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Feature extraction for animal fiber identification

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ABSTRACT

Fiber identification has been a very important task in many industries such as wool growing, textile processing, archaeology, histochemical engineering, and zoology. Over the years, animal fibers have been identified using physical and chemical approaches. Recently, objective identification of animal fibers has been developed based on the cuticular information of fibers. Effective and accurate extraction of representative features is essential to animal fiber identification and classification. In the current work, two different strategies are developed for this purpose. In the first method, explicit features are extracted using image processing. However, only implicit features are used in the second method with an unsupervised artificial neural network. It is found that the use of explicit features increases the accuracy of fiber identification but requires more effort on processing images and solid knowledge of what features are representative ones.

Keywords: Feature extraction, animal fiber, image processing, hybrid system, principal component analysis

1. INTRODUCTION

Animal fibers can be obtained from hair or skin covers of various mammals. There are many occasions where animal fibers need to be identified and classified. For example, in textile/wool industry, the identification and classification of animal fibers is a routine task in certain cases where animal fibers from a range of animals are commercially utilised. These animal fibers include wool fibers from sheep and specialty hair fibers, such as mohair from Angora goats, alpaca fibers from camels of Llama genus, cashmere fibers from cashmere goats, etc [1]. There has long been a desire to distinguish various animal fibers so that it can be determined whether the product is pure and blended. When it is identified as blended product, the blending rate needs to be decided. Evolution of the contents or blending rate in the product has also been undertaken during the processing.

Distinguishing animal fibers has been a very complicated and challenging task. Since all animal fibers are comprised of essentially the same keratin and belong to the protein group [2], they have very similar physical and chemical properties even when they are obtained from different species. Cuticular characteristics of animal fibers from different species are subtly different and they often vary widely from the same species due to their growing nature. Many other factors such as hereditary or genetic constitution, nutrition condition, geographical location and environmental variation lead to the cuticular appearance of the fiber varying within the same type of animals, even along the same fiber (from tip to root) [2]. All these factors greatly impose difficulties in accurately identifying and classifying animal fibers.

The key issues in animal fiber identification and classification are feature selection and extraction. Therefore, the methods such as burning test, solubility test, staining test and density test are not adequate for animal fiber identification since they based on the difference on physical and chemical properties or appearance for different kinds of fibers. In the current work, in order to develop an objective, repeatable, reliable, and possibly standard method for identification and classification of animal fibers, two models are developed to extract features and the techniques used to extract the features are model dependent. In the first model, only the pre-designed features, which can be clearly identified, are used. While in the second model, an unsupervised artificial neural network is used to extract the most representative and holistic (global) features from the input images of animal fibers.

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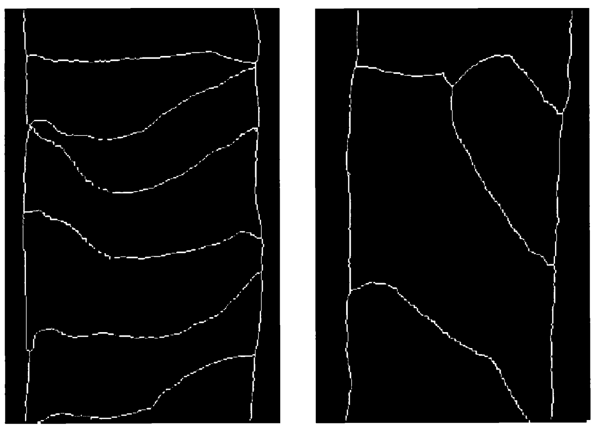
2. MATERIALS AND MODEL DEVELOPMENT

2.1 Materials

The materials used in this work are Merino and Mohair fibers. As shown in Figure 1, the patterns of a Merino fiber are visually different from those of a Mohair fiber. Scales of the Mohair fiber have distant margins, a regular diameter and irregular mosaics while scale edges of the Merino fiber are more likely to be parallel to each other [3].



(a) Merino fiber (b) Mohair fiber

Figure 1. Scales of different fibers

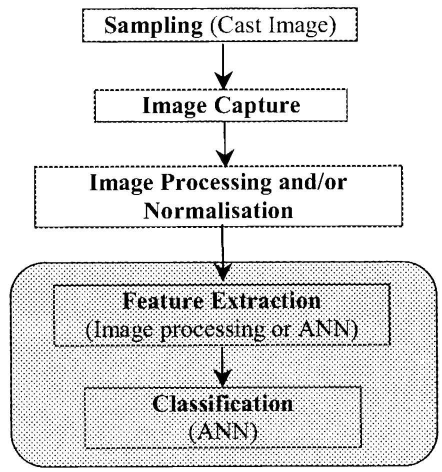


Figure 2. Animal fiber identification system

2.2 Model development

An intelligent fiber identification and classification system [4] is developed in this work whose structure is shown in Figure 2 by integrating image processing and artificial neural networks. There are two different models in the system where both models have an ANN classifier. The difference between these two models is how the scale features of the animal fibers are extracted. There are five steps in the classification system.

- *Sampling*: To prevent superficial scale patterns of animal fibers from being blurred by transverse markings raised from scale edges on the under surface, cast images of fibers were captured by using optical microscopy. To make casts, fiber specimens were mounted on microscope slides in various media. Provided that the laboratory manipulation is skilful, the surface-scale patterns of the fibers can be faithfully reproduced [5]. The best mounting agent for general work is medical-grade, white mineral oil or colorless nail polish of good quality. No swelling occurs during mounting process and any mount so made can be used for identification purposes. *ORLY®*, a high quality nail varnish as the mounting medium, was used in this work and static cast images of these fibers were obtained.

- *Image capture*: Cast images of prepared samples were captured with a Sony CCD camera mounted on an Olympus optical microscope with a magnification of 400. Digitisation was done with a video capture card. Image resolution is 800 by 600 pixels with a depth of 8 bits (256 grey levels). Images of scale patterns were randomly taken from an arbitrary location of fibers along the fiber length and in an arbitrary direction. No visual reference to the fibers influenced the order of images in the database.

- *Image processing and/or normalization*: Image processing is used for feature extraction in the first model while the images are normalised in the second model before they are trained or tested with the artificial neural networks for feature extraction and classification.

- *Feature extraction*: By using image-processing technology, feature vectors with nine independent meaningful attributes are extracted in the first model for each scale of the fiber population from imaging processing and composed of a feature vector instance. In the second model, neural networks are used to extract the intrinsic information before presenting them into the classifier network. The goal is to transfer input data into as few bits as possible while

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maximally preserving the source information in the input data. Thus data compression can be modelled as a projection operation or feature extraction where the goal is to find a set of bases that produce a large concentration of signal power in only a few components.

- *Fiber classification*: A Multilayer Percepton (MLP) is used for fiber classification. It has one hidden layer and a tanh (hyperbolic tangent) activation function is used in the processing elements of the hidden layer and output layer. A bias activation function is also applied to the processing elements in the output layer.

3. FEATURE EXTRACTION

3.1 Model I: Feature extraction with image processing

Before scale features of animal fibers can be extracted, fiber images need to be processed. The digital color images of animal fibers are taken using the equipment and techniques discussed above. The RGB components of these images are converted to a HSV color representation, which is a form more appropriate for image processing. As an example, the transformation of an original color image of an animal fiber (Figure 3a) results in a corresponding HSV representation (Fig. 3b).

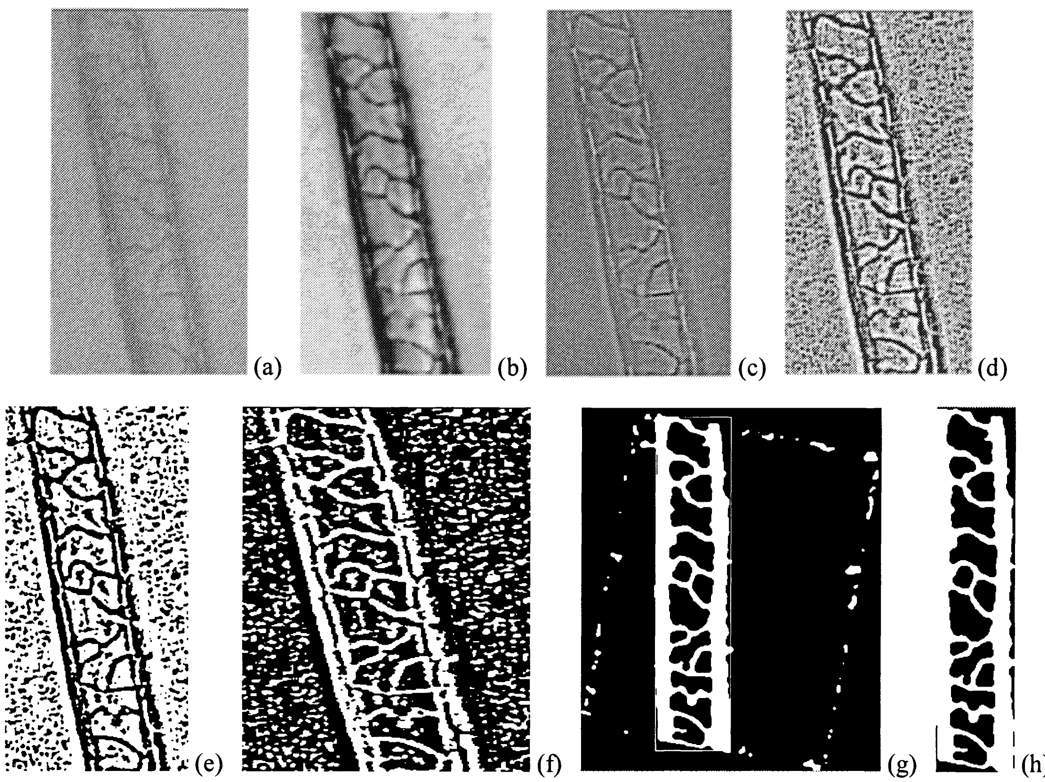

Figure 3. (a) Original RGB image (b) V image (c) image after high pass filtering (d) image after histogram equalization (e) Image after thresholding operation (f) image after inverting (g) image after rotation with overlaying the bounding box on image (h) extracted section (object) from (g)

A high-pass filtering is applied to the input images as the first step to enhance scale edges and eliminate gradually changing global effects such as light variations from raw optical images. Obviously, some shadows (with slow changing values) can be observed which make the edges between fiber and background blurred. These shadows are largely due to imperfect illuminations and poor sampling. The outlines of the fiber body and scale margins need to be enhanced and those gradually changing global effects such as lighting variations need to be eliminated. A two-dimensional high pass (or sharpening) filter is applied to enhance local contrast and suppress slow changing values. This moving mask is overlaid over the input image. The average gray value of the pixel is computed under the mask and the average value is subtracted from the value of the

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central pixel [6]. The moving average kernel of a size in pixels is specified as 7 by 7 in width and height. The effect of applying high pass filter on the V image (Fig. 3b) split from HSV image is shown in Fig. 3c.

After filtering, images had a very low contrast and the bands occupied in their histograms were very narrow. A histogram equalization technique is used to stretch the images' pixel values to a wider range and make scale edges more visible to allocate more gray levels where there are more pixels and to allocate fewer levels where there are few pixels. An example of histogram equalization is image gray level scaling: the pixels in the range [a, b] are expanded to fill in the range [z_1, z_k]. The image after histogram equalization (Fig. 3d) has a histogram with a significant spread, indicating a higher contrast.

A single-level thresholding operation is employed to produce a binary image based on an adaptive thresholding value and the values of image pixels and to segment input -scale images into background, edges of scales, and fiber bodies. Thresholding the picture is the most common way to extract objects from a picture. The thresholding operation can produce binary images based on the specified threshold levels and the labels of image pixels since the background has different label from fiber outline and scale edges after previous processes are performed. The thresholded image is shown in Fig. 3e. The thresholding level is varied to suit variation in local or neighbourhood input image level. This image is a binary image with two levels of value, 1 showing white background and 0 showing black fiber outlines and scale edges although there are lots of noises on them. For further processing, this image is inverted: black background and white fiber outlines and scale edges (Fig. 3f) which will be used to extract fiber region and to align the main axes of all fibers with the vertical line by rotating their major axes to vertical line (with either tip up or root up).

Each fiber portion located was automatically rotated to a certain direction, eg., fiber vertical direction. In this operation, an output image at least large enough to accommodate the entire rotated image is produced, with the central pixel of the rotated image corresponding to the central point of the input image. The background area extends farther than necessary to contain the original rotated image when the input image is not square. The center of the rotation is the centriod of the images. The binary image (Fig. 3f) is rotated at an angle calculated and aligned with the y-axis as shown in Fig. 3g.

Some interactive operations, such as choosing interest region and assignment of some constants, are also used. To extract the fiber images (gray-level or binary) from the background, the bounding box of the fiber region is calculated (Fig. 3g). A rectangular subimage bounded by the bounding box from its input image (top input) is extracted by an extract operator. The subimage is specified by the object received from the bottom input of the extract operator. The corresponding segmented image is shown in Fig. 3h.

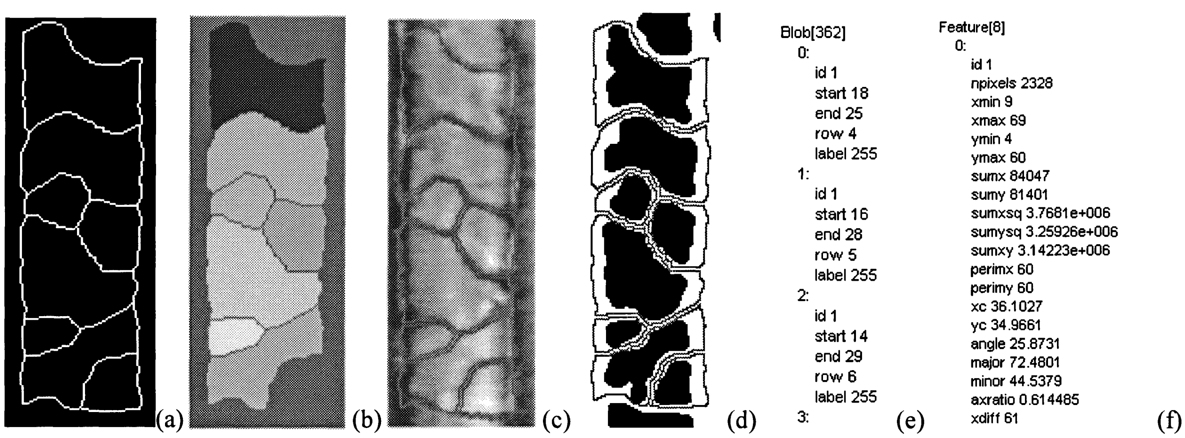

Figure 4. (a) Scale margins, (b) plot scale blobs with color code, (c) and (d) overlaying the perimeters of scale blobs on the image in the gray level image (81×216 pixels) and Fig. 4.18 (a) respectively, (e) blob vectors, and (f) feature vectors for all blobs found

However, to prepare the input database for the first classification system, the feature vectors of the scales in the binary images need to be extracted. To do so, the binary images like the one in Fig. 3h need further processing with some morphological operations. Since the shapes of animal fiber scales are the major concerns in this work, the image in Fig. 3h is thinned to its skeleton (Fig. 4(a)). Thinning is an image processing operation in which binary image regions are reduced to lines that approximate their centerlines, i.e skeletons. The purpose of thinning is to reduce the image components to their essential information so that further analysis and recognition are facilitated. Thinning is commonly used in the preprocessing stage of shape analysis applications.

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The skeleton operator is used to remove pixels from scale objects in the binary input image until a single pixel wide skeleton is reached. On each pass the objects in the image are eroded by a one pixel wide boundary, provided the pixels are not part of a single pixel wide skeleton. After each execution of this operator, an output image is generated at the top output port along with a value at the bottom output port. This value represents the number of pixels removed from the image and is an integer object. When the value reaches zero the objects have reduced to a single pixel wide skeleton. The image will be eroded until no more pixels are to be removed. Then the skeleton image is pruned so that extraneous short branches are deleted. The skeletonized fiber image is shown in Fig. 4a. Fig. 4b shows the scale blobs in different colors. In Figs. 4c and 4d, the skeletons are overlaid on the gray level image and binary image, respectively.

Since the scale blobs touching the image border are cut off by the image frame, they are deselected (Fig. 4). The blob vectors obtained are shown in Fig. 4e. In this way, the other scale blobs are selected and their features are extracted. The sample feature vector for a scale blob is shown in Fig. 4 f. These fields can be obtained for all blobs selected.

However, only the most representative features or fields will be used in this work for animal fiber classification as introduction of too many features in the classifier will significantly increase the computing effort to achieve a reasonable accuracy of classification. Introduction of more features into a classifier may not improve the accuracy of the prediction and sometimes deteriorate the classification. Nine features are used in Model I for animal fiber classification. They are angle between major axis of the best fitted ellipse and fiber major axis (F1), lengths of major and minor axes of the best fitted ellipse (F2 and F3), maximum and minimum radial distances squared from the gravity center in each scale cell (F4 and F5), area of a scale cell (F6), total length of perimeter around a scale edge (F7), differences along major axis of the fiber and in its perpendicular direction in each scale (F8 and F9) [7].

3.2 Model II: Feature extraction with an unsupervised artificial neural network

Neural network classifiers generalize better when they have a small number of independent inputs [8]. It is desirable to reduce the dimensionality d of high dimensional input pattern to a lower dimensional sub-space M ($M<d$) to extract the intrinsic information before presenting them into the classifier network. The goal of this procedure is to transfer input data into as few bits as possible while maximally preserving the source information in the input data. This means that as much information as possible from the source must be squeezed into each bit. Thus data compression can be modelled as a projection operation or feature extraction where the goal is to find a set of bases that produce a large concentration of signal power in only a few components. Principal component analysis (PCA), which is an optimal linear feature extractor, is such a technique [8]. From the input space, PCA finds an orthogonal set of M directions where the input data has the largest energy and extracts M projections from these directions in an ordered fashion. The orthogonal directions are called as the eigenvectors of the correlation matrix of the input vector, and the projections as the corresponding eigenvalues.

PCA can be easily implemented using unsupervised neural networks through Hebbian learning [9]. Unsupervised neural network is particularly well suited to perform feature extraction because what the most important features of a given pattern are is normally unknown in compression problems. Unsupervised learning networks utilize the idea of correlation between projected data (to a subspace M) and original input data to process signals. In terms of network construction, this sort of networks normally consists of a single hidden layer of neurons or Processing Elements (PEs).

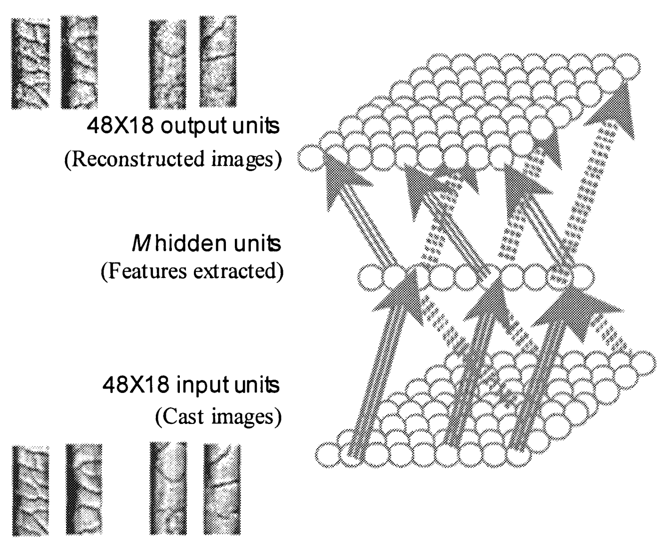

Figure 5. Feature extraction with neural networks

The number M of the hidden units in the network determines the size of subspace, that is, the number of principal components or features used to represent the input images and train classifier neural network. The outputs of the hidden layer

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are the features obtained by projecting the input images onto the subspace of M dimension which is 80, 50 and 20, respectively, used in this work (Fig. 5). These features will be used as inputs in the supervised network for classification.

4. FIBER CLASSIFICATION

A Multilayer Percepton (MLP) was used for fiber classification. It has one hidden layer and a tanh (hyperbolic tangent) activation function is used in the processing elements of the hidden layer and output layer. A bias activation function is also applied to the processing elements in the output layer. The features extracted with image processing and unsupervised artificial neural networks are used, as the inputs in input layer while the fiber classes are the outputs in output layer.

In model one, an input file composed of nine scale feature vectors extracted by image processing and its corresponding desired output file are assigned. By setting 0.5 as the decision boundary, a very small percentage of the merino and mohair fibers are wrongly classified during training and testing. There is a spike close to one or zero on the decision distribution curves for both merino or mohair scales, indicating that the decisions made are quite distinct and very accurate. Very small number of mohair scales are classified as merino scales in the training and testing. Therefore these mohair scales are considered by the ANN classifier to possess the characteristics of a typical merino scale. As the classification process of animal fibers is not from individual scales but an assembly of scales in fiber sections, the performance of the ANN is significantly improved by considering the assembled information of all scales in a fiber section. If the assembled information of all scales from a fiber section is considered and then used for training or testing the ANN, the fiber can be very easily identified as either a merino or a mohair fiber [3].

In model II, if more features are extracted from the original images, a smaller amount of epochs is required to achieve the same accuracy while further computation contributes little to improve accuracy. However, if the number of the features exceeds a certain level, the improvement in the prediction accuracy is very limited. Although the accuracy of the classification with more features is higher during training, it cannot guarantee the achievement of a generalised model. Although using more features improves the accuracy in classifying fiber during training, it reduces the generalization abilities of the classifier during test. It is also observed that the classification accuracy is higher for mohair fibers in both training and test, which means that mohair fibers have more common characteristics perceived by the ANN classifier. This coincides with the prediction in model I.

5. CONCLUSIONS

Two different models were developed in this work to extract features from images of two representative animal fibers, ie merino and mohair. In the first model, the explicit features were extracted using image processing while the implicit features were obtained by an unsupervised artificial neural network in the second model. A supervised ANN was then used to identify and classify these two types of fiber. It is found that the classification accuracy is higher for mohair fibers during both training and test, which means that mohair fibers have more common characteristics perceived by an ANN classifier.

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