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Automatic pattern separation of jacquard warp-knitted fabric by supervised multi-scale Markov model

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In this study, an automatic pattern separation approach using supervised multi-scale Markov model has been proposed. Gaussian low-pass filter has been used to smoothen the jacquard texture produced by various lapping movements, and the noise appearing during the capturing procedure is eliminated. Then the pyramidal multi-scale wavelet decomposition is adopted to lessen calculation burden and prepare specimens for subsequent pattern separation. In view of the non-stationary jacquard fabric image signals, the modified multi-scale MRF model is presented, which can fully capture and utilize correlations over sets of both inter-scale sub-images and intra-scale neighborhoods, and take the influence of weave structure and illumination condition into account. Finally, a supervised parameter estimation method is put forward to carry out pattern separation in Bayesian frame, in which the cost function changes with the decomposition scale, and parts of parameters are obtained by training in advance. Experimental results show that the proposed method is suitable for the pattern separation of jacquard warp-knitted fabric.

Keywords: Jacquard warp-knitted fabric, Multi-scale wavelet decomposition, Modified Markov model, Pattern separation, Supervised parameter estimation

Jacquard warp-knitted fabric has a wide variety of application ranging from garment accessories to furnishing fabric. However, pattern separation for jacquard warp-knitted fabric may be a tedious but very important process in the drafting phase. Traditionally, the pattern was portrayed and segmented manually on a transparent paper. Even with the development of computer technology, the process still requires a good deal of labour to scan jacquard fabric and outline the pattern using simple mapping tool such as lasso. In this case, to develop a rapid, efficient and automatic pattern separation system for jacquard warp-knitted fabric has its urgent need.

Currently, there are a few related literatures dedicated to the study of pattern separation for fabric. The studies mainly focus on colored planar fabrics (e.g. printed fabrics) and colored solid-structure fabrics (e.g. embroidery fabrics), thus the corresponding clustering algorithms are mainly based on the value of color, such as fuzzy C-mean (FCM)[1], Gaussian mixture model (GMM)[2] and self-organization map(SOM)[3]. However, there is hardly any work aiming at jacquard warp-knitted fabric image.

To address the problem of pattern separation for jacquard warp-knitted fabric, this study proposes an automatic pattern separation algorithm based on multi-scale wavelet texture decomposition, modified Markov random field (MRF) model and supervised parameter estimation method.

Experimental

Image Capture and Preprocessing

Jacquard warp-knitted fabric images are captured and digitized in gray-scale model by ScanMaker 4900 flat scanner which has a linear CCD, CCFL light source and Hi-speed USB(USB 2.0) connectivity, giving 4800dpi(H)×2400dpi(V) optical resolution, 7ms/line at 1200dpi and 48-bit internal color depth. The captured images consist of 8-bit gray-scale, 512×512 pixels and are saved in BMP format with 300 dpi, as shown in Fig. 1. This figure displays a striped lace, a representative jacquard warp-knitted fabric, which is constitutive of four textures including background. To reduce the interference of deformed texture and noise, we adopt Gaussian low-pass filter[4], which will retain the main information of original image in low frequency, remove the noise and smoothen the texture in high frequency.

Multi-scale Wavelet Decomposition

Most of the jacquard fabric image signals are non-stationary, and consist of information in both time and frequency domain. Therefore, we adopt Haar wavelet transform and the pyramidal multi-scale structure for decomposition of jacquard fabric images. As a base function, Haar wavelet is a ladder-shaped discontinuous function which has a fairly fast speed. Through the multi-scale wavelet decomposition, the original jacquard fabric image $f(x, y)$ is represented by a set of

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sub-images at several scales, and the iterative computation of each approximation coefficient matrix of the original image will lead naturally to a pyramidal multi-scale structure.

It is worth noting that the approximation coefficient matrix has most of the low frequency components and possess most of the energy of the original image. Accordingly, the pyramidal multi-scale wavelet decomposition and the Haar wavelet basis not only are suitable for human visual system proceeding images but also can lessen calculation burden and shorten computation time.

Modified Multi-scale MRF Model

In MRF model, the procedure of image separation may be treated as an estimation of unknown region image, where the observed data are the feature field *Y* extracted to describe the image characteristics and the unknown data are the label field *X* expressing which category the gray pixels belong to. Therefore, the image separation is to assign each pixel a class label or search for an approximate global optimal evaluation of X based on the maximum posteriori (MAP) or maximum posteriori marginal criterion in Bayesian frame.

Let *S* is a $M\times M$ square lattice, the jacquard fabric image $f(x,y)$ having *K* distinct regions of texture is defined on *S*. Given that the jacquard fabric image has *N* scales decompositions by Harr wavelet as mentioned above, and at n^{th} $(0\leq n<N)$ scale the label value depends on the parent coefficient $p(s)$, three uncle coefficients u(s) and eight second-order neighborhood coefficients c(s) as shown in Figs 2 and 3, so it is proposed that in the label field *X* the joint probability $P(X=x)$ of inter-scales is

$$P(x_s^{(n)} \left| x_{\rho(s)}^{(n+1)}, x_{u(s)}^{(n+1)}) = P(x_{s_1}^{(n+1)}, x_{s_2}^{(n+1)}, x_{s_3}^{(n+1)}, x_{s4}^{(n+1)}) \right.$$
$$= \frac{\theta^{(n)}}{5}[2\delta(x_s^{(n)}, x_{\rho(s)}^{(n+1)}) + \delta(x_s^{(n)}, x_{\rho(s)+(1,0)}^{(n+1)}) + \delta(x_s^{(n)}, x_{\rho(s)+(0,1)}^{(n+1)})$$
$$+\delta(x_s^{(n)}, x_{\rho(s)+(1,1)}^{(n+1)})] + \frac{1-\theta^{(n)}}{M} \qquad \ldots (1)$$

In Eq. (1), $\delta(,)$ is sampling function, $s_i^{(n+1)}$ (*i*=1, 2, 3 and 4) denotes one parent coefficient and three uncle coefficients. $\theta^{(n)} \in [0,1]$ is the inter-scale correlation coefficient, which represents the probability of having the same label value between child coefficient and parent coefficients. As the arrows shown in Fig.2, between inter-scales the label values depend upon the prior label information, therefore the Eq. (1) is a causal model and different with the traditional Gibbs distribution model. In view of the effect of second-order neighborhood coefficients as the dotted lines in Fig. 2, we adopt doubleton clique energies which are given as follows:

$$V_c(x_s^{(n)}, x_{s+\tau}^{(n)}) = \begin{cases} -\beta & \text{if } x_s^{(n)} = x_{s+\tau}^{(n)} \\ \beta & \text{if } x_s^{(n)} \neq x_{s+\tau}^{(n)} \end{cases} \qquad \ldots (2)$$

where $\tau \in J$={(-1,-1), (-1,0), (-1,1), (0,-1), (0,1), (1,-1), (1,0), (1,1)}. For example, when τ=(0,-1), $x_s^{(n)} = x_{s-1}^{(n)}$ And the local conditional probability is

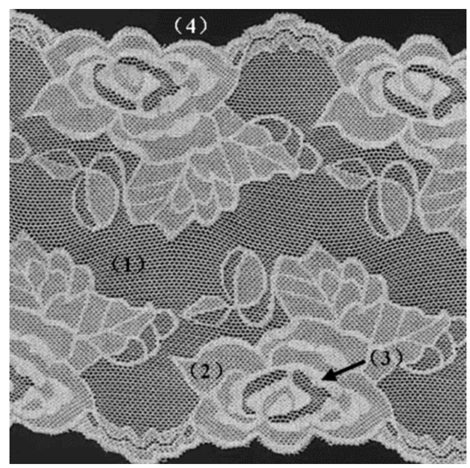

Fig. 1 — Jacquard warp-knitted fabric image

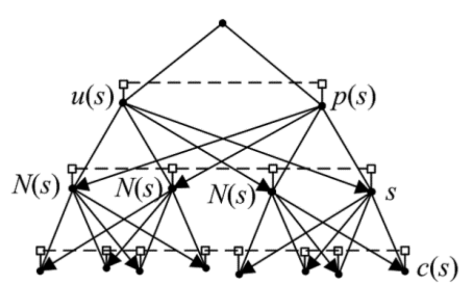

Fig. 2 — Hierarchical model

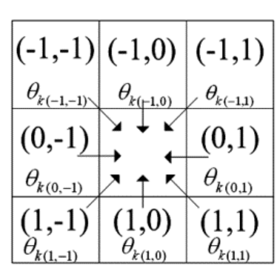

Fig. 3 — Second-order neighborhood system

$$P(x_s^{(n)} \left| x_{\eta(s)}^{(n)} \right.) = \frac{\exp[-\sum_{\tau\in J} V_c(x_s^{(n)}, x_{s+\tau}^{(n)})]}{\sum_{x_s} \exp[-\sum_{\tau\in J} V_c(x_s^{(n)}, x_{s+\tau}^{(n)})]} \quad \ldots (3)$$

Because the intra-scale label value relays on second-order neighborhood system and is frequently updated in iterative process, the intra-scale model is non-causal. Taking into account the computation complexity of Eqs (1)-(3), we will adopt the multi-objective optimization to approximate the prior distribution. The multi-objective optimization method consists of two steps. Firstly, the coarse separation is obtained by inter-scale iteration with the causal model. Secondly, we will acquire the fine separation by intra-scale iteration with the non-causal model.

As far as the subimage $y^{(n)}$ at n^{th} scale, we adopt the multi-scale GMRF model with second-order neighborhood, which is taken into account the influence of yarn color, weave structure and the illumination condition. And the model is characterized by the local conditional probability density function (PDF) as follows:

$$f(y_s^{(n)} \left| x_s^{(n)} = k, y_{\eta_s}^{(n)} \right.) = \frac{1}{(\sqrt{2\pi})^D \left| \sum_k^{(n)} \right|^{1/2}} \exp\left[-\frac{1}{2} (e_{k,s}^{(n)})^T (\textstyle\sum_k^{(n)})^{-1} e_{k,s}^{(n)} \right] \quad \ldots (4)$$

where k is clustering label; D denotes the dimension of $y_s^{(n)}$; $\sum_k^{(n)}$ stands for covariance matrix; and $e_{k,s}^{(n)}$ represents the noise with zero-mean Gaussian distribution, i.e. $e_{k,s}^{(n)} = \left[e_{k,s}^{(n)}(1), e_{k,s}^{(n)}(2), ..., e_{k,s}^{(n)}(D) \right]$. Spatial correlation coefficient of $e_{k,s}^{(n)}(d)$ is

$$e_{k,s}^{(n)}(d) = \left[y_s^{(n)}(d) - \mu_k^{(n)}(d) \right] - \sum_{d_t=1}^{D} \sum_{\tau\in\eta_s} \theta_{m,dd_t}^{(n)}(r) [y_{s+\tau}^{(n)}(d_t) - \mu_k^{(n)}(d_t)] \cdots (5)$$

where η_s is the offset of the neighborhood sites of $s(x, y)$; $\mu_k^{(n)}$ is the mean vector; and $\theta_{m,dd_t}^{(n)}$ is the neighborhood correlation coefficient between d and d_t.

Supervised Pattern Separation

According to the Bayesian rules, the joint probability distribution of the feature field Y and the label field X is expressed as follows:

$$P(X = x, Y = y) = \prod_{n\in\{0,1,\ldots,N-1\}} \prod_{s\in S^{(n)}} [f(y_s^{(n)} \left| y_{n_s}^{(n)}, x_s^{(n)} \right.) P(x_s^{(n)} \left| x_{\partial_s^{(n)}} \right.)] \cdots (6)$$

where $\partial_s^{(n)} = \{ p(s), u(s), N(s) \}$. Based on MAP, the process of pattern separation consists of minimizing a certain expected cost and Bayesian risk. A cost function is represented below:

$$C(x, x') = 1 - \delta(x, x') \quad \ldots (7)$$

$$\delta(x, x') = \begin{cases} 0 & \text{if } x = x' \\ 1 & \text{if } x \neq x' \end{cases} \quad \ldots (8)$$

where x and x' denote the current configuration and the desired action respectively. In Eq. (8), if $x \neq x'$, the cost function is equal to one, which is a fairly large cost especially in multi-scale analysis. So, we propose the modified cost function as follows:

$$C(x, x') = \sum 2^{N-n} \times [1 - \delta(x^{(n)}, x^{(n)\prime})] \quad \ldots (9)$$

$$1 - \delta(x^{(n)}, x^{(n)\prime}) = 1 - \prod \delta(x_i^{(n)}, x_i^{(n)\prime}) \quad \ldots (10)$$

From Eqs (9) and (10), it can be seen that the cost function changes with the decomposition scale. The larger the decomposition scale, the more is cost function effect on segmentation result and vice versa, which is suitable for human visual perception.

By combing Eqs (1), (4) and (9), Eq. (6) can be transformed into:

$$\hat{x}_s^{(n)} \approx \arg\max_{x_s^{(n)}} \left\{ P(x_s^{(n)} \left| x_{\partial(s)}, y \right.) \right\}$$
$$= \arg\max_{x_s^{(n)}} \{ f(y_{d(s)} \left| x_s^{(n)}, y \right.) p(x_s^{(n)} \left| x_{\partial(s)} \right.) \} \quad \ldots (11)$$

$$f(y_{d(s)} \left| x_s^{(n)}, y \right.) = $$
$$f(y_s^{(n)} \left| x_s^{(n)}, y_{n_{ij}}^{(n)} \right.) \prod_{t\in c(s)} [\sum_{x_t^{(n-1)}} f(y_{d(s)} \left| x_t^{(n-1)}, y \right.) P(x_t^{(n-1)} \left| x_{p(t)}^{(n)}, x_{u(t)}^{(n)} \right.)] \cdots (12)$$

From the equations mentioned above, it can be seen that pattern separation is carried out with the estimated parameters. However, to start iterative process in the feature field Y and the label field X, initial values, such as $\mu_k^{(n)}, \sum_k^{(n)}, \theta_{m,\tau}^{(n)}, \alpha^{(n)}$ and β, should be obtained in advance. Among these initial values, $\alpha^{(n)}$ and β are constants and set empirically. To reduce the misjudgment rate, the other parameters ($\mu_k^{(n)}$, $\sum_k^{(n)}$ and $\theta_{m,\tau}^{(n)}$ are the mean vector, covariance matrix and neighborhood correlation coefficient of clustering region k at n^{th} scale) are obtained by training and leaning.

Results and Discussion

The proposed approach has been performed on MATLAB R2010b platform with a personal computer equipped with PD 2.0 GHz CPU and 2.5G memory. In order to evaluate the performance of our proposed method, we adopt two quantified indexes, i.e. classification accuracy ratio (CAR) and Kapp coefficient (KC)[5] as shown in Eqs (13) and (14). Larger CAR and KC value denote the optimal separation result.

$$CAR = \frac{\sum N_{ii}}{N} \times 100\% \qquad \ldots (13)$$

$$KC = \frac{N\sum N_{ii} - \sum (N_{i+}N_{+i})}{N^2 - \sum (N_{i+}N_{+i})} \times 100\% \qquad \ldots (14)$$

As shown in Fig. 4 (a) and the corresponding quantitative indexes in Table 1, the traditional clustering method such as FCM is not competent to separate pattern for jacquard warp-knitted fabric, for which the image signals are non-stationary. Figure 4 (b) demonstrates that the traditional MRF model cannot fully capture and utilize correlations over sets of inter-scales. Moreover, the single-scale MRF model will increase calculation burden and computation time, as it can be seen in Table 1 that 98s is fairly long. For Fig. 4 (c) and the corresponding indexes, the significant characteristic is the longest computation time. The reason is that the expectation maximization (EM) algorithm is applied in unsupervised parameter estimation, which obtains the optimum by iterations and cannot avoid local optimization, resulting the scattered clustering especially in the mesh part of striped lace.

Besides, we compare our proposed method with other new texture segmentation algorithms, such as the approach based on Von Mises circular distributions[6]. In term of both identification accuracy indexes, i.e. CAR and KC, and computation time, the better performance is achieved by our proposed method, for which the new method is not aiming at jacquard warp-knitted fabric images and is sensitive to the noise influenced by weave structure, distorted loop and illumination condition, etc. Meanwhile, our proposed method adopts training and learning to obtain the parameters, which may increase the clustering accuracy and decrease the calculation burden. Therefore, the supervised multi-scale Markov model is suitable for the pattern separation of jacquard warp-knitted fabric as shown in Fig.4 (e) and Fig.5.

Table 1 — Quantitative indexes of pattern separation results

Method	CAR %	KC %	Computation time, s
FCM	72.3	75.6	12
Traditional single-scale MRF model	78.6	80.5	98
Traditional multi-scale MRF model with unsupervised separation	82.2	83.9	112
Separation method based on Von Mises circular distributions	90.5	88.7	73
Proposed method	96.8	95.3	60

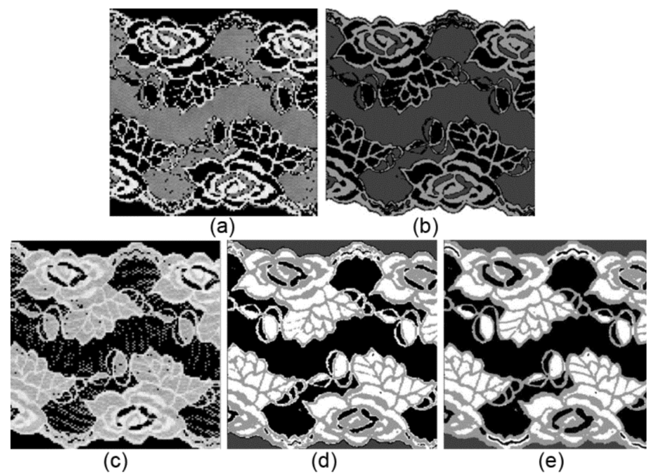

Fig. 4 — Pattern separation results by (a) FCM, (b) traditional single-scale MRF model, (c) traditional multi-scale MRF model with unsupervised separation, (d) the separation method based on Von Mises circular distributions, and (e) our proposed method.

Fig. 5 — Original jacquard warp-knitted fabric image and pattern separation result by proposed method

Conclusion

The automatic pattern separation for jacquard warp-knitted fabric using supervised multi-scale Markov model has been proposed in this paper. We use Gaussian low-pass filter to smoothen the jacquard texture which is mainly produced by various lapping movements of guide bars in manufacturing process, and eliminate the noise appearing during the capturing procedure. Then the pyramidal multi-scale wavelet decomposition is adopted to lessen calculation burden and cut down computation time, which is suitable for human visual system. Since the jacquard fabric image signals are non-stationary, we present the modified multi-scale MRF model, in which the inter-scale causal model and intra-scale non-causal model can fully capture and utilize correlations over sets of both inter-scale sub-images and intra-scale neighborhoods, and take into account the influence of yarn color, weave structure and illumination condition. In MRF model, pattern separation is carried out with the estimated parameters in Bayesian frame, so a supervised parameter estimation method is put forward, in which the cost function will change with the decomposition scale and parts of parameters, such as the mean vector, covariance matrix and neighborhood correlation coefficient, are obtained by training and leaning in advance. Experimental results show that the proposed method is superior to the traditional techniques, such as FCM, traditional single or multi-scale MRF model, in the aspects of classification accuracy ratio, Kapp coefficient and computation time.

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References

1 Xu B G & Lin S, *AATCC Rev*, 2(2002) 42.
2 Lachkar A, Benslimane R, D'Orazio L & Martuscelli E, *Text Res J*, 97(2006) 301.
3 Kuo C F J, Kao C Y & Chiu C H, *Text Res J*, **79**(2009) 1235.
4 Zhang Y H, Zhang Y S & He Z F, *Image Vision Comput*, 29(2009) 1402.
5 Xiao F P & Feng X Z, *The Segmentation and Information Extraction of High Resolution remote Sensing Images*(China Science Press, Beijing), 2012, 80.
6 Jean-Pierre D C, Frédéric G, Antoine R & Christian G, *J Electron Imaging*, 21(2012) 1102.