A New Iris Recognition Method based on Neural Networks

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Abstract: This paper presents a novel approach of iris recognition based on feedforward neural networks. The features used in this approach are based on the contour of the iris-pupil boundary obtained from radius vector functions and is named "iris signature". The proposed technique used is translation, rotation, and scale invariant. The classification is performed using two different neural network structures, the *Multilayer Feedforward Neural Network (MFNN)* and the *Radial Basis Function Neural Network (RBFNN)*. These feedforward neural networks have not been applied before on iris signatures. Since iris signature is 1D, it simplifies the structure of neural networks. Hence the proposed method has lesser complexity than the existing neural networks based techniques. The results obtained from a small size data base are very promising.

Keywords: MFNN, RBFNN, Iris, Radius Vector Functions,Iris Signature

Introduction

In 1987, the concept of automated iris recognition was proposed by Flom and Safir [1]. It does not appear, however, that this team ever developed and tested a working system. Early work toward actually realizing a system for automated iris recognition was carried out at Los Alamos National Laboratories, CA [2]. Subsequently, two research groups developed and documented prototype iris recognition systems; one by Daugman [3, 4], and the other by Wildes et al. [5, 6, 7]. The algorithms developed by Daugman in [3] are currently being used by many commercial and public entities including British Telecom, US SandiaLabs, UK National Physical Laboratory, NCR, Oki, IriScan, Iridian, Sensar, and Sarnoff. All these reported a false match rate near 0 in all their tests, some of which involved millions of different iris pairings [8]. In this algorithm, the recognition principle is the failure of a test of statistical dependence on iris phase structure encoded by multi-scale quadrature wavelets. Wildes et al. [6] in his algorithm exploit a user interface that operators should find easier and less annoying to use. In this approach iris is illuminated using a diffuse light source coupled with polarization optics. The algorithm localizes the iris in an image using a histogram based model fitting approach. The method for representing and matching a given iris image involves registering a captured image to a stored model, filtering with isotropic bandpass filters and subsequent correlation matching. Recently, we have also witnessed many new algorithms including the algorithm by Boles & all [9] which decomposes the iris contour using the wavelet transforms, and by Sanchez-Reillo et al. [10], where Gabor filters are used. The algorithm developed by D. de Martin-Roche et al is based on dyadic wavelet transform zero-crossing [11].

Over past few years there has been considerable interest in the development of neural network based pattern recognition systems because of their ability to classify nonlinear data. H. Shah-Hosseini and R. Safabakhsh proposed a class of neural network which is named Time Adaptive Self Organizing MAP (TASOM) [12], that can automatically adjust learning rate and neighborhood size of each neuron. They have tested their algorithm with some standard data sets including the iris plant, breast cancer, and BUPA liver disease data. This method however has not been applied for iris recognition. In [13], El-Bakry proposed a fast cooperative modular neural network based iris recognition system. The method was applied earlier to detection of human faces in cluttered scenes [14]. Another neural networks based iris recognition was developed by Onsy Abdel Alim, and Maha Sharkas [15]. They proposed two feature extraction techniques based on the 2D Gabor wavelets, and the 2D DCT. They used multi-layer perceptron (MLP) NN with back-propagation which consists of 1 hidden layer and 3 output neurons to identify 3 different persons. The achieved recognition rate using the DCT coefficients was about 96 % compared to 92 % obtained using the Gabor coefficients. In [16], an iris recognition system based on self-organizing MAP neural network was proposed which reached to 83 % overall accuracy. Another proposed system in [17] uses multilayer perceptron (MLP) NN as a flexible classifier with modified Co-Occurrence Matrix derived features (COM).

In this work, a novel technique is proposed for representing the iris using only its inner boundary (iris signature). The classification is performed using both the MFNN and the RBFNN. These feedforward neural networks have not been applied before on iris signatures.

This paper is organized as follows: Section 1 gives a motivation for using Neural Networks for iris recognition. Overview of the Proposed method is presented in section 2. Feature extraction and iris pattern recognition are given in sections 3 and 4, respectively .In section 5, simulation results are presented. Finally concluding remarks are given in section 6.

1 Why Neural Networks?

An artificial neural network (ANN) is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. ANNs have been applied to an increasing number of real-world problems of considerable complexity. Their most important advantage is in solving problems that are too complex for conventional technologies. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. Other advantages include:

- Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
- Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
- Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
- Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

2 Overview of the Proposed Method

In this work, the technique used for extracting the iris features is translation, rotation, and scale invariant. The main steps of the algorithm are:

Feature Extraction

1. The process starts by locating the outer and inner boundaries of the iris.
2. The second step is to find the contour of the inner boundary i.e., the iris-pupil boundary.
3. Finally the iris is represented by "Radius Vector Functions" and is named "Iris Signature".

Classification

Two neural networks techniques have been implemented

1. Classification using a Multilayer Feedforward Neural Network (MFNN).
2. Classification using a Radial Basis Function Neural Network (RBFNN).

Figure 1 illustrates the the main steps of our method.

3 Feature Extraction

3.1 Localizing the Iris

The first step locates the iris outer boundary, i.e. border between the iris and the sclera. This is done by performing edge detection on the gray scale iris image.In this work, the edges of the irises are detected using the "Canny method" which finds edges by finding local maxima of the gradient. The gradient is calculated using the derivative of a Gaussian filter.

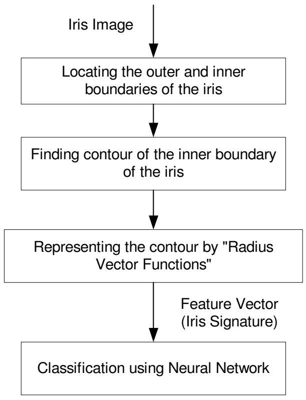

Figure 1: Proposed Approach

The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is robust to additive noise, and able to detect ”true” weak edges. Figures 2, and 3 are the original and edge images, respectively.

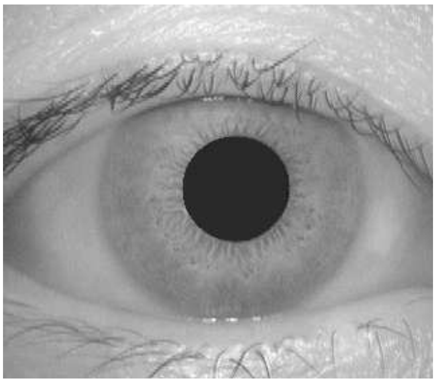

Figure 2: Image of a sample iris [18]

3.2 Finding the Contour

Next we need to find the inner boundary of the iris, i.e the frontier between the iris and the pupil. For this, the centroid of the detected pupil is chosen as the reference point (x_c, y_c). Given that the edges 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 first from this reference point. The other points are found by searching for the first ”one” in all directions. Once all points on the inner contour are detected, the edge point on the inner boundary with maximum distance from the centroid is taken as reference. The radius vector method is then used to represent the iris contour.Upsampling

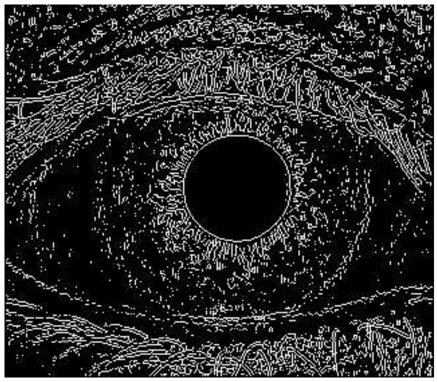

Figure 3: Edges of the sample Iris

and downsampling processes are used to normalize the length of the obtained contour. Finally, the 1-D feature vector obtained is named ”iris signature”. A sample of iris signature is shown in Figure 4

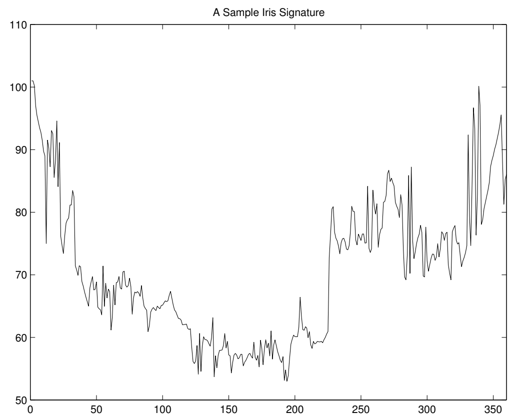

Figure 4: A Sample of Iris Signature

4 Iris Pattern Recognition

The extracted iris signatures obtained above are used for classification. For this purpose, both the MFNN and the RBFNN are used. The results are discussed below.

5 Experiment Results

For our experiments we used 10 different iris images obtained by Daugman’s Website [19] .

5.1 Results using the MFNN

We used MFNN consisting of single hidden layer with 30 neurons and an output layer with 10 neurons. The backpropagation algorithm is used to update the weights. For training of NN, noisy iris samples are generated by adding Gaussian noise at 10 dB and 20 dB SNRs. Training is performed on 70% of these noisy iris samples. Then testing is carried on the remaining data at different SNRs. The SNR represents the quality of the acquired image which may be corrupted with effects due to environment, quantization or digitization of the image. Tables 1 and 2 represent the classification results for different classes at 10 dB and 30 dB SNRs, respectively. In tables, "T_r" and "I_d" stands for true and identified classes, respectively. Noticed that an 11th class is displayed in the tables. This class represents the case when a given iris is not assigned to any of the 10 class. Recognition percentage increases by increasing SNR from 10 dB to 30 dB.

5.2 Results using the RBFNN

Using the same set up as above, the RBFNN was then used for classification. A network with 10 centers was designed and found optimal for our problem. Having the same nonlinear approximation capability as the MFNN, similar results were obtained at different SNRs. The distinguishing feature of the RBFNN is obviously its lower computational complexity and hence the efficiency in time compared to the MFNN. The simulation time is found at least half than that of the MFNN. The simplicity of the architecture is also notable with just one layer and 10 neurons. Classification behavior of RBFNN is shown in Table 3. The average classification obtained by by both the networks was 97 %. This accuracy increases to about 99 % at 30 dB SNR or more.

Table 1: Percentage Recognition for MFNN with 10 dB SNR.

	I_{d_1}	I_{d_2}	I_{d_3}	I_{d_4}	I_{d_5}	I_{d_6}	I_{d_7}	I_{d_8}	I_{d_9}	$I_{d_{10}}$	$I_{d_{11}}$
T_{r_1}	97	0	0	0	0	0	0	0	0	0	3
T_{r_2}	0	96	0	0	0	0	0	0	0	0	4
T_{r_3}	0	0	98	0	0	0	0	0	0	0	2
T_{r_4}	0	0	0	96	0	0	0	0	0	0	4
T_{r_5}	0	0	0	0	95	0	0	0	0	0	5
T_{r_6}	0	0	0	0	0	97	0	0	0	0	3
T_{r_7}	0	0	0	0	0	0	98	0	0	0	2
T_{r_8}	0	0	0	0	0	0	0	97	0	0	3
T_{r_9}	0	0	0	0	0	0	0	0	97	0	3
$T_{r_{10}}$	0	0	0	0	0	0	0	0	0	99	1

Table 2: Percentage Recognition for MFNN with 30 dB SNR.

	I_{d_1}	I_{d_2}	I_{d_3}	I_{d_4}	I_{d_5}	I_{d_6}	I_{d_7}	I_{d_8}	I_{d_9}	$I_{d_{10}}$	$I_{d_{11}}$
T_{r_1}	98	0	0	0	0	0	0	0	0	0	2
T_{r_2}	0	99	0	0	0	0	0	0	0	0	1
T_{r_3}	0	0	99	0	0	0	0	0	0	0	1
T_{r_4}	0	0	0	100	0	0	0	0	0	0	0
T_{r_5}	0	0	0	0	99	0	0	0	0	0	1
T_{r_6}	0	0	0	0	0	98	0	0	0	0	2
T_{r_7}	0	0	0	0	0	0	97	0	0	0	3
T_{r_8}	0	0	0	0	0	0	0	98	0	0	2
T_{r_9}	0	0	0	0	0	0	0	0	99	0	1
$T_{r_{10}}$	0	0	0	0	0	0	0	0	0	100	0

Table 3: Percentage Recognition for RBFNN with 10 dB SNR.

	I_{d_1}	I_{d_2}	I_{d_3}	I_{d_4}	I_{d_5}	I_{d_6}	I_{d_7}	I_{d_8}	I_{d_9}	$I_{d_{10}}$	$I_{d_{11}}$
T_{r_1}	95	0	0	0	0	0	0	0	0	0	5
T_{r_2}	0	95	0	0	0	0	0	0	0	0	5
T_{r_3}	0	0	98	0	0	0	0	0	0	0	2
T_{r_4}	0	0	0	97	0	0	0	0	0	0	3
T_{r_5}	0	0	0	0	96	0	0	0	0	0	4
T_{r_6}	0	0	0	0	0	97	0	0	0	0	3
T_{r_7}	0	0	0	0	0	0	98	0	0	0	2
T_{r_8}	0	0	0	0	0	0	0	96	0	0	4
T_{r_9}	0	0	0	0	0	0	0	0	97	0	3
$T_{r_{10}}$	0	0	0	0	0	0	0	0	0	98	2

6 Discussions and Conclusions

In this paper, the problem of iris recognition is discussed in details. A novel technique is proposed for representing the iris using only its inner boundary (iris signature). The classification is performed using both the MFNN and the RBFNN. Since iris signature is 1D, it simplifies the structure of neural networks and thus, the proposed method has lesser complexity than the existing neural networks based techniques. The MFNN and RBFNN gave similar recognition rates, whereas the RBFNN is preferred in terms of computation load. Our results are currently being expanded to larger databases such as the Chinese Iris Database.

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