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Person Identification Using Iris Recognition

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Abstract—**The authentication of people using iris-based recognition is a widely developing technology. Personal identification system consists of localization of the iris region, extracting iris features, generation of data set of iris images and then iris pattern recognition. This paper presents an iris detection and recognition method, which adopts the wavelet transform to extract iris texture features and an artificial neural network as classifier. The classification is done using Multi Layer Perceptron with sigmoid transfer function. The classification accuracy obtained is 92.14% and MSE is 0.0052. The corresponding FRR and FAR is 0% and 7.8% respectively.**

Index Terms—**Artificial neural network, iris segmentation, pupil detection, wavelet transform.**

I. INTRODUCTION

Personal identification based on biometrics has been receiving extensive attention in public security and information security domains. The biometrics identification uses physiological characteristics of humans and distinguishes one from another. Biometrics refers to automatic identity authentication of a person on a basis of one's unique physiological or behavioral characteristics. To date, many biometric features have been applied to individual authentication. The commonly used biometrics features include speech, fingerprint, face, voice, hand geometry, signature, DNA and so on. The iris, a kind of physiological feature with genetic independence, contains extremely information-rich physical structure and unique texture pattern, and thus is highly complex enough to be used as a biometric signature. Statistical analysis reveals that irises have an exceptionally high degree-of-freedom and thus are the most mathematically unique feature of the human body more unique than fingerprints. Hence, the human iris promises to deliver a high level of uniqueness to authentication applications that other biometrics cannot match. Iris region is the part between the pupil and the white sclera. This field is sometimes called iris texture. The human iris is not changeable and is stable. From one year of age until death, the patterns of the iris are relatively constant over a person's lifetime. Fig. 1 shows the iris image from the CASIA iris database.

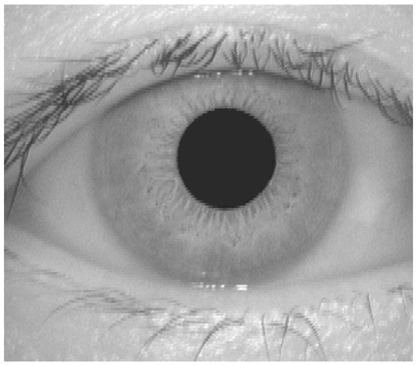

Fig 1. An eye image

Iris recognition consists of the iris capturing, preprocessing and recognition of the iris region in a digital eye image. Each of these steps uses different algorithms. In iris Localization step, the determination of the inner and outer circles of the iris and the determination of the upper and Lower bound of the eyelids are performed. The inner circle is located between the iris and pupil boundary, the outer circle is located between the sclera and iris boundary.

II. LITERATURE SURVEY

John Daugman developed a method for visual recognition of personal identity using the structure of human's iris. The center of pupil and the inner boundary of the iris is detected by the integro differential operator. The visible texture of the person's iris in a real time video image is encoded in a compact sequence of multiscale 2-D Gabor wavelet coefficients, whose most significant bit comprises of 256 byte 'iris code'. The identification is done using the EXOR operations of the iris codes at the rate of 4000 per second.

Hao Meng and Cuping Xu developed a system for identification of persons based on Gabor wavelets. On the texture feature extraction the transforms of Gabor wavelet is introduced. Dividing the frequencies of Gabor into two bands different Gabor scale parameters are selected in every band and the appropriate location parameters are chosen. The binary codes generated are used for iris recognition.

F. Hasin realized an iris recognition system using neural networks on Altera FPGA. Back propagation is used for iris recognition. The neural network architecture comprises of three layers, input layer, hidden layer and output layer.

III. METHODOLOGY

The block diagram of the system is shown in fig 2.

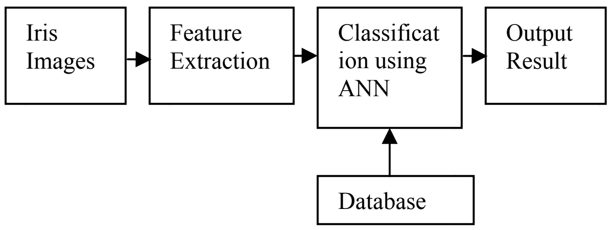

Fig 2: Block Diagram of proposed system

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Iris images are taken by CASIA iris image database. The feature extraction is done by using wavelet transform. Data sets will be prepared using features obtained by the feature extraction technique. These obtained features are fed to the ANN for the classification.

A. IRIS IMAGES

The images from CASIA iris image database are taken. It contains 7 images of 108 persons, both left as well as right eye images. They are of 280 x 320 bitmap images.

B. IRIS PREPROCESSING

The iris recognition consists of image acquisition, iris segmentation, feature extraction and feature comparison.

C. Iris Localization/segmentation

In this step the actual iris region is isolated from the eye image. The iris region can be approximated by two circles, one for the iris/sclera boundary and the other, interior to the first the iris pupil/boundary. The eyelids and eyelashes normally occlude the upper and lower parts of the iris region. Also specular reflections can occur within the iris region corrupting the iris pattern. A technique is required to isolate and exclude these parts as well as locating the circular iris region. In order to determine the pupil boundary and iris edges, the location of the pupil center is required. The pupil and the iris centers are not concentric. The pupil center is first located. The pupil part of the eye yields a near tone of black and occupies most area of the image. For pupil edge detection, a linear threshold is applied to the image as stated below in equation (1).

$$G(x) = \begin{cases} F(x) > 70: 1 \\ F(x) \leq 70: 0 \end{cases} \tag{1}$$

Where F is the original image and G is the image obtained after thresholding. Pixels with intensity greater than empirical value of 70 (in a 0 to 256 scale) are considered as

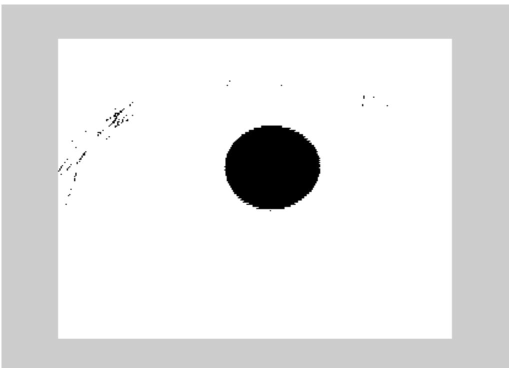

Fig. 3: Pupil Detection

white pixels and assigned a logical '1'. Pixels with intensity smaller than or equal to the empirical value 70 are considered as black pixels and assigned a logical '0'. Fig 3 shows the image obtained after applying the threshold. It can be seen from the fig. that some part of the eyelashes also satisfy the threshold condition. But the eyelashes are not needed. To remove it the image is complemented and the input image is treated as a matrix. From the input image the 8 level connected pixels are obtained. From this matrix the pupil region is obtained by making the region of maximum connected pixels white. To get the edges of the pupil consider two matrices hor_center (1* 320) and ver_center (280*1) that pass through the center. From the center consider only the left part. This matrix consists of 1's and 0's. Flip this matrix. Get the position of the first pixel with value '0'. From this value calculate the left edge of the pupil. Repeat the procedure to get the right, top and bottom edges of the pupil. By doing this we get left, right, top and bottom edge of the pupil. This method efficiently segregates the pupil from rest of the eye. This method has proves to be very efficient when tested on the CASIA iris image database. It correctly detects the pupil region for all the iris images tested. The pupil region after segmentation is shown in fig 4. The pupil radius is the distance between the edge detected and the center of the pupil. The horizontal and the vertical radii are thus obtained. In most of the cases they are of same value, but in few images they differ by a small value.

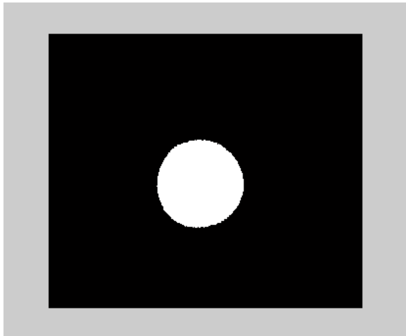

Figure 4: Segmented pupil region

After calculating the pupil center and the radius, the left and right iris edges are detected. For this starting from the right edge of the pupil till the end of the image, a window size of 15 is taken. The average of every 15 pixels is calculated. Then a difference of every two successive pixels is calculated. The point where the difference is positive, the right edge of the iris is located. Similar process is executed to locate the left edge of the iris. After locating the left and right edges of the iris, the portion outside these edges is made white. The segmented iris region is shown in fig 5.

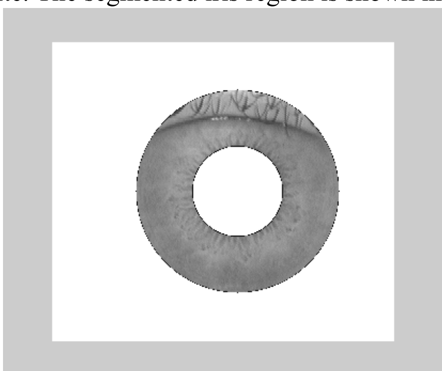

Figure 5: Iris segmented image

Once the iris region is successfully segmented from an eye image, the next stage is to transform the iris region so that it has fixed dimensions in order to allow comparisons. The dimensional inconsistencies between eye images are mainly due to the stretching of the iris caused by pupil dilation from varying levels of illumination. Other sources of inconsistency include, varying imaging distance, rotation of the camera, head tilt, and rotation of the eye within the eye socket. In order to transform the iris image a height= 2* ry is considered. The right side of iris is considered first. The iris region corresponding to 2 ry is taken for comparison. Consider a baseline = height/ no.of rows. A matrix of 100 rows and 50 columns is created between the start and end points of the iris region. The values of iris are stored in the matrix created excluding the pupil region. The same procedure is repeated for the left side. Another matrix of 100 rows and 50 columns will be created. Concatenate the two matrices to get a final matrix of 100 rows and 100 columns. Repeat these steps on all the input images and create a database of only the iris images. Fig 6 shows the concatenated iris image. The process is repeated on all the input images to form a database of the iris images of all the persons. This database is then stored in a separate file for feature extraction.

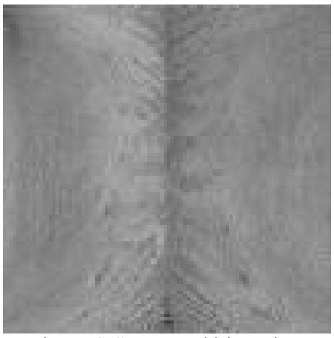

Figure 6: Segmented iris region

D. Feature Extraction

The feature extraction part is very important part for the entire iris recognition process. The iris images thus obtained are then used for feature extraction. A discrete wavelet transform is applied to the iris image to get the wavelet coefficients. A large number of wavelet families are available like Haar, Daubechies, Mexican Hat, Morlet etc.

The Haar wavelet transform is used to calculate the wavelet coefficients in this system. Total 50 coefficients of every iris image is calculated. The coefficients of all the persons are saved in a single matrix. The single value decomposition (svd) is applied to these coefficients. Out of the 50 coefficients only 6 coefficients are considered for comparison. Thus a training set is formed containing 6 coefficients of every image. The coefficients are then converted into binary and then applied as inputs to the Artificial Neural Network.

E. Feature comparison

An artificial neural network is used for feature comparison.

F. Artificial Neural Network

The word 'Neural Network' has been motivated from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, non-linear and parallel computer (information processing system) .It has the ability to organize its structural constituents known as neurons, so as to perform certain computations. At birth, a brain has great structure and the ability to build up its own rules through what we usually refer to as experience.

An **artificial neural network (ANN)**, often just called a "neural network" (NN), is a mathematical model or computational model based on biological neural network . It consists of an interconnected group of artificial network and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

A neural network is a massively parallel-distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two aspects:

Knowledge is acquired by the network from its environment through a learning process.

Inter neuron connection strengths, known as synaptic weights are used to store the acquired knowledge.

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective.

Models of a Neuron:

A neuron is an information-processing unit that is fundamental to the operation of a neural network. The block diagram shows a model of a neuron, which forms the basis for designing neural networks.

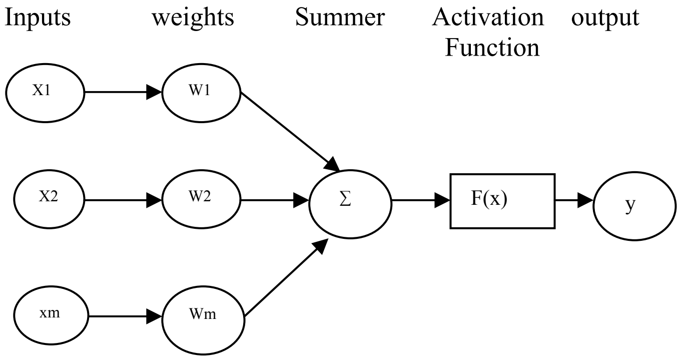

Figure 7: Model of a neuron

Here we identify three basic elements of the neuronal model:

1. A set of synapses or connecting links, each of which is characterized by a weight or strength of its own. Specifically, a signal xj at the input of synapse j connected to neuron k is multiplied by the synaptic weight wkj. The first subscript refers to the neuron in question and the second subscript refers to the input end of the synapse to which the weight refers.
2. An adder for summing the input signals, weighted by the respective synapses of the neuron.
3. An activation function for limiting the amplitude of the output of the neuron. The activation function is also referred to as squashing function in that it squashes (limits) the permissible amplitude range of the output signal to some finite value.

G. Learning Rules and Activation functions

The learning rule is defined as a procedure for modifying the weights and biases of a network. (This procedure may also be referred to as a training algorithm.) The learning rule is applied to train the network to perform some particular task. Supervised learning is used in this system. The weights are adjusted so as to make the difference in the actual output and the targeted output as small as possible.

The activation functions are applied to the weighted sum of the inputs of a neuron to produce the output. There are a various number of activation functions used in the designing of the neural network. Some of the common activation functions are sigmoid function, linear function, and exponential activation function.

H. Design of Neural Network

A multilayer feed forward network is designed for this particular application with the following details:
No. of neurons in first layer = 80
No. of neurons in the hidden layer = 300
No. of neurons in output layer = 20
No. of epochs = 50000
Activation function: Sigmoid

The wavelet coefficients are applied to the input layer. The network is then trained using the above details. After the training the network is used for identification.

IV. RESULTS

In this system images of 20 persons are considered. Six images per person are taken (3 images of left eye and 3 images of right eye). The wavelet coefficients for these 120 images are calculated and stored. Six coefficients per image are calculated. From these 4 images of every person are used to train the neural network. (2 images of left eye and 2 images of right eye). The coefficients of these 4 images are then converted to binary and applied to the neural network for training. Sample wavelet coefficients of 4 images are listed in the table 1.

TABLE I. SAMPLE WAVELET COEFFICIENTS OF 4 IMAGES.

Sample wavelet coefficients					
231	238	244	232.5	241.5	260
237.5	253	243	247	240	251.5
213.5	226	226	262.5	252.5	260.5
208.5	216	211	223.5	265	272

These are the coefficients when Haar Wavelet is used. The network is then trained using the training set of Haar wavelet coefficients. The training set for the images of the first person is listed in the table 2.

TABLE II. TRAINING SET OF FIRST IMAGE

Haar wavelet coefficients of first person						Person
55.46	1.57	1.12	0.62	0.613	0.56	1
55.79	1.47	1.14	0.67	0.606	0.58	1
54.07	1.93	1.20	0.70	0.687	0.62	1
57.31	1.77	1.23	0.74	0.629	0.59	1

After training the network is tested. The network is then used for classification. If an image of the 20 persons listed above is applied, then it results into an authorized person and displays the name of the person. Else it displays 'unauthorized person'. The testing set for an authorized person is listed in the table 3.

TABLE III. SET OF AN AUTHORIZED PERSON

Haar wavelet coefficients of an authorized person					
55.799	1.4705	1.1404	0.67359	0.60661	0.5867

The training set for an unauthorized person is listed in the table 4.

TABLE IV. SET OF AN UNAUTHORIZED PERSON

Haar wavelet coefficients of an unauthorized person					
15745	295.22	262.27	202.61	189.49	175.59

These sets are compared with the coefficients of the authentic users which were used to train the neural network. If there is a match, then the user is authentic and it displays the name of the user. If the coefficients do not match then the user is not authentic and it displays 'Unauthorized person'. The above procedure is repeated for 20 persons (120 images) and the comparative analysis is displayed in Table 5.

TABLE V. COMPARISON FOR VARIOUS WAVELETS

	Haar	**Db1**	**Db2**	**Db8**
Classification Accuracy	92.14%	90.17%	90%	89.28%
MSE	0.005219	0.005	0.00563	0.0053
FAR	0%	0%	0%	0%
FRR	7.80%	9.20%	10%	10.70%

V. CONCLUSION

The features of iris are extracted using the wavelet transform. The wavelet coefficients are obtained using Haar, db1, db2 and db8 and corresponding training set were prepared for each wavelet transform. These inputs are fed to Multi Layer Perceptron Neural Network for classification. The comparison for classification accuracy using wavelet coefficients of Haar, db1, db2 and db8 wavelets has been carried out. The corresponding MSE is calculated with FAR and FRR. The comparative analysis is displayed in Table 5. It is concluded from table 5 that for haar wavelet the obtained classification accuracy is 92.14% with MSE 0.0052 and FAR and FRR are 0% and 7.80% respectively. Thus iris recognition is an accurate biometric to identify the persons.

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