Eigenface-Gabor Algorithm for Features Extraction in Face Recognition

Gualberto Aguilar-Torres, Karina Toscano-Medina, Gabriel Sanchez-Perez, Mariko Nakano-Miyatake, Hector Perez-Meana

***Abstract*—** This paper provides a study on Face Recognition Algorithms; several methods are used to extract image face features vector, which presents small inter-person variation. This feature vector is feed to a multilayer perceptron to carry out the face recognition or identity verification tasks. Proposed system consists in a combination of Gabor and Eigenfaces to obtain the feature vector. Evaluation results show that proposed system provides robustness against changes in illumination, wardrobe, facial expressions, scale, and position inside the captured image, as well as inclination, noise contamination and filtering. Proposed scheme also provides some tolerance to changes on the age of the person under analysis. Evaluation results using the proposed scheme with identification and verification configurations are given and compared with other feature extraction methods to show the desirable features of proposed algorithm**.**

***Keywords*—** Gabor transform, face recognition, eigenfaces, orthogonal transforms, neural networks, identity verification, Walsh transform.

I. Introduction

SEVERAL person recognition systems using biometric features such as fingerprint, iris pattern, voice and face, etc. have been proposed during the last several years to provide alternatives to the growing necessity for access control in some strategic points such as: airports, government and military facilities, countries borders, etc., as well to sensitive information. These systems, depending in their particular application, can be divided in person identification and identity verification, where the task of the first group is to determine who is the most probable person, while the task of second group is to determine if the person is the whom he/she claims to be.

The face image as biometric feature has been widely used because its high acceptance between persons and easy capture [1]-[5], however this feature has very high intra-person variations comparing with other features, such as iris pattern and fingerprints [1]. The intra-person variations of the face image derive mainly from changes in facial expressions, illumination conditions as well as because the use of some accessories such as eyeglasses and muffler, etc. These variations make the face recognition a very difficult task [4]. However because its advantages are overcome the potential disadvantages, several face recognition algorithms have been proposed to solve the still remaining problems. Thus during the last years have been proposed template-based face recognition methods [6], face recognition using eigenfaces methods [7]-[9], Bayesian algorithms [4], geometric feature based methods [10]-[11] and Walsh transform based algorithms [12]-[13], etc. Other related systems that also have been applied are face region locating method proposed in [3], the deformable model proposed in [14] and face recognition methods using the Karhunen-Loeve transform [15], etc. Recently several authors have proposed the combination of different features to improve the face recognition rate [16].

On the other hand, the discrete Gabor Transform, that presents some relation with the human visual system, has been successfully used in several applications such as fingerprint enhancement [17], signature recognition [18], image compression [19] etc.

This paper proposes a robust and reliable automatic face recognition system in which the feature extraction is performed using 2D Gabor Transform, Eigenfaces, discrete Walsh transform and discrete cosine transform, which presents enough small intra-person variation and considerably large inter-person variation, a desirable feature in any recognition system. Next after the feature vectors are estimated, they are introduced to the multilayer neural networks for face image identification or identity verification. Computer simulation shows that proposed system is robust against variations in the illumination condition, wardrobe, facial expressions, changes of image size, contamination by noise and image shifting, as well as to age variation of the person under analysis. Evaluation results are also giving to compare the performance of proposed algorithm with other previously proposed feature extraction methods.

II. Face Recognition Algorithms

The proposed face recognition system can perform either, face identification and identity verification tasks. In the first case

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the system output provides the identity of the person with highest probability, while in the second case the system determines is the person is whom he/she claims to be. In both cases consists of a features vector extraction stage, an artificial neural network, ANN, and a decision stage that takes the acceptation or rejection decision. Next section describes the proposed face identification and identity verification systems.

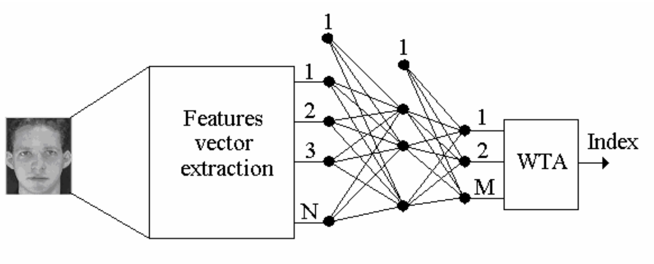


Fig. 1 Proposed face identification system

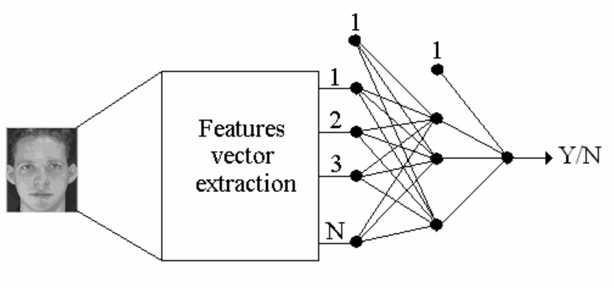


Fig. 2 Block diagram of proposed identity verification system,

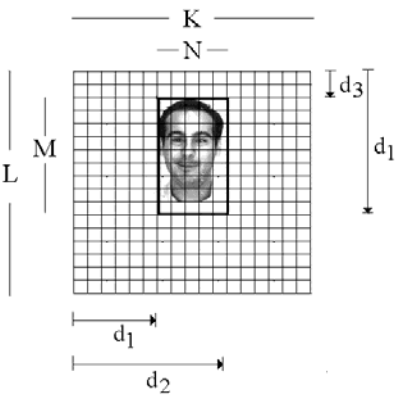


Fig. 3 Face segmentation method

A. GABOR EXPANSION

To estimate the features vector, firstly the region of the picture containing the face under analysis is segmented as shown in Fig. 3, using the procedure described in Table 1. Next *NM* captured image is divided in M_xM_y receptive fields each one of size $(2N_x+1)(2N_y+1)$ (Fig. 4), where $N_x=(N-M_x)/2M_x$, $N_y=(M-M_y)/2M_y$. This fact allows that the features vector size be independent of the captured image size.

Next, the central point of each receptive field whose coordinates are given by (c_i,d_k), where $i=1,2,..,N_x$; $k=1,2,3,\dots,N_y$, are estimated. Subsequently the first point of the cross-correlation between each receptive field and the $N_\omega N_\phi$ Gabor functions is estimated using eqs. (1)-(4), where N_ω denotes the number of normalized radial frequencies and N_ϕ the number of angle phases as follows

$$w(x,y,\omega_m,\phi_n)=g(x'_n,y'_n)\left(\cos\omega_m(x'_n+y'_n)+j\sin\omega_m(x'_n+y'_n)\right) \quad (1)$$

where $m=1,2,\dots,N_\omega$ and $n=1,2,3,..,N_\phi$, ω_m is the *m-th* normalized radial frequency,

$$g(x'_n,y'_n)=\left(\frac{1}{2\pi\lambda\sigma^2}\right)\exp\left(-\frac{(x'_n/\lambda)^2+y'^2_n}{2\sigma^2}\right) \quad (2)$$

is the Gaussian function, σ^2 is the radial bandwidth, λ λ is Gaussian shape factor and (x'_n,y'_n) is the position of the pixel (x,y) rotated by an angle ϕ_n as follows

$$(x'_n,y'_n)=\left((x\cos\phi_n+y\sin\phi_n),(-x\sin\phi_n+y\cos\phi_n)\right) \quad (3)$$

Table 1 Procedure used to segment the face region

```
P=K/v, R=L/v
J=2
For m=1; R-1 Do
1  d_r=X(jv,mv)-X((j-1)v,mv)
   IF abs(d_r)<ε and j<P Then
      j=j+1
      Goto 1
   ELSE
      X_r(m)=j
   j=P
2  d_l=X(jv,mv)-X((j-1)v,mv)
   IF abs(d_r)<ε and j>2Then
      j=j-1
      Goto 2
   ELSE
      X_l(m)=j
End
m=2
For j=1; P-1 Do
3  d_u=X(jv,mv)-X(jv,(m-1)v)
   IF abs(d_r)<ε and j<R Then
      m=m+1
      Goto 3
   ELSE
      Y_u(j)=m
   j=R
4  d_l=X(jv,mv)-X(jv,(m-1)v)
   IF abs(d_l)<ε and j>2Then
      m=m-1
      Goto 4
   ELSE
      Y_l(j)=m
end
d_1=max(X_r(m))-v, m=1,2,..,R-1
d_2=max(X_l(m))+v, m=1,2,..,R-1
d_3=max(Y_u(j))-v, j=1,2,….,P-1
d_4=max(Y_l(j))+v,  j=1,2,….,P-1
```

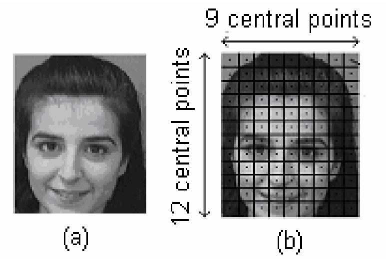


Fig. 4 (a) Original image (b) 108 receptive fields and central points estimation (x,y).

Thus the cross-correlation between the Gabor functions, given by eqs. (1)-(3), with each receptive field can be estimated as,

$$h(u,v)=\sum_{x=-N_x}^{N_x}\sum_{y=-N_y}^{N_y} I(x-c_i, y-d_k)w(x,y,\omega_m,\phi_n) \qquad (4)$$

where $u=M_y*(i-1)+k$ and $v=N_\omega(m-1)+n$.

Next, to avoid complex valued data in the features vector we can use the fact that the magnitude of $h(u,v)$ presents a great similarity with the behavior of the complex cells of the human visual system [18]-[21]. Thus the magnitude of $h(u,v)$ could be used instead of its complex value. However, as shown in eq.(4) the number of elements in the features vector is still so large even for small values of M_x, M_y, N_ϕ y N_ω. Thus to reduce the number of elements in the features vector, we can average $h(u,v)$ to obtain the proposed features vector $M(u)$ which is given by

$$M(u)=\frac{1}{N_v}\sum_{v=1}^{N_v}\left|h(u,v)\right| \qquad (5)$$

where $N_v=N_\phi N_\omega$. Figure 5 illustrate this procedure.

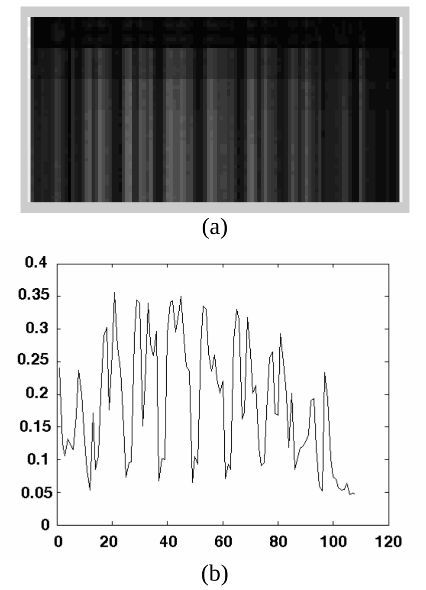


Fig. 5 a) Features extracted from each receptive field $h(u,v)$. b) Estimated feature vector $M(u)$.

B. EIGENFACES

The objective of the recognition by the Eigenfaces method is to extract relevant information from face image, encode this information as efficiently as possible and compare them with each model stored in a database. 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 [10].

The idea of using eigenfaces was motivated by a technique developed by Sirovich and Kirby [5] for efficiently representing pictures of faces using principal component analysis. They argued that a collection of face images can be approximately reconstructed by storing a small collection of weights for each face and a small set of standard pictures.

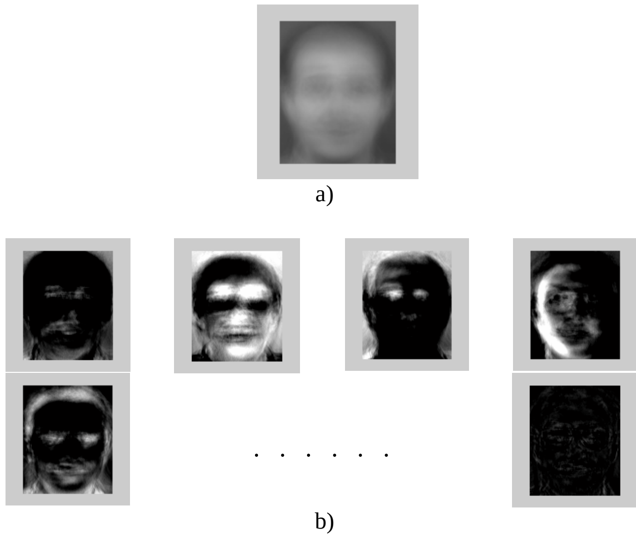


Fig. 6. a) Average face. b) Eigenfaces.

The Eigenfaces computation is as follows: Let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3, \ldots \Gamma_M$. The average face of the set is defined by $\Psi=\frac{1}{M}\sum_{n=1}^{M}\Gamma_n$. Each face differs from de average by the vector $\phi_n=\Gamma_n-\Psi$. An example training set is shown in Figures 9 and 10, with the average face shown in figure 6a. This set of very large vectors is then subject to principal component analysis, which seeks a set of M orthonormal vectors μ_n and their associated eigenvalues λ_k which best describes the distribution of the data. The vectors μ_k and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix

$$C=\frac{1}{M}\sum_{n=1}^{M}\phi_n\phi_n^T=AA^T \qquad (6)$$

where the matrix $A=[\phi_1\phi_2\ldots\phi_M]$, A^T is a transposed matrix. The matrix C, however, is N^2 by N^2, and determining the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors. Fortunately we can determine the eigenvectors by first solving a much smaller M by M matrix problem, and taking linear combinations of the resulting vectors.

Consider the eigenvectors v_n of A^TA such that

$$A^T A v_n = \lambda_n v_n \tag{7}$$

Premultiplying both sides by A, we have

$$AA^T A v_n = \lambda_n A v_n \tag{8}$$

from which we see that Av_n are the eigenvectors of $C = AA^T$.

Following this analysis, we construct the M by M matrix $L = A^TA$, where $L_{m,n} = \phi_m^T \phi_n$, and find the M eigenvectors v_n of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces u_n

$$u_n = \sum_{k=1}^{M} v_{nk}\phi_k = Av_n, \quad n = 1,\ldots.,M \tag{9}$$

With this analysis the calculations are greatly reduced, from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (M). In practice, the training set of face images will be relatively small ($M \ll N^2$), and the calculations become quite manageable. The associated eigenvalues allow us to rank the eigenvectors according to their usefulness in characterizing the variation among the images.

Once the Eigenfaces have been calculated, the image is projected onto "face space" by a simple operation,

$$\omega_n = u_n(\Gamma - \Psi) \tag{10}$$

for n=1,….,M. This describes a set of point-by-point image multiplications and summations. Some Eigenfaces are shown in figure 6b.

The weights form a vector $\Omega^T = [\omega_1, \omega_2, \ldots, \omega_M]$ that describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. Finally, 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

$$\varepsilon_k^2 = \|\Omega - \Omega_k\|^2 \tag{11}$$

where Ω_k is a vector describing the kth face class.

C. DISCRETE WALSH TRANSFORM

The discrete Walsh transform (DWT) is one of the most important techniques as well as the discrete Fourier transform in the field of signal processing [22]-[23]. The DWT works well for digital signals due to the fundamental function called the Walsh function. The Walsh function has only +/- 1, and is the system of orthogonal functions. In general, the Walsh function can be generated by the Kronecker's product of the Hadamard matrix H's.

First, the 2-by-2 Hadamard matrix H_2 is defined by

$$H_2 = \begin{bmatrix} + + \\ + - \end{bmatrix} \tag{12}$$

where the symbols + and – mean +1 and -1, respectively. Furthermore, calculating the Kronecker´s product between two H_2's, the 4-by-4 Hadamard matrix H_4 is easily given as follow:

$$H_4 = H_2 \otimes H_2 = \begin{bmatrix} +H_2 & +H_2 \\ +H_2 & -H_2 \end{bmatrix} = \begin{bmatrix} + + + + \\ + - + - \\ + + - - \\ + - - + \end{bmatrix} \tag{13}$$

where the symbol ⊗ indicates the Kronecker's product.

The frequency characteristics can be given by the Hadamard matrix. Along each row of the Hadamard matrix, the frequency is expressed by the number of changes in sign. The number of changes is called "sequence". The sequence has the characteristics similar to the frequency.

The Walsh function can be expressed as each row of H_N, where N is order on Hadamard matrix. Therefore, DWT is known as a kind of the Hadamard transform, where H_N has some useful following characteristics.

Thus, the DWT and the inverse DWT are defined as follows:

$$V = \frac{1}{N} H_N B \tag{14}$$

$$B = H_N V \tag{15}$$

where B is the sampled data vector, HN is the Hadamard matrix, i.e. Hadamard-ordered Walsh functions. V is the DWT of B. V is called Walsh spectrum.

The 2D-DWT does the DWT toward the images of m-by-n pixels. The 2D-DWT and the 2D-IDWT are defined as follows:

$$F = \frac{1}{MN} H_M f H_N \tag{16}$$

$$f = H_M F H_N \tag{17}$$

where f is the sample data matrix and F is the 2D-DWT of f. F is called 2-dimensional Walsh spectrum. In case of orthogonal transform of the image, the 2D-DWT is more efficient than the DWT. However, to use 2D-DWT, the row and column numbers of sample data, matrix must be 2^n (n is a natural number) respectively, because Hadamard matrix can be generated by the Kronecker's product of Hadamard matrix H_2.

Figure 7 shows an example:


a)

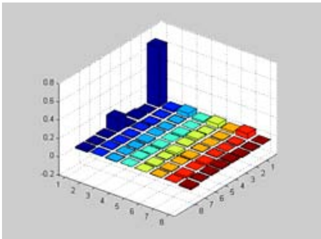
b)

c)

Fig. 7. a) Original image, b) Image with reduced pixel, c) DWT spectrum in a group of 8 x 8 pixels.

D. DISCRETE COSINE TRANSFORM

The DCT is used in many standard image compression and stationary video as the JPEG and MPEG, because it presents excellent properties in codifying the outlines of the images that, in fact, has been one of the main reasons to be selected into almost all the coding standards.

The cosine transform, like the Fourier transform, uses sinusoidal basis functions. The difference is that the cosine transform basis functions are not complex; they use only cosine functions and not sine functions [24]. 2D DCT based features are sensitive to changes in the illumination direction [25].

The idea of using the transform for facial features extraction is summarized as follows: the given face image is analyzed on block by block basis given an image block I(x, y), where x,y = 0,1,..., Np−1, and result is an Np x Np matrix C(u,v) containing 2D DCT coefficients. The DCT equations are given by formulas (18), (19), (20) [24][25][26][27] [28][29] below:

$$C(u,v)=\alpha(u)\cdot\alpha(v)\cdot\sum_{x=0}^{N_p-1}\sum_{y=0}^{N_p-1} I(x,y)\cdot B(x,y,u,v) \tag{18}$$

for u,v = 0, 1,2,..,Np−1 where

$$\alpha(u)=\begin{cases}\sqrt{\dfrac{1}{N}} & for\quad u=0\\ \sqrt{\dfrac{2}{N}} & for\quad u=1,2,N-1\end{cases}$$
$$\alpha(v)=\begin{cases}\sqrt{\dfrac{1}{N}} & for\quad v=0\\ \sqrt{\dfrac{2}{N}} & for\quad v=1,2,N-1\end{cases} \tag{19}$$

$$B(x,y,u,v)=\cos\left[\frac{(2x+1)u\pi}{2N}\right]\cos\left[\frac{(2y+1)v\pi}{2N}\right] \tag{20}$$

To ensure adequate representation of the image, each block overlaps its horizontally and vertically neighboring blocks by 50%, thus for an image which has N_Y rows and N_X columns, there are N_D blocks found by following formula:

$$N_D=(2(N_Y/N_P)-1)x(2(N_X/N_P)-1) \tag{21}$$

Compared to other transforms, DCT has the advantages of having been implemented in a single integrated circuit because of input independency, packing the most information into the fewest coefficients for most natural images, and minimizing block like appearance [21][22].

An additional advantage of DCT is that most DCT coefficients on real world images turn out to be very small in magnitude [21].

Figure 8 shows an example:


a)

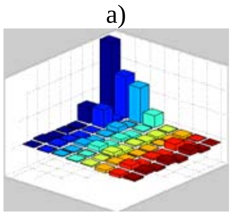
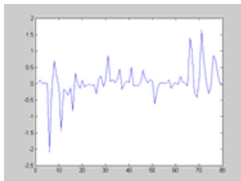
b)

c)

d)

Fig. 8. a) Original image. b) Image with reduced pixel, c) DCT spectrum in a group of 8 x 8 pixels, d) Feature vector.

E. FACE IDENTIFICATION STAGE

When the proposed system is required to perform a face identification task, after the feature vector is estimated as mentioned, it is feed into a multilayer perceptron neural network with N_xN_y neurons in the input layer and M neurons in the output layer trained using the backpropagation algorithm [30], where N_xN_y is the number of receptive fields and M is the number of faces to be identified.

After the training, i.e. during normal operation, to carry out the identification task, the neural network output vector is feed into a winner takes all (WTA) circuit whose output is the index related to the most probable face.

F. IDENTITY VERIFICATION STAGE

This ANN is trained using the backpropagation algorithm [30to provide an output closed to one when the people is who he/she claims to be and closed to cero or minus one otherwise. Finally ones the ANN is trained, i.e. during normal operation, the neural network output is passed through a threshold to take the final decision. Here if the output is larger than the threshold, the identification is considered positive. Otherwise the identification is considered to be negative. This threshold is a compromise between the false acceptance and false rejection because to minimize the false acceptance the threshold must be closed to one although this will increase the false rejection rate.

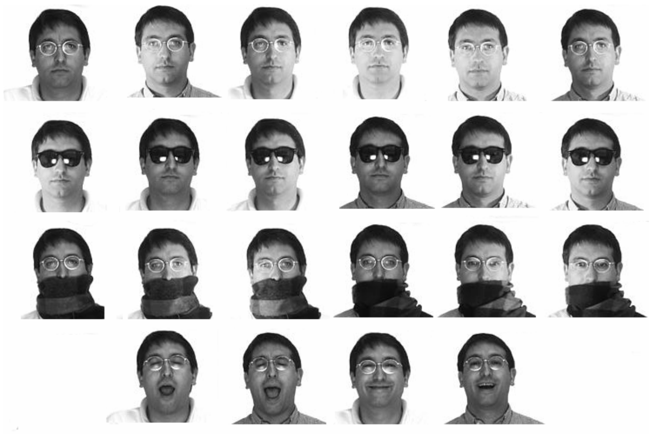


Fig. 9. Examples of face images provided in the AR database.

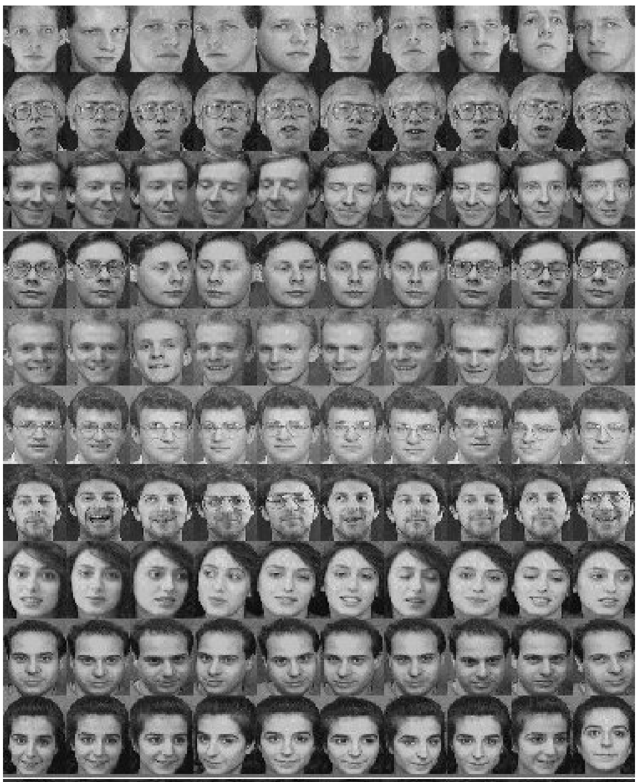


Fig. 10. Examples of face images provided in the ORL database.

Other possibility is to include an upper and lower thresholds such that is the ANN output is larger than the upper threshold the identification is considered to be positive, if the ANN output is smaller than the lower threshold the identification is considered negative, and otherwise the identification process is repeated using a new input picture. This choice reduces the positive identification and rejections errors, although the computational complexity is also increased.

III. Evaluation Results

To evaluate the proposed system two different databases were used. "The AR Face Database", which has a total 5,670 face images that includes face images with several different illuminations, facial expression and partial occluded face images with transparent eyeglasses, dark eyeglasses and scarf, etc. and the ORL database, created by Olivetti Research Laboratories in Cambridge UK.

The ORL database consists of 300 face images of 30 different peoples. Here there are 10 different images of each people, each one with different illumination, rotation angle, inclination, hair stile, etc.

Some examples of the face image include in these databases are shown in Figs. 9 and 10.

As mentioned, to features extract by Gabor method the face image is divided in 108 receptive fields (9 x 12 blocks) centered at point (x_0, y_0), (Fig. 4), doing the number of receptive fields is independent of the face image size. Next to estimate the feature vector, in each receptive field, six different normalized spatial frequencies, $f_1=\pi/2$, $f_2=\pi/4$, $f_3=\pi/8$, $f_4=\pi/16$, $f_5=\pi/32$, $f_6=\pi/64$, together with 9 different phases $\phi_1=0$, $\phi_2=\pi/9$, $\phi_3=2\pi/9$, $\phi_4=\pi/3$, $\phi_5=4\pi/9$, $\phi_6=5\pi/9$, $\phi_7=2\pi/3$, $\phi_8=7\pi/9$, $\phi_9=8\pi/9$ where used.

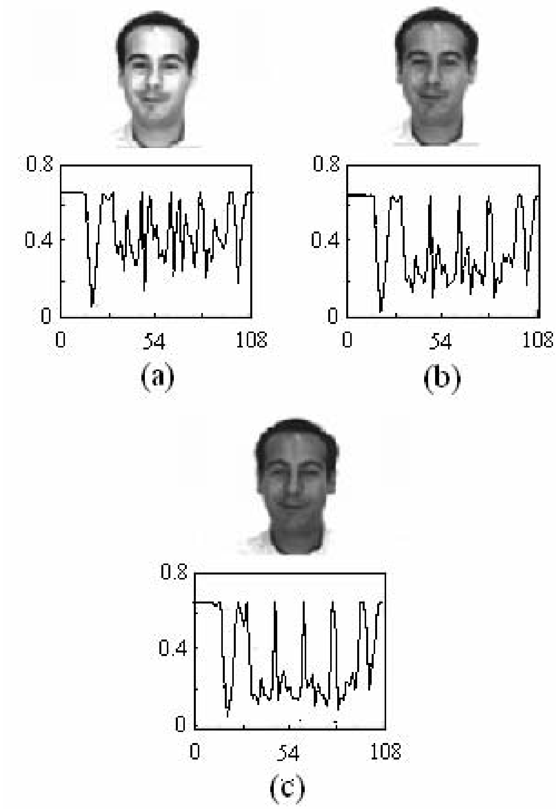


Fig. 11. Features vectors of the same face with different illumination.

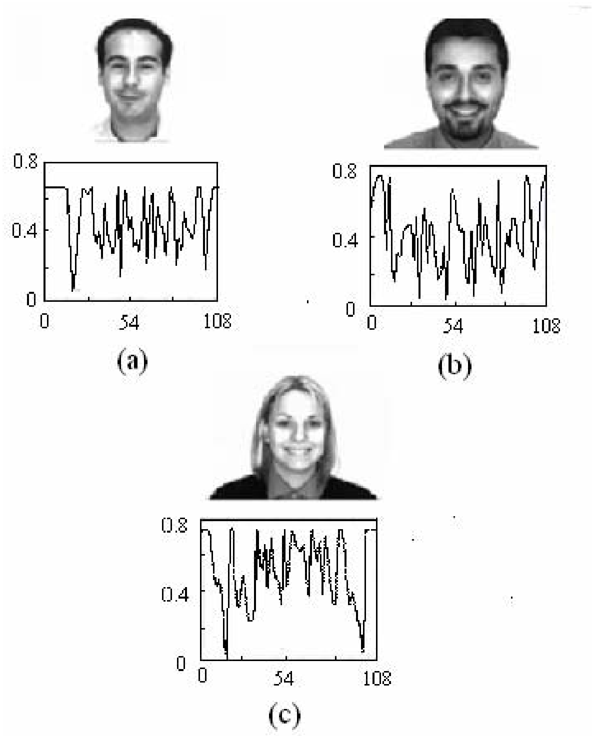


Fig. 12. Features vectors of three different faces.

Figure 11 shows the features vector extracted from the same face with three different illumination conditions and Fig. 12 shows the feature vector extracted from three different faces. These figures show that the Gabor functions provide feature vectors with small enough intra-person variation and considerably large inter-person variation that allows an accurate identification and identity verification, as shown in table 2.

Figure 13 shows the features vector extracted from the same people with different ages from 28 to 57 years old. As shown in this figure, the extracted feature vectors are quite similar when different ages are not so large, allowing an accurate identification. However when the age difference becomes larger the feature vectors extracted may presents large variations that difficult a correctly identification. This fact is illustrated in Fig. 13.

Finally, the figure 14 shows the features vector extracted from the same face with different size image.

To evaluate the robustness of proposed system from the intra-person variation point of view and the inter-person variation discrimination capacity point of view, several tests were carried out using face images with several variations including: illumination, level variations, facial expression, etc., as mentioned, adding to the original variations in the AR Database, several other alterations such as filtering using Gaussians and Medium filters, contamination with impulsive and Gaussian noise and several geometric modifications introduced to the face image such as resizing, rotation and shifting.

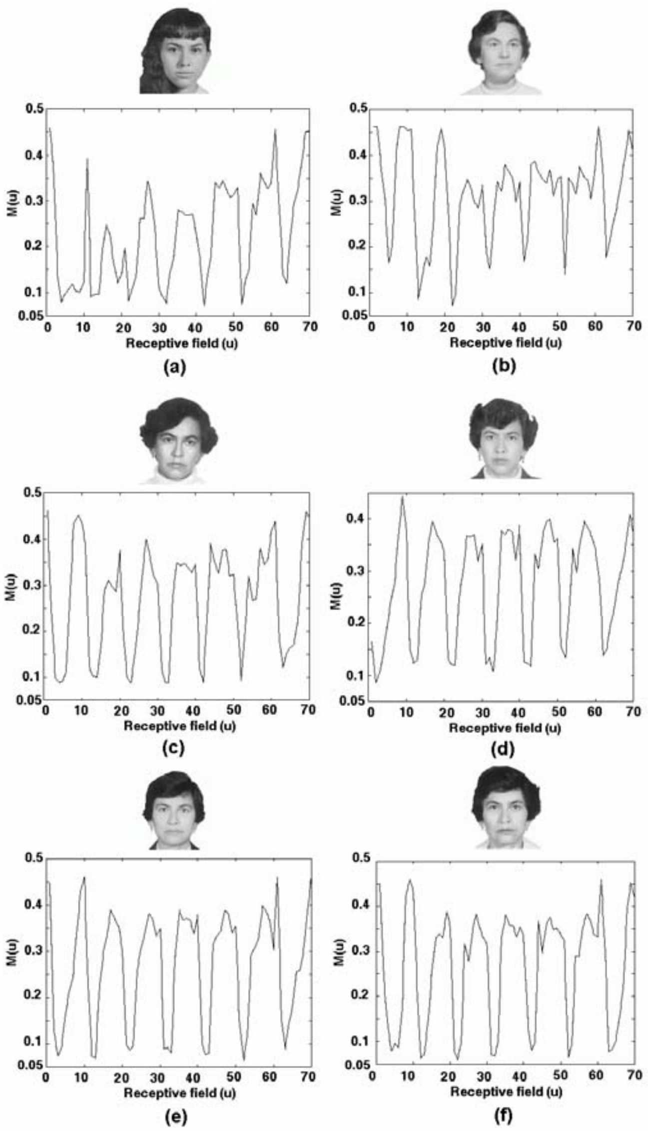


Fig. 13 Feature vectors extracted from face images of one person with different ages (a) 28 years. (b) 35 years. (c) 40 years. (d) 42 years. (e) 53 years. (f) 57 years.

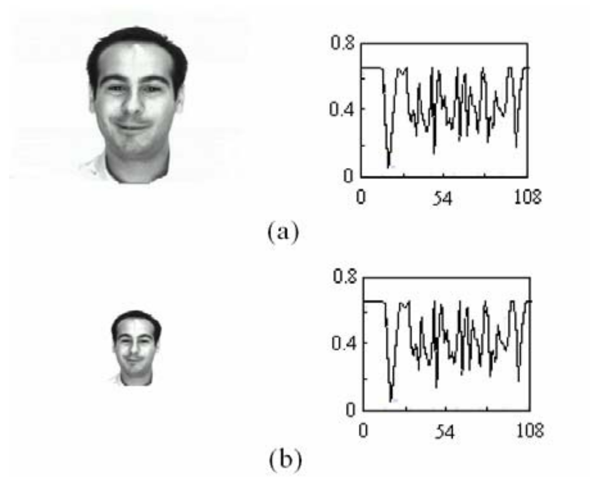


Fig 14 Feature vector extracted from images with different size of the same person.

The backpropagation neuronal network was trained using feature vectors extracted from 150 different persons and tested using 150 feature vectors among the face images not used in the training process.

In the case of the personal identification using face images with different ages, the neural networks was trained with 25 feature vectors and it was evaluated using 60 feature vectors.

To evaluate the verification system, the neuronal network was trained with 50 vector features and tested with 72 feature vectors that were not used in the training process, while in the case of the personal verification using face images with different ages, the neural networks was trained with 10 feature vectors and it was evaluated using 24 feature vectors that weren't used in training process.

The evaluation results, under the above mentioned conditions are shown in Table 2. This table shows that the proposed system is robust against variation of illumination level, facial expression, and partial occluded face image with use of accessories such as eyeglasses, muffler, etc. as well as to contamination by different kind of noise.

The proposed system is also enough robust against median and Gaussian filtering as well as to some geometrical transforms such as resizing and shifting. However the proposed system is vulnerable to rotation, because in this situation the rotated face image cannot be identified. Although in the verification task the system shows robustness against rotation operation of angles until 10º.

Finally, the performance of the proposed system when it is required to verify the identity of one person using face images registered at different ages is fairly good, taking in account that the variation of face images in different ages (20 years differences) is considerably large.

Table 2 Performance of proposed algorithm under several face image conditions

Image variation	Identification rate	Verification rate
Illumination	85.67%	99.33%
Facial expression	83.75%	99.21%
Accessories	83.50%	99.23%
Gaussian filter	84.30%	99.54%
Median filter	81.60%	99.19%
Gaussian noise	84.72%	99.43%
Impulsive noise	84.56%	98.76%
Resize	85.40%	99.30%
Rotation 5°	32.70%	90.20%
Rotation 10°	20.50%	87.20%
Shifting	85.10%	98.61%
Age	X	83.30%

The performance of proposed face recognition algorithm was compared with the recognition performance provided by other previously proposed methods such as: The eigenfaces method, discrete cosine transform and the discrete Walsh transform based method. To these end five face images of each one of the 150 persons, provided by the ORL database, are used for training and the other five for testing.

Figures 15 shows the resulting features vector extracted using the eigenface method from images face of the same people with different rotation, while in Fig. 16 are shown the features vectors extracted from 3 different peoples.

Using the ORL database as mentioned before an identification rate of 83% and a verification rate of 99.3% were achieved.

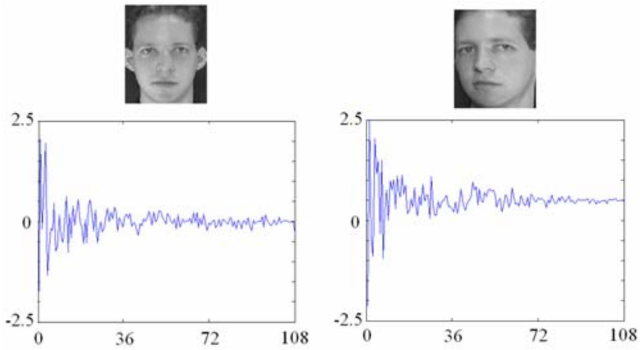


Fig. 15 Face images with different rotation and their feature vectors extracted using the eigenfaces method.

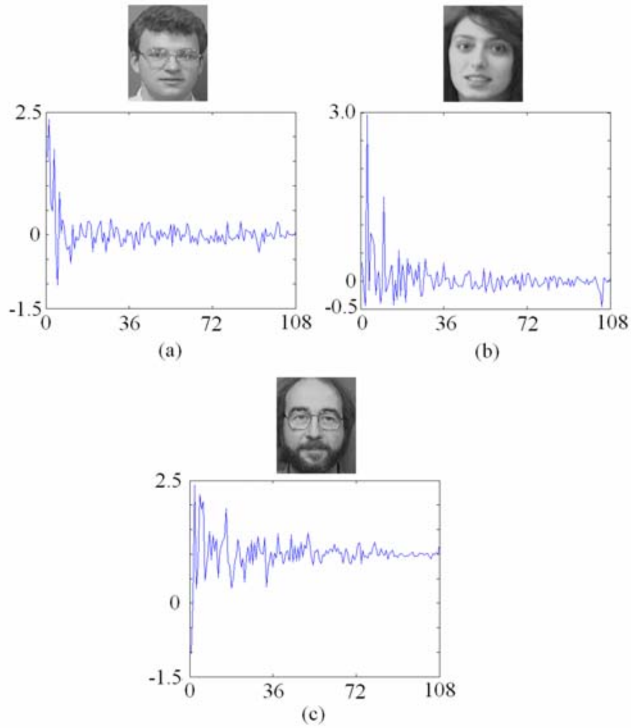


Fig. 16 Face images of several persons together with their feature vectors extracted using the eigenfaces method.

A recently proposed method uses the discrete Walsh transform (DWT) for face feature vector extraction [12]. Figure 17 shows the features vectors extract using the DWT from images of the same people, while in Fig. 18 features vectors extracted from face images of different peoples are shown.

Using the features vector extracted from the DWT the system achieves a recognition performance of 75.33% and a verification performance of 90.3%. These figures show that the eigenfaces method provides a good intra-person consistency and an enough large inter-person variability allowing a reasonable good recognition performance.

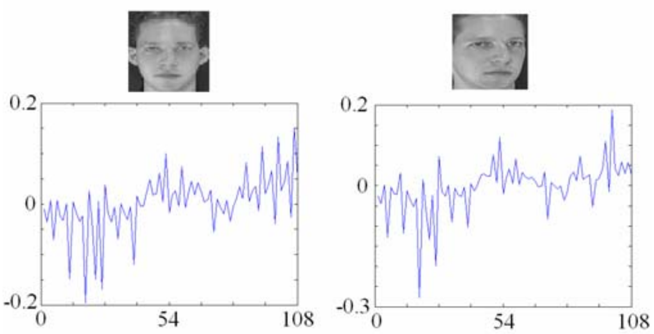


Fig. 17 Face images with different rotation and their feature vectors extracted using the discrete Walsh transform.

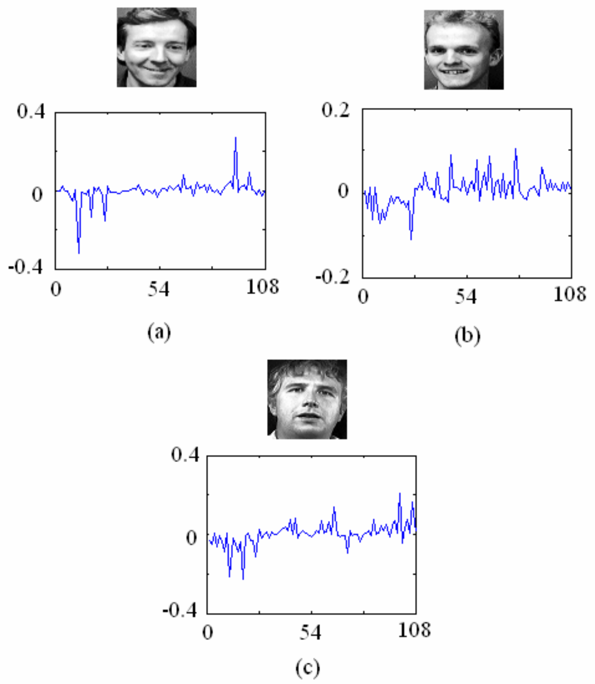


Fig. 18 Face images of several persons together with their feature vectors extracted using the discrete Walsh transform.

Other method used for feature extraction is the discrete cosine transform (DCT) [29]. Figure 19 shows the features vectors extract using the DCT from images of the same people, while in Fig. 20 features vectors extracted from face images of different peoples are shown.

Using the features vector extracted from the DCT the system achieves a recognition performance of 78.33% and a verification performance of 95.1%.

Finally, the performance of proposed system can be improved combining the features vectors extracted using the discrete Gabor transform, together the eigenfaces method. In such case the classification performance becomes 92% while the verification performance becomes 99.85%.

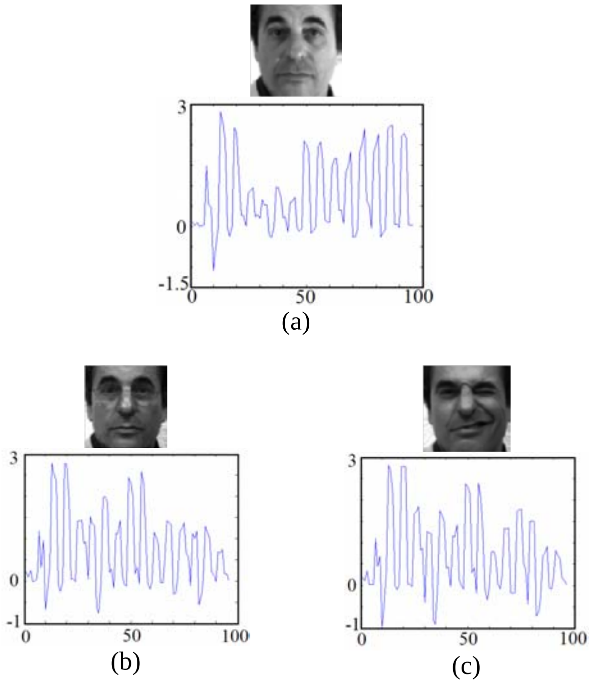


Fig. 19 Face images with different expressions and their feature vectors extracted using the discrete cosine transform.

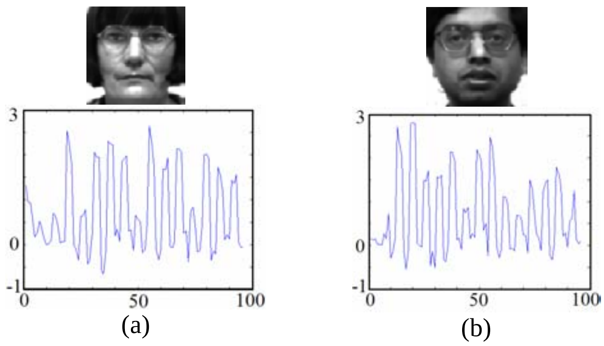


Fig. 20 Face images of two persons together with their feature vectors extracted using the discrete cosine transform.

Table 3 provides a summary of the classification and verification performance of a face recognition systems using the four features vector extraction mentioned above together with the performance of the face recognition system using a feature vector extracted using a combination of the Gabor transform and the eigenfaces methods.

Evaluation results shown that proposed face recognition Gabor-Eigenfaces algorithm provides better performance than other previously proposed methods such as the Eigenfaces, Gabor, discrete Cosine transform and the discrete Walsh transform based methods.

Figure 21 shows the way in which the features vectors were united for the combination. One can see that the input vector for the neuronal network has a greater length, i.e. 258 coefficients.

Figure 22 shows the proponed system in this paper.

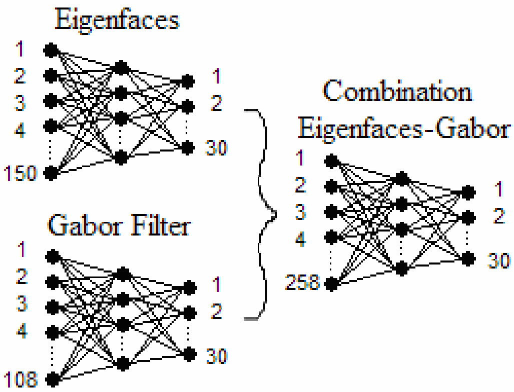


Fig. 21. Combination of Eigenfaces and Gabor in a neuronal network.

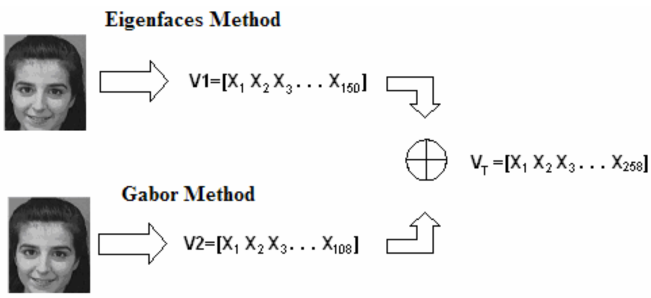


Fig. 22. Proposed System.

Table 3 Recognition performance of proposed algorithms and other previously reported face recognition algorithms

Algorithm	Identification	Verification
Eigenfaces (EF)	83.00%	99.67%
Discrete Walsh Transform	75.33%	90.33%
Discrete Gabor Transform	85.67%	99.33%
Discrete Cosine Transform	78.33 %	95.1 %
Discrete Gabor Transform together with eigenfaces	92.10%	99.85%

IV. CONCLUSIONS

In this paper we proposed an automatic face recognition system in which the face image is divided in 108 receptive fields. Next the cross-correlation of each receptive field with 54 Gabor functions with 9 different angles and 6 frequencies are estimated, which are then averaged to obtain the feature vectors of each one of the 108 receptive fields. The feature vector is then fed into a multilayer neural network to recognize the face image.

The evaluation results by computer simulation show that the performance of proposed face identification system is quite robust against changes in illumination, wardrobe, facial expressions and additive noise, blurred images (filters), resizing, shifting and even with some age changes.

The proposed identity verification system can verify correctly the input face images with different illumination level, different facial expression, with some accessories, as well as when the face images pass through some common image processing such as filtering, contamination by noise and geometrical transformation (rotating, shifting, resizing). Computer simulation shows that the proposed system performs better than some previously proposed algorithms using such as the eigenfaces method, the Discrete Cosine Transform and the Discrete Walsh Transform.

The combination of methods to obtain the feature vector, such as Gabor and Eigenfaces, deliver a higher percentage of recognition. Therefore, the system proposed in this paper is a combined system.

Finally, we can emphasize four advantages of the proposed system: Compact extraction of the face information, easy implementation, robustness against several condition changes and common image processing.

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