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Fuzzy Pattern Recognition and Classification of Animal Fibers

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Abstract

Several techniques, including chemical and physical approaches, have been previously developed to differentiate between animal fibers. Since all animal fibers are comprised of essentially the same keratin, they cannot be effectively distinguished by existing physical or chemical technique. In this paper, a fuzzy neural pattern recognition system is developed to classify two typical animal fibers - mohair and merino. Two multilayer networks are used with the unsupervised network being used for automatic feature extraction while the supervised network serving as the classifier based on the information extracted from unsupervised network. It is found that this hybrid network can accurately classify the two fibers and the accuracy improves with the increase in the features being extracted from the unsupervised network.

1. Introduction

Characteristics of animal fiber scale patterns are still served as major evidence in identification and subsequent classification of animal fibers [10]. Whenever blending of wool and specialty animal fibers is involved, or when any of these fibers is to be identified, resort must be made to microscopic analysis. Therefore, identification and classification of animal fibers are actually a task of scale pattern recognition and classification.

Recently, Robson [5] used an objective and repeatable approach to extract scale pattern features of merino and cashmere, and to perform discrimination between these fibers. However, this method is based on some prior subjectively selected features of scales, such as scale length, scale area, etc., and a linear discrimination function. The method also needs sophisticated image processing techniques to extract these features. Rather than a linear discrimination function, a nonlinear discrimination function is applied to classify merino and mohair fibers by using a nonlinear artificial neural network (NANN) [8]. The nonlinear discrimination function is superior in the classification of merino and mohair scales [8]. However, the classification process of animal fibers is actually not from individual scale patterns but images of fiber sections. The assembled information of all scales in a fiber section should be considered for identification and classification purpose [7].

In pattern recognition and classification applications, feature extraction and discrimination function are the most important aspects. To automatically perform these different tasks, a kind of hybrid system is needed. The current paper develops such a system to automatically perform classification of animal fibers. The system, WoolNet, is a hybrid artificial neural network (HANN) model and consists of an unsupervised network and a supervised network.

2. Materials

Two kinds of animal fibers, merino and mohair, Were used and were collected from a wide range of sources. While mohair fibers are grown by Angora goat, merino (wool) fibers are grown by sheep. Like other animal fibers, the cortex of either merino or mohair fiber is protected by a cuticle of flatted cells known as scales. The scales overlap one another. The shape and arrangement of the cuticle scales form characteristic patterns of animal fibers, which are useful in their identification and classification. There are many terms used to describe these scale patterns. As described by Wildman [10], most merino fibers have scale patterns with prominent and near margins while mohair's scales are only faintly visible and hardly overlap; the number of scales per 100 microns in mohair fibers is lower than that of fine merino fibers, etc.

3. Methodology

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.



Figure 1. Schematic of WoolNet

3.1 WoolNet

While the sampling, image capture and image preprocessing form an input subsystem, a HANN -WoolNet to classify merino and mohair fibers is developed by integrating a data compression network into a decision-making network (Figure 1). The compression network works in an unsupervised fashion but the decision-making network works in a supervised manner. Thus WoolNet is composed of two segments, i.e. an unsupervised neural network and a supervised neural network (Figure 2). These networks perform different tasks and co-operate with each other. The unsupervised neural network trained with Sanger's rule [6] performs principal component analysis (PCA) to automatically extract features from 48X18 pixels cast images of fiber sections and compress them to M units in the hidden layer, respectively. The activities of the hidden units in the unsupervised neural network is serviced as inputs to the supervised neural network. They are also transferred to the output units of the unsupervised neural network to reconstruct input images. 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.

To solve pattern identification and classification problems, WoolNet first undergoes a training session. During this session, input patterns in a training data set are repeatedly presented into the unsupervised segment of WoolNet until the features are stable; the feature vectors are presented into the supervised segment along with the category to which each particular pattern belongs. 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 then presented to the network. The final task for the network is to calculate their feature vectors by



Figure 2. Structure of the WoolNet

projecting these new patterns to the reduced subspace and correctly classify them.

3.2 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. The best mounting agent for general work is medical-grade, white mineral oil or colorless nail polish with good quality. A high quality nail varnish, ORLY[®], was used as the mounting medium. 537 fiber samples, 269 merino and 268 mohair fibers, which were randomly taken from different ranges of sources, were prepared into slides..

3.3 Image capture

Cast images of prepared samples were captured by means of a Sony CCD camera mounted on an Olympus optical microscope with a magnification of 400. Digitization was done on a video capture card in a Pentium 133 PC. Image resolution is 800 by 600 pixels with a depth of 8 bits (256 gray levels).

3.4 Image Normalization

To a large extent, the successful implementation of neural networks depends on several techniques including input data normalization (or pre-processing), feature extraction, and training. To obtain normalized images with the size of 48 by 18 pixels, the following steps were used:

Slant normalization: Three major steps in the automated alignment process to align fiber image were used by rotating its major axis to vertical line (with either tip up or root up): filter/binarize image, detect portion of fiber body, and determine alignment, i.e. decide the angle of rotation by using Hough transform [3].

Size normalization: Fiber image was scaled to 18 pixels in diameter with locked aspect ratio in the directions of diameter and length. The resulting image was cropped or clipped at 48×18 pixels. Such windows were presented as 864 dimensional vectors of 256 gray-level values.

Brightness normalization: To prevent the use of first order statistics for discrimination, the images were adjusted to the same mean brightness and variance by using histogram equalization [4].

3.5 Unsupervised Compression Network

As mentioned above, reducing dimensionality of the images provides a more tractable input to the classifier network. Other than that, neural network classifiers generalize better when they have a small number of independent inputs [1]. It is desirable to reduce the dimensionality d of high dimensional input pattern to a low dimensional sub-space M (M < d) for extracting 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 modeled 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. 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 by unsupervised neural networks through Hebbian learning [2]. 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.

To reconstruct an original image, the outputs of hidden layer nodes are also transferred to the output layer of the unsupervised segment by multiplying them with the transpose of weight matrix between input and hidden layer of the unsupervised network. A 48×18 image is recreated. This image shows how much of the original information in the input has been captured in the *M* features. The closer to the original image the reconstructed image looks, the more information the features have caught.

The learning rate (step size) to 0.005 was set, and linearly decay to 0.0005 within the first 100 epochs. The number of PEs in the input layer was set to 864 to receive the input images, which equals to the number of elements in the input vectors $(48 \times 18 \text{ pixels})$ for each exemplar in the database. The number (*M*) of units in the hidden layer or the number of features extracted by this segment was varied from 80, 50 to 20 for comparison. The number of the PEs in the hidden layer determined the number of input PEs in the input layer of the supervised neural network. The number of PEs in the output layer of the unsupervised neural networks was also set to 864 to reconstruct the images.

3.6 Feature Extraction with Unsupervised Network

Of a data set of 537 864-demensional image vectors, we randomly divide them into a training data set composed of 235 merino and 232 mohair examples or 467 samples in total; and a test data set composed of 34 examples of merino and 36 examples of mohair or 70 patterns in total to verify the network. Each input pattern is normalized to the same range [-1,1] to fit the range of the network.

In order to guarantee efficient learning, the unsupervised neural network is trained independently from the followed supervised neural network. For each number of PEs (80, 50, or 20 respectively) in the hidden layer of the unsupervised network, the WoolNet was trained for 900 epochs. Some input image exemplars of merino and mohair fibers in the training data set and their reconstructed images are plotted in Figure 3.

3.7 Supervised classification networks

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). The ingredients for supervised learning are therefore the input, the desired response, the definition of error and a learning law. Error is typically defined through a cost function while learning law is a systematic way of changing the weights of the network such that the cost is minimized. In supervised learning the most popular learning law is error backpropagation. In many pattern recognition and classification applications, Multilayer perceptrons (MLPs), a kind of feedforward neural networks trained with error backpropagation algorithm, are able to use the information contained in input data and learn how to relate the input data to desired responses in a supervised manner. Theoretically, they can construct nonlinear decision boundaries between the different classes in a semi-parametric fashion and approximate virtually any input-output map. Rather than a standard MLP ANN, a generalized feedforward neural network (GFNN) paradigm with one hidden layer is integrated to the compression network as the network classifier segment of the WoolNet. The generalized MLP solves the problem much more efficiently.

There are two phases in training this supervised segment of WoolNet with the back-propagation algorithm. The first phrase is referred to as forward phrase and the second as the backward phrase.

Forward phrase: In the forward phrase, each PE in the network performs summation operation of its weighted inputs and subsequently applies a non-linear operation through its activation function. When *l*th feature vector corresponding to *l*th input is transferred to the PEs in the input layer of the generalized MLP network. Then its effects propagate forward through the weighted connections in the generalized feedforward neural networks and the layers' responds are computed Mean squared error (MSE) is calculated over all exemplars contained in the training set. This error criterion is used to modify the system in the later phrase so that the minimum error of the performance surface is achieved.

Backward phrase: The backward phrase, on the other hand, starts at the output layer by propagating the error signals toward the input PEs of the generalized feedforward neural networks and recursively computing the error derivative δ (i.e., local gradient) for each PE. The former process is called error backpropagation while the latter is called gradient search. Then the weights are changed to minimize the errors, i.e. the learning process is performed in this phrase.

The error back-propagation algorithm applies a correction to the synaptic weight of the network based on its localized portion of the input signal and its localized portion of error. When this algorithm is used for weight change, the state of the system is doing gradient descent; moving in the direction opposite to the largest local slope on the performance surface. In other words, the weights are being updated in the direction of down.

MSE is one of the most widely used error criteria, which is calculated as the squared Euclidean distance between the network's outputs and the desired responses for each input exemplar. When the mean square error (MSE) is minimized, the power of the error (i.e. the power of the difference between the desired and the actual ANN output) is minimized. The goal of a classifier is to minimize this cost function by changing its weights. In this work, momentum learning is the method used to update weights of the network toward a direction of minimizing the mean squared errors between the desired values and outputs of the PEs in the output layer.

After the first segment of WoolNet was trained, the feature vectors of input images were stable and transferred to the supervised network. For each number of nodes (20, 50, and 80 respectively) in hidden layer of unsupervised network, the training data set was loaded into WoolNet. The second segment of the WoolNet was turned on and trained with error back propagation algorithm and started learning the relationship between the features extracted by the unsupervised network and fiber types.

4. Results and Discussion



Figure 3. Input images and their reconstructed images with different number of features (M): (a) Input image, (b) M=80, (c) M=50, (d) M=20

The compression operation plays a very important role because it will determine the features that the classifier network learns from and finally affects the accuracy of identification and classification in a later phase. Figure 3 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. In the input images shown in the first row, many noises are observed, which may come from lighting source, mounting medium or defective sampling technique. There are fewer noises in the input images of merino fibers and their scale margins are more visible than those of mohair fibers. As shown in the remaining rows, consequently, all reconstructed images of merino fibers are much clearer and closer to the corresponding input images than those of mohair fibers. This indicates that the quality of reconstructed images improves with the quality of input images in the input layer.

When three different values of the number M of features are tried, the unsupervised network learns the important parts of some input patterns even from 20 features especially when the input images have good quality. The qualities of the reconstructed images become better with more features. For example, the images in the second row, which are reconstructed by the unsupervised network from 80 features, are subjectively distinct although they are not identical to the input images. From 50 features the reconstructed images are still close to the input images but not as clear as from 80 features. When the number of features extracted is reduced to 20, the reconstructed images become more significantly blurred comparing to these from 80 or 50 features. However, some of the reconstructed images can still be recognized, such as those of merino fibers. It means that the unsupervised network is able to extract the information contained in the input data to represent them.



Figure 4. ANN convergence

After all, the unsupervised PCA network is able to reduce the dimension of input images to a subspace with a much lower dimension and extract sufficient features to represent not only the input images in the training data set but also the test images not seen by the network before. The higher quality of input images can be achieved by using scanning electronic microscopy (SEM) and appropriate coating techniques. This will further improve the accuracy of representation produced by the unsupervised network.

The performance of the supervised ANN for classification can be observed in Figures 4 and 5. 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 (Figure 4). 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.



Figure5. Training and test using different features

Although the accuracy of the classification with more features is higher during training, it cannot guarantee the achievement of a generalized model (Figure 5). 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 criteria to accurately classify a fiber during test. This leads to the deterioration in the classification rate during test with more features.

It is also observed that the classifying accuracy is higher for mohair fibers in both training and test which means that mohair fibers have more common characteristics (Figure 5). This coincides with the observation by using integrated optical, image processing, and artificial neural network model [8].

5. Conclusions

Classification of two popular animal fibers, merino and mohair, is a typical task of pattern recognition and classification. To solve this problem, a hybrid artificial neural network - WoolNet has been 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 optimized by considering both the reproductions of input images and classification accuracy.

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