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Hybrid Features Based Iris Recognition using Neural Network Classifier

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Abstract – **This paper presents a neural network (NN) architecture for a system of recognition of people through the biometric measurement of the iris. In this system, a database of the human iris is processed by means of image processing methods. The coordinates of the centre and radius of the iris are obtained and a cut of the area of interest is performed eliminating the noise around the iris. The inputs to the neural network architecture are the processed iris images and the output is the number of the person identified. This work proposes the hybridization of features like Gabor wavelet, grey level difference matrices (GLDM) and wavelet moments for extracting features from the images to train the neural network. The classification accuracy obtained with the hybrid approach on the images is 98.6% with 60:40 ratio of training and testing respectively.**

Keywords – **Gabor Wavelet, GLDM, Neural Network, Wavelet Moment.**

I. Introduction

Knowing how to determine the identity of a person automatically is always a problem. In a world that is becoming increasingly interconnected, it is more than necessary to recognize users in order to give them access to a building or to allow them to use specific resources, etc. It is therefore urgent to have automatic and reliable authentication systems in order to be able to combat fraud and to meet the very high requirements in various fields ranging from crossing international border crossings to accessing personal information. In addition, passwords and identity cards cannot provide vital authentication functions such as non-repudiation and detection of multiple registrations. For example, users can easily deny the use of a service by claiming that their password was stolen or guessed. Individuals can also hide their true identity by presenting duplicates of falsified identity documents.

As a result it becomes increasingly clear that these mechanisms are not sufficient to reliably determine the identity of a person and that a stronger mechanism for identification based on something you are, Namely biometrics, is more than necessary. Biometrics is thus an alternative to the old modes of identification. It involves identifying a person based on their physical or behavioural characteristics [1]. The face, the fingerprints, the iris, etc. are examples of physical characteristics. The voice, the writing, the rhythm of typing on a keyboard, etc. are behavioural characteristics. These characteristics, whether innate like fingerprints or acquired as signature, are attached to each individual and therefore do not suffer from the weaknesses of methods based on knowledge or possession [1].

Biometric systems based on a single modality are called modal unified systems. Although some of these systems [1] have led to considerable improvements in terms of reliability and accuracy, they suffer from problems in the learning phase, due mainly to the non-universality of biometric characteristics, Exposure to biometric impersonation, and inadequate accuracy of noisy data [2].

Therefore, uni-modal biometric systems may not be able to achieve the desired performance requirements in real world applications. One way to overcome these problems is to use multimodal biometric authentication systems, which combine information from multiple modalities to make a decision. Studies have shown that multimodal biometric systems can perform better than uni-modal systems [3].

Several multimodal biometric systems using different strategies have been proposed by different authors [4] [5].

The main objective of this paper is to implement an iris recognition framework using hybridization of features like Gabor wavelet, grey level difference matrices (GLDM) and wavelet moments for training to neural network (NN). The CASIA database images are adapted for proposed research work. Rest

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of paper is organized as follows. Section 2 presents the proposed methodology followed by the simulation and results in section 3 and finally the conclusion and future aspects are detailed in section 4.

II. Proposed Methodology

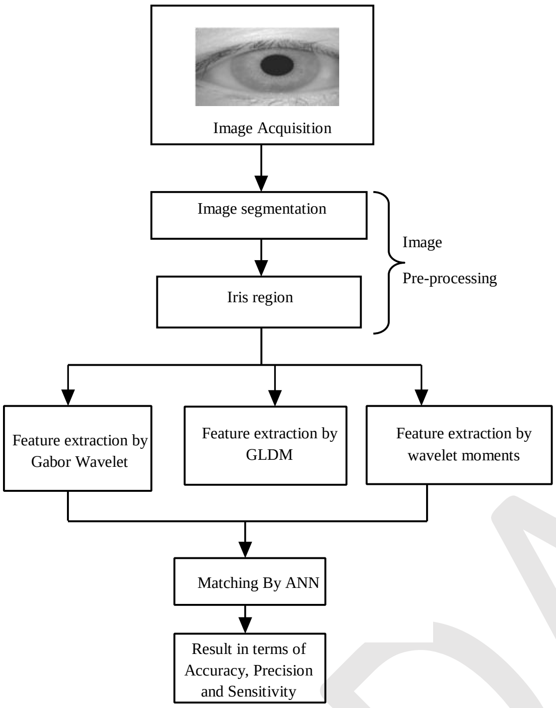

Figure 1: Flow diagram of iris recognition

A. *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 [6].

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 [7].

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.

B. *Feature Extraction*

There are three features have been considered for proposed iris recognition.

1) *Gabor Wavelet*

Gabor's Eye, developed by Dennis Gabor, is extensively used as a treatment of images because the Gabor wavelets salient properties: the localization frequency and selectivity in orientation. Frequency representations and orientation of Gabor are according to biometric recognition system [8]. The article [8] (the first is in Nature) indicate that representation by Gabor Wavelet of iris images irrespective of variations in illumination. The Gaussian envelope for iris recognition is represented as follows:

$$\psi_{u,v}(z) = \frac{\left\|K_{u,v}\right\|^2}{\sigma^2} e^{\frac{\|k_{u,v}\|^2\|z\|^2}{2\sigma^2}} \left[e^{ik_{u,v}z} - e^{-\frac{\sigma^2}{2}}\right] \quad (1)$$

Where $z = (x; y)$ is the coordinate point $(x; y)$. Where u and v are orientation and frequency respectively for kernels of Gabor. $\|.\|$ is the standard operator and σ is standard deviation of the Gaussian envelope.

The Gabor wavelet is the representation of convolution product of frequency and orientation claimed from equation (1). The convolution of image I and of a kernel of Gabor $\psi_{u,v}(z)$ is defined by:

$$G_{u,v}(z) = I(z) * \psi_{u,v}(z) \quad (2)$$

The interest of using Gabor Wavelet to extract iris features is capturing face information in orientations and resolutions. In addition, they are invariant of illumination, distortions and variations in scale. Therefore, if only the amplitude response is considered, “Jet” and it has been widely used in the oldest systems, such as the DLA and the EGBM. Note that these are methods based on the characteristic points which must be detected very precisely. Several metrics have been tested for characteristics based on Gabor and the one that is most often used is the cosine distance.

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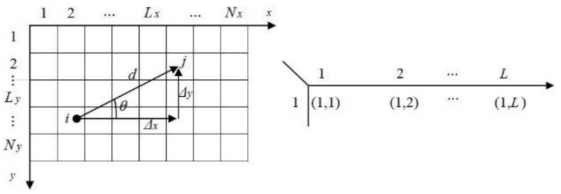
2) *Gray Level Difference Matrices (GLDM)*

Texture is one of the most important characteristics for the identification of objects of interest in an image. The GLDM method is a texture analysis technique based on the absolute difference between pairs of gray levels or the average gray level of an image.



(a) (b)
Figure 2: (a) Original image and (b) GLDM matrix [9]

With this method we obtain a vector $H(\theta, d)$, of equal size to the number of gray levels of the image, where d is the distance between the pixel pair and θ is the direction 'N) [9].

Given a function of the intensity of the image $I(i, j)$ and a displacement vector $\delta = (\Delta x, \Delta y)$, the absolute difference is obtained in the following manner:

$$I_\delta(i, j) = |I(i, j) - I(i + \Delta x, j + \Delta y)| \quad (3)$$

And the probability density of $I_\delta(i, j)$ is denoted by p_δ.

An example of the calculation of the GLDM matrix with a distance $d = 1$ and the angle $\theta = 0°$ is shown below:

$$I(x,y) = \begin{bmatrix} 1 & 1 & 2 & 2 & 2 \\ 1 & 1 & 2 & 2 & 2 \\ 1 & 3 & 3 & 3 & 3 \\ 3 & 3 & 4 & 4 & 4 \\ 3 & 3 & 4 & 4 & 4 \end{bmatrix}$$

$$GLDM = [15 \quad 4 \quad 1 \quad 0 \quad 0] \quad (4)$$

The texture descriptors that are obtained from this method are described below:

Mean: It describe the thickness of the texture. The mean is small when the values of $p_\delta(i)$ are concentrated near the reference pixel and it is large when the values are far from the reference pixel.

$$MEAN = \frac{1}{N}\sum_{i=1}^{N} i p_\delta(i) \quad (5)$$

Entropy: It measures the homogeneity of the histogram. The entropy is large when the values of $p_\delta(i)$ are equal and it is small when the values are unequal.

$$ENTROPY = -\sum_{i=1}^{N} p_\delta(i)\log(p_\delta(i)) \quad (6)$$

Contrast: This is the second moment of $p_\delta(i)$ that is, its moment of inertia with respect to the origin.

$$CONTRAST = \sum_{i=1}^{N} i^2 p_\delta(i) \quad (7)$$

Variance: It is a measure of the dispersion of gray level differences with respect to a distance d.

$$\sigma_D^2 = \sum_{i=1}^{N}(i - MEAN)^2 p_\delta(i) \quad (8)$$

3) *Wavelet Moments*

The wavelet transform is used to decompose low frequency images so as to differentiate high frequency components, in view of its capacity to catch particular transformed information of extracted image.

The arrangement of the data into multi resolution frequency permits to confine the frequency segments acquainted by intrinsic values due with expression or extraneous components (i.e. light) into several sub bands. These techniques cut away these different sub bands, and spotlight on the sub bands which contain the most applicable data.

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:

$$M = M_a^1 + \{M_h^1 + M_v^1 + M_d^1\} \quad (9)$$

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:

$$M = M_a^4 + \sum_{i=1}^{4}\{\{M_h^i + M_v^i + M_d^i\}\} \quad (10)$$

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:

$$DWT_{x(n)} = \begin{cases} dd_{j,k} = \sum img(n) hh^*{}_s(n - 2^s r) \\ ap_{j,k} = \sum img(n) ll^*{}_s(n - 2^s r) \end{cases} \quad (11)$$

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.

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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:

$$\mu_{mn} = \frac{1}{N}\sum_{i,j=1}^{N} ap_{ij} \tag{12}$$

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

$$\sigma_{mn} = \sqrt{\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|I_{mn}(i,j)| - \mu_{mn})^2}{N-1}} \tag{13}$$

Where $I_{mn}(i,j)$ represents 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:

$$f_g = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01} \dots \dots . \mu_{45}, \sigma_{45}) \tag{14}$$

C. Classification by 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 is a type of multi-layer feed forward network in which each layer is connected by transfer functions and can fulfil arbitrary nonlinear mapping. It is widely applied in stock price, petroleum price, economic time sequence, network flow and other nonlinear areas and attained satisfactory performance. The structure of back propagation neural network is shown in Figure 3.

The basic learning process of the back propagation neural network algorithm is as follows [10]:

1. Initialize the connection weights w_{ij}, v_{jt} and threshold θ_j in the back propagation neural network.
2. Input the first learning sample couples to the back propagation neural network.
3. Compute the input u_j of each neural unit and the output h_j in the hidden layer. The equation is:
$$u_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j \tag{15}$$
$$h_j = f(u_j) = \frac{1}{1+\exp(-u_j)} \tag{16}$$
4. Compute the input l_t of each neural unit and the output y_t in the output layer. The equation is:
$$l_t = \sum v_{jt} h_j - \gamma_t \tag{17}$$
$$y_t = \frac{1}{1+\exp(-l_t)} \tag{18}$$
5. Compute the weights error δ_t which is connected to the neural unit t in the output layer.
$$\delta_t = (c_t - y_t) y_t (1 - y_t) \tag{19}$$
In the equation (19), c_t represents the expectation of the sample.
6. Compute the weights error δ_j which is connected to the neural unit j in the hidden layer.
$$\delta_j = \sum_{t=1}^{q} \delta_t v_{jt} h_j (1 - h_j) \tag{20}$$

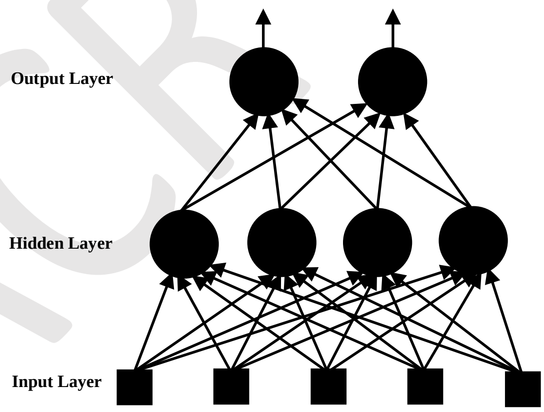

Figure 3: Structure for back propagation neural network [11]

III. SIMULATION AND RESULTS

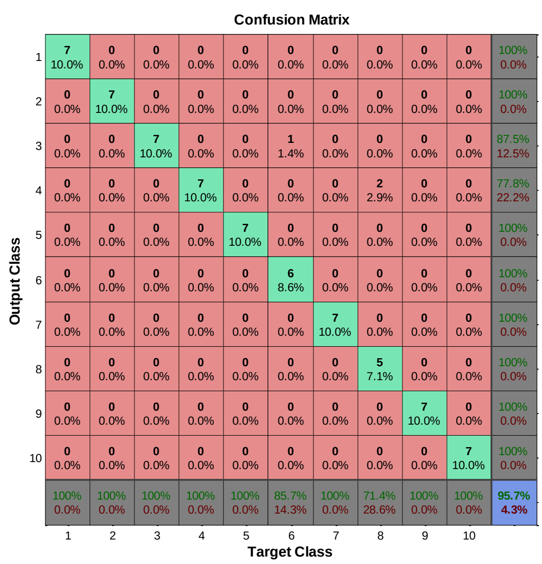

Figure 4: Confusion matrix plot for Gabor wavelet

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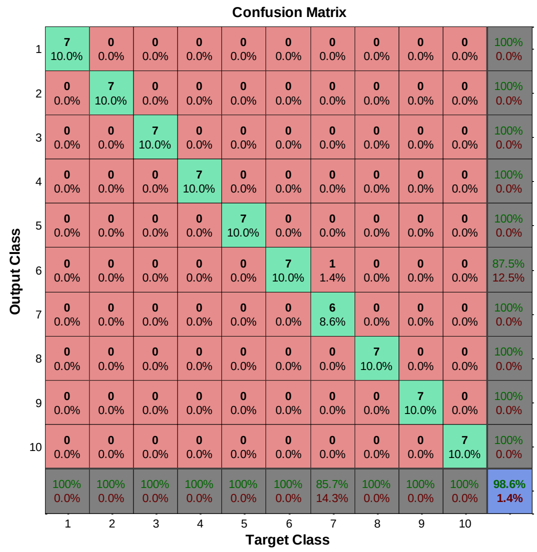

Figure 5: Confusion matrix plot for Gabor wavelet + GLDM + wavelet moments

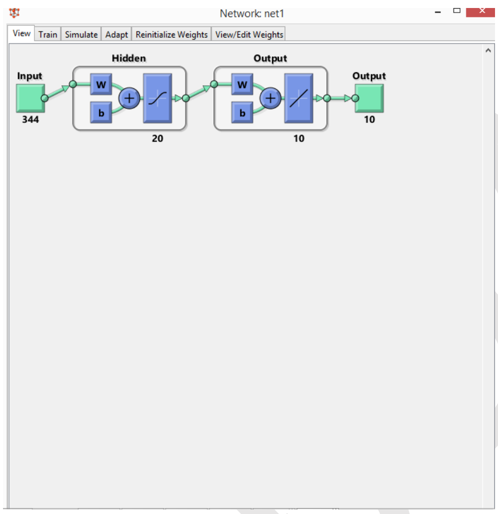

Figure 6: Architecture of neural network

Table 1: Comparative results of different methods in proposed iris recognition

Method	**Accuracy in percentage**
Gabor Wavelet	95.7%
Hybrid approach by Gale et al. (2016) [6]	98%
Gabor Wavelet + GLDM + Wavelet Moments (Proposed)	98.6%

IV. 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 (Gabor wavelet + GLCM + Wavelet moments) is used with neural network classifier, achieved accuracy is 98.6%. It is interesting to see the iris feature extraction in future, iris images obtained in less controlled environments, for example, under different lighting conditions.

To make this research more valuable and fascinating the accompanying recommendation have been proposed for further enhancements:

- The method can be implemented for Iris images using contact lenses and iris images with multi scale and orientation.
- The methods can also be implemented for any other face/fingerprint recognition systems for better time complexity.
- Other matching algorithms can also be used for improvement in recognition accuracy.

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