adjoining pixels. The gray correlativity of the same geometric position is represented by the condition probability of some gray level at a pair of image point. The texture can be quantitatively described.

The correlation of each of the four pairs of corresponding angles and the co-occurrence matrix are expressed as follows: The $f(j, k)$ represents one $N \times N$ digital image and its gray is G. For draw the pixel related position shall induce two parameters d and θ, and d is the distance between two pixels. And the related position can distinguish as the vertical ($\theta = 0^{\circ}$) right opposite angle ($\theta = 45^{\circ}$), perpendicular ($\theta = 90^{\circ}$), and left opposite angle ($\theta = 135^{\circ}$). And these four corresponding positions are defined as:

$$
\begin{aligned}
\theta = 0^{\circ} \quad & R_H(d):\ k-m=0,\ |l-n| = d \\
\theta = 45^{\circ} \quad & R_{RD}(d):\ (k-m=d, l-n=-d) \text{ or} \\
& (k-m=-d, l-n=d) \\
\theta = 90^{\circ} \quad & R_V(d):\ |k-m| = d,\ l-n = 0 \\
\theta = 135^{\circ} \quad & R_{LD}(d):\ (k-m=d, l-n=d) \text{ or} \\
& (k-m=-d, l-n=-d)
\end{aligned}
\tag{7}
$$

$$M(i,j,d,0^{\circ}) = \{R_H(d),\ f(k,l) = i,\ f(m,n) = j\}$$

$$M(i,j,d,45^{\circ}) = \{R_{RD}(d),\ f(k,l) = i,\ f(m,n) = j\}$$

$$M(i,j,d,90^{\circ}) = \{R_V(d),\ f(k,l) = i,\ f(m,n) = j\}$$

$$M(i,j,d,135^{\circ}) = \{R_{LD}(d),\ f(k,l) = i,\ f(m,n) = j\}$$

Symbol { } means sum of all conditions, and co-occurrence matrices M are the functions of i, j, d and θ four parameters. Before obtaining the texture characteristics, all values of the co-occurrence matrices M need to be normalized, the co-occurrence matrices, C_{ij}, can be expressed as:

$$C_{ij} = \frac{M_{ij}}{\sum_{i=0}^{N}\sum_{j=0}^{N} M_{ij}} \tag{8}$$

The present study employs the feature factor of the texture proposed by Haralick [10]. In the co-occurrence matrices worked out, the four feature factors are selected to represent the image. Suppose the normalized matrix is C_{ij}, then these four feature factors are as follows:

A. Angular second moment (a measure of picture homogeneity):

$$\phi_1 = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} p_{ij}^2 \tag{9}$$

B. Contrast (a measure of variation in intensity):

$$\phi_2 = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i-j)^2 p_{ij} \tag{10}$$

C. Correlation (a measure of gray-tone linear dependencies):

$$\phi_3 = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \frac{(1-\mu_x)(1-\mu_y)p_{ij}}{\sigma_x \sigma_y}$$

$$\mu_y = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} j p_{ij},\quad \mu_x = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} i p_{ij} \tag{11}$$

$$\sigma_x = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i-\mu_x)^2 p_{ij},\quad \sigma_y = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i-\mu_y)^2 p_{ij}$$

D. Entropy (another measure of homogeneity):

$$\phi_4 = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} p_{ij} \log(p_{ij} + \varepsilon) \tag{12}$$

Variation Normalization

After obtaining feature value and before inputting the value into the input layer of SOM network, variation normalization should be done first in order to avoid the great difference in the range of the variables input which will lead to the failure to express the significance of the variable in small range to the extent that the variables in big range control the learning process of the whole network and affect the learning effect. Therefore interval mapping is employed in the present study to map the minimum and maximum value of the variable to the expected maximum and minimum value. The method is as follows:

1. To find out the *Min* and *Max* of the output parameter of the same nature;
2. To designate the expected $D_{\max}$ and $D_{\min}$ when input variable is normalized;
3. To normalize the date through the following equation:

$$V_{new} = D_{\min} + \frac{V_{old} - Min}{Max - Min}(D_{\max} - D_{\min}) \tag{13}$$

V_{new} is the value after the normalization.

Self-organizing Map (SOM) Network

In 1973 Kohonen proposed SOM network [11] which is a neural network based on competitive learning. In SOM network, the neural network on the output layer is arranged in the form of matrices in the one-dimensional and two-dimensional space. According to the present output vector, the mutual competition will strive for the opportunity to adjust the value vector and the neural network on the final output layer will be displayed in the output space in the meaningful topological structure in accordance with the features of the input vector. Since the resultant topological structure can respond to the characteristic of the input vector itself, the fabric texture can be recognized and classified in the present study. Figure 3 is the architecture of SOM network.

SOM network adopts the conception of neighborhood to have the output processing units mutually influenced. The neighborhood will diminish during the network learning process.

1. Figure out the distance of each output layer unit in the training example

After loading each instance example, the distance between

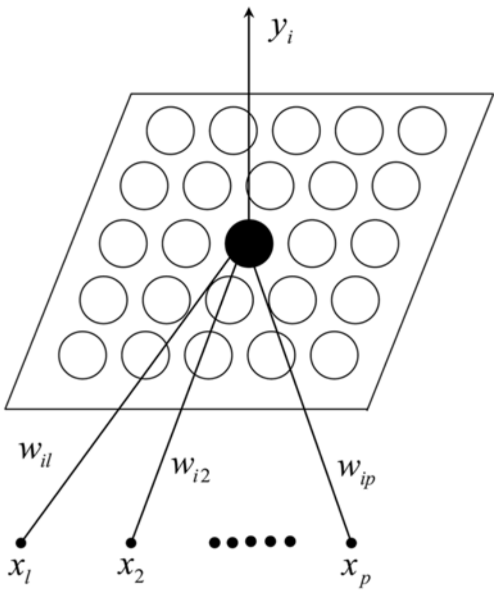

Figure 3. Architecture of the learning vector quantization network.

each output layer unit and the input vector shall be figured out. Here comes the equation:

The squaring of $\|X(C) - C(C_j)\| = X(C)$ and Euclidean distance of $X(C_j)$

$$= [X(C) - X(C_j)]' \cdot [X(C) - X(C_j)]$$
$$= \sum_i [X_i(C) - X_i(C_j)]^2 \tag{14}$$

$X(C)$ = The characteristic vector of training example C

$X(C_j)$ = The corresponding characteristic vector of the processing unit on the jth output layer
= The weighted value between the jth output layer unit and jth input layer unit

$X(C_j)$: The ith element of the characteristic vector of training instance C
= W_{ij}

$X(C_j)$: The ith element of the corresponding characteristic vector on the ith output layer unit

2. Find out winner

The output layer with the shortest distance is referred to as winner which is expressed in the following equation:

$$\text{IF } \|X(c) - X(c_h)\| = \min_h \|X(c) - X(c_h)\| \tag{15}$$

Then winner is the processing unit on the jth output layer

3. Adjust the connection weighted value of input layer and output layer

The weighted value of the network connection entails modification. The related equation is as follows:

$$\Delta W_{ij} = +\eta \cdot (X - W_{ij}) \cdot R\_factor_j \tag{16}$$

where

η = Learning rate

R_factor_j = Neighbor coefficient of the processing unit on the jth output layer
$= f(R, r_j)$

It can be seen that what requires modification is not the connection weighted value of the winner alone. Actually it is related to the neighborhood between output layer and the winner (neighborhood center). The greater the neighborhood is, the smaller the coefficient is. Correspondingly, the connection weighted value tends to be smaller.

Materials and Experimental

Materials

The equipment employed in the experiment is Pentium 4-2.6 GHz 1G DDR, Canon scanner 9950F. There are altogether 120 training instances shared in the experiment. The fabrics for experiments include plain weave, twill weave and satin weave of shuttle-woven fabric, and single jersey, double jersey of the jersey fabric as well as the non-woven fabric. The cloth sample is 1 in × 1 in in size.

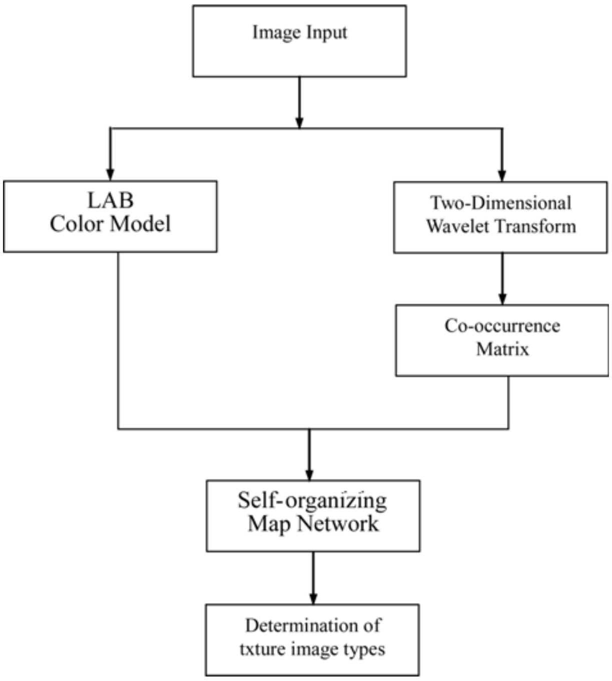

Figure 4. Texture image recognition flow chart.

Experimental

We used Borland Delphi as a software tool to develop this system. The experimental flow chart can be referred in Figure 4. Firstly, the Canon scanner 9950F with the resolution of 600 dpi was used to digitize the fabrics image in gray-scale model. The captured image consists of 600 × 600 pixels. Secondly, characteristic value of the *CIE-Lab* color model was obtained. Thirdly, the double layer resolution structure of wavelet transform was used to decompose the image into 4 smaller images, each of which is 1/16 of the original size. In terms of texture analysis the Wavelet transform is used to treat the low-frequency sub-image and diagonal high-frequency sub-image on the second layer. Firstly, co-occurrence matrices were figured out under the conditions that pixel distance is 1, direction 0 and degree 90. Then we calculated the texture features [10] such as angular second moment, entropy, homogeneity and contrast. When classifying features, we used SOM network to input the texture features first and then employed the training instances to classify the fabric types which cover 6 types, namely, plain weave, twill weave, satin weave, single jersey, double jersey and non-woven fabric.

Results and Discussion

Figure 5 presents the fabric textures that need to be recognized in the present study. The image size is 600 × 600 pixels, Figure 5(a), plain weave interlaces with longitude up and down the woof, and the direction of the next one is just opposite to the previous one; Figure 5(b), twill weave is characterized by obvious slanting lines on the surface, directions of lines

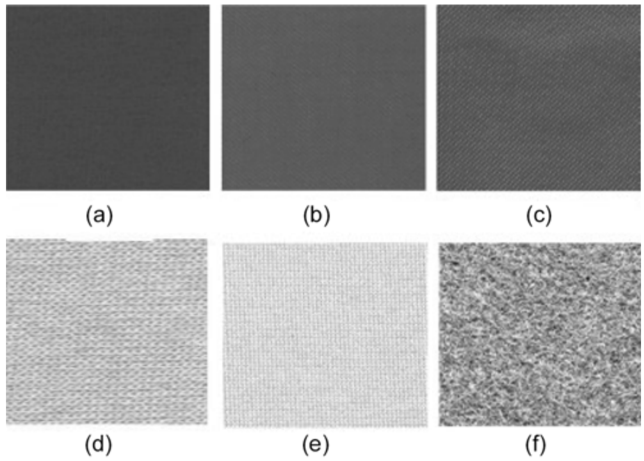

Figure 5. (a) Plain weave, (b) twill weave, (c) satin weave, (d) single jersey, (e) double jersey, and (f) non-woven fabric.

are not the same in the right and left, and the cloth is of firm quality; Figure 5(c), satin weave is formed by irregular interval longitude and woof voile. Floating voile of long surface can make beautiful luster, but it is of less fastness, mainly because of few interlace of longitude and woof voile; Figure 5(d), single jersey is made from knotting voile in round by knitting machine. Weaving method is same as manual weaving; Figure 5(e), Double jersey is based on the weaving theory of single jersey, using multiple-cycle to weave knitting, strengthening fabric intensity, intensity and opacity; Figure 5(f), non-woven fabric is a relatively special fabric, which does not need spinning process, and it is made by extruding and

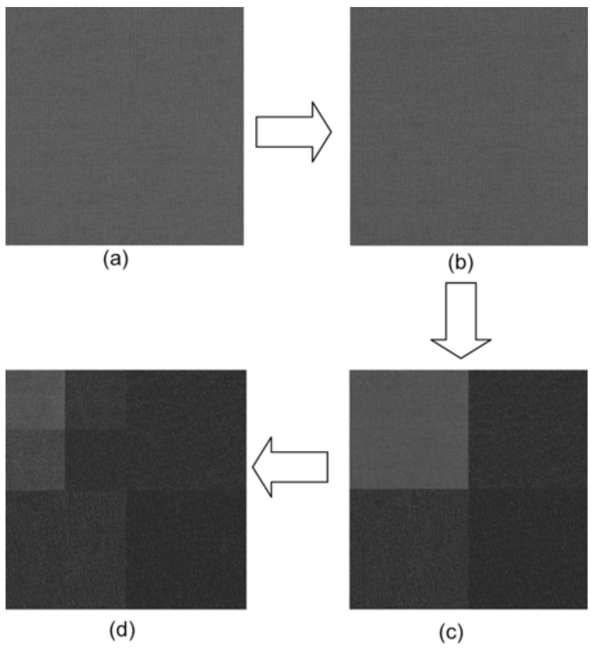

Figure 6. (a) Plain weave of image, (b) plain weave of gray image, (c) four sub-images of the first layer of wavelet transformations, and (d) four sub-images of the second layer of wavelet transformations.

agglutinating fiber. Take Figure 6(a) for instance, we used *CIE-Lab* color model to first figure out the characteristic value and then transformed the image into gray-level image for Wavelet transform, as is indicated in Figure 6(b). Then the we took the Wavelet transform resolution structure on the second layer, as in Figure 6(c,d). Its sub-image is 150 × 150 in size. The sub-image is not distorted and the texture of the original image is completely preserved. So the final recognizing result won't be affected and the time for calculating the image will be reduced in co-occurrence matrices. Following that, we calculated 16 characteristic values of the texture such as angular second moment, entropy, homogeneity and contrast in accordance with the co-occurrence matrices (pixel distance 1, direction 0, degree 90) However, in terms of the design of neural network, we input 19 characteristic values (calculated by *CIE-Lab* color model and co-occurrence matrices) as the SOM network. The output value is the result of using 20 × 20 rectangular network topology to express neural network. After 1000 times of learning with 120 training instances to be distributed into the different networks, we adopted 120 training instances for SOM network experiment and set the optimum network structure parameters: random number of the initial weighted value: 0.456, initial learning rate: 0.5, learning decrease rate: 0.975 and minimum learning rate: 0.1. The clustering of the training instances as in Figure 7 revealed it is output nerve cells of training examples, arranged in planar space in 20 × 20 matrix arrangement, based on input vector, competing together for obtaining opportunities to adjust weight value vector. At last output nerve cells are exhibited in the output space in topological structure based on input vector, *x*, *y*-axis referring to the topological coordinate of each output nerve cell that after 1000 times of learning, 20 × 20 rectangular network topology and SOM network was clustered into 6 types: plain weave, twill weave, satin weave, single jersey, double jersey and non-woven fabric. The result of clustering testing instances was shown in Figure 8. It is the best weight value vector of test examples based on training examples, exhibiting the characteristics of input vector in topological structure, *x*, *y* axis referring to the topological coordinate of

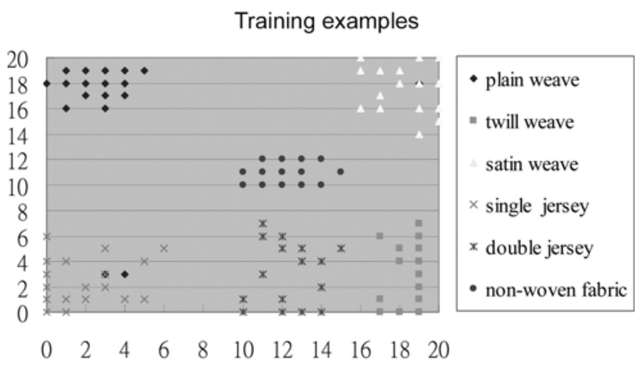

Figure 7. Every categorized training examples distribution in outputting the unit.

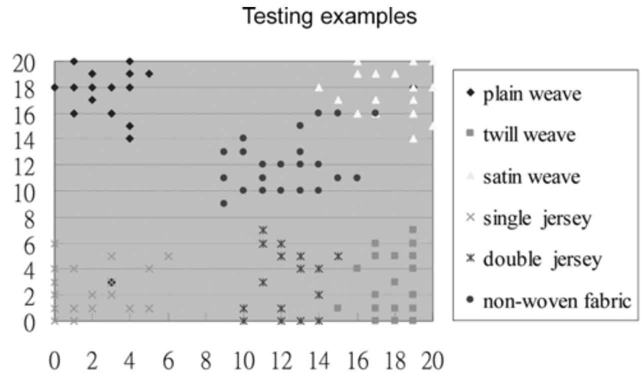

Figure 8. Every categorized testing examples distribution in outputting the unit.

each output nerve cell that the connection weighted value modified by the training instances was capable of verifying the result of clustering training instances in 20 × 20 rectangular network typology, Comparing and validating Figure 7 and Figure 8, this research method can classify fabrics of different structures and models quickly and correctly.

Conclusion

Fabric image, through wavelet transform, uses co-occurrence matrices to work out characteristic of texture; then through SOM network, it uses clustering to classify fabrics, and because the texture changes of satin weave, satin weave and non-woven fabric are similar, SOM network will be classified as one group on clustering analysis and cause misjudge; therefore, adding color can amend the misjudge caused by mutual interference. In the experiment the classifier adopts the unsupervised learning network SOM network. During both training and testing instances, there is no need for adding output variables. We took advantage of clustering characteristic to categorize the same physical property from the training instances to achieve the classification of fabric textures. The result revealed that the SOM network employed in the study is quite applicable to the classification of fabric textures. In particular, we used Wavelet transform to decompose the fabric image into a two-layer resolution structure, which reduces not only the size for image analysis but also the operation time for texture analysis and recognizing. The method employed in the study can ensure the fast and correct classification of fabric of different textures, and overcome the inconveniences brought about by manual detection and the non-objective judgment.

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