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Automatic recognition of weave pattern and repeat for yarn-dyed fabric based on KFCM and IDMF

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ABSTRACT

This paper proposes an automatic recognition method to analyze the weave pattern and repeat of yarn-dyed fabrics. Firstly, the warp and weft floats of preprocessing yarn-dyed fabric images with the solid color are segmented through gray projection method. The kernel fuzzy c-means clustering (KFCM) algorithm is utilized to classify the weave points based on the texture features of gray means, gray variances and gray level co-occurrence matrix (GLCM). The exact state of the two floats is judged by comparing average gray means of each cluster. With warp floats (1s) and weft floats (0s), fabric image is represented as binary value weave diagram and coded digital matrix. Then, improved distance matching function (IDMF) is employed to obtain the weave repeat of weave diagram, which is used to correct error floats and improve the accuracy of identification result. Moreover, IDMF is directly applied to yarn-dyed fabrics with different color yarns and obtained the accurate weave repeat with faster speed. The experimental results have shown that the proposed algorithm can recognize weave pattern and repeat accurately and faster, and output the corresponding binary value weave diagram of the identified fabric.

1. Introduction

The weave structure as one of the important fabric structural characteristics is the foundation of reproduction and redesign fabric in textile industry. However, it is still recognized by manual inspection with the help of magnifying glass and microscope, which are tedious and time-consuming work. Meanwhile, identification results are easily influenced by the subjective human factors, physical and psychological load and fatigue. With the rapid development of computer vision, the automatic, speedy and efficient methods for recognition weave pattern and repeat of yarn-dyed fabric are desperately needed to reduce labor cost and improve the efficiency of textile enterprises.

The fabric is composed of warp and weft floats [1] which are mutually perpendicular and interlaced yarns. Warp and weft floats refer to vertical and horizontal yarns overlapping each other respectively. In the process of detecting fabric weave patterns, the two major parameters need to be resolved: (1) segmentation the weave points, (2) detection the type of weave points.

Some recent researches on the application of computer vision have developed for fabric weave pattern and repeat recognition. Xin et al. has put forward to the active grid model (AGM) to identify weave pattern of fabrics [2]. Hu et al. has employed gray level co-occurrence to analyze the fabrics texture [3]. Another recognition method has analyzed the identification of segmented warp and weft floats in the fabric image to determine fabric weave patterns or repeats [4–8]. These methods mentioned above can identify several fabric weave patterns and repeats. However, the corresponding fabrics weave diagrams have not been outputted. These methods have low recognition rates and need human intervention. It cannot satisfy demands for reproduction in textile enterprises. Hence, it is important to develop an automatic recognition method with correct weave diagrams and accurate recognition rates.

In view of the mentioned issues, in this paper, the gray projection method is used to segment warp and weft floats of yarn-dyed fabric images with one color yarn after pre-processing. Then, KFCM algorithm is employed to divide all the weave points into warp floats group and weft floats group to obtain the weave patterns of fabric images through the texture feature values. Based on classification results of KFCM, a fabric weave pattern matrix composed of 0s (warp floats group) and 1s (weft floats group) can be obtained. Finally, weave repeat which is obtained through improved distance matching function is used to correct the error classification floats. Besides, the correct corresponding weave diagrams and accurate weave repeats of identified yarn-dyed fabrics are outputted.

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2. Experimental

2.1. Fabric images acquisition and pre-processing

In this paper, the experimental samples which contain yarn-dyed fabric images with one color yarn, double color yarns and three color yarns are scanned by CanonScan 9000F scanner with a resolution of 2400 dpi. For fabric images scanning, it is very important to obtain the clear images and arrange warp and weft yarns properly along horizontal and vertical directions to achieve the best performance for weave points and repeat detection.

With some external factors interference, weave patterns of fabric images are not clear, which may affect the classification accuracy of warp and weft floats. While top-hat transform is corrected the influence of uneven illumination and used for bright objects on a dark background, and bottom-hat transform is for the opposite, then they are both adopted to enhance digital images. Top-hat transform is the difference between original image and image open operation result, and bottom-hat transform is the difference between image close operation result and original image, so they are defined as follows:

$$\text{Top-hat transform}: T_{\text{hat}}(I) = I - (I \circ b) \quad (1)$$

$$\text{Bottom-hat transform}: B_{\text{hat}}(I) = (I \bullet b) - I \quad (2)$$

where, I is the original image, b is the structural elements, $\circ$ is the open operation, $\bullet$ is the close operation.

Top-hat transform has some characteristics of high pass filtering, which enhances image edge information, while bottom-hat transform can outstand boundaries among interconnected goals. Therefore, the combination of top-hat and bottom-hat transform is used to enhance image, which makes the gray of image foreground and background stretch further and highlight related targets and details. The original image adds the result of top-hat transform and then subtracts bottom-hat transform to improve the contrast of the image effectively, which can be expressed as follows:

$$I' = I + T_{\text{hat}}(I) - B_{\text{hat}}(I) \quad (3)$$

Though Eq. (3), the enhanced image I' is shown in Fig. 1(b). Besides, the average filter is employed to remove noise of fabric image.

2.2. Capture the warp and weft floats

In order to capture weave points, gray projection method [5,9] is employed to segment the overlapping area in gray image. According to the pixels of interstices between yarns with relative lower gray levels, the local lowest values of horizontal and vertical gray projections will be obtained. Suppose $I(x, y)$ is a $M \times N$ gray image. Therefore, the horizontal and vertical gray projection of the whole image is defined, respectively, as $H(y)$ and $V(x)$ in follows:

$$H(y) = \sum_{x=1}^{N} I(x, y) \quad (4)$$

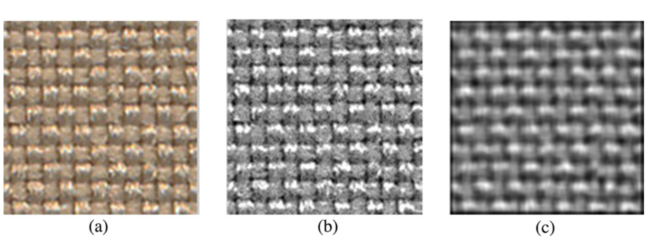


Fig. 1. Comparison between original, enhanced and average filtered fabric image. (a) The original image. (b) The enhanced image by top-hat and bottom-hat transform. (c) The average filtered image.

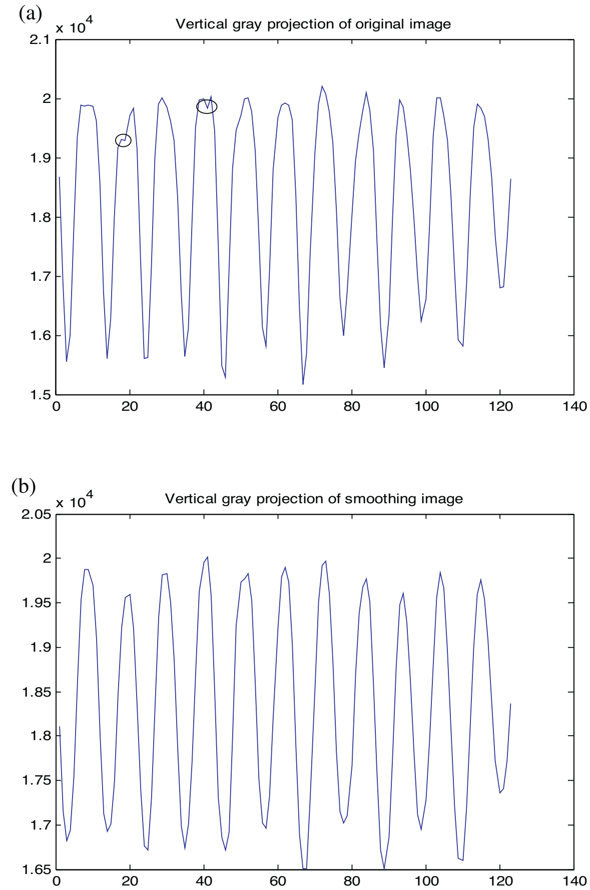


Fig. 2. The vertical gray projection curve of plain weave image. (a) The original projection curve. (b) The smoothing projection curve.

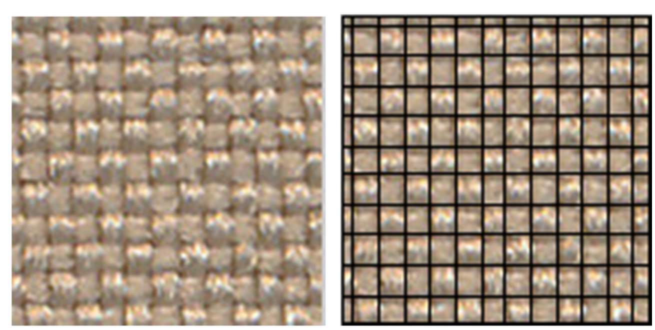


Fig. 3. The segmentation result of weave points.

$$V(x) = \sum_{y=1}^{M} I(x, y) \quad (5)$$

Due to the complexity of fabric images, there are some small waves in the whole projection curve, which are the local minima affected yarn location detection. Hence, average filter is used to smooth the curves. Fig. 2 shows the vertical gray projection of original and smoothing plain weave image. From the smoothing gray projection curve, the locations of local lowest values corresponding to interstices between yarns are obtained. By finding the local lowest values of horizontal and vertical gray projections, warp and weft separation lines are found, respectively. Therefore, warp and weft floats are segmented by the intersecting warp separation lines and weft separation lines (Fig. 3(b)).

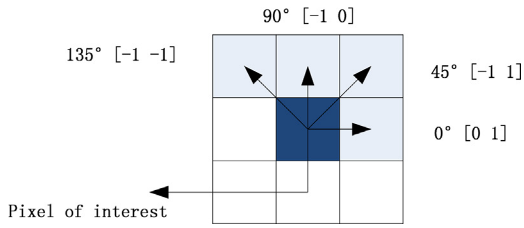
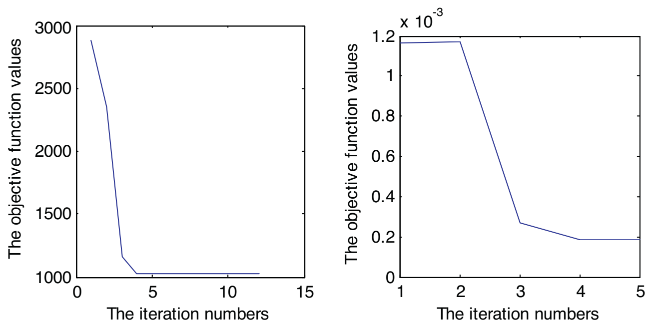


Fig. 4. The schematic of gray-level co-occurrence matrix.



(a) (b)

Fig. 5. The change curves of objective function values by FCM (a) and KFCM (b) algorithms, respectively.

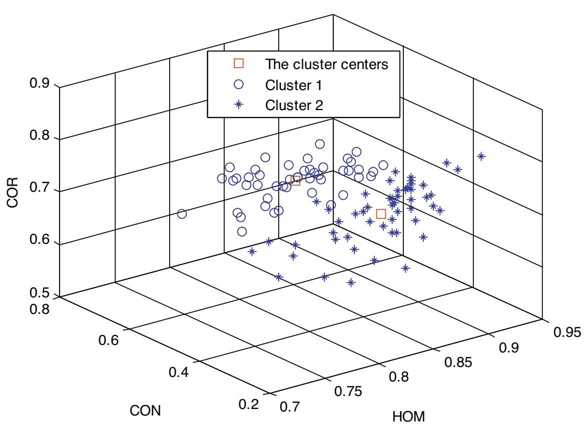


Fig. 6. The KFCM clustering results.

2.3. Texture feature extraction

Then, the weave points are obtained. In view of determining the state of overlapping areas, their texture features should be extracted as inputs of classifier to classify the weave points.

The texture feature of an image is represented by the change of image gray level. Therefore, the first-order texture feature values include gray mean and gray variance; the second-order texture feature values include angular second moment, contrast, correlation and homogeneity obtained by gray level co-occurrence matrix (GLCM) are employed to extract texture feature values of weave points. The GLCM [10,11] of an image presents statistic characteristics of gray level under the condition of a certain spatial position. Besides, GLCM which analyzes image local model can reflect the comprehensive information about direction, adjacent interval and rangeability. The two parameters affect GLCM calculation, θ and d, where θ is the position angle between two pixels, and d is the distance between two pixels. The $C(i, j; d, \theta)$, i – row and j – column element of gray level co-occurrence matrix, describes all appeared probability of gray value i and j in θ direction and d distance. Because GLCM is hard to describe texture features directly, some irrelevant statistics (ASM, CON, COR, HOM) based on GLCM are used to extract the texture feature of fabric images, which not only reduce the amount of calculation but also improve the accuracy of classification.

Suppose $f(i, j)$ is an $M \times N$ grayscale image. So the six features are shown as follows:

- Gray mean:

$$\mu = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j) \tag{6}$$

- Gray variance:

$$\sigma^2 = \frac{1}{M \times N} = \sum_{i=1}^{M}\sum_{j=1}^{N} (f(i,j)-\mu)^2 \tag{7}$$

- Angular second moment (or energy):

$$\mathrm{ASM} = \sum_{i=1}^{M}\sum_{j=1}^{N} C(i,j)^2 \tag{8}$$

- Contrast:

$$\mathrm{CON} = \sum_{i=1}^{M}\sum_{j=1}^{N} (i-j)^2 \cdot C(i,j) \tag{9}$$

- Correlation:

$$\mathrm{COR} = \sum_{i=1}^{M}\sum_{j=1}^{N} \frac{ijC(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y} \tag{10}$$

with

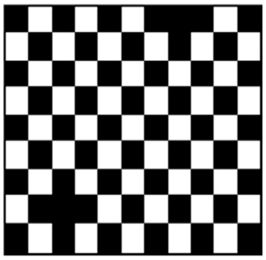
$$\mu_x = \sum_{i=1}^{M}\sum_{j=1}^{N} iC(i,j), \quad \mu_y = \sum_{i=1}^{M}\sum_{j=1}^{N} jC(i,j)$$

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

- Homogeneity:

$$\mathrm{HOM} = \sum_{i=1}^{M}\sum_{j=1}^{N} \frac{C(i,j)}{1+\left|i-j\right|^2} \tag{11}$$

According to the above defining characteristic of GLCM, the texture features of weave points are obtained. In this study, each float calculates multiple GLCM values to form a feature vector to avoid recognition errors caused by lack of texture feature information. It is defined that the value of direction θ are 0°, 45°, 90°, 135°, and the distance d is 1 in GLCM method (Fig. 4). Therefore, 18-dimensional feature vector which contains GLCM features of angular second moment, contrast, correlation and homogeneity in four directions and one distance, gray mean and gray variance are obtained for each weave point.

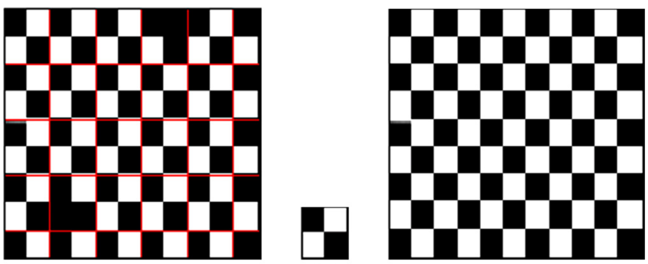


(a)

$$\begin{vmatrix} 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \end{vmatrix}$$

(b)

Fig. 7. The black–white digital image and coded digital matrix of Fig. 2(a) after FCM classified warp and weft floats.



(a) (b) (c)

Fig. 8. The recognition results of plain weave. (a) The recognition result of weave repeat by IDMF. (b) The weave repeat. (c) The error correction result of warp and weft floats.

2.4. Kernel fuzzy c-means clustering

As the most widely used unsupervised clustering method, fuzzy c-means clustering (FCM) can be applied to several applications, for example, image analysis, pattern recognition, image segmentation and so on. FCM [12,13] is based on minimizing objective function by organizing feature data sets $X = \{x_1, x_2, \ldots, x_k, \ldots, x_n\} \in R^p$ into different clusters. $u_{i,k} \in [0, 1]$ is the membership degree of x_k in ith cluster, meanwhile, it should satisfy the constraint conditions: $\sum_{i=1}^{c} u_{i,k} = 1$. The minimizing objective function is calculated as follows:

$$J_m(U, V) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{i,k}^{m} \left\| x_k - v_i \right\|^2 \tag{12}$$

where, n is the number of data set, c is the number of clusters with $1 < c \le n$, U is membership degree matrix, V is the cluster center matrix and v_i is the center of ith cluster, $m \in (1, +\infty)$ is a weighting exponent affecting the clustering fuzzy degree, $\left\| x_k - v_i \right\|$ is the distance between data x_k and centers of categories v_i.

However, FCM provides the sum of membership of each data object for all kinds of clusters is 1, which presupposes the influence of each object for all kinds of clusters is equal. This assumption may lead to data objects exist classification error of isolated points and noise points based on their large membership.

For the sake of solving the mentioned problem, kernel function is introduced into FCM to optimize data object characteristics and overcome the influence of isolated points and noise points for realizing more accurate clustering. Fuzzy c-means clustering based on kernel function (KFCM) [14,15] is mapping data object characteristics into high-dimensional feature space with non-linear mapping which is better to identify, extract and amplify the useful features. From Fig. 5, compared with FCM algorithm directly on the characteristics of data objects, KFCM algorithm obtains minimum objective function values within the shortest number of iterations. Therefore, KFCM can obtain better clustering effect and faster global convergence speed.

Define a nonlinear map as $\Phi : x \to \Phi(x) \in F$, where $x \in X$. X and F refer to data space and transformed feature space with higher dimension, respectively. KFCM minimizes the objective function as follows:

$$J_m(U, V) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m} \left\| \Phi(x_k) - \Phi(v_i) \right\|^2 \tag{13}$$

where $\left\| \Phi(x_k - v_i) \right\|^2 = K(x_k, x_k) + K(v_i, v_i) - 2K(x_k, v_i)$. In order to improve computing speed of the algorithm and simplify operational procedures, this section uses Gaussian kernel function which is established as following:

$$K_G(x, y) = \exp\left[-\frac{\|x - y\|^2}{2\sigma^2} \right] \tag{14}$$

KFCM is adopted to classify the warp and weft floats by their k dimensions texture feature values.The KFCM algorithm is implemented as follows:

Step 1: Set initial parameters: the parameter of Gaussian kernel function $\sigma = 150$, cluster number at $c = 2$, weighting exponent at $m = 15$, terminative precision at $\varepsilon = 0.00001$, the maximum number of iterations $T = 100$. Initializing each clustering center $v_i (i = 1, 2, \ldots, c)$.

Step 2: Update the membership degree matrix U using:

$$u_{i,k} = \frac{(1/(K(x_k, x_k) + K(v_i, v_i) - 2K(x_k, v_i)))^{1/(m-1)}}{\sum_{j=1}^{c} (1/(K(x_k, x_k) + K(v_j, v_j) - 2K(x_k, v_j)))^{1/(m-1)}} \tag{15}$$

Step 3: Update the cluster center matrix V by following equation:

$$v_i = \frac{\sum_{k=1}^{n} u_{i,k}^{m} K(x_k, v_i) x_k}{\sum_{k=1}^{n} K(x_k, v_i) u_{i,k}^{m}} \tag{16}$$

Step 4: If $\left| J^{(t+1)} - J^{(t)} \right| \le \varepsilon, (1 \le t \le T)$ or $t > T$, then stop the iteration, otherwise $t = t + 1$, and back to Step 2.

Because the dimension of texture features is more than three dimensions, the classification results cannot be shown in a single diagram. Given this, the clustering of KFCM by the three texture features (HOM, CON and COR) for a fabric sample is shown in Fig. 6.

Through KFCM algorithm, weave points are divided into two classes. However, their exact states have not yet been determined. Since warp floats of fabric structure generally located in the surface, then it presents relative high brightness in the reflection image. By analyzing average gray mean values of each classified cluster, their actual states can be recognized. In other words, the cluster with relative higher average gray mean values is determined as warp float, that is, the warp yarn is crossed over the weft yarn, and the other cluster is weft float.

2.5. Improved distance matching function

By KFCM algorithm, a certain number of misjudgment floats are existed in the classification results of weave points. Hence, using superposition of distance matching functions (DMFs) followed by computation of their forward differences, texture-periodicity is detected automatically to correct the error classification floats. Compared with Fourier transform, autocorrelation, co-occurrence matrices and entropy methods, the proposed method can automatically extract texture periodicity which does not need manual extraction of the peaks or computation of co-occurrence matrices or fixing of thresholds.

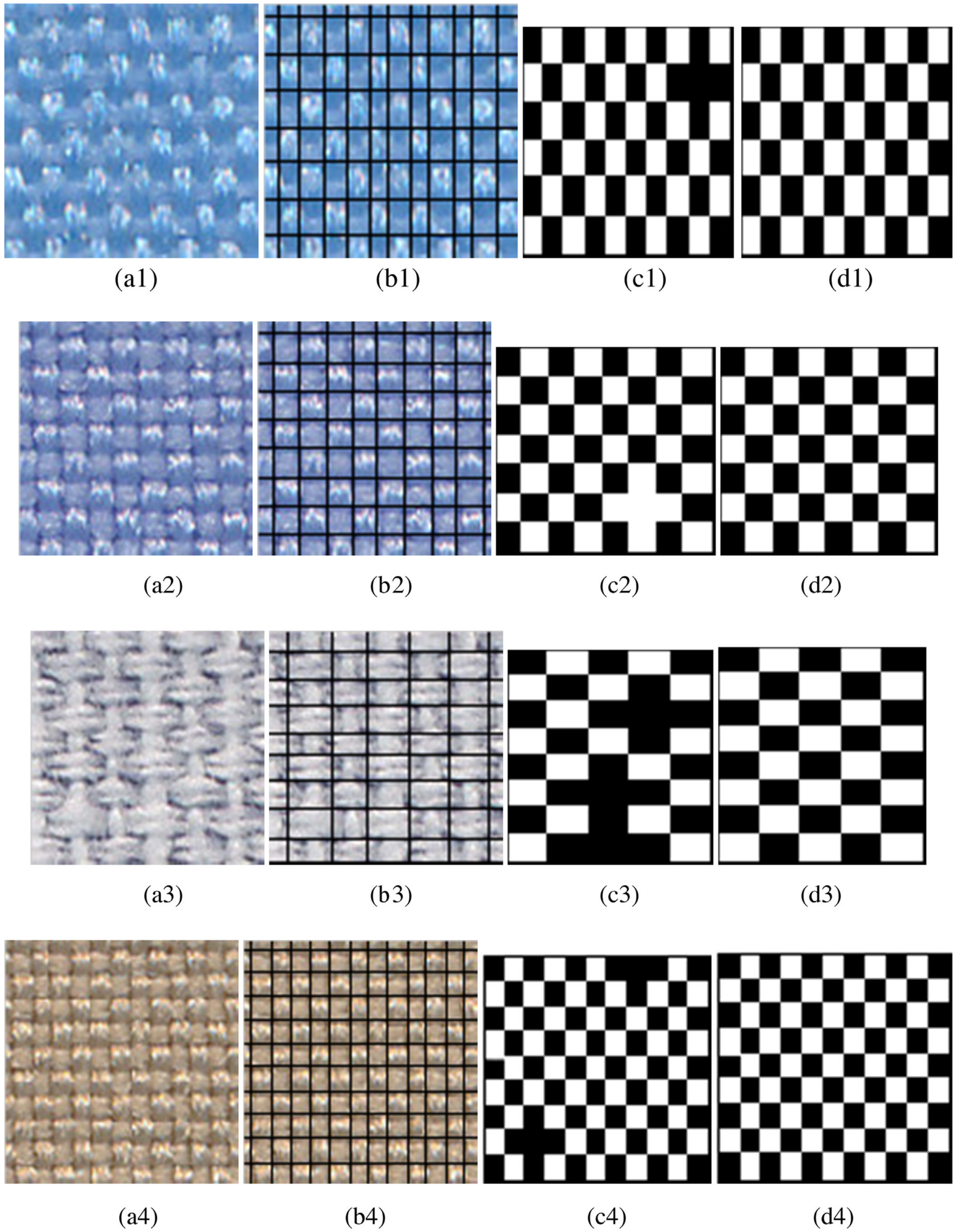


Fig. 9. Results of automatic recognition weave pattern of fabrics with the solid color. (a1–8): Image samples with plain, twill and satin weave; (b1–8): the warp and weft floats segmentation results; (c1–8): the classification results by KFCM; (d1–8): the corresponding weave pattern of fabrics by the error floats correction (black block represents weft floats and white one represents warp floats).

Table 1
Detection error rate of weave points in different texture samples.

Sample	a1	a2	a3	a4	a5	a6	a7	a8	Average
Error rate	1.67%	1.78%	7.5%	2.02%	2.5%	2.78%	1.67%	2.5%	2.8%

For a one-dimensional image function g with N pixels, the DMF can be defined as [16]

$$\lambda(p) = \sum_{i=1}^{N-p} [g(i) - g(i+p)]^2 \tag{17}$$

where p is the periodic variable and $1 < p < N-1$. When p is a period of image function g, it may satisfy$g(i) = g(i+p)$. Hence, the DMF is

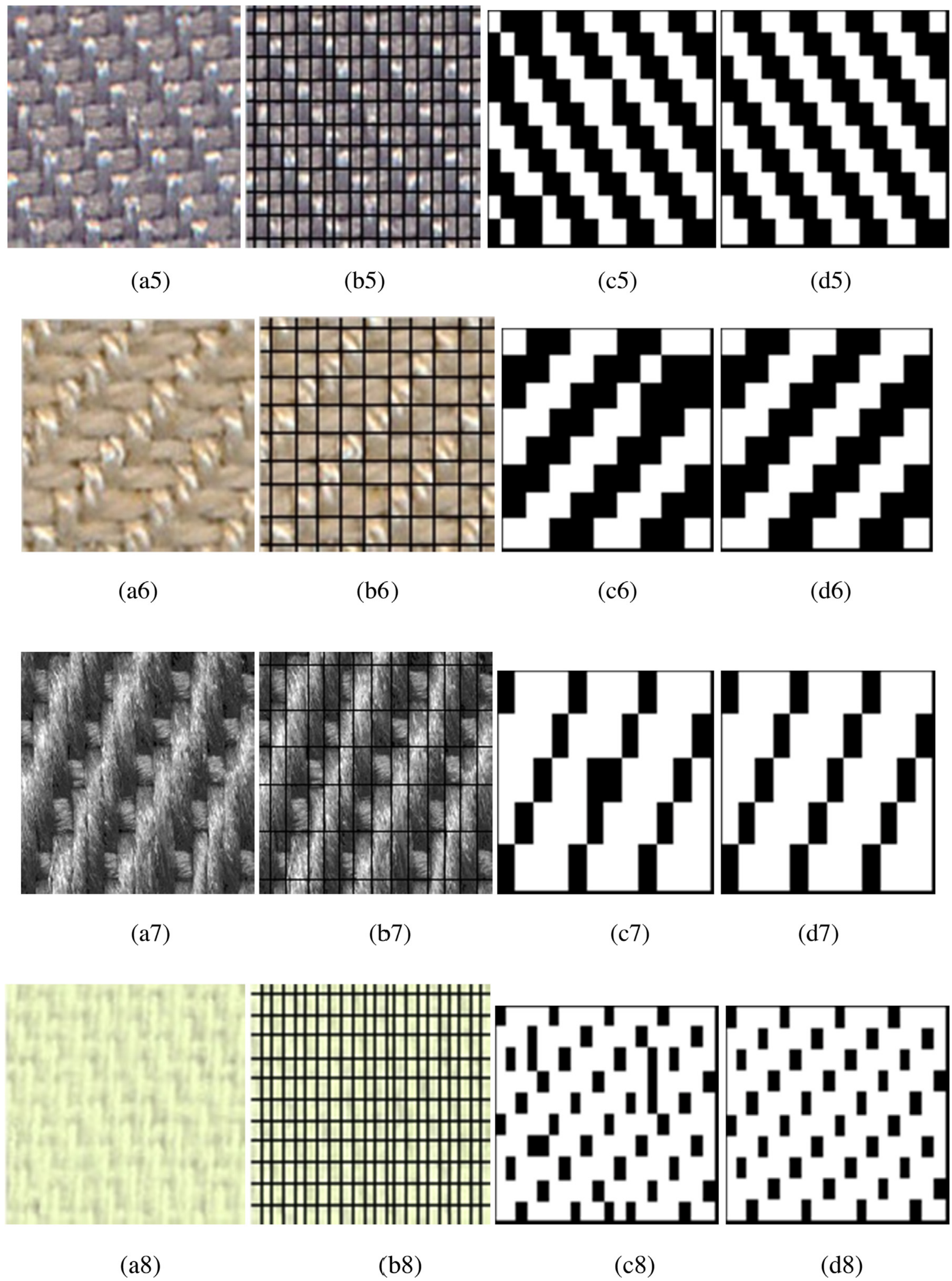


Fig. 9. *Continued.*

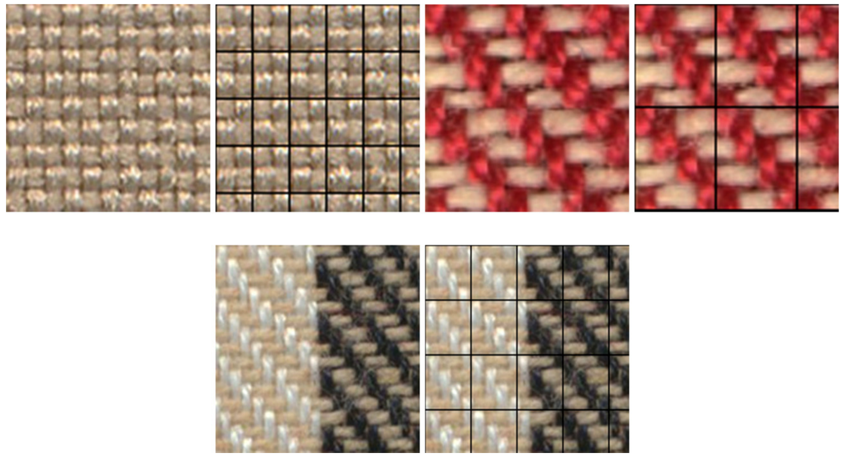


Fig. 10. The weave repeat extraction of yarn-dyed fabrics with one color yarn, double color yarns and three color yarns.

$$\lambda(p) = \sum_{i=1}^{N-p} [g(i) - g(i+p)]^2 = 0. \quad (18)$$

Gray fabric image can be consider as a two-dimensional function $f(x, y)$ of size $M \times N$. Based on periodic similarity of each row and column of fabric image, take row or column as one-dimensional function and sum one-dimensional function of all rows or columns as the result of improved distance matching function (IDMF). It improves the accuracy in detecting row and column periods. The IDMF [17] can be written as

$$Sum_{\lambda x}(p_r) = \sum_{x=1}^{M} \sum_{y=1}^{N-p_r} [f(x, y) - f(x, y+p_r)]^2$$
$$Sum_{\lambda y}(p_c) = \sum_{y=1}^{N} \sum_{x=1}^{M-p_c} [f(x, y) - f(x+p_c, y)]^2 \quad (19)$$

When p_r and p_c are the row and column periods, the IDMF can be written as follow according to Eq. (18).

$$Sum_{\lambda x}(p_r) = \sum_{x=1}^{M} \sum_{y=1}^{N-p_r} [f(x, y) - f(x, y+p_r)]^2 = 0$$
$$Sum_{\lambda y}(p_c) = \sum_{y=1}^{N} \sum_{x=1}^{M-p_c} [f(x, y) - f(x+p_c, y)]^2 = 0 \quad (20)$$

In order to extract the periodicities automatically, the forward difference of IDMF is utilized. The characteristic of IDMF of a 1D signal is that its slope change direction at a point corresponds to the periodicity or periodicity multiples. By obtaining the location of the maximum in second forward difference on overall IDMF, the period p can be extracted faster and automatically.

3. Results and discussion

3.1. Weave pattern recognition results and error correction

By KFCM algorithm, classification results of warp and weft floats can be obtained. From Fig. 7(a), it is easily found that two weave points are misjudged and the error rate reaches 2%. In order to reveal fabric weave pattern clearly, warp floats are denoted by white pixel value (1s), and weft floats are donated by black pixel value (0s). For a fabric sample, a coded digital matrix A, which represents the warp and weft floats after KFCM algorithm, is formed with 1s and 0s (Fig. 7(b)). Then, the basic weave repeat is employed to detect error classified floats by IDMF. Because the majority of weave points are detected correctly, the weave repeat with maximum probability of occurrence is taken as fabric weave repeat (Fig. 8(b)). Then weave repeat is used to correct the error classified floats and the final weave pattern diagram (Fig. 8(c)) of the samples are obtained correctly.

To validate the effectiveness of the proposed method, 8 fabrics with the solid color of different texture patterns are as the experimental samples. The results of weave pattern recognition are shown in Fig. 9. Image (a1–a4) are plain weaves with different yarn appearances and yarn counts. Image (a5–a7) are twill weaves, which are 2/2 left twill fabric, 2/2 right twill fabric and 3/1 right twill fabric. Image (a8) is satin fabric. Image (b:) are the floats segmentation results. Image (c:) are the classification results of weave points which have removed the edge points to improve the recognition accuracy. Image (d:) are the corresponding weave pattern of fabrics by the error floats correction. The percentages of incorrectly classified weave points of all weave points in each sample are shown in Table 1. The error may be caused by a local defect of the fabric surface, uneven illumination, a bad segmentation, or the low quality of fabric image. Since more than 90% weave points are correctly recognized. After the error correction of IDMF, the recognition rates increase to 100%.

3.2. Weave repeat extraction

To demonstrate the universality of IDMF further, the yarn-dyed fabric with one color yarn, double color yarns and three color yarns are also used as samples. The experimental samples are filtered the edge weave points to make weave repeats more clearly and visualization through gray projection method. The weave repeats which are accurate recognized are shown in Fig. 10. The experimental results confirm the effectiveness of the detection method. Besides, the detection time is about 1 s. Compared with other weave repeat extraction methods, IDMF has significant advantages for automatic periodicity extraction without the need of human intervention. IDMF is a good method for weave repeat recognition, which has faster computation speed, accurate recognition results, and strong robustness on samples noise.

4. Conclusion

This paper develops a system of automatic identification weave pattern and repeat of yarn-dyed fabrics based on KFCM and IDMF. By some morphological operations, the contrast of fabrics is enhanced. The gray projection method is utilized to cut out the weave points to obtain its texture features. With the 18-dimensional texture features, KFCM algorithm which is one of the main technical of unsupervised pattern recognition and widely used in image processing and analysis is applied to classify the overlapping areas into two categories namely the warp and weft floats. Compared with the FCM and GAFCM, KFCM has better classification effect, faster convergence speed of objective function, and shorter running time. Then, on account of warp floats with high brightness in the reflection image, the average gray mean value of each class is calculated to determine the exact state of warp and weft floats. Finally, the recognition results can obtain the black–white digital image and digital matrix of the fabric weave pattern by error correction. The experimental results reflect that the weave patterns of yarn-dyed fabrics in the solid color are successfully identified. Besides, the IDMF is utilized to extract the weave repeat accurate and faster compared with other weave repeat extraction methods. Nevertheless, the research objects of recognition weave patterns are only the solid color fabrics. Therefore, the yarn-dyed fabrics with multicolor and high complexity should be identified its weave patterns in the next stage of the research to achieve reproduction and redesign fabric in textile industry.

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References

[1] D. Zheng, G. Baciu, J. Hu, Entropy-based fabric weave pattern indexing and classification, Int. J. Cogn. Inform. Nat. Intell. (IJCINI) 4 (2010) 76–92.
[2] B. Xin, J. Hu, G. Baciu, X. Yu, Investigation on the classification of weave pattern based on an active grid model, Text. Res. J. 79 (2009) 1123–1134.
[3] Y. Hu, C.X. Zhao, H.N. Wang, Directional analysis of texture images using gray co-occurrence matrix, in: 2008 IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application, 2008, pp. 277–281.
[4] F. Ajallouian, H. Tavanai, M. Palhang, S.A. Hosseini, S. Sadri, K. Matin, A novel method for the identification of weave repeat through image processing, J. Text. Inst. 100 (2009) 195–206.
[5] X. Wang, N.D. Georganas, E.M. Petriu, Fabric texture analysis using computer vision techniques, Instrum. Meas. 60 (2010) 44–56.
[6] C.-F.J. Kuo, C.Y. Shih, C.E. Ho, K.C. Peng, Application of computer vision in the automatic identification and classification of woven fabric weave patterns, Text. Res. J. 80 (2010) 2144–2157.
[7] R. Pan, W. Gao, J. Liu, H. Wang, Automatic recognition of woven fabric pattern based on image processing and BP neural network, J. Text. Inst. 102 (2011) 19–30.
[8] D. Zheng, Y. Han, J.L. Hu, A new method for classification of woven structure for yarn-dyed fabric, Text. Res. J. 84 (2014) 78–95, 0040517513483858.
[9] R. Pan, W. Gao, J. Liu, H. Wang, X. Zhang, Automatic detection of structure parameters of yarn-dyed fabric, Text. Res. J. 80 (2010) 1819–1832.
[10] R.M. Haralick, K. Shanmugam, I.H. Dinstein, Texture features for image classification, IEEE Trans. Syst. Man Cybern. 3 (1973) 610–621.
[11] J. Jing, J. Wang, P. Li, Y. Li, Automatic classification of woven fabric structure by using learning vector quantization, Procedia Eng. 15 (2011) 5005–5009.
[12] J. Keller, R. Krisnapuram, N.R. Pal, Fuzzy Models and Algorithms for Pattern Recognition and Image Processing, vol. 4, Springer, 2005.
[13] C.-F.J. Kuo, C.Y. Shih, J.Y. Lee, Automatic recognition of fabric weave patterns by a fuzzy C-means clustering method, Text. Res. J. 74 (2004) 107–111.
[14] Y. Shi, Y. Shi, Remote sensing image classification and recognition based on KFCM, in: Computer Science and Education (ICCSE), 2010 5th International Conference on IEEE, 2010, pp. 1062–1065.
[15] J.H. Wang, W.J. Lee, S.J. Lee, A kernel-based fuzzy clustering algorithm, in: Innovative Computing, Information and Control, 2006. ICICIC'06. First International Conference on IEEE, 1, 2006, pp. 550–553.
[16] G. Oh, S. Lee, S. Yong Shin, Fast determination of textural periodicity using distance matching function, Pattern Recognit. Lett. 20 (1999) 191–197.
[17] V. Asha, P. Nagabhushan, N.U. Bhajantri, Automatic extraction of texture-periodicity using superposition of distance matching functions and their forward differences, Pattern Recognit. Lett. 33 (2012) 629–640.