Feature extraction and face recognition using auto associative memories

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Abstract— **Face recognition is an important tool for verification and identification of an individual. It can be of significant value in safety and commerce applications. Currently there are a numerous method to recognize and identify a person in an image. These methods can be divided into two categories: geometric methods and global methods, the performance of these methods depends on the precision with which relevant information is extracted from the face (as some of the face and eyes, nose, mouth ...).**

This paper presents a face recognition approach based on auto associative memory which is an advantage of neural networks in the field of pattern recognition.

Keywords— **Face detection, Face recognition, Associative memory, Auto associative memory and Legendre moments.**

Introduction

The face detection problem has been treated by several different methods and technology with the aim to find the best extract the image face that allows a better recognition rate.

According Hjelmås and Low [1], methods of face detection can be classified into global approach and local approach in which the face is analyzed as a whole, locate and bring together the different elements of the face.

Face recognition is based on our ability to recognize people; she has no great difficulties for a human being why he thinks a computer system that will play this role. There are many approaches to remedy this problem. We can also divide the facial recognition methods in three categories in general [3]: global methods (the full face as a source of information) among these techniques Faces clean, DCT Networks is cited neurons, LDA [2]. Local methods (the Eigen Object (EO), the HMM (Hidden Markov Models)) [4] and hybrid methods this technique is to combine several methods to solve the identification problem.

The most commonly used in object recognition techniques in the last year are: neural networks [2] principal component analysis (PCA) [5], the independent component analysis (ICA), support vector machine (SVM) [6], neural networks Learning Vector Quantization LVQ-RN [4].

One of the Most Important Application of neural networks is the associative memories All which area exploratory tool in our work.

Any process automatic face recognition should take into account several factors that contribute to the complexity of its task, because the face is a dynamic entity that is constantly changing under the influence of several factors. Fig. 1 illustrates the principle itself.

This work is organized as follows: in Section 1 we will treat the acquisition phase and pretreatment face, Section 2 describes the feature extraction method by Legendre moments and in Section 3 our methods face recognition by auto associative memories.

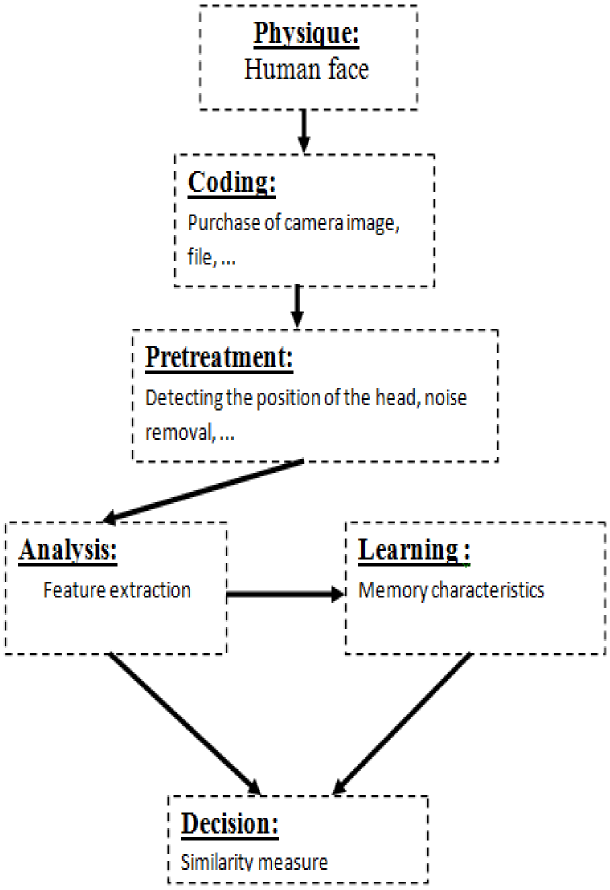


Fig. 1: The process of face recognition.

I. PRETREATMENT

After the image acquisition (extract the real world for a two-dimensional representation of objects in 2D), this can be static (Camera, Scanner, etc…) or dynamic (Camera, Web Cam), in this case we will be a movie. At this level we will have a raw image.

International Journal on Optimization and Applications
IJOA. Vol 1, Issue No. 1, Year 2021, www.usms.ac.ma/ijoa

The raw image can be affected by various factors causing its deterioration, it can be noisy, to overcome these problems, there are several treatment methods and image enhancement, such as: standardization, histogram, equalization, etc.

This step is very important because it should influence the next steps in my memory we've used this three pre-treatment methods: normalization, binarization and filtering.

1. NORMALIZATION

The normalization consists of two processes: geometric and photometric. Geometric normalization is necessary because the size of the face within the image acquired may vary depending on the distance between the acquisition module and the person (Fig.2).

The photometric normalization step attempts to eliminate or reduce the effects of the illumination of image. In some cases, the step of photometric normalization can be applied before, or before and after the step of geometric normalization. It can also be applied during the detection phase.

Normalization of the image is scaled to a fixed size for all images in database.

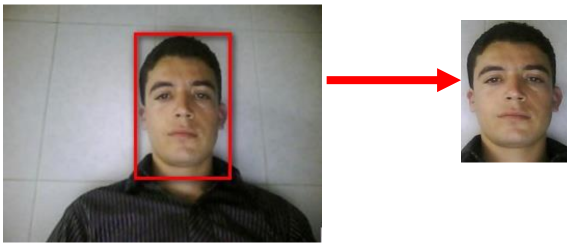


Fig. 2: Geometric form of the image right and photometric normalization left

2. BINARIZATION

A method for binarization is required to transform the image in black and white in order to facilitate the next steps including the extraction of features (Fig. 3).

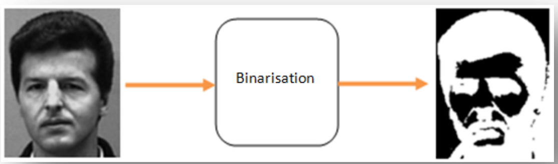


Fig. 3: Binarization of face image

II. FEATURE EXTRACTION

In pattern recognition and image processing, feature extraction is a particular form of reduced dimensionality. When the input of an algorithm is too important to be treated, the percentage of redundancy is very important causing a disturbance and images can't be treated well (lots of data but not much information), then the input data will be transformed into a reduced representation of all functions (also called feature vector). Transformation of input data is called feature extraction.

In this step we used the Legendre moments of our image to extract face features the most relevant.

The moments of Legendre, were first introduced by Teague [4]. They belong to the class of orthogonal moments and have been used in several applications of pattern recognition [17].

The two-dimensional Legendre moments of order (p + q), image intensity function f (x, y) are defined as [18]:

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \int_{-1}^{1} \int_{-1}^{1} P_p(x)\, P_q(y) f(x,y) dxdy$$

With p, q =0, 1, 2, 3, 4 …

Or P_p (x) P_q (y) are called Legendre polynomials defined as follows:

$$P\ (x) = \sum_{k=0} (-1)^{\frac{-k}{2}} \frac{1}{2} \frac{(p+k)!\, x^k}{\left(\frac{p-k}{2}\right)!\left(\frac{p+k}{2}\right)!\, k!}$$

For p-k = pair , p, q = 0, 1, 2, 3 … x Є [-1, 1] degree (Pp(x)) = p.

Finally the moment of Legendre order (p + q) of a digital image f (x, y) is:

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \sum_x \sum_y P_p(x) P_q(y) f(x,y)$$

The recurrence relation of Legendre polynomials, Pp (x) is given as follows [17]:

$$P\ (x) = \frac{(2p-1)xP_{-1}(x) - (p-1)P_{-2}(x)}{p}$$

Where P_o (x) = 1, P_1 (x) = x and p> 1. Since the region of definition of Legendre polynomials is within [-1, 1], a square image of N x N pixels with intensity function f (i, j), 0 ≤ i, j ≤ (N - 1), across the region -1 <x, y<1.

In the result, equation (1) can now be expressed as discrete as follows [17]:

$$L_{pq} = \lambda_{pq} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_p(x_i) P_q(y_j) f(i,j)$$

Where the normalization constant is:

$$\lambda_{pq} = \frac{(2p+1)(2q+1)}{N^2}$$

x_i and y_i denote the normalized pixel coordinates in the interval [-1, 1], which are given by [17]:

$$x_i = \frac{2i}{N-1} - 1$$

And $$y_j = \frac{2j}{N-1} - 1$$

The Legendre polynomials are characterized by the property of orthogonality, in fact:

$$\int_{-1} P_p(x)P_q(x)dx = \frac{2}{(2p+1)}\delta_{pq}$$

δ_{pq} is the Kronecker symbol checking the following property:

$$\delta_{pq} = \begin{cases} 1 & sip = q \\ 0 & ailleurs \end{cases}$$

We are a square matrix whose elements represent the Legendre moments of our face image, we represent this matrix must enter an auto associative memory that must operate in the learning stage.

$$L = \begin{bmatrix} 7.6250 & 2.6250 & 47.9855 & 41.4609 \\ -0.5735 & -2.7433 & -0.4849 & -12.0448 \\ 45.6531 & 15.7750 & 282.3619 & 245.0041 \\ 7.5450 & -15.1418 & 70.2490 & -14.4766 \end{bmatrix}$$

Fig. 4: Feature extraction by Legendre

III. Learning using Auto associative memories

Associative memory in the designation, the term memory refers to the storage function of these networks, and the term the associative addressing mode, since it must provide information to the network for one that is stored: c 'is a memory addressable by its contents.

With auto-associative memories, provide some of the information stored for the stored information (e.g. part of the face to get the entire face).

The applications of these memories are essentially the reconstruction of signals and their recognition.

Each neuron is connected to all others, and all entries. The transfer function is usually the identity. The evaluation can be done synchronously or asynchronously.

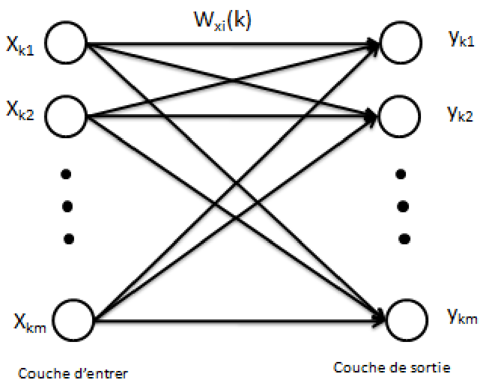


Fig. 5: Associative Memory

With
X_k: Input Vector.
$X_k = [x_{k1}, x_{k2}, \ldots, x_{km}]$.
Y_k: output vector.
$Y_k = [y_{k1}, y_{k2}, \ldots, y_{km}]$.
W_{ki} (k): weight of memory.
And
k: Number of stimuli
m: number of neurons

For an auto associative memory input vector equal to the output $Y_k = X_k$.

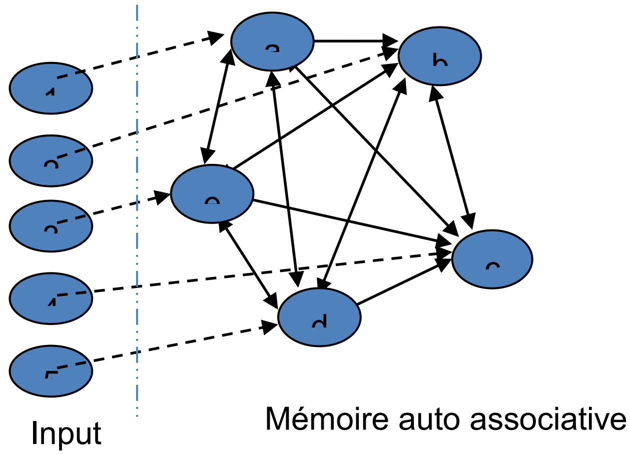


Fig. 6: Auto associative memory model

Learning by auto associative memory type is supervised. That is to say that the training set consists of pairs of vectors associated with input and output, and is based on the Hebb rule.

$$W = L * L^T$$

L: The Matrix features

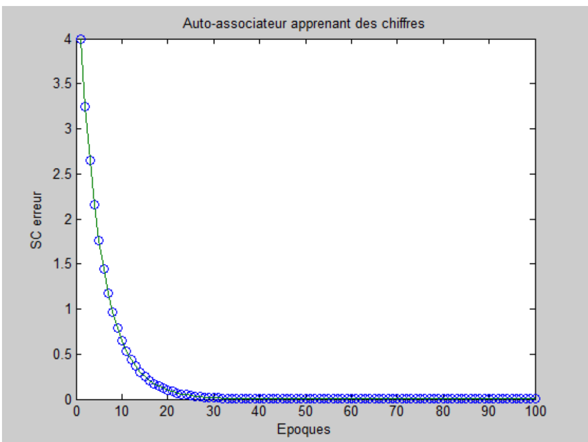
On leaving the auto associative memory must be obtained another matrix O calculated as follows:

$$O = W * L$$

With an error:

$$e = \sum |t - O|$$

The error is calculated using iterations as shown in the figure below:



International Journal on Optimization and Applications
IJOA. Vol 1, Issue No. 1, Year 2021, www.usms.ac.ma/ijoa

Fig. 8: The error based on iterations

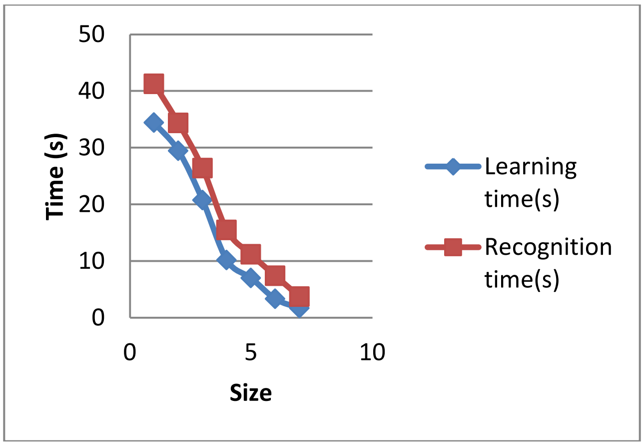
IV. EXPERMENTAL RESULTS

In this part of the face recognition factor of time plays a very important role. Learning a large database requires significant time requires the attachment of the smallest size possible, taking into account the loss of information when the set size is small.

The table below shows the change in the learning time and recognition based on the size of the image for a face database of images.

Table 1: Time for learning and recognition based on the size

Size	Learning time(s)	Recognition time(s)
52 x 46	34,38	41,26
50 x 40	29,45	34,33
44 x 32	20,71	26,37
30 x 22	10,15	15,45
25 x 18	7,00	11,15
18 x 12	3,32	7,38
12 x 8	1,66	3,72



The decision is part of the system or on the edge of an individual belonging to all the faces or not, and if so what is its identity. So the decision is the culmination of the process. It can enhance the recognition rate (reliability) as determined by the rate of correctness of the decision.

In this step of the recognition, we repeat the same procedure as step of learning, wish means we must extract the matrix of characteristics for each test face image, and using the matrices stored auto associative memories by calculating the output matrix. Finally, we traverse the corresponding face image.

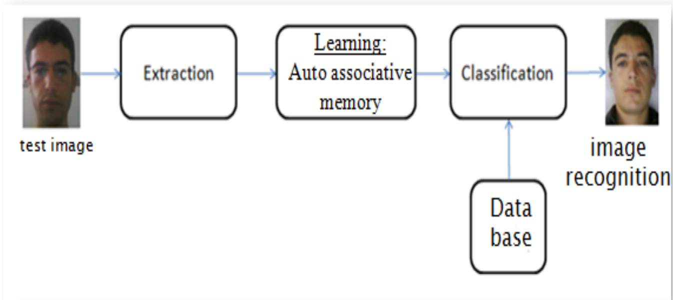


Fig. 8: The process of *face recognition by associative memory self.*

The table below shows the recognition rate for deferent size used:

Table 2: Recognition rate for each size

Size	Rate
52 x 46	100%
50 x 40	94%
44 x 32	90%
30 x 22	88%
25 x 18	90%
18 x 12	81.8%

The poor rate of recognition when the small size and depends on the lack of information extracted from a small face image.

Conclusion

In our present work it has led to encouraging result ant force which explains the auto associative memories in the field of face recognition. This work is based on the extraction of information from the Legendre moments of each image considered as a matrix of characteristics, which then turn on the auto associative memory models of learning and classification.

The results obtained for each image studied are quite encouraging and have shown that memories auto associative adapts well to changes in face images. However, its discriminatory ability is not very strong. In addition, the weaknesses of associative memories come from the weight calculation and estimation of activation function.

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