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Design and analysis of bio metric for personal identification in security systems: A functional Approach

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ABSTRACT

Biometrics offers greater security and convenience than traditional methods of personal recognition. In some applications, biometrics can replace or supplement the existing technology. In others, it is the only viable approach.With an increasing emphasis on security, automated personal identification based on biometrics has beenreceiving extensive attention over the past decade.Iris recognition, as an emerging biometric recognition approach, is becoming a very active topic in both research and practical applications. In general, a typical iris recognition system includes iris imaging, iris livens detection, and recognition. This paper focuses on the last issue and describes a new scheme for iris recognition from an image sequence. We first assess the quality of each image in the input sequence and select a clear iris image from such a sequence for subsequent recognition.

I INTRODUCTION

Biometrics is the technique of verifying a person's identity from a physical characteristic (e.g. fingerprint, hand print, face, scent, thermal image, or iris pattern), or personal trait (e.g. voice pattern, handwriting, or acoustic signature).Biometrics has several advantages compared with traditional recognition. In some applications, it can either replace or supplement existing technologies; in others, it is the only viable approach to personal recognition. With the increasing infrastructure for reliable automatic personal recognition and for associating an identity with other personal behavior, concern is naturally growing over whether this information might be abused to violate individuals' rights to anonymity. We argue here, however, that the accountable, responsible use of biometric systems can in fact protect individual privacy.Biometric identification may be preferred over traditional methods (e.g. passwords, smart-cards) because its information is virtually impossible to steal. In this study, we concentrate on iris recognition technique,because it provides a great uniqueness among people even between twins. Compared with other biometrics, iris is more stable and reliable for identification. The human iris, an annular part between the pupil (generally, appearing black in an image) and the white sclera as shown in Figure. 1, has an extraordinary structure

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and provides many interlacing minute characteristics such as freckles, coronas, stripes, etc. These visible characteristics, which are generally called the texture of the iris, are unique to each subject.

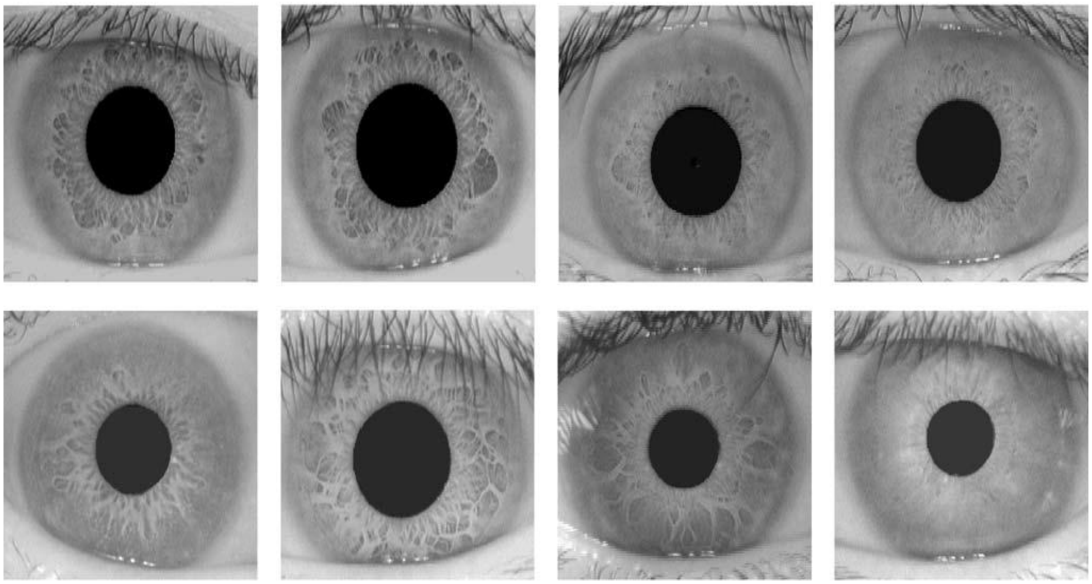

Figure. 1. Iris samples. Images in the first row are from both eyes of two Chinese, and the first two in the second row are from Chinese and the last two from French

II IRIS RECOGNITION SYSTEM

An iris recognition system is composed of 3 main stages.

Preprocessing Stage: The first stage of the iris recognition is the preprocessing stage. The input to this stage is the eye image and the aim isto detect and extract the iris portion from the eye image. (Figure 2)

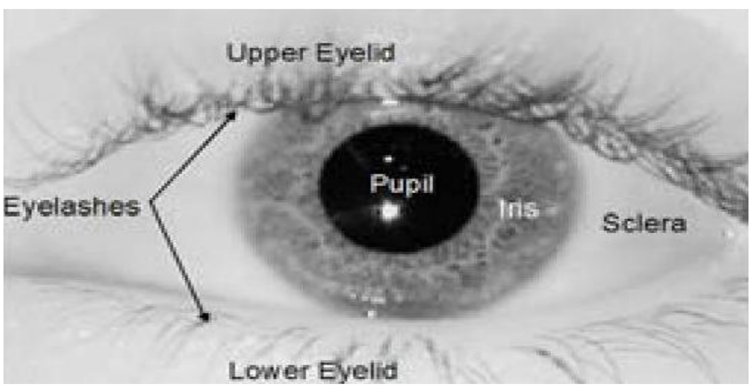

Figure 2. Image illustrating different portions of the eye

The aim is to detect the iris portion which can be approximated by two circles, one is the iris/sclera (outer)boundary, and another interior to the first is the iris/pupil(inner) boundary. The eyelids and eyelashes normally occlude the upper and lower parts of the iris region. The first step in the preprocessing stage is to apply one of the edge detection techniques to get an edge map of the iris image to enable determining all boundaries of the iris. In this work, we used a modified version of the canny edge detection technique[1] which allowed for weighting of the gradients and uses a multiple stage algorithm to detect awide range of edges.The next step after getting the edge map of the eye imageis to apply a circular Hough transform to detect the two circles of the iris/sclera (outer) and iris/pupil (inner)boundary. After that a linear Hough transform [6] is appliedto detect the upper and lower eyelids if they exist.

The Feature Extraction Stage: In order to provide accurate recognition of individuals, the most discriminating information present in the iris patternmust be extracted. In this work, two different featureextraction techniques have been used; the wavelet transform, and the Gabor filter.

A.Wavelet Transform

A 2D discrete Wavelet transform (2D DWT) is used to extract the feature from the iris image. The2D DWT algorithm produces four sub bands at every stage, each one is 1/4 the size of the input image size to that stage.These four sub bands are denoted HH, HL, LH, and LL withthe first letter denoting the filter applied horizontally and the second letter the filter applied vertically (H= High-pass,L=Low-pass). One stage of the 2D DWT is shown below in Figure 3.

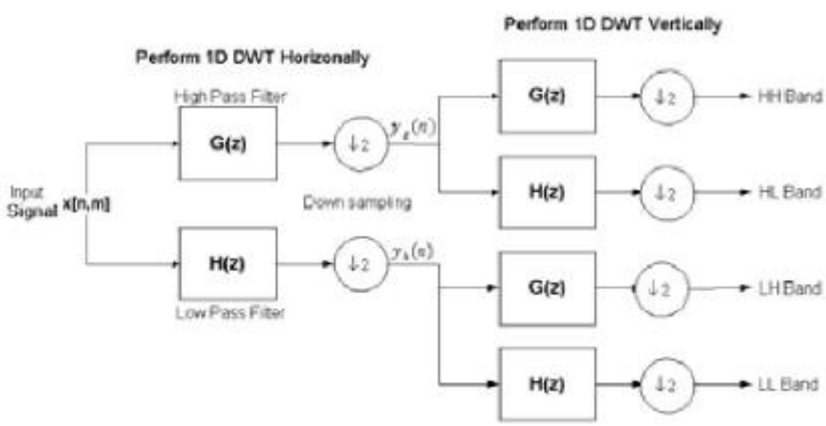

Figure 3. 2D discrete wavelet transform

Different mother wavelets have been tried in this study: Haar, Daubechies, Biorthogonal, Coiflet, Symlet and Meyer.The results obtained from each wavelet have been compared with the others.For the 360X60 iris image obtained from the preprocessingstage, we apply the wavelet transform four times in order toobtain four 23 x 4 sub

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images in the last level (when using the Haar mother wavelet). For the feature vector, we tried toget all features in one sub band (HH, HL or LH) in the forth level and the average value of the features of the same subimage in the three upper levels appear in Figure 4.

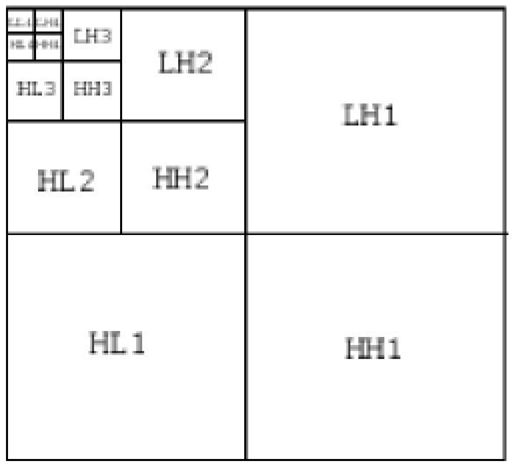

Figure 4. Conceptual Diagram for 4 levels 2DWavelet Decomposition

B. The Gabor Filter

Gabor filters have gaussian shape both in the spatial and frequency domains. For this reason, they are stable in terms of several transformations including translation, rotation, and scaling. Also their noise tolerance is remarkable. This robustness makes Gabor filters appealing for object recognition and therefore widely used to extract features from iris image in the iris recognition system.Feature extraction was implemented by convolving the normalized iris pattern with ID Gabor wavelets. The 2Dnormalized pattern is broken up into a number of ID signals,and then these ID signals are convolved with ID Gabor filter.The rows of the 2D normalized pattern are taken as the ID signal; each row corresponds to a circular ring on the iris region.

The Recognition Stage

In this stage the identification and verification of different iris is done by comparing the feature vector extracted from the iris with the other feature vectors to identify the personwith this iris. In our system we used three different techniques to do the matching:

1) Hamming Distance.

2) Learning Vector Quantization (L VQ).

3) Probabilistic Neural Networks (PNN).

A. The Hamming Distance

The Hamming distance between two strings of bits is the number of corresponding bit positions that differ. Using the Hamming distance between two bit patterns, a decision canbe made as to whether the two patterns were generated from the same iris or from different irises. Because we used the Hamming Distance as a matching algorithm, we need tohave binary feature vectors. Therefore, all feature vectors aredigitized before using the Hamming distance technique.Hamming distance HD can be made using XOR function as:

$$HD = \frac{1}{N}\sum_{i=1}^{N} X_I \otimes Y_I \qquad (1)$$

Where N is the number of bits in the feature vector, Xi is the ith feature of the tested iris, and Y, is the ithfeature of the iris template. If two bit patterns are completely independent, such as iris templates generated from different irises, the Hammingdistance between the two patterns will be close to 1. If twopatterns are derived from the same iris, the Hammingdistance between them will be close to 0, since they arehighly correlated and the bits should agree between the twoiris codes.

B. Learning Vector Quantization (LVQ)

An input vector x is picked at random from the input space.If the class labels of the input vector x and a weight vector w agree, the weight vector w is moved in the direction of theinput vector x. If, on the other hand, the class labels of theinput vector x and the weight vector *w* disagree, the weightvector w is moved away from the input vector x.

The LVQ network is composed of three layers, an input layer, a competitive layer, and an output layer. The numberof neurons in each layer depends on the input data andclasses of the system. The input neurons are as many as theinput iris features of the training pattern, and the number ofthe output neurons is equal to the number of classes to whichiris patterns classified. The LVQ algorithm proceeds asfollows:

1. Suppose that the weight vector w_c is the closest to theinput the input vector x_i. Let μ_{wc}denote the classassociated with the weight vector w_c, and μ_{xi} denote theclass label the input vector x_i. The weight vector w_c isadjusted as follow:

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a. If $\mu_{wc} = \mu_{xi}$ then

$$w_c(n+1) = w_c(n) + \alpha_n[x_i - w_c(n)] \qquad (2)$$

b. If, on the other hand, $\mu_{wc} \neq \mu_{xi}$, then

$$w_c(n+1) = w_c(n) - \alpha_n[x_i - w_c(n)] \qquad (3)$$

2. The other weight vectors are not modified.

C Probabilistic Neural Network (PAW)

The Probabilistic Neural Network (PNN) model, describedby D.F. Specht et al. Probabilistic Neural Networks (PNN) feature a feed forward architecture and supervised training algorithm. In its learningalgorithm each training input pattern is used as the connection weights to a new hidden neuron. In effect, each input pattern is incorporated into the PNN model. A PNN consists of d input units comprising the input layer, where each unit is connected to each of the n pattern units, each pattern unit is, in turn, connected to one and only one ofthe c category units. The connections from the input topattern units represent modifiable weights w, which will betrained. The next layer of a PNN is that of the pattern units.There is one unit for each pattern, implementing a window, and the window size is a free parameter (the smoothing parameter).Each category unit computes the sum of the pattern units connected to it as shown in Figure 5.

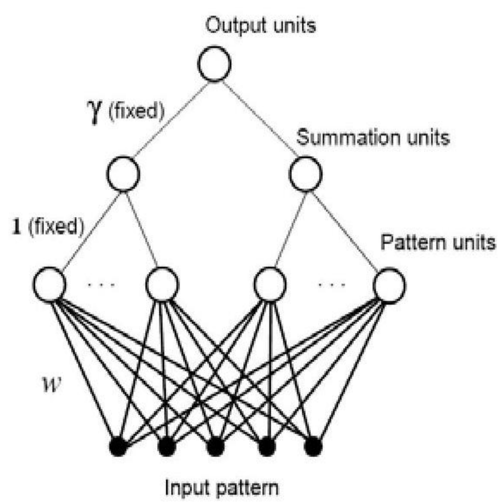

Figure 5: The PNN scheme

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III CONCLUSION

Based on the results obtained the following conclusions can be made:

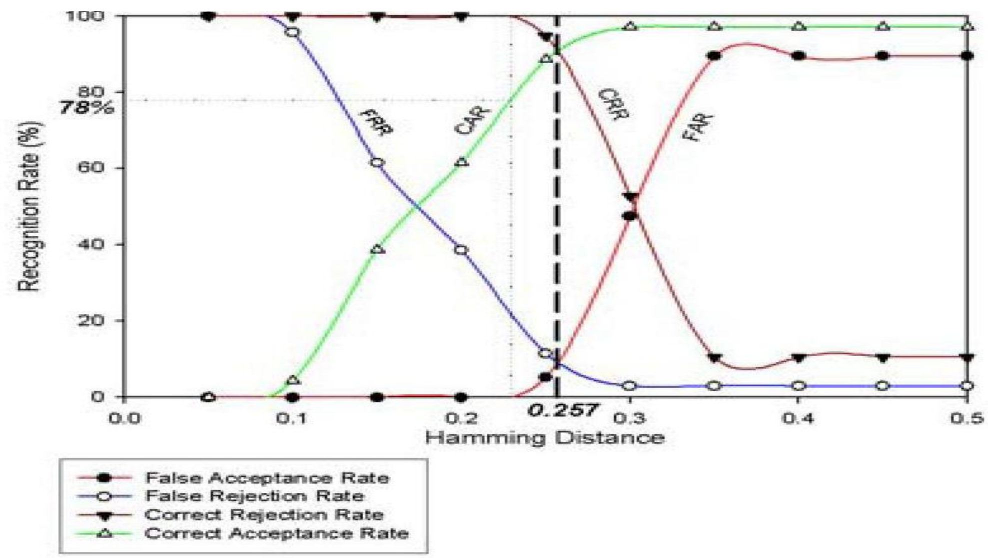

Figure 6: False Acceptance, Correct Acceptance, False acceptance and False Rejection Rates using Haar mother Wavelet using CASIA database

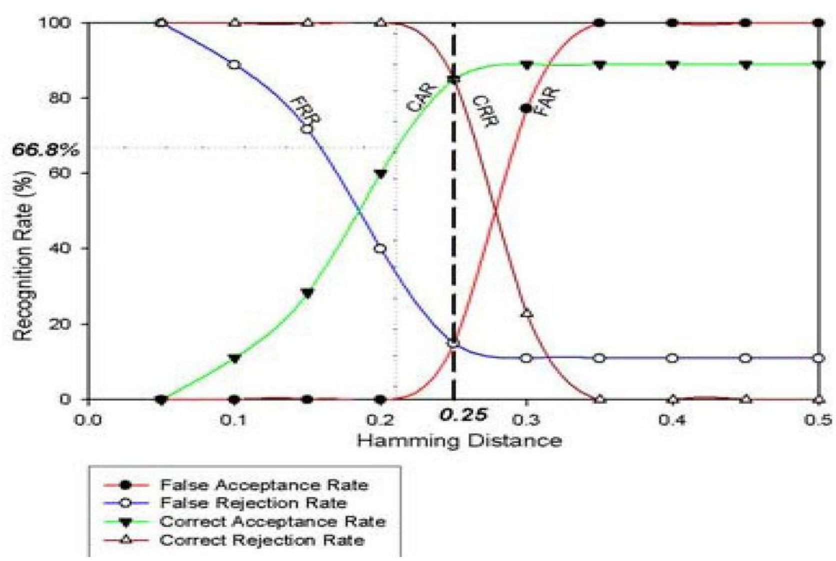

Figure 7: False Acceptance, Correct Acceptance, False acceptance and False Rejection Rates using Haar mother Wavelet using UBIRIS database

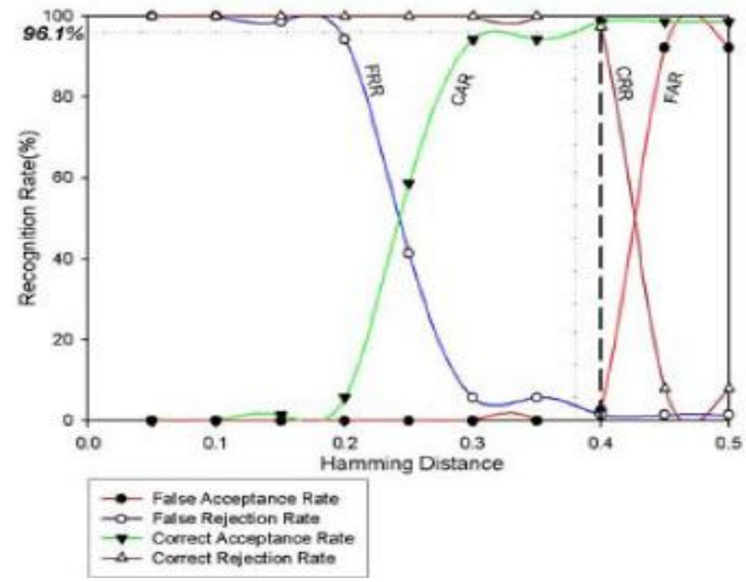

Figure 8. False Acceptance, Correct Acceptance, False Acceptance and False Rejection Rates using Gabor filter with CASIA database

The preprocessing stage of the system is the most difficult part of the system; it is the stage where thehighest failure rates occur as it is completelydependent on the quality of the input image.

Among different mother wavelets, the Haar wavelet gives the best performance.

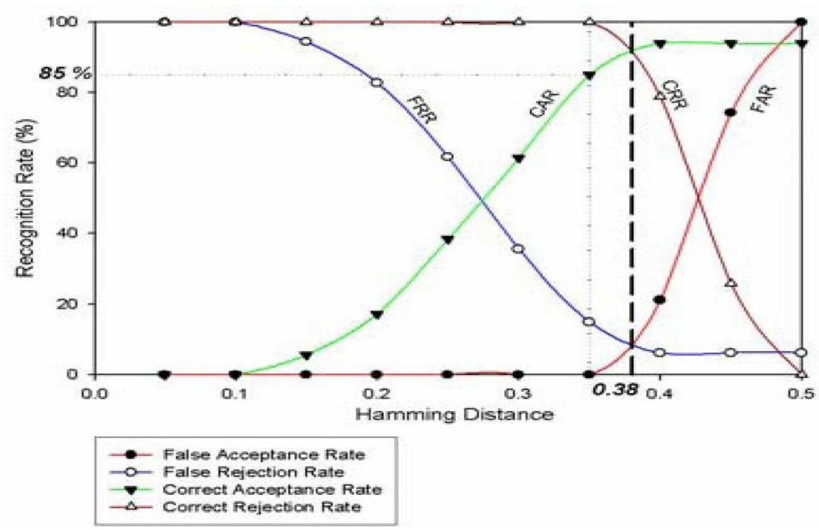

Figure 9 False Acceptance, Correct Acceptance, False Acceptance and False Rejection Rates using Gabor filter with UBIRIS database

Using Haar wavelet, HL sub image gives the best result. Gabor filter gives an accurate recognition of the system and the most complicated feature vector and consumes more time and space.

Hamming distance gives best results according to simplicity and gives good recognition rate. PNN learned all the training patterns correctly, andgive the best results in the test data with Haar 98.15%, with dblO and syml 96.3%.

LVQ failed to learn some of the training patterns, so the recognition rate is 92.6%. By excluding theclasses LVQ failed to learn, the recognition rate will arise to 97.2%.

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