GaoMing Jiang, Dan Zhang, HongLian Cong, AiJun Zhang, Zhe Gao

Engineering Research Center of Warp Knitting Technology, Ministry of Education, Jiangnan University,
Wu xi, Jiangsu, 214122, P.R.China
E-mail: jiang@526.cn

Automatic Identification of Jacquard Warp-knitted Fabric Patterns Based on the Wavelet Transform

Abstract
In view of the fact that the design of jacquard warp knitting patterns is time-consuming, this paper proposes a rapid segmentation method to divide the multi-textural regions of jacquard warp-knitted fabric which could be used for automatic identification of fabric patterns to improve the efficiency of design. After pretreatment, the images scanned were decomposed by a two-layer two-dimensional wavelet transform and the standard deviations of five channels were extracted as the eigen values. Then, after giving the cluster centers, a multi-channel clustering was made combined with a K-means clustering algorithm. Finally the removal of noises caused by classification errors was needed , after which an accurate identification image was obtained. The experiments show that this method can achieve automatic texture segmentation of jacquard warp-knitted fabric with more than three textural regions. The identification results have high regional consistency, and the segmentation accuracy is up to 92%. The method can also adapt to a variety of mesh regions. Besides this, the approach is fast and can simplify craft personnel's traditional process of pattern tracing classification when it is combined with CAD. Through this method, the efficiency of jacquard warp-knitted product designing can be improved a lot.

Key words: *Jacquard, warp-knitted fabric, pattern, automatic identification, wavelet transform.*

Introduction

Texture can be considered as gray scale (colour) changes in a certain form in the space to produce patterns (modes) [1]. Therefore the texture is a regional feature. The description of texture contains consistency, density, roughness, regularity, direction, frequency and phase position, etc [2, 3]. Observers often evaluate and classify textures based on these visual characteristics.

The key characteristic of jacquard warp-knitted fabrics is the multi-texture and different regions in the fabric have different textural properties, shown in ***Figure 1***. Each texture region (such as the A/B/C region shown in ***Figure 1.c***) is formed by a kind of specific jacquard tissue, thus each jacquard region presents a structural character. The smallest unit of the region is called the jacquard unit, which can be divided into a basic unit and combined unit. In the jacquard design grids, the basic unit can be commonly expressed by a single color of red/green/blue/white; while the combined unit is a kind of complex jacquard element, expressed as the combination of red, green, blue and white i.e. four basic colours, as shown in ***Figure 2***. This jacquard unit repeats and forms a jacquard area, which is why these structured areas have significant texture features in view of their iconography.

Because of various textures, jacquard fabrics have rich effects and are widely used as indoor decorative fabrics, fashion fabrics and lace fabrics. However, due to the difficulty and complication of classifying and dividing each texture region, especially the mesh regions, when a sample design is given, designers must trace the contour according to different effect arrangement levels (textures), and then realise the transfer from the jacquard fabric image (***Figure 3.a***) to the original jacquard pattern design (***Figure 3.b***). It is mainly based on manual operations and severely reduces the work efficiency.

Thus it is highly desirable to develop an automatic identification method for jacquard warp-knitted fabric patterns. In view of the textural characteristics of jacquard warp-knitted fabrics, this paper simulated the human visual system and adopted texture image segmentation method to get each pattern design area

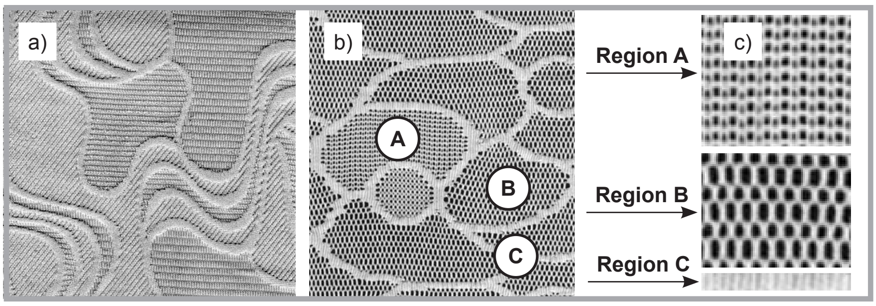

Figure 1. *Multi-texture regions of Jacquard warp-knitted fabric.*

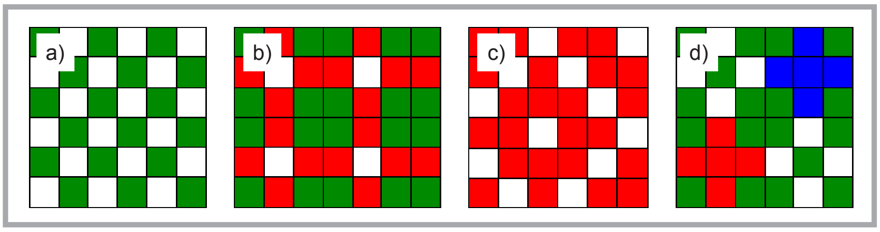

Figure 2. *Combined Jacquard unit.*

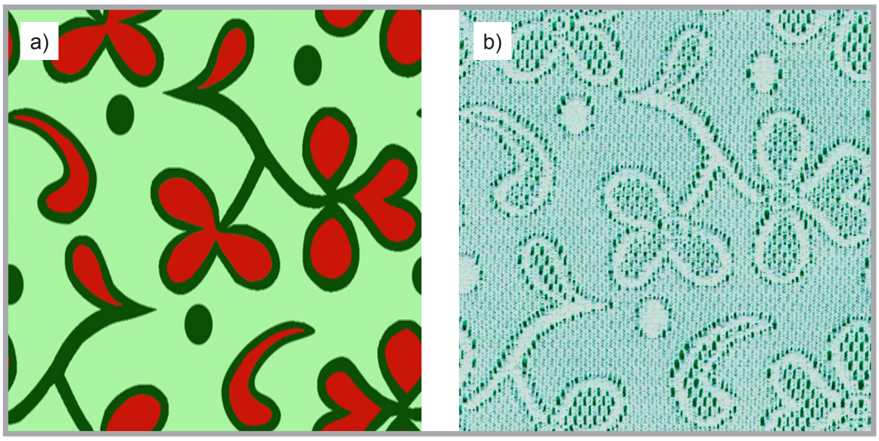

Figure 3. Design of Jacquard warp knitted fabric pattern; a) scanning image of jacquard fabric, b) original jacquard pattern design.

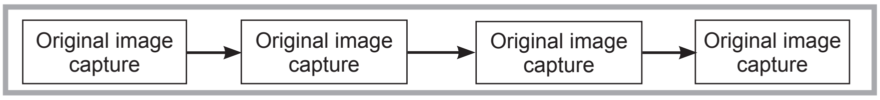

Figure 4. Fabric image pre-processing process.

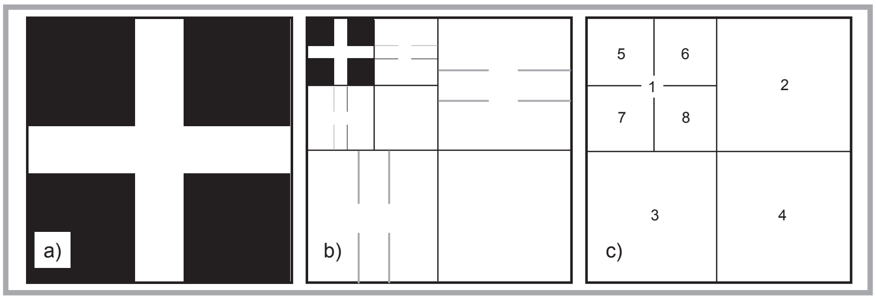

Figure 5. Schematic diagram of two layers of wavelet decomposition; a) original image, b) result diagram, c) schematic diagram of channels.

accurately and quickly. This new method can meet the requirements of designers to transfer the scanning image of the jacquard sample to the original design rapidly.

Texture image processing

The texture image segmentation process includes these steps:

pretreatment of scanned image
→ wavelet decompounding to extract textural properties
→ multi-channel K-means clustering to classify textures
→ original image reconstruction
→ noise removal.

Pretreatment of scanned image

Pretreatment of the fabric image is the premise of textural property extraction and classification, whose aim is to remove noises carried by the fabric itself, or brought in during the scanning process, and also enhance useful information through some basic image processing methods. Aiming to obtain a jacquard warp-knitted scanned image, during the process of pretreatment, the authors summed up the pre-processing steps, shown in ***Figure 4***.

In order to get gray-scale images which conform to the human visual system, the researchers used the weighted average method, in which the weight could be customised. Because human eyes have the highest sensitivity to green, while to blue it is the lowest, ***Equation 1*** is used to accomplish the gray-scale conversion:

$$x(j,k) = 0.30\,R(j,k) + 0.59\,G(j,k) + 0.11\,B(j,k) \qquad (1)$$

Where: $x(i,k)$ refers to the grey value of one pixel at the coordinate of (j,k); $R(j,k)$, $G(j,k)$ & $B(j,k)$ refer to the three components of Red, Green and Blue separately in the RGB colour model at the coordinate of (j,k).

Extraction of textural properties based on the wavelet transform

This study is to be applied in production practice, hence the implementation of the algorithm is made through VC++ programming. Taking the requirements of the speed of the algorithm into account, unnecessary algorithm expenditures are minimised. The fabric pattern with only two types of texture can be classified quickly using Law's texture energy measurement method [4]; while with three or more types of texture, the researchers must use the wavelet decomposition in order to achieve clear identification. Human vision has the features of multi-channel and multi-resolution, hence the researchers can use the wavelet transform to extract textural properties.

The general idea of this algorithm is as follows: In the frequency domain, the wavelet transform is used to decompose the jacquard warp-knitted texture image into low-frequency sub-bands (the basic structure of the texture) and a series of high-frequency sub-bands (details) of different directions, and then the characteristics of each sub-band are extracted for the formation of eigenvectors to describe the complex texture [5].

After inputting the image to be identified, the researchers employed low-pass decomposition filters $\{h_0[k]\}$ and a high-pass decomposition filter $\{h_1[k]\}$ to divide the original image into sub-band images according to different frequency bands and resolutions [6]. Through the experiment on the jacquard warp-knitted fabric pattern, a db4 wavelet was chosen because it could ensure that the textural properties needed could be extracted from the low-frequency sub-band as much as possible. Its decomposition filter is as follows:

1) Low-pass decomposition filter $\{h_0[k]\}$
[-0.0106 0.0329 0.0308
-0.1870 -0.0280 0.6309
0.7148 0.2304]

2) High-pass decomposition filter $\{h_1[k]\}$
[-0.2304 0.7148 -0.6309
-0.0280 0.1870 0.0308
-0.0330 -0.0106]

Taking the accuracy and speed into account, the layer of the wavelet decomposition was chosen as 2, that is to say the original image was transformed two-layer two-dimensionally, and the image gray scale was quantified as 16 levels. The results and schematic diagram of the channels after decomposition are shown in ***Figure 5***.

The follow-up treatment of the segmentation results was to select the standard deviation of pixels of the 2nd, 3rd, 5th &

6th channels as an eigen value. The programming formula is:

$$xiaobo[i].xiangsu[j][k].e =$$

$$= \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}\left|x(j,k)-\overline{x(i)}\right|}{MN} \quad (2)$$

$$\overline{x(i)} = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}x(j,k)}{MN} \quad (3)$$

where: *xiaobo*[*i*].*xiangsu*[*j*][*k*].*e* is the eigen value; *i* refers to the wavelet channel number, ranging from 2, 3, 5, 6 to 7 five channels; *xiangsu*[*j*][*k*] refers to the pixel whose coordinate is (*j,k*) in channel I; $x(i,k)$ represents the gray scale value of one pixel at the coordinate of (*j,k*); $\overline{x(i)}$ is the average value of all the gray scale values in the image of channel I, and MN is the image size of the current channel i.

And then the researchers worked out the maxi mum eigen value of each channel, and normalised all the eigen values. 5 available feature vectors were achieved from 5 channels, which can be expressed by:

{*xiaobo*[2].*xiangsu*[*j*][*k*].*e,*
xiaobo[3].*xiangsu*[*j*][*k*].*e,*
xiaobo[5].*xiangsu*[*j*][*k*].*e,*
xiaobo[6].*xiangsu*[*j*][*k*].*e,*
xiaobo[7].*xiangsu*[*j*][*k*].*e*},

then they were used in K-means clustering.

Texture classification and image reconstruction

Using the K-means clustering which was based on neighbor rule, selecting the Euclidean distance as the distance measure, and making the sum of the squared error as the criterion function to minimise the following indicator:

$$E = \sum_{i=1}^{K}\sum_{x\in Q_j^{(i)}}\left\|g(x)-\mu_j^{(i+1)}\right\|^2 \quad (4)$$

where $Q_j(i)$ refers to the summation of the feature points which are endowed to class *j* after the i^{th} iteration, and μ_j refers to the average value of class j. Hence the formula above gives the distance sum between each feature point and the mean value of its corresponding class.

Then the multi-channel clustering process is as follows:

1) To improve the clustering speed, click the original image *K* times manually to get *K* points as initial cluster centers, and the number of categories is K.
2) Based on the eigen value proposed through wavelet analysis, we can make clustering segmentation on channels 5, 6 and 7 of the second-level wavelet, and three feature vectors can be constructed at the coordinate of (*j,k*) of each pixel; then to check the distance between it and *K* cluster centers, the squared error is used as shown in ***Equation 4*** to classify pixels to *K* categories for each channel; this is called the first cluster segmentation;
3) In the segmentation results, the gray scale value of the pixels in the same region is then changed into the average energy, in order to prevent that some of the components play a dominant role in the clustering. The average energy is given by ***Equation 5***:

$$x(i,j) = E_k = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|x(i,j)\right| \quad (5)$$

4) Symmetrical interpolation expansion is used to double the image resolution. Assuming the size of the original image is *M*×*N*, the number of texture categories is *Q*, and the image's size is (*M*/2)×(*N*/2), which was got through the previous hierarchical clustering (the third step above), in which each pixel can be defined as *L*(*k*, *l*), where *k* = 0, 1, 2, 3, (*M*/2) - 1, *l* = 0, 1, 2, 3, (*N*/2) - 1, then the image is expanded to half the size of the original image symmetrically. For example:

$$\begin{bmatrix}1 & 2 & 3\\ 4 & 5 & 6\end{bmatrix} \qquad \begin{bmatrix}1 & 1 & 2 & 2 & 3 & 3\\ 1 & 1 & 2 & 2 & 3 & 3\\ 4 & 4 & 5 & 5 & 6 & 6\\ 4 & 4 & 5 & 5 & 6 & 6\end{bmatrix}$$

a) b)

Figure 6. *Symmetric interpolation expansion; a) original image, b) interpolated expanded image.*

The segmented image is shown in ***Figure 6.a***, which is a 2 × 3 matrix. The expanded image by interpolation is shown in ***Figure 6.b***, which is enlarged to a 4 × 6 matrix. Using this simple interpolation method, a more smooth edge can be got.

5) Calculate the normalised standard deviation of each pixel in the expanded image, and then cluster with the two channels (channels 2 and 3) decomposed in the first level wavelet decomposition. (the same as in step 2); three feature vectors can then be constructed at the coordinate of each pixel, and all the pixels are classified to K categories.
6) Re-use the simple interpolation method shown in step 4 to obtain the final segmentation result of the original image. Though the segmentation accuracy is not high because of the coarse-scale decomposition, the segmentation result has basically met the requirements of pattern identification.

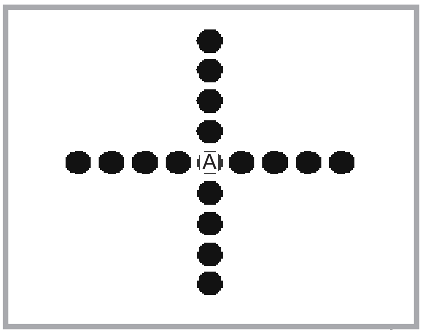

Figure 7. *Schematic diagram to remove noise.*

Noise removal

In order to improve regional consistency in the identification image, 16 pixels were located up and down, left and right of the current pixel, and then noise was removed by contrasting the values.

The contrasting is shown in ***Figure 7*** where point A's pixel value is *P*(*x,y*); *x* and *y* represent the coordinates of the point. The blue points in ***Figure 7*** represent the 16 pixels, whose gray values are as follows:

{*P*(*x*-1,*y*), P(*x*-2,*y*), P(*x*-3,*y*), P(*x*-4,*y*),
P(*x*+1,*y*), P(*x*+2,*y*), P(*x*+3,*y*), P(*x*+4,*y*),
P(*x,y*-1), P(*x,y*-2), P(*x,y*-3), P(*x,y*-4),
P(*x,y*+1), P(*x,y*+2), P(*x,y*+3), P(*x,y*+4)}.

Compare *P*(*x,y*) to the 16 values, if *P*(*x,y*) does not account for 50%, then change its value to the pixel value whose proportion is the largest in the 17 values.

Algorithm evaluation

By means of a manual click to get clustering centers, and combined with the rapid methods (texture property extraction and segmentation) mentioned above, a more accurate pattern identification result can be achieved. ***Figure 8*** shows some of the results.

In order to evaluate this automatic identification algorithm objectively, ***Equa-***

tion 6 was used to evaluate the accuracy of the texture image segmentation [7]:

$$\text{Total accuracy rate of segmentation} = \frac{N_c}{N_t}\times 100\% = (1-\frac{N_w}{N_t})\times 100\% \quad (6)$$

where: N_c represents the number of pixels correctly classified; N_t represents the number of pixels to be classified; and N_W refers to the number of pixels wrongly classified.

Take the following measurement: Firstly, identify the fabric image manually, and take the manual identification as a standard, then compare the results with the automatic identification to calculate the number of pixels which are wrongly classified, and finally calculate the total accuracy. ***Table 1*** shows the results.

The test image had the same total number of pixels, which were 262 144. From ***Table 1***, it can be seen that the average operation time of the algorithm is 2992 ms, and the mean value of the total accuracy rate 92.52%.

Combined with the automatic identification results of ***Figure 8***, it is can be noticed that there is some inevitable noise in some small areas due to the non-uniform arrangement of the jacquard net; the identification image eventually has obvious colour differences among the various regions, and the image has good regional coherence. We can also find that the accuracy of the edge identified is good, and the comprehensive identification accuracy is high.

Designers can take the automatic identification image as a jacquard design (plan of weave), and import it into appropriate design software directly to do the follow-up treatment, such as the design (plan of weave), change of colour, and jacquard tissue coverage.

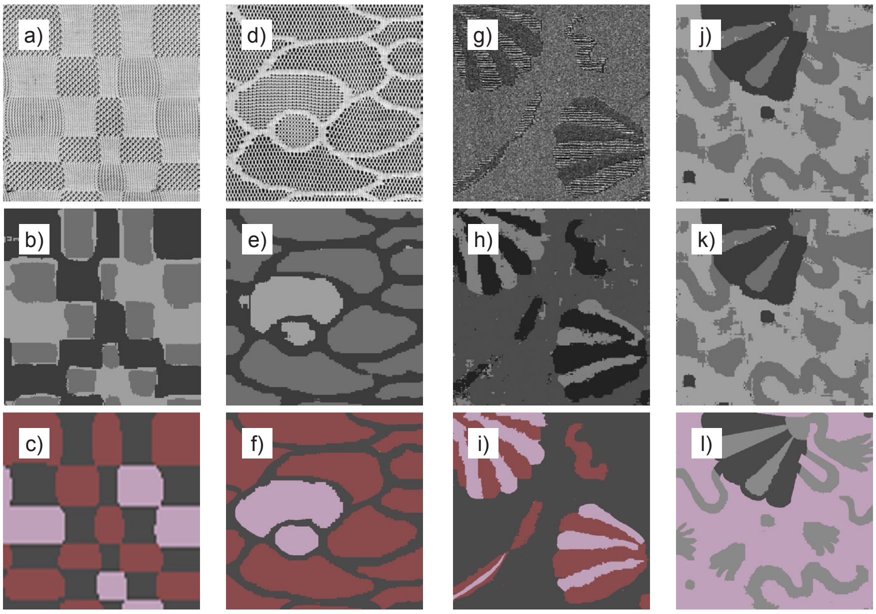

Figure 8. *Automatic identification results of wavelet transform method; a), d), g), j) image of original fabric; b), e), h), k) image of automatic identification; c), f), i), l) artificial identification.*

Table 1. *Test result of the automatic identification.*

Test item	Figure a	Figure d	Figure g	Figure j	Mean value
Number of categories	3	3	3	3	3
Operation time, ms	2844	3015	3000	3109	2992
Total accuracy rate, %	91.73	94.14	93.20	90.99	92.52

Conclusions

1) This paper proposes an automatic identification method for the pattern of jacquard warp-knitted fabric based on texture properties. The pretreated image was transformed and decomposed by the Db4 wavelet to extract 5 standard deviations as eigen values, and then the pixels of the jacquard warp-knitted fabric image were classified with multi-channel clustering. Finally noise removal operation was used to achieve 3 or more texture areas of automatic identification.
2) The identification results reveal that the algorithm mentioned in this paper can give exact segmentation results and the area divided has high consistency and edge accuracy. Although there is a small amount of image noise due to the non-uniform arrangement of the jacquard net. The mean value of the total accuracy rate is 92% or more; besides, the identification time is short and the average running time is within 3 s.
3) Because of the disturbances from different forms of mesh in the regions, a small quantity of noises exists in the image. In follow-up work the algorithms can be applied to the CAD system to help designers edit the image of fabric with the image amending function, which can greatly simplify tracing the contour manually, and improve the efficiency of Jacquard warp knitting fabric design.

In further researches, the authors will consider the combination of support vector machines or artificial neural networks, and try automatic identification on common Jacquard organisation in order to improve the design efficiency.

Acknowledgment

The authors acknowledge the financial supports from the Independent Scientific Research Plan, Jiangnan University (JUSRP51404A).

References

1. Zhang Y. *Image Engineering*. 2nd Edition, Tsinghua University Press, 2007: 280.
2. Haralick RM, Shanmugam K, Dinstein IH. Textural features for image classification. *IEEE Transactions on Systems, Man and Cybernetics* 1973;SMC-3, 6: 610-621.
3. Liu X. Summary of texture research. *Application Reasearch of Computers* 2008; 25, 8: 2284-2287.
4. Zhang D, Jiang G ,Cong H. Automatic identification method of Jacquard warp-knitted patterns with net. *Journal of Textile Research* 2010; 31, 10: 45-49.
5. Semler L, Dettori L, Furst J. Wavelet-Based texture classification of tissues in computed tomography. In: *18th IEEE Symposium on Computer Based Medical System* 2005: 265-270.
6. Kumar A, Pang GKH. Defect detection in textured materials using Gabor filters. *IEEE Transactions on Industry Applications* 2002; 38, 2: 425–440.
7. Liu Y. *Active Contour Models based on Texture Subspace Components for Image Segmentation*. Dalian University of Technology, Master thesis, 2009: 39.

Received 14.10.2011 Reviewed 24.07.2012