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Recognition for woven fabric pattern based on gradient histogram

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To identify woven fabric pattern, a robust recognition method is presented in this paper. Firstly, using gray image of woven fabric through gray projection, we correct the warp deviation and segment crossed-area of warp and weft. Then, based on the gradient histogram information, we get the texture features of crossed-area, which can determine the state of crossed-area. Through which we can obtain the recognition preliminarily, which can overcome the effects of scale and color change of woven fabric and achieve high accuracy. According to the woven fabric periodicity, the error recognition is corrected. This method is validated with real woven fabric images, which can get woven fabric pattern diagram successfully. According to the extensive tests, we concluded that this method can achieve the recognition of woven fabrics with complex patterns and colors.

Keywords: woven fabric pattern; recognition; gradient histogram information; fuzzy C-means (FCM); deviation correction

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Introduction

In textile industry, recognition for woven fabric pattern mainly relies on manual operations with the help of microscopes at present, which not only consumes a lot of manpower and time, but also bring errors by different detectors. Furthermore, complex woven fabric cannot be recognized because the human eyes are easily fatigued. Therefore, it is necessary to establish an automatic identification system for woven fabric pattern to improve the level of textile testing. Lim and Kim (2011) developed an integrated hardware and software system, which could analyze various woven fabric structures initially through a series of image analysis technique and an artificial neural network. Shinohara (2008) analyzed the structure of textile fabrics from three dimensional images obtained from its X-ray computed tomography. However, these two approaches used expensive equipment to get woven fabric images, which was unfit for the actual production.

In recent years, with the development of image processing technology, the automatic recognition for woven fabric pattern has been studied widely. In summary, there are two kinds of approaches among previous studies. One is analyzing the overall characteristics of the woven fabric image and training a classifier to determine woven fabric structure types. Jeffrey Kuo and Tsai (2006) applied the co-occurrence matrix to calculate the texture characteristics, and then the learning vector quantization network is adopted as a classifier to categorize the type of weaving texture. Salem and Nasri (2009) also used the co-occurrence matrix and chose to support vector machine classifier to assort the type of woven fabric. Jing, Wang, Li, and Li (2011) used learning vector quantization neural network to recognize the woven fabric pattern, which improved the classification performance as well as the computational efficiency. However, this approach is very sensitive to the selected training data set for the learning algorithm.

The other kind of approach is to do segmentation for the crossed-area firstly, and then giving the types of the crossed-area (i.e. the type of yarn floated on the surface in crossed-area) by clustering. The crossed-area is detected by the extracted features of crossed- area of the woven fabric in most methods. Kang, Kim, and Oh (1999) used the geometry information of crossed-areas in the woven fabric reflected image to determine the state of the crossed-area. But, it is invalid when the thickness of yarn changes. Based on Fourier analysis and texture analysis, Lachkar, Gadi, Benslimane, D'Orazio, and Martuscelli (2005) realized crossed-area detection, which is useful for simple woven fabric with skewness or with non-periodic design. However, the computational complexity is high in Lachkar's approach. Then, Jeffrey Kuo, Shih, and Lee (2004) used fuzzy C-means (FCM) algorithm to classify the floats with texture features, and three basic weave patterns can be clearly identified. Xin, Hu, Baciu, and Yu (2009) put forward a method based on the active grid model to identify the weave pattern of woven fabrics. Pan, Gao, Liu, Wang, and Zhang (2010) set up a woven fabric pattern database to recognize the woven pattern including yarn-dyed fabric, which had good fault tolerant ability. Wang and Georganas (2011) proposed a novel automatic method for woven fabric structure identification. Firstly, the texture features based on gray level occurrence matrix were optimized by

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applying principal component analysis. Then, the optimized texture features were analyzed by FCM clustering for classifying the different crossed-area states. Finally, the texture orientation features were calculated to determine the exact state of crossed-area.

There are several questions among the existed methods based on feature extraction.

First of all, the recognition methods are interfered by the variations in lighting condition and the thickness of yarns, which may lead to failure detection. Furthermore, color woven fabrics are hard to be recognized. Moreover, the crossed-area cannot be segmented due to the deviation between weft and warp yarns. To segment the crossed-area, 2-D spatial domain gray projection along the horizontal and vertical directions is adopted. While, in some actual woven fabric images, the weft yarns and the warp yarns are not perpendicular to each other, which will lead to wrong segmentation for the crossed-area.

This paper exploits a new structure recognition method for woven fabrics based on image processing technology. Firstly, gray projection in domain space is used to correct the deviation of yarns. And based on the corrected result, the crossed-area of the warp and weft yarn is segmented. Secondly, gradient histogram features for each crossed-area is extracted. On this basis, the crossed-areas of woven fabric are divided into two categories preliminarily through FCM algorithm. The state of crossed-area is determined by clustering center vector. Thirdly, according to woven fabric periodicity, we correct the error recognition of crossed-areas and get woven fabric pattern diagram successfully.

The paper is organized as follows. In the next section, the entire recognition process is described in detail. Then, in the section 'Experimental results and analysis', we present recognition results of our method and comparison with other methods.

Woven fabric pattern recognition

Image acquisition and pre-processing

Woven fabric images are scanned by the USB electronic microscope. The weft yarns are horizontal when scanning. Several woven fabric images with different kinds of structures and colors are shown in Figure 1.

Gray image is extracted from original color image, and then median filtering with 3 × 3 masks and eroding are implemented to the gray image. The woven fabric images after pre-processing are shown in Figure 2.

Crossed-area segmentation

Crossed-area segmentation is important for crossed-area recognition. Because the brightness inside the yarns of woven fabric is higher than the gap between yarns, we adopt the 2-D spatial-domain gray projection approach to segment the crossed-area. The gray projection curves along the horizontal and vertical directions are calculated and smoothed by Gaussian filtering. The peaks and valleys in the two curves corresponded to the center of yarns and the gap between yarns, respectively. Crossed-area segmentation result is shown in Figure 3.

Ideally, the weft yarns and the warp yarns are perpendicular to each other. The crossed-area can be segmented accurately based on the gray projection curves. The weft yarns are horizontal when scanning. Therefore, the warp yarns should be vertical. However, there is a small angle deviation between the warp yarns and the vertical direction in most woven fabric images, which can be seen in Figure 1(d) and (g). In this case, it is very difficult to find distinct peaks and valleys from the vertical gray projection curve. We take Figure 1(d) as example. The weft yarns are horizontal, but the warp yarns are not vertical, which can be seen in Figure 4. The crossed-areas cannot be segmented correctly in this condition.

2-D spatial-domain gray projection is used to correct the warp yarns deviation. Firstly, the weft yarns through the horizontal gray projection curve are segmented, as shown in Figure 4.

When considering a single weft yarn, the deflection angle of the warp yarn is small, and the weft and warp yarns can be considered perpendicular. For each weft yarn, gray projection curve is calculated along the vertical direction. The gray projection curves for all weft yarns are shown in Figure 5, where *P*-axis stands for the number of pixels along horizontal direction, and *G*-axis describes the sum of gray value along the vertical direction.

Deviation correcting process is as follows:

Step 1: Compute valley points of each projection curve and store them in an array in order.
Step 2: A local minimum point (x_1,y_1) on the first weft yarn is selected as the first reference point, where x_1 and y_1 are the pixel coordinates along horizontal direction and vertical direction, respectively.
Step 3: Then, we search the valley on the next weft yarn as the next reference point (x_i,y_i) one by one (the difference of horizontal coordinate between the two adjacent reference points is within 10 pixels), until the last reference point (x_l,y_l).
Step 4: Calculate the position difference between the first and the last reference points as following:

$$\Delta x = x_l - x_1, \tag{1}$$

$$\Delta y = y_l - y_1, \tag{2}$$

$$\theta = \arctan(\Delta y / \Delta x), \tag{3}$$

where θ is the deviation angle.

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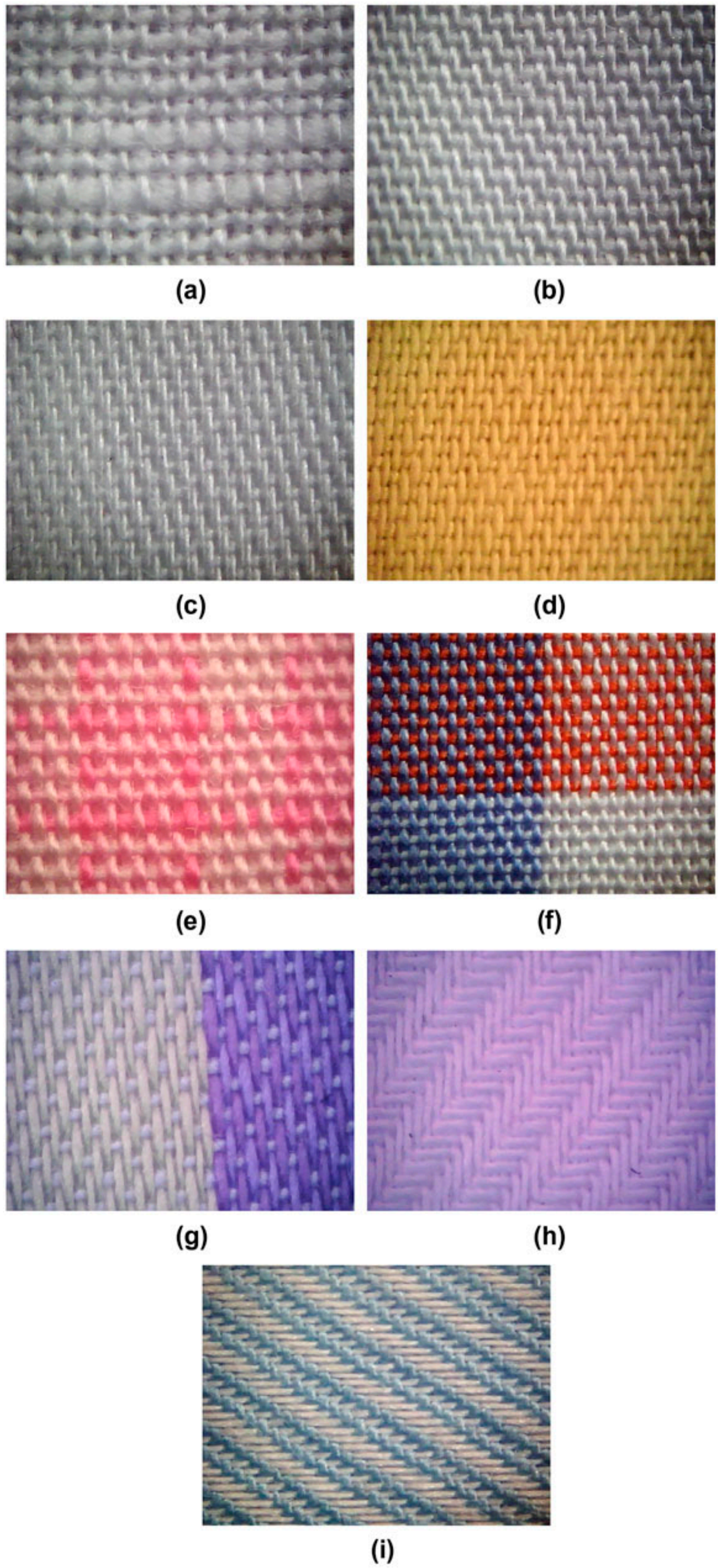

Figure 1. Woven fabric sample images.

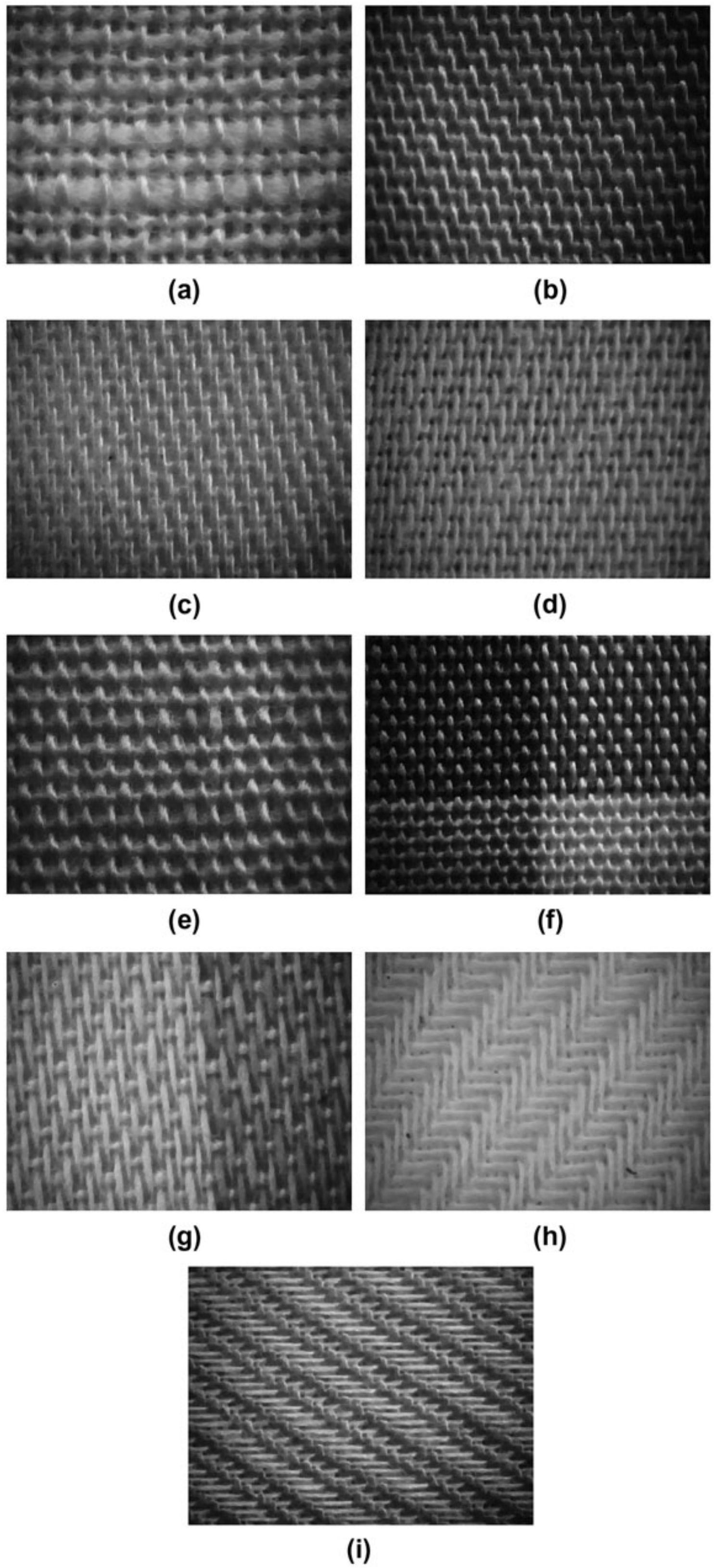

Figure 2. Pre-processed images.

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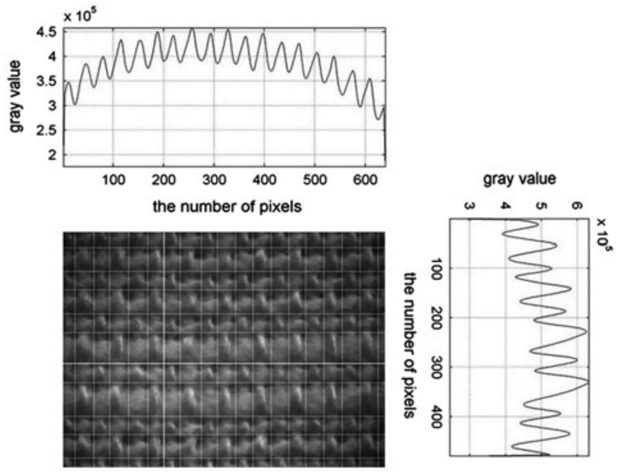

Figure 3. Segmentation result for the crossed-areas of Figure 2(a).

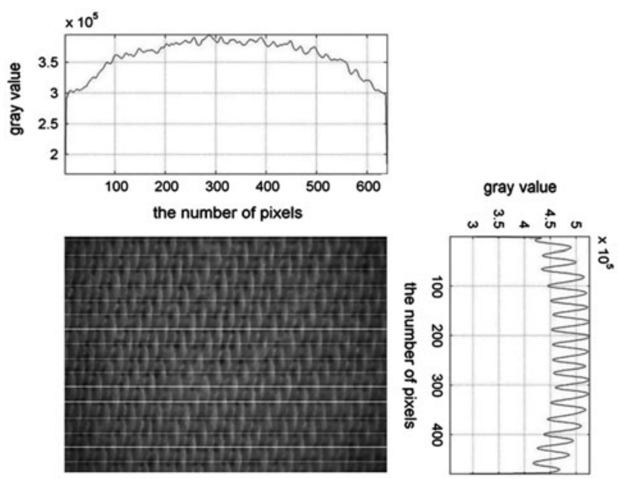

Figure 4. Weft yarn segmentation result for the crossed-areas of Figure 2(d).

Step 5: Compute the mean deviation angle $\overline{\theta}$ for the valley points from a third part in the middle section of the weft yarns. $\overline{\theta}$ is taken as the final deviation angle for correction.

Step 6: Perform coordinate transformation based on:

$$\begin{cases} b'=b \\ a'=a+b\tan\overline{\theta} \end{cases}, \tag{4}$$

where (a, b) and (a', b') are the coordinates in the uncorrected image and the corrected image, respectively, which is shown in Figure 6.

The corrected image is given in Figure 7(a). By using 2-D spatial-domain gray projection, we get the segmentation result, as shown in Figure 7(b).

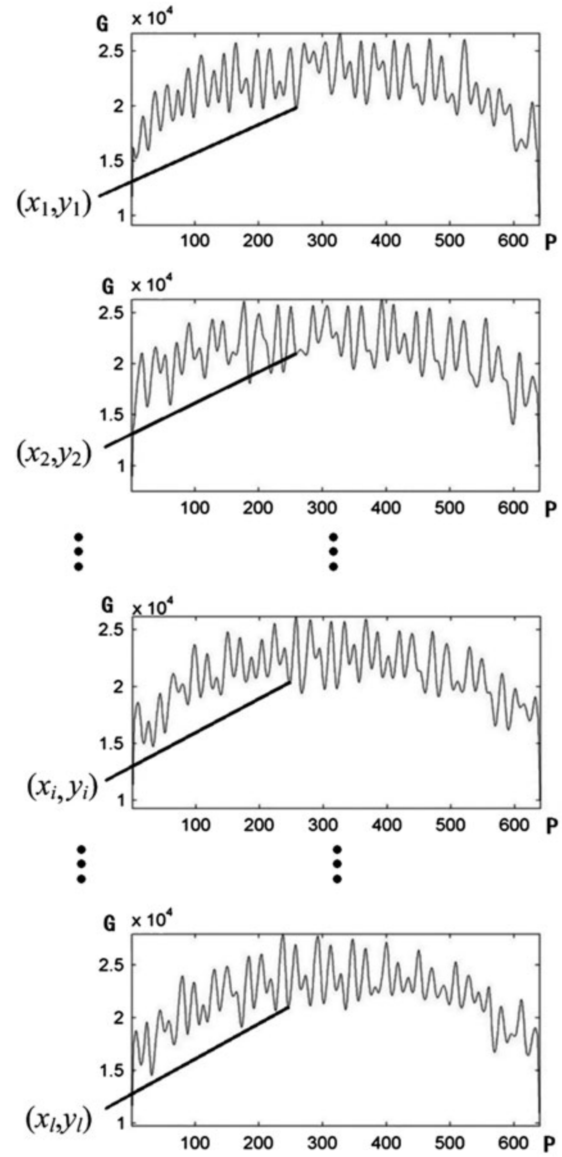

Figure 5. Gray projection of every weft yarn and the adjacent weft yarns corresonding local minmum point of Figure 2(d).

Feature extraction based on gradient information

In Figure 7(b), the image is divided into a number of crossed-areas of the weft and warp yarns. The warp crossed-areas mean that the warp yarn is floating on the weft yarn, and the weft crossed-areas reverse. To get the type of crossed-areas, features should be extracted from each crossed-area for recognition. Because of the impact of uneven illumination and diversity of fabric structure and dyed yarns, the gray information is not suitable for distinguishing the type of crossed-areas.

Dalal and Triggs (2005) proposed the Histograms of Oriented Gradient feature for pedestrian detection. This

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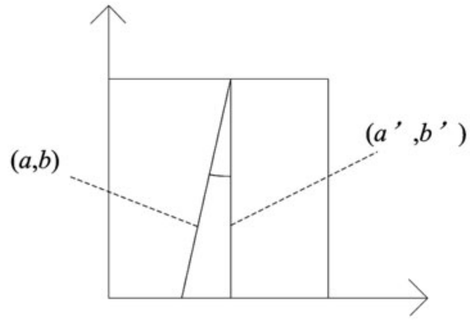

Figure 6. Coordinate transformation diagram.

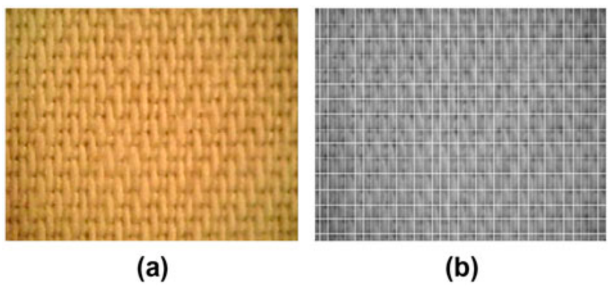

Figure 7. Corrected image and segmetation result of Figure 1(d). (a) Corrected image. (b) Segmetation result.

feature is calculated by the statistical gradient orientation and strength in the grid rectangular areas, which can overcome the interference of a variety of pedestrian posture and clothing color and reflect the target outline in a complex background. In this paper, based on the idea of Dalal and Triggs (2005), we get the gradient histogram feature for recognition of woven fabric pattern.

Firstly, the gradient value and the gradient orientation of each pixel in a crossed-area are calculated:

$$\begin{cases} I_x(i,j) = I(i,j+1) - I(i,j-1) \\ I_y(i,j) = I(i+1,j) - I(i-1,j) \\ g(i,j) = \sqrt{I_x^2(i,j) + I_x^2(i,j)} \end{cases}, \tag{5}$$

$$o(i,j) = \begin{cases} \arctan(I_y(i,j)/I_x(i,j)), & (I_x(i,j) > 0) \\ \arctan(I_y(i,j)/I_x(i,j)) + \pi, & (I_y(i,j) > 0, I_x(i,j) < 0) \\ \arctan(I_y(i,j)/I_x(i,j)) - \pi, & (I_y(i,j) < 0, I_x(i,j) < 0) \end{cases}, \tag{6}$$

where $I_x(i,j)$, $I_y(i,j)$ is the gradient value along vertical and horizontal direction. $g(i,j)$ and $o(i,j)$ are the gradient module and orientation of pixel (i,j), respectively. Secondly, the gradient histogram for each crossed-area is computed. The gradient orientation $o(i,j)$ is spaced over (−180°, 180°) based on Equation (6), which is divided into 16 bins at 22.5° intervals, as shown in Figure 8.

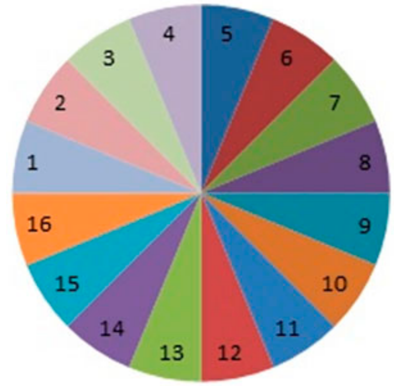

Figure 8. Gradient orientation interval division diagram.

The gradient module $g(i,j)$ is accumulated into orientation bins over crossed-area spatial regions. After normalization, the 16-dimensioned vector is obtained for each crossed-area. The warp crossed-areas and the weft crossed-areas with their gradient histograms are shown in Figure 9.

From Figure 9, we can see that the warp crossed-areas and the weft crossed-areas have different distribution of gradient histogram, which can provide the basis for recognition. While, the crossed-areas from the same type have similar gradient histogram, even they are different in size or brightness.

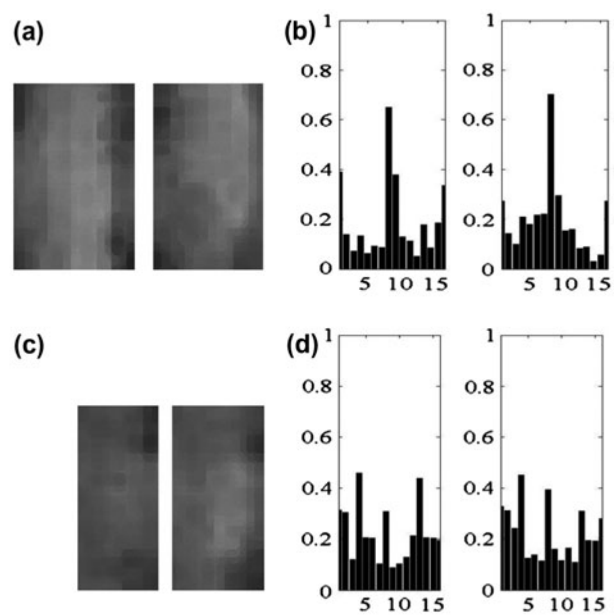

Figure 9. Warp and weft crossed-areas and their gradient historgram. (a) The warp crossed-areas. (b) Gradient histogram of the warp crossed-areas. (c) The weft crossed-areas. (d) Gradient histogram of the weft crossed-areas.

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Preliminary recognition based on FCM clustering

We use FCM clustering to recognize two different cross-areas preliminarily. FCM clustering can be viewed as an optimization problem that tries to optimize the following objective function:

$$J(U,V) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}\|x_j - v_i\|^2, \tag{7}$$

where c is the number of clusters, $m \in (1,+\infty)$ is a weighting exponent, n is the number of samples, and u_{ij} expresses the degree of membership of the jth sample belonging to the ith fuzzy group.

The main steps of FCM clustering are as follows:

(1) Set the number of clusters $c = 2$, weighting exponent $m = 2$, and termination parameter $\varepsilon = 10^{-3}$.
(2) Initialize degree of membership matrix U and the number of iteration $t = 1$.
(3) Update the cluster centers:

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}}, \quad i = 1,2,\ldots,c. \tag{8}$$

(4) Calculate the distance from the sample with cluster centers:

$$d'_{ij} = d_{ij}/r_{ij}^2, \quad t = t+1, \tag{9}$$

where d_{ij} is Euclidean distance between the sample and the cluster center, r_{ij} is the correlation coefficient of the sample and the cluster center.

(5) Update the degree of membership:

$$\begin{aligned} u_{ij} &= \left[\sum_{k=1}^{c}\left(\frac{d'_{ij}}{d'_{kj}}\right)^{\frac{2}{m-1}}\right]^{-1}, \quad d'_{ij} \neq 0 \\ u_{ki} &= 1, u_{ij} = 0, (i \neq k), \quad d'_{ij} = 0. \end{aligned} \tag{10}$$

(6) If $|J^{t+1} - J^{t}| \leq \varepsilon$, stop iteration, otherwise return (3).

Then, the crossed-areas are divided into two groups. For the computer-simulated woven fabric, in which the crossed-area type is known, we calculate the clustering center vectors as the recognition standard. For the tested woven fabric, the crossed-area type can be determined through computing the correlation coefficient between the clustering center vectors of the tested woven fabric and that of the computer-simulated woven fabric. When the correlation coefficient between the clustering center vector of the tested woven fabric and the clustering center of warp crossed-areas in computer-simulated woven fabric is larger, they are determined as the same type, and vice versa. Preliminary recognition results are shown in Figure 10.

Figure 10. Preliminary recognition results for Figure 7(a).

Error recognition correction

The proposed method is of high accuracy, there is only a small amount of error recognition in Figure 10. However, the weave pattern cannot be recognized in this condition. Therefore, the correction of error recognition is necessary. Because woven fabric is consisted of the standard unit, which is the basic weave pattern, the errors can be corrected by using the repetitive distribution along horizontal and vertical directions.

Firstly, we should get the size of the fabric unit N. The feature vector of each weft yarn is obtained by combining all the fabric crossed-areas vectors in the current weft yarn. Then, the fabric unit size can be obtained by calculating the correlation coefficient of the first weft yarn with others. Two weft yarns with the same structure which has big correlation coefficient, then N is determined. For example, the fabric unit in Figure 10 is 3×3 (i.e. $N = 3$). Figure 10 is divided based on N and the results are shown in Figure 11.

Secondly, the basic weave pattern is obtained. The weft crossed-areas and the warp crossed-areas are denoted by 0 and 1, respectively. The $N \times N$ unit slides on the preliminary recognition diagram (from left to right and from top to bottom) with step length N, and the mean values of the units with same structure are calculated. On this basis, the basic weave pattern can be

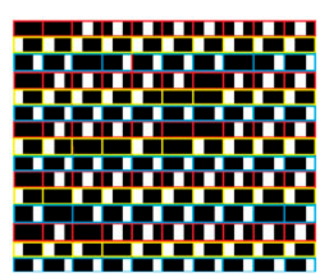

Figure 11. Divided diagram of the preliminary recognition results.

Table 1. Basic weave pattern in Figure 11. (a) Mean values of the 3 × 3 units (b) the standard unit.

1	0.2	1	1	0	1
0.14	1	1	0	1	1
1	1	0.08	1	1	0

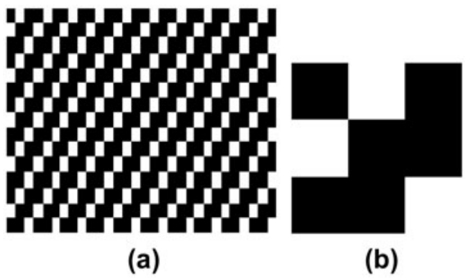

Figure 12. Corrected recognition results and its basic weave pattern. (a) Corrected recognition results. (b) Basic weave pattern. The size of recognition result image may be not correspond to the original woven fabric image completely, because the yarns located on the edge of woven fabric image are not involved in recognition.

obtained. Table 1 gives the mean values of the 3 × 3 units and the standard unit in Figure 11.

Each unit is corrected by the basic weave pattern. The corrected recognition results for Figure 10 is shown in Figure 12.

Experimental results and analysis

In general, there are two feature extraction methods for crossed-areas. One is based on the approach of Ref. Wang and Georganas (2011). The other one is Ref. Jeffrey Kuo, Shih, and Lee (2004), which can only recognize monochrome woven fabrics, and it is sensitive to the change of light. Our recognition method for woven fabric based on gradient histogram feature is more robust. In this section, the proposed method is compared with the approach of Ref. Wang and Georganas (2011) through many experiments.

Group 1: The preliminary recognition results of the two methods for simulated woven fabrics. The yarn is neatly arranged with uniform thickness in simulated woven fabric images. From Figure 13, we can see that our approach can get good results.

Group 2: The experiment results for the real woven fabrics with simple patterns. The real woven fabrics have diverse structures. The thickness and the color of yarns in a woven fabric image may be different, and the illumination of the image is uneven. Four real woven fabric images and their preliminary recognition results are shown in Figure 14. The images include white plain fabric with different thickness of yarns, white twill, and

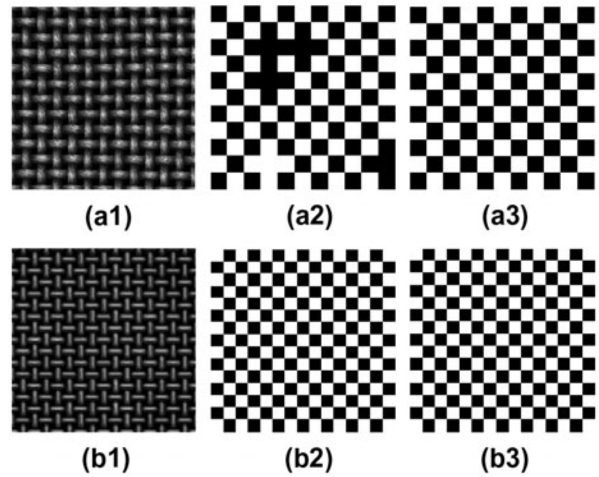

Figure 13. Preliminary recognition results of the two methods for computer-simulated woven fabrics. (a1) and (b1) are original images. (a2) and (b2) are preliminary recognition results based on the approach of Ref. Wang and Georganas (2011). (a3) and (b3) are preliminary recognition results of proposed method.

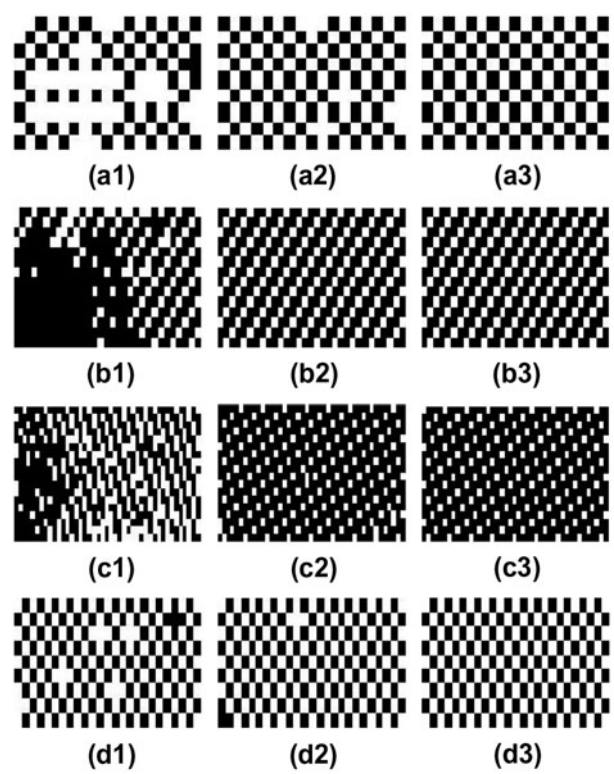

Figure 14. Preliminary recognition results of the two methods for real woven fabrics (Figure 1(a) white plain fabric, Figure 1(b) white twill fabric, Figure 1(c) white stain fabric, Figure 1(e) colorful plain fabric). (a1)–(d1) are preliminary recognition results based on the approach of Ref. Wang and Georganas (2011). (a2)–(d2) are preliminary recognition results of proposed method. (a3)–(d3) are error-corrected results based on proposed method.

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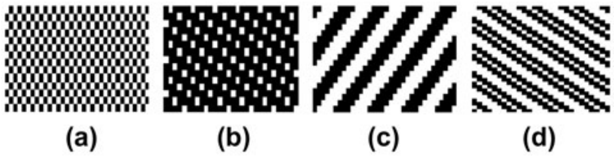

Figure 15. Recognition results of woven fabrics with complex patterns and colors (Figure 1(f) colorful plain fabric, Figure 1(g) colorful satin fabric, Figure 1(h) 4/4 monochrome diverse pattern fabric, Figure 1(i) 4/4 colorful diverse pattern fabric). (a)–(d) are recognition results. The deviation-corrected image will shrink smaller than the original.

stain with uneven illumination, and colorful woven fabrics. It is apparent that the approach of Ref. Wang and Georganas (2011) is sensitive to the thickness and color of yarns illumination. Our approach is not affected by factors above and obtains good results.

Group 3: The experiment results for the real woven fabrics with complex patterns. The proposed method cannot only achieve recognition for the plain, twill, and stain woven fabrics, but also obtain the desired results for woven fabrics with complex patterns and colors, which can be seen in Figure 15. While, the method based on Ref. Wang and Georganas (2011) fail to recognize the complex woven fabrics.

Conclusion

An automatic recognition method for woven fabric pattern is proposed in this paper. Firstly, the warp deviation is corrected and the crossed-areas are segmented using gray projection curves. Secondly, the gradient histogram feature of crossed-area is extracted. Thirdly, improved FCM algorithm is used to obtain the preliminary recognition for crossed-areas. At last, error recognition is corrected according to the woven fabric periodicity. We carry out experiment for computer-simulated and real woven fabric images. Experiment results show that the method combined the gradient histogram feature and the improved FCM algorithm can overcome the effects of thickness and color of yarns changing, uneven illumination, and give high recognition accuracy. The proposed method is more robust in this paper.

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