AN ALGORITHM FOR IRIS IDENTIFICATION USING FOURIER DESCRIPTORS

M. Deriche, M. Mohandes, J. Bakhashwain

Department of Electrical Engineering
King Fahd University of Petroleum and Minerals

ABSTRACT

In this paper, a new biometric identification approach based on the human iris is proposed. The main idea of the technique is to represent the features of the iris with the extracted contour of the inner iris. The extracted boundary includes a wealth of information about the person to allow accurate identification. The technique is fundamentally different from previous techniques that assume the circulatory nature of the inner iris. The iris extracted contours are normalized, the Fourier descriptors are computed, a feature vector is extracted and fed to a statistical classifier. Preliminary results showed a classification success of around 96%. The technique is *robust* to additive noise, *cropping, scale, rotation, translation*, and is *computationally efficient*.

1. INTRODUCTION

One of the main threats that IT systems and security environments are exposed to is that of unwanted intruders. This is normally solved by user identification schemes based on passwords, secret codes, or identification cards. Schemes based only on passwords or secret codes can always be cracked by intercepting the presentation of such passwords, or even by counterfeiting. On the other hand, an intruder can attack systems based on identification cards by stealing, copying or simulating these. However, even schemes based on both cards and passwords, such as smart cards, have been found vulnerable to ”expert” attacks.

During the last few years, we have witnessed a substantial growth in a new breed of algorithms for person identification using biometrics. Biometric technologies are automated methods for recognizing a person based on a physiological or behavioral characteristic. Examples of human traits physical characteristics used in biometrics include: voice, fingerprints, hand shape, retinal scan, handwritten signatures, etc, [1]. Unfortunately, most of these methods are highly invasive: typically, the person is required to make physical contact with a sensing device (e.g., finger or hand contact) or otherwise take some special action (e.g. recite a specific phonemic sequence). One possible alternative to these methods is automated face recognition. As with all pattern recognition problems, the key issue is the relation between inter-class and intra-class variability: objects can be reliably classified only if the variability among different instances of a given class is less than the variability between classes. Therefore, in the case of face recognition, difficulties arise from the fact that the face is a ”deformable” object displaying a variety of expressions, as well as being an active 3D object whose image varies with viewing angle, pose, illumination, and age.

Automated iris recognition is yet another alternative for non-invasive verification and identification of people. Verification happens when the person identifies himself/herself and the machines either confirms of rejects the identity, while in identification, the person does not have to identify himself/herselft and it is up to the machine to either identify the person (if he is in the database) or reject him/her. Interestingly, the spatial patterns that are apparent in the human iris are highly distinctive to the individual [2]. Like the face, the iris is an overt body that is appropriate for remote (i.e., noninvasive) assessment. Unlike the human face, however, the variability in appearance of any one iris might be well enough constrained to make it possible to design an automated recognition system based on currently available machine vision technology. Some properties of human iris that proved its suitability for use in identification include:

1. The impossibility of surgically modifying it without high risk of damaging the user’s vision.

2. Its physiological response to light, which provides the detection of a dead or plastic iris, avoiding this kind of counterfeit.

3. As a planar object its image is relatively insensitive to angle of illumination, and changes in viewing angle cause only affine transformations; even the non-affine pattern distortion caused by pupillary dilation is readily reversible.

4. Finally, the ease of localizing eyes in faces, and the distinctive annular shape of the iris, facilitate reliable and precise isolation of this feature and the creation of a size-invariant representation.

Several researchers have shown that while the general structure of the iris is genetically determined, the particulars of its minutiae are critically dependent on conditions in the embryonic mesoderm from which it develops. Therefore, there are not ever two irises alike, not even for identical twins [2].

The objective of the paper is to present a new approach to iris recognition using contours of the inner iris and a statistical classifier.

2. PROPOSED TECHNIQUE

In this work, the proposed technique, used for extracting features of the iris, is translation, rotation, and scale invariant. The feature extraction and classification stages are discussed below while the setup of the database and related preliminary work are omitted because of lack of space.

Iris Localization and Feature Extraction

1. The process of feature extraction starts by locating the outer and inner boundaries of the iris.
2. The second step finds the contour of the inner boundary i.e., the iris-pupil boundary.
3. Finally, the contour is represented using the "Radius Vector Method" and is named "iris signature".

Classification

1. To identify the contour extracted from the previous step, a statistical classifier is used. In particular, the contour are normalized, then we use Fourier Descriptors as features extracted from the contours. As a classifier, we use the minimum distance statistical classifier. The advantages of such classifier is its low computational load and efficiency as will be explained latter.

In the next sections, the steps mentioned above are discussed in more details.

3. LOCALIZING THE IRIS

3.1. Edge Detection

The first step locates the iris outer boundary, i.e. border between the iris and the sclera. This is achieved through edge detection on the gray scale iris image. In our work, we investigated the performance of several edge detection techniques, in particular:(1) The *Sobel, Prewitt, and Roberts methods* which find the edges using certain approximations to the derivative, (2) The *Laplacian of Gaussian method* that finds edges by looking for zero crossings after filtering the image with a Laplacian of Gaussian filter, (3) The *Zero-cross method* that finds edges by looking for zero crossings after filtering the image with a filter specified by the operator, (4) The *Canny method* that finds edges by looking for local maxima of the gradient. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if these are connected to strong edges.

After numerous experiments, we decided to use the Canny technique which we found more robust than all of the others across a number of iris images.This method is therefore less likely to produce false edges.

3.2. Finding the Contour

The second step is to find the inner boundary, i.e. i.e the frontier between the iris and the pupil. For this, the centroid of the detected pupil is first found and taken as reference point (x_c, y_c). Knowing that the edges of the boundary are represented by binary ones, the top and bottom extreme points (i.e. (x_c, y_{min}), and (x_c, y_{max})) of the inner boundary are detected from this reference point by searching for the first one. Once these extreme points are detected, a similar search for the first one is made for all the points on the left $(x < x_c)$ as well as on the right $(x > x_c)$ of the reference point. Finally, all the boundary points are stored in one dimension vector.

4. FEATURE EXTRACTION

One of the most crucial stages for characterizing the iris is the representation of the contour by a function. This function can be any of the following:

1. The cross-section function (for symmetric figures)
2. The radius-vector function (for a star-shaped figures)
3. The supports function (mainly for convex figures)

Since the inner boundary of iris is not necessary symmetric and convex, so the radius vector was our preferred choice for finding the contour. This vector is explained below.

4.1. Radius-Vector Functions

The contour of a figure is described by the radius-vector function. So a reference point must be chosen inside the figure. The figure is then translated such that this point lies at the origin. The resulting figure must be a star-shaped with respect to the origin. This means that for every contour point, the whole line segment from the center to the point must be inside the figure. Note that if the star-shaped set is not satisfied because of small irregularities on the contour, the figure may be transformed to a star-shaped one through smoothing. The *radius-vector function* $r_X(\varphi)$ depends on the angle φ made by the line emanating from o with the x-axis. The function $r_X(\varphi)$ is equal to the length of the line segment from o to the contour point x in which the φ-ray intersects the boundary. This function characterizes the contour X precisely meaning that X can be uniquely reconstructed if we are given $r_X(\varphi)$.

The map $X \to r_X$ transforms figures into elements of a function space. If such figures can produce continuous radius-vector functions, then the Banach space C[0, 2π] is suitable. It is easy to calculate φ and $r_X(\varphi_i)$ for every point x_i in the contour X. So in general φ_i is not equidistant. The resulting data can be modified by interpolation to obtain equidistant interpolation nodes. Errors associated with this interpolation may be neglected if the raster is fine enough.

In our scheme, the contours of irises obtained by the radius vector method are made same size by upsampling and downsampling processes and thus the technique is made scale invariant. The 1-D data so obtained is called ”iris signature” and with all signatures of length 360.

Previous research has shown that contours are more robust to additive noise than other available functions mentioned above. Additionally, to standardize our analysis, the followed is implemented:

1. All iris signatures are rotated to start at the highest value of the radius. (rotation invariance)
2. This maximum value is normalized to 1. (scale invariance)
3. All iris signatures are shifted to the center of gravity of the iris contour (after finding the contour). (translation invariance)

5. IRIS PATTERN RECOGNITION

The iris signatures obtained are then used for classification. The objective here is to compare the iris-signature of an unknown iris, with one of the known iris-signatures stored in a certain database. The process consists of two phases: Training and Classification.

5.1. Fourier Descriptors (FD)

The problem that we need to solve now is that of: (i) representing each of the iris signatures from the database with a certain feature vector, (ii) then comparing a given unknown iris signature to the ones in the database.

Here, we propose to define the feature vector as the vector of Fourier Descriptors of the iris signature. Such feature vectors are then used as input to a statistical classifier. There are a number of versions for the Fourier Descriptors discussed in the literature, many of which depend on the problem of interest. In this work the following definition is used [3]:

$$R(k) = log(|\sum_{i=1}^{N} r(i)e^{-j2\pi\frac{ki}{N}}|) \quad (1)$$

where N is the length of the iris signature $r(i)$, and $k = 1, .., M$ where M is the length of the Fourier Descriptors vector. We adopted the above definition as modulus is a shift invariant expression. Because the coefficients may vary substantially, we used the log to reduce the range.

5.2. Feature Selection

The FD vector can be used in its row format as feature vector and hence can be used in conjunction with the statistical classifier. However, as we decided on a size of the FD, M, of a large size (M=512), we needed to develop a process whereby we are able to reduce the size of the feature vector. To make the proposed system simple and fast, we investigated the different techniques to reduce the size of the feature vector.

There are essentially three different ways for selecting d features from a set of M features:

5.2.1. First d Coefficients

This is the most direct technique for selecting features. It is based on the assumption that for most signals, the first few coefficients contain most energy contained in the signal. In particular, such coefficients represent the low frequency behavior of the signal being analyzed. However, such technique is expected to perform very poorly with iris contours as most irises have similar rounded shape (low frequency behavior), but the differences are more in the high frequency details.

5.2.2. Largest d Coefficients

This approach relies on the concept of compression using wavelets. The coefficients are selected based on a certain threshold. Such approach is known as shrinkage technique when wavelets coefficients are used. Rather than taking the magnitudes of the largest coefficients, one can only use the indices of such coefficients as feature vector.

5.2.3. Criterion-Based Search

Feature selection can be formulated as an optimization problem that consists of, given a set of M features, select a subset of size d that maximizes a certain cost function. In this work, we will use the performance of the classifier as criterion. There are numerous feature selection methods available in the literature. A well known algorithm is the Branch and Bound (BB) which is an optimal method for monotonic feature sets. However, the method exhibits a high computational cost. Another well established technique is the sequential floating search method (SFSM) [4]. The algorithm starts with a null feature set and, at each step, the best feature that satisfies a certain criterion is included with the current feature set. The SFSM can either proceed in increasing or decreasing order until the desired size d is reached.

In this work, we carried extensive experiments to examine the performance of the abovementioned feature selection techniques. Obviously, the computational cost of the SFSM is highest among all the techniques. However, as its performance was much higher than that of the other techniques, we decided to use the SFSM technique as a benchmark for the classification procedure discussed next. Using the database of iris signatures we collected, we carried extensive training to find the optimal FD coefficient indices from the signatures. We selected a size of $d = 40$ features as we found that performance stabilizes after this level.

5.3. Statistical Classifier

A statistical classifier using the feature vector consisting of the most important SFSM FD coefficients with $d = 40$ was selected. We implemented the ”minimum distance to iris i” strategy where a prototype FD vector is first formulated for each of the irises using 10 images for each of the irises [5]. Besides the low computational load and the simplicity of such classifier, the classifier was found to achieve good classification accuracy as discussed below.

6. INITIAL EXPERIMENTAL RESULTS

In our experiments, we collected 500 different irises (25 people, 2 eyes, 10 images for each eye) , using a high quality HP digital camera, from 50 individuals (left and right eye are considered separate). 7 from these 10 were used for training and the remaining 3 were used for testing.

The average classification accuracy achieved was 96.66%. 40% of these cases exhibited a 100% accuracy. When noise was added to the images used for testing at an SNR of 10 db, the average accuracy dropped to 90.06%, then to 86% at 2 db SNR. We noticed that for some irises that were heavily distorted, such as part of the iris being covered, the classifier was giving unsatisfactory results. Fortunately, there were only few cases that fell under this category.

In summary,we have shown, that a simple representation of the iris followed by a statistical classifier can achieve excellent recognition rates. The scheme presented here has the advantage if being computationally efficient and is robust to observation noise.

7. CONCLUSION

The visual appearance of an individual and in particular his/her iris is highly distinctive, therefore, it has promise as a basis for robust biometric assessment. We have shown that optimal feature selection together with Fourier descriptors and a simple statistical classifier operating on the contour irises can results in reliable iris identification systems. The proposed system is simple, has a low a computation complexity, and is robust to additive noise.

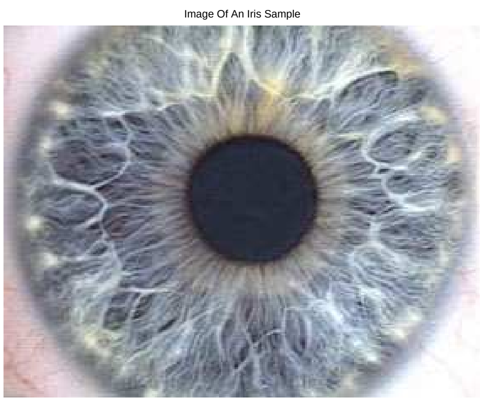

Fig. 1. Image of a sample iris

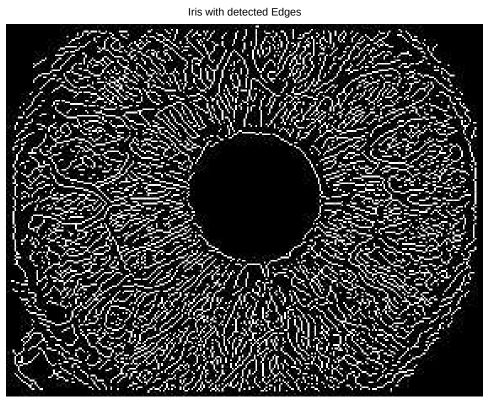

Fig. 2. Edges of the sample Iris

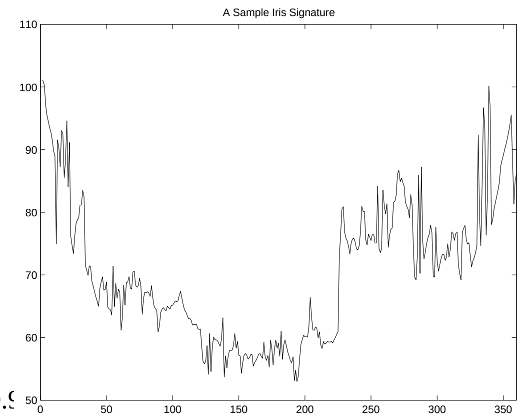

Fig. 3. A Sample of Iris Signature

8. REFERENCES

[1] A. K. Jain, R. Bolle, S. Pankanti, et al., “Biometrics: Personal identification in networked society,” *Kluwer Academic Publishers*, 1999.

[2] J. Dougman, “High Confidence visual recognition by test of statistical independence,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, pp. 1148–1161, 1993.

[3] C. Zahn, R. Roskies, “Fourier descriptors for plane closed curves,” *IEEE Trans. Comuters*, pp. 269–281, 21 1972.

[4] P. Pudil, J. Novovicova, J. Kittler, “Floating serch methods in feature selection,” *Pattern Recognition Letters*, pp. 1119–1125, 15 1994.

[5] R. Duda, P. Hart, “John Wiley,” *Pattern classification and scene analysis*, 1973.