Pair of Iris Recognition for Personal Identification Using Artificial Neural Networks

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Abstract

Pair of iris recognition is very effective for person identification due to the iris unique features and the protection of the iris from the environment and aging. In addition it is well suitable to embark upon accidental or ophthalmological disease issue. This paper presents a simple methodology for pre-processing pair of iris images which means both left and right eye of human(instead of either right or left eye) and the design and training of feedforward artificial neural network for iris recognition system. Three different iris image data partitioning techniques and two data coding are proposed and explored. We also experiment with various number of hidden layers, number of neurons in each hidden layer, input format (binary vs. analog) percent of data used for training vs testing, and with the addition of noise. Our recognition system achieves high accuracy despite using simple data preprocessing and a simple neural network.

Keywords:

Pair of iris recognition, feedforward neural networks, Backpropagation training algorithm, Pre-processing, data partitioning.

1. Introduction

Biometric measures [1] such as recognizing one's fingerprints, face, iris and voice greatly help in person identification authentication, and authorization. Pair of iris recognition has the high potential and noninvasive personal verification. This is because each person's iris is unique even for twins and hardly changes while other biometric measures are quite intrusive to the operator and offer little possibility of covert evaluation. In fact, the eyelid, cornea and aqueous humor protect the iris. Furthermore, the iris is relatively immune to aging, and the wearing of contact lenses or glasses. In addition to that pair of iris recognition system well suitable to embark upon accidental and ophthalmological issue. Therefore, pair of iris recognition is a biometric technique which can be trusted for producing accurate and correct results. As irises differ in size, shape, color and patterns, they offer high confidence for recognizing a person's identity by mathematical analysis. Typically, iris recognition software based on advanced mathematical techniques such as wavelets and real-time hardware with high resolution camera(s) is employed. In this work we take a different approach aiming at simplifying the iris recognition system with high accuracy.

Our approach is characterized by (i) the use of artificial neural networks and (ii) simple mathematical analysis and pre-processing the pair of iris. The paper presents a methodology for pre-processing iris images and getting them ready for artificial neural network processing. The paper also presents the design and training of an artificial neural network for recognizing several pair of iris.

2. Related and Background Work

2.1 Iris Recognition

The iris patterns have a wonderful and rich structure and are full of complex textures in contrast to other physiological characteristics. The iris is the colored circular part of the eye between the pupil and sclera. When security is highly desired, iris recognition is a preferred method of identification because the iris patterns are hardly affected by the environment and can hardly be lost. The iris texture is unique from one person to another. Some of the iris features include furrows, ridges, arching ligaments, zigzag collarets, and crypts.

We next review relevant background work, Daugman [2] used 2D Gabor filters and phase coding to generate a 2048 binary feature code for the iris. Wildes [3] used the Hough transform to locate the iris and a Laplacian pyramid with four resolution levels to generate the iris code. Boles and Boashash [4] built a 1D representation of the grey level signature of the iris and applied to it zero-crossing of the dyadic wavelet transform to generate the iris representation. Wang and Tan [5] used a bank of Gabor filters to capture the iris profile. Based on a 2D Haar wavelet, extracted high frequency information to generate an 87 binary code and employed an LVQ neural network for classification. Zhang and ma [6] employed an intersecting cortical model (ICM) neural network to generate the iris codes and the Hamming distance between the compared iris codes. This ICM neural network is a simplified model of pulse – coupled neural network (PCNN), which has excellent performance for image segmentation, so the coding process is fast enough.

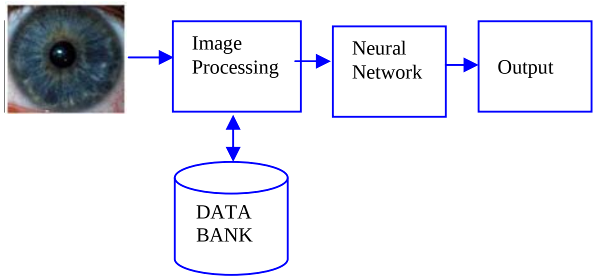


Fig. 1. Block Diagram of iris recognition.

2.2 Other Biometric Techniques

A biometric system is essentially a pattern recognition system that operates by acquiring physiological and / or behavioral characteristic data from a person, extracting some features from the acquired data, and comparing these features against a recorded feature set in the database [8] for the purpose of determining or confirming the person's identity. Biometric applications include computer systems security, secure electronic banking, mobile phones, credit cards, secure access to buildings, health and social services. By using biometrics a person could be identified based on her / his Physiological and / or identity rather than her / his possession (card, token, key) or her / his knowledge (e.g. password, PIN).

Desirable characteristics of a biometric recognition system include (i) universality: The feature should apply to every person or special alternative tests should be administered to those who do not apply, e.g. blind or person without fingerprints (ii) uniqueness: the system should extract and compare a feature unique to each person (iii) longevity: the feature should not vary with time, (iv) collectability: the feature must be easily collectible (v)accuracy: the system should deliver accurate recognition, and (vi) tampering: the technique should be hard to tamper.

2.3 Artificial Neural Networks

Artificial neural networks model biological neural networks in the brain and have proven their effectiveness in a number of applications such as classification and categorization, prediction, pattern recognition and control. An artificial neural network consists of interconnected groups of artificial neurons. Such a network performs computation and manipulates information based on the connectionist approach in a similar but simpler fashion than the brain would perform. Many types of artificial neural networks [7] exist including feed forward neural networks, radial basis function (RBF) networks, Kohonen self-organizing networks, recurrent networks, stochastic neural networks, modular neural networks, dynamic neural networks, cascading neural networks, and fuzzy neuro networks. Multi-layer perception [8] (MLP) is perhaps the most popular, where neurons in a feedforward type network perform a biased weighted averaging of their inputs and this sum is then subjected to a transfer function, in order to limit the output value. The MLP is an example of feedforward artificial neural network with multiple layers and where each neuron output in one layer feeds as input to the neurons in the next layer as shown in fig. (2).

We chose our artificial neural network for iris recognition of the feedforward type due to its simplicity and its suitability for this application.

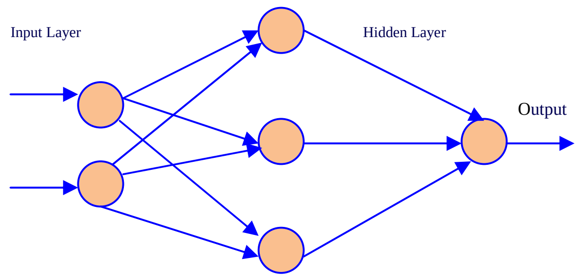


Fig. 2. MLP neural network

We also employ the back propagation algorithm for supervised training of our network, a well known and widely used algorithm. The training algorithm minimizes the error between the obtained output and the required target output by finding the lowest point or minimum in the Error surface. Starting with initial weights and thresholds, the training algorithms look for the global minimum of the error surface. Usually, the slope of the error surface, at the present location and guides the next move down.

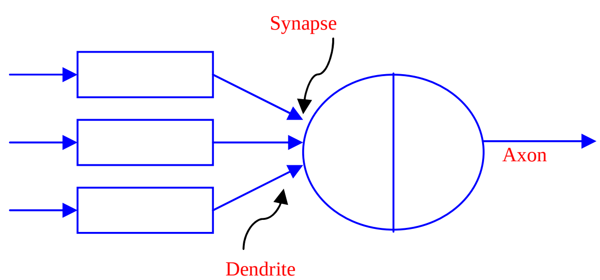


Fig. 3. Artificial neuron model

An artificial neuron models a real neuron as depicted in fig.(3). First, electric signals from other neurons are multiplied by weights (represented by the rectangles in fig.(2) and then are input into the artificial neuron. The weighted signal values are them summed by an adder ("Σ" in fig.2) and the sum is subjected to a transfer function ("T" in fig.2) which is one of : (i) linear, where the output is proportional to the weighted sum of inputs; (ii) threshold, where the output is one of two values based on whether the weighted sum is greater or smaller than the threshold value; and (iii) sigmoid, a non – linear function which most closely mimics real neurons. Artificial neural networks are composed of several artificial neurons as a real neuron network is composed of many real neurons. Artificial neural networks come in different forms and shapes.

3. Proposed Work

3.1 Preprocessing

To implement the pair of iris recognition system we gathered pair of iris images for training and testing the neural network, we decided to select iris images of the same color (brown) in order to create more difficult situations for our recognition system to detect and achieve higher recognition accuracy. Up close, the irises that have been collected are different in their patterns and shapes although from a further distance, the irises images look similar to each other. We collected and pre-processed 20 brown colored pair of iris images of different persons(both left and right) from the iris database (Chek image database). The iris images were between 400 KB and 500 KB and were not ready for processing but had to be pre-processed. For instance the white Sclera and black pupil are visible in all the images. Additionally, the relevant content of the binary iris image was not ready to be fed to an artificial neural network for processing.

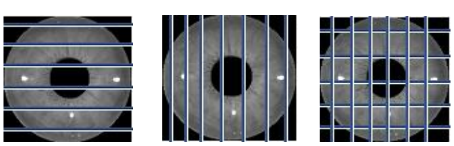
In our work we manually manipulated the images as our focus was on the design of artificial neural network by using Adobe Photoshop, Java program(Lin,xxx) and Excel spread sheet to retrieve the required iris images with the exclude of sclera and pupil.The DAT file as input to Brain Maker simulator obtained from Netmaker application.

3.2. Iris Image Data Partitioning

As it is desired to reduce the cost of the artificial neural network, and as Brain maker limits the number of neurons per layer, the iris image's RGB matrix had to be partitioned to reduce as much possible the number of values fed as input to the neural network. For that purpose, we considered three simple date partitioning techniques pictured in fig.4.

1. Horizontal strip partitioning (rows)
2. Vertical strip partitioning (columns)
3. Block partitioning.

In horizontal strip (row) partitioning we divided the RGB matrix into r=(10, 25) horizontal strips and summed all the RGB values of all pixels falling in one horizontal strip, when r was set to 10 or 25, and as the image contains 100 x 100 pixels, each horizontal strip, contained the RGB values of 100/10(25)= 10 (4) rows of 100 pixels each, and a 1000 (400) RGB values were summed into one number representing that horizontal strip.



Rows Columns Blocks

Fig. 4. Data partitioning techniques: horizontal (left), vertical (middle), block (right).

Similarly, in vertical strip (column) partitioning, we divided the RGB matrix into c = (10, 25) vertical strips and summed all the RGB values of all pixels falling in one vertical strip. When C was set to 10 (25), and as the image contains 100 x 100 pixels, each vertical strip contained the RGB values of 100 / 10 (25) = 10 (4) columns of 100 pixels each, and 1000 (400) RGB values were summed into one number representing that vertical strip. In block partitioning, the image was divided into b = (16, 25) square blocks. When b was set to 16 (25), and as the image contains 100 x 100 pixels, each block consists of 25 x 25 (20 x 20) pixels whose RGB values were summed into one number per block.

Each horizontal / vertical strip or block was thus represented by one number which was fed as one input into the artificial neural network for identifying a match / no match of the presented iris image. Our data partitioning techniques are characterized by simplicity and fast processing, compared to more complicated techniques based on wavelets, and are key to reduce the system cost.

4. Performance Issues

As the NetMaker accepts DAT files as inputs, these DAT, files containing the sums of RGB values in the various strips and blocks previously discussed were prepared for that purpose. Neural network training and testing experiments were conducted for two different data encodings: binary and analog. In binary coding, each sum is converted into 6 bits for both horizontal and vertical strip partitioning and 4 bits for block partitioning. These numbers are governed by the maximum number of neurons per layer (=64) acceptable by the BrainMaker Simulator.

Table 1: Experiments results with 10 horizontal or vertical strips, or 16 blocks.

Experiment description	Incorrect detection	Accuracy (%)
(Rows) Analog input: with one hidden layer (10 neurons)	5/15	66.67
(Columns) Analog input: with one hidden layer (10 neurons)	5/15	66.67
(Blocks) Analog input: with one hidden layer (10 neurons)	2/15	86.67
(Blocks) Analog input: with one hidden layer (50 neurons)	1/15	93.34
(Blocks) Analog input: with one hidden layer (10 neurons each)	2/15	86.67
(Blocks) Analog input: with one hidden layer (5 and 10 neurons)	2/15	86.67
(Rows) Binary input: with one hidden layer (50 neurons) and without noise	10/15	33.33
(Columns) Binary input: with one hidden layer (50 neurons)	10/15	33.33
(Blocks) Analog input: with one hidden layer (64 neurons)	10/15	33.33

Table 2: Experiments results with 10 horizontal or vertical strips, or 16 blocks.

Experiment description	Incorrect detection	Accuracy (%)
(Rows) Analog input: with one hidden layer (25 neurons)	6/15	60
(Columns) Analog input: with one hidden layer (25 neurons)	6/15	60
(Blocks) Analog input: with one hidden layer (25 neurons)	4/15	73.33
(Blocks) Analog input: with one hidden layer (25 neurons)	6/15	60
(Blocks) Analog input: with one hidden layer (25 neurons each)	7/15	53.33
(Blocks) Analog input: with one hidden layer (25 and 50 neurons)	7/15	53.33

The best accuracy (93.34%) was obtained with 10 block partitioning with 10 neurons in the input layer and 50 neurons in the hidden layer and 1 hidden layer only. When the number of neurons in the hidden layer was reduced to 10 neurons to match the number of neurons in the input layer, the accuracy dropped to 86.66%. This accuracy result was obtained with 1 or 2 hidden layer of 10 neurons each, or with the first hidden layer containing 5 neurons and the second hidden layer containing 10 neurons. Also increasing the number of hidden layers from 1 to 2 reduced the accuracy. Another advantage of our approach is that our neural network directly issues a match or no match output while in other's work, a neural network computer an iris code which must later be subjected to a Hamming distance computation to indicate a match.

5. Conclusion

Pair of iris recognition is an efficient biometric method for personal identification and verification, which provides more security due to iris unique and plentiful complex structure by its nature. In this paper we addressed the problem pair of iris recognition using a simple feedforward artificial neural network trained with the backpropagation algorithm. We described a pre-processing method to prepare the neural network inputs from the pair of iris images. Our approach uses simple RGB value summing in each partition and a simple MLP feed-forward neural network and issues a match/no match result without having to subject iris codes to Hamming distances. In this paper block partitioning results high performance and accuracy of 93.34% was obtained than the other two partitioning methods. All these features lead to high performance of the biometric system to provide high security. In future, the implementation system cost can be reduced by using single neural network and to support various colors of iris patterns.

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