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Iris Recognition using GLCM and Wavelet Moments with Neural Network Classifier

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Abstract –**The recognition of the iris is one of the most booming biometric modalities in recent years, due to its unique character as a biometric and biological feature, which makes identification and verification systems based in iris are one of the most accurate and very difficult to impersonate.**

We present a modular neuronal network architecture for a system of recognition of people through the biometric measurement of the human iris. In this system, a database of the human iris is processed by means of image processing methods. The coordinates of the center and radius of the iris were obtained for then perform a cut of the area of interest eliminating the noise around the iris. The inputs to the modular neural network architecture were the processed iris images and the exit is the number of the person identified. The integration of the modules was done with the integrator of the gate network type. This paper proposes the hybridization of features like GLCM and wavelet moments for training to neural network (NN). Calculated accuracy of hybrid based approach claims 97.1% with 60:40 ratio of training and testing respectively.

Keywords –**GLCM, Iris, NN, Wavelet Moments.**

I. INTRODUCTION

Biometrics is defined as the study of methods for the measurement of physical, biological or behavioural attributes, which are used for the identification of people. Within the field of biometrics, fingerprints the face and iris are currently considered the most used biometric methods. The use of the iris biometric modality in specific applications involves a series of 7 factors identified [1] that are present in an identification system of this nature:

Universality (everyone has the characteristic), means that every person has the texture characteristics of the iris.

Uniqueness (the characteristic is different for everyone), means that the texture features of the iris are different enough for each individual, so that they can be distinguished from each other. The iris pattern is epigenetic (not genetically determined).

Differentially (high discriminative power due to its entropy). The randomness of the iris pattern has a high dimensionality which is higher than the 266 degrees of freedom [2].

Permanence (the characteristic remains invariant in the time of life, except for changes of pigmentation in time), means that the texture of the iris remains invariant over time.

Measurement (the feature is easy to capture), refers to the ease of acquisition of the iris texture image. The acquired image must be in a format that allows subsequent processing and extraction of the set of relevant features.

Performance, refers to the accuracy, speed and robustness of the technology used throughout the process.

Acceptability (the feature is non-invasive), refers to how well people accept technology in the biometric modality of the iris. The capture of the iris image is non-invasive.

Imitability (imitability of the characteristic), relative to the ease or not of the human iris being imitated or falsified using artifacts or substitutes.

An iris recognition system can operate in two modes. In authentication-verification mode, the system performs a one-to-one comparison of the set of iris features, captured with a template (IrisCode) stored in an iris database, in order to verify if the person is who they say they are in the identification mode the system performs a one-to-many comparison against an iris database, to establish the identity of an unknown individual. The system will be successful in identifying the person if the comparison of the input iris with an iris template in the database is within a previously defined threshold. The identification mode can also be used for "positive recognition (the user does not have to provide any information about the template to be used) or for the" negative recognition "of the person where the system determines whether the person is the one (implicit or explicitly) denies being. The recognition of iris is currently one of the most accurate biometric techniques. However, the performance of such systems can be reduced in non-ideal conditions, such as non-voluntariness, movement or non-collaboration [3]. In an iris recognition system, pre-processing, especially the

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location of the iris, plays a very important role .The speed and performance of such a system are crucial and are limited to a large extent by the location or segmentation of the iris. The segmentation of the iris includes finding the borders of the iris (inner and outer) and the eyelashes (upper and lower) [4]

In addition to the set of pixels, taking into account this problem modelling, we can apply joint grouping techniques to construct consensus segmentations. This proposal contributes to obtaining more precise and robust segmentations. The proposed scheme was evaluated in international databases Casia.V4-Thousand, proving to be a promising approach to achieve substantial increases in the efficiency in the recognition of people by the iris. Another important task in the recognition process is the extraction of features from the texture patterns [5] of the iris. The general concept of Biometric Process of Extraction of Traits is defined as the process applied to the biometric sample with the intention of extracting distinguishing and repeatable numbers or labels that can be comparable to those extracted from other biometric samples. However, a key issue and an open theme in iris recognition is how to achieve a better representation of iris texture information using a compact set of traits. Over the past 30 years a large number of algorithms have been proposed that seek a better description of the texture of the human iris. The problem is still finding features that are robust to the different conditions in which the images can be captured. This chapter also describes a representation of the texture of the iris based on the features of the ordinal co-occurrence matrix (OCMF) for an iris recognition system that increases recognition accuracy [6, 7].

II. Properties of Iris

The iris is an internal organ of the eye located behind the cornea and the aqueous humour, which consists of a network of connective tissues, fibres, rings and colorations that constitute a distinctive mark of people when seen at close range. The texture of the iris has no genetic expression and its morphogenesis is completely random [8].

The properties of the iris that enhance its use for the identification of people include: a) unrepeatability in two individuals, b) impossibility of modifying it without risk of losing sight, c) it is a pattern with high randomness , and d) its ease of registration at close range. But it also has some disadvantages such as: a) its small size makes it difficult to acquire certain distances, b) it is a mobile target, c) it is located on a curved, wet surface and reflective, d) his image is usually affected by lashes, pads and light reflections, and e) his deformations are not elastic when the pupil changes in size [7].

Chai et al. [9] propose a general framework for the analysis of iris texture based on the concept of ordinal measurements (OMs). In their revolutionary proposal they codify the ordinal relation between several patches (regions) of the normalized image using quantitative values. These quantitative values can represent the result of ordinal comparisons among a large number of parameters within the regions of the image. For example, the shape of the region, location of the region, average intensity of the pixel values in the region, the result of filtering the region (using different filters such as Gabor, Wavelet, etc.). This variety of parameters allows the development of custom work frames for each specific application and need. The experimental results reach the first place in the state-of-the-art, both in effectiveness and efficiency.

III. Proposed Methodology

Motivated by the results obtained by [9] and their flexibility for the fusion based feature extraction in biometric recognition of the iris, it is proposed to use the PCA and block based to represent the texture features of the iris. Figure 1 represents the flow diagram of the new proposal, which shows the peculiarities of the use of various features in the stage of extraction of traits. The main steps of the method will be explained below:

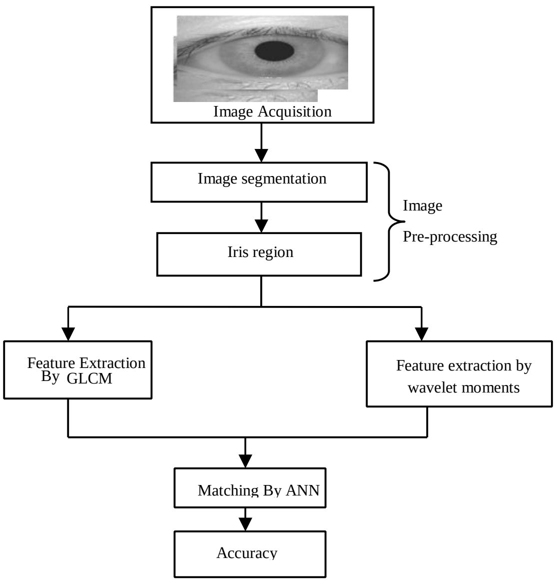

Figure 1: Flow diagram of iris recognition

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Pre-Processing

We worked with a database of human iris obtained from the Automation Institute of the Chinese Academy of Sciences (CASIA). It consists of 7 images per person, out of a total of 108 individuals, giving a total of 756 images. The dimensions of the images are 320 × 280, in BMP format [10].

Obtaining coordinates of the center and radius of iris and pupil. To obtain the coordinates of the center and radius of the iris and the pupil of the images of the CASIA V1 database, the method developed by [11].

First, edge detection is applied with the canny method; then the process continues using a gamma adjustment of the image; to the resulting image obtained previously a non-maximum suppression is applied; subsequently the threshold method is applied to the image.

Finally, the Hough transform is applied to find the maximum in the Hough space and, therefore, the parameters of the circle (row and column of the center of the iris and its radius).

In order to obtain the coordinates of the center and radius of the pupil, the same previous process is carried out, only taking into account at the end the coordinates of the center and radius of the iris to determine those of the pupil.

Main input image of IRIS is further cropped according to calculated coordinate from above process and this cropped image is used for feature extraction.

Feature Extraction

There are two features has been consider for proposed Iris recognition.

GLCM

The most commonly used method for mathematically measuring texture is the grey level co-occurrence matrix, or GLCM (Grey Level Co-occurrence Matrix), based on 2nd order statistics. It is a histogram of the grey levels of two dimensions for a pair of pixels (reference pixel and neighbour). This matrix approximates the probability of joint distribution of a pair of pixels.

Second Order: are the measures that consider the co-occurrence relation between groups of two pixels of the original image and at a given distance,

Texture Measures

Up to this point we have detailed how a normalized matrix, expressed as probability, is created for a given spatial relationship between two neighbouring pixels. Once constructed, different measurements can be derived from this matrix, in this section some of them are defined, and the measurements whose calculations can be performed manually due to their simplicity are developed in greater depth.

The following is a brief explanation of some textural measures:

Homogeneity:

It is calculated by equation (1).

$$\sum_{i,j=0}^{N-1} P_{i,j} /1 + (i-j)^2 \quad (1)$$

Where $P_{i,j}$ the probability of co-occurrence of gray is values i and j , for a given distance.

The difference between this GLCM averages the arithmetic mean of the grey values of the window pixels is noted. The mean in the co-occurrence matrix is not simply the average of the original values of the grey levels in the window. The value of the pixel is not weighted by its frequency per se, but by the frequency of its co-occurrence in combination of a certain value of the neighbouring pixel.

Contrast:

It is the opposite of homogeneity, that is, it is a measure of local variation in an image. It has a high value when the region within the scale of the window has a high contrast.

$$\sum_{i,j=0}^{N-1} P_{i,j} \, (i-j)^2 \quad (2)$$

Where $P_{i,j}$ the probability of co-occurrence of gray is values i and j , for a given distance.

Correlation:

$$\sum_{i,j=0}^{N-1} P_{i,j} \left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_i^2)}}\right] \quad (3)$$

The result is between -1 and 1.

As it arises from the equation, this measure is calculated differently from the previous measures, so the information it provides is essentially different, it is independent of the other measures. Therefore it is expected that it can be used in combination with another textural measure.

Some properties of the Correlation are:

- An object has a higher correlation within it than between adjacent objects.
- Nearby pixels are more correlated with each other than more distant pixels.

Wavelet Moments

Discrete Wavelet Transform (DWT)

The method of wavelet decomposition namely discrete wavelet transform has been used widely to decompose the features of image data. This research work uses 4-level DWT decomposition on image set. The application of DWT on an image results in four subgroups with approximation and detailed coefficients. The approximation coefficient is reconciliation (A), which is input image itself but with reduced size. Whereas the detailed coefficients are horizontal (h), vertical (v) and diagonal (d). The application of single level DWT on an image M, results in sub-groups given as:

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$$M = M_a^1 + \{M_h^1 + M_v^1 + M_d^1\} \quad (4)$$

To further reduce the dimension of input data, DWT can be applied N times to get N-level decomposition. Therefore at the end of four level DWT, image can be represented as:

$$M = M_a^4 + \sum_{i=1}^{4}\{\{M_h^i + M_v^i + M_d^i\}\} \quad (5)$$

At the end of 2-level DWT, input image with $m \times n$ is approximated to $\frac{m}{2} \times \frac{n}{2}$

DWT employees Fourier transform to convert time domain image into frequency domain. The mathematical expression of DWT is given by:

$$DWT_{x(n)} = \begin{cases} dd_{j,k} = \sum img(n) hh^*{}_s(n - 2^s r) \\ ap_{j,k} = \sum img(n) ll^*{}_s(n - 2^s r) \end{cases} \quad (6)$$

Where, $dd_{j,k}$ represents detailed coefficients and $ap_{j,k}$ are the approximate coefficients of DWT transform. Functions $hh(n)$ *and* $ll(n)$ are high and low pass filter respectively. Parameters s *and* r are wavelet scale and translation factors respectively.

It is assumed that we are interested in images or regions that have homogenous texture, therefore the mean and standard deviation are expressed as:

Mean

For a random variable vector A made up of N scalar observations, the mean is defined as

$$\mu_{mn} = \frac{1}{N}\sum_{i,j=1}^{N} ap_{ij} \quad (7)$$

Where ap_{ij} approximate coefficient, N scalar observations, μ_{mn} is the mean value of wavelet values.

$$\sigma_{mn} = \sqrt{\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|I_{mn}(i,j)| - \mu_{mn})^2}{N-1}} \quad (8)$$

Where $I_{mn}(i,j)$ the observed values of the sample items are, μ_{mn} is the mean value of these observations, and N is the number of observations in the sample. σ_{mn} is the standard deviation of wavelet values.

A feature vector f_g(wavelet moments) is created using μ_{mn} and σ_{mn} as the feature components:

$$f_g = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01} \dots \dots . \mu_{45}, \sigma_{45}) \quad (9)$$

Modular neural network

The above extracted feature values can be combined to get optimal dataset for neural network training.

Learning Process: Back Propagation

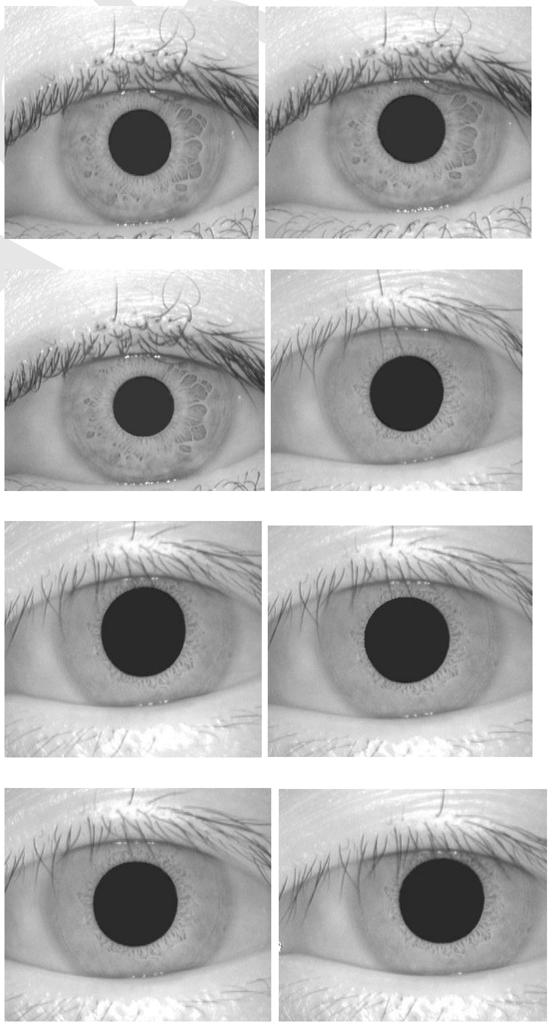
Back Propagation Neural Network (BPNN) generates complex decision boundaries in feature space. BPNN in specific circumstances resembles Bayesian Posterior Probabilities at its output. These conditions are essential to achieve low error performance for given set of features along with selection of parameters such as training samples, hidden layer nodes and learning rate. In else case, the performance of BPNN could not be evaluated. For W number of weights and N number of nodes, numbers of samples (m) are depicted to correctly classify future samples in following manner:

$$m \geq O\left(\frac{W}{\epsilon}\log\frac{N}{\epsilon}\right) \quad (10)$$

The theoretical computation of number of hidden nodes is not a specific process for hidden layers. Testing method is commonly entertained for selection of these followed in the constrained environment of performance.

IV. Results And Discussion

The scheme is validated for CASIA V1 databases. In the case of the CASIA V1 database, Table 1 show the accuracy of different methods proposed. , only with the difference that the fusion process is shown as a step after obtaining the best set of accuracy. In this case, in the fusion process, there is a substantial increase in efficiency.



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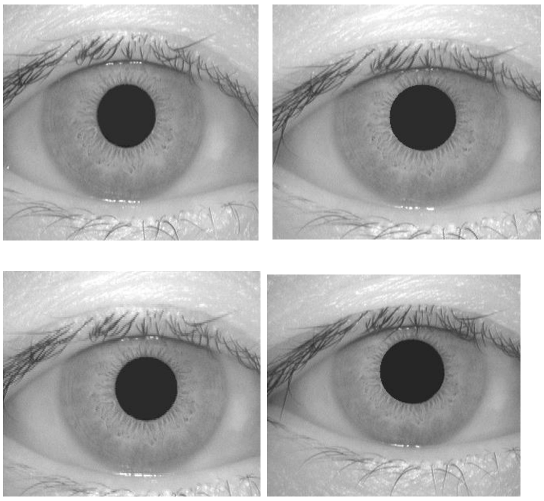

Figure 2: IRIS database CASIA V1

The table below explains the accuracy achieved by 60:40 training and testing sample from database respectively. The feature extracted from different Wavelet moments form different filter banks of wavelets is trained separately in neural network according to above mentioned training scenario, the calculated accuracy claims Coif1 wavelet outperform then Harr and Sym4 wavelets. GLCM feature is calculated separately but achieved accuracy is poor then Wavelet i.e. 70 %. Further to improve the accuracy hybrid approach shown in Table 1 is proposed by combining the two extracted features. GLCM + Coif1 gives higher accuracy i.e. 97.1 %.

Table 1: Result of different methods in iris recognition method

Methods	**Accuracy in percentage**
Wavelet Moments using Sym4 filter bank	85.7%
Wavelet Moments using Haar filter bank	85.7%
Wavelet Moments using Coif1 filter bank	91.4%
GLCM	70%
GLCM + Haar	91.4%
GLCM + Sym4	91.4%
GLCM + Coif1	97.1%

V. CONCLUSION

The recognition of iris is currently one of the most accurate biometric techniques. In an iris recognition system, pre-processing, especially iris segmentation, plays a very important role. The raw iris image is segmented with canny edge detector .Further hybrid features (GLCM + Wavelet) is used with neural network classifier, achieved accuracy is 97.1 %. It is interesting to see the iris feature extraction in future, iris images obtained in less controlled environments, for example, under different lighting conditions.

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