Applying DWT and PCA with Artificial Neural Network for FACE RECOGNITION

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Abstract_ This manuscript presents, Face recognition by combining different extraction approaches combining PCA (principal Component Analysis), DWT (Discrete wavelet transform) and neural networks. This method consists of four steps: i) Preprocessing, ii) Dimension reduction using DWT, iii) feature extraction using PCA and iv) classification using neural network. To validate this work, we have tested this technique on frontal images of the ORL and Yale databases.

Keywords - Face Recognition, Biometrics, PCA, Neural Networks, Feature extraction, eigenfaces , DWT.

I. INTRODUCTION

With the development of computers, the idea of automatic recognition is born, it is the beginning of modern biometrics, it has gained considerable attention and many approaches have been developed and proposed by the scientific community using several methods based on fingerprints, iris, voice or face.

Facial modality is distinguished from the rest of the other modalities by the simplicity of the identification systems, and receives an increased attention because of its non-invasive nature, in the sense that it does not require the cooperation of the individual.

Before detailing the techniques used in this paper, we will present first an overview of studies done by researchers in cognition and facial recognition.

The first work on face recognition began in the early 1970s [5]. But it's just the last thirty years that research on face recognition has grown extensively and became of a great interest. For this reason, many several approaches have been proposed in the literature [3], they can mainly be classified into three groups:

- Local approaches: they extract facial features by focusing on the critical points of the face such as the nose, mouth, eyes; which will generate more details.

- Global approaches: their principle is to use the entire surface of the face as a source of information regardless of local features such as eyes, mouth ... etc.

- Hybrid approaches: they combine both types of methods, potentially offering the best of both.

Global approaches use the face in its entirety as the recognition system input, and perform a statistical projection of images (high-dimensional space) in a space of faces (smaller size). One of the best known methods in this category is called "eigenfaces" introduced by Turk and Pentland [1] is based on the Principal Component analysis (PCA) of faces.

Another popular technique is called Fisherfaces based on the Linear Discriminant Analysis (LDA), which subdivides the faces into classes while maximizing the inter-class variance (between two different individuals) according to the Fisher criterion [2].

Among the other global methods, we find: Bayesian approaches, and the SVM method [8], which uses Support Vector Machine (SVM), Active Appearance Models (AAM) [7] or the "Local Binary Pattern "(LBP) method [9] were used in order to easily model pose variations, lighting and expression in comparison to local methods.

Local approaches use local features as inputs of the recognition system. Therefore, there is an extraction phase of these local settings such as the nose, mouth and eyes.

For the recognition, or regions containing these elements, or the geometric relationships between them from side or face views.

The most popular local approach is the Elastic Bunch Graph Matching (EBGM) [4]. From the image of the face, it locates the feature points (eyes, mouth, nose, etc ...). A virtual elastic lattice is then applied to the face image from these points.

Hybrid approaches permits to combine the advantages of global and local methods by combining geometric features with local appearance characteristics. They increase the recognition performance when changing pose, illumination and facial expressions. More recently, the algorithm of Log Gabor PCA (LG-PCA) [6] performs a convolution with oriented Gabor wavelets around some characteristic points of the face in order to create vectors containing the location and the value of local energy amplitudes; these vectors are then sent to a PCA algorithm to reduce the data size.

In this paper, first the PCA technique's of how to extract the discriminate feature vectors and dimension reduction using DWT (Discrete wavelet transform) is illustrated, and then, the practical adjustments necessary to implement the hybrid identification technique called Neural-PCA are outlined. After that, the experimental results obtained by each method by analyzing their performance, followed by a discussion with results interpretation are presented.

II. EIGENFACE ANALYSIS

Face recognition by eigenfaces is one of the global approaches. Each face image is regarded as a vector in a space having as many dimensions as there are pixels in the image. The image features are extracted by a mathematical dimensionality reduction based on principal component analysis (PCA). This approach was originally proposed by Turk and Pentland in 1991 [1].

The method is based on eigenfaces as on the first eigenvectors , hence the term eigenfaces. The base formed by these vectors is a space that is used to represent the images of the faces. People are thus given a vector belonging to each of their images. That being said, the recognition is performed by comparing the coefficients of projection of a test face with those of the training faces.

A. principle of the method Eigen Faces

After selecting the faces in which we will work, the idea of this method is to represent each image as a vector and then regroup them to form a matrix of vectors called image matrix; this matrix is denoted Γ .

Assume Γ_i a $N^2 \times 1$ vector corresponding to an image I_i with size $N \times N$. The goal is to represent Γ in a lower dimensional space, it must be orthogonal (each pair of component vectors bases are orthogonal to each other), in order to discriminate the images.

We present in what follows the main steps of the eigenface method.

Step 1

This step defines the images of people, suppose that M is the number of images ranging from I_1 , I_2 ,…, I_M .

These images must be centered and have the same size.

Fig.1 Example faces of the base ORL

Step2

This step consists in representing each image I_i by a vector Γ_i . For this, we will superimpose the columns of each image.

Step 3

This step consists in calculating the average faces and representing them in a vector Ψ .

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

Step 4:

This step consists in removing the average of the image matrix, in other words:

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removing everything in common between the individuals. The resulting matrix Φ is obtained as follows:

$$\Phi_i = \Gamma_i - \Psi \quad \text{.............................. (2)}$$

Step 5

This step consists on building the covariance matrix C of the matrix Φ. The covariance matrix represents the interaction between individuals.

$$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T = A \times A^t \quad (N^2 \times N^2) \text{..(3)}$$

Where

$$A = [\Phi_1 \Phi_2 ... \Phi_M] \quad (N^2 \times M) \text{ .... (4)}$$

Step 6

This step consists on calculating the eigenvectors which constitutes our area of study. These vectors u_i are derived from the covariance matrix $C = AA^T$.

Consider the matrix $A^T A$ ($M \times M$), if we try to calculate its eigenvalues, we notice that they are the same as those of the matrix C. In addition, there is a relation between the eigenvectors of both matrices which is the following: $u_i = A v_i$.

It is to note that for the matrix AA^T we have N^2 eigenvalues and eigenvectors. And for the matrix $A^T A$ we have M eigenvalues and eigenvectors.

Thus, the M eigenvalues of $A^T A$ correspond to M larger values of the matrix AA^T (in correspondence with their eigenvectors).

Step 7

This step is quite simple to make, it is to take K eigenvectors corresponding to the K largest eigenvalues.

B. **The Eigenfaces**

Once the base vectors are found, it only remains to determine the representation of faces in our new space, for this, the procedure is as follows:

Each face (minus average) will be represented as a linear combination of K the selected eigenvectors.

$$\hat{\phi}_i - mean = \sum_{j=1}^{K} w_j u_j \quad \text{.................... (5)}$$

$$w_j = u_j^T \phi_i \quad \text{... (6)}$$

So each training face ϕ_i will be represented in the space as follows:

$$\Omega_i = \begin{bmatrix} w_1^i \\ w_2^i \\ . \\ . \\ . \\ w_K^I \end{bmatrix} \quad i = 1, 2, ..., M$$

Therefore, by the application of PCA, an input face vector of dimension n is reduced to a feature vector in a subspace of dimension m.

C. **choosing the dimension of the area:**

The problem that remains to be resolved is the choice of K, the dimension of the space.

For this, we will need a threshold (percentage) called: amount of information. The goal is to represent a certain amount of information in a minimum of base vectors. If, for example, we want to represent 70% (0.70) of the information then K is found as:

$$\frac{\sum_{i=1}^{K} \lambda_i}{\sum_{i=1}^{N} \lambda_i} > THRESHOULD \quad \text{................. (7)}$$

We then find the minimum of the distances to all of the faces stored in the database, and the closest matching one is recognized. It should be noted that if the distance is greater than some threshold t, then the person is classified as unrecognized. t must be determined experimentally.

D. **Operating principle**

The recognition system being used is based on an eigenfaces-based global method. The overall architecture is shown in Figure 2.
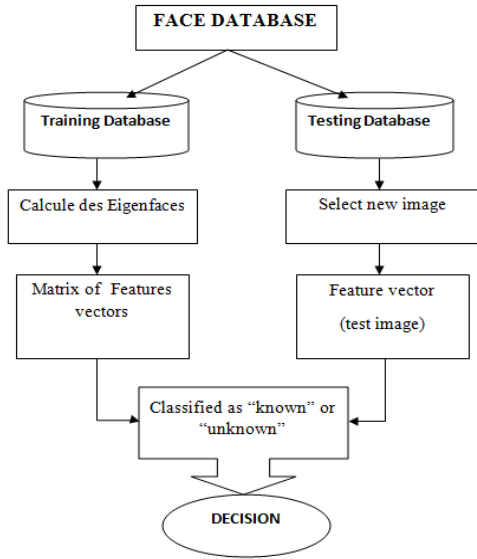
Fig. 2 - Block diagram of the PCA-based system

E. **Discrete wavelet transform (DWT)**

Discrete Wavelet Transform is a popular tool in image processing and computer vision, because of its ability to capture localized time-frequency information of image extraction. The decomposition of the data into different frequency ranges allows us to isolate the frequency components introduced by intrinsic deformations due to expression or extrinsic factors (like illumination) into certain sub bands. Figure 3 shows various subbands in 1-level and two level decomposition of wavelet.
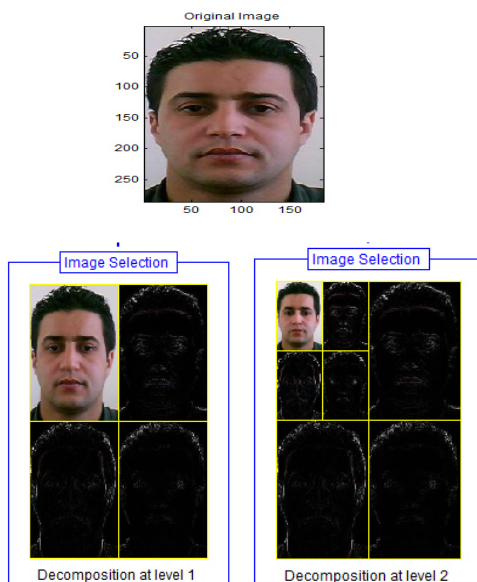

Fig.3- *Wavelet decomposition in different levels*

III. **Face recognition using the Neural-PCA approach**

The neural network being used in this paper is a multi-layered network using a backpropagation algorithm for training; it has a single hidden layer, the input number N depends directly on the size of the image. In order to reduce the network's training time, a reduction of the size of face images of the all database (image size ORL database used 92 x 112 in dimension ~ 32 x30) is performed.

In this approach, the network receives as input the actual 960 values which correspond to the 960 pixels of the input image (the image size ~ 32 x 30, Figure.3).

A. **Effect of the choice of the network's topology**

The performances of the network (Multi-Layer Perceptron MLP) depend on the weight's initialization, the training's step and the number of neurons in the hidden layer; that is why we made several tests before preserving a topology that gives the best performance (training is stopped when the mean square error is ≤ 0.001). The reported recognition rates are the average rates of the six partitions obtained from the basis of test for each method and for each retained number of eigenvectors. Choosing the appropriate number depends on the applied method and the used database of faces.
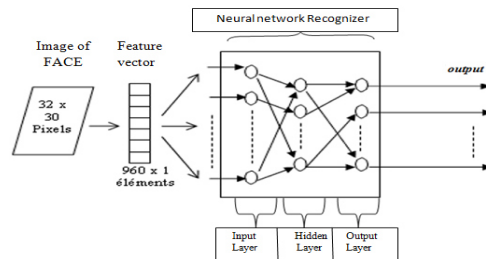

Fig. 4 - The architecture of the proposed model of neural network.

The principle of our hybrid Neural-PCA has three stages: i) a step of normalizing faces, ii) extraction of features and size reduction by the main component analysis approach and iii) hybrid approach for face classification, which comprises on compacting the number of coefficients needed to represent a face matrix by combining the PCA with neuronal recognition. This system's performances are due to the representing power of the PCA and the generalization of the neural network of type MLP.
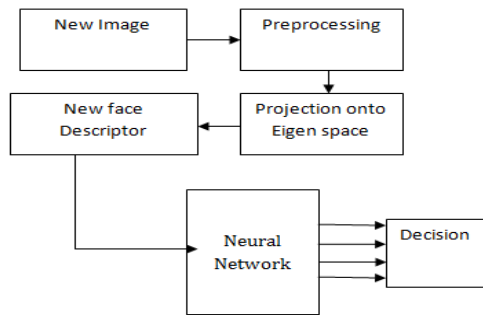
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Fig. 5 - The architecture of the proposed Neural-PCA model

IV. FACE RECOGNITION SYSTEM: PRINCIPLES AND EXPERIMENTATION

The problem of face recognition is defined as follows: given a face image, we want to determine the identity of that person. To do this, it is necessary to have the reference images, in the form of a database of faces of all known people by the system. Each face is associated to a feature vector. These characteristics are assumed to be invariant for a single person, and differ from each person to another. The recognition is based then on comparing the feature vector of the face subject of recognition with those of each face in the database. This allows to find the person with the most similar face, which is the one whose vector is the most similar.

A. Faces Database

To evaluate the performance of the proposed methods, two databases are employed: the ORL database and Yale database.

The ORL database of AT&T laboratory [10] University of Cambridge, contains ten images, with "Portable Gray Map" (PGM) format, of 40 people with different angles and facial expressions. The size of each image is 92x112 pixels, with 256 gray levels per pixel. The other database is the Yale's face images [11], the latter consists of 165 gray-leveled frontal face images of 15 persons, with 11 images for each person. Both databases are presented for both systems as test sets to see the relative performance of the two approaches.

After collecting the face image at different times using a capture device (webcam) to form our own database "own Database". The database includes 100 JPG face images taken in 10 different subjects (N = 10) each recorded in 10 different views.

Fig 6 – Sample images of "Own Database".

B. Experimentation and results

From the recognition system presented in fig.2, various tests were carried out according to different numbers of eigenvectors.

The base used is the Olivetti Research Laboratory face database also called ATT face database [10] was divided into two bases, one for training and one for testing.

A preprocessing step is performed at the beginning to render the images to compare uniform. This preprocessing is carried out on both images (images of the database and the images in question). it permits to convert all the images in the same format to ensure data consistency.

After gathering the faces in a single matrix, we obtain a matrix of images; then, the average face of all collected facial images is calculated. This image can be seen as the gravity center of the whole matrix. After that, data is then adjusted in comparison with the average. The average image is then subtracted from each image Fig. 7.
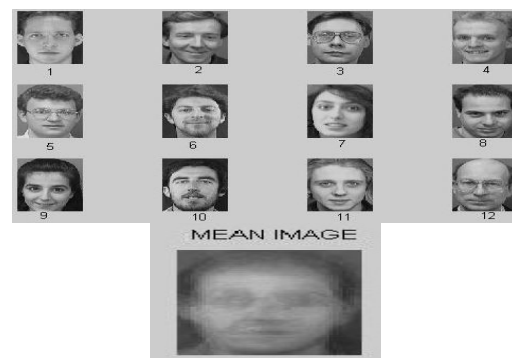

Fig. 7- Normalized faces from the ORL database and their average face

The possible number of eigenfaces fig.8 is equal to the number of face images of the entire training set. Nevertheless, faces can be approximated using only the best eigenfaces (having the largest eigenvalues which represent, in fact, most of the variance in the set of face images), thereby reducing the calculations.

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Fig. 8 - Eigenfaces

After calculating the eigenvectors (eigenfaces), the classification step is the phase in which the face recognition system assigns a test face to a class from those of the training set according to a certain well-chosen criterion. In our case, we used the Euclidean distance.

To test the effect of the eigenvalues number on the PCA, the first experiment is to take different numbers of eigenvectors (eigenfaces). Table 1 compares the best recognition rate obtained using different percentages of eigenfaces.

Numbers of Eigenfaces	50%	60%	75%	100%
Recognition Rate	41.43 %	48.56 %	68.57 %	91.42 %

Tab1. Recognition rate (%) obtained as a function of different numbers of eigenvectors.
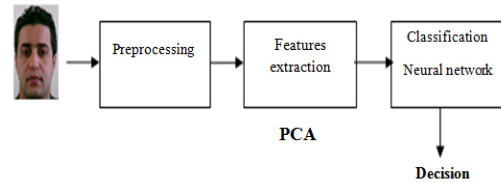

Fig 9. Neural-PCA system

To get a higher recognition rate, we have made a series of experiments to choose the best topology MLP based on parameters as follows:

performance function	MSE
Activation function	Tansig
desired error	0.001
Hidden layer number	100
Number epochs	600
Layer input	Feature vector
Layer output	Each output for a face

Tab2. The parameters training of MLP

Table 3 illustrates the recognition rate (RR) and the effectiveness of the proposed systems with a training error (in order of 10^{-3}), with 100 neurons in the hidden layer and a transfer function "tansig". It is to notice that the performance of the second system which uses the Neural-PCA technique is the best (the best recognition results were obtained).The system has achieved a 94.66% of identification rate based on ORL database,

Tab 3 - Result of recognition for each database, RR: the recognition rate. N: The number of classes distinguished people in each database .

Face recognition System	Algorithm of Recognition: Matching Module	Time of Training	Recognition Rate （RR）					
			ORL Database N [40]		YALE Database N [15]		OWN Database N [10]	
			Train set	Test set	Train set	Test set	Train set	Test set
« System 1»	Neural network	32 min 9 sec	93%	89.3%	91.4 %	87%	91%	89 %
« System 2 »	Neural network : NEURAL-PCA	1 min 34 sec	98%	94.66%	94.3 %	91.2 %	95%	93.5 %

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And 91.20% based on Yale's database with a maximum training time of 1 minute and 34 seconds for both databases, compared to the first system, where the rate (RR) is 89.3% and 87%, with a maximum training time of 32 minutes and 9 seconds. This means, that the second system is better than the first in terms of recognition rate and computation time.

As a result of these multiple experiments, we find that the Neural-PCA method gives the best recognition results, which confirms the suitability of this approach .

V.CONCLUSIONS AND OUTLOOK

In this paper, A face recognition approach based on DWT , PCA and neural network has been proposed.

The feature extraction by PCA and DWT is one of the steps which can greatly reduce the number of dimensions of the vector appearing at the input of a network. Indeed, this reduces the number of components while keeping the information characterizing the object to be analyzed without loss of information

In this paper, we presented the results of various performed experiments. The Neural-PCA face recognition system proposed in this paper is based on a hybrid approach for feature extraction with neural network classification. The experiments on the ORL database, Yale and our database, show its superiority toward the PCA and the MLP in terms of recognition rate, computation time, and in the recognition and training phases. This performance is due to both the hybrid projection combining the representative power of the PCA with DWT and the discriminating power of multilayer perceptron.

As an outlook, initially an extension of this work can be considered in the design and implementation of a system for the detection and localization of the face with enough high performance, another one is to apply this system to other bases of faces with large variations in lighting and pose, as well as the possibility to use an approach based on local elements of the face.

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