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Automatic Classification of Woven Fabric Structure Based on Computer Vision Techniques ⋆

Xuejuan Kang [a,*], Mengmeng Xu [b], Junfeng Jing [b]

[a] *Electrical Engineering Department, Xi'an Aeronautical University, Xi'an 710077, China*
[b] *School of Electronics and Information, Xi'an Polytechnic University, Xi'an 710048, China*

Abstract

Traditionally woven fabric structure classification is based on manual work in textile industry. This paper proposes an automatic approach to classify the three woven fabrics: plain, twill and satin weave. Firstly 2-D wavelet transform is used to obtain low frequency sub-image in order to reduce the analysis of fabric images. Then graylevel co-occurrence matrix (GLCM) and Gabor wavelet are adopted to extract the texture features of pre-processing fabric images. Finally Probabilistic Neural Network (PNN) is applied to classify the three basic woven fabrics. The experimental results demonstrate that the proposed method can automatically, efficiently classify woven fabrics and obtain accurate classification results (93.33%).

Keywords: Woven Fabric Structure; Automatic Classification; 2-D Wavelet Transform; GLCM; Gabor Wavelet; PNN

1 Introduction

In traditional textile industry, analysis and recognition of woven fabric structure mostly depend on manual inspection, which requires a long time and many professional workers. To improve work efficiency, it is necessary to propose an innovative and efficient method for fabric structure recognition. With the development of technology, the application of computer vision and image processing is becoming more dominant. Image processing has been introduced into texture classification, which can automatically and accurately classify woven fabric structure [1].

The analysis of fabric texture [2] has been studied since the mid-1980s in Japan, which progresses from optical computing to digital image processing. Recently, some relevant researches have been developed for automatic analysis of woven fabric structure. Haralick et al. [3] proposed a method of image graylevel co-occurrence matrix, and took its four feature parameters of energy, contrast, correlation, entropy as image features to identify fabric images. Melendez et al. [4] used

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*Corresponding author.
Email address: 67807595@qq.com (Xuejuan Kang).

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the convolution images by Gabor filters as texture features. These feature extraction methods have good recognition results. Hu [5] put forward a method of fabric automatic classification based on Bayesian statistics. Shin et al. [6] developed an unsupervised recognition method using fuzzy c-means clustering in the spatial domain. Salem et al. [7] used support vector machine to classify fabric weave patterns. Another identification method [8, 9] analyzed warp and weft floats to determine the fabric weave patterns. These methods can successfully classify several woven fabrics. However, real-time and fault-tolerant abilities of current woven fabric classification methods are low.

Hence, this paper introduces an approach for recognition and classification of woven fabrics with real-time and fault-tolerant abilities based on computer vision technique. Firstly, pre-processing image is decomposed into 7 sub-images by two layer wavelet transform, and low frequency sub-image LL2 are taken as processing sample to reduce the analysis of fabric images. Then, GLCM and Gabor wavelet are used to extract texture features of woven fabrics. Finally, an appropriate classifier, probabilistic neural network, is applied to recognize woven fabrics in the classification phase. The flow chart of fabric texture image recognition is shown as Fig. 1, and it illustrates the recognition process.

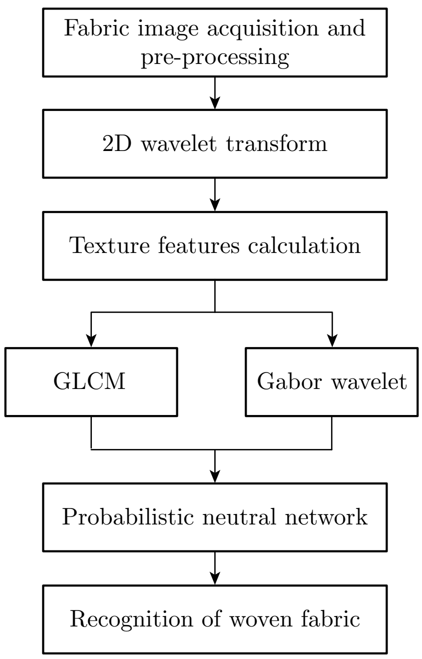


Fig. 1: Flow chart of fabric texture image classification

2 Experimental Methods

2.1 2-D Wavelet Transform

In order to reduce the amount of calculation and remove noise, 2-D wavelet transform [10] is adopted to process woven fabric images. Wavelet transformation is a local transformation between time domain and frequency domain, which can extract information from the signal effectively. It can conduct multi-scale detail analysis for function and signal by flex and translation, and solve the problem that Fourier transforms cannot solve.

2-D wavelet transform is made by sampling interval in rows and columns after inner product between an original image and a wavelet basis image. Each convolution can decompose the 1-D convolution on rows and columns, because scale function and wavelet function are separable. After the first layer of wavelet transform, original image is decomposed into four sub-images: a low-frequency approximate sub-image LL1 and three high-frequency detailed sub-images (a horizontal sub-image HL1, a vertical sub-image LH1, and a diagonal sub-image HH1). In the second layer of wavelet decomposition, the low-frequency part (LL1) is only decomposed as mentioned above, it then produces the different frequency band outputs. Fig. 2 shows the diagram of two layer wavelet decomposition.

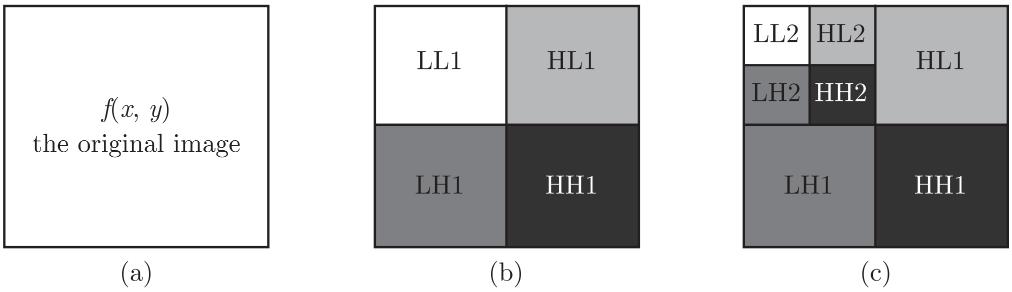


Fig. 2: The two layer wavelet decomposition. (a) The original image. (b) The first layer wavelet decomposition. (c) The second layer wavelet decomposition

2.2 Graylevel Co-occurrence Matrix

The Graylevel Co-occurrence Matrix (GLCM) of an image can reveal comprehensive information of gray level [11, 12], which are about directions, adjacent interval and rangeability. So far, it has been proved to be a good method of texture analysis in theory and experiment. GLCM has been brought out in 1973 by Haralick [3]. It describes grey value i and j, the two pixels' all appeared probability matrix $C(i, j, d, \theta)$ in θ direction and d distance. θ is the position angle between two pixels. Distance d is the distance between two pixels, generally according to the test image to determine. Generally, four common statistics are used to extract image texture characteristics: angular second moment (energy), contrast, correlation and entropy, which are not only convenient for computation but also giving a higher accuracy of classification.

- **Angular second moment (Energy):**

$$ASM = \sum_{i=1}^{M}\sum_{j=1}^{N} C(i, j, d, \theta)^2 \tag{1}$$

- **Contrast:**

$$CON = \sum_{i=1}^{M}\sum_{j=1}^{N}(i-j)^2 C(i, j, d, \theta) \tag{2}$$

- **Correlation:**

$$COR = \sum_{i=1}^{M}\sum_{j=1}^{N} \frac{ijC(i, j, d, \theta) - \mu_x\mu_y}{\sigma_x\sigma_y} \tag{3}$$

with

$$\mu_x = \sum_{i=1}^{M}\sum_{j=1}^{N} iC(i,j,d,\theta), \qquad \mu_y = \sum_{i=1}^{M}\sum_{j=1}^{N} jC(i,j,d,\theta)$$

$$\sigma_x = \sum_{i=1}^{M}\sum_{j=1}^{N} (i-\mu_x)^2 C(i,j,d,\theta), \qquad \sigma_y = \sum_{i=1}^{M}\sum_{j=1}^{N} (j-\mu_y)^2 C(i,j,d,\theta)$$

- **Entropy:**

$$ENT = -\sum_{i=1}^{M}\sum_{j=1}^{N} C(i,j,d,\theta) lgC(i,j,d,\theta) \tag{4}$$

It is defined that the value of direction θ of $0°, 45°, 90°, 135°$, and distance d is 1 in GLCM method. Therefore, 16-dimensional GLCM features of angular second moment, contrast, correlation and entropy in four directions and one distance are obtained for each identified fabric image.

2.3 Gabor Filter

As the good multi-scale and multi-orientation decomposition of 2-D Gabor filter in frequency domain, it is applied into computer vision and image processing widely. 2-D Gabor function is the result of modulation by 2-D Gaussian function [13] with trigonometric function. By using Gabor function, the local frequency domain information in different scales and different orientations can be obtained. A 2-D Gabor function $g(x, y)$ and its Fourier transform G(μ, ν) can be expressed as:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left\{-\frac{1}{2}\left(\frac{x_1^2}{\sigma_x^2} + \frac{y_1^2}{\sigma_y^2}\right)\right\} exp(2\pi j f_0 x_1) \tag{5}$$

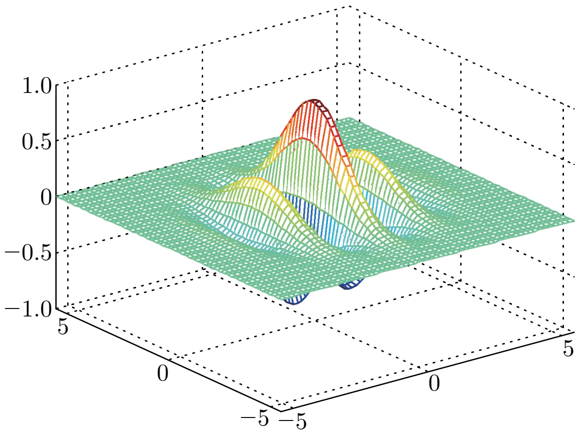
$$G(\mu,\nu) = exp\left\{-\frac{1}{2}\left(\frac{(\mu - f_0)^2}{\sigma_\mu^2} + \frac{\nu^2}{\sigma_\nu^2}\right)\right\} \tag{6}$$

where, f_0 is mid-frequency, $x_1 = (xcos\theta + ysin\theta)$, $y_1 = (-xsin\theta + ycos\theta)$, $\theta = \frac{n\pi}{K}$ and K is the total number of orientations, $n \in [0, K]$. σ_x, σ_y are the variances along x axis and y axis respectively. $\sigma_\mu = \frac{1}{2\pi\sigma_x}$, $\sigma_\nu = \frac{1}{2\pi\sigma_y}$.

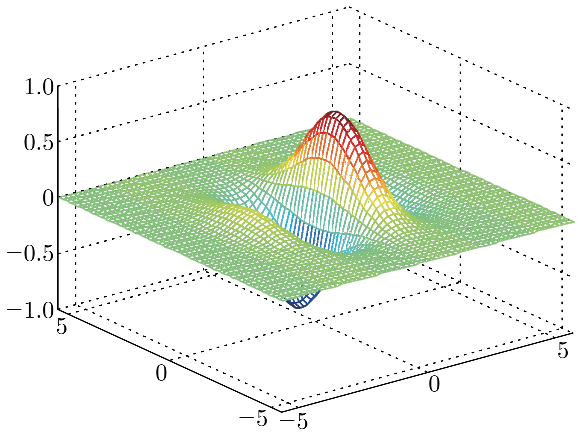
The real part of 2-D Gabor function shown as Eq. (7) acts as an even symmetric Gabor filter to make image smoothing. While the imaginary part of 2-D Gabor function is used for detecting fabric edge part as an odd symmetric filter to be shown as Eq. (8). The relationship of two portions and integrated Gabor filter can be described as Eq. (9). General responses of real part and imaginary part from 2-D Gabor function are exhibited in Fig. 3.

$$g_e(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left\{-\frac{1}{2}\left(\frac{x_1^2}{\sigma_x^2} + \frac{y_1^2}{\sigma_y^2}\right)\right\} cos(2\pi f_0 x_1) \tag{7}$$

$$g_o(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left\{-\frac{1}{2}\left(\frac{x_1^2}{\sigma_x^2} + \frac{y_1^2}{\sigma_y^2}\right)\right\} sin(2\pi f_0 x_1) \tag{8}$$



(a)



(b)

Fig. 3: The real part (a) and imaginary part (b) of a basic Gabor function

$$g(x,y) = g_e(x,y) + jg_o(x,y) \tag{9}$$

Based on 2-D Gabor function, because the imaginary part not only requires a mass of calculations, but also contributes little to extract texture features, the real part of 2-D Gabor function is used to extract the texture features. Then Gabor function can be formulated as Eq. (7). In order to cover the frequency space of the texture images as best as possible, a reasonable oscillation frequency and filter orientation must be selected, which can extract the features well. Fig. 4 shows 5×8 Gabor filters. In each scale, filters are spread equally in the $0 - 180°$. In the different scales, Gabor filters play a similar role of microscopes. After designing a group of Gabor filters, the filtered images are from the convolution between input image and each Gabor filters. Finally, the mean and standard deviation of filter images can be calculated as texture features. Therefore, after using Gabor wavelet method, 80-dimensional Gabor features can be obtained for each detected fabric image.

2.4 Probabilistic Neural Network

Probabilistic Neural Network [14] is proposed by Specht in 1990 and a kind of supervised neural network based on Bayesian minimum risk criteria (the Bayesian decision theory). Besides, it is not only an artificial neural network based on statistical principle but also a feedforward network taking Parzon window function as an activation function. Compared with the traditional neural network, PNN has more significant advantages especially in pattern classification and faster training speed. The PNN consists of four layers (input layer, pattern layer, summation layer and contest layer), and its basic structure is shown in Fig. 5.

Input layer passes texture features of training samples to network by linear transfer function. Pattern layer calculates the matching relation between input texture features and each training pattern, and the number of neurons in pattern layer is equal to the sum of each category of training samples, the output of each pattern unit is through following non-linear operator.

$$f(X, W_i) = exp\left[-\frac{(X - W_i)^T(X - W_i)}{2\delta^2}\right] \tag{10}$$

where, W_i is the linked weight from input layer to pattern layer; δ is the smoothing factor which plays a vital role in the process of classification; $X = [x_1, x_2, ..., x_n]$. In view of this, PNN classifier

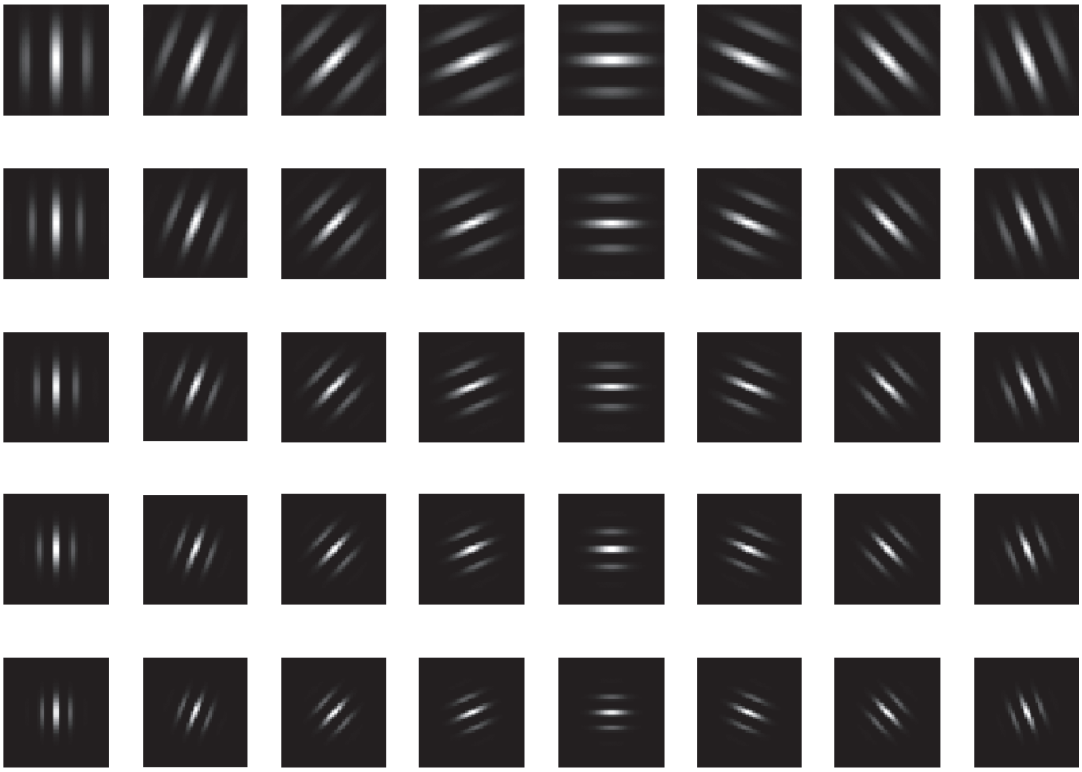


Fig. 4: A group of Gabor filters from five scales and eight orientations

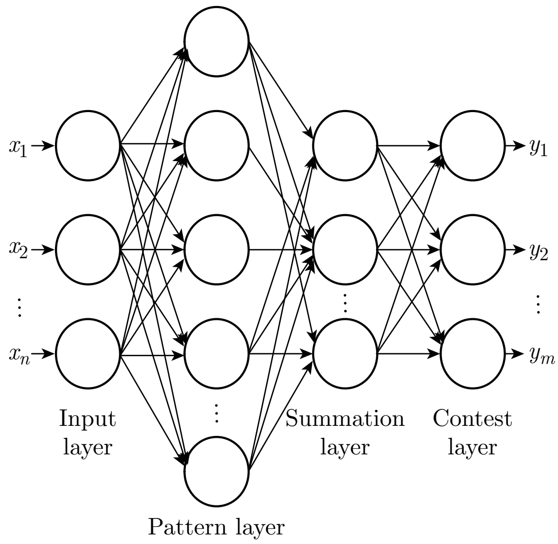


Fig. 5: The structure of PNN

completes the work of nonlinear learning algorithm with high accuracy character using linear learning algorithm. Summation layer accumulates estimate probability density which belongs to a certain class according to Eq. (10). This unit simply adds output which belongs to their own class of pattern layer unit. The last layer is contest layer, which is composed of simple threshold discriminator whose role is to choose a neuron with a maximum posterior probability density in each type as output of the whole system. Neuron with the biggest posterior probability density outputs 1 which corresponds to this class is the pattern category of classified sample, and other neurons output 0.

Compared with other methods, PNN classifier does not need to be multiple fully calculated, and can be stably converged to Bayesian optimal solution. In the training pattern samples under certain circumstances, only the smoothing factor needs to be adjusted, PNN network can converge with faster speed.

3 Results and Discussion

In this paper, experimental samples include plain, twill, and satin weaves are acquired by Canon-Scan 9000F under the same external condition. There are 45 groups woven fabric images which contain 15 groups of plain, twill and satin weaves. Meanwhile, 10 images per class were chosen as the training samples and the rest as testing samples. Fig. 6 shows some samples of experimental

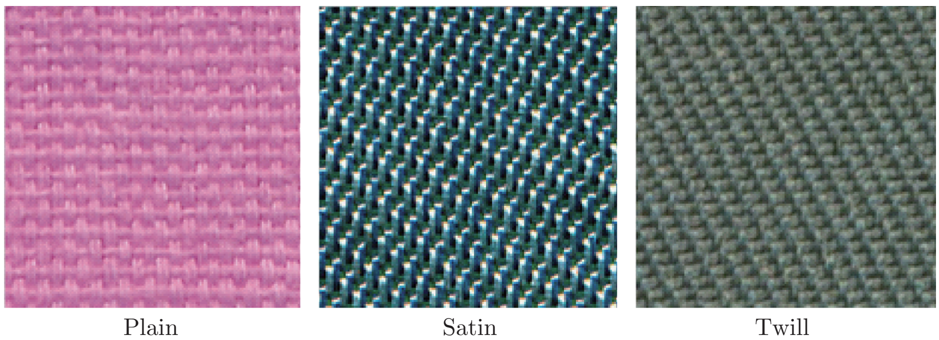


Fig. 6: Woven fabric samples

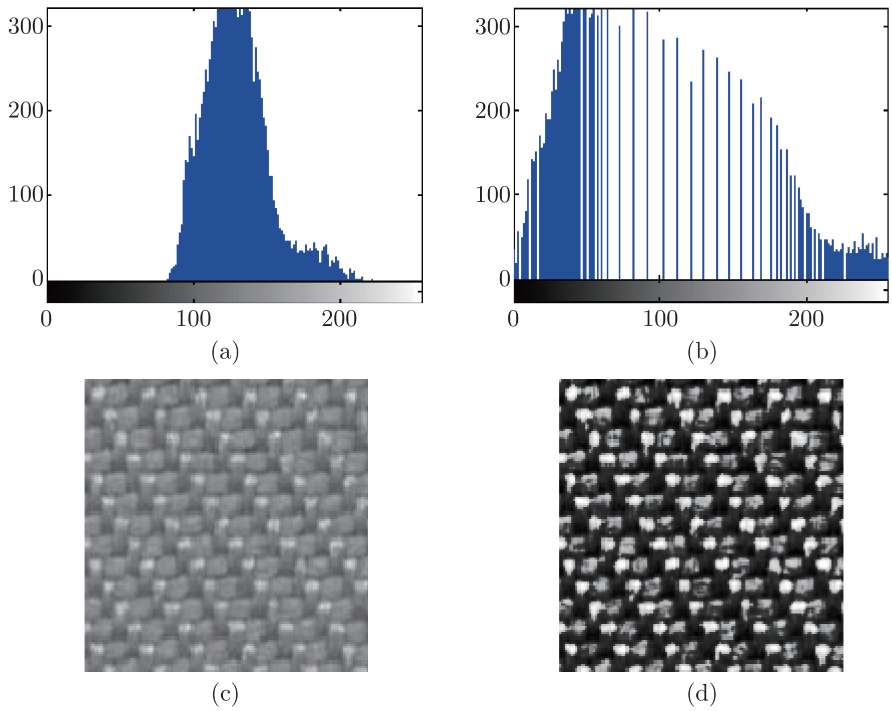


Fig. 7: Pre-processing effect of fabric image. (a) The histogram of gray fabric image. (b) The histogram of the enhanced fabric image. (c) The gray fabric image. (d) The enhanced fabric image

woven fabric images. The captured RGB images are resized into 256 × 256 pixels and converted into gray images for improving processing speed. Furthermore, due to the pixel of gray images that are too concentrated, double-peak Gaussian function for histogram equalization is used to distribute images gray level in lower and higher graylevel so that images contrast can be enhanced. The results of twill woven fabric are shown in Fig. 7.

After image pre-processing, 2-D wavelet transform decomposition is used to reduce the size of the original image. Take the plain weave for example, Fig. 8 (b) shows that the low-frequency sub image LL1 with the size of 128 × 128 after the first wavelet transform. The LL1 image is then decomposed by the second wavelet transform, and 64 × 64 low-frequency sub image LL2 (Fig. 8 (c)) is obtained.

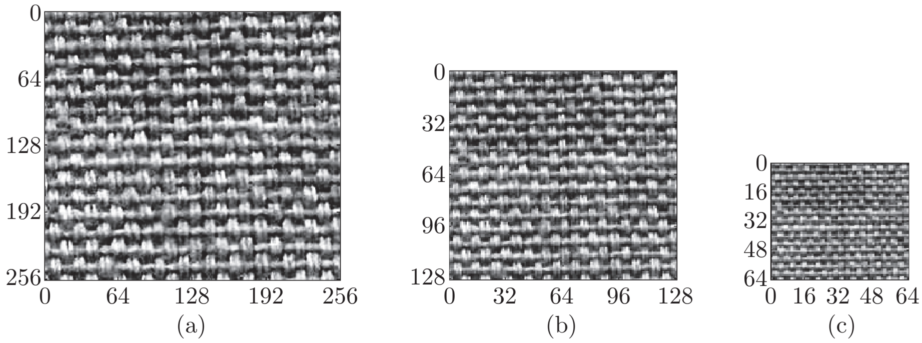


Fig. 8: The result of two layer wavelet decomposition of the plain weave. (a) The plain weave. (b) The LL1 image. (c) The LL2 image

Through 2-D wavelet transform decomposition, the size of fabric images is reduced. Then, 96-dimensional features which include 16-dimensional GLCM features and 80-dimensional Gabor features for each fabric image can be obtained quickly. At the end of the process, 45 woven fabrics can be classified by PNN. In this phase, the particularly important thing is to choose the appropriate value of the smoothing factor δ, which directly affects the final classification results. If δ value is too small, PNN classifier can be used as the most adjacent classifier, which leads to classification results that are not obvious. If δ value is too large, it can cause difficulties in the

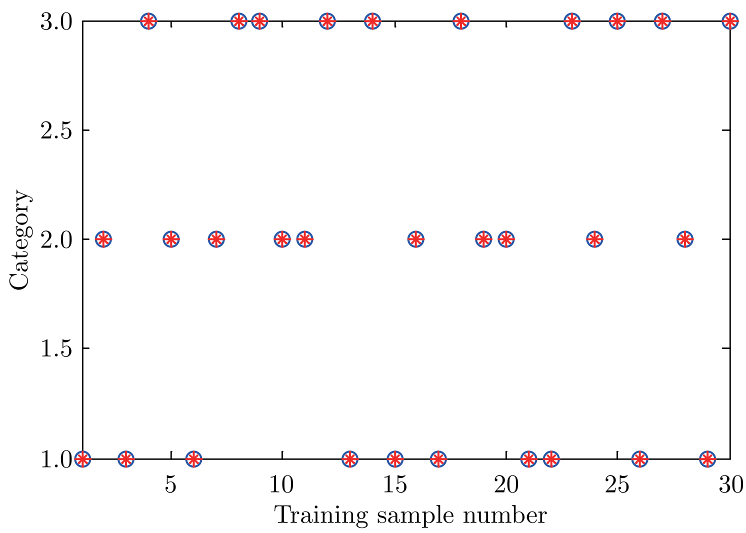


Fig. 9: The training classification results of PNN network with GLCM and Gabor features

process of network computing. Therefore, various δ values are used to train the PNN to obtain optimal classification effect in simulation process. It should be noted that the blue circles and the red stars in Fig. 9 represent training results of sample categories and actual sample categories respectively. Besides, the blue triangles and the red stars in Fig. 10-12 symbolize prediction results of sample categories and actual sample categories. Therefore, if one symbol interlaces another, it means that the samples are classified correctly and vice versa. From Fig. 9, the training effects of 30 training samples achieve the best performance, and training accuracy reached 100%. Besides, network training time is 0.5 second. For further examining the extrapolation performance, the other 15 testing samples are used to make prediction through applying the successful trained PNN. The testing classification result is shown in Fig. 10. From Fig. 10, it can be easily found that only one test sample is identified as wrong and classification accuracy reaches 93.33%. Comparatively speaking, classification accuracy only using the GLCM features is 86.67% (Fig. 11), and classification accuracy only using the Gabor wavelet features is 80% (Fig. 12).

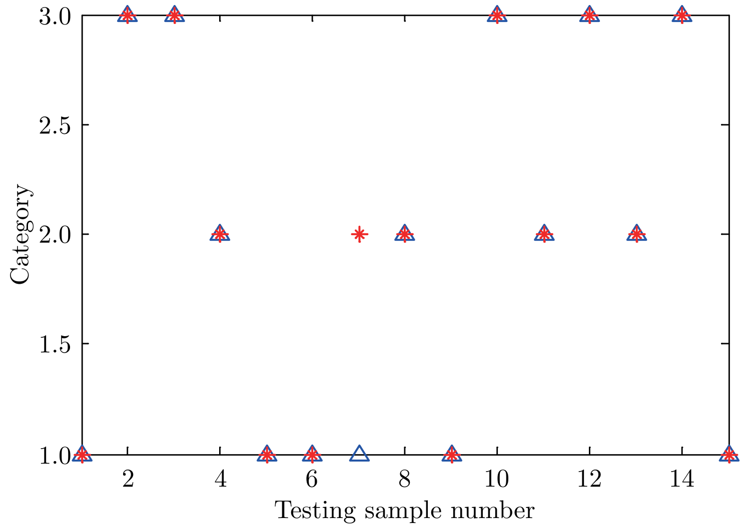


Fig. 10: The testing classification results of PNN network with GLCM and Gabor features

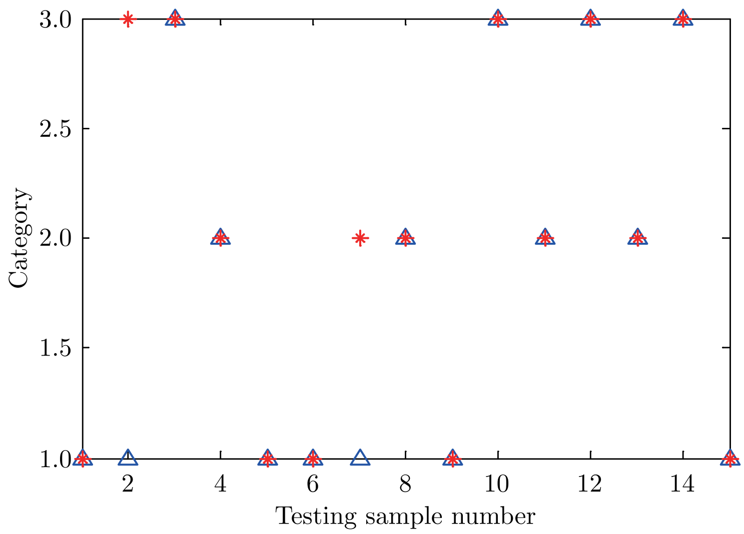


Fig. 11: The testing classification results of PNN network only with GLCM features

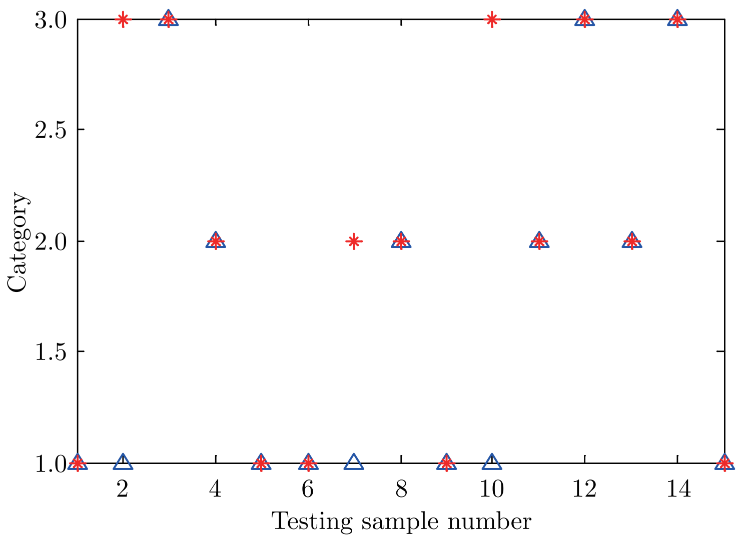


Fig. 12: The testing classification results of PNN network only with Gabor features

4 Conclusion

An automatic and efficient classification method is proposed in this paper including image pre-processing, feature extraction, fabric pattern recognition and so on. Using 2-D wavelet transform to process fabric image can not only reduce the size of fabric image but also shorten the running time of texture analysis. Then, GLCM and Gabor wavelet are used to extract texture features of fabric images. Compared with BP network and LVQ network, PNN classifier has simple network learning process, faster training speed and a powerful pattern classification ability. PNN is a method of pattern recognition, which has good generalization ability and classification capacity. Furthermore, PNN will not get into local optimal point problem. The experimental results show that the methods of feature extraction and image pattern recognition are accurate and efficient, and woven fabrics recognition system gains the best classification results (93.33%) with a faster speed. With the rapid development of computer technology and image processing technology, woven fabric image automatic identification and classification could promote the development of textile industry.

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