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Identification of Extremely Similar Animal Fibers Based on Matched Filter and HOG-SVM

WENYU XING[1], NA DENG[2], BINJIE XIN[3], YIWEN LIU[1], YANG CHEN[1], AND ZHENGYE ZHANG[1]

[1]School of Electric and Electronic Engineering, Shanghai University of Engineering Science, Shanghai 201620, China
[2]Research Department, Shanghai University of Engineering Science, Shanghai 201620, China
[3]Fashion College, Shanghai University of Engineering Science, Shanghai 201620, China

Corresponding author: Binjie Xin (xinbj@sues.edu.cn)

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ABSTRACT Identification of extremely similar animal fibers has always been one of the challenging research topics in the textile field. In this paper, an improved image-based recognition method was proposed for the identification of extremely similar animal fibers including cashmere and wool. A total of 100 groups of wool and 100 groups of cashmere fiber images were collected using the self-developed microscope image analysis system. The contrast of original fiber micro images usually was not high enough and some impurities always existed during the slicing process, so the matched filters were first applied for these images to extract the enhanced fiber binary texture, which only needs to set reasonable segment length and the threshold for different fiber images to eliminate impurities and background. Then, the high-dimensional texture features of the original color images, gray images, and the images processed by matched filter were extracted by calculating and analyzing the histogram of oriented gradient (HOG). The 200 sets of original color images, gray images, and processed images were divided into the training set and testing set according to different proportions, and the recognition expert system based on the support vector machine (SVM) could be trained and validated accordingly. The experimental results show that the recognition accuracy of the fiber images processed by matched filter was obviously improved compared with that of the other two data sets, and the recognition rate reaches the highest with 92.5%. It also proves that the proposed algorithm in this paper can classify and identify extremely similar wool and cashmere fibers more quickly and effectively compared with other texture feature extraction and identification algorithms.

INDEX TERMS Extremely similar fibers, image identification, matched filter, HOG, SVM.

I. INTRODUCTION

Identification of extremely similar animal fibers has always been one of the important quality evaluation works in textile field, especially the recognition of wool and cashmere fibers. With the development of economy and the increase of import and export trade, the trade volume of cashmere is also increasing rapidly. Because wool and cashmere have similar colors and handle feeling, the production of mixed cashmere and wool often occurs. In order to maintain the fairness and stability of the market order, the identification of wool and cashmere fibers has become a top priority.

Traditional fiber identification methods mainly include chemical analysis methods, biological methods and so on. Chen and Wang used the NAOH solution to test the solubility of wool and cashmere fibers under different conditions, and quantitatively analyzed the difference between them by comparing the difference in alkali solution concentration [1]. Vineis *et al.* proposed a UPLC/ESI-MS method for identifying wool and cashmere which was used to extract the enzymatic digestion of keratin and analyze the peptide, then the quantitative analysis and classification of fibers can be realized [2]. Tang proposed a method for fiber analysis based on mitochondrial DNA. This method can quantitatively analyze the components of wool and cashmere mixture by designing polymerase chain reaction primers and probes to react with 12S ribosome gene [3]. Although these methods also can achieve the analysis and identification of fiber types, they often require higher equipment, operate more complex,

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and can only achieve the analysis of a small number of fibers, the efficiency is low.

In recent years, some researchers gradually used digital image processing and machine learning methods to analyze and identify fibers, the key of which is the processing of fiber images and the extraction of texture features. For the processing of fiber images, the traditional method is mainly using the Sobel [4], Laplacian [5], Prewitt [6], Log [7] or other operators to directly detect and extract the edge or texture of the original images [8]. Moreover, different algorithms also can be combined to get the hopeful results. However, this kind of edge extraction algorithm can only achieve better results for images with better contrast, it seems to be more troublesome and inefficient to use the combination algorithm for image processing.

The texture feature analysis methods can be divided into five types: statistical method, geometric method, structural method, spectral method and model method [9], [10]. Each type contains a variety of specific feature extraction algorithms. At the same time, many methods have been used in the field of wool and cashmere similar fiber recognition in recent years. Zoccola *et al.* proposed a fiber identification method based on the near infrared spectroscopy which mainly identified the species by analyzing the differences between the spectra of different animal fibers [11]. Lu *et al.* used the Pairwise Rotation Invariant Co-occurrence Local Binary Patterns to represent the cashmere and wool fibers. Each fiber image was converted to a vector, which is a histogram of LBPs extracted from fiber images, and then these vectors could be fed into the SVM for a supervised classification [12]. Zhong *et al.* proposed a novel method for the identification of wool and cashmere based on projection curves. They used three different methods to reveal the embedded numerical features of the mathematical replica and adopted the SVM algorithm to recognize the fiber types [13]. Lu *et al.* used bag-of-words and spatial pyramid match for the identification of micrographs of cashmere and wool. It constructed a bag-of-words model to describe the fiber features and took the SVM as the classifier to identify different fibers [14]. Xing *et al.* proposed a novel digital analysis method for identifying the cashmere and wool fibers, which was mainly based on the idea of multi-scale analysis. They firstly decomposed the original image by wavelet decomposition, then extracted the texture features of each layer sub-images using Gauss Markov Random Field (GMRF), and realized the recognition of fiber types by analyzing the difference of texture features between wool and cashmere at different decomposition scales [15]. Jiao *et al.* used the gray level co-occurrence matrix to extract the texture features of cashmere and wool fibers. Then these texture features would be used as input parameters of support vector machine to realize the recognition of wool and cashmere [16]. Yuan *et al.* used the improved Tamura texture feature to analysis the final texture images and identify the cashmere and wool fibers by neural network [17].

Although quite a lot of researches have been done to provide the effective methods to identify the extremely similar wool and cashmere fibers, there are still many problems waiting for solution. For example, these algorithms were usually adopted to analyze the whole texture of fiber images and extract a little features, it requires a large amount of sample set and needs long time, and the image pre-processing method was cumbersome. Therefore, in order to solve these existing problems much better, the researchers still need to do further study to achieve the identification of extremely similar fibers more accuracy and quickly.

In this paper, a novel method based on matched filter was proposed to process the original fiber images, which can directly obtain the enhanced fiber binary texture images with removing background and noise and doesn't require other pre-processing steps. Meanwhile, the method based on histogram of oriented gradient and support vector machine were used to extract the highly dimensional texture features of the filter output images by analyzing the features of fiber local images and achieve the automated identification of extremely similar fiber images in self-developed microscope image analysis system.

II. PROPOSED METHODOLOGY

The proposed method consists of three steps as shown below in Fig. 1. In the first step, the matched filter was designed for the pre-processing of input fiber micro images. In the second step, the histogram of oriented gradient algorithm was applied on the filter output images to extract the texture features. In the third step, the support vector machine was adopted to analysis the experiment data and identify the cashmere and wool fibers.

A. MATCHED FILTER

Matched filter [18]–[20] means that after filtering, the ratio of instantaneous signal power to average noise power at the output end of the filter is maximum. When the useful signal and noise enter the filter at the same time, the useful signal peaks at a moment, and the noise signal is suppressed. Considering that wool and cashmere fibers have the following characteristics:

- Fibers have smaller curvature and can be represented by piecewise linear segments as parallel pairs.
- The fineness of the fibers varies in a small range, and the two fiber outlines are approximately parallel.
- The contrast between texture and background is low. Traditional methods cannot extract texture contours accurately.

Therefore, a Gauss kernel filter for texture and edge detection can be designed based on these characteristics. If the fineness of the fiber matches the scale of the filter, strong response output will be generated and noise signal will be removed. Then the filtered image will be binarized by threshold segmentation, so as to realize the extraction of fiber edges and the segmentation of texture images.

The definition of a two-dimensional Gauss kernel function is described as follows:

$$K(x, y) = -\exp(-x^2/2\sigma^2), \quad |y| \leq L/2 \tag{1}$$

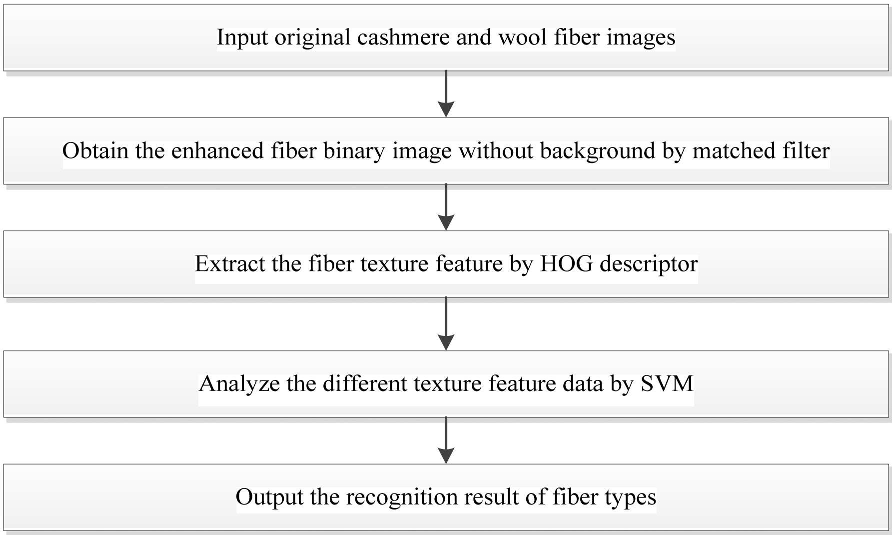


FIGURE 1. **Flow chart of the proposed method.**

where σ is the scale parameters of filters, L is the length of the segment for which the fibers are assumed to have a fixed orientation. Therefore, in order to extract fibers in different directions accurately, it is necessary to design templates in different directions by rotating Gauss kernel function. Let $p(x,y)$ be a discrete point in the kernel function and θ_i be the orientation of the ith kernel, so the rotation matrix is defined as:

$$r_i = \begin{bmatrix} \cos\theta_i & -\sin\theta_i \\ \sin\theta_i & \cos\theta_i \end{bmatrix} \tag{2}$$

The $p(x,y)$ in the rotated coordinate system is shown as:

$$p_i = [u, v] = pr_i^T \tag{3}$$

And the ith kernel is shown as equation (4). N is the neighborhood whose range of values is defined as equation (5).

$$K_i(x, y) = -\exp(-\mu^2/2\sigma^2), \quad \forall \overline{p_i} \in N \tag{4}$$

$$N = \{(u, v) \mid |u| \leq 3\sigma, |v| \leq L/2\} \tag{5}$$

In order to make the filtering response of the filter template to uniform background area zero, the kernel function is further modified, and the final convolution mask is obtained as:

$$K_i'(x, y) = K_i(x, y) - A_i, \forall \overline{p_i} \in N \tag{6}$$

$$A_i = \sum_{\overline{p_i} \in N} K_i(x, y)/A \tag{7}$$

where A_i is the mean value of the kernel, A is the number of points in N. In the experiment, the twelve different direction Gaussian templates are designed between 0° and 180°, and the appropriate template length and scale parameters are selected for different fiber images, then the edge and texture of the fibers will be extracted by matched filtering. Moreover, by setting a reasonable threshold, if the magnitude of the filtered output at a given pixel location exceeds the threshold, the pixel is labeled as a part of the fiber texture.

B. HOG FEATURE EXTRACTION

Histogram of oriented gradient (HOG) [21], [22] is a feature descriptor used for object detection in computer vision and image processing. It constructs features by calculating and counting the gradient direction histogram of the local area of the image. Compared with the traditional feature description method, HOG operates on the local cells of the image, so it keeps good in-variance to the geometric and optical deformation of the image, and can extract the texture features of the image more accurately. Its algorithm flowchart is shown in Fig. 2.

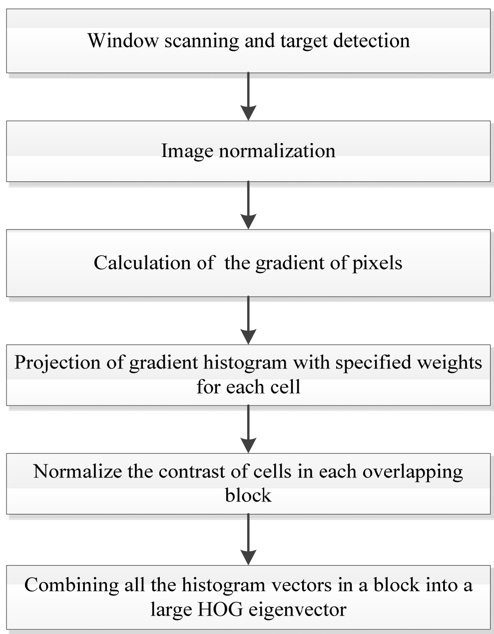


FIGURE 2. **Flow chart of the HOG algorithm.**

For the HOG feature extraction [23] of extremely similar wool and cashmere fiber images, the specific flow is as follows:

1) The cashmere and wool fiber images are input and converted into gray-scale.
2) Gamma correction method is used to standardize the color space of the input image. It can adjust the contrast of the image, reduce the impact of local shadows and illumination variation, and reduce noise interference. Gamma compression formula is shown as equation (8) and the number of gammas usually selects 1/2.

$$I(x, y) = I(x, y)^{gamma} \tag{8}$$

3) The gradient (including size and direction) of each pixel in the image is calculated to extract the effective information of the edge and outline of the fibers. The gradient of the pixels (x,y) in the image is defined as:

$$\begin{cases} G_x(x, y) = I(x, y+1) - I(x, y-1) \\ Gy(x, y) = I(x+1, y) - I(x-1, y) \end{cases} \tag{9}$$

where $G_x(x,y)$, $G_y(x,y)$ and $I(x,y)$ represent horizontal gradient, vertical gradient and pixel value respectively. At the same time, the magnitude and direction corresponding to the gradient of the pixel are shown as follows.

$$G(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2} \tag{10}$$

$$\alpha(x, y) = \arctan \frac{G_x(x, y)}{G_y(x, y)} \tag{11}$$

4) The image is divided into small cells, then the descriptor of each cell can be formed by counting the gradient histogram of each cell.
5) By concatenating the feature descriptors of all cells in a block into one block, the feature descriptor of the block can be obtained.
6) The HOG feature descriptor of the whole fiber image can be obtained by concatenating all the blocks in the image. The final feature vector is defined for classification.

The schematic diagram of HOG operator is shown in Fig. 3. As can be seen from the Fig. 3, the whole image interval is composed of several square lattices, which are mainly represented by three parameters: the number of histogram channels per cell, the number of cell units in each block, and the number of blocks in the whole image.

C. MULTIVARIATE CLASSIFICATION MODELS

HOG feature dimension is high, and its combination with support vector machine (SVM) classifier has been widely used in image identification [24], [25]. The SVM method maps the sample space into a high-dimensional or even infinite-dimensional feature space (Hilbert Space) mainly through a non-linear mapping, which transforms the non-linear separable problem in the original sample space into a linear separable problem in the feature space [26], [27]. At the same time, in order to avoid the computational complexity caused by too high dimension, SVM applies the expansion theorem of kernel function which is the radial

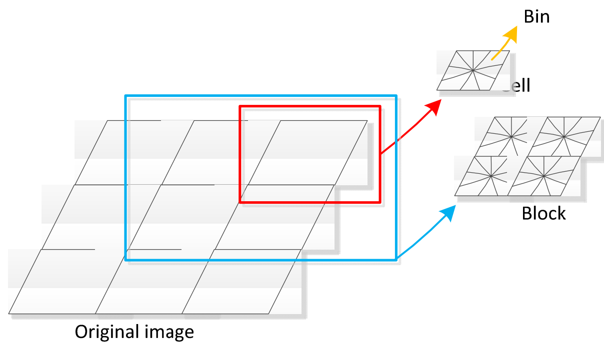


FIGURE 3. Schematic representation of HOG operator.

basis function in this paper. It does not need to know the explicit expression of the non-linear mapping. It only needs to establish a linear learning machine in the high-dimensional feature space to achieve effective image classification without increasing computational complexity.

In this paper, the original fiber images, the fiber gray images and the fiber images processed by matched filter are extracted by HOG operator respectively, and then the three data-sets are divided into training set and testing set according to the same proportion respectively, and the support vector machine is used to train and test the fiber recognition framework. Finally, by comparing the recognition accuracy of three kinds of data sets, we can judge whether the improved fiber recognition algorithm proposed in this paper is more effective. The flow chart of SVM experiment is shown in Fig. 4.

III. MATERIALS AND SYSTEMS

200 sample fibers including 100 wool and 100 cashmere fibers from Australia were used to validate the self-developed algorithm. The proposed image acquisition and analysis system are established as follows.

Fiber images were observed with 10 × 50 magnification via an optical microscopic system, which was manufactured by Suzhou Huiguang Technology Limited Company under SOPTOP, and captured via the digital CMOS camera under 6.3 Megapixel USB 3.0. Microscope images were stored in 'png' format as 3072 × 2048 pixels in size. Each image only contained one cashmere or wool fiber, whose majority of trunk was clear. The fiber micro-image acquisition system is shown in Fig. 5.

The MATLAB 2016b was mainly used to process the fiber images and develop the algorithm system. Meanwhile, the computer hardware environment for software operation includes Inter Core i5-4200M (2.5 GHz) CPU, 4GB running memory and 64-bit operating system.

IV. EXPERIMENT AND RESULTS

A. ANALYSIS OF ORIGINAL IMAGES PRE-PROCESSING

The size of the original fiber micro images captured by the microscope is 3072 × 2048 pixels, because the size

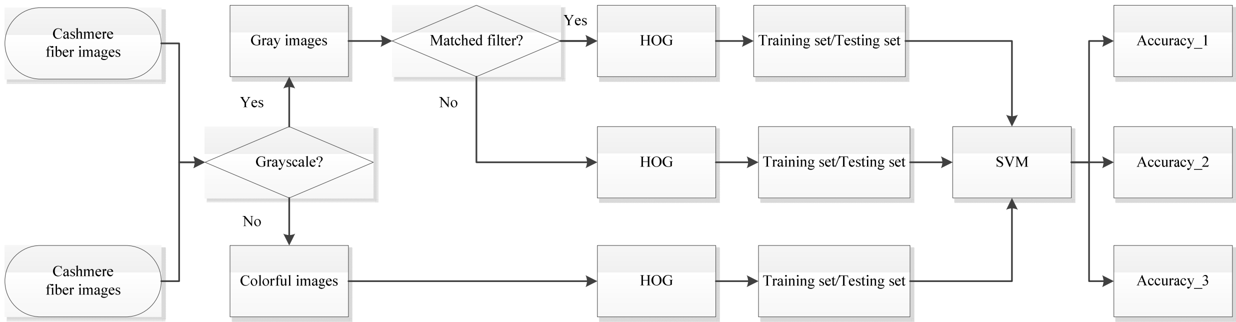


FIGURE 4. Fiber recognition flowchart of SVM classifier.

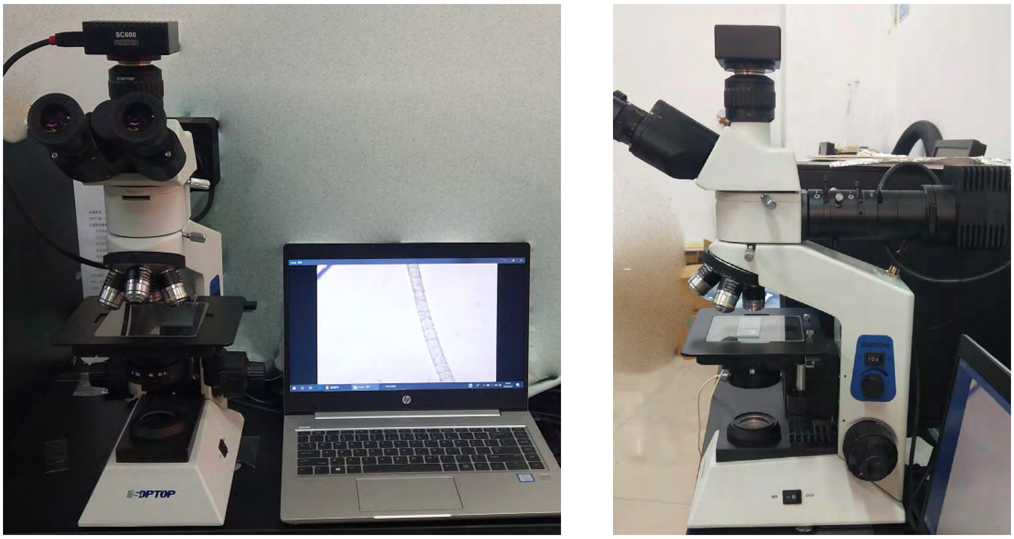


FIGURE 5. The fiber micro-image acquisition system.

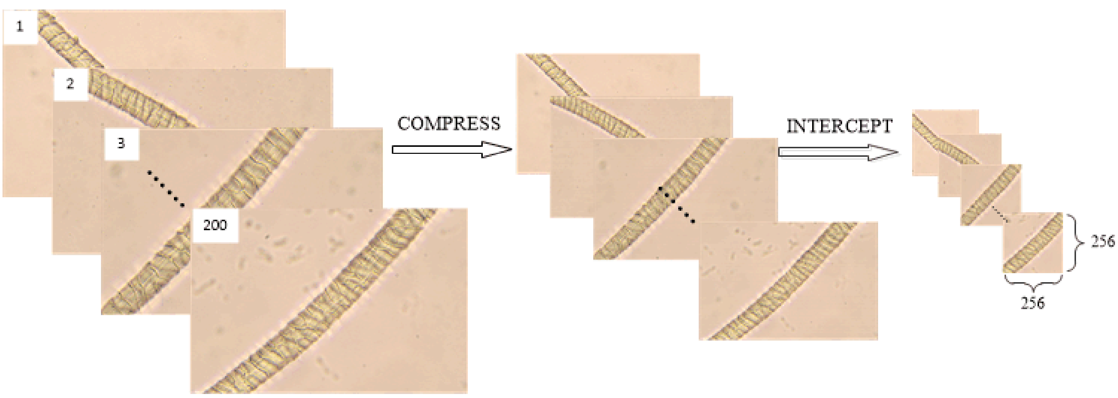


FIGURE 6. Process diagram display of image pre-processing.

of the image is too large, the calculation is more complex, and the purpose of the study is to classify wool and cashmere fibers quickly, so the resolution requirement of the images is not particularly strict. Therefore, the wool and cashmere fibers collected before the experiment should be compressed in advance to extract HOG features much simpler and the effective fiber area with size of 256×256 pixels was intercepted for follow-up experiments. The process diagram of the above processing steps is shown in Fig. 6.

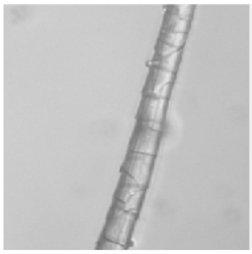
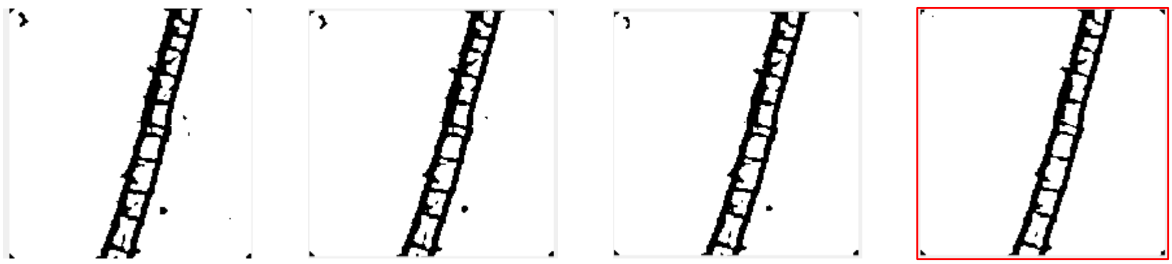


FIGURE 7. An example of cashmere fiber gray image.

After graying the fiber images, they were put into the matched filter. When the filter scale parameter was set to 2 and the interval was 15°, there were 12 different directions of Gaussian templates. Then the input images were filtered by selecting the appropriate template length (L) and threshold (T), and the edges and texture contours of the fibers were extracted clearly. A cashmere fiber shown in Fig. 7 was taken as an example to introduce the processing procedure of matched filter. As a result, when the number of template length remained constant with 9, with the increase of threshold value, the isolated noise points in binary image decreased gradually shown in Fig. 8. When the number of thresholds remained constant with 150, with the increase of template length, the texture image of the fiber was becoming clearer and clearer shown in Fig. 9. As can be seen from the red rectangular frame labeling of Fig. 8 and Fig. 9, when $L = 9$ and $T = 150$, this cashmere fiber had the best processing effect. Meanwhile, when the traditional edge extraction algorithms were selected, including Sobel, Roberts, Prewitt and Log, to process the cashmere fiber image directly, the processing results are shown in Fig. 10. It was found that the traditional algorithm was not suitable for the texture detection of those fiber images with low contrast between texture and background compared to the matched filter. And when the traditional image pre-processing methods were used to obtain the texture binary image without background and

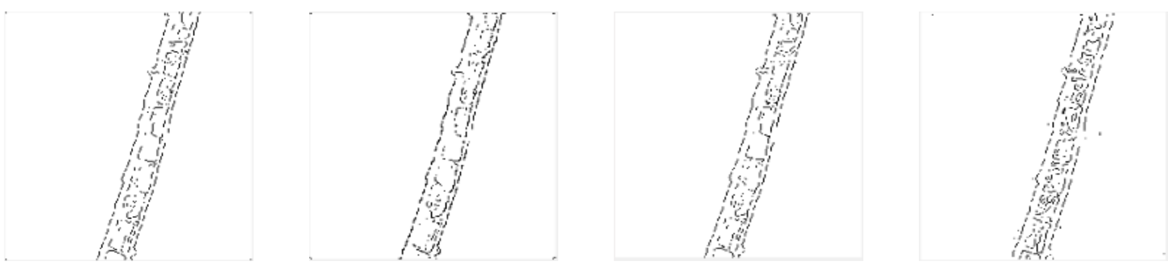


T=90 T=110 T=130 T=150

FIGURE 8. Fiber images when threshold changes.

L=2 L=5 L=9 L=15

FIGURE 9. Fiber images when template length changes.



(a) (b) (c) (d)

FIGURE 10. The effect map of traditional edge extraction algorithms: (a) Sobel; (b) Roberts; (c) Prewitt; (d) Log.

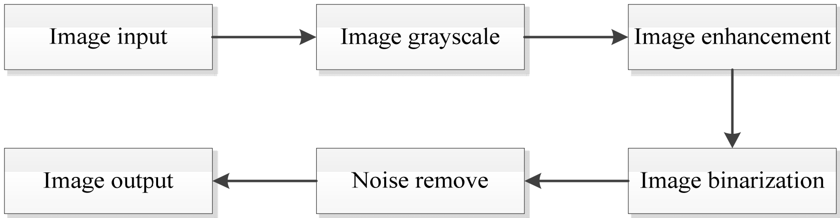


FIGURE 11. Flow chart of traditional image pre-processing.

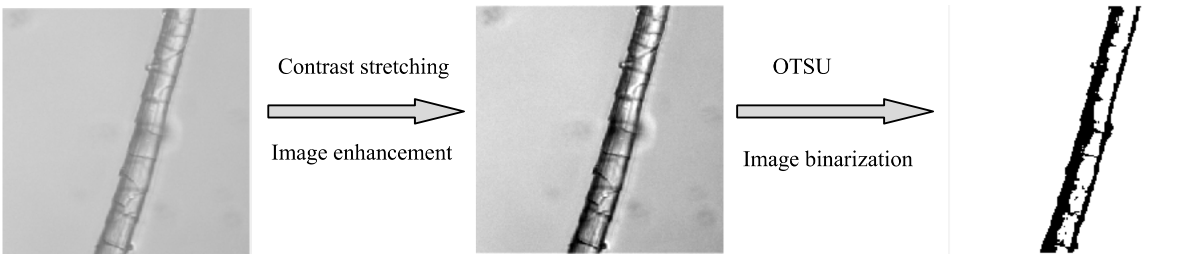


FIGURE 12. Traditional enhanced binary image processing.

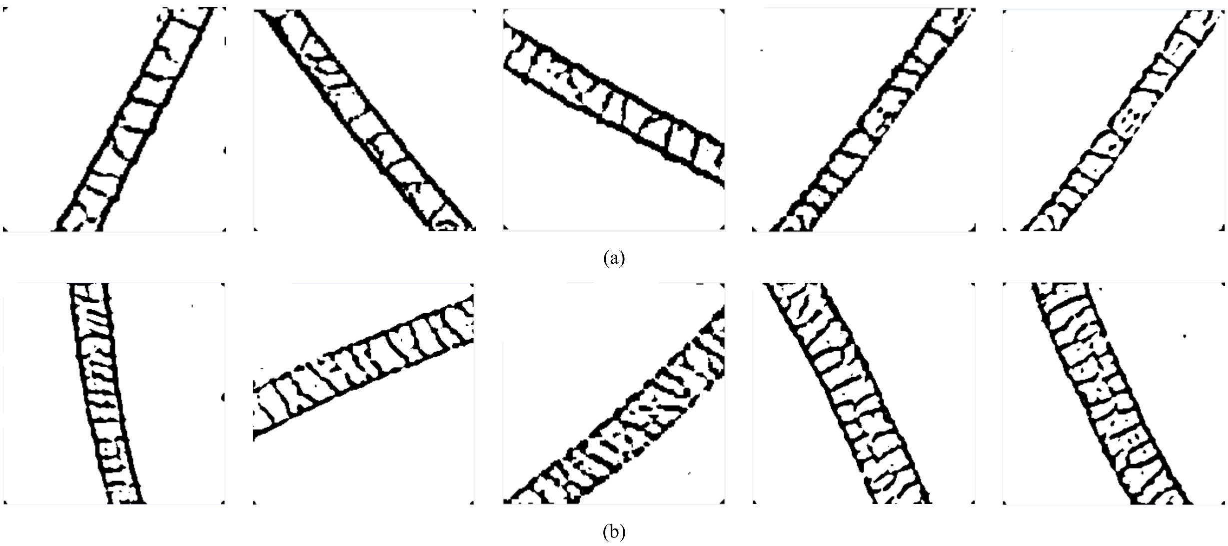


FIGURE 13. Part of fibers proposed by matched filter: (a) Cashmere; (b) Wool.

noise, the flow chart of the algorithm is shown in Fig. 11 and the images of processing process is shown in Fig. 12. The contrast stretching algorithm was firstly used to enhance the fiber gray images according to the gray histogram and then the OTSU algorithm was adopted to process the enhanced image, the enhanced texture binary image could be obtained. If there was noise in the final images, it also could be processed by the de-noise algorithms. Therefore, compared with the matched filter which only needs to set appropriate double thresholds to realize image processing, these traditional image pre-processing method was much more complex. What's more, the binary texture images of partially wool and cashmere fibers proposed by matched filter are shown in the Fig. 13 to demonstrate the reliability of the algorithms.

B. TEXTURE FEATURE EXTRACTION AND IDENTIFICATION

Then the HOG was used to extract the texture feature of original color images, gray images and binary images processed by matched filter respectively. In the experiment, the gradient direction was divided into nine sections, that was each cell contained nine histogram channels. The gradient magnitude of the nine histogram channels of the sample image is shown in Fig. 14, which also showed that each cell would have nine eigenvalues. Then 16×16 pixels were used as a cell unit and 2×2 cells were selected to form a block, so the sketch of the eigenvalue calculation process of the whole fiber image is shown in Fig. 15. What's more, the texture features' number of three kinds of input images were calculated shown in Tab. 1 and it took about only

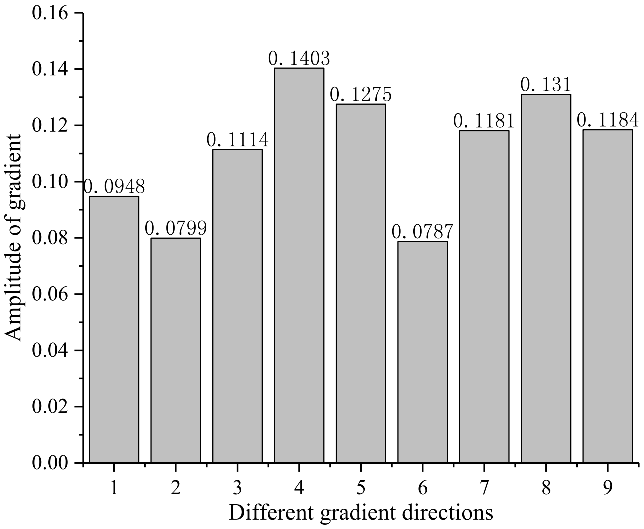


FIGURE 14. Amplitude of different gradient directions.

one second approximately for each fiber image to extract features.

A total of 100 wool (w) fibers and 100 cashmere (c) fibers was used to obtain the high-dimensional HOG feature data-sets of original color images, gray images and processed images. According to the ratio of 6:4, 7:3, 8:2 and 9:1, the above three data sets were divided into different training set and testing set, which were input to the two-class support vector machine for training and identification. The recognition accuracy of the three input images are shown in the Tab. 2, 3 and 4 below. As we all known, when the ratio of training set to test set was 9:1, the number of test sets was small. Although the recognition rate of three data sets was all high, the reliability of the results was low. At the same time, it could be seen from Fig. 16 that when the training set and the testing set were in three other proportions, the recognition accuracy of the images processed by matched filter was higher than that of the other two kinds of fiber images. When the ratio of testing set to training set was 8:2, the recognition rate reached the highest with 92.5%. It also can be seen from Fig. 17 that when the training set and the test set were in different proportions, the proposed algorithm all could achieve the recognition framework training and the verification of the experimental samples in a relatively short time. In conclusion, the two figures proved that the proposed algorithm could be used to identify the types of wool and cashmere extremely similar fibers quickly and accurately.

V. PERFORMANCE COMPARISON WITH OTHER FEATURE EXTRACTION METHOD

A. COMPARISON WITH OTHER HIGH-DIMENSIONAL FEATURE DESCRIPTORS

In addition to the HOG feature operators, there have been many other image feature descriptors in previous studies, including Local Binary Pattern (LBP) [28], Scale Invariant Feature Transform (SIFT) [29], Haar [30], Harris [31] and so on. At the same time, deep learning is also gradually applied in feature extraction and image classification.

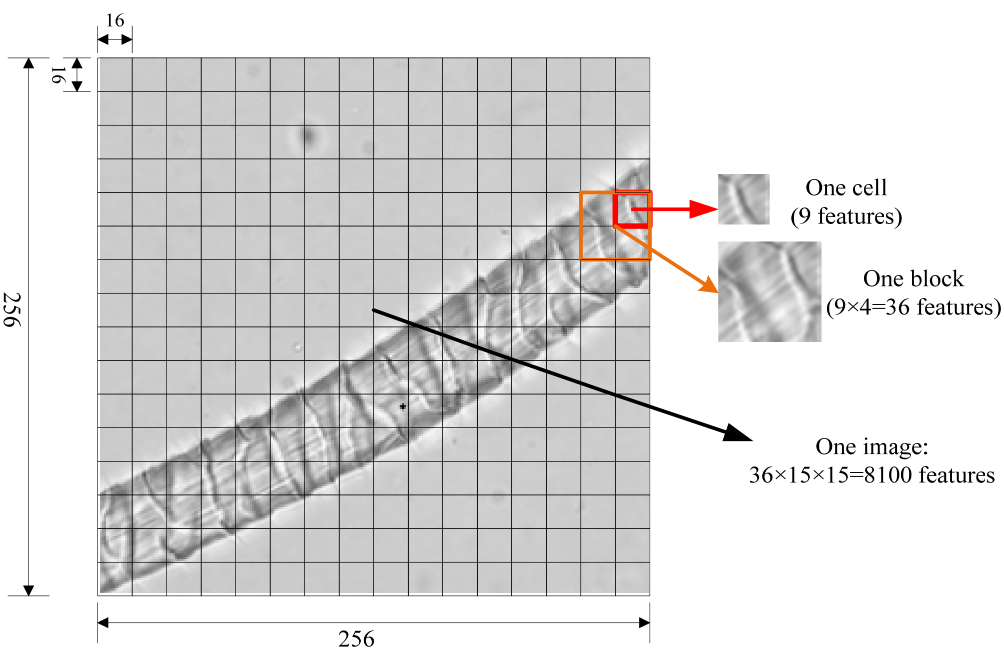
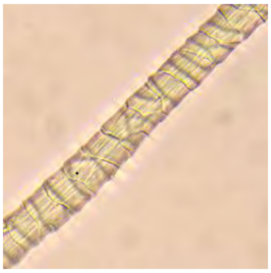
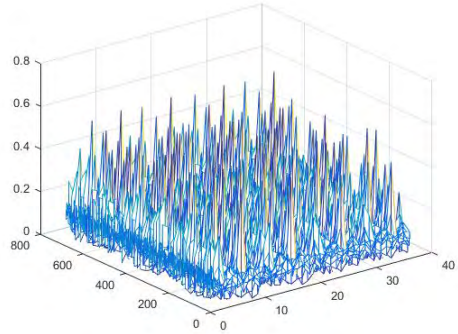
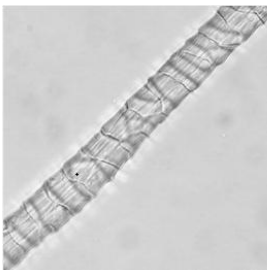
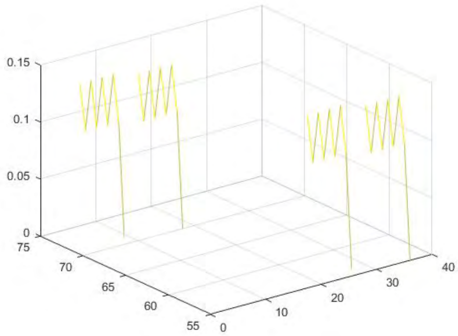
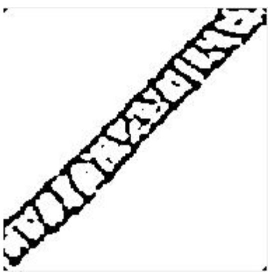
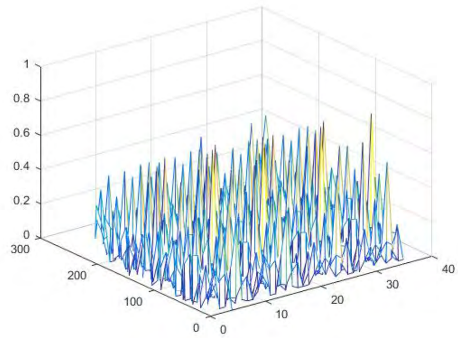


FIGURE 15. Graphics of texture feature calculation of fiber gray image.

TABLE 1. Feature extraction result display of three kinds of input images.

Indexed image	Input image	Grid representation of HOG features	Number of features
Original image			25380
Gray image			8100
Processed image			8100

However, these kinds of algorithms also has its own advantages and disadvantages shown as follows, which leads to the limitations in identifying extremely similar wool and cashmere fibers.

(1) Haar feature operator was firstly proposed by Papageorgious in face identification. There are two kinds of rectangles in its feature template including white and black, and the template feature values are defined as white rectangular pixels and reduced black rectangular pixels. However, rectangular features are only sensitive to some simple graphical structures and can only describe the structure of specific orientation, while the direction of fibers in wool and cashmere sample images is different, so Harr feature descriptor cannot be used to extract accurate features.

(2) Deep learning algorithm is widely used in automatic image classification, but because wool and cashmere fiber texture features are extremely similar, the application of deep learning algorithm may lead to the long training time and low recognition rate.

TABLE 2. Recognition accuracy of original color images.

Proportion (training set: testing set)	Specimens	Correct identification		
		Number	Accuracy (%)	Mean-value (%)
6:4	c	27	67.5	68.8
	w	28	70.0	
7:3	c	26	86.6	81.6
	w	23	76.6	
8:2	c	17	85.0	77.5
	w	14	70.0	
9:1	c	10	100.0	95.0
	w	9	90.0	

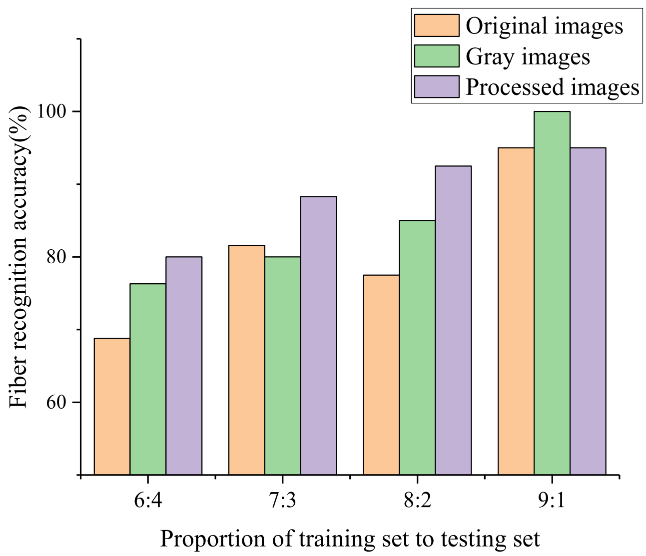


FIGURE 16. Comparison of identification results of different input images.

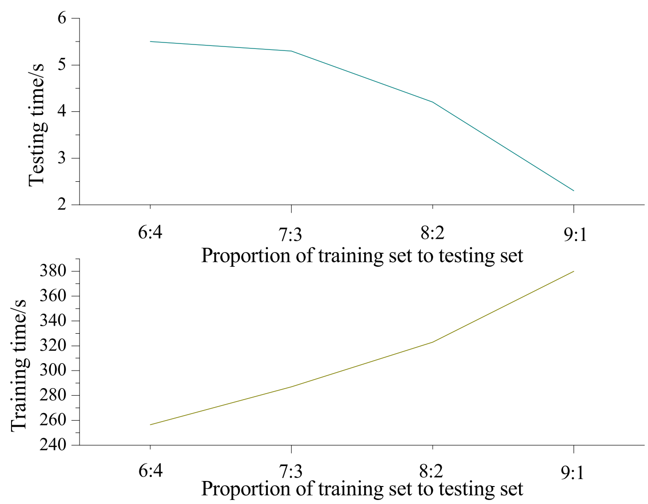


FIGURE 17. Support vector machine training and testing time in different data set proportions.

So far, no researchers have applied deep learning for extremely similar fiber recognition.

The two algorithms mentioned above cannot be applied to the recognition of wool and cashmere extremely similar fibers because of their respective defects. Because HOG, LBP, SIFT and Harries feature descriptors can extract texture features locally, and have rotation invariance for the same fiber images, they can be well used to extract features from different animal fiber images. Therefore, in order to prove the validity of the proposed method, LBP, SIFT and Harries operators were used to extract texture features of wool and cashmere extremely similar fiber images proposed by matched filter, and then the same support vector machine classifier was used to identify different types of fibers according to different proportion of training set to testing set.

When the LBP descriptor was used to extract the texture features, the fiber images was firstly processed by the LBP algorithm shown in Fig. 18(a). Then the detection window was divided into 16x16 cells, and the LBP values were calculated by comparing the gray values with the eight adjacent pixels. Then the feature vectors describing the whole image were formed by counting the histograms of each cell.

When the SIFT descriptor was adopted to extract the texture features, it detected extreme points by constructing scale space, and then the feature points were obtained by

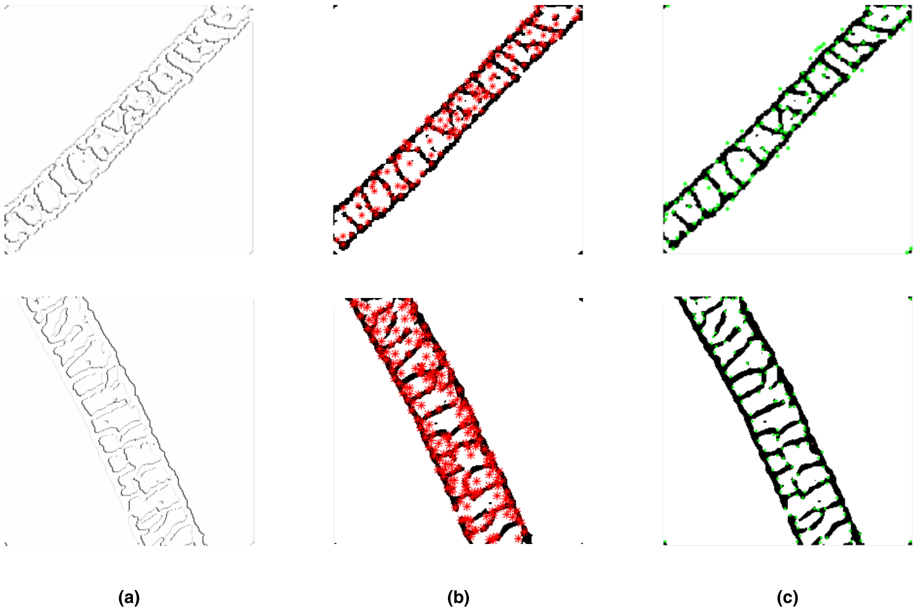


FIGURE 18. Charts of computing processes for different characteristic operators. (a) LBP; (b) SIFT; (c) Harris.

filtering and locating the extreme points accurately, as shown in Fig. 18(b). Finally, the 16×16 domain was selected as the center of the feature point, and the relative direction of the sampling point and the feature point was weighted by Gauss into the direction histogram containing eight bins, so the final feature value could be obtained to describe the fiber texture.

When the Harries descriptor was adopted to extract the texture features, the corner points of the image shown in Fig. 18(c) were obtained by detecting the change of gray value of the pixels in the window, and were used as the surface texture features of the fibers.

It can be seen from the result of HOG-SVM classifier that when the ratio between training set and testing set was 8:2 and 7:3, the recognition accuracy and the reliability were high, so the other three feature sets were analyzed by using these two ratios. The identification result of the three feature descriptor are shown in Tables 5 to 7 respectively. And the comparison is shown in Fig. 19 from which it can be known that these fiber identification accuracy were lower than the method proposed in this paper.

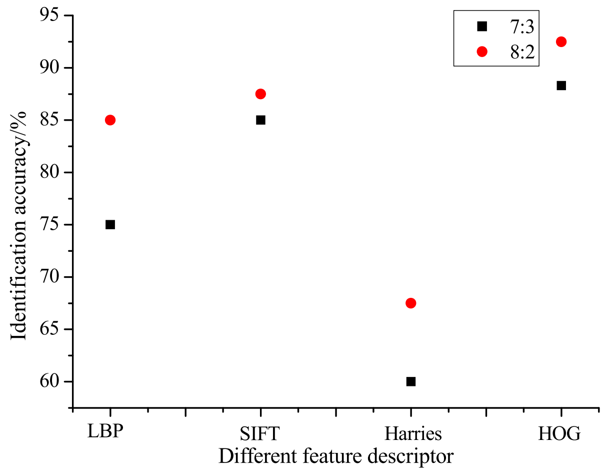


FIGURE 19. Comparison of recognition accuracy of different feature descriptors.

B. COMPARISON WITH THE EXISTING METHODS FOR FIBER FEATURES EXTRACTION

At present, there also have been many fiber texture feature extraction methods used for the identification of cashmere and wool extremely similar fibers presented in the introduction. For example, Lu et al. used the bag-of-visual-word algorithm to extract the texture features of different cashmere and wool fibers and the identification accuracy was 86% [14]. Xing et al. used the GMRF method to extract the wool and cashmere fiber texture features and the final identification accuracy was 90.07% [15] Jiao et al. used the co-occurrence matrix for the texture analysis of fibers and the final identification accuracy was 91.93% [16]. Yuan et al. used the Tamura texture analysis method to describe the fiber surface texture feature and the final identification accuracy was 81.17% [17]. Although some algorithms can achieve high recognition rate compared with the method proposed in this paper, they require a large number of sample data sets.

From the performance comparison with the existing method and the other feature descriptors shown in Fig. 20, it can be known that the method proposed in this paper can reach a higher fiber identification. What's more,

TABLE 3. Recognition accuracy of gray images.

Proportion (training set: testing set)	Specimens	Correct identification		
		Number	Accuracy (%)	Mean-value (%)
6:4	c	29	72.5	76.3
	w	32	80.0	
7:3	c	22	73.3	80.0
	w	26	86.7	
8:2	c	16	80.0	85.0
	w	18	90.0	
9:1	c	10	100.0	100.0
	w	10	100.0	

TABLE 4. Recognition accuracy of images after matched filtering processing.

Proportion (training set: testing set)	Specimens	Correct identification		
		Number	Accuracy (%)	Mean-value (%)
6:4	c	33	82.5	80.0
	w	31	77.5	
7:3	c	27	90.0	88.3
	w	26	86.7	
8:2	c	18	90.0	92.5
	w	19	95.0	
9:1	c	10	100.0	95.0
	w	9	90.0	

TABLE 5. Recognition accuracy of LBP feature descriptor.

Proportion (training set: testing set)	Specimens	Correct identification		
		Number	Accuracy (%)	Mean-value (%)
7:3	c	22	73.3	75.0
	w	23	76.7	
8:2	c	17	85.0	85.0
	w	17	85.0	

compared with the traditional image-based methods, the proposed method could use fewer fiber sample images, so it can greatly improve the efficiency of fiber identification. Therefore, it could be used to identify the cashmere and wool extremely similar fibers much more accurately and quickly.

TABLE 6. Recognition accuracy of SIFT feature descriptor.

Proportion (training set: testing set)	Specimens	Correct identification		
		Number	Accuracy (%)	Mean-value (%)
7:3	c	25	83.3	85.0
	w	26	86.7	
8:2	c	18	90.0	87.5
	w	17	85.0	

TABLE 7. Recognition accuracy of Harries feature descriptor.

Proportion (training set: testing set)	Specimens	Correct identification		
		Number	Accuracy (%)	Mean-value (%)
7:3	c	17	56.7	60.0
	w	19	63.3	
8:2	c	13	65.0	67.5
	w	14	70.0	

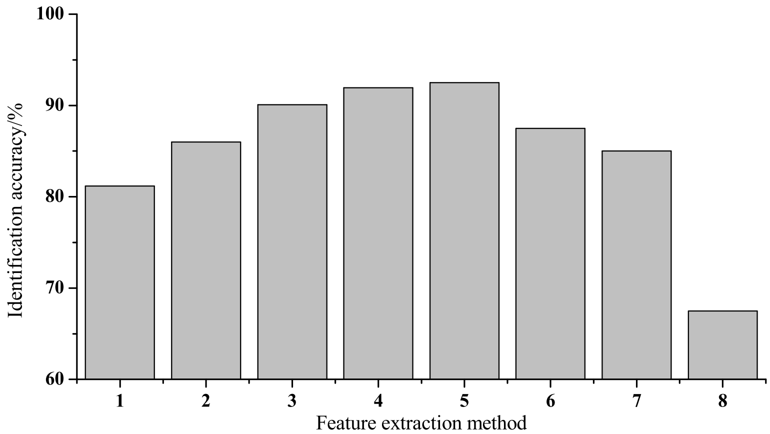


FIGURE 20. Comparison of recognition accuracy of different feature extraction algorithms.

VI. CONCLUSIONS

An improved image identification algorithm was proposed for identifying extremely similar animal fiber images such as wool and cashmere. In this method, the original fiber images were filtered by matched filter to obtain the fiber texture binary images without background and noise. Then, the HOG feature operator was used to extract texture features from the output images of the filter, and SVM was used to train and classify the high-dimensional feature sets. This method can obtain clear and noiseless texture images without complicated image pre-processing, the identification accuracy of fiber images processed by matched filter had been significantly improved compared with the original unprocessed fiber images. Meanwhile, the identification accuracy of the method proposed in this paper was higher compared with the different high-dimensional feature descriptors using same data set and the existed methods in published articles with self data sets. The result proved that the accuracy and efficiency of the method proposed in this paper was great for identifying the extremely similar fibers. This method works well to extract fiber contours and identify fiber species in ordinary optical microscope, it could be also extended well to the image-based object classification in other fields. In the future, in order to explore the difference more accurately between similar fibers, we will study the application of deep learning algorithm in the field of similar fibers feature extraction and identification, and design a more efficient and accurate wool and cashmere fiber identification system.

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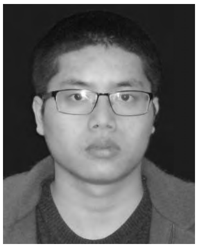
WENYU XING received the B.S. degree in automation from Shanghai Polytechnic University, Shanghai, China, in 2017. He is currently pursuing the M.S. degree in intellisense and control with the School of Electric and Electronic Engineering, Shanghai University of Engineering Science, Shanghai. His research interests include digital image processing, computer vision, and similar fibre identification.

NA DENG received the B.S. degree in electrical engineering from the Shandong University of Technology, Zibo, China, in 1999, the M.S. degree in control theory and control engineering from Qufu Normal University, Qufu, China, in 2002, and the Ph.D. degree in control theory and control engineering from Donghua University, Shanghai, China, in 2008. She is currently an Associate Research Fellow with the Shanghai University of Engineering Science. Her research interests include digital image processing, computer vision, and digital textile technology.

BINJIE XIN received the B.S. degree in textile engineering from Qingdao University, Qingdao, China, in 1996, the M.S. degree in textile materials and product design from Donghua University, Shanghai, China, in 1999, and the Ph.D. degree in textile science and technology from The Hong Kong Polytechnic University, Hong Kang, China, in 2009. He is currently a Professor with the Shanghai University of Engineering Science. His research interests include digital textile technology and functional material development.

YIWEN LIU received the B.S. degree in automation from Shanghai Polytechnic University, Shanghai, China, in 2018. She is currently pursuing the M.S. degree in intellisense and control with the School of Electric and Electronic Engineering, Shanghai University of Engineering Science, Shanghai. Her research interests include digital image processing and computer vision.

YANG CHEN received the B.S. degree in electrical engineering and automation from the Nanjing Jincheng College, Nanjing, China, in 2017. She is currently pursuing the M.S. degree in intellisense and control with the School of Electric and Electronic Engineering, Shanghai University of Engineering Science, Shanghai, China. Her research interests include digital image processing and image fusion.



ZHENGYE ZHANG received the B.S. degree in electrical engineering and automation from the Nanjing Jincheng College, Nanjing, China, in 2017. He is currently pursuing the M.S. degree in traffic engineering with the School of Electric and Electronic Engineering, Shanghai University of Engineering Science, Shanghai, China. His research interests include digital image processing and fibre identification.