A Literature Review of Techniques applicable to Mammalian Hair Identification

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Abstract

The identification of mammals using hair is important in the fields of forensics, medicine and ecology. The application of pattern recognition to such a process of identification may assist in reducing the subjectivity of the process, as manual methods rely on the interpretation of a human expert rather than quantitative measures. Despite limited literature on the application of image pattern recognition to hair identification, methodologies relevant to this application can be found in other fields, such as aquaculture , medicine and other biometric studies. Feature extraction methodologies used in these fields include Haralick numbers, moments, filter banks and skeletal graphs. Classifiers employed in these fields include linear classifiers, distance algorithms, neural networks and graph matching algorithms. These pattern recognition strategies are examined with emphasis on their application to the hair identification of Southern African mammals. A discussion on these strategies reveals that the techniques used in rotifer identification, human iris identification and hybrid fingerprint matching have the best potential for adoption to hair pattern recognition.

1 Introduction

The identification of mammals using hair is important in the fields of forensics and ecology (Keogh, 1983). In ecology, this practice is useful in identifying prey and the mammals that inhabit an area (Perrin and Campbell, 1980). As a result, manual photographic reference systems and keys exist to aid ecological researchers identify mammals using their hair patterns. However, manual pattern matching systems are subjective as they depend on the interpretation of the researcher rather than quantitative measures (Verma et al., 2002).

Pattern recognition systems offer quantitative measures that are less subjective through the numeric and statistical analysis of patterns. Such systems mirror the five design steps carried out in developing a generic classification system (Figure 1) as proposed by Theodoridis and Koutroumbas (2003). The sensor phase is concerned with the input and pre-processing of raw pattern images . The feature generation step deals with the extraction of single measurements and a set of such measurements is termed a feature vector. Since more features than necessary are generated, the feature selection stage will eliminate features that present low quality or redundant information. Classifier design involves

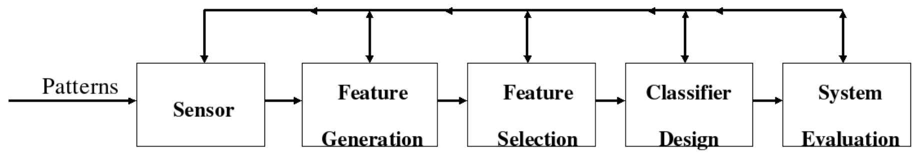

Figure 1: Phases carried out in designing a classification system (Theodoridis and Koutroumbas, 2003)

the deployment of mechanisms that place patterns in their correct classes and system evaluation determines the performance of the system.

Despite limited literature directly focused on hair pattern recognition, studies using techniques easily adoptable to hair pattern recognition are available in the literature. Such studies are found in the fields of aquaculture (Yang and Chou, 2000), medicine (Forero et al., 2004) and biometrics (Sanchez-Avila and Sanchez-Reillo, 2005).

This review examines the approaches found in these studies with emphasis on their adoption to the hair pattern recognition of Southern African mammals. Section 2 of the review discusses hair characteristics used in identification and explores the implications they provide for a hair pattern recognition system. Section 3 reviews studies that employ techniques that can be adopted to hair pattern recognition. Finally a discussion on the applicability of the reviewed techniques is given in the form of a proposed hair pattern recognition process in Section 4.

2 Hair characteristics used in identification

Most types of hair consists of three layers of keratinized cells, that is, the cuticle making up the outer layer, the cortex forming the middle layer and the medulla resulting in the inner layer (Keogh, 1983). These three layers form the hair structure patterns used in the classification of hair.

The main type of hair used in the manual hair identification of Southern African mammals is guard hair, which is the long and coarse outer hair found in the coats of mammals (Perrin and Campbell, 1980). This type of hair shows the greatest variation in scale patterns used to identify hair. In addition, cross-sectional patterns are used to identify hair (Keogh, 1983). Both the scale and cross-sectional patterns and the implications they have on a pattern recognition system are examined in the following sections.

2.1 Common scale patterns

Commons scale patterns form the overlapping of the outer keratinized cells of a hair known as the cuticle (Keogh, 1983). The most common scale patterns found are mosaic, chevron,

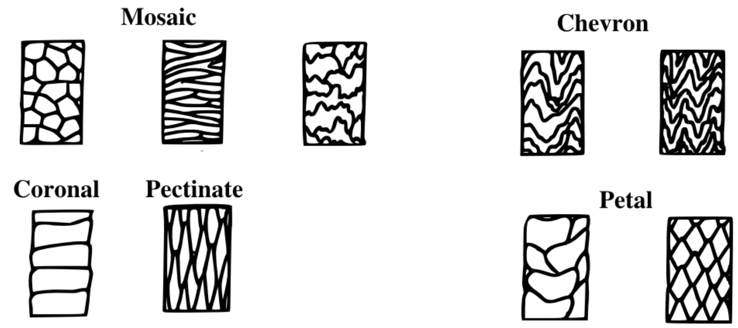

Figure 2: Common Scale Patterns found in Southern African mammals(Keogh, 1983)

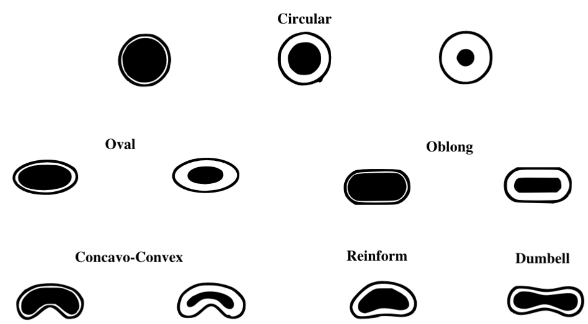

Figure 3: Common Cross-Sectional Shape (Keogh, 1983)

coronal and petal patterns (Figure 2). While the texture of these patterns varies greatly between species of mammals, it may also vary along a single hair (Perrin and Campbell, 1980). The inter-species hair textural variation allows for the identification of a species and potential problems from single hair variation are overcome by the explicit sampling of patterns from either the base, middle, or tip of a hair.

2.2 Common cross-sectional patterns.

Cross-sectional patterns arise from the relative size of keratinized cells that make up the cortex and those that make up the medulla (Keogh, 1983). Common patterns found in the cross-sections are circular, oval, oblong and concavo-convex (Figure 3). The different shapes found in these patterns, together with scale patterns are used to identify mammal hair.

2.3 Implications for pattern recognition systems

A hair must be considered as a whole entity by a pattern recognition system as opposed to a collection of its characteristics (Verma et al., 2002). This policy arises from the inability to quantitatively determine the relative importance of hair characteristics with relation to each other and assign different weightings to each . Therefore a pattern recognition system should not weight scale patterns over cross-sectional patterns and vice-versa, but should holistically consider both types of pattern when determining the identity of a hair.

A hair pattern recognition system must process scale patterns and cross-sectional patterns in different manners as scale patterns are texture characteristic whereas cross-sectional patterns are shape based. This does not violate the policy mentioned above, as long as weights are not assigned to the results of processing either pattern. The next section reviews applications employing strategies that may be applicable to hair pattern recognition.

3 Related studies

This section reviews studies that utilise techniques with potential to be employed in hair pattern recognition. Each study is reviewed under of the five generic pattern recognition phases presented by Theodoridis and Koutroumbas (2003) (Figure 1).

3.1 Hair-MAP forensic hair identifier

The Hair Morphological Analysis (Hair-MAP) system compares a input human hair to a database of known hairs (Verma et al., 2002). This study differs from the hair pattern recognition problem this review is concerned with, as it seeks to identify human individuals using the intra-human variation of hair as opposed to identifying a species using inter-species variation. Therefore, the Hair-MAP system only considers the texture of the cortex, the medulla type, colour and shaft diameter of a hair, instead of cross-sectional and scale patterns. However, the cortex texture classification approach taken in this study may be useful in hair scale pattern classification, since hair scale patterns are texture characteristic.

3.1.1 Sensor

776 images compiled from 25 individuals, contributing 20 hairs each made up the initial input sample analysed in this study (Verma et al., 2002). The hair images from nine individuals were selected, based on their clarity, for use in the study. These images were converted to grey-scale in order for features to be extracted from the cortex texture.

3.1.2 Feature extraction

14 features may be extracted from cortex texture images using Haralick texture analysis (Verma et al., 2002). These extracted features, known as Haralick numbers, describe texture in terms of the pixel grey-level distribution in the image and examples of such features include the angular second moment, correlation, contrast and entropy (Blunsden, 2004).

3.1.3 Feature Selection

No feature selection is required for features extracted using Haralick texture analysis, as the entire texture is represented using the 14 Haralick numbers (Verma et al., 2002).

3.1.4 Classification

An back propagation neural network is used to determine whether an input cortex texture is finer, similar or rougher than a query cortex texture (Verma et al., 2002). This neural network comprises 28 input processing elements corresponding to the 14 Haralick numbers that describe each texture, a hidden layer of 20 processing elements and an output layer of 3 processing elements, each corresponding to the output classes.

3.1.5 Evaluation

Despite a targeted accuracy of 84% for the neural network during its training, an accuracy of 55% was achieved during the testing of the neural network (Verma et al., 2002). This low result suggests that this technique is not ideal for use in a hair pattern recognition process and therefore, other techniques must be explored.

3.2 Hybrid fingerprint matcher

A hybrid fingerprint matcher includes ridge structure information to perform a more accurate match than conventional fingerprint matchers (Ross et al., 2003). The process of classifying ridge structure patterns is considered in this review as scale patterns have a similar line based texture.

3.2.1 Sensor

A total of 2560 images collected from different fingers on 160 individuals made up the input sample of the hybrid fingerprint matcher study (Ross et al., 2003). The images were converted to grey-scale and an image enhancement algorithm was applied to the images to produce clearer ridge definitions.

3.2.2 Feature extraction

The extraction of features from ridge structure patterns is done using a set of Gabor filters which produce a set of feature vectors (Ross et al., 2003). Such a filter bank consists of 8 filters each set to operate at different orientations to produce a set of rotation invariant features. A feature vector is composed of the variance of each pixel calculated from filtering a ridge structure image. Therefore, a ridge structure image is represented by 8 feature vectors each corresponding to a filter in the Gabor filter bank.

3.2.3 Feature Selection

Feature selection is not performed in ridge structure pattern classification as all the features extracted are used in the classification process mentioned next.(Ross et al., 2003).

3.2.4 Classification

Each of the 8 feature vectors generated are matched up to the corresponding 8 training feature vectors of each known ridge structure pattern by a Euclidean distance algorithm

(Ross et al., 2003) . The Euclidean distance algorithm calculates the distance between two vectors which represents the dissimilarity of two vectors (Theodoridis and Koutroumbas, 2003). The distance between each feature vector and the training feature vector at the same orientation is summed for all 8 feature vectors . The training feature vector that produces the lowest distance is considered as the closest match.

3.2.5 Evaluation

The false acceptance rate and the false rejection rate are evaluation methods used in biometrics (Zhang, 2000). The false acceptance rate describes how often a positive match is reported when it is meant to be negative and the false rejection rate describes how often a negative match is reported when it is meant to be positive. The equal error rate describes the point where both false acceptance and false rejection rates are minimised and is calculated as the rate at which the false acceptance rate and the false rejection rate are equal.

The hybrid fingerprint matcher's equal error rate is 4% and Ross et al. (2003) provide a receiver operating characteristic curve showing that equal error rate of the ridge structure classifier is slightly higher than 4%. This accuracy indicates that the techniques employed in this study have potential to be successfully used in a hair pattern recognition process.

3.3 Human iris identification

A human iris may be identified using features extracted from texture analysis (Sanchez-Avila and Sanchez-Reillo, 2005). This technique of iris identification may be adopted to the texture analysis of hair scale patterns.

3.3.1 Sensor

30 images from each eye from 50 people were taken over an 11 month period at various times of the day and converted to grey-scale in this study (Sanchez-Avila and Sanchez-Reillo, 2005). The grey level range of the pixels of each image was spread across the 255 gray levels available, to obtain a maximum representation of variation within the image.

3.3.2 Feature extraction

An utilisation of Gabor filters similar to that employed by the hybrid fingerprint matcher may be employed in human iris identification (Sanchez-Avila and Sanchez-Reillo, 2005). However, in this case four orientations are used resulting in four feature vectors. In order to compensate for scaling and light intensity variations, the four filtered images of the iris are split into a number of small square sections (256 to 1860 in this study) and the mean energy for each section is calculated. Thus the size of a feature vector will be dependant on the number of small sections into which the iris is split.

3.3.3 Feature Selection

Feature selection is not performed in human iris identification as all the features extracted are used in the classification process mentioned next.

3.3.4 Classification

The binary Hamming algorithm measures the distance between two feature vectors by counting the number of features in a feature vector that differ from the corresponding features in a training feature vector (Theodoridis and Koutroumbas, 2003). This algorithm may be implemented by either a biometric recognition method or biometric verification method (Sanchez-Avila and Sanchez-Reillo, 2005). Biometric recognition assigns an iris to a class with the least Hamming distance regardless of how high the distance is, hence ignoring the quality of the match. Biometric verification adds an extra constraint on the previous method by rejecting all matches that have a Hamming distance higher than a threshold value. Therefore, this method only considers a match if it meets a minimum quality requirement.

3.3.5 Evaluation

The biometric recognition method had accuracy rates of 95.3% and 98.3% reported for feature vectors of size 256 bits and over 992 bits respectively (Sanchez-Avila and Sanchez-Reillo, 2005). This indicates that increasing the number of small sections, hence the size of the feature vectors, will increase the correct classification rate up to certain point, for example 992 bits in this study.

The false acceptance rate and false rejection rate are used in evaluating the biometric verification method. The lowest equal error rate of 3.3% was achieved from feature vectors with a bit length of 1860 bits and the highest equal error rate was lower than 10%. The low equal error rate of the biometric verification stage shown in these results and the ability to reject poor quality matches makes the biometric verification method a more attractive option to use in hair pattern recognition than the biometric classification method.

3.4 Rotifer identification

A rotifer is a micro-organism used to feed fish in their larval stage and the detection of different types of rotifer in a image containing surrounding debris is done through rotifer shape identification (Yang and Chou, 2000). The curved nature of rotifers and cross-sectional shapes suggests that the shape based identification used in this study may be useful in classifying hair cross-sectional shapes.

3.4.1 Sensor

957 rotifer sample images in three sample batches with 203, 375 and 379 in each sample batch were used in this study (Yang and Chou, 2000). Since the rotifers were prepared in iodine before photography, the red channel was dominant in the RGB images acquired.

Therefore, the red channel of the image was extracted and this image was used to produce the grey-scale images used in the next step.

3.4.2 Feature extraction

Shape features are extracted using Hu's seven moments and an additional 5 higher order moments, as Hu's seven moments are insufficient to classify rotifers (Yang and Chou, 2000). These 12 moments form the features passed to the feature selection process and the first stage of the rotifer classification process, that is debris elimination.

3.4.3 Feature Selection

6 moments out of the 12 initially generated moments in rotifer feature extraction are selected for input into the second stage of the rotifer classification process (Yang and Chou, 2000). These 6 moments are selected using the ratio of the inter-class variation to the intra-class variation of each moment. Moments with inter-class variations greater than their intra-class variations are selected. However all 12 features are used in the first part of the rotifer classification system used to eliminate debris.

3.4.4 Classification

The first stage of rotifer classification involves eliminating the debris surrounding a rotifer (Yang and Chou, 2000). This two class problem requiring objects to classed as either rotifers or debris can be carried out using either a similarity distance algorithm or probability histograms.

The second stage of rotifer classification uses a back propagation neural network consisting of 7 input processing elements corresponding to the 6 selected moment features and the area of an object. In addition, a single hidden layer of 5 processing elements and an output layer of 3 processing elements corresponding to the known three types of rotifer, were deployed in the network. A total of 185 rotifer samples were used to train this neural network.

3.4.5 Evaluation

The overall accuracy rate obtained from using probability histograms in eliminating debris at first classification stage was 97.34%. The use of probability histograms was the more appropriate technique employed at the debris elimination stage as it produced a lower classification rate of 2.61% as compared to the classification rate of 6.48% of the similarity distance measurement. The reported performance of the artificial neural network employed at the second classification stage was 93.15% . These results indicate the high feasibility of identifying shape feature based objects, such as hair cross-sectional patterns, from a noisy environment.

3.5 Tuberculosis bacteria identification

Tuberculosis bacteria shape varies from that of a long curved nature to a more circular shape (Forero et al., 2004). This varied curved morphology resembles that of hair cross-sectional shapes and therefore, the techniques employed in this study may be applicable to hair cross-sectional pattern classification.

3.5.1 Sensor

397 negative sample images were taken from 31 individual and 75 positive sample images from 4 individuals were obtained for this study (Forero et al., 2004). Bacteria objects were initially separated from the background using color thresholding as objects likely to be bacteria obtain a green colour during the manual preparation stage. In addition a morphological closing process was employed to complete the boundaries of an object in an image , followed by the binarization of the image to enable the feature extraction process mentioned next.

3.5.2 Feature extraction

The features of such tuberculosis bacteria may be extracted from an image using Hu's 7 moments , eccentricity and compactness (Forero et al., 2004). Eccentricity is a moment based feature that measures the ratio between the maximum radius of an object and its minimum radius (Theodoridis and Koutroumbas, 2003). Compactness is another moment based feature which measures the degree to which an object's shape is similar to a circle. These features are passed to the feature selection stage mentioned next.

3.5.3 Feature Selection

The first four Hu's moments, eccentricity and compactness are the most appropriate features for tuberculosis bacteria identification and these features are selected using the mean, variance and independence as criteria (Forero et al., 2004).

3.5.4 Classification

A classification tree is constructed to utilise information from the selected features (Forero et al., 2004) . The minimum Mahalanobis distance between the Hu's moment features of the input object and of each bacteria cluster, is recorded and compared in the top part of the tree to a threshold value . The lower parts of the tree compare the compactness and eccentricity features of the input object against known compactness and eccentricity values. The threshold value is calculated from running test classifications and the known compactness and eccentricity values are calculated from the observed shape characteristics of bacteria found in training samples. The leaf nodes of the classification tree, either correspond to a tuberculosis bacteria object or a non tuberculosis bacteria object to be rejected.

3.5.5 Evaluation

Sensitivity is the rate of providing a positive match correctly and specificity is the rate of providing a negative match correctly(Nichol and Mendelman, 2004). The results reported in this study show that a threshold value of 10 provides the best sensitivity and specificity values for bacteria samples, 91.43% +/- 2.75 and 100% respectively (Forero et al., 2004) . However, these results must considered in the context of the number of sample bacteria (110 positive samples) used in the study, which Forero et al. (2004) term as limited . This consideration raises uncertainty about the extensibility of the study's techniques outside the scope of the limited sample base and their usefulness in a hair pattern recognition process.

3.6 Skeletal Graphs

An object in a skeletonized binary image is represented by a set of thin lines that preserve the shape of the object and this set of lines is known as the skeleton or medial axis (DiRuberto, 2004). A skeleton consists of 3 types of skeletal points namely, junction points connecting more than 1 line to other lines, end points that correspond to the end of a line and curve points joining one line to another. The use of skeletal graphs may be adopted in scale pattern classification, since skeletal graphs deal with thin lines similar to those that make up scale patterns.

3.6.1 Sensor

Input images for skeletal graphs are converted into thin representations using thinning or skeletonization algorithms (DiRuberto, 2004) . These images must either be converted into a binary or grey-scale representation for the skeletonization algorithm to operate on the image.

3.6.2 Feature extraction

An attributed skeletal graph is composed of a set of nodes, a set of links and a value for each node (DiRuberto, 2004). The set of nodes correspond to end points and junction points and the value assigned to each node is obtained by passing the value of the skeletal point corresponding to the node, to a morphological distance function. The set of links correspond to the lines joining skeletal points and each link is represented as a vector of 6 weighted values . This graph representation of the shape of an object is scale, rotation and translation invariant.

3.6.3 Feature Selection

No feature selection is required in the use of skeletal graphs (DiRuberto, 2004).

3.6.4 Classification

The graduated assignment algorithm is used to match an input graph to a set of template graphs in complexity *O(n)* (DiRuberto, 2004). This algorithm applies an energy function to calculate the distance between two graphs represented as matrices. The energy function uses a match matrix which describes whether the nodes in one graph correspond to the nodes in another, link weights and the node attribute values to calculate the distance. An input graph is classified in the same class as the template class which generates the least distance from the graduated assignment algorithm.

3.6.5 Evaluation

The results reported in this study were achieved from an evaluation where an input shape was selected from 9 different classes and matched against all other objects in a database. Rotated and reflected variations of the query object provided the top matches and lowest energy values as they are morphologically the same as the query object. The next highest matches were of slightly different objects in the same class and followed by objects in other classes with the highest energy values. This ordering of results shows the feasibility of using skeletal graphs to classify objects within a database and the potential for their adaptation to ordering scale patterns according to their classes.

4 Discussion on the applicability of techniques

In this section, the applicability of the reviewed techniques to hair pattern recognition is discussed by means of a proposed hair pattern recognition process drawing on these techniques. Techniques are selected on their potential for adoption in a pattern recognition process.

4.1 Sensor

All the studies mentioned in this review with the exception of skeletal graphs and tuberculosis bacteria identification take grey-scale images as input into their pattern recognition process. The strategy employed in rotifer identification of extracting an image in its dominant RGB colour channel and converting this image to grey-scale may be adopted to gain a clearer grey-scale representation of hair-cross-sectional patterns (Yang and Chou, 2000).

The image enhancement algorithm employed by Ross et al. (2003) in the hybrid fingerprint matcher may assist in producing more clearly defined input scale patterns and the morphological closing algorithm used by Forero et al. (2004) may be used to fill any missing boundaries of hair cross-sectional shapes. The next section deals with extracting features from the pre-processed input images.

4.2 Feature extraction

4.2.1 Scale pattern feature extraction

Since scale patterns are texture characteristic, the texture feature extraction methods in the reviewed studies may be considered for the feature extraction from scale patterns. The reviewed studies that employ texture feature extraction methods are the Hair-MAP forensic hair identifier (Verma et al., 2002), the human iris identification study (Sanchez-Avila and Sanchez-Reillo, 2005) and the hybrid fingerprint matcher study (Ross et al., 2003) .

The use of Haralick numbers as employed in the cortex texture feature extraction process of the Hair-MAP system is eliminated as option since the cortex classification process reported an average success rate of 55%. The fingerprint ridge structure feature extraction technique may be more useful in hair scale pattern feature extraction than the human iris biometric feature extraction technique since the fingerprint ridge structure is more similar to a hair scale pattern. Therefore, it may be assumed that the use of Gabor filters as applied in the hybrid fingerprint matcher's ridge feature extraction method shows the best potential for adoption to hair scale pattern feature extraction.

4.2.2 Cross-sectional pattern feature extraction

The rotifer and tuberculosis bacteria identification studies provide feature extraction strategies that may be used for feature extraction from cross-sectional patterns (Yang and Chou, 2000; Forero et al., 2004). Both these studies utilise Hu's moments with the rotifer identification study using an additional 5 higher order moments. These five higher order moments are specific to the identification of rotifers and therefore, these may be dropped from the features extracted. However the use of these five higher order moments illustrates the idea of integrating higher order moments to improve the quality of extracted features, when required. In addition the compactness and eccentricity features as extracted in tuberculosis bacteria identification, may be useful as cross-sectional patterns have a curved nature which is well described by these features.

4.3 Feature Selection

Since none of the texture feature extraction studies needed any feature selection, this stage may be skipped for the features extracted from scale patterns. However the moment features that represent cross-sectional patterns need to be selected as these features present redundant data (Forero et al., 2004). Since the hair pattern recognition process discriminates between known classes of hair patterns (Keogh, 1983), the use of the ratio of the inter-class variation to the intra-class variation of each moment is appropriate in eliminating the moments that provide little inter-class variation (Yang and Chou, 2000).

4.4 Classification

4.4.1 Scale pattern classification

Both the hybrid fingerprint matcher study and the human iris detection study use distance algorithms to classify the feature vectors obtained from the feature extraction process (Ross et al., 2003; Sanchez-Avila and Sanchez-Reillo, 2005). The human iris identification biometric verification process may be the more appropriate strategy for classifying feature vectors, as it employs the Hamming distance algorithm using a rejection threshold. This provides for qualitative results as a match below a certain level is discarded.

4.4.2 Cross-sectional pattern classification

The debris elimination stage employed in rotifer identification may be used to eliminate any debris similar to a cross-sectional pattern and prevent the mis-classification of debris as a cross-sectional pattern (Yang and Chou, 2000).

The use of a classification tree as employed in bacteria identification implies the calculation of pre-determined threshold, eccentricity and compactness values (Forero et al., 2004). The calculation of these predetermined values, done through manual observation, limits the number of known shape types that may be identified to the number that are manually observed . Therefore the use of the classification tree is rejected in favour of the artificial neural network approach used in rotifer identification. The main advantage of this decision is that a large number of samples may be used to train an artificial neural network through observation of the output of the network as opposed to calculating static look-up values when using a classification tree.

4.4.3 Overall system classification

Since the hair pattern recognition process is split into 2 sections, scale pattern classification and cross-sectional pattern classification, the output from both these processes must be combined to form produce a final classification. This is similar to the Hair-MAP system where the outputs from the classification of the cortex texture, the medulla type, color and shaft diameter of the hair was passed to a Fisher Line Discriminant for final classification (Verma et al., 2002). However, the use of a Fisher Line Discriminant is appropriate for the 2 class problem handled by Hair-MAP and classifiers such as decision trees and neural networks are more appropriate for more complicated problems. Therefore, the multi-class hair pattern recognition problem of concern in this review may need such a complex classifier in its final classification stage.

The output from the final classification stage of the Hair-MAP system reports the degree of certainty that the system had in determining a result. This approach may be useful in reporting the certainty of likely identities of an input hair passed to a pattern recognition process.

Stage	Scale Pattern Classification	Cross-sectional Pattern Classification
Sensor	Grey-scale conversion, Fingerprint ridge enhancement algorithm	Grey-scale conversion , Morphological closing algorithm
Feature Extraction	Gabor Filters (Hybrid fingerprint matcher study)	Moments (Rotifer identification study); Eccentricity, Compactness (Tuberculosis bacteria identification study)
Feature Selection	None needed	Ratio of inter-class to intra-class variation (Rotifer identification study)
Classifier Design	Thresholded Hamming distance algorithm (Human iris identification study)	Artificial neural network (Rotifer identification study)
System Evaluation	Equal error rate (Human iris identification study)	Monitoring neural network monitoring rate (Rotifer identification study)

Table 1: Summary of applicable techniques from reviewed studies

4.5 Evaluation

The evaluation techniques for the hair pattern recognition process depends on the decision to use a thresholded Hamming distance algorithm for scale patterns and an artificial neural network for cross-sectional patterns. The results from using the Hamming distance algorithm may be evaluated using the equal error rate as employed in human iris identification (Sanchez-Avila and Sanchez-Reillo, 2005). The results from the artificial neural network may be monitored through the observation of the accuracy rate produced, as was done in the rotifer identification study (Yang and Chou, 2000).

5 Conclusion

The studies that provide the bulk of strategies to be employed are the rotifer identification, the hybrid fingerprint matcher and human iris identification studies. The results given by (DiRuberto, 2004) show that skeletal graphs are a potential alternative that may be used in hair scale pattern classification . However the results given are taken from an initial experiment and a further study on this technique's effectiveness needs to be done.

Table 1 shows a mixture of techniques at the various stages of the proposed hair pattern recognition process . However, it must taken into consideration that the combination of techniques from various applications may not be possible because of the dependencies between the stages employed within each study. It may be the case, for example, that classifiers employed by the hybrid fingerprint matcher study work best with feature extractors from the same study. A study of the application of the selected techniques for hair pattern recognition is required to prove effectiveness of the hair pattern recognition process shown in Table 1.

References

Blunsden, S. (2004). Texture classification using non-parametric markov random fields. Master's thesis, School of Informatics, University of Edinburgh.

DiRuberto, C. (2004). Recognition of shapes by attributed skeletal graphs. *Pattern Recognition*, 37(1):21–31.

Forero, M. G., Sroubek, F., and Cristóbal, G. (2004). Identification of tuberculosis bacteria based on shape and color. *Real-Time Imaging*, 10(4):251–262.

Keogh, H. J. (1983). A photographic reference system of the microstructure of the hair of southern african bovids. *South African Journal of Wildlife Research*, 13(4):89–132.

Nichol, K. L. and Mendelman, P. (2004). Influence of clinical case definitions with differing levels of sensitivity and specificity on estimates of the relative and absolute health benefits of influenza vaccination among healthy working adults and implications for economic analyses. *Virus Research*, 103(1-2):3–8.

Perrin, M. R. and Campbell, B. S. (1980). A key to the mammals of the andries vosloo kudu reserve(eastern cape), based on their hair morphology, for use in predator scat analysis. *South African Journal of Wildlife Research*, 10(1):1–14.

Ross, A., Jain, A., and Reisman, J. (2003). A hybrid fingerprint matcher. *Pattern Recognition*, 36(7):1661–1673.

Sanchez-Avila, C. and Sanchez-Reillo, R. (2005). Two different approaches for iris recognition using gabor filters and multiscale zero-crossing representation. *Pattern Recognition*, 38(2):231–240.

Theodoridis, S. and Koutroumbas, K. (2003). *Pattern recognition*. Elsevier Academic Press, second edition.

Verma, M. S., Pratt, L., Ganesh, C., and Medina, C. (2002). Hair-map: a prototype automated system for forensic hair comparison and analysis. *Forensic Science International*, 129(3):168–186.

Yang, C.-Y. and Chou, J.-J. (2000). Classification of rotifers with machine vision by shape moment invariants. *Aquacultural Engineering*, 24(1):33–57.

Zhang, D. D. (2000). *Automated Biometrics*. Kluwer Academic Publishers.