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Biometric identification of the face

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Abstract: *In this paper, we propose a face recognition algorithm, based on the principal component Analysis approach. In the proposed algorithm, the global information is extracted using eigenface then we use Euclidian distance to classify vector feature. The performance of the proposed algorithm is tested on AR face databases.* It contains over 2,500 color images corresponding to 125 people's faces (69 men and 56 women). Images feature frontal view faces with different facial expressions, illumination conditions, and occlusions (sun glasses and scarf). No restrictions on wear (clothes, glasses, etc.), makeup, hair style, etc. were imposed to participants.

Keywords: *Biometrics, Principal components Analysis, Eigen face, Identification of the face.*

1. Introduction

The face is our primary focus of attention in social intercourse, playing a major role in conveying identity and emotion. Although the ability to infer intelligence or character from facial appearance is suspect, the human ability to recognize faces is remarkable. We can recognize thousands of faces learned throughout our lifetime and identify familiar faces at a glance even after years of separation. This skill is quite robust, despite large changes in the visual stimulus due to viewing conditions, expression, aging, and distractions such as glasses, beards or changes in hair style. Face recognition has become an important issue in many applications such as security systems, credit card verification and criminal identification. For example, the ability to model a particular face and distinguish it from a large number of stored face models would make it possible to vastly improve criminal identification **[1].**

The first step of human face identification is to extract the relevant features from facial images. The second step is classification. The paper is organized as follows. In Section 2 we discuss the eigenface approach. Section 3 gives the experimental results of the method on the AR face database. Section 4 concludes the paper.

2. The eigenface approach

Much of the previous work on automated face recognition has ignored the issue of just what aspects of the face stimulus are important for identification. This suggested to us that an information theory approach of coding and decoding face images may give insight into information content of face images, emphasizing the significant local and global features. Such features may or may not be directly related to our intuitive notion of face features such as the eyes, nose, lips, and hair.

In the language of information in a face image, encode it as efficiently as possible, and compare one face encoding with a database of models encoded similarly. In mathematical terms, we wish to find the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images, treating an image as a vector in a very high dimensional space **[2].**

The algorithm for the facial recognition using eigenfaces is basically described in figure 1:

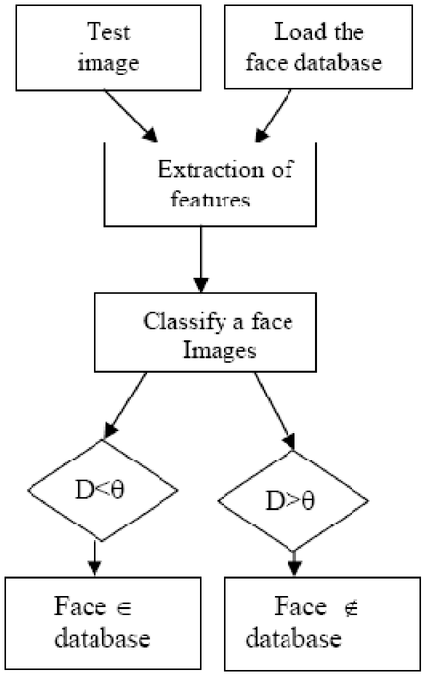

Figure 1: *The algorithm of recognition*

2.1 Loading the database

During this phase, we load the database. In general, we apply many transformations before loading. Indeed, the signal contains information useful to the recognition and only the relevant parameters are extracts. The model is compact representations of the signal which make ease the phase recognition, but also reduce the quantity of data to be stored.

2.2 Extraction of features

The first step, let a face image I(x,y) be a vector of dimension N^2.

$$\begin{pmatrix} a_{1,1} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,m} \end{pmatrix} \longrightarrow \begin{pmatrix} a_{1,1} \\ \vdots \\ a_{n,1} \\ \vdots \\ a_{1,m} \\ \vdots \\ a_{n,m} \end{pmatrix} \quad (1)$$

Then, let the training set of face images be Γ_1, Γ_2, Γ_3…, Γ_M. The average face of the set is defined by **[3]:**

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} \Gamma_i \qquad (2)$$

Each face differs from the average by the vector:

$$\Phi i = \Gamma i - \Psi \text{ , } i = 1 \ldots M \qquad (3)$$

In the next step the covariance matrix C is calculated according to

$$C = \sum_{i=1}^{N} \Phi_i \Phi_i^T = A\, A^T \qquad (4)$$

The matrix C is N^2 by N^2, and determining the N^2 eigenvectors and eigenvalues is an intractable task foe typical image sizes. We need a computationally feasible method to find these eigenvectors.

$$\begin{pmatrix} e_i = & Av_i \\ \lambda_i = & \mu_i \end{pmatrix} \qquad (5)$$

From M eigenvectors (eigenfaces) e_i, onlyM_1 should be chosen, which have the highest eigenvalues. The higher the eigenvalue, the more characteristic features of a face does the particular eigenvector describe. Eigenfaces with low eigenvalues can be omitted, as they explain only a small part of characteristic features of the faces. After M_1 eigenfaces e_i are determined, the ‘training’ phase of the algorithm is finished.

The process of classification of a new (unknown) face Γnew to one of the classes (known faces) proceeds in two steps.
First, the new image is transformed into its eigenface components. The resulting weights form the weight vector Ω_T [3]:

$$W_k = e_k^T (\Gamma_{new} - \Psi) , k =1\ldots\ldots\ldots..M', \Omega_T = [w_1, w_2, ..., w_{M'}] \quad (6)$$

2.3 Face image Classification

The weights form a vector Ω_T = $[w_1, w_2 ... w_{M'}]$ that describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The vector may then be used in a standard pattern recognition algorithm to find which of a number of predefined face classes, if any, best describes the face. The simplest method for determining which face class provides the best description of an input face image is to find the face class k that minimizes the Euclidian distance **[2]:**

$$\varepsilon_k^2 = \left|\left|\Omega - \Omega_k\right|\right|^2 \qquad (7)$$

2.4 Recognition

Our system is a system of identification, so the system must guess the identity of the person. The system compares the vector characteristic of the test image with the different models contained in the database (type of problem 1: n) using the Euclidean distance.

In identification mode, we talk about open problem since it is assumed that an individual has no model in the database (impostor) may seek to be recognized. So, you're doing a study on the database of learning for the appropriate threshold θ which allows us to identify whether that person is in our database or not he is an imposter.

The execution of the biometric system is estimated by measuring the rate of false acceptance (FAR) and the rate of false rejection (FRR).

$$FRR = \frac{\text{false rejection numbers}}{number\ of\ customers}$$

$$FAR = \frac{\text{false acceptance numbers}}{number\ of\ impostors}$$

3. Experiment

To illustrate the efficiency of the system, we use a color database. This database is the AR face **[4]**, presented in the following figure.

This face database was created by Aleix Martinez and Robert Benavente in the Computer Vision Center (CVC) at the U.A.B. It contains over 2,500 color images corresponding to 125 people's faces (69 men and 56 women). Images feature frontal view faces with different facial expressions, illumination conditions, and occlusions (sun glasses and scarf). No restrictions on wear (clothes, glasses, etc.), makeup, hair style, etc. were imposed to participants. Each person participated in two sessions, separated by two weeks (14 days) time. The same pictures were taken in both sessions **[4]**.

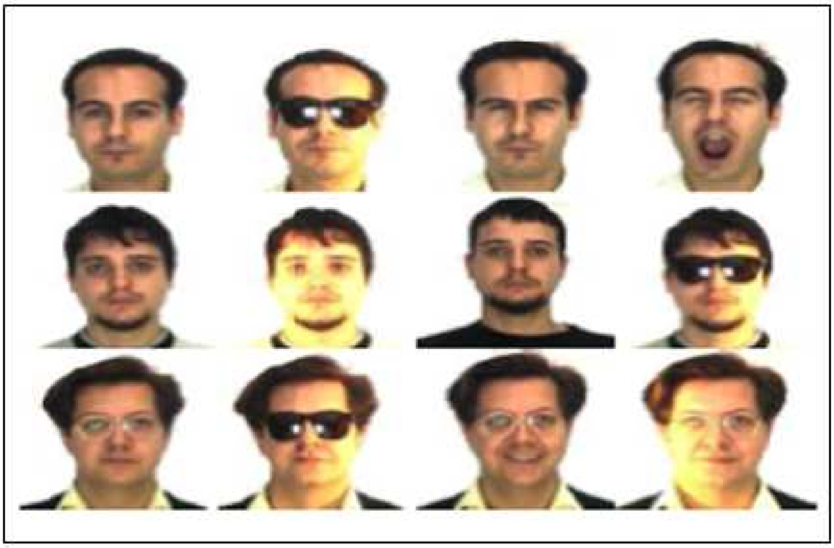

Figure 2: *AR Face*

The design of a system of pattern recognition requires a basis of learning and a validation to assess the performance of the method. So we divided the base in 3 parts:

- The first part includes 1500 image of the face: 100 people and each person has 15 images with different facial expressions. This part is for learning.
- The second part comprises 500 images face, the same people that the next part but each person with 5 images totally different than before. This part is for validation.
- And finally, the third part comprises 380 people are impostors who are not on the basis of learning. It is like the second, used for validation.

We have two databases to study: the first consists of 500 images, 5 poses for each person and the second is composed of 1500 poses image 15 per person.

4. Results

We present in this part results from the Eigen face algorithm using a two different database of learning. Below is a table which threshold is equal to $1.5\ 10^{16}$:

Table 1: Error rate

	FAR	FRR	EER
1^{ere} database	39.74 %	31.45 %	32.77 %
2^{eme} database	0.53%	14%	11%

According to table 1 we have EER equal to 32.77% for the first database, is very high which makes the application less reliable. This is due to the influence of the change of light and change poses to our database on Eigen face, which leads us to try to reduce its error rate with an increase in the database of learning. For the second database, the error rate has clearly decreased by 32.77% to 11%. It notes that the number of images in the database have an important influence on the performance of the application and the improvement of error rates.

The two figures below show the ROC curve of the two databases:

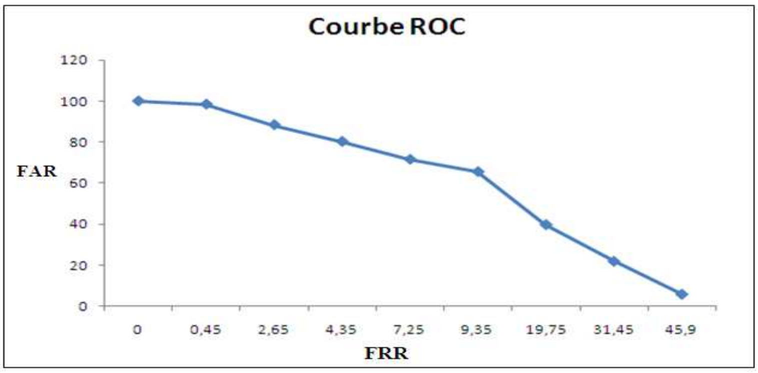

Figure 3: *ROC curve 1*

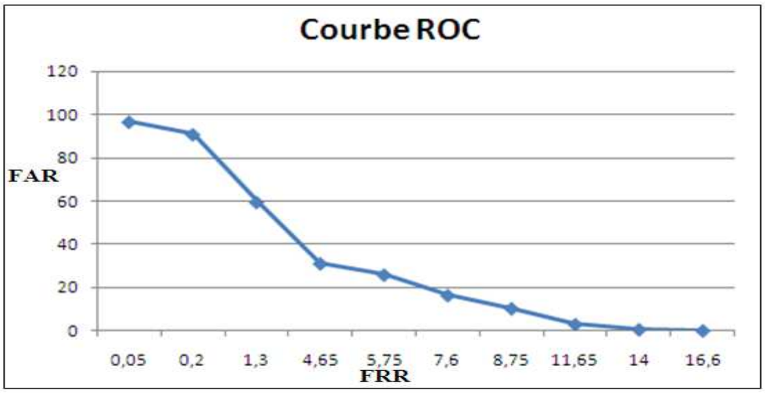

Figure 4: *ROC curve2*

We note that both error rate FRR and FAR are inversely proportional increases if FRR increases FAR decreases, therefore we must choose a compromise between FAR and FRR.

The results published in the literature, show errors that vary between 0.3% and 5% for the rate of false acceptance and between 5% and 45% for the rate of false rejection **[5]**. However, the protocol used for learning and the test varies from one section to another. It is therefore difficult to compare the error of classification.

Thus, in **[6]**, Hjelmas reported error rates of classification ERR = 15% on the database ORL, using a vector features consisting of the coefficients

Gabor. In **[7],** the author made face recognition with the method Laplacianfaces on the database YALE, he found ERR = 11,3%. In the following table we show a comparison between the different approaches.

Table 2: *Comparison between the different approaches*

Approach	EER
laplacianfaces	15%
Gabor	11,3%
Eigenface	11%

The increase of the number of the basis of learning shows the robustness of our application, compared to the first study with an error ERR = 11%, against an error e = 32.77%. Our performances are slightly higher than **[7]** and better than **[6].**

5. Conclusion

The algorithm PCA is a global method using primarily the grayscale pixels of an image. The simplicity to implement this algorithm contrasts with a strong sensitivity to changes in lighting, poses and facial expression. That is why we increase the number of poses for each person. Nevertheless, the PCA requires no a priori knowledge on the image.

The results we obtain for our approach tested on the database AR face are successful compared to some article in the literature and comparable to other results.

The principle that you can construct a sub-vector space retaining only the best eigenvectors, while retaining a lot of useful information, makes the PCA an algorithm effective and commonly used in reducing dimensionality where it can then be used to upstream other algorithms as the LDA, for example, or SVM to improve the results of our application.

To conclude, we can say that the recognition of individuals remain a complex problem, in spite of current active research. There are many conditions real, difficult to model and envisage, which limit the performances of the current systems in terms of reliability and real time.

As future work, PCA can be used to upstream other algorithms as the LDA, for example, or SVM to improve the results of our application. We propose to extend the developed algorithm by adding other biometric techniques to obtain a multimode system. In addition we propose the implementation of such an algorithm on a target technology in order to benefit from the performances provided by this technology.

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