Identification method of cashmere and wool based on texture features of GLCM and Gabor

Yaolin Zhu, Jiayi Huang, Tong Wu and Xueqin Ren

Abstract
The common texture feature extraction method is only in spatial or frequency domain, leading to insufficient texture information and low accuracy. The main aim of this paper is to present a novel texture feature analysis method based on gray level co-occurrence matrix and Gabor wavelet transform to sufficiently extract texture feature of cashmere and wool fibers. Firstly, the gray level co-occurrence matrix is constructed to calculate the four texture feature vectors including of contrast, angular second moment, dissimilarity and energy in spatial domain, and four texture feature vectors, which are contrast, angular second moment, mean and entropy, in frequency domain is obtained through Gabor wavelet transform and Gray-Scale difference statistics method. Then, because the contrast and angle second moment are used as descriptors of fiber image in both spatial and frequency domain, they are fused respectively by introducing a weight to make linear addition, making eight feature values compose a 6-dimensional feature vector. Finally, these feature vectors are fed into the Fisher classifier. The experimental results show that the identification accuracy of the proposed algorithm is improved by 0.682% compared to use 8-dimensional feature vectors describing the sample image. It verifies that the fused method based on texture feature in spatial and frequency domain is an effective approach to identify fibers of cashmere and wool.

Keywords
Cashmere and wool, gray level co-occurrence matrix, Gabor wavelet transform, Fisher classifier

Date received: 12 October 2020; accepted: 4 January 2021

Introduction
Because the structure and morphology of cashmere and wool fibers are very similar, it is difficult to distinguish them. Cashmere fiber with the characteristics of expensive price and soft material is a kind of rare animal fiber, so that it has become one of the extremely significant raw material in the textile industry. However, a number of law-breakers have used wool as expensive cashmere products to obtain high profits. It is urgent to distinguish the two.

In recent years, the identified methods have five categories including physical method, chemical method, biological method, image method and deep convolution network method. In the former three ones, there are commonly identifying methods of microscope method, DNA detection method, solution method, etc. Their shortcomings are complex operation, worse stability of the detection results, and low accuracy. The deep convolution network, a time-consuming method, requires massive
Sample size and expensive experimental devices. However, the image method with small experimental error and high accuracy is frequently applied in the field of identifying similar animal fiber. Jiao proposed to use the GLCM to extract the texture features and the Support Vector Machine (SVM) model to classify, showing over 90% of accuracy. Yuan et al. extracted six indexes of texture feature of fiber images by an improved extraction method of the Tamura texture feature. Then using the BP neural network to identify and get 81.17% of accuracy. Xing et al. put forward analyzed wavelet multi-scale by the Gaussian random field model and adopted the Support Vector Machine (SVM) model to identify, acquiring 90.07% of the identification accuracy. Lu et al. introduced the SURF features into the field of similar animal fiber and reached 93% of accuracy. When extracted texture feature to identify, the texture information only gained in spatial domain or frequency domain is used as the description of the fiber image, resulting in inadequate texture information and lower accuracy. Thus, the effective fusion of texture features in spatial domain and frequency domain can obtain more complete texture information to improve accuracy.

In this paper, we put forward an identification method based on gray level co-occurrence matrix and Gabor wavelet transform. Firstly, the gray level co-occurrence matrix is constructed to calculate the four texture feature vectors including of contrast, angular second moment, dissimilarity, and energy in spatial domain, and four texture feature vectors, which are contrast, angular second moment, mean and entropy, in frequency domain is obtained through Gabor wavelet transform and Gray-Scale difference statistics method. Then, because the contrast and angle second moment are used as descriptors of fiber image in both spatial and frequency domain, they are fused respectively by introducing a weight to make linear addition, making eight feature values compose a 6-dimensional feature vector. Finally, these feature vectors are fed into the Fisher classifier. The experimental results show that the identification accuracy of the proposed algorithm is improved by 0.682% compared to use 8-dimensional feature vectors describing the sample image. It verifies that the fused method based on texture feature in spatial and frequency domain is an effective approach to identify fibers of cashmere and wool.

**Research methods**

**System framework process**

This paper proposes an identification method of texture feature based on gray level co-occurrence matrix and Gabor wavelet transform. The algorithm mainly involves image pre-processing, constructing gray level co-occurrence matrix to extract texture information in spatial domain and adopting the Gabor wavelet transform and the Gray-Scale difference statistics method to extract texture feature in frequency domain. In addition, the fused vectors of texture feature is identified by establishing the Fisher classifier. Figure 1 shows the flow chart of system framework.

**Step 1: Image pre-processing.** Pre-processing wool and cashmere images to obtain clear texture information, which is obtained by the image processing algorithm including grayscale, the Sobel edge detection, morphological filling, edge extraction, and removal background.

**Step 2: Fiber texture feature extraction in spatial domain.** The texture information of fiber image is extracted by gray level co-occurrence matrix in spatial domain, acquiring four secondary statistics: contrast (CON), angular second moment (ASM), dissimilarity (IDM), and energy (ENG).

**Step 3: Fiber texture features extraction in frequency domain.** The Gabor wavelet transform and the Gray-Scale difference statistics method are used to obtain texture feature in frequency domain. First is to select the optimally impact factors of constructing Gabor filter in frequency domain. And then is to calculate four characteristic values such as contrast (CON), angular
second moment (ASM), mean (MEAN) and entropy (ENT) by adopting Gray-Scale difference statistics method.

Step 4: Texture Feature fusion. The values of texture feature in spatial domain and frequency domain are respectively obtained by the second and third steps. Because the contrast and angular second moment exist in both domains, they are fused respectively by introducing a weight to make linear addition, making them consist a 6-dimensional feature vector.

Step 5: Identification. The whole fiber images, which are divided into training samples and testing samples, are fed into the Fisher classifier to determine the Y0 of surface in accordance with the inter-class scatter matrix and the average value of fiber texture feature values. It is final to verify the classified effect and obtain the accuracy with utilizing test set.

Improved algorithm

The described method of texture feature mainly involves five types: signal processing, statistical, geometric, structural, and model analysis method.18–21 The former two ones, which contribute to combine spatial and frequency domain to analyze texture features, are chiefly applied in our algorithm. In order to get sufficient and effective texture information of image, it is critical to use the optimal parameters constructing Gabor filter and determine the fused weight of two kinds of texture features with regard to the improvement of identification accuracy in this article.

Selection of parameters based on Gabor. The extraction of texture feature in frequency domain is based on Gabor wavelet transform,12–14 which is making the convolution operation of Gabor filter and original image. Then the converted fiber image is extracted texture feature values by adopting the Gray-Scale difference statistics method.15–17 Consequently, the construction of the optimal Gabor filter is one of the vital factors to get texture feature in frequency domain. The Gabor filter with frequency $f$ and orientation by coordinate rotation given by

$$G(x, y; f, \theta) = \exp \left\{ -\frac{1}{2} \left[ \left( \frac{x_p}{s_x} \right)^2 + \left( \frac{y_p}{s_y} \right)^2 \right] \right\} \cos(2\pi f x_p) \cos(\theta)$$

Where $x_p = x \cdot \cos \theta + y \cdot \sin \theta$; $y_p = -x \cdot \sin \theta + y \cdot \cos \theta$. $x$ and $y$ represent initial ordinates, while represent ordinates after rotation. The space constants and define the Gaussian envelope along the axes of $x$ and $y$.

Firstly, we use Gabor filter banks with five frequency and four orientations, $f = \{1,2,3,4,5\}$ and $\theta = \{0, \pi / 8, \pi / 4, 3\pi / 8\}$, total 20 Gabor filters are constructed to obtain the multi-scale and multi-orientation image of frequency domain. In addition, four feature values corresponding to the fiber image in frequency domain are calculated by utilizing Gray-Scale difference statistics method. What’s more, inputting these feature vectors of the corresponding filter into the Fisher classifier, and determining the optimal Gabor filter by obtaining the highest identification accuracy.

So it is critical to select frequency $f$ and orientation $\theta$ for the Gabor filter. In order to reduce the amount of calculation, this article adopts the method of selecting two parameters one-by-one. First is to determine the orientation $\theta$. Randomly selecting 20 cashmere and wool fiber images, supposing the frequency as 3 and setting the orientation $\theta$ respectively as 0, $\pi / 8$, $\pi / 4$ and $3\pi / 8$ to calculate four feature values in frequency domain by adopting the Gray-Scale difference statistics method. The corresponding orientation under the largest difference is chosen by calculating the standard deviation, which mean the difference of feature values of frequency domain in the different orientation. Then is to select the frequency $f$. Setting the frequency as 1–5 and having selected orientation $\theta$ to calculate corresponding to four feature values in frequency domain by adopting the Gray-Scale difference statistics method. The frequency $f$ is confirmed by finding the maximum difference, which is used the method of difference between means of these feature values. Therefore, the $\theta = \pi / 8$ and $f = 2$ are set as the parameters of constructing the Gabor filter.

Feature fusion. In order to make full use of the texture information in the gray image, extracting the GLCM and Gabor features of the fiber to construct the texture feature vector.18–21 Suppose that the feature vector obtained by GLCM in spatial domain is $F_{GLCM} = [f_{con}, f_{asm}, f_{den}, f_{ent}]$, and got by making use of Gabor wavelet transform and Gray-Scale difference statistics method in frequency domain is $G_{gabor} = [g_{contrast}, g_{mean}, g_{mean}, g_{ent}]$. Because the contrast and angle second moment, which respectively represent the response to the clarity of the fiber image and the measure of gray distribution and fineness of the texture, are used as descriptors of fiber image in both spatial and frequency domain. So they are respectively fused by linearly adding the weight. We gain the $F$ of 6-dimensional feature vector by combining texture features in spatial and frequency domain.

$$F = \omega F_{GLCM} + (1-\omega)G_{gabor}$$

$$= \omega [f_{con}, f_{asm}, f_{den}, f_{ent}] + (1-\omega) [g_{contrast}, g_{mean}, g_{mean}, g_{ent}]$$

$$= [\omega f_{con}, \omega f_{asm}, \omega f_{den}, \omega f_{ent}] + (1-\omega) [g_{contrast}, g_{mean}, g_{mean}, g_{ent}]$$

Where $f_{con}$ and $g_{con}$ represent the contrast, $f_{asm}$ and $g_{asm}$ represent the angular second moment, $f_{den}$, $f_{ent}$, $g_{mean}$, and $g_{ent}$ are respectively represent dissimilarity, and
energy, mean and entropy. These statistical features is calculated by using the following formulas:

\[ f_{con} = \sum_{i,j=1}^{G} c_{ij}(i-j)^2 \]  
\[ f_{aim} = \sum_{i,j=1}^{G} c_{ij} / \sqrt{1+|i-j|^2} \]  
\[ f_{dis} = \sum_{i,j=1}^{G} c_{ij} |i-j| \]  
\[ f_{eng} = \sum_{i,j=1}^{G} c_{ij}^2 \]  
\[ g_{con} = \sum_{i,j=1}^{G} p_{Ai(j)}^2 \]  
\[ g_{con} = \sum_{i,j=1}^{G} p_{Ai(j)}^2 \]  
\[ g_{mean} = \sum_{i,j=1}^{G} p_{Ai(j)} / m \]  
\[ g_{ent} = -\sum_{i,j=1}^{G} p_{Ai(j)} \log_2 p_{Ai(j)} \]

Where \( c_{ij} \) was defined as \( c_{ij} = p_{ij} / \sum_{i,j=1}^{G} p_{ij} \), \( p_{ij} \) represents the number of occurrences of gray levels \( g_i \) and \( g_j \) and \( G \) is the total of gray levels. \( p_{(i)} \) represents the probability when the gray value of the image is taken as \( i \). The total number of gray value of image is represented as \( m \).

In formula (2), a weight \( \omega \), which is determined by comparing the identified accuracy, is introduced in this texture feature fusion. The 8-dimensional feature vector is fused into the 6-dimensional feature vector as the overall description of texture feature. Set the value of \( \omega \) as 0–1 in sequence, and calculate the identification accuracy under the corresponding weight according to the experimental method. The corresponding weight in the highest accuracy is the optimal.

**Experimental results and analysis**

A total of 200 fiber sample images including 100 cashmere fibers and 100 wool fibers were captured for the study by the scanning electron microscope magnified 1000 times. They were all captured and stored in the computer with a size of \( 275 \times 275 \) pixels. Part of original cashmere and wool fibers are shown in Figure 2.

**Experimental result of image pre-processing**

One cashmere fiber image, which is shown in Figure 3(a). The captured fiber images is processed to remove background. Figure 3(b) mainly obtains the skeleton outline of the fiber though Sobel edge detection and image binarization. Figure 3(c) gains a closed fiber area by dilating the fiber edge and (d) fills the holes in the fiber by using the mathematical morphology. Figure 3(e) is the result of the removing noise by eroding these noise. Removing background in the original image is shown in Figure 3(f).

**Identification**

After a series of pre-processing operation on the captured images, the first step is to extract four statistics in spatial domain by adopting the gray level co-occurrence matrix algorithm. And the second is to extract texture feature values from the image of frequency domain after the Gabor wavelet transform by adopting the Gray-Scale difference statistics method. Finally, 200 groups vectors of texture feature are fed into the Fisher classifier.

In addition to Gabor wavelet transform, Fourier transform is the most common one in the process of spatial-frequency conversion. Table 1 shows the recognition results under different transformation methods. By using Gabor wavelet transform, the recognition result reaches 86.41%, which is 26% higher than that of Fourier transform. The recognition rate of combining gray level co-occurrence matrix with Gabor transform is 23% higher than Fourier transform when adopting the method of fusing into an eight dimensional feature vector. What’s more, it is found that when the ratio of training set and testing set
is 7:3, the identified rate of cashmere and wool reaches the highest. Hence, 7:3 is set as the ratio of training set and testing set in the absence of special instructions.

A group of six feature vector is obtained by adding the weight as the description of the texture feature of a single image. The identified result of different weights is shown in Figure 4. It is easy to find that different identification accuracy follows different weights. When the weight value is less than 0.8, the identified result tends to be stable. In this figure, these lines of each color represent the recognition result in different proportion of training set and testing set. According to the figure, the accuracy of the green line is the optimal, and the corresponding ratio is 7:3. Meanwhile, when the weight is set as 0.18, we found that the accuracy reaches the highest no matter in the ratio of training set and testing set, thus the optimal identification result can be achieved.

Different fusion methods, including fused into 8-dimensional and 6-dimensional feature vector, can cause quite

---

Table 1. Compared by different transform method.

| Train:Test | 3:7 | 4:6 | 5:5 | 6:4 | 7:3 | Mean  |
|------------|-----|-----|-----|-----|-----|-------|
| GLCM       | 66.58 | 63.33 | 70 | 67.5 | 70 | 67.48 |
| Gabor      | 87.15 | 85 | 84 | 88.75 | 87.15 | 86.41 |
| Fourier    | 52.86 | 59.17 | 59 | 63.75 | 61.67 | 59.29 |
| GLCM + Fourier | 62.86 | 68.34 | 72 | 65 | 70 | 67.64 |
| GLCM + Gabor | 89.29 | 88.84 | 90 | 90 | 93.35 | 90.30 |

---

Figure 3. Cashmere image pre-processing: (a) original image, (b) Sobel edge detection, (c) dilation, (d) filling margin, (e) removing noise, and (f) removing background.

Figure 4. Comparison of different weights.
different identification results. The compared result among different dimension feature vectors is shown in Figure 5. The solid line represents the fusion into 6-dimensional feature vector, and the dotted line represents the fusion into 8-dimensional feature vector. It is clearly noticed that the recognition result fusing into six dimensional feature vector is better no matter of which training set and testing set proportion, improving 0.682% of the average accuracy.

Table 2 shows the identification results when the cashmere and wool sample size ratios are set at 4:5, 5:5, and 5:4, no matter in the spatial domain, frequency domain or fused texture feature by adding the weight. The study shows that the recognition rate is respectively up to 90% and 93.33% in the case of frequency domain and the fusion of texture features. It is obvious that the best classification effect can be achieved only in the same number of cashmere and wool fiber images.

Although these previous identification method based on the texture feature can better identify cashmere and wool fibers, there still are some issues in the process of experiment and identification accuracy also need to improve. Therefore, it is necessary to improve and design the identification algorithm based on texture feature analysis. The method in this paper has an obvious improvement, as show in Figure 6. A better result can be obtained by combining texture feature of the spatial and frequency domain.

**Conclusion**

In this paper, we present an identified method of texture feature based on gray level co-occurrence matrix and Gabor wavelet transform. The fiber images were firstly processed by the image processing algorithm, which includes the Sobel edge detection, morphological filling, edge extraction and so on, to obtain clear texture information after removing background. Then, the multi-directional gray co-occurrence matrix is constructed to calculate the GLCM features in the spatial domain. And the texture feature values are extracted from the image of the frequency domain after the Gabor wavelet transform by adopting the Gray-Scale difference statistics method. In the end, these 6-dimensional feature vectors, which are constructed though the method of linear addition, are fed into Fisher classifier. The experimental results show that the identification accuracy of the proposed algorithm is improved by 0.682% compared with 8-dimensional feature vectors. However, there are still shortcoming including less samples, rough surface of existing some fibers and some fuzzy images. So in the future, we will collect more high-quality fiber images and expand the experimental data to improve the identified accuracy.

**Declaration of conflicting interests**

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

**Funding**

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was support by the program general projects of Shaanxi Provincial Department of Science and Technology Key R & D (No.2019GY-098), the service local science research plan of Shaanxi Provincial Department of education (No.18JC012),
Science and technology innovation new town project of Yulin science and Technology Bureau (No.2018-2-24), Shaoxing Keqiao District West Textile Industry Innovation Research Institute Project (No.19KQYB10) and Science and Technology plan project of Yulin City (No.CXY-2020-052).

ORCID iD
Jiayi Huang https://orcid.org/0000-0001-7277-6113

References
1. Lin PM. Detection method for distinguishing wool from cashmere. *West Leather J* 2019; 41(18): 160.
2. Fei J, Xie LM, Wu J, et al. Method and its application for quantifying cashmere and wool mixture based on MALDI-TOF-MS proteomic analysis. *Adv Text Technol J* 2019; 5(27): 1–6.
3. Su Y and Hou F. Effect of decolorization on fiber identification of wool/cashmere/polyester blended fabric. *Wool Text J* 2020; 48(6): 43–46.
4. Wang F and Jin XY. The application of mixed-level model in convolutional neural networks for cashmere and wool identification. *Int J Clothing Sci Technol* 2018; 30(5): 710–725.
5. Jiao MY. A recognition method of cashmere and wool based on gray level co-occurrence matrix. *J Chengdu Text Coll* 2017; 34(3): 126–129.
6. Yuan SL, Lu K and Zhong YQ. Identification of wool and cashmere based on texture analysis. *Key Eng Mater* 2015; 671: 385–390.
7. Xing WY, Deng N, Xing BJ, et al. Investigation of a novel automatic micro image-based method for the recognition of animal fibers based on Wavelet and Markov Random Field. *Micron J* 2019; 119: 88–97.
8. Lu K, Luo JL, Zhong YQ, et al. Identification of wool and cashmere SEM images based on SURF features. *J Eng Fibers Fabr* 2019; 14(1): 1–9.
9. Cheng X, Wang HF, Zhou JM, et al. DTFA-Net: dynamic and texture features fusion attention network for face antispooﬁng. *Complexity* 2020; 2020: 1–11.
10. Armi L and Fekri-Ershad S. Texture classiﬁcation approach based on combination of edge & co-occurrence and local binary pattern. *Int Online J Image Process Pattern Recognit* 2019; 1(2): 1–29.
11. Fekri-Ershad S. A robust approach for surface defect detection based on one dimensional local binary patterns. *Indian J Sci Technol* 2012; 5(8): 1–7.
12. Wang SP, Zhao WG, Zhang GY, et al. Identiﬁcation of structural parameters from free vibration data using Gabor wavelet transform. *Mech Syst Signal Process* 2021; 147: 107122.
13. So Y, Kim J and Hwang H. Fabric defect detection using a hybrid particle swarm optimization-gravitational search algorithm and a Gabor ﬁlter. *J Opt Soc Am A Opt Image Sci Vis* 2020; 37(7): 1229–1235.
14. Zhang Q, Li HG, Li M, et al. Feature extraction of face image based on LBP and 2-D Gabor wavelet transform. *Math Biosci Eng* 2019; 17(2): 1578–1592.
15. Zhang XL, Xue HR and Xiaojing G. Milk somatic cells recognition based on Gray-Scale difference statistics. *MATEC Web Conf* 2018; 173: 1–4.
16. Liu H, Zhang YS, Zhang YH, et al. Texture feature extraction of flame image based on Gray—Scale difference statistics. *Control Eng China* 2013; 20(2): 213–218.
17. Xu ZL, Shao YB and Yao TZ. Tongue image classification based on Grayscale difference. *Comput Sci Appl* 2020; 10(2): 190–199.
18. Raheja JL, Kumar S and Chaudhary A. Fabric defect detection based on GLCM and Gabor filter: a comparison. *Optik* 2013; 124(23): 6469–6474.
19. Garg M and Dhiman G. A novel content-based image retrieval approach for classiﬁcation using GLCM features and texture fused LBP variants. *Neural Comput Appl* 2020; 1(32):1–18.
20. Lohitashva BH, Manjunath Aradhya VN and Guru DS. Violent video event detection based on integrated LBP and GLCM texture features. *Revue d'Intelligence Artificielle* 2020; 34(2): 179–187.
21. Fekri-Ershad S. Texture classiﬁcation approach based on combination of edge & co-occurrence and local binary pattern. In: *Int’l conf. IP, comp. vision, and pattern recognition, IPCV’11*, 2011, pp. 626–629.