Proceedings of the 4th WSEAS Int. Conf. on Information Security, Communications and Computers, Tenerife, Spain, December 16-18, 2005 (pp453-459)

Automatic Recognition of Faces by Neural Networks and Principal Component Analysis

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Abstract : - In this paper, we propose a new " hybrid " method for the recognition of faces combining the neural networks with the principal component analysis. By using the geometrical approach, we carry out a preliminary classification of the faces by PCA before using a neuronal classifior (PMC). The results, compared with those of the PCA and PMC classifiors, give a clear improvement in term of classification. To carry out our tests, we used a very rich data base created in the Laboratory of Automatics and Informatics of Guelma " LAIG ".

Mots clés : Geometrical approach, neural networks (NN), principal component analysis (PCA), classification, neural-PCA.

1 Introduction

The human faces recognition [1] [2] [3] is currently regarded as one of the most significant tasks to take up the challenge in pattern recognition [4] [5] [6].

The face identification technique most used is that which corresponds so that we use naturally to recognize a person. In particular characteristics of the eyes, the nose and the mouth [7]. Within the framework of the search of our group, which is interested primarily in the recognition of faces, we used several methods for classification and thus the decision of the identity of the person. In this paper, we present a new approach which consists with the hybridization of the neural networks with the principal component analysis.

This paper is shared in 5 sections: in section 2 we present our data base, in section 3 we give a short outline on the extraction of the primitives of each face which is based on the geometrical aspect, section 4 is reserved for the PCA and NN methods as well as their hybridization. We finish by the conclusion and the prospects for our study.

2 DATA BASE

We gathered a data base of 8000 facial images of 100 people (50 men and 50 women) within the LAIG. The total size of the data base is 40,08 GB.

For each person, we took 8 different sequences comprising the faces in various positions and various states from illumination with and without smiling from which we recovered 80 images. This same operation was carried out two months (60 days) later with the same people.

The system of acquisition used as well as the principle of storage and the nomenclature of the faces in the following paragraphs.

Knowing that the number of images per subject is very large, we chose to digitize the images in the form of sequences animated of a few seconds and safeguarded in format (Audio-video AVI). The various images of the sequence, thereafter, are extracted and safeguarded in format JPG.

The images are serious 174 by 144 pixels with 24 bits and they are stored on CDs ROM with precise references. The male images are stored under the reference " H-xx-yz-w.jpg " and female under the reference " F-xx-yz-w.jpg ", where:

'xx' represent the number of the person (from " 00 " to " 50 " for the two sexes),

'y' represent the session (0 for the sequence of December and 1 for the sequence of March),
'z' represent the state of the person (Z = 1: 8 according to various positions' and various states of illumination with and without smiling),
'w' the number of the image (W = 0: 9 bus 10 images are extracted from each state).

The 8 séquences are recorded depending on the following states:

(1) Better lighting by pronouncing the phrase 'automatic recognition of the visages',
(2) Poor lighting by pronouncing the phrase ' automatic recognition of the visages',
(3) Weak lighting by pronouncing the phrase 'automatic recognition of the visages',
(4) Smiling state, with normal lighting,
(5) Left profile 45° with normal lighting,
(6) Left profile 90° with normal lighting,
(7) Right profile 45° with normal lighting,
(8) Right profile 90° with normal lighting.

The figure1 illustrates two samples of the faces base of the LAIG.

Figure 1: Sample of the data base created at the LAIG

3 Extraction of the primitives

3.1 Importance and complexity of the face object

The human beings recognize the ones the others by several characteristics divided to primary and secondary. These last relate to all the temporary characteristics such as: clothes, manners, the color and length of the hair, wearing of barb, moustache...[7]. The primary characteristics includes especially the physiological aspect such as: size, the shape of the body (large or thin), the color of the skin, the form of the face and its characteristics.

The face is the most discriminating characteristic. This is with its wealth of characteristics which vary between the geometry, the texture and the colors of different areas of the face: eyes, the mouth, nose, the franc, cheeks and the amount [9].

The extraction of the primitives of the face is a very complex task especially if it is a question of extracting the geometrical characteristics. This operation consists to [7]:

- Locate the characteristic elements of the face.
- Calculate the distances between these elements.

This requires specific conditions of lighting and position of the head [10]. For that we used a face data base created within our laboratory exploitable for this application and well others in the field of the recognition of faces. The images used result from catches of frontal sights with a fixed lighting.

3.2 Extraction of the geometrical properties

The face is constituted of a whole of not very mobile structures which can undergo deformations and which present a significant contrast compared to their space environment.

The extraction of the characteristics of the face consists in first of all locating the eyes. The nose and the mouth will be then required by using the geometry of the face.

The existence of a reflexion of the light projected frontally on the face, on the level of the irises, enables us to locate the eyes by making a simple sweeping of the matrix image to research the position of the pixels having a maximum of energy.

To locate the nose and the mouth [7] [11], we used space-time information in order to characterize the points having recorded the strongest variation of intensity during the sequence. The resulting image named I_{som} is given by (1):

$$I_{som}=\sum_{i=0}^{i=n}\sqrt{\left(\left(\frac{\partial I(x,y,t)}{\partial x}\right)^2+\left(\frac{\partial I(x,y,t)}{\partial y}\right)^2+\mu\left(\frac{\partial I(x,y,t)}{\partial t}\right)^2\right)} \qquad (1)$$

with :
$I(x,y,t)$: Intensity of the gray level.

x, y : Space components.

t : Temporal component .

μ : A standardizationterm depending on the temporal sampling of the sequence and the movement of the face.

n : Number of the acquired images.

The localization of the nose and the mouth consists in seeking along the mediator passing by the irises, the two areas having the strongest values on the I_{som} image.

On figure 2, we have the results of the automatic extraction of the geometrical parameters of four faces.

Figure 2 *:* Example of results of the extraction of the distances from faces

4 Neural Networks and Principal Component Analysis

4.1 Principal component analysis Method

The principal objective of the PCA is to succeed in expressing a complex data system of unspecified size, represented by a table says "Individuals/Variables", in a smaller number of dimensions, while minimizing the loss of generated information [12] [13] [14] [15].

The mathematical implementation of the PCA can be divided into 7 principal stages [16]:

Stage 1: Preparation of the data

The data to be treated by the PCA are stored in a table X of "individus/variables" type of the form:

$$X = \text{individus} \begin{array}{c} \\ 1 \\ \ldots \\ n \end{array} \begin{array}{c} \text{variables} \\ \begin{array}{ccc} 1 & \ldots & p \end{array} \\ \begin{bmatrix} x_1^1 & \ldots & x_p^1 \\ \ldots & \ldots & \ldots \\ x_1^n & \ldots & x_p^n \end{bmatrix} \end{array} \quad (2)$$

with :

p : variables, represented in columns,

n : individuals, represented in lines,

x^i_j : values taken by each variable, for each individual, such as :

$$(x_j^i)_{(1 \le i \le n, 1 \le j \le p)} \forall (i, j), x_j^i \in \Re \quad (3)$$

The problem is that, if we analyze directly the matrix X, the results would be distorted by the relative variables values (for example, if the values were measured in different units). To reduce these effects, we must prepare the data for the treatment. That consists in using a center-reduced version Xcr of the matrix X. To center matrix X, we withdraw from each value the average of its variable. To reduce the centered matrix, we divide each value by the standard deviation of his variable.

Stage 2 : Calculation of the correlation coefficients matrix.

In this stage, we calculate the correlations matrix of the data contained in table Xcr, noted " Corr ".

Stage 3: Calculation of the eigenvalues and the eigenvectors of the correlations matrix

The eigenvalues and the eigenvectors of the matrix "Corr" are the factors used to build the principal components.

Stage 4 : Classification of the eigenvectors in the descending order of the associated eigenvalues:

Then, we have the factors in the descending order of the quantity of information which they express. It is also possible to express as a percentage the importance of each one, in order to visualize the relative importance of the principal components. Let us note by " U " the matrix whose columns are the eigenvectors of " Corr " classified by descending order of their associated eigenvalues.

Stage 5 : Calculation of the principal components matrix
The components principal matrix, noted CP, contains the co-ordinates of the individuals in the space formed by those. They are calculated by the following expression : CP = Xcr U

Stage 6 : Graphics representations

Stage 7: classification of the faces
By using the max of the correlation between the face to be recognized (projected on the graphic representation of the faces) and all the data base.

The goal of the PCA being to summarize a given situation, the grahic representation is the final and the most significant phase of this process, because it makes possible to have quickly an outline of what numerical calculation cannot provide. It is a question of using the principal components matrix, previously calculated, to represent the individuals in a form of clouds of points, in plans or vectorials spaces of two or three principal components.

4.2 Application of the PCA on faces objects

Our application consists in classifying a whole of faces of 40 people including 20 women and 20 men with an aim of recognizing them. The information extracted from each face is represented by the whole of the distances corresponding to the 40 people. For each person, we took 5 measurements deduced, each one, from a short images sequence. Entirely, we used 200 images with 8 dimensions where each dimension represents a distance marking one of the features of the face (see figure 1).

By sorting the eigenvalues in the descending order as well as the eigenvectors associated, we obtained the distribution graph of the eigenvalues of figure 3.

The calculation of the components makes it possible to give a new co-ordinates for each person. These results make it possible to establish a new representation according to the 2 or the 3 first principal components (principal axes) instead of the 8 preceding dimensions.

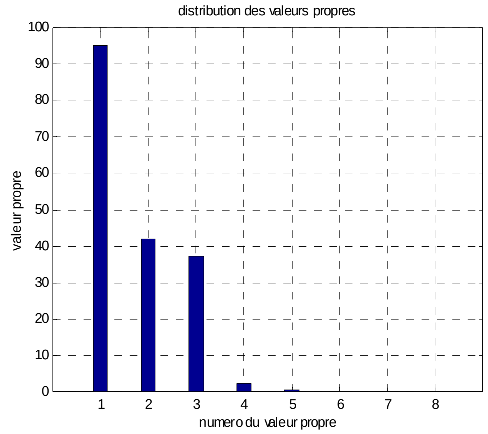


Figure 3 : Graph of the eigenvalues distribution

Figure 4 illustrates the representation of the 40 people (with 5 faces each one) in the plan of the principal components 1 and 2.

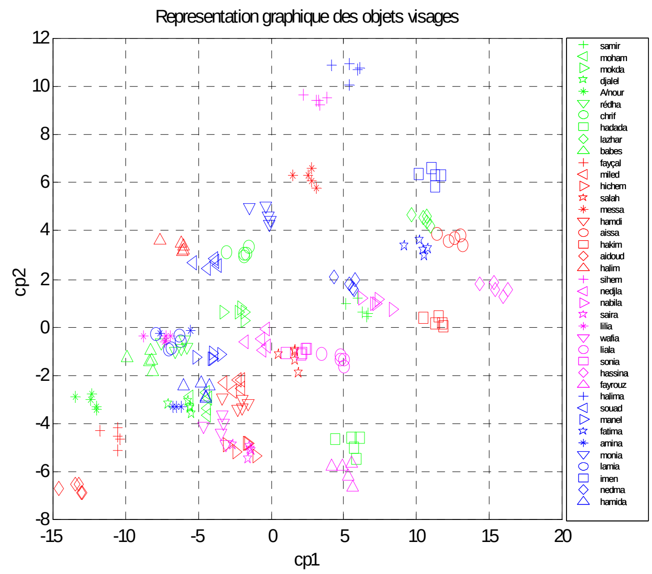
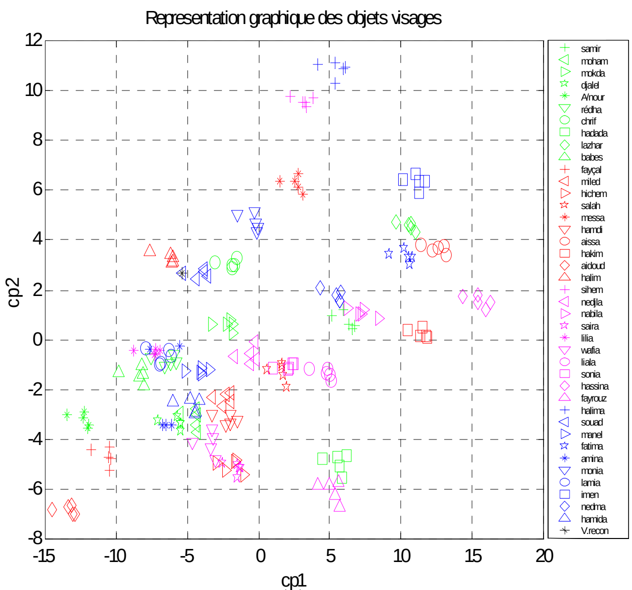


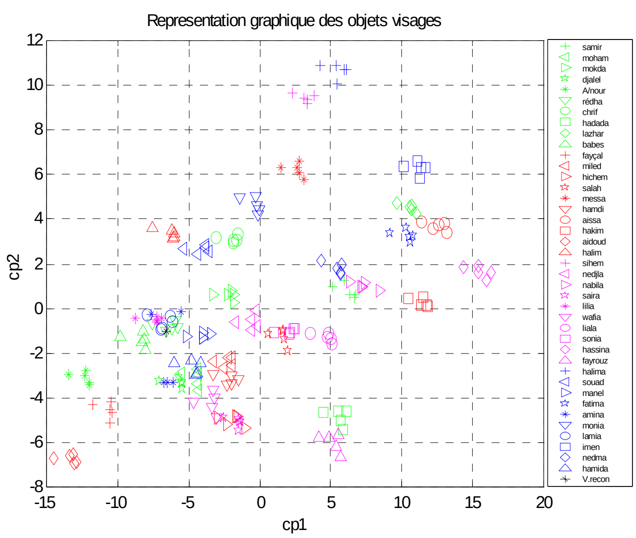
Figure 4 : Graphic representation of the faces objects on PC1 and PC2

According to this representation, we note that each person represented is separated from the different one, but there are classes which overlap because, certainly, the resemblance of some people between them. For the classification of a person to be recognized, we project these components on this representation from which we will be able, thereafter, to decide membership or not this person with the whole of the classes represented.

Figure 5 illustrates the projection of two people (man: redha (A), woman: souad (b)) to recognize in the field of the principal components 1 and 2. On these figures, we notice the clear coincidence of the person to be recognized with a class representing the face of the considered person (souad et redha).



(a)



(b)

Figure 5 : Graphic representation of the people souad(a) and redha (b) classification

By making tests of recognition on the whole of the people of the data base, we could calculate the rates of recognition and rejection on the basis of projection and test.

Table 1 shows that the method led to very good results.

	Rate of recognition	Rate of rejection
Projection base	100%	0%
Test base	91.5%	8.5%

Table 1 : Results of the PCA method

4. 3 Hybridization of the PCA and the NN

The in principal component analysis is a method which led to considerable results in the classification field and with its simplicity and its reliability it almost does not present a disadvantage.

The Neural Networks [17] [18] [19] form also part of the best methods and thus generally used in this field, only their rate of recognition always remains to be improved (see table 2). For this reason, we tested hybridization of these two methods [20].

	Rate of recognition	Rate of rejection
Projection base	99%	1%
Test base	91%	9%

Table 2 : Results of the NN method

Let us recall that the parameters of the method of the PCA, which is the co-ordinates of the people along the principal axes, correspond to the lines of the matrix (200x8) of the principal components where each line gathers 8 parameters of one of the 200 faces.

The idea [1] on which we based ourselves to develop this new method, is: instead of providing to the network neurons the 8 distances, we replace them by the 8 parameters of the PCA.

That led us to choose the following PMC structure [21] [22]: 8 neurons of entry, 30 neurons for the hidden layer and 40 for the exit layer (representing 40 faces to be discriminated). The activation function is the sigmoid unipolar one.

By considering a step of training of 0.75, we obtained, after 500 iterations, a maximum error of 0.0267. The evolution curve of the error ccording to the iteration count is represented in figure 6.

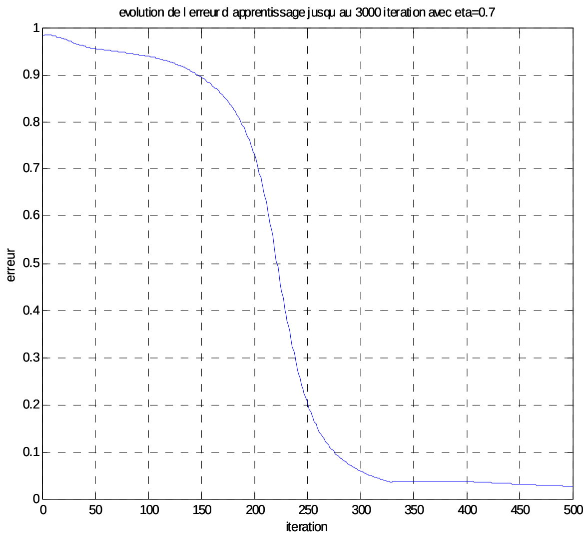


Figure 6 : Error evolution according to the iteration count

The results, illustrated in table 3, obtained by this hybridization method (NN-PCA) are better than those obtained by using one of two methods PCA or NN separately.

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	Rate of recognition	Rate of rejection
Projection base	99%	1%
Test base	94,5%	5.5%

Table 3 : Results of the hybrid method NN-PCA

5 Conclusion and prospects

We note a considerable improvement (3 %) of the recognition rate of the test base. This carries out us to conclude that thanks to the performances of the method of analysis in principal component we could improved the results of the networks of neurons.

This, enables us to conclude that: thanks to the performances of the method of principal component analysis, we could improve the results of the neural networks method.

Another advantage, more significant, is that of the computing time, which we did not present in this paper, where we note a clear improvement...

These results remain preliminary, because we obtained them with a data base taken under quite specific conditions. It would be more beneficial, if we manage to find these same results under other conditions of acquisition of the sequences images.

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