A Face Recognition Algorithm using Eigenphases and Histogram Equalization

Kelsey Ramirez-Gutierrez, Daniel Cruz-Perez, Jesús Olivares-Mercado, Mariko Nakano-Miyatake, and Hector Perez-Meana

***Abstract*—** This paper proposes a face recognition algorithm based on histogram equalization methods. These methods allow standardizing the faces illumination reducing in such way the variations for further features extraction; which are extracted using the image phase spectrum of the histogram equalized image together with the principal components analysis. Proposed scheme allows a reduction of the amount of data without much information loss. Evaluation results show that the proposed feature extraction scheme, when used together with the support vector machine (SVM), provides a recognition rate higher than 97% and a verification error lower than 0.003%.

***Keywords*—** Histogram Equalization, Fast Fourier Transform, Principal Component Analysis, Support Vector Machine.

I. Introduction

BIOMETRICS consists of a set of automated methods for recognition or verification of individuals using physical or behavioral characteristics of such; as face, fingerprint, signature, voice, etc. This technology is based on the fact that each single person is unique and has distinctive features that can be used for identification [2]-[7].

Face recognition has been a topic of active research since the 80's, proposing solutions to several practical problems. Face recognition is probably the biometric method easier to understand, because we identify people by mainly their faces. However the recognition process used by the human brain for identifying faces has not a concrete explanation. Because it is now essential to have a reliable security systems in offices, banks, businesses, shops, etc. several approaches have been developed, among them the face-based identity recognition or verification systems are a good alternative for the development of such security systems [4].

Over the past two decades, the problem of face recognition has attracted substantial attention from various disciplines and has witnessed an impressive growth in basic and applied research, product development, and applications. Several face recognition systems have already been deployed at ports of entry at international airports in Australia and Portugal [5], most of them provides fairly good recognition rates although presents several limitations due to the illumination conditions.

All about the world, governments and private companies are putting biometric technology at the heart of ambitious projects, ranging from access control and company security to high-tech passports, ID cards, driving licenses, and company security. One of most important areas of biometric technology is face recognition [7]. There are basically two types of features that can be extracted from a person, which are: Physical biometrics such as [8]: Fingerprint, face features, hand geometry, Iris and pattern retina patterns, vein patterns and DNA; behavioral biometrics [8] such as: speaker and voice patterns, signature and handwriting features, keystroke dynamics and gait patterns, etc.

The general structure of a biometric system, shown in Fig. 1, consists of a capture pattern stage in which physical or behavioral samples are captured. The feature extraction stage estimates a template that unambiguously characterizes the biometric pattern under analysis. The produced template order must have a reduced number of data with a small as possible intra pattern variation, while keeping the inter pattern variation as large as possible. In the comparison stage, a new input pattern is compared with the template estimated in the feature extraction stage. This stage usually optimized during the training period. Finally the decision stage decides whether the extracted features vector agrees or disagrees with the estimated template.

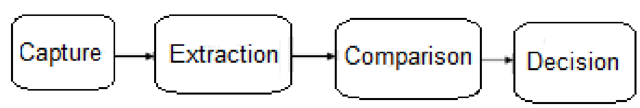

Fig.1 General Structure of a biometric system

This paper proposes a face recognition algorithm in the histogram of the image is equalized to improve the illumination of the face images to be evaluated [9]. Once these images are equalized and reduced, the algorithm proceeds to extract the features of the face under analysis using the information contained in the phase spectrum, together with the Principal Component Analysis (PCA). Then the features vector obtained using the PCA is used to train a Support Vector Machine.

II. Proposed System

Figure 2 shows the general structure of proposed face identification and identity verification system which consist of a pre-processing stage, a Principal Component Analysis stage (PCA); and a recognitions or verification and a decision stages. Thus, firstly the face image under analysis is feed into a pre-processing stage in which the histogram equalization is used to reduce the distortion produced by changes in the illumination conditions, improving in such way the face image contrast. Next the phase spectrum is estimated using the FFT which is

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processed by the PCA stage, where a matrix containing the feature vectors of each face is estimated, which allows the construction of a model for each face that will be used later by the Recognition/Verification stage of the system, to take a final decision. Finally the estimated feature vector is used together with the Support Vector Machine (SVM), to perform the face identification or identity verifications tasks.

Next sections provide a description of the pre-processing, PCA and verification stages.

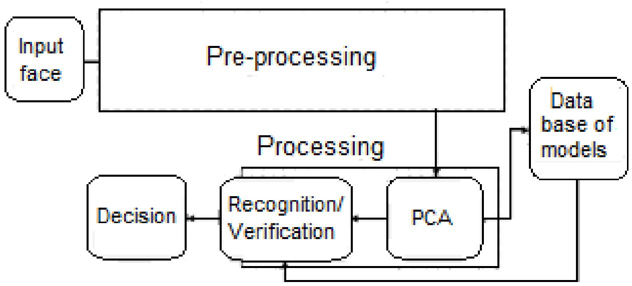

Fig. 2 Block Diagram of the Recognition/Verification System

A. Preprocessing Stage

The preprocessing stage of proposed system consists of a histogram equalization algorithm and image phase spectrum estimation using the fast Fourier transform.

1. Histogram Equalization

The histogram equalization has been a widely used image processing technique for speech enhancement, which has the property of increasing the global contrast of an image; while simultaneously compensating for the illumination conditions present at the image acquisition stage. It represents a useful preprocessing task, which can provide an enhanced face image, improving in such way the robustness of face recognition algorithms operating under different illumination conditions [10]. The main objective of this technique is to enhance the discriminative information contained in the facial images and ensure that environmental factors, such as the ambient illumination present at the image acquisition stage, do not influence the process of facial-feature-extraction [11].

The histogram manipulation [9]-[11], which automatically minimizes the contrast in areas too light or too dark of an image, consists of a nonlinear transformation that it considers the accumulative distribution of the original image; to generate a resulting image whose histogram is approximately uniform. On the ideal case, the contrast of an image would be optimized if all the 256 intensity levels were equally used. Obviously this is not possible due to the discrete nature of digital data of the image. However, an approximation can be achieved by dispersing peaks in the histogram of the image, leaving intact the lower parts. This process is achieved through a transformation function that has a high inclination where the original histogram has a peak and a low inclination in the rest of the histogram.

Consider *r* to denote continues intensity values of the image to be processed, which takes vales in the range [0, L-1], with r=0 denoting the black and L-1 the white. For *r* satisfying these conditions the transform function is given by:

$$s = T(r) \qquad 0 \leq r \leq 1 \tag{1}$$

This produces a level of *s* for each pixel value *r* in the original image. Assuming that the transformation *T(r)* is a single-valued and monotonically increasing function in the interval $0 \leq r \leq 1$; and $0 \leq T(r) \leq 1$ for $0 \leq r \leq 1$, the gray levels in an image may be viewed as random variables in the interval [0, L-1].

One of the fundamental descriptors of a random variable is its probability density function (PDF). Let $p_r(r)$ and $p_s(s)$denote the probability density functions of random variables *r* and *s*, respectively, where p_r and p_s are, in general, different functions. From a basic probability theory elementary result, it follows that, if $p_r(r)$ and *T(r)* are known and satisfies condition (a), then the probability density function $p_s(s)$ can be obtained as follows:

$$p_s(s) = (L-1)p_r(r)\left|\frac{dr}{ds}\right| \tag{2}$$

Thus, the probability density function of the transformed variable, *s*, is determined by the gray-level PDF of the input image and the chosen transformation function, *T(r)*.

A transformation function of particular importance in image processing has the form

$$s = T(r) = (L-1)\int_0^r p_r(w)dw \tag{3}$$

For discrete values we deal with probabilities and summations instead of probability density functions and integrals. Thus the probability of occurrence of gray level r_k in an image is approximated by

$$P_r(r_k) = \frac{n_k}{n} \qquad k = 0,1,2,\dots,L-1 \tag{4}$$

where, *n* is the total number of pixels in the image, $n_k$is the number of pixels that have gray level r_k, and *L* is the total number of possible gray levels in the image. Thus the discrete version of eq. (3) becomes

$$S_k = T(r_k) = (L-1)\sum_{j=(r_j)0}^{k} p_r \tag{5}$$

$$S_k = (L-1)\sum_{j=0}^{k}\frac{n_j}{n} \tag{6}$$

for $k = 0,1,2,\dots,L-1$. Thus, a processed (output) image is obtained by mapping each pixel with level r_k in the input image to a corresponding pixel with level s_k in the output image via Eq. (6). As indicated earlier, a plot of $p_r(r_k)$ versus r_k is called a *histogram.* The transformation or mapping given in Eq. (6) is called histogram equalization or histogram linearization [11]. The equalization effect is shown in Fig. 3.

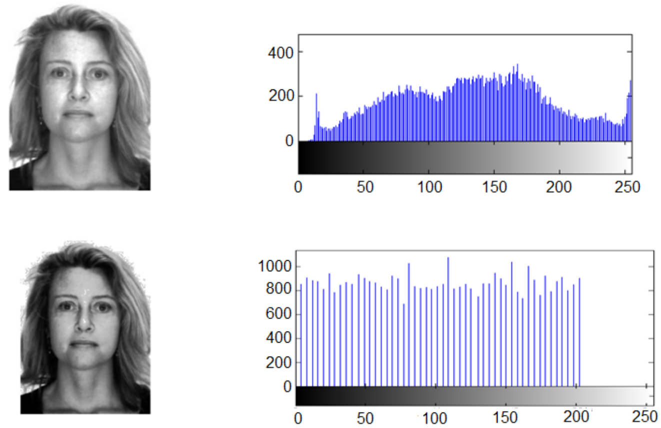

Fig. 3 Histogram equalized image face.

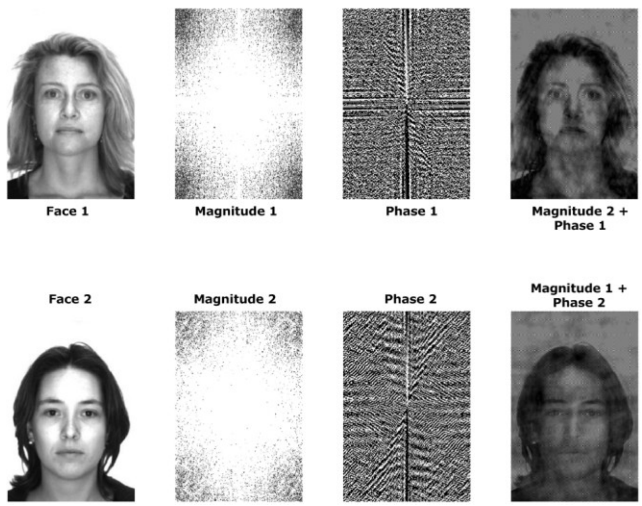

Fig. 4 Oppenheim experiment showing that the phase spectrum contains must information about the face image.

2. *Phase Spectrum Estimation*

The feature extraction plays a very important role in the any pattern recognition system. To this end, the proposed algorithm is based in the histogram equalization and the phase of the Image. The use of the phase spectrum is based on the fact that the phase information of an image retains the most of the intelligibility of an image as shown in Fig. 4. [12], [13].

During the training period as well as during the recognition or verification operation, all images are equalized before the phase spectrum estimation.

B. Principal Component Analysis

The Principal Component Analysis (PCA) is one of the most thoroughly investigated approaches in pattern recognition [13]. Sharkas [14] used the PCA to efficiently represent face pictures of faces, establishing that any face image can be, approximately, reconstructed from a small collection of weights for each face and a standard face image. The weights describing each face are obtained by projecting the face image onto the eigenpicture. In mathematical terms, the eigenfaces are the principal components of the faces distribution, i. e. the eigenvectors of the covariance matrix of the face images set. The eigenvectors are ordered to represent different amounts of variation, respectively, among the faces. Then each face can be exactly represented using only the eigenvectors that corresponds to the largest eigenvalues [14].

The PCA is a standard tool in modern data analysis, widely used in diverse fields from neuroscience to computer graphics, because it is a efficient, non-parametric method for extracting relevant information from confusing data sets. [15]

To develop a PCA analysis of input images, firstly consider that each image is stored in a vector of size NxM

$$x^i = \left[x_1^i \dots x_N^i\right]^T \tag{7}$$

Next, subtract from each training images the average image is follows that

$$\bar{x}^i = x^i - m, \tag{8}$$

Where

$$m = \frac{1}{P}\sum_{I=1}^{p} x^i \tag{9}$$

Next, using the training images given by (8), and combining them into a data matrix of size NxP, where P is the number of training images and N is the image size. Here each column is a single image, that is

$$\bar{X} = [\bar{x}^1, \bar{x}^2 \dots, \bar{x}^P]^T \tag{10}$$

Next, the covariance matrix is estimated as

$$\Omega = \overline{XX}^T \tag{11}$$

This covariance matrix has up to P eigenvectors associated with non-zero eigenvalues, assuming P<N. The eigenvectors are sorted, from high to low, according to their associated eigenvalues. The eigenvector associated with the largest eigenvalue is the eigenvector that finds the greatest variance in the images. The eigenvector associated with the second largest eigenvalue is the eigenvector that finds the second most greater variance in the images. This trend continues until the smallest eigenvalue is associated with the eigenvector that finds the least variance in the images. Then the eigenvalues and corresponding eigenvectors must be computed for the covariance matrix. Thus

$$\Omega \mathrm{V} = \Lambda \mathrm{V} \tag{12}$$

where V is the set of eigenvectors associated with the L eigenvalues. Once the eigenvalues are estimated, the eigenvectors $v_i \in V$ are sorted according to their corresponding eigenvalues $\lambda_i \in V$ from the highest to the lowest value, keeping only the eigenvectors associated with the P larger eigenvalues. This matrix of eigenvectors is the eigenspace V, where each column of V is an eigenvector of Ω [16] , That is

$$\mathrm{V} = [v_1, v_2, \dots, v_P] \tag{13}$$

Thus, finally the reduced space is obtained as

$$Y = V^T \bar{X} \tag{14}$$

The feature extraction process using the Principal Component Analysis is illustrated in Fig. 5.

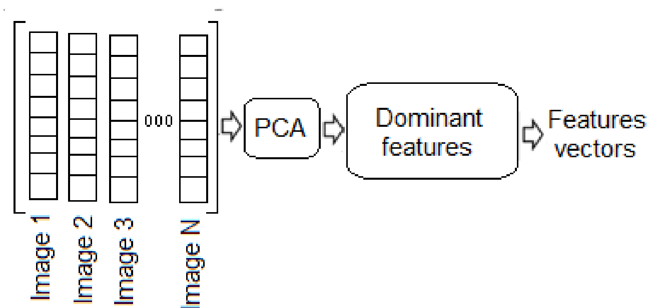

Fig. 5 Features estimation using Principal Component Analysis

C. Recognition and Verification

The recognition and verification tasks are carried out using the Support vector machines which are basically a binary patterns classification algorithm, whose objective is to assign each pattern to a class [17], [18].

Consider the problem of separating the training set of vectors $(x_1, y_1), \ldots, (x_I, y_I), \epsilon\ R^n$which belong to two separate classes $(y_i = \{1, -1\})$. Here the goal is to separate the training vectors into two classes by a hyperplane.

$$(\vec{w} \cdot \vec{x}) + b = 0\ , w\ \epsilon\ R^n\ y\ b\ \epsilon\ R, \tag{17}$$

where hyperplane $(wx) + b = 0$ satisfies the conditions:

$$(\vec{w} \cdot \vec{x}) + b > 0 \quad if \ \ y_i = 1 \tag{18}$$

$$(\vec{w} \cdot \vec{x}) + b < 0 \quad if \ y_i = -1 \tag{19}$$

Combining the last two conditions, we obtain:

$$y_i[(\vec{w} \cdot \vec{x}) + b] \geq 1, i = 1,2, \ldots, l \tag{20}$$

where w is a vector, normal to the separation hyperplane and b is a constant. The separation hyperplane represented by w is the one that maximizes the distance, m, between two classes; or the minimization of the functional.

$$\Phi(w) = \frac{\|w\|^2}{2} \tag{21}$$

Therefore, the optimization problem can be reformulated as an unconstrained optimization problem using Lagrange multipliers and its solution would be given by the identification of saddle points of the Lagrange functional [19].

In the past few years, SVMs aroused the interest of many researchers being an attractive alternative to multi-layer feed-forward neural networks for data classification, regression or PCA [20]. The basic formulation of SVM learning for classification consists in the minimum norm solution of a set of linear inequality constraints. So, it seems useful to exploit the relation between these two paradigms in order to take advantage of some peculiar properties of the SVMs: the "optimal" margin of separation, the robustness of the solution, the availability of efficient computational tools. In fact, the SVM learning problem has no non-global solutions and can be solved by standard routines for quadratic programming (QP); in the case of a large amount of data, some fast solvers for SVMs are available [21], [22]. The Support Vector Machine (SVM) structure is shown in Fig. 6.

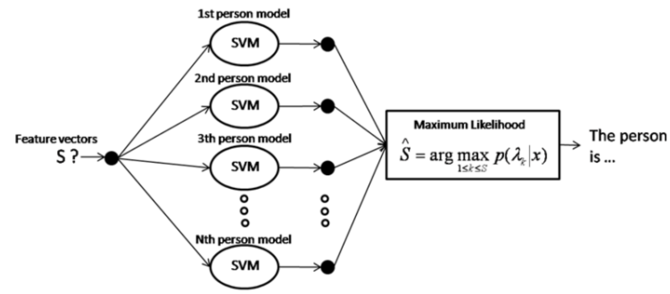

Fig. 6 Support vector machine structure for N persons.

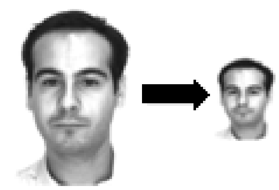

Fig. 7 Decimated face image to reduce the amount of data before factures vector estimation.

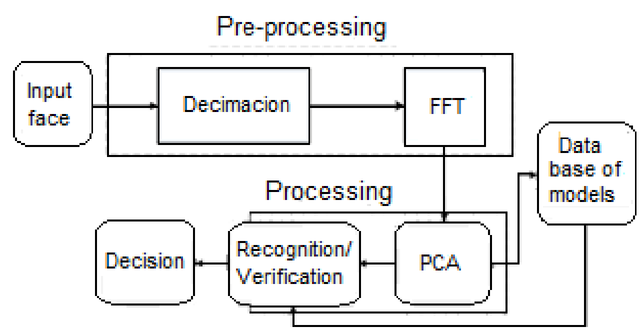

Fig. 8 First modification of proposed face recognition system

D. Modified Structures

There are some variants of the face recognition algorithm presented above, respecting the pre-processing stage, which may improve the face recognition performance of proposed algorithm. In such modifications, the main difference is the way in which histogram equalization and the phase spectrum are computed before the feature spectrum estimation.

In the first modification, which is used for comparing the evaluation results, in the pre-processing stage the face image is decimated to reduce the image size as shown in Fig. 7. Next the FFT is computed to estimate the phase spectrum, without performing the histogram equalizing. Finally PCA is applied to the face image phase spectrum to estimate the features vector with is then inserted into a SVM to carry out the recognition or identity verification tasks. Thus the only difference between this scheme, shown in Fig. 8, and the previously described face recognition scheme is the image face decimation.

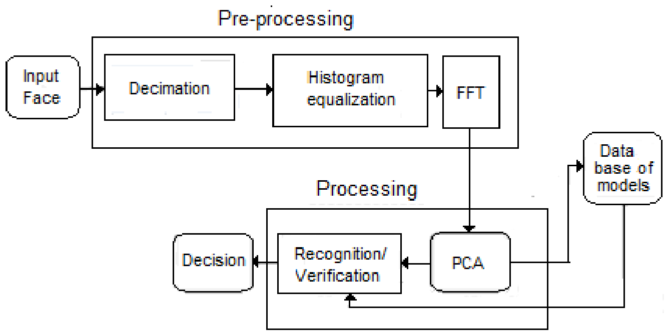

Fig. 9 Second modification of proposed face recognition system

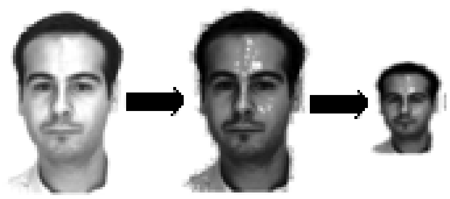

Fig. 10 Decimated face image to reduce the amount of data, together with the image face equalization, before factures vector estimation.

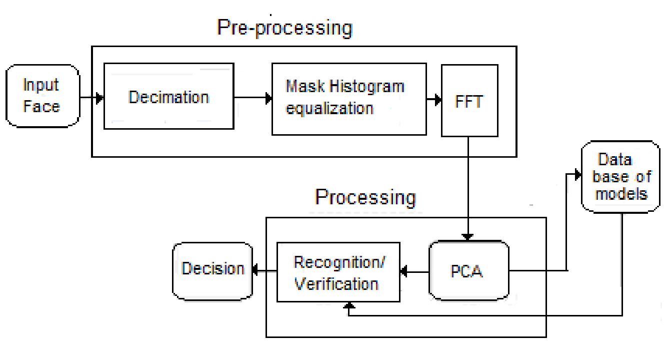

Fig. 11 Third modification of proposed face recognition system

On the second variant, shown in Fig. 9, the face image is firstly decimated to reduce the amount of data to be processed. Next the face image histogram is equalized to reduce the effects of the illumination changes, before the phase spectrum estimation using the Fourier Transform. This process is illustrated in Fig. 10. After the image histogram equalization, the features vector is estimated using the PCA which is inserted into SVM to carry out the recognition or verification tasks.

This schema provides a fairly good recognition performance when the face image has not occlusions, because when the image under analysis has some occlusions, the histogram equalization may distort the face image instead of improve it. To reduce the occlusions effect, a third variant is proposed shown in Fig. 11, in which the face image is firstly segmented in blocks of size 3x3 or 6x6. Next the histogram equalization is applied to each block, which concatenated to reconstruct the face image under analysis, as shown in Fig. 12. Finally the Fourier Transform is applied to the whole image to estimate the phase spectrum, which is used to estimate the features vector using the PCA. Finally the estimated feature s vector is feed into a SVM to carry out the recognition or verification tasks.

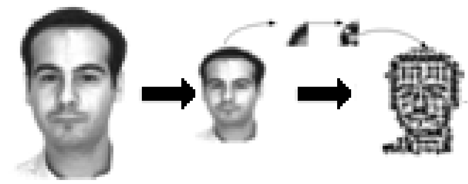

Fig. 12 Decimated face image to reduce the amount of data, together with the image face equalization by blocks, before the phase spectrum estimation.

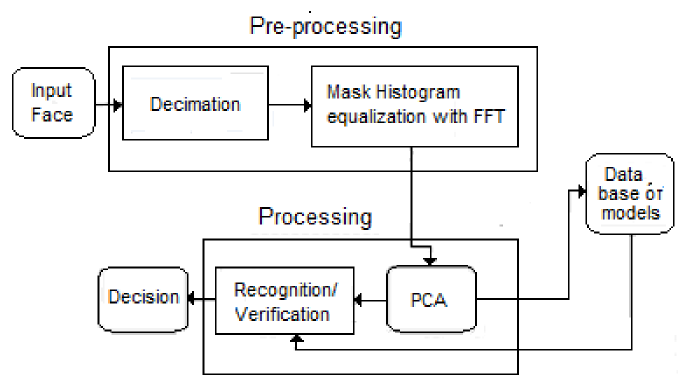

Fig. 13 Third modification of proposed face recognition system

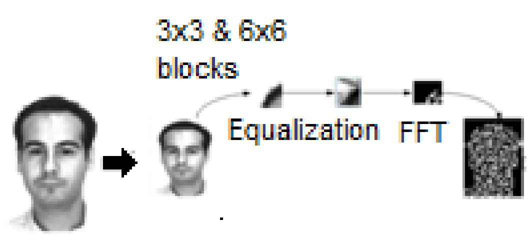

Fig. 14 Decimated face image to reduce the amount of data, together with the image face equalization by blocks and phase spectrum estimation in each block.

In the fourth and last variation, shown in Fig. 13, the original image firstly is decimated to reduce the amount of data. Then the resulting image is divided in blocks of 3x3 or 6x6 pixels which are then equalized using such blocks, as in the previous structure. Next the Fast Fourier Transform (FFT) is applied to, each block, to estimate the phase spectrum of the face image, as shown in Fig. 14. Finally these blocks are concatenated to reconstruct the phase spectrum of the face image, which is obtained using the estimated phase of each block. This is used by the PCA stage to estimate the features vector, which is feed into the SVM for carrying out the recognition or identity verification tasks.

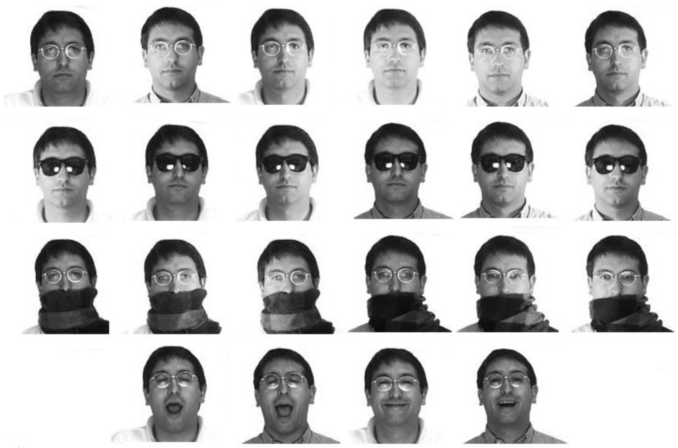

Fig. 15 Examples of the face images contained in the AR Data Base used for evaluation of proposed face recognition system.

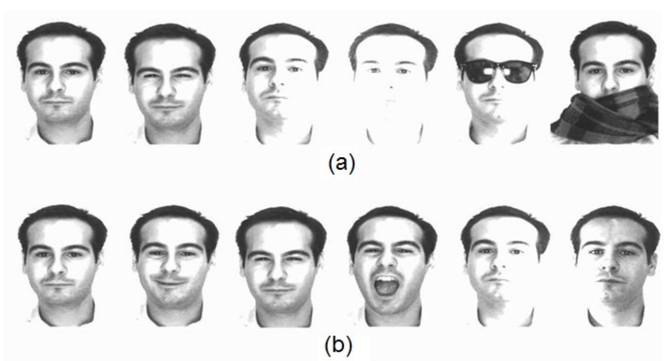

Fig. 14 Example of faces used for training of proposed face recognition methods, (a) faces with occlusion and (b) faces without occlusion.

III. EVALUATION RESULTS

To evaluate different the performance of proposed algorithm "The AR Face Database" is used, which has a total of 5,670 face images that includes face images with several different illuminations, facial expression and partial occluded face images with sunglasses and scarf, as shown in Fig. 15

The proposed face recognition system was evaluated using person identification as well as identity verification configurations. In the first case, the system outputs determines the identity of the person with the highest probability among a set of known persons, while in the second case, the system determines if the person is whom he/she claims to be. To this end, firstly the system is trained with two different groups, the denominated Group A which consists of ten faces without occlusion; and a second group or Group B, consisting of ten faces with occlusion. These groups of faces are used to obtain a model that later will be used on the recognition and verification phases. The Fig 16 shows some examples of these two groups of faces.

The tests realized using person identification and verification are divided in two groups. In the Type I the faces utilized on training are included during testing, while in Type II the faces utilized during training are not included during testing. In all cases the provided results were obtained applying these set of images to the proposed system and its variations.

Table 1 shows the recognition performance of the proposed algorithm using equalization of the whole image. The performance of standard eigenphase algorithm without histogram equalization is shown for comparison. Table 2 and 3 shows the performance of face recognition algorithms using modifications 3 and 4 with block size of 3x3 and 6x6.

	Without Equalization		**With Equalization**	
	Group A	Group B	Group A	Group B
Type I	80.86%	96.41%	80.21%	96.27%
Type II	78.05%	95.88%	77.3%	95.72%

Table 1 Recognition results with and without equalization.

	Mask Equalization 3x3		**Mask Equalization 6x6**	
	Group A	Group B	Group A	Group B
Type I	81.58%	96.58%	81.04%	95.95%
Type II	78.87%	96.07%	78.25%	95.35%

Table 2 Recognition results with mask equalization.

Table 4 shows the performance of proposed algorithm with histogram equalization of the whole image when it is required to carry out a verification task, The performance of conventional eigenphases algorithm is also shown for comparison. Table 5 and 6 shows the verification performance of proposed using modifications 3 and 4 with block sizes equal to 3x3 and 6x6.

	Mask Equalization FFT 3x3		**Mask Equalization FFT 6x6**	
	Group A	Group B	Group A	Group B
Type I	85.67%	97.57%	84.4%	97.37%
Type II	83.56%	97.75%	82.10%	96.98%

Table 3 Recognition results with mask equalization FFT.

		Without Equalization		With Equalization	
		% FA	*% FR*	*% FA*	*% FR*
Type I	*Group A*	0.007	14.72	0.13	5.38
	Group B	0.005	33.87	0.02	28.29
Type II	*Group A*	0.008	16.88	0.15	6.17
	Group B	0.0067	38.86	0.03	32.45

Table 4 Verification results with and without equalization.

		Mask Equalization 3x3		Mask Equalization 6x6	
		% FA	*% FR*	*% FA*	*% FR*
Type I	*Group A*	0.029	9.51	0.02	11.34
	Group B	0.003	37.61	0.02	28.89
Type II	*Group A*	0.03	10.91	0.02	11.34
	Group B	0.003	37.12	0.02	28.89

Table 5 Verification results with mask equalization.

		Mask Equalization FFT 3x3		Mask Equalization FFT 6x6	
		% FA	*% FR*	*% FA*	*% FR*
Type I	*Group A*	0.72	0.73	1.53	1.14
	Group B	1.51	11.85	0.72	13.04
Type II	*Group A*	0.83	2.30	1.76	1.31
	Group B	0.83	14.96	1.73	13.60

Table 6 Verification results with mask equalization FFT.

In order to observe how robust the system can be, we realized the verification test for access control, in which it is assumed that the people is required do not wear glasses, hats nor scars, so during the verification test it were omitted the faces with occlusion. To this end we realized also two types of verification; the Type I where faces utilized on training are included, and the Type II where faces utilized on training are not included. The evaluation results are shown in tables 7 to 9.

	Without Equalization		With Equalization	
	% FA	*% FR*	*% FA*	*% FR*
Type I	0.006	5.21	0.007	4.26
Type II	0.006	5.21	0.007	4.26

Table 7 Verification results to access control with and without equalization.

	Mask Equalization 3x3		Mask Equalization 6x6	
	% FA	*% FR*	*% FA*	*% FR*
Type I	0.004	6.78	0.019	3.37
Type II	0.004	6.78	0.019	3.37

Table 8 Verification results to access control with mask equalization.

	Mask Equalization FFT 3x3		Mask Equalization FFT 6x6	
	% FA	*% FR*	*% FA*	*% FR*
Type I	0.57	0.45	1.15	0.29
Type II	0.759	0.599	1.5211	0.390

Table 9 Verification results to access control mask equalization FFT.

IV. Conclusions

In this paper, we have presented a face recognition and verification algorithm based on histogram equalization, with different ways to preprocess the face before getting the feature vector using Principal Components Analysis. On the results presented in the past section we can observe that in recognition the best percentages are those where the faces with occlusion were used to obtain the model. Also we can observe that the highest percentage of recognition is with mask equalization with FFT of 3x3 size and with occlusion, with known faces the recognition was of 97.57% and with the not known faces was of 97.75%.

On verification results we can see that the lowest percentage on false acceptance, are those where the mask equalization was applied, where the lowest percentage is for the mask of 3x3 with 0.003% on the cases where occlusion was not used to obtain the SVM Model.

On Verification tests for access control, lower error rates of false acceptance were obtained using a 3x3 mask with a rate of 0,004%, which is a very good percentage.

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