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Artificial Neural Networks based Classification Technique for Iris Recognition

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ABSTRACT
Iris recognition is one of the challenging problems inhuman computer interaction. An automated iris recognition system requires an efficient method for classification of iris region in the face sequence, extraction of iris features, and construction of classification model. In recent years, Neural Networks (NN) has demonstrated excellent performance in a variety of classification problems. In this paper, we have used a simple 2dimensionaldiscrete wavelet transform (DWT) representation which captures the small differences in the image that is desired for the current applications. The DWT is used to generate feature images from individual wavelet sub bands. The results of our studies show that, the system gives about 90.00%recognition rate.

General Terms
Biometrics, Personal Identification System.

Keywords
Iris Recognition, Discrete wavelet transform, Classification model, Neural Networks, Pattern Recognition, Machine Learning.

1. INTRODUCTION
In the last century, the biometrics has started playing its important role when most of the conventional authentication mechanisms are failing to do better. Biometric recognition refers to the automatic recognition ofthe individuals based on physiological and behavioural characteristics. Biometrics made it possible to confirm an individual identity based on "who she is" rather than by "what she possesses".

Identification of a person becomes very important in many situations such as access to restricted areas, while going for credit cards, and every other situation to authenticate the uses in many of the places. Most of the existing methods have limited capabilities in recognizing relatively complex features in realistic practical situations. The objective of this correspondence is to present a new approach for recognizing humans from images of the iris of the eyes under practical conditions.

The iris has unique features and is complex enough to be used as a biometric signature [2]. Given the observed stability of iris morphology over human lifetime and estimated probability for the existence of two similar irises at 1 in 10^{72}[1], the use of iris biometric has been increasingly encouraged by both government and private entities. Iris was suggested as an optical finger print, possessing a highly detailed and unique texture which remains unchanged throughout life time.

It has several advantages over fingerprint and many other forms of authentication process. It can be accessed from some distance, protected from physical damage and surgical modification is difficult and risky. The involuntary contraction of the pupil in response to light can be used to test against artifice.

This paper describes an experimental implementation of a iris recognition system using artificial neutral network, precisely a feed forward neural network with back propagation learning (FF) and a learning vector quantization network (LVQ)techniques.

Artificial neural network (ANN) is a powerful tool for pattern classification problems. Researchers in iris recognition used neural networks for the purpose of developing a model, which operates directly on an image representation of iris. Since the introduction of the backpropagation algorithm, the multilayer feed forward neural network (MLFFNN) classifiers have become popular. These classifiers do not assume any distribution for the probability density functions and hence hey give better recognition performance than conventional classifiers. The advantage of neural networks for iris recognition is the feasibility of training a system to capture the complex class conditional density of the iris patterns.

The paper is organized as follows: In section 2, we describe the iris data base used in the study and its representation. In section 3, we describe the ANN based approach for iris recognition. In section 4, we present our studies on recognition of iris. Final section gives the conclusions from this study.

2. IMAGE DATABASE
There are presently many public and freely available iris image databases for biometric purposes: Two databases of eye photographs were used. First the UBIRIS [12] database were captured under natural lighting and heterogeneous imaging conditions, which comprises of 10 photographs of each eye. Sample images are shown below in Fig. 1. Second the University of Bath database with 20 photographs of each eye, the images incorporate few of noise, almost exclusively related with eyelid and eyelash obstruction.

After excluding all eyes where one or more pictures were not segmented correctly, 53 eyes from UBRIS and 48 eyes from Bath were left for the experiment. Prior to any processing, pictures from both databases were downscaled to 400*300 pixels and converted to gray scale.

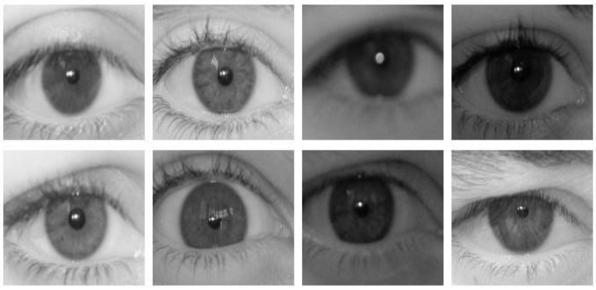

Fig 1: Sample Images of UBIRIS database

3. A CLASSIFICATION SYSTEM FOR RECOGNITION OF IRISUSINGWAVELETS AND ANN

We implemented the recognition method described by Daugman[6] and compared the obtained results when following the method as described by the author and using the proposed iris division and classification strategies.

3.1 Segmentation

Segmentation is the first step in iris recognition which finds the location of an iris in a given image. The method followed in this paper is based on Daugman(1993)[4]. Proencaet. al.(2005)[12] assumes the pupil and iris to have a circular shape and applies the following integro-differential operator to find both the inner and outer iris borders, given by

$$max_{(r,x_o,y_o)} \left| G_\sigma(r) * \frac{\delta}{\delta r} \oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r} ds \right| \quad (1)$$

The operator above searches over the image domain(x,y) for the maximum in the blurred partial derivative with respect to increasing radius r, of the normalized contour integral of I(x,y) along a circular arc ds of radius and center coordinates(x0,y0).

This algorithm usually searches the whole range of the image. This paper estimates the center of the pupil and iris and searched only a small range around the estimated center for the actual center, to decrease processing time. The center estimation required all intensity values above a certain threshold to maximum, thus roughly isolating the pupil, which is usually dark. Consequently a Gaussian blur was applied to eliminate noise, and the intensity minimum of the resulting image was taken as the estimated pupil and iris center.

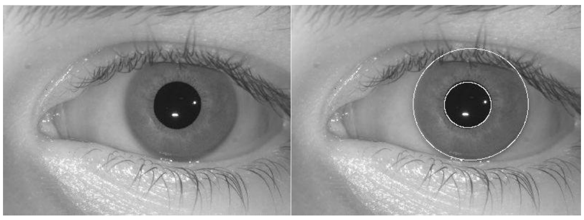

Fig 2: Image of an eye from the University of Bath image database. The center of the iris is estimated by thresholding and blurring the image to find the darkest part (the pupil). The area around the presumed center is than scanned using a circular edge detector.

3.2 Preprocessing

The size of an iris may vary due to the distance from the camera. It also expands in response to light. Normalization of image to a fixed size to correct for the varying size of one individual iris and to compare differently sized irises from different people is necessary.

This paper followed Ma et al. (2003)[10] and projected the iris from a Cartesian coordinate system into a doubly dimensionless pseudo polar coordinate system; a process that also corrects for the fact that the pupil might not be centered in the exact center of the iris. This can be thought of as un-wrapping the iris and is denoted as:

$$I_n(X\,Y) = I_0(x,y) \quad (2)$$

$$x = x_p(\theta) + \left\{\left(x_i(\theta) - x_p(\theta)\right)\right\}\frac{Y}{M} \quad (3)$$

$$y = y_p(\theta) + \left\{\left(y_i(\theta) - y_p(\theta)\right)\right\}\frac{Y}{M} \quad (4)$$

$$\theta = {2\pi X}/{N} \quad (5)$$

In is a M x N (60x450) normalized image, (xp(θ),yp(θ)) and(xi(θ),yi(θ)) are the coordinates of the inner and outer boundary points in the direction θ in the original image Io. Subsequently background illumination is removed from the normalized image (see fig. 3). To that end, the average intensity for 15x15 pixel tiles are calculated.

The array of mean intensity is rescaled to the size of the original image using bi-cubic interpolation and then subtracted from the original image to correct for variation in lighting conditions. The contrast in the image is enhanced using the built-in Matlab function histeq, and intensity values are rescaled to zero-mean and values in the range [1+1].Two methods were used to remove the effect of noise from eyelid occlusion in the angular exclusion condition, a section of 30° around the top and the bottom of the iris was excluded, when normalizing the image. In the radial exclusion condition, a ring, around the outside of the iris was excluded. The diameter of the ring is 20 pixels in the normalized image, which corresponds to one third of the radius in the original image

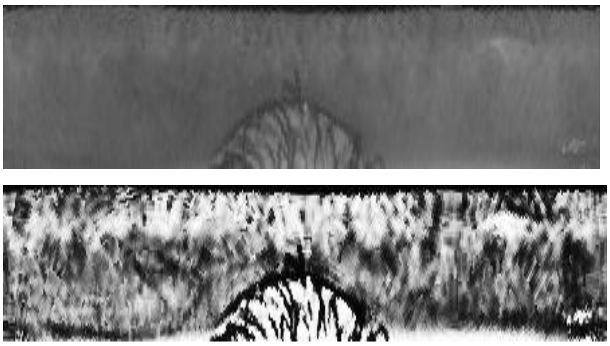

Fig. 3: Image of an Iris normalizes to a polar coordinate system. In the lower background illumination is removed and contrast enhanced

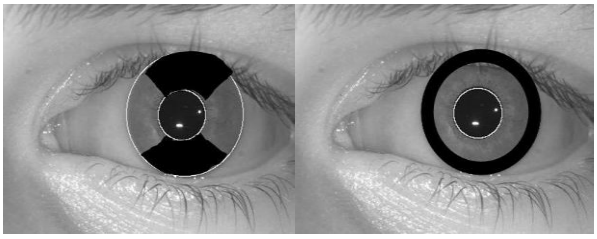

Fig. 4: Schematic representation of the parts of the iris to be excluded (in black). Left: angular exclusion of a 30° section around the top and bottom ofthe iris. Right: exclusion of a ring around the outside of the iris.

3.3 Feature Extraction

The wavelet transform has been used for feature extraction in several iris recognition systems. This paper follows the idea of Lim et al., (2003) [9], which uses the fourth-level high frequency information of a 2D Haar wavelet decomposition of an iris image. The detail sub-image from the fourth transformation was used. This means starting from the normalized and enhanced 450x60 iris image, the fourth sub-image has a dimension of 29x4. These values and the average values of the three remaining high-pass filter areas are used to create a 119 element feature vector. Wavelet decomposition was accomplished using the function wavedec2 from the Matlab Wavelet Toolbox.

3.4 Classification

Neural networks were used to classify iris images. In particular a feed forward neural network with back propagation learning (FF) and a learning vector quantization network (LVQ) were used. The feed forward neural network was set up with input layer, one hidden layer and output layer. The output layer had 48 units for images from the Bathdatabase and 53 units for images from the UBIRIS database, that is, the same number of units as classes. The hidden layer had either the same number of units as the output units, or 100units, which is in both cases roughly twice the number of output units. The input layer, naturally, had 119 units.

The feed forward neural network used a log-sigmoid transfer function and was trained using gradient descent backpropagation with momentum and adaptive learning rate (traind gx in the Matlab Neural Networks Toolbox). The initial learning rate was 0.1. When simulating the network, the output unit with the highest activation was selected as winner, and determined the classification of the input. The learning vector quantization network was set up with 200 competitive neurons and a learning rate of 0.2. Training lasted 100 epochs. The standard Matlab learning function learnlv1 was used for training.

4. EXPERIMENTAL RESULTS

To enable the effective test of the proposed classification strategy, we analyzed the available iris data bases and selected the most appropriate for our purposes. We have used the database described in section 2, which are available public iris image databases and the data sets used in our experiments.

FF and LVQ were tested for classification of images from the Bath and the UBIRIS data bases. The correct segmented iris images were used for these experiments. Therefore 48 eyes, with 20 images each were available from the Bath database and 53 eyes, with 10 images each were available from the UBIRIS database. The setup of the system in which every image was assigned a category, resulted only one kind of error, which is misclassification. The performance might be slightly varied every time the network is initialized different as weight initialization and training are random processes every time the network is initialized. Therefore always 10networks with the same parameters were initialized and trained and the average performance is given. Comparison is made between use of the complete normalized iris image as input, or a truncated version. This state is either an angular exclusion around the top and the bottom of the iris or a radial exclusion of the outer parts of the iris.

Furthermore the effect of training set size is assessed. In case of the Bath image database either 10 or 5 images per class were used for testing. In case of the UBIRIS database either 6or 4 images were used for training. Results in the form of Percent Correct Classification, depending on the size of training set and selection of iris image used in feature extraction, have been summarized in the tables 1-4:

Table 1.Feed forward network with 100 hidden units and images from the Bath database

FF, BATH	**Size of training set**	
Input Image	10	5
Complete	90.0%	84.9 %
Angular Exclusion	83.7 %	79.4 %
Radial Exclusion	89.3 %	86.7 %

Table 2.Feed forward network with 100 hidden units and images from the UBIRIS database

FF, UBIRIS	**Size of training set**	
Input Image	6	4
Complete	84.7 %	73.1 %
Angular Exclusion	82.3 %	72.8 %
Radial Exclusion	81.3 %	70.3 %

Table 3.LVQ network with 200 hidden units, 100 epochs of training and images from the Bath database

LVQ, BATH	**Size of training set**	
Input Image	10	5
Complete	93.3 %	88.5 %
Angular Exclusion	92.7 %	88.5 %
Radial Exclusion	94.1 %	93.9 %

Table 4.LVQ network with 200 hidden units, 100 epochs of training and images from the UBIRIS database

FF, BATH	**Size of training set**	
Input Image	6	4
Complete	93.3 %	88.5 %
Angular Exclusion	92.7 %	88.5 %
Radial Exclusion	94.1 %	93.9 %

5. CONCLUSION AND SUMMARY

Even though the same method was used for feature extraction and similar method was used for classification, the classification rate obtained was not as high that of Lim et al.(2003) [9]. The reason for that is the larger size of their training set spanning 15 images. From the results thus discussed in this work we can thus conclude that the size of the training set has a major impact on the classification results.

Comparing the two databases, one finds that recognition rates are higher for images from the Bath database. This is also the case if the size of the training set is comparable. Therefore it is likely that the effect is due to the quality of the images. While UBIRIS contains noisy images, where the iris might be occluded by eye lids or reflections, the images in the Bath base are all of high quality and very similar.

Comparing the classification algorithms; the LVQ network scores better than the FF network, when classifying images of the Bath database and the UBIRIS database, however only in the case when only 4 inputs were used for training. When the training set was slightly larger, i.e. 6 inputs, the FF network performed better in classifying UBIRIS images.

Summarizing, it can be said that a working iris recognition system has been established, which is capable of segmenting an iris in a photograph of an eye and classify it using neural networks. The various parameters affecting the system have been studied. The recognition rates are still low for practical applications and needs to be improved in future.

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