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Introduction

In 1998, the first SPIE International Symposium on Multispectral Image Processing and Pattern Recognition was held at the Huazhong University of Science and Technology, Wuhan, China. That symposium was a great success, at which scientists, engineers, and graduate students from more than 20 countries and regions made about 130 presentations of their new research results concerning image processing and pattern recognition. Of the more than 300 papers presented, nine were selected to be published in a special issue on image processing and pattern recognition of the *International Journal of Pattern Recognition and Artificial Intelligence*.

Today, the second SPIE International Symposium on Multispectral Image Processing and Pattern Recognition has attracted 500-odd high-level papers from 24 countries and regions in the world. The scale is larger than before and more departments are represented. It is our belief that this symposium is bound to score even greater successes. As one of the SPIE series of academic symposia, it will be held once every other year.

Image processing, filtering, and analysis are the foundations for computer vision and analysis, and image matching is a very important application. These topics have long since aroused extremely great interest of numerous researchers; more than 50 papers are included in this volume. These proceedings of the conference on Image Matching and Analysis will promote the academic exchange among researchers of different countries and regions, and the deepening of the relevant investigations and applications.

We extend our thanks to all the authors and committe members present for their contributions to the success of the said symposium!

Bir Bhanu
Jun Shen
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Contents

Image Processing and Pattern Recognition in Textiles

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ABSTRACT

Image processing and pattern recognition have been successfully applied in many textile related areas. For example, they have been used in defect detection of cotton fibers and various fabrics. In this work, the application of image processing into animal fiber classification is discussed. Integrated into/with artificial neural networks, the image processing technique has provided a useful tool to solve complex problems in textile technology. Three different approaches are used in this work for fiber classification and pattern recognition: feature extraction with image process, pattern recognition and classification with artificial neural networks, and feature recognition and classification with artificial neural network. All of them yields satisfactory results by giving a high level of accuracy in classification.

Keywords: Pattern recognition, Classification, Hybrid artificial neural networks, Animal fibers

1. INTRODUCTION

Computer vision system and image process techniques have used in many textile applications. They have been used in the evaluation of raw materials properties such as fiber cross section [1] and gravimetric black contents in cotton fibers [2], and in the evaluation of fabric quality ie recognition of fabric weave patterns [3] and detecting defects in fabric [4].

Animal fibers such merino, mohair and cashmere fibers have very similar scale patterns which are hard for an inexperienced personnel to distinguish between them. Animal hair fibers of the same type are not unique in terms of structure and properties because of their growing nature. Furthermore, labelling textiles to indicate their composition requires analytical means for control, not only for the final product but also for the raw materials and during all stages of processing [5]. Therefore, establishing a reliable and objective test method to differentiate them is a fundamental problem urgently requiring a solution.

Since its publication in 1954, The Microscopy of Animal Textile Fibers [6] has provided an evidence of identification for a range of fibers and is still the major reference for fiber identification by using microscope and by comparing fiber pictures with pictures published. This sort of fiber examination can provide positive identification of the principal natural fiber types. Although it is a fast and convenient method, the judgement is basically subjective. Consequently, the accuracy of this kind examination still greatly depends on knowledge, experience and memory of the microscopist.

In addition, natural fibers show a fairly wide variation in appearance. No specific specimen will look exactly like the pictures published. So a sufficient number of fibers should be examined to cover the range of appearance in any specimen. This increases the testing cost and time. Recently, Robson [7, 8] reported an approach in fiber identification by using image processing. In the current work, Artificial Neural Network will be implemented into an image processing system for fiber identification and classification after the extraction of fibers' scale information with image processing method and artificial neural networks.

2. MATERIALS AND FEATURE EXTRACTION

The materials used in this work are merino and mohair fibers. The patterns of a merino fiber are visually different from those of a mohair fiber (Figs. 1a and 1b). 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.

Two types of common animal fibers, merino and mohair, were used as the samples for this project. The fibers were randomly collected from those being used in a factory. After scouring the fibers, their cast images were made on microscope slides using the method devised by Wildman and Manby [6]. 22 merino and 38 mohair samples were prepared.

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Images of prepared samples were captured by means of a Sony CCD camera mounted on an Olympus microscope with a magnification of 400. Digitisation was done on a video capture card in a Pentium 133 PC. Image's resolution is 640×480 pixels with a depth of 8 bits (256 grey scales).

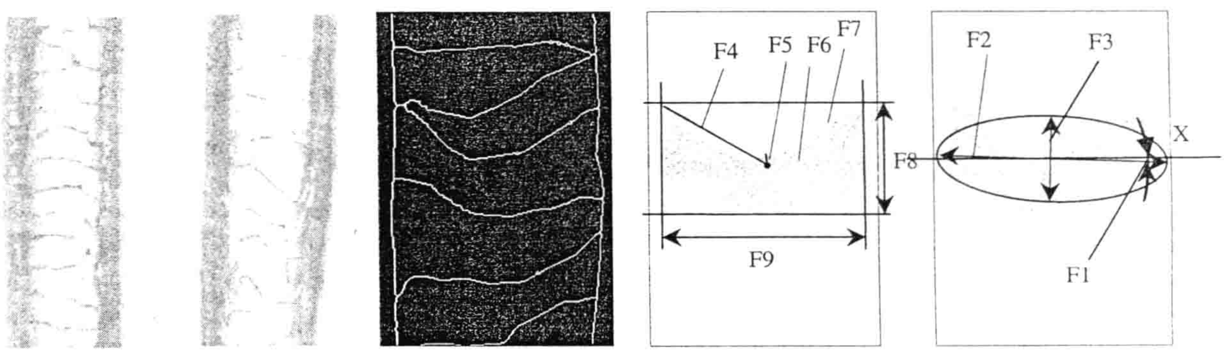
To characterise scale patterns, imaging software WiT5.2, which is a powerful visual programming package for designing computer algorithms with executive block diagrams, was used to convert visual characteristics into measurable features. Several techniques [6] of image processing were employed and explained as follows:

- *Filtering:* A high-pass filtering with a kernel of 9×9 pixels was applied to the input images to enhance scale edges and eliminate gradually changing global effects such as light variations from camera images.
- *Contrast Stretching:* This operation is to allocate more grey levels where there are most pixels and to allocate fewer levels where there are few pixels. Thus this operation has the effect of improving image contrast.
- *Thresholding*: Thresholding is an operation in which the value of each pixel in the result depends on the value of the corresponding input pixel relative to one or more values known as thresholds.
- *Interactive Operations:* Some interactive operations were also involved, such as choosing interest region, i.e. choosing fiber portions and assignment of some constants.
- *Rotating*: Each fiber portion located would be automatically rotated to a certain direction, eg., the vertical line.
- *Morphological Operations*: Before performing feature extraction of scale patterns, the images need cleaning up after previous processing and only showing scale edges. This is done by using a combination of basic morphological operations, such as erosion and dilation operations to eliminate unwanted noise pixels and fill small holes in the scale edges' outlines. A skeletonization operation is iteratively applied to thin the image to a single pixel thick skeleton.

After these operations, fiber edges and the scale edges are clearly presented (Fig. 1(c)). In scale pattern analysis, each scale pattern of a fiber is described by nine geometric features extracted from image processing to convert its visual characteristics. These features are, angle of major axis of the best fit ellipse (F1), lengths of major and minor axes of the best fit ellipse (F2 and F3 respectively), maximum and minimum radial distances squared from the gravity center in each scale cell (F4 and F5 respectively), area of a scale cell (F6), total length of perimeter around a scale edge (F7), and differences in x- and y-coordinates in each scale (F8 and F9 respectively). The nine features are explained in Figs. 2d and 2e.

3. IDENTIFICATION AND CLASSIFICATION FROM FIBER FEATURES

After the nine features were extracted with image processing technique using the procedures discussed above, an artificial neural network (ANN) can be trained to identify and classify scales as either merino's or mohair's from their feature vectors given as inputs in the input layer of the ANN. Training algorithm, stopping criteria and representative training set are the most important and practical aspects related to training an ANN model. The total training iteration number and the cross-validation set were specified. The training stopped once either the iteration number or the mean square error (MSE) of the cross-validation set reached their prescribed values. The mean square error of the training set was then analyzed to evaluate the performance of the training.



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

Figure 1. (a): Cast image of merino (b) cast image of mohair (c) processed image of a merino fiber; (d) and (e): Definition of F1 to F9

There are nine nodes, which were the nine feature vectors extracted from each of merino and mohair fibers, in the input layer while two nodes are served as desired outputs and labeled as "Merino" and "Mohair" respectively in accordance with the fiber type. For the desired output, all merino fibers are specified as one while all mohair fibers specified as zero. For the desired output two, mohair fibers are specified as one and all merino fibers as zero. Thus the desired output vector for merino is encoded as $[1,0]^T$ and the desired output vector for mohair as $[0,1]^T$. If the values produced in the output one in the output layer of ANN are greater than 0.5, the input scales are judged as merino's while those values are less than 0.5, the input scales are judged as mohair's. The closer to 1 the values are, the more confidently the network identifies scales as merino's; the closer to 0 the values are, the more confidently the network identifies scales as mohair's. Of the samples measured 61 scales from two merino fibers and four mohair fibers are used as the test set. The rest of the experimental data is randomized and employed as the training data set in which one-tenth is selected and used as the data for cross validation to stop the training as discussed above.

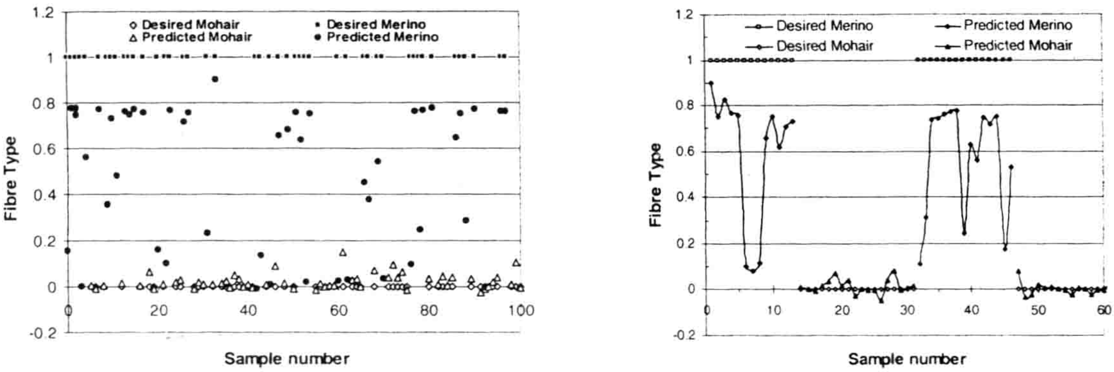
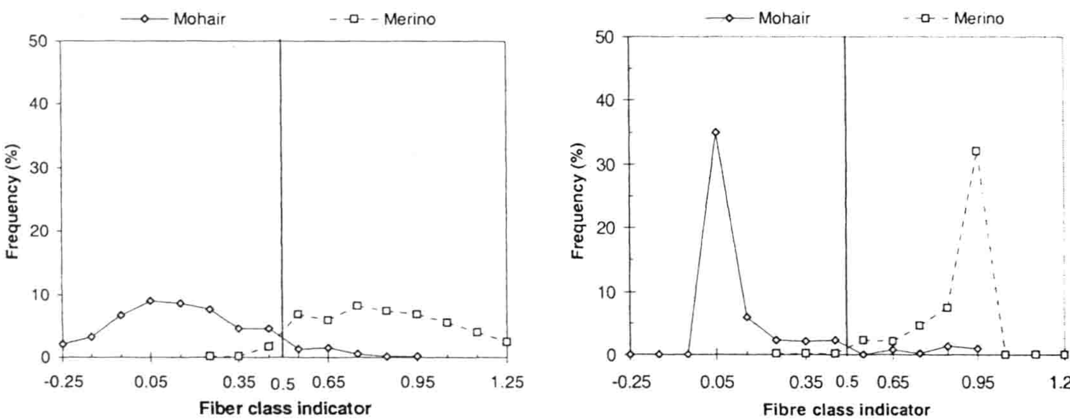


Figure 2. Comparison of desired and predicted fiber types (1 - merino, 0 - mohair): (a) training data (randomized) (b) test data

After training multiple times, the optimal number of nodes in hidden layer, 19, i.e., a 9-19-2 network, is obtained. The training and test results from output one are shown in Figure 2. As shown in Fig 2(a), where the training results from 100 specimens randomly selected from training data set are illustrated, all scales of mohair fibers are correctly identified with very high confidence by the network while the features for some scale patterns of merino fibers seem to be those of mohair fibers as the predicted scale types tend to approach 0 (for output one where mohair fibers are specified as zero). From the testing results shown in Fig. 4(b), the network shows very similar performance of identification on testing data set to that on the training data set. The network identifies 100% (33 out of 33) mohair's scale patterns with a high confidence, i.e., their predicted values in output one produced by the network are less than 0.5 and very close to 0 which represents the class of mohair fibers. Comparatively, 75% (21 out of 28) merino's scale patterns are correctly identified by the network with less confidence. Thus the network yields an 88% overall identification rate for testing data set.



(a) Linear ANN (b) Nonlinear ANN

Figure 3. Predication of linear and nonlinear artificial neural network classifiers: Fiber indicator 0 – mohair, fiber indicator 1 - merino

However, if the assembled information of all scales from a fiber section is considered and then used for testing the ANN, the fiber can be very easily identified as either merino or mohair. In Fig. 2(b), the features between points 0-15 and 31-45 represent two different merino fiber sections while the other two groups of points represent four mohair fiber sections. Thee mohair fibers are easily classified not only from the information of their individual scales but also from the assembled information of fiber sections as all the values produced are close to "0" and have very small variations. For a section of merino fiber, its scales show a bigger variation in characteristics, i.e., majorities of scales show the characteristics of a typical merino fiber while some other scales seem to have the characteristics presented by a typical mohair fiber. From this point of view, merino fibers can be identified by the ANN with higher identification rate based on the assembled information of fiber sections. Obviously, the features which represent two sections of merino fibers are totally different from those of four mohair fiber sections in Fig. 2(b).

A MLP with one or more than one hidden layer of nonlinear PEs can conduct a nonlinear discriminant function while an ANN without any hidden layer can perform a linear discriminant function. The former is called nonlinear ANN while the latter is called linear ANN. In this work, the comparison study of these two classifiers on animal fibers - merino and mohair –was also conducted to show the complexity of the features.

The difference of classification performance between nonlinear ANN and linear ANN can been clearly identified by analyzing the distribution curves of the output unit one over a fiber class indicator range of (–0.25, 1.25) by both ANNs on training data set (Figures 3). It is found that there is a very similar trend in classification for both training and testing.

If 0.5 is set as the decision boundary or the intercept point, a very small percentage of the merino and mohair fibers is wrongly classified by both linear ANN and nonlinear ANN during training and testing since the tails of distribution curves slightly exceed the boundary. As the tails in Figure 3a are extended flatly and widely, the linear ANN classifies the two clusters of scale patterns with less confidence. In Figure 3b, a spike close to one or zero can be seen on the decision distribution curves of nonlinear ANN for merino or mohair scales, indicating the decisions made by nonlinear ANN are quite distinct. It is also found that the fiber class indicator for a very small number of mohair scales is predicted up to more than 0.9 in the training and these scales are classified as merino scales. This indicates that these mohair scales possess the characteristics of a typical merino scale.

When a stricter decision rule for fiber classification is set, the nonlinear ANN presents a much more accurate classification of merino and mohair scales. For example, if only fiber class indicator between 0 ± 0.1 or 1 ± 0.1 is accepted as either mohair or merino scales respectively, more than 70% of the scales can be accurately identified either as mohair or merino scales using nonlinear ANN (Fig 3b). However, only about 28% of the scales are accurately classified with linear ANN when the same decision rule is used (Fig 3a). However, as the classification process of animal fibers is not from individual scales but fibers, the performance of nonlinear ANN as a fiber classifier can be significantly improved by considering the assembled information of all scales in a fiber section (Figure 2).

4. PATTERN RECOGNITION AND CLASSIFICATION FROM SCALE IMAGES (WoolNET)

Generally, a pattern recognition and classification system is an operational system that minimally contains [9]:

- An input subsystem that accepts sample pattern vectors and
- A decision-making subsystem that decides the class to which an input pattern vector belongs.

4.1. Model development

WoolNet is composed of two segments, i.e. an unsupervised neural network and a supervised neural network (Figure 4). These networks perform different tasks but co-operate with each other. The information of the hidden units in the unsupervised neural network is serviced as inputs to the supervised neural network. The input units of the supervised neural network receive the feature vectors extracted from the unsupervised neural network while its output units yield fiber classes.

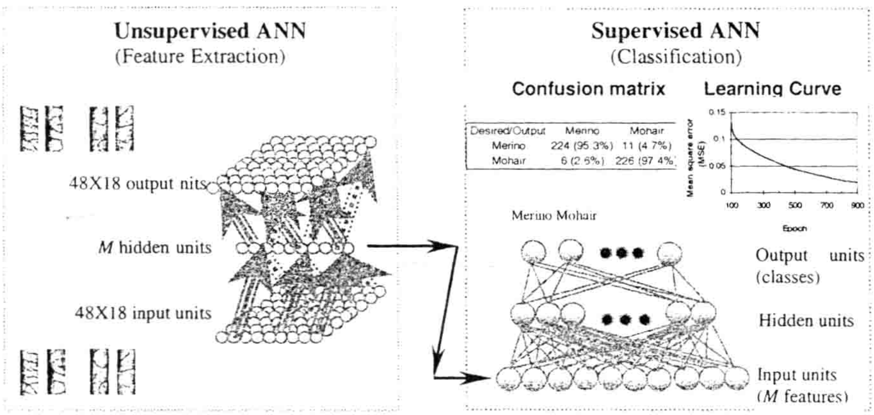
The same materials and image capturing techniques as these described above in section 2 are used. After that, the images were normalized. The successful implementation of neural networks depends on several techniques including input data normalization (or pre-processing), feature extraction, and training. After capturing the gray-scale images, the images need to be normalized or pre-processed in order for the feature extraction to be effective. The normalization process includes: Slant normalization, Size normalization, and Brightness normalization.

4.2. Unsupervised Compression Network and Supervised ANN Classifier

Reducing dimensionality of images provides a more tractable input to the classifier network. Other than that, neural network classifiers generalise better when they have a small number of independent inputs. It is desirable to reduce the dimensionality d of high dimensional input pattern to a low dimensional sub-space M ($M<d$) by extracting the intrinsic information before presenting them into the classifier network.

To solve pattern identification and classification problems, HANN first undergoes a training session. A set of new scale patterns, which have not been seen before but belong to the same population of the patterns used to train the network, is presented to the network. The final task for the network is to calculate their feature vectors by projecting these new patterns to the reduced subspace and correctly classify them.

A supervised neural network learns from the input and the error (i.e. the difference between the output of the network and the desired response). There are two phases in training this supervised segment of HANN with back-propagation algorithm. The first phase is referred to as forward phase and the second as the backward phase.



(a) Unsupervised neural networks (b) Supervised network

Figure 4. Structure of the WoolNet.

4.3. Results and discussion

Figure 5 compares the reconstructed images with their corresponding input images in the training data set and testing data set. The first row shows some exemplars of input images from both merino (left) and mohair fibers (right) used in the training and test data sets; the second, the third and the fourth rows show corresponding reconstructed images from 80, 50, and 20 features, respectively. It indicates that the quality of reconstructed images improves with the quality of input images in the input layer.

The performance of the supervised ANN for classification can be observed in Figure 6. If fewer features are used to extract information from the original images, a smaller amount of epochs is required to achieve a quite high accuracy (f=20) while further computation contributes little to improve accuracy. However, if the features exceed a certain level, the improvement in the prediction accuracy is very limited as the average cost for features of 50 and 80 remains at a very similar level. Although the accuracy of the classification with more features is higher during training, it cannot guarantee the achievement of a generalized model (Figure 6). When the classification rate for the features of 50 and 80 in the training is higher than that of 20, it is generally lower with the test data set. This means that with 20 features, the major characteristics of both the merino and mohair fibers have been extracted and used for classification. Although using more features improves the accuracy in classifying fiber during training, it needs to meet more strict criteria to accurately classify a fiber during test. This leads to the deterioration in the classification rate during test with more features.

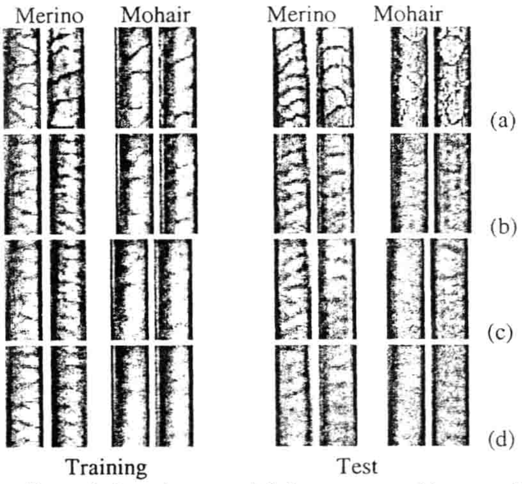


Figure 5. Input images and their reconstructed images with different number of features (M): (a) Input image, (b) M=80, (c) M=50, (d) M=20

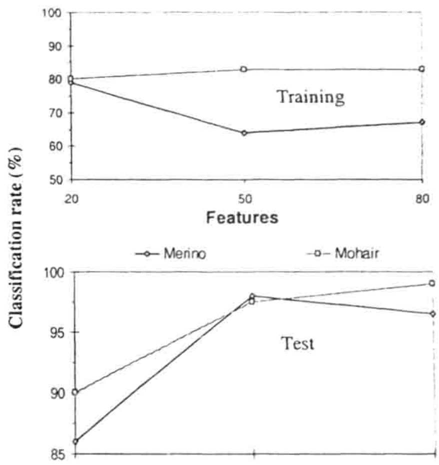


Figure 6.Training and test using different features

5. CONCLUSIONS

Application of image processing and pattern recognition in textile technology in textile technology is discussed. Specifically two popular animal fibers, merino and mohair, is classified using different strategies. One is to classify the fibers with their features extracted using image processing while in another model, a hybrid artificial neural network, WoolNet, was developed. The WoolNet consists of two segments, an unsupervised feature extraction network followed by a supervised classifier network. The number of features or principal components can be optimised by considering both the reproductions of input images and classification accuracy.

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