Iris & Face Verification using Decision Level Fusion Technique

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ABSTRACT
Biometric user authentication techniques have evoked an enormous interest by science, industry and society in the recent past. Scientists and developers have constantly pursued the technology for automated determination or confirmation of the identity of subjects based on measurements of physiological or behavioral traits of humans. The ultimate goal of any biometric user authentication is to adopt the concepts for natural recognition or authentication of subjects, find techniques to automate this process and to implement these techniques in such way that a minimum of authentication errors occur.

KEYWORDS
Biometric, Imagefusion, multimodal, verification, PCA.

1. INTRODUCTION
An iris recognition system in order to verify both the uniqueness of the human iris and also its performance as a biometric identification. A biometric system provides automatic identification of an individual based on a unique feature or characteristic possessed by the individual. Iris recognition is regarded as the most reliable and accurate biometric identification system available. The iris recognition system consists of an automatic is able to localize the circular iris and pupil region, occluding eyelids and eyelashes, and reflections. The extracted iris region was then normalized into a rectangular block with constant dimensions to account for imaging inconsistencies.

For Face Verification Principal Component Analysis (PCA) is one of the most successful techniques that have been used in image recognition and compression. Biometric data is only one component in wider systems of security. Typical phases of Biometric security would include Collection of data (the biological characteristic), Extraction (of a template based on the data), Comparison (with another biological characteristic) and Matching. enrollment, authentication, identification and long-term storage are arranged. The purpose of PCA is to reduce the large dimensionality of the data space

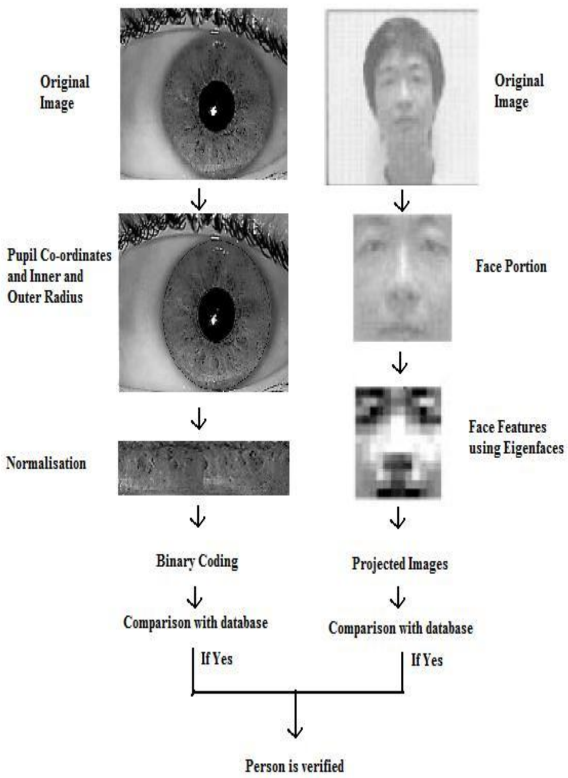

Figure1. Design steps in Biometric System

2. MORPHOLOGICAL OPERATIONS
Sets in mathematical morphology represent objects in an image. For example, the set of all black pixels in binary image is a complete morphological description of the image. In binary images, the sets in questions are members of the 2-D integer space Z2. Here, some basic morphological operations with their mathematical equations are discussed.

The ***reflection*** of set *B*, denoted $\hat{B}$, is defined as

$$\hat{B} = \{w|w = -b,\ \ for\ b \in B\} \qquad (1)$$

It means that set $\hat{B}$ is the set of elements, *w*, such that *w* is formed by multiplying each of the two coordinates of all elements of set *B* by – 1.

The ***translation*** of set *A* by point $z = (z_1, z_2)$ denoted $(A)_z$, is defined as

$$(A)_z = \{c|c = a + z,\ \ for\ a \in A\} \qquad (2)$$

2.1 Dilation

With *A* and *B* as sets in Z^2, the dilation of *A* by *B*, denoted as $A \oplus B$. It is defined as

$$A \oplus B = \left\{ z \middle| \left(\hat{B}\right)_z \cap A \neq \phi \right\} \tag{3}$$

This equation is based on obtaining the reflection of B about its origin and shifting this reflection by *z*. The dilation of *A* by *B* then is the set of all displacements, *z*, such that $\hat{B}$ and *A* overlap by at least one element. Set *B* is commonly referred to as the structuring element in dilation, as well as in other morphological operations.

2.2 Erosion:

With *A* and *B* as sets in Z^2, the erosion of *A* by *B*, denoted as $A \ominus B$. It is defined as

$$A \ominus B = \{ z | (B)_z \subseteq A \} \tag{4}$$

In words, this equation indicates that the erosion of *A* by *B* is the set of all points z such that *B*, translated by *z*, is contained in *A*

2.3 Discrete Cosine Transform

The term image transform refers to a class of unitary matrices used for representing images. Images are expanded in terms of a discrete set of basis arrays called basis images. Energy conservation, energy compaction, de-correlation are the important properties of these transforms. Image transforms like Discrete Fourier Transform (DFT), DCT can be factored as Kronecker products of several smaller sized matrices, which leads to fast algorithms for their implementation [4]. The two dimensional DCT of an N x N image f(x, y) is defined as

$$C(u,v) = \propto_u \propto_v \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \cos\left(\frac{(2x+1)\pi u}{2N}\right) \cos\left(\frac{(2y+1)\pi v}{2N}\right) \tag{5}$$

Where, $0 \le u \le M-1,\ 0 \le v \le N-1$

$$\propto_u,\ \propto_v = \begin{cases} \sqrt{\frac{1}{N}} & for\ u, v = 0 \\ \sqrt{\frac{2}{N}} & for\ u, v \neq 0 \end{cases}$$

It is obvious from the above equation that for *u* = *v* =

$$C(u,v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \tag{6}$$

Thus, the first transform coefficient is the average value of the sample sequence. This value is referred to as the DC Coefficient. All other transform coefficients are called the AC Coefficients. The DCT is real, orthogonal, fast and separable transform. It has excellent energy compaction for highly correlated data.

2.3 Discrete Wavelet Transform

The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression. Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where scalability and tolerable degradation are important.

Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets Wavelets are obtained from a single prototype wavelet y (t) called mother wavelet by dilations and shifting:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \tag{7}$$

Where 'a' is the scaling parameter and b is the shifting parameter. The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies. Multi-resolution analysis: analyzes the signal at different frequencies giving different resolutions. The 2-D wavelet transform is given by:

2.4 Haar, Daubechies, Morlet, and Symlet Wavelets

The Haar sequence is now recognized as the first known wavelet basis and extensively used as a teaching example in the theory of wavelets.

The Haar wavelet is also the simplest possible wavelet. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions, such as monitoring of tool failure in machines.

The Haar wavelet's mother wavelet function ψ(t) can be described as

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2, \\ -1 & 1/2 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

And it's scaling function φ(t) can be described as

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

Most previous implementations have made use of Gabor wavelets to extract the iris patterns. But, since we are very keen on keeping our total computation time as low as possible, we decided that building a neural network especially for this task would be too time consuming and selecting another wavelet would be more appropriate. We obtain the 5-level wavelet tree showing all detail and approximation coefficients of one mapped image obtained from the mapping part. When comparing the results using the Haar transform with the wavelet tree obtained using other wavelets we found that the Haar wavelet gave slightly better results. Our mapped image is of size 100x402 pixels and can be decomposed using the Haar wavelet into a maximum of vertical coefficients cD1v to cD5v, Horizontal coefficients cD1h to cD5h and diagonal coefficients cD1d to cD5d [1].

Since cD4h repeats the same patterns as the previous horizontal detail levels and it is the smallest in size, then we can take it as a representative of all the information the four levels carry. The fifth level does not contain the same textures and should be selected as a whole. In a similar fashion, only the fourth and fifth vertical and diagonal coefficients can be taken to express the characteristic patterns in the iris-mapped image. Thus we can represent each image applied to the Haar wavelet as the combination of six matrices:

1) cD_4^h and cD_2^h
2) cD_4^v and cD_2^v
3) cD_4^d and cD_2^d

Other than Haar, there are different wavelets are also applied to achieve good accuracy. Symlet, Daubechies and Morlet are also applied.

Both the scaling sequence (Low-Pass Filter) and the wavelet sequences, here be normalized to have sum equal 2 and sum of squares equal 2. In some applications, they are normalised to have sum $\sqrt{2}$, so that both sequences and all shifts of them by an even number of coefficients are orthonormal to each other.

$$P_A(X) = \sum_{k=0}^{A-1} \binom{A+k-1}{A-1} 2^{-k} X^k$$

Symlets are only near symmetric; consequently some authors do not call them symlets. The idea consists of reusing the function m_0 introduced in the *dbN*, considering the $|m_0(\omega)|^2$ as a function *W* of $z = e^{i\omega}$. Then we can factor *W* in several different ways in the form of $W(z) = U(z)\overline{U(\frac{1}{z})}$ because the roots of *W* with modulus not equal to 1 go in pairs. If one of the roots is z_1, then $\frac{1}{z_1}$ is also a root. By selecting *U* such that the modulus of all its roots is strictly less than 1, we build Daubechies wavelets *dbN*. The *U* filter is a "minimum phase filter." By making another choice, we obtain more symmetrical filters; these are symlets. The symlets have other properties similar to those of the *dbN*s.

In mathematics, the Morlet wavelet, named after Jean Morlet, was originally formulated by Goupillaud, Grossmann and Morlet in 1984 as a constant κσ subtracted from a plane wave and then localised by a Gaussian window:

$$\Psi_\sigma(t) = c_\sigma \pi^{-\frac{1}{4}} e^{-\frac{1}{2}t^2} (e^{i\sigma t} - \kappa_\sigma)$$

where $\kappa_\sigma = e^{-\frac{1}{2}\sigma^2}$ is defined by the admissibility criterion and the normalisation constant c_σ is:

$$c_\sigma = \left(1 + e^{-\sigma^2} - 2e^{-\frac{3}{4}\sigma^2}\right)^{-\frac{1}{2}}$$

The Fourier transform of the Morlet wavelet is:

$$\hat{\Psi}_\sigma(\omega) = c_\sigma \pi^{-\frac{1}{4}} \left(e^{-\frac{1}{2}(\sigma-\omega)^2} - \kappa_\sigma e^{-\frac{1}{2}\omega^2}\right)$$

The "central frequency" ω_Ψ is the position of the global maximum of $\hat{\Psi}_\sigma(\omega)$ which, in this case, is given by the solution of the equation:

$$(\omega_\Psi - \sigma)^2 - 1 = (\omega_\Psi^2 - 1)e^{-\sigma\omega_\Psi}$$

2.5 Binary Coding

It is very important to represent the obtained vector in a binary code because it is easier to find the difference between two binary code-words than between two number vectors. In fact, Boolean vectors are always easier to compare and to manipulate. In order to code the feature vector we first observed some of its characteristics. We found that all the vectors that we obtained have a maximum value that is greater than 0 and a minimum value that is less than 0. Moreover, the mean of all vectors varied slightly between -0.08 and -0.007 while the standard variation ranged between 0.35 and 0.5. If "Coef" is the feature vector of an image than the following quantization scheme converts it to its equivalent code-word:

If Coef(i) >= 0 then Coef(i) = 1
If Coef(i) < 0 then Coef(i) = 0

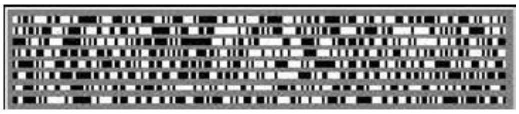

Figure 1: Binary Coded Iris Template

The next step is to compare two code-words to find out if they represent the same person or not. This test enables the comparison of two iris patterns. This test is based on the idea that the greater the Hamming distance between two feature vectors, the greater the difference between them.

3. FACE VERIFICATION

The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called Eigen space projection. Eigen space is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images (vectors). The ICA can be called as generalization of PCA method. PCA considered image elements as random variables with Gaussian distribution and minimized second-order statistics. Clearly, for any non-Gaussian distribution, largest variances would not correspond to PCA basis vectors. Independent Component Analysis (ICA) minimizes both second-order and higher-order dependencies in the input data and attempts to find the basis along which the data (when projected onto them) are – statistically independent. PCA is appropriate when the samples are from one class or group. In contrast, LDA Linear Discriminant Analysis (LDA) finds the vectors in the underlying space that best discriminate among classes.

3.1 Principal Component Analysis (PCA)

To get the feature vectors, we follow the below steps.

1. Create a 1-D vector out of each image by concatenating each row one after another.

Feature Extraction Method	FAR %	FRR %	Time (msec.)	No. of Images are rejected
DCT	0.0	11.2	2.2	99
DWT	0.0	10.7	2.8	92
Haar	0.0	7.2	3.1	64
Daubechies	0.0	7.4	3.2	66
Symlet	0.0	9.1	3.3	55
Morlet	0.0	8.7	3.4	78

2. Calculate the mean pixel value by taking mean of corresponding pixels of all the images and subtract it from the same pixel value of each image to get the mean centered images.

3. Combine all the training images into one data matrix. We will get MN*P dimension matrix.

4. Calculate the covariance matrix by following eqn.
Covariance matrix = Transpose (Data Matrix)* Data Matrix.
We will get a matrix of dimension P*P.

5. Compute the Eigen values and Eigen vectors of the covariance matrix by Cyclic Jacobi method. We will get 'C' column vectors of P elements each. i.e. each vector is of P X 1 dimension. (C <=P)

6. Multiply the Eigen column vector with the data matrix to get column vectors of dimension MN * 1.

$$MN * P \ * \ P * 1 \rightarrow MN * 1$$

7. Normalizing each vector by dividing it by its norm to get the eigen vectors same as what we obtain in the general procedure. MN*1.

8. Order the obtained eigen vectors in the order of their eigen values and form a matrix out of that to get the eigen space $MN * C \ , \ (C <= P)$.

9. Now project all the centered training images on this eigen space to get the feature vectors and store them in the database.

$$(1 * MN) * (MN * P) \rightarrow (1 * P)$$

So the Database size is $[P \ * \ P]$.

4. EXPERIMENT RESULTS

All experiments are performed on MATLAB 9.0 on 4 GB RAM. core 2 duo processor (DELL).

Experiment 1. Experiment performed on IIT Delhi Database, to detect iris pupil and iris boundaries. Time required and accuracy with Canny edge detection and Hough transform technique, Histogram and thresholding technique and morphological operation.

Method	Time (msec.)	Accuracy%
Canny and Hough	34	96
Histogram and Thresholding	23.3	98
Morphological Method	11.8	95

Table 1: Comparison of Feature Extraction Methods

Conclusion 1. Morphological method is more suitable in order to achieve favorable accuracy with less time required as compared to other method.

Experiment 2. Experiment is performed with different feature extraction methods on IIT Delhi Database with 224 persons' left and right both iris images (including good and partial information images) using Hellinger Distance.

Conclusion 2. Here, for good accuracy Haar and Daubechies Wavelets are giving good results, with 2% FRR. But Haar less time requires than Daubechies, but more time requires than DCT and DWT. Overall, Haar is best suitable technique for iris recognition. Haar wavelet is more suitable in trade of between time required and good accuracy.

Experiment 3. Experiment is performed with different kinds of set of training images on IIT Delhi 50 persons' left and right both iris images (including good and partial information images) with Haar wavelet and Hellinger Distance.

No. of Person	FAR %	FRR %	No. of Images are rejected
50	0.0	2.0	4 out of 200 test
100	0.0	2.3	9 out of 400 test
150	0.0	4.3	26 out of 600 test
200	0.0	6.1	49 out of 800 test
224	0.0	7.2	70 out of 896 test

Table 2: Comparison of Feature Extraction Methods

No. of Training Images	FAR %	FRR %	No. of Images are rejected out of 200 test
1	0.0	80	160
2	0.0	10	20
3	0.0	5	10
4	0.0	3.5	7
5	0.0	1	2
6	0.0	0	0

Table 3: Comparison of different no. of training set of images

Conclusion 3. Here, as no of training set of images increases performance increases. Out of 10 sample images 5 images are used as training and rest of 5 are used as testing.

Experiment 4. Experiment is performed on partial information iris images with face images of 10 persons' real database with PCA technique at feature level fusion.

No. of Person	FAR %	FRR %	Result
10	0.0	4.0	94%

Table 4: Face results with PCA of 10 person image

Conclusion 4. Individually iris verification for partial information images gives 91% result. But with help of face features (PCA Technique), result achieved up to 94%.

5. CONCLUSION

- Morphological method to detect iris boundaries requires more than 50% time less than other method and achieves favorable accuracy (95%).
- For iris recognition, Haar wavelet is best among of all other feature extraction techniques for considerable time consumption and accuracy. It gives 100% results for good iris images and 92.8% for 224 Persons' good and partial information.
- The same way, our traditional comparison Euclidean and Hamming Distance, Hellinger and Cityblock Distances are better and give good result with low FRR, with favourable time consumption and complexity among all Distance Metrics family. Hellinger and Cityblock reduce 2-4% FRR as compared to Euclidean and Hamming.
- As no. of training images increase accuracy increases. With 6 training images (3 Right + 3 Left) for 50 persons, Haar wavelet technique achieves 100% accuracy.
- In iris verification, individually for only partial information images gives 91%, but with additional help of face features, accuracy is increased to 94%.
- As no. of person increase efficiency decreases.
- As set of training images increases efficiency increases.

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