The identification of mammalian species through the classification of hair patterns using image pattern recognition

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Abstract

The identification of mammals through the use of their hair is important in the fields of forensics and ecology. The application of computer pattern recognition techniques to this process provides a means of reducing the subjectivity found in the process, as manual techniques rely on the interpretation of a human expert rather than quantitative measures. The first application of image pattern recognition techniques to the classification of African mammalian species using hair patterns is presented. This application uses a 2D Gabor filter-bank and motivates the use of moments to classify hair scale patterns. Application of a 2D Gabor filter-bank to hair scale processing provides results of 52% accuracy when using a filter-bank of size four and 72% accuracy when using a filter-bank of size eight. These initial results indicate that 2D Gabor filters produce information that may be successfully used to classify hair according to images of its patterns.

CR Categories: I.5.4 [Computing Methodologies]: Pattern Recognition—Computer Vision

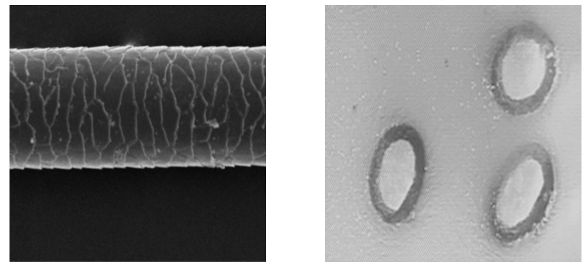
1 Introduction

Hair characteristics are utilised by researchers in the fields of forensics and ecology to identify mammalian species from their hair. An example of this practice is scat analysis in zoology [Keogh 1983]. This entails determining the feeding behaviour of predators by identifying prey species through the hair extracted from predator scat.

Two important characteristics used by researchers are hair scale patterns formed by the cuticle and hair cross-sectional patterns formed by the cortex and medulla (Figure 1). Manual photographic reference systems and keys have been developed to aid researchers in their usage of these patterns to classify species according to their hair [Perrin and Campbell 1980].

However, as with other forms of manual pattern recognition, this practice suffers from the subjectivity introduced by its reliance on a researcher's interpretation as opposed to a reliance on quantitative mathematical measures [Verma et al. 2002].

The study presented in this paper is the first to apply automated image pattern recognition techniques to the problem of classifying



(a) (b)

Figure 1: Examples of two main hair characteristics, (a) Scale Pattern and (b) Cross-section Pattern.

African mammalian species using hair patterns. This provides a computer-based, quantitative hair classification aid to researchers based on the numerical and statistical analysis of hair patterns.

Only details of the hair scale pattern process are given as the cross-section process is still under implementation. It is expected that the inclusion of the cross section process will lead to an improved classification of species with unique cross section patterns.

This paper is organised as follows: Section 2 discusses image pattern recognition techniques found in related work. Section 3 outlines the design of the hair pattern recognition process developed in the study and Section 4 describes implementation of the process. Finally Section 5 presents some initial results from the implementation.

2 Related Work

The Hair Morphological Analysis (Hair-MAP) system is the closest study to the one presented in this paper [Verma et al. 2002]. Hair-MAP holds a database of hairs attributed to known individuals and determines whether an input human hair matches any of the hairs in the database. Therefore, the system uses hair to identify human individuals by taking advantage of the intra-species variation found in human hair. This variation is represented by the texture of the cortex, the medulla type, colour and shaft diameter of a hair.

The study presented in this paper differs from Hair-MAP, as it seeks to identify a species using the inter-species variation of hair as opposed to identifying individuals within a species using the intra-species variation of hair. The inter-species variation of a hair is best represented by hair scale and cross-section patterns [Keogh 1983] which are texture and shape based respectively (Figure 1). Therefore, techniques from studies which classify patterns similar to hair scale patterns are utilised in this study.

Iris recognition [Daugman 2004] and ridge-based fingerprint matching [Jain et al. 2000; Ross et al. 2003] are applications which

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require the recognition of patterns similar to scale patterns. An overview of the techniques found in these applications is given next.

2.1 2D Gabor Filters

The discovery that the receptive fields of the simple cells in a mammal's visual cortex can be modelled using Gabor functions has lead to the widespread application of 2D Gabor filters in the field of computer vision [Lee 1996]. Two such applications are feature extraction in iris recognition [Daugman 2004] and ridge-based fingerprint matching [Jain et al. 2000].

Filtering an image pattern with 2D Gabor filters produces feature vector representations of the pattern which contain its local and global configuration. These feature vectors, referred to as the *IrisCode* [Daugman 2004] and *FingerCode* [Jain et al. 2000] in iris recognition and fingerprint matching implementations respectively, allow for rapid matching to be carried out using either the Hamming or Euclidean distance measures.

Given the similarities between hair scale patterns and fingerprint ridge patterns, the approach provided in ridge-based fingerprint matching is adapted for this study.

3 Design

The scale pattern process mirrors the five stages of a generic classification system [Theodoridis and Koutroumbas 2003]. Table 1 gives an overview of the overall design. The details of hair scale pattern process are laid out below in more detail.

3.1 Sensor

The first stage, sensor, deals with the gathering and image preprocessing of hair images. Two cases are taken into consideration and these are the rotation and scale variations that occur during the image capture of a hair scale pattern.

Scale pattern images are not rotation invariant, hence each image is micrographed at a standard orientation that is employed consistently for all image capture. This standardisation assists in producing rotation invariant features in the feature extraction stage as only two orientations need to be considered during classification. These are an images' original orientation and its 180 degree rotation. At this stage, the value of the original orientation chosen as the standard is irrelevant as long as it is consistently employed for all images. The 180 degree rotation conveniently produces the same image that would have been captured if the hair was micrographed from the opposite side.

The scaling variances resulting from image capture are catered for through the resizing of images to a standardised size. This allows for the extraction features from the same number of pixels for all images.

The translation variation of the images is unimportant, as scale patterns are observed not to vary greatly along the length of a hair. Similarly a reflection variation of an input image, is unimportant as it is unnatural for such a variation to take place. Such a variation would only exist if a mirror image of a hair is taken.

Finally each image's histogram is stretched to represent the texture information contained in it using the entire greyscale intensity range. These images are passed to the feature extraction phase designed next.

3.2 Feature Extraction

Features are extracted from pre-processed images in this stage and represented in a numerical format. A filter-bank of 2D Gabor filters is used to extract features from a pre-processed scale pattern image. The Gabor filter used in this study is an even symmetric Gabor filter given by :

$$\begin{aligned} G_{\theta,f}(x,y) &= e^{\left\{\frac{-1}{2}\left[\frac{x'^2}{\delta_x^2}+\frac{y'^2}{\delta_y^2}\right]\right\}\cos\left(2\pi f x'\right)}, \\ x' &= x\sin\theta + y\cos\theta, \\ y' &= x\cos\theta - y\sin\theta, \end{aligned} \tag{1}$$

[Ross et al. 2003].

The variables of the Gabor filter as used in the study are explained as follows:

1. f is the frequency of each filter in the filter-bank and this is derived from the average distance between the ridges that form the scale patterns.
2. The values of δ_x and δ_y are set to the average thickness of the ridges that form the scale patterns .
3. The θ variable corresponds to the orientation of each filter and is the only variable that differentiates each filter in the filter-bank. The number of filters used in the filter-bank determines the values of θ.

Features presenting redundant information are often generated and in order to provide refined discriminatory information to the classifier stage, a feature selection stage is undertaken.

3.3 Feature Selection

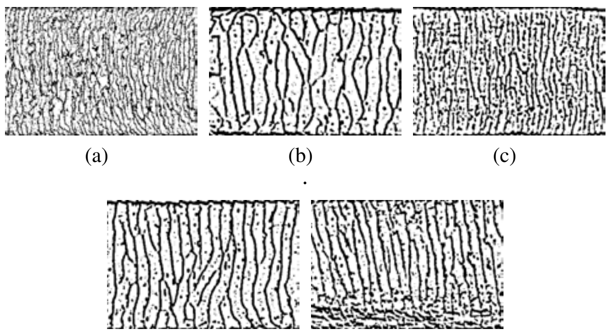
Feature selection is done in the study by tessellating a filtered image into smaller squares as shown in Figure 5. A value for each square is calculated from the pixels in the square and these values are held in a feature vector of the tessellated image. This process compresses the information contained in the filtered image and provides a representation of the local and global variations in the scale patterns. This technique has been demonstrated to be effective in texture based fingerprint matching[Jain et al. 2000; Ross et al. 2003].

3.4 Classifier

The classifier stage places patterns represented by the selected features into appropriate classes or training sets. The training sets are represented by feature vectors whose dimensions depend on the size of the Gabor filter-bank used in feature extraction and the number of features obtained from feature selection. The final step of the approach deals with evaluating the results from the entire process.

Table 1: Design used in the hair pattern recognition study based on the five generic pattern recognition system stages.

Stages	Hair Scale Pattern Process
Sensor	Image orientation standardisation, histogram stretching and image size standardisation.
Feature Extraction	2D Gabor filter-bank.
Feature Selection	Filtered images are tessellated into squares and each feature is calculated from pixel values residing in a square.
Classifier Design	Euclidean distance measure.
System Evaluation	Variables are optimised to improve the performance of the process.



(a) (b) (c)

(d) (e)

Figure 2: Variation in scale pattern. Images have been manipulated to emphasize the pattern. (a) Blue Wildebeest. (b) Impala. (c) Jackal. (d) Springbok. (e) Zebra.

3.5 Evaluation

The results from the process are monitored and used as a basis to change variables in the previous stages until the entire process is at its optimal performance.

A description of the implementation of the hair scale pattern process is given next.

4 Implementation

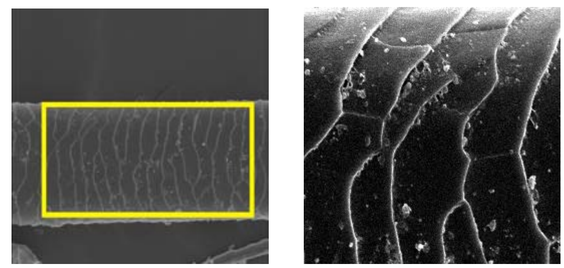
This study focuses on classifying hairs into one of five known classes. These classes are defined by the five initial species chosen for the study, namely: blue wildebeest, impala, jackal, springbok and zebra.This sample allows for the discriminatory ability of the test model to be ascertained as it contains species with similar hair patterns and species with different hair patterns. For example, impala, springbok and zebra have similar scale patterns, whereas jackal and blue wildebeest have a scale pattern distinct from the rest of the species in the sample (Figure 2).

A test model is implemented as a Java plug-in for a public domain graphics application, ImageJ [ImageJ 2005]. The hairs are obtained from a collection of mammal hair in the Rhodes University Zoology Department.

4.1 Scale Pattern Process

4.1.1 Sensor

An initial sample of 100 scale pattern images, comprising 20 images of each selected species, are gathered using a scanning electron microscope. The raw images are taken at magnifications varying from 600X to 400X and are output at a size of 1024x1024 pixels. The images are micrographed horizontally as shown in Figure 3(a) in order to standardise the orientation of the patterns captured. Images with the least noise in the sample are selected for training and testing in this study. This results in a final selection of 40 images (15 images for training and 25 images for testing) from the initial sample which are pre-processed as follows:



(a) (b)

Figure 3: (a) Raw input image with ROI emphasised and (b) pre-processed image converted to grey-scale, re-sized and histogram stretched.

ImageJ provides a rectangular region of interest (ROI) tool and this tool is used to manually segment the scale pattern from the background of an input image. However, scaling variations may occur as images are micrographed at various magnifications and a user has the freedom to define ROIs of various sizes. These scaling variations are catered for as follows:

Since scale patterns do not vary according to the width of a hair, it is safe to restrict the user to define ROIs with a height equivalent to the width of the hair. This allows the capture of the entire variation of a single scale running vertically down a hair. The ROI is also restricted to have a width that is equal or greater than its height as shown in 3(a).

An image to be processed during the rest of the sensor stage is cut from a square region inside the defined ROI. The square region's height and width are equivalent to the height of the ROI. This eliminates scaling variations that arise from the definition of different sized ROIs, as the image cut from the ROI has a height and width standardised to the width of a hair.

The resulting square image is scaled to a standard size of 256x256 pixels to eliminate any variations that arise from image capture at various magnifications. This allows for the size standardisation of scale pattern images while avoiding artifacts that would arise from the direct rescaling of an image defined by the initial ROI.

This new 256x256 image is converted to greyscale and its histogram is stretched. Finally, the image is passed to the feature extraction stage.

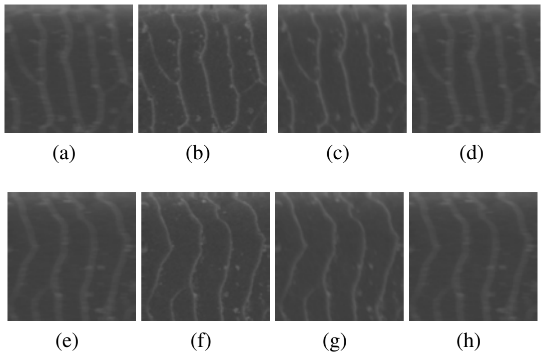


Figure 4: Filtered images of springbok scale pattern image. (a)-(d) correspond to the original image filtered with filters at orientations set at 0,45,90 and 135 degrees. (e)-(h) corresponds to the original image rotated by 180 degrees filtered with filters at orientations set at 0,45,90 and 135 degrees.

4.1.2 Feature Extraction

Each Gabor filter in the filter-bank produces a version of the input image that has been filtered at the orientation of the filter. More specifically this filtering is performed in the study by convolving the input image with each of the Gabor filters in the filter-bank each set to a size of 15×15.

The Gabor filter variables as explained in Section 3.2 are set to the following values:

1. The average distance between the ridges that form the scale patterns is determined from 25 pre-processed scale pattern images (five images from each species) and amounts to 40 pixels. Therefore the frequency f is set to $\frac{1}{40}$.

2. The average thickness of the ridges that form the scale patterns is calculated from the same images used in calculating f . The average ridge thickness amounts to 4 pixels and therefore the values of $\delta_x$and δ_y are set to 4.

3. The values of 0, 45, 90, 135 degrees are set when four filters are used and the additional values of 22.5, 67.5, 112.5, 157.5 degrees are included when eight filters are used. A filter-bank of four filters is required for capturing global fingerprint texture information and a filter-bank of eight filters is required to capture both local and global fingerprint texture information [Jain et al. 2000]. Since eight filters perform better than four filters in fingerprint matching, this study investigates whether the same applies to hair scale patterns by testing both sizes of filter-bank.

Given the standardised orientation of the input image as mentioned in Section 3.1, an input image may only be at one of two orientations, that is, at 0 degrees or its 180 degree rotated equivalent. In order to provide rotation invariant features, each filter is applied to the input image and its 180 degree rotated copy.

In summary filtering an input image with a bank of 2D Gabor filters in this study results in 2 × (the size of the filter-bank) filtered images being produced. Figure 4 shows the results of an image and its 180 degree copy that has been filtered by a filter-bank of four filters. The images that result from the filtering are passed to the feature selection stage .

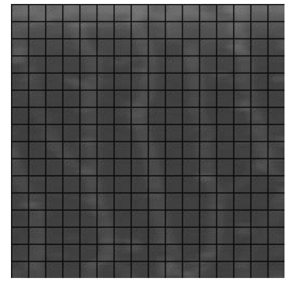


Figure 5: Tessellated Image

4.1.3 Feature Selection

The filtered image is tessellated into squares of size 16x16 pixels and a feature value for each square is calculated using the average absolute deviation from the mean [Jain et al. 2000]. The average absolute deviation from the mean is given by:

$$V_{i,\theta} \quad = \quad \frac{1}{n_i}\left(\sum_{n_i} \mid F_{i\theta}(x,y) - P_{i\theta} \mid\right) \tag{2}$$

The variables in equation 2 are explained by as follows:

1. $F_{i\theta}$ is the image that resides in the ith square of the filtered image resulting from a Gabor filter oriented at θ.

2. $n_i$refers to the number of pixels in the ith square.

3. $P_{i\theta}$is the mean of the pixel values residing in $F_{i\theta}(x,y)$.

This results in a feature vector of 256 elements being produced from each filtered image. Finally the feature vectors obtained from images filtered by the same filter in the Gabor filter-bank are summed together. For example, the feature vectors obtained from the images in Figure 4(a) and 4(e) are summed together as they were filtered by the same filter. This results in rotation invariant feature vectors that are passed to the classification stage.

4.1.4 Classification

The values assigned to the feature vectors of a training set are obtained by taking the average of the feature vectors from three images of the corresponding species.

An input hair pattern is classified by summing the Euclidean distances between its feature vectors and the training set feature vectors of each known hair class. The hair pattern is classified into the class of the closest training set.

5 Results

The same image samples are used for both the tests from which the following results are reported. The tests are carried out on a machine with an Intel Pentium 4 3.0 GHz processor and 1gigabyte of RAM. The samples comprise of five images from each of the five known species under study.

The first test uses a filter-bank of 4 Gabor filters for feature extraction producing four feature vectors of size 256 for each hair. Classification with this filter-bank takes approximately 2 seconds to

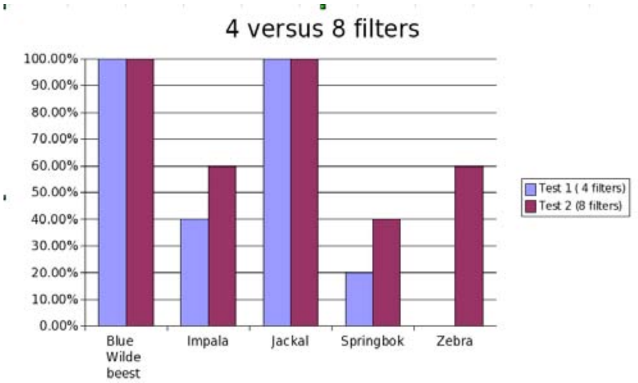


Figure 6: Chart comparing results from the first two tests

complete. An overall accuracy rate of 52% correct classifications is recorded with 100% success in identifying jackal and blue wildebeest. However, 40% and 20% correct classifications of springbok and impala are achieved respectively. No correct classifications of zebra are achieved during this test.

The second test utilises a filter-bank of 8 Gabor filters for feature extraction producing eight feature vectors of size 256 for each hair. Classification with this filter-bank is slower than when a filter-bank of 4 filters is used, as it takes approximately 5 seconds to complete. An improved overall accuracy rate of 72% is achieved with the same success rate as the previous test in identifying jackal, blue wildebeest and springbok. However, the correct classification rate for impala and zebra improves to 40% and 60% respectively. Figure 6 shows a comparison of the results from the first and second test.

The results from the first two tests show that the application of Gabor filters in the feature extraction of hair scale patterns allows for the classification of hair. The results also show that the use of eight Gabor filters performs better than four Gabor filters.

However, the input sample used in this study is small and therefore the results may reflect the current implementation' s ability to classify patterns within the small sample. A larger test sample will be used to verify whether the current hair scale processing implementation can classify hair outside the initial sample gathered.

6 Conclusion

The first computer-based classification of African mammalian species is successfully demonstrated in this paper through the application of pattern recognition techniques to hair scale pattern images. 2D Gabor filters provide classification information that when compressed, through image tessellation, allows for this classification to be done using the Euclidean distance measure.

6.1 Future Work

Since hair scale patterns vary in terms of texture and hair cross-section patterns vary in terms of shape, a separate process to classify each is needed. The implementation and testing of the cross-section processing stage needs to be completed with the aim of improving the current results obtained from the hair scale pattern processing stage.

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