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Automatic pattern segmentation of jacquard warp-knitted fabric based on hybrid image processing methods

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This paper reports an automatic pattern separation approach for jacquard warp-knitted fabric, which includes bilateral filter, pyramidal wavelet decomposition and improved fuzzy c-means (FCM) clustering. First, jacquard warp-knitted fabric images are captured and digitized by a scanner in gray mode, and then the bilateral filter is adopted to smoothen the fabric textures formed by various lapping movements of jacquard fabric and to reduce the noise appearing in capturing process. Next, multi-scale wavelet decomposition is applied to lessen calculation burden and to shorten computation time. Finally, the modified FCM clustering is proposed, in which the Mercer Kernel function is used to make some features prominent for clustering, and a weight function is proposed to measure the similarity between the data and the clustering center. The experimental results reveal that this hybrid method can achieve fast and accurate pattern segmentation. It is proved that this study is suitable for the pattern separation of jacquard warp-knitted fabric.

Keywords: Bilateral filter, Fuzzy e-means clustering, Jacquard warp-knitted fabric, Pattern separation, Wavelet decomposition

On account of multifarious patterns, jacquard warp-knitted fabric plays an important role in knitted fabrics, and is one of favorite garment accessories. However, manual separation of pattern from the jacquard warp-knitted fabric sample is tedious and time consuming, which could take up to nearly 70% of the total design time. Therefore, it is desirable to develop an automatic pattern separation method for warp-knitted computer aided design (CAD) system.

In general, the related literature on the study of pattern separation focuses on two types of fabrics. Some of the studies are focused on printed fabric, in which genetic algorithm or co-occurrence matrix is employed to figure out the feature value, then color separation algorithms, such as self-organization map and supervised back-propagation neural network, are used[1,2]. Others concentrate on the color separation of machine embroidery fabric based on Gustafson-Kessel (GK) clustering algorithm[3]. However, jacquard warp-knitted fabric is different from both printed and embroidery fabrics.

The pattern of jacquard warp-knitted fabric comes from its weave structure, which consists of inlay, looped, fall-plate and lappet jacquard weave[4]. Take three-stitch technology of looped jacquard weave (Fig. 1), for example 1-0/1-2// is the primary type. Based on the primary type, we can obtain other lapping movements by the guide bar's shifting from original motion trail, i.e. 1-0/2-3// and 2-1/1-2//. The corresponding texture in fabric surface of 1-0/1-2// is the region as shown in Fig. 2 (a). By comparison of 1-0/1-2//, the underlap of 2-1/1-2// is shorten, which is the chaining weave and the mesh region in fabric surface as shown in Fig. 2 (b). On the contrary, extending the underlap [Fig. 1 (b)] will obtain the thick surface texture as shown in Fig. 2 (c). Thus, various jacquard fabric surface form varieties of textures under illumination.

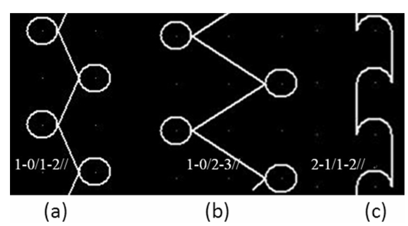

Fig. 1—Three-stitch technology of looped jacquard weave [(a) 1-0/1-2//, (b) 1-0/2-3// and (c) 2-1/1-2//]

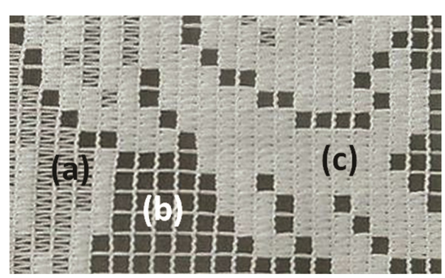

Fig. 2—Three corresponding fabric textures of the weaves in Fig. 1 [(a) texture 1 region, (b) texture 2 region and (c) texture 3 region]

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In view of the characteristics of jacquard warp-knitted fabric, in this study we propose a hybrid pattern separation method including bilateral filter, pyramidal wavelet decomposition and improved FCM clustering. Firstly, bilateral filter is adopted to reduce the noise and to smoothen the jacquard fabric image. Secondly, the pyramidal wavelet decomposition with the Haar wavelet is used to lessen calculation burden and to shorten computation time. Finally, we propose the improved clustering with the Mercer Kernel function which can decrease the iterations and improve the classification accuracy.

Experimental

Image Capture and Pre-treatment

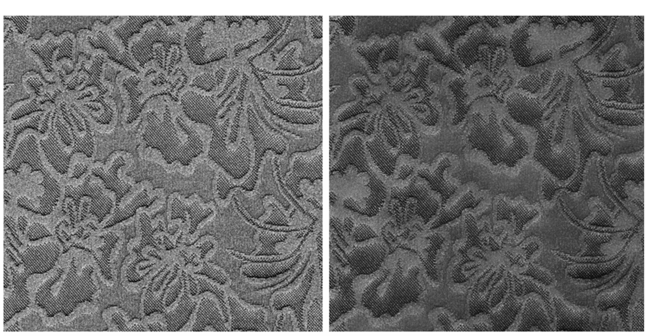
Jacquard warp-knitted fabric images are captured and digitized by Canon CanoScan LiDE 210 flatbed scanner equipped with contact image sensor (CIS), three color red-green-blue light-emitting diodes (RGB LEDs) and hi-speed Universal Serial Bus (USB) 2.0, giving 4800 dpi × 4800 dpi maximum color resolution with a vivid 48-bit color depth or 16-bit grayscale depth. As shown in Fig. 3(a), it is an upscale lingerie fabric, and the acquired image has been transferred to the one which consists of 8-bit gray-scale, 512 pixel × 512 pixel and are saved in bitmap (BMP) format with 300 dpi.

Bilateral Filter

Various lapping movements of jacquard fabric forms three-dimensional fabric surface and the corresponding textures on image. Three-dimensional fabric surface will cause inconsonant reflection under the illumination of scanner in capturing process, which results in the noise, as shown below:

$$f(x,y) = f_o(x,y) + n(x,y) \quad \dots (1)$$

where $f(x,y)$, $f_o(x,y)$ and $n(x,y)$ denote the captured image, original image and noise, respectively.



(a) (b)

Fig. 3—Jacquard warp-knitted fabric image [(a) original image and (b) filtered image]

To reduce the noise and to smoothen the texture simultaneously, we adopted the bilateral filter. Bilateral filtering is a non-linear filtering technique, which develops the concept of Gaussian smooth filter by weighting the filter coefficients with relative pixel intensities[5]. Gaussian and bilateral filters are defined below:

Gaussian filter

$$f(x,y) = \frac{1}{2\pi\sigma_s^2} e^{-\frac{x^2+y^2}{2\sigma_s^2}} \quad \dots (2)$$

Bilateral filter

$$\hat{f}(x,y) = \frac{\sum_{(i,j)\in S_{x,y}} w(i,j)\, g(i,j)}{\sum_{(i,j)\in S_{x,y}} w(i,j)} \quad \dots (3)$$

$$w(i,j) = e^{-\frac{|i-x|^2+|j-y|^2}{2\delta_s^2}} \times e^{-\frac{|g(i,j)-g(x,y)|^2}{2\delta_d^2}} \quad \dots (4)$$

where $S_{x,y}$ is the neighborhood of the point at (x, y) with the size $(2N + 1)\times(2N + 1)$; and δ_s and δ_d denote the standard deviation of spatial domain and intensity domain respectively. Both δ_s and δ_d determine the level of smoothness. For more rough jacquard fabric surface, the larger values of δ_s and δ_d are needed. Setting δ_d to zero will reduce the bilateral filter to a simple Gaussian filter. As shown in Fig. 3(b), the bilateral filter cannot only effectively smoothen the jacquard fabric image, but also keep the edges of image, which is the difference between bilateral filter and Gaussian filter.

Pyramidal Wavelet Decomposition

Due to the inconsonant reflection under the illumination, the signals of jacquard fabric image are non-stationary, which are located both in time and frequency domain at the same time. Therefore, we adopted the wavelet transform acting as a mathematical microscope in image processing. Through the wavelet transform, we can observe and analyze any parts of the fabric image by just adjusting the resolution[6].

The algorithm of the wavelet decomposition is shown below:

$$f(x,y) = \sum_{n=1}^{N}\sum_{k,l\in Z}\left(f_{HL}^{(n)}\psi_{n,k}(x)\phi_{n,l}(y) + f_{LH}^{(n)}\phi_{n,k}(x)\psi_{n,l}(y) + f_{HH}^{(n)}\psi_{n,k}(x)\psi_{n,l}(y)\right) + \sum_{k,l\in Z} f_{HH}^{(N)}\phi_{N,k}(x)\phi_{N,l}(y) \quad \dots (5)$$

$$f_{LL}^{(n)} = \sum_{m,n,k,l\in Z} \bar{h}_{m-2k}\,\bar{h}_{n-2l}\, f_{LL}^{(n-1)} \quad \dots (6)$$

$$f_{HL}^{(n)} = \sum_{m,n,k,l \in Z} \bar{g}_{m-2k} \bar{h}_{n-2l} f_{LL}^{(n-1)} \quad \dots (7)$$

$$f_{LH}^{(n)} = \sum_{m,n,k,l \in Z} \bar{h}_{m-2k} \bar{g}_{n-2l} f_{LL}^{(n-1)} \quad \dots (8)$$

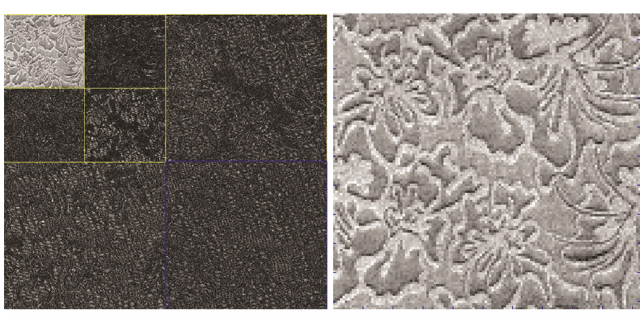
$$f_{HH}^{(n)} = \sum_{m,n,k,l \in Z} \bar{g}_{m-2k} \bar{g}_{n-2l} f_{LL}^{(n-1)} \quad \dots (9)$$

where $f(x, y)$ and N denote the original fabric image and the decomposition scale respectively; ψ and ϕ are the base function and scaling function, among which we adopt the Haar wavelet as the base function in view of its orthogonality and fast speed; and $\bar{g}$ and $\bar{h}$ represent high and low-pass filter. Obviously, the wavelet decomposition will generate four sub-images, i.e. $f_{HH}^{(n)}$, $f_{HL}^{(n)}$, $f_{LH}^{(n)}$ and $f_{LL}^{(n)}$. The process is iterated on the approximation sub-image $f_{LL}^{(n)}$, and the pyramidal wavelet decomposition will be formed as shown in Fig. 4. From Eq. (6) and Fig. 4, we can find that the approximation sub-image at 2nd scale reserve most of the detail information and energy of the original image, however the size is only one-fourth of the original image, which can greatly lessen calculation burden and shorten the computation time.

Improved FCM Clustering

There are two typical clustering methods, i.e. unsupervised clustering and supervised clustering. To reduce the computation time and to improve the pattern separation efficiency, the unsupervised clustering is more suitable. Therefore, we adopted the FCM clustering method.

FCM clustering is developed by Dunn and Bezdek, which allows one piece of data to belong to two or more fuzzy categories[7]. However, the traditional FCM clustering is sensitive to initial data and is easy to trapped into local optimization. So we proposed the improved FCM clustering. In our proposed method, the Mercer Kernel function has been used to realize the map from the initial specimen space to high dimensional feature space, which makes some features prominent for clustering.



(a) (b)

Fig. 4—Pyramidal wavelet decomposition of the jacquard fabric image
[(a) two scales wavelet decomposition and (b) approximation subimage at 2nd scale]

The corresponding algorithm is expressed below:

$$J = \sum_{i=1}^{c} \sum_{k=1}^{n} (u_{ik})^m \left\| \phi(x_k) - \phi(v_i) \right\|^2 \quad \dots (10)$$

$$\left\| \phi(x_k) - \phi(v_i) \right\|^2 = K(x_k, x_k) + K(v_i, v_i) - 2K(x_k, v_i) \quad \dots (11)$$

$$K(x, y) = \phi(x)^T \phi(y) \quad \dots (12)$$

where m denotes any real number greater than 1, u_{ik} denotes the degree of membership of x_i in the cluster k; and ||*|| denotes the norm expressing the similarity between any measured data and the center. If we choose $K(x, y) = \exp(-\left\| x - y \right\|^2 / \sigma^2)$ as kernel function, we will obtain $K(x, x)$=1. Therefore, Eq. (10) will be

$$J = 2\sum_{i=1}^{c} \sum_{k=1}^{n} (u_{ik})^m (1 - K(x_k, v_i)) \quad \dots (13)$$

To minimize Eq. (13), the u should obey the constraint condition, as shown below:

$$u_{ik} = \frac{\left(\frac{1}{(1 - K(x_k, v_i))}\right)^{\frac{1}{m-1}}}{\sum_{j=1}^{c} \left(\frac{1}{1 - K(x_k, v_j)}\right)^{\frac{1}{m-1}}} \quad \dots (14)$$

$$v_i = \frac{\sum_{k=1}^{n} \mu_{ik}^m K(x_k, v_i) x_k}{\sum_{k=1}^{n} \mu_{ik}^m K(x_k, v_i)} \quad \dots (15)$$

From Eq. (15), it can be observed that a weight function $K(x_k, v_i)$ is given to x_k for measuring the similarity between the data x_k and the clustering center v_i. When the distance between x_k and v_i becomes large, the value of $K(x_k, v_i)$ will diminish. If the value of $K(x_k, v_i)$ decreases to be fairly small, it will be discarded according to the criterion, as shown below:

$$x_{kj} = \frac{\sum_{i=1}^{c} \mu_{ik}^{m} K(x_k, v_i) v_i}{\sum_{i=1}^{c} \mu_{ik}^{m} K(x_k, v_i)} \quad \ldots (16)$$

Results and Discussion

The proposed approach has been performed on MATLAB R2011a platform with a personal computer equipped with Intel Core i3-3240 processor (3M Cache, 3.4GHz) and 4GB Dual Channel DDR3 SDRAM at 1600MHz.

To evaluate the performance of our proposed method, two quantified indexes are adopted, i.e. Kapp coefficient (KC) and classification accuracy ratio (CAR)[8]. KC is a statistical measure of inter-rater agreement or inter-annotator agreement for categorical items. CAR denotes the percentage of correct pixel categorization. The corresponding algorithm is expressed as follows:

$$KC = \frac{N \sum N_{ii} - \sum (N_{i+} N_{+i})}{N^2 - \sum (N_{i+} N_{+i})} \times 100\% \quad \ldots (17)$$

$$CAR = \frac{\sum_{i=1}^{M} N_{ii}}{N} \times 100\% \quad \ldots (18)$$

$$N_{i+} = \sum_{j=1}^{M} N_{ij} \quad \ldots (19)$$

$$N_{+i} = \sum_{i=1}^{M} N_{ji} \quad \ldots (20)$$

where N and M represent the total number of pixels and clusters, and N_{ii} denotes the number of accurate classification in the cluster i.

Apart from the proposed approach, there are two traditional FCM methods used for comparison, i.e. FCM $1^{\#}$ and FCM $2^{\#}$. FCM $1^{\#}$ adopts bilateral filter, multi-scale decomposition and FCM clustering with traditional kernel function. FCM $2^{\#}$ uses Gaussian filter and FCM clustering with traditional kernel function.

As shown in Fig. 5 and the corresponding quantitative indexes in Table 1, under the same pre-condition, the practical iterations of FCM $1^{\#}$ is more than double to that of our proposed method, which is accompanied with the longer computation time and the lower classification accuracy. The difference between FCM $1^{\#}$ and our proposed method confirms the fact that the traditional FCM clustering method is sensitive to the noise and couldn't conquer the problem of local optimization [Fig. 5(a)]. But on the contrary, the Mercer Kernel function with similarity weigh in proposed method can decrease the iterations and improve the classification accuracy. The performance of FCM $2^{\#}$ is fairly unacceptable. Firstly, the Gaussian filter smoothens the jacquard surface texture, but can't keep the edges of image [Fig. 5(b)]. Then the computation time of FCM $2^{\#}$ become four times to that of our proposed method, as the algorithm without wavelet transform will increase the calculation burden and computation time for subsequent clustering.

Apart from evaluating these characteristics mentioned above, we still compare the proposed method with other texture segmentation approaches, such as the Markov random field (MRF) which is one of the typical probabilistic graphical algorithms. Although the MRF method is not dedicated to jacquard fabric image, it behaves well and has a wide variety of application in texture segmentation. As shown in Fig. 5(d) and the corresponding information in Table 1, the MRF method is susceptible to the noise, which will tremendously increase the iterations and is easy to drop into local optimization.

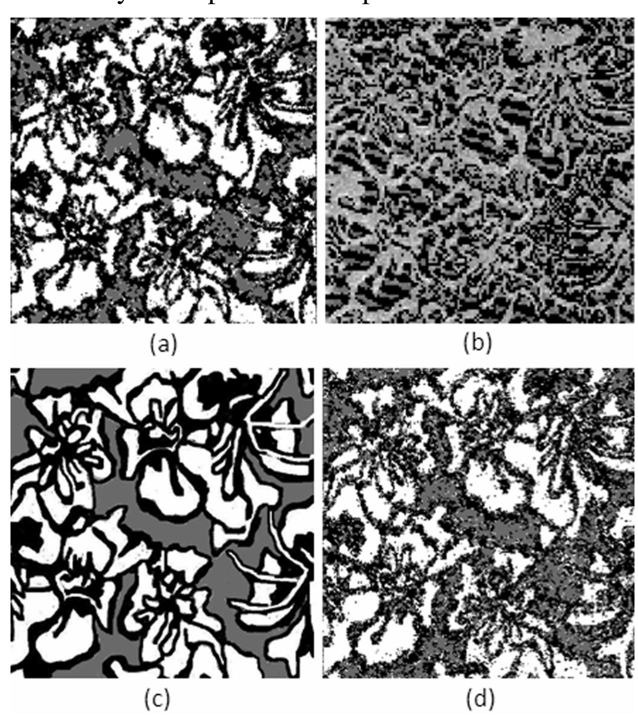


Fig. 5—Pattern separation results by [(a) FCM $1^{\#}$, (b) FCM $2^{\#}$, (c) proposed approach, (e) MRF method]

Table 1—Quantitative indexes of pattern separation results

Method	Clustering number	Terminal condition ε	Maximum iterations	Practical iterations	Computation time	KC	CAR
FCM 1#	3	0.01	100	20	17	83.8	86.3
FCM 2#	3	0.01	100	38	32	45.2	51.6
Proposed method	3	0.01	100	8	8	95.32	97.25
MRF	3	/	/	/	58	75.1	78.9

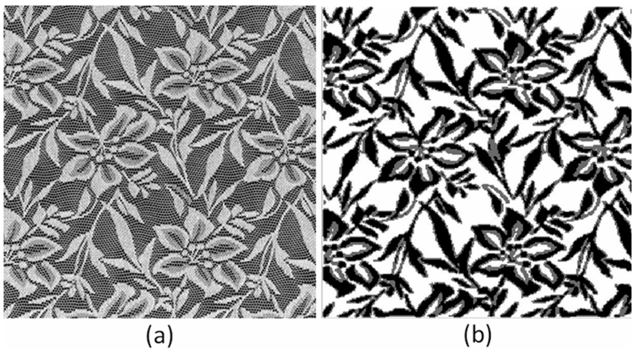


Fig. 6—Original lace fabric and pattern separation result [(a) original lace fabric and (b) pattern separation result by proposed method]

Therefore, a hybrid pattern separation method including bilateral filter, pyramidal wavelet decomposition and improved FCM clustering is suitable for the pattern separation of jacquard warp-knitted fabric, as shown in Figs 5(c) and 6.

In this paper, we propose a hybrid pattern separation method. Several characteristics of this method can be mentioned as follows. To smoothen the fabric textures formed by various lapping movements of jacquard fabric and to reduce the noise appearing in capturing process, the bilateral filter is adopted, which can keep the edges of image. The pyramidal wavelet decomposition with Haar wavelet base is used to process the non-stationary signals of jacquard fabric image, in which the approximation sub-image reserves most of the detail information and energy of the original image. Therefore, the subsequent clustering with sub-image can lessen calculation burden and shorten computation time. In view of the fact that the traditional FCM clustering is sensitive to noise and easy to trap into local optimization, we propose the modified FCM clustering, in which to make some features prominent for clustering the Mercer Kernel function is used to realize the map from the initial specimen space to high dimensional feature space, and a weight function is proposed to measure the similarity between the data and the clustering center. Results show that the hybrid pattern separation method is feasible and applicable.

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