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Face Recognition Using Frequency Domain Feature Extraction Methods

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1. Introduction

The development of security systems based on biometric features has been a topic of active research during the last years, because the recognition of the people identity to access control is a fundamental issue in this day. Terrorist attacks happened during the last decade have demonstrated that it is indispensable to have reliable security systems in offices, banks, airports, etc.; increasing in such way the necessity to develop more reliable methods for people recognition. The biometrics systems consist of a group of automated methods for recognition or verification of people identity using the physical characteristics or personal behavior of the person under analysis.

In particular, face recognition is a task that humans perform carry out routinely in their daily lives. Face recognition is the most common form human beings have of telling one another apart. Faces are universal, and they provide a means to differentiate individuals. An advantage of biometric face recognition compared to other biometric is the ability to capture a facial image with a camera from a distance and without the subject's knowledge. The face recognition has been a topic of active research because the face is the most direct way to recognize the people. In addition, the data acquisition of this method consists, simply, of taking a picture with or without collaboration of the person under analysis, doing it one of the biometric methods with larger acceptance among the users. The face recognition is a very complex activity of the human brain. For example, we can recognize hundred of faces learned throughout our life and to identify familiar faces at the first sight, even after several years of separation, with relative easy. However it is not a simple task for a computer. Thus to develop high performance face recognition systems, we must to develop accurate feature extraction and classification methods, because, as happens with any pattern recognition algorithm, the performance of a face recognition algorithm strongly depends on the feature extraction method and the classification systems used to carry out the face recognition task. Thus several feature extraction methods for using in face recognition systems have been proposed during the last decades, which achieve high accurate recognition. Among the situations that drastically decrease the accuracy and that must be considered to develop high performance face recognition method we have: partial occlusion, illumination variations, size change, rotation and translation of the capture image, etc. To solve these problems several efficient feature extraction methods have been proposed, several of them

using frequency domain transforms such as Discrete Gabor Transform, Discrete Cosine Transform, Discrete Wavelet Transform, etc.

The face image as biometric feature has very high intra-person variations comparing with other features, such as iris pattern and fingerprints (Reid, 2004). These variations make the face recognition a very difficult task (Chellappa, Wilson and Sirohey, 1995). 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 (Brunelli, Poggio, 1993), face recognition using eigenfaces methods (Turk and Pentland, 1991; Moghaddam, Wahid and Pentland, 1998), Bayesian algorithms (Chellappa, Wilson and Sirohey, 1995), geometric feature based methods (Smith, 2002; Tanaka, Ikeda and Chiaki, 1998) and Walsh transform based algorithms (Yoshida, Kamio and Asai, 2003; Shanks, 1969), etc. Other related systems that also have been applied are face region locating method proposed in (Baron, 1981), the deformable model proposed in (Lanitis, Taylor and Cootes, 1995) and face recognition methods using the Karhunen-Loeve transform (Kirby and Sirovich, 1990), etc. Recently several authors have proposed the combination of different features to improve the face recognition rate (Hallinan, Gordon, Yullie, Gablin and Mumford, 1999). 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 (Hong, Wan and Jain, 1998), signature recognition (Cruz, Reyes, Nakano and Perez, 2004), image compression (Daugman, 1988), etc.

In this chapter, several frequency domain feature extraction methods based on the Discrete Gabor Transform, Discrete Wavelet Transform, Discrete Cosine Transform, Discrete Walsh-Hadamard Transform, Eigenfaces, and Eigenphases are analyzed. These feature extraction methods are used with different classifiers such as artificial neural networks (ANN), Gaussian Mixture Models (GMM) and Support vector machines (SVM) to evaluate each method.

2. Face recognition algorithms

The face recognition systems can perform either, face identification and identity verification tasks. In the first case 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 general, in both cases consists of three modules: face detection, feature extraction, and matching. Face detection separates the face area from background. Feature extraction is performed to provide effective information that is useful for distinguishing between faces of different persons. In the identification process, for face matching, the extracted feature vector of the input face is matched against those of enrolled face in the database. In the verification process, the extracted feature vector of the input face is matched against versus one feature vector. Face recognition percentages depend too much on features that are extracted to represent the input face.

2.1 Discrete Gabor transform

To estimate the features vector, firstly the NM captured image is divided in $M \times M$ receptive fields each one of size $(2N_x+1)(2N_y+1)$, 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.

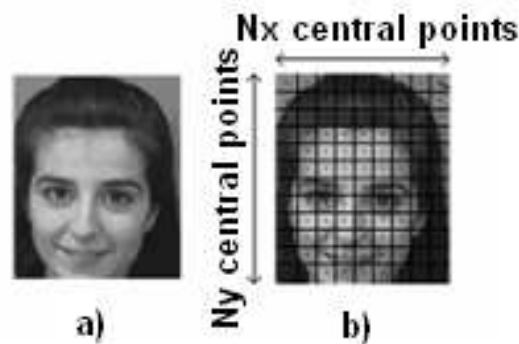


Fig. 1. a) Original image b) $N_x \times N_y$ receptive fields and central points estimation (x, y)

Next, the central point of each receptive field whose coordinates are given by (c_i, d_k) , where $i=1, 2, \dots, N_x$ and $k=1, 2, 3, \dots, N_y$, are estimated. Subsequently the first point of the cross-correlation between each receptive field and the $N_\omega N_\phi$ Gabor functions are 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:

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

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

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

is the Gaussian function, σ^2 is the radial bandwidth, 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

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

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

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

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. 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 and 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

$$M(u) = \frac{1}{N} \sum_{v=1}^{N_v} |h(u, v)| \quad (5)$$

where $N_v = N_\phi N_\omega$. Figure 2 illustrates the results of this method. One can see that for the same person with different rotations the feature vector has a similarity, but with another person is very different.

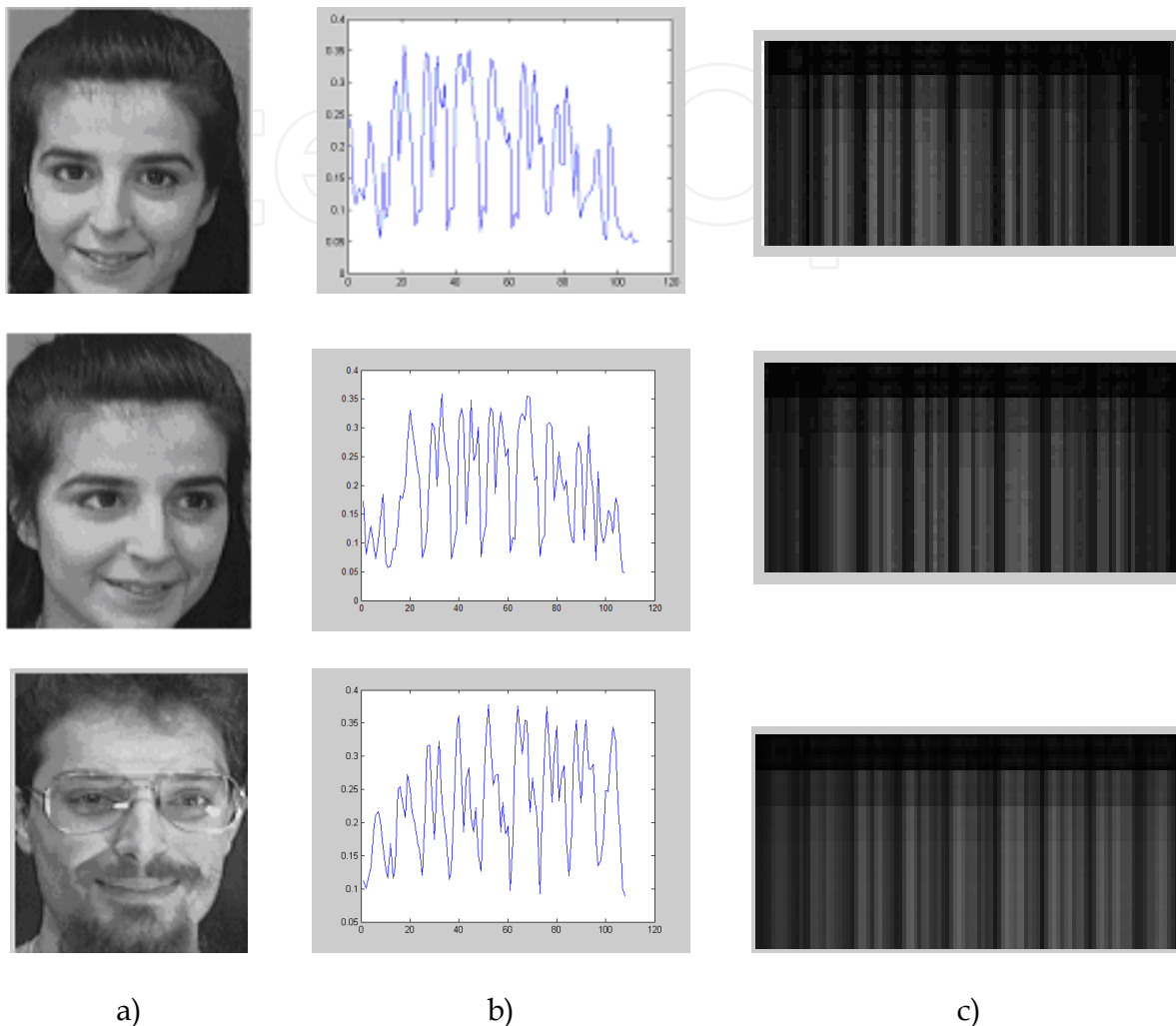


Fig. 2. a) Original images, b) Estimated features vectors, c) Features extracted from each receptive field $h(u,v)$.

2.1.1 Results

To evaluate this method two different databases were used. "The AR Face Database", which 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. A Backpropagation neuronal network was trained with feature vectors of 50 face images and tested with feature vectors of 72 face images that were not used in the training process. To carry out the personal verification using face images with different ages, the neural network was trained with feature vectors extracted from 10 different images and evaluated using feature vectors extracted from 24 images do not used in training process. The evaluation results, under the above mentioned conditions are shown in Table 1.

Identification Percentage	Verification Percentage
85.6%	99.3%

Table 1. Results using Discrete Gabor Transform

2.2 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 (Scott, 1999). 2D DCT based features are sensitive to changes in the illumination direction (Conrad, Kuldip, 2003). 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 $x, y = 0, 1, \dots, N_p - 1$, and result is an $N_p \times N_p$ matrix $C(u, v)$ containing 2D DCT coefficients. The DCT equations are given by formulas (6-9) below:

$$C(u, v) = \alpha(u) \cdot \alpha(v) \cdot \sum_{x=0}^{N_p-1} \sum_{y=0}^{N_p-1} I(x, y) \cdot B(x, y, u, v) \quad (6)$$

for $u, v = 0, 1, 2, \dots, N_p - 1$ where

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} \text{ for } & u = 0 \\ \sqrt{\frac{2}{N}} \text{ for } & u = 1, 2, N - 1 \end{cases} \quad (7)$$

$$\alpha(v) = \begin{cases} \sqrt{\frac{1}{N}} \text{ for } & v = 0 \\ \sqrt{\frac{2}{N}} \text{ for } & v = 1, 2, N - 1 \end{cases}$$

$$B(x, y, u, v) = \cos \left[\frac{(2x+1)u\pi}{2N} \right] \cos \left[\frac{(2y+1)v\pi}{2N} \right] \quad (8)$$

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:

$$N_D = (2(N_y / N_p) - 1) * (2(N_x / N_p) - 1) \quad (9)$$

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 (Feichtinger and Strohmer, 1998; Kamio, Ninomiya, and Asai, 1994). An additional advantage of DCT is that most DCT coefficients on real world images turn out to be very small in magnitude (Feichtinger and Strohmer, 1998).

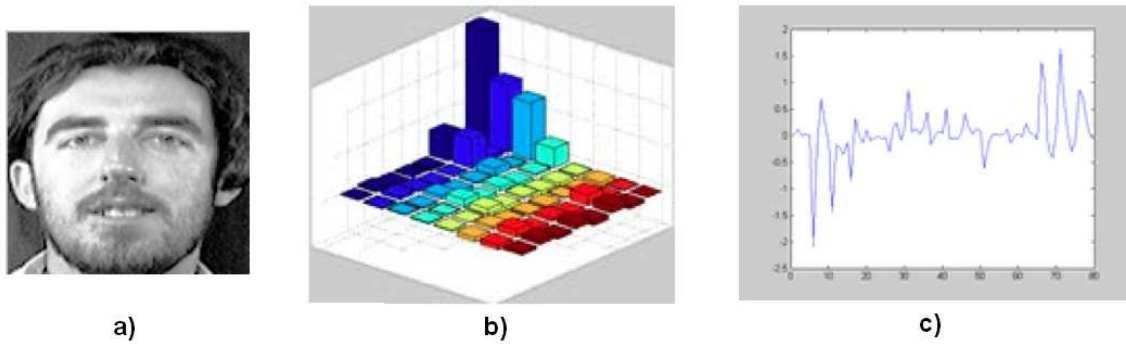


Fig. 3. a) Original image, b) Reducing image, c) Spectrum of a block, d) Feature vector

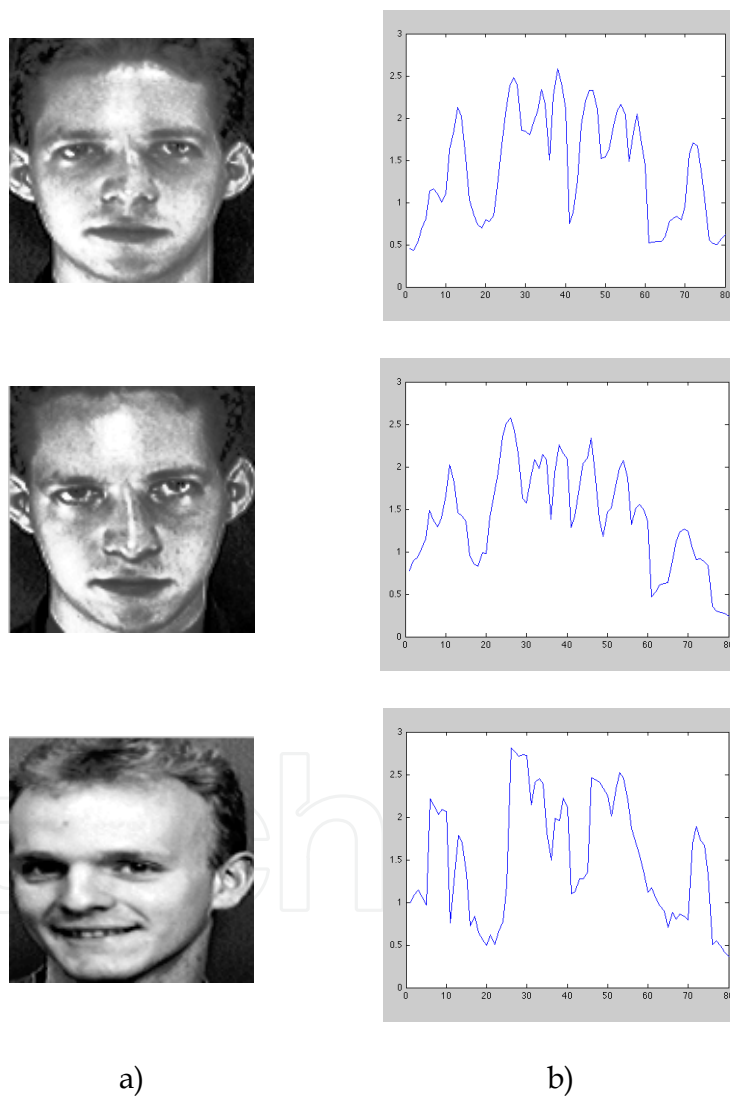


Fig. 4. a) Original images, b) Feature vectors.

Figure 3 shows an example. Figure 3a shows the input image. Figure 3b shows the frequency coefficients in a block of 8×8 and finally Figure 3c shows the characteristic vector of the face. To form the feature vector, in each block were selected the first 10 coefficients in zig-zag to be later concatenated. Figure 4 shows the feature vectors using DCT. One can see

that for the same person with different distance the feature vector has a similarity, but with another person is very different.

2.2.1 Results

To evaluate this method were used the same conditions mentioned for Gabor's method. The results are shown in table 2.

Identification Percentage	Verification Percentage
79.7 %	95.1%

Table 2. Results using Discrete Cosine Transform

2.3 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 (Kamio, Ninomiya and Asai, 1994; Mar and Sheng, 1973). 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

$$H_2 = \begin{bmatrix} ++ \\ +- \end{bmatrix} \quad (10)$$

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:

$$H_4 = H_2 \otimes H_2 = \begin{bmatrix} +H_2 + H_2 \\ +H_2 - H_2 \end{bmatrix} = \begin{bmatrix} ++++ \\ +-+- \\ ++-- \\ +--+ \end{bmatrix} \quad (11)$$

where the symbol \otimes indicates the Kronecker's product. The Hadamard matrix can give the frequency characteristics. Along each row of the Hadamard matrix, the number of changes in sign expresses the frequency. 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:

$$V = \frac{1}{N} H_N B \quad (12)$$

$$B = H_N V \quad (13)$$

where B is the sampled data vector, H_N 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:

$$F = \frac{1}{MN} H_M f H_N \quad (14)$$

$$f = H_M F H_N \quad (15)$$

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 $2n$ (n is a natural number) respectively, because Hadamard matrix can be generated by the Kronecker's product of Hadamard matrix H_2 .

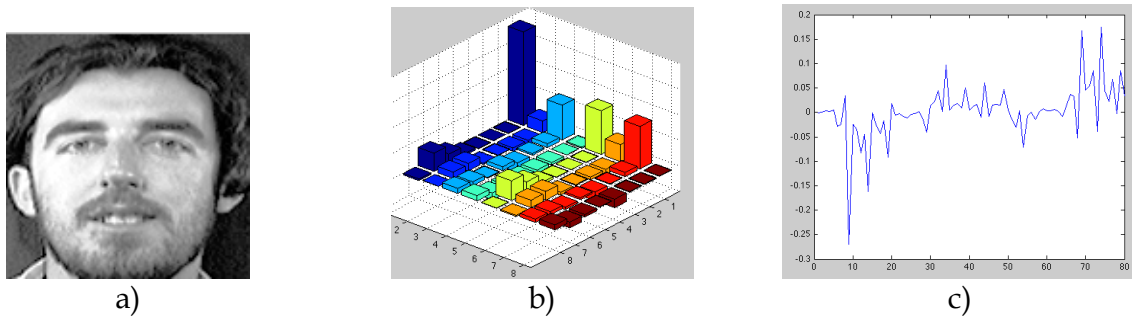


Fig. 5. a) Original image, b) Spectrum of a block, c) Feature vector

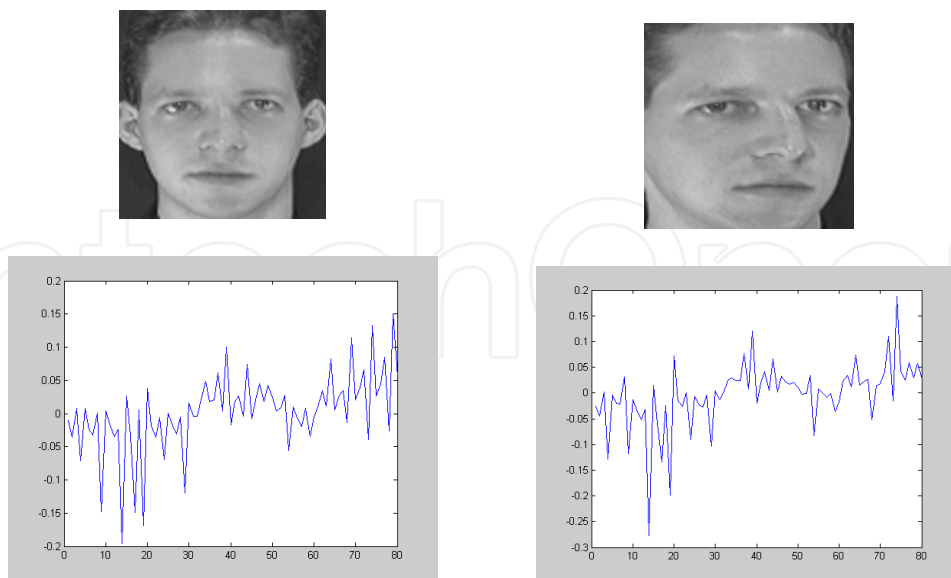


Fig. 6. Input images and features vectors of the same person.

Figure 5 shows the input image, the frequency coefficients in a block of 8×8 and the feature vector respectively. Figure 6 shows two images of one same person but with different

rotation. The feature vectors have a very similar despite the change and the figure 7 shows that the feature vectors change significantly when the input faces are different people.

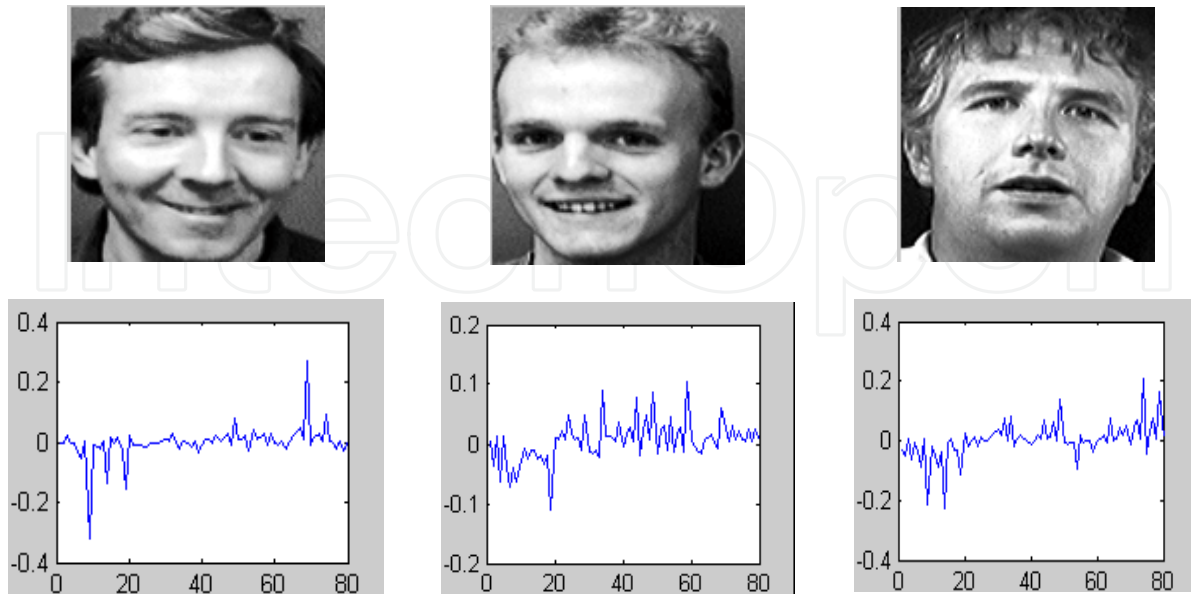


Fig. 7. Input images and features vectors of the same person.

2.3.1 Results

To evaluate this method were used the same conditions mentioned for Gabor's method. The results are shown in table 3.

Identification Percentage	Verification Percentage
76.2 %	90.3%

Table 3. Results using Discrete Walsh Transform

2.4 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 (Smith, 2002).

The idea of using eigenfaces was motivated by a technique developed by Sirovich and Kirby (Sirovich and Kirby, 1987) 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.

The Eigenfaces computation is as follows: Let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3, \dots, \Gamma_M$. The average face of the set is defined by

$$\Psi = \frac{1}{M} \sum_{n=1}^M \Gamma_n \quad (16)$$

Each face differs from the average by the vector

$$\phi_n = \Gamma_n - \psi \quad (17)$$

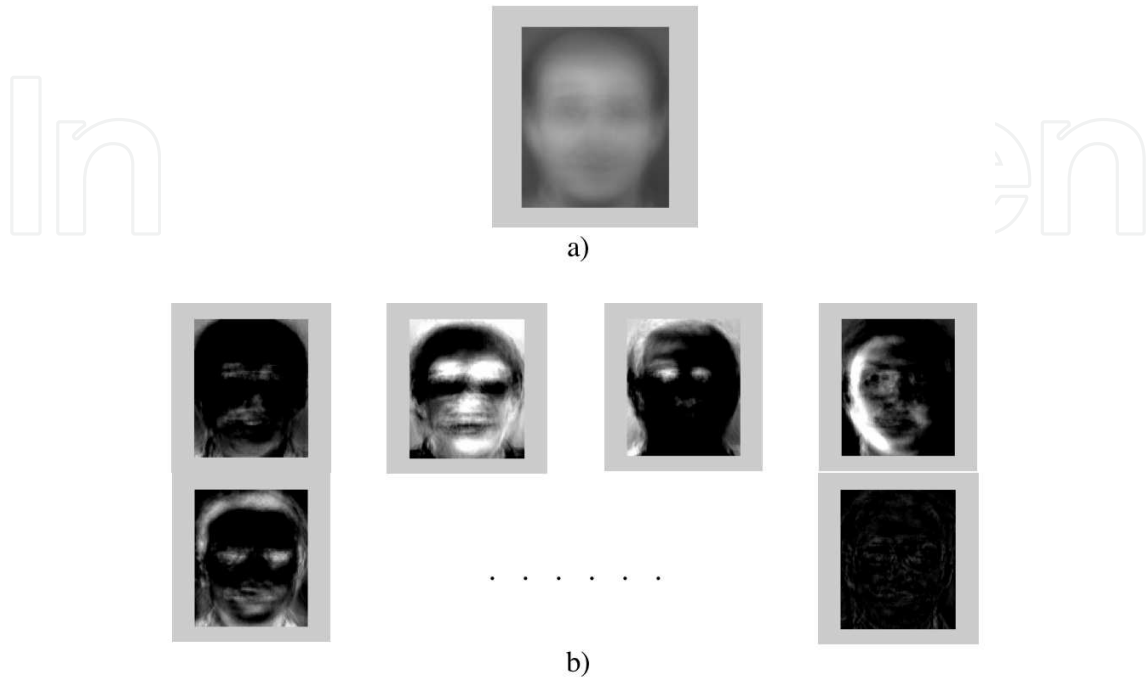


Fig. 8. a) Average face. b) Eigenfaces

The 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

$$C = \frac{1}{M} \sum_{n=1}^M \phi_n \phi_n^T = AA^T \quad (18)$$

where the matrix $A = [\phi_1 \phi_2 \dots \phi_M]$, 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 $A^T A$ such that

$$A^T A v_n = \lambda_n v_n \quad (19)$$

Premultiplying both sides by A , we have

$$AA^T A v_n = \lambda_n A v_n \quad (20)$$

from which we see that Av_n are the eigenvectors of $C = AA^T$. Following this analysis, we construct the M by M matrix $L = A^T A$, 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

$$u_n = \sum_{k=1}^M v_{nk} \phi_k = A n_n, \quad n = 1, \dots, M \quad (21)$$

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.

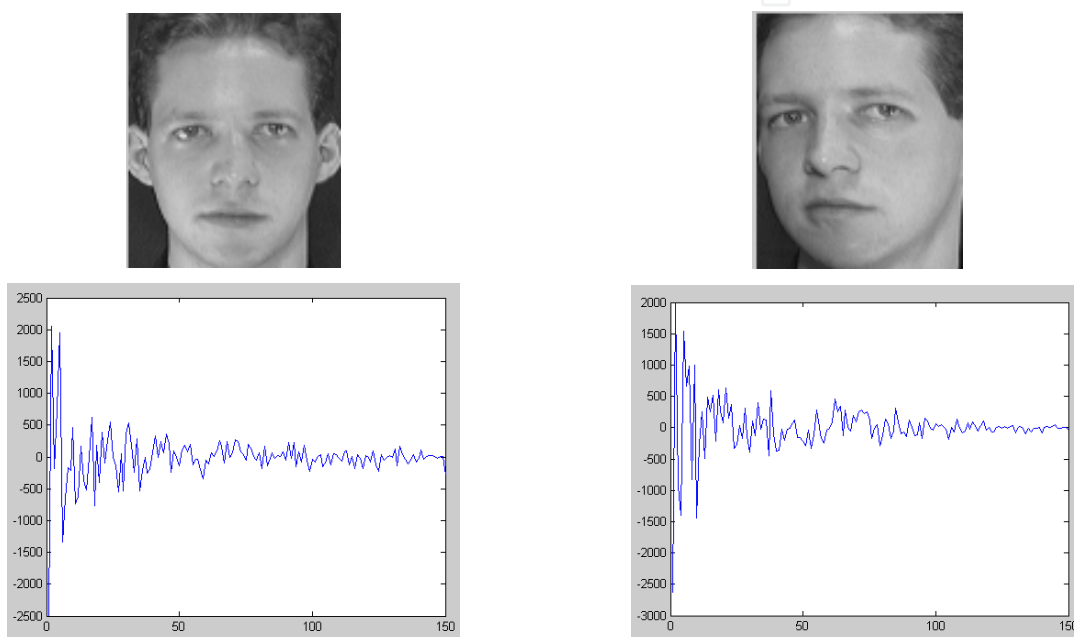


Fig. 9. Face and feature vectors of the same person.

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

$$\omega_n = u_n (\Gamma - \Psi) \quad (22)$$

for $n=1, \dots, M$. This describes a set of point-by-point image multiplications and summations. Some Eigenfaces are shown in figure 8b.

The weights form a vector $\Omega^T = [\omega_1, \omega_2, \dots, \omega_M]$ 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

$$\varepsilon_k^2 = \|\Omega - \Omega_k\|^2 \quad (23)$$

where Ω_k is a vector describing the k th face class. Figure 9 shows the feature vectors of the same person with different rotation using the Eigenfaces method.

Figure 10 shows the feature vectors of different people using the Eigenfaces method.



Fig. 10. Images of different people and their feature vectors.

2.4.1 Results

To evaluate this method were used the same conditions mentioned for Gabor's method. The results are shown in table 4.

Identification Percentage	Verification Percentage
83 %	99.6%

Table 4. Results using Eigenfaces

2.5 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is a special case of the WT that provides a compact representation of a signal in time and frequency that can be computed efficiently it is easy to implement and reduces the computation time and resources required. Wavelet transform (WT) has been widely applied to engineering fields, including signal and image processing, geophysical signal processing, computer vision and encoding, speech synthesis and analysis, signal singularity detection and spectrum estimation, pattern recognition quantum physics, hydrodynamics, fractal and chaos theory, etc. The wavelet theory adopts gradually precise step sizes of time domain or space domain for high frequency, and thus can focus on any details of an analyzed target.

The DWT of a given signal x is estimated by passing it through a series of low pass and high pass filters (Fig. 11). First the samples are passed through a low pass filter with impulse response $g(n,m)$ resulting in a convolution of the two. The signal is also decomposed simultaneously using a high-pass filter $h(n,m)$. The detail coefficients are the high-pass filter outputs and the approximation coefficients are the low-pass ones. It is important that the two filters, related to each other, are known as a quadrature mirror filter. However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are:

$$Y_{LOW}(n,m) = \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} x(n,m)g(2n-k,2m-j) \quad (24)$$

$$Y_{HIGH}(n,m) = \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} x(n,m)h(2n-k,2m-j) \quad (25)$$

This decomposition reduces the spatial resolution since only a quarter of each filter output allows characterizing the face image. However, because each output has bandwidth equal to a quarter of the original one, the output image can be decimated to reduce the image size.

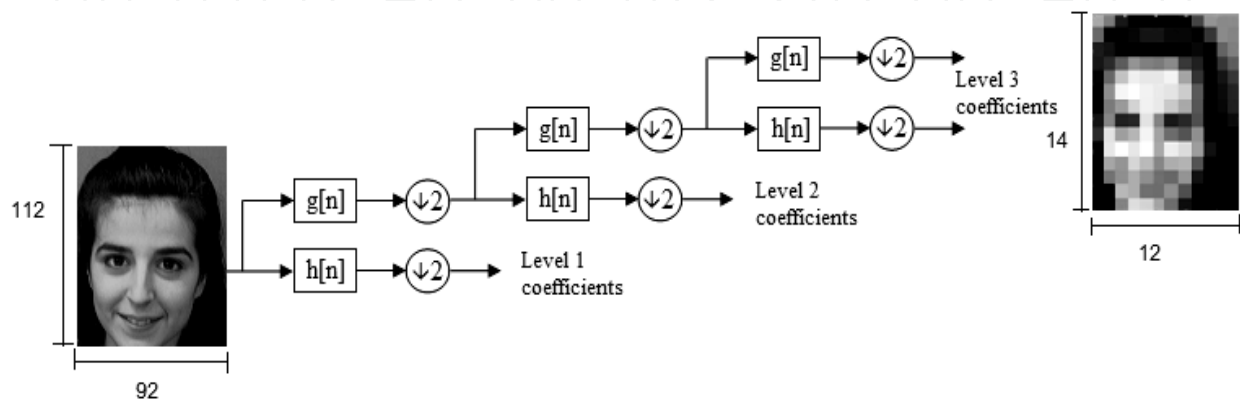


Fig. 11. 3 level wavelet decomposition

Here only the approximation coefficients are used to characterize the face image. This decomposition is repeated to further increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters and then down-sampled. This is represented as a binary tree with nodes representing a sub-space with different time-frequency localization. The tree is known as a filter bank. At each level in the above diagram the signal is decomposed into low and high frequencies. Due to the decomposition process the input signal must be a multiple of 2^n where n is the number of levels.

2.5.1 Results

To evaluate this method was used a SVM classifier. The feature vectors of training images obtained as mentioned above are applied to a SVM to obtain the optimal model of each class; these models are used in the classification stage. Where the input of each one is the feature vector of the face to classify and the output is an approximation of each model.

Since the support vector machine is a supervised system, it needs a smaller amount of information in the training stage to obtain a model capable of separating the classes successfully.

To evaluate this methods "The AR Face Database" was used, which has a total of 5,670 face images of 120 people (65 men and 55 women) that includes face images with several different illuminations, facial expression and partial occluded face images with sunglasses and scarf. The training set consists of images with and without occlusions, as well as illumination and expressions variations. Here the occlusions are a result of using sunglasses and scarf. These images sets and the remaining images of the AR face database are used for testing. The results are shown in table 5.

Identification Percentage	Verification Percentage
92.5 %	99.2%

Table 5. Results using Discrete Wavelet Transform

2.6 Eigenphases

Oppenheim et al (Oppenheim, 1981) have shown that phase information of an image retains the most of the intelligibility of an image. This is also demonstrated by Oppenheim's experiment shown in Figure 12.

Their research also shows that given just the phase spectrum of an image, one can reconstruct the original image up to a scale factor, thus phase information is the most important in representing a 2D signal in the Fourier domain. We have taken two face images; one from person 1 and one from person 2 as shown. The Fourier transform of both images were computed, and the respective phase spectrum and magnitude spectrum were extracted. We then synthesized new frequency array using the phase spectrum of person 1 combined with the magnitude spectrum from person 2. Similarly we took the phase spectrum from person 1 and combined it with the magnitude spectrum of person 2. We observe, that the synthesized face images closely resemble the face image from which the corresponding phase spectrum was extracted from, thus supporting the proposition that phase spectrum contains most of the intelligibility of images.

Since we have established that the complex phase spectrum contains most of the image information, it seems logical to seek to model the image variation by modeling the variation in the phase spectrum of a given sequence of training images.

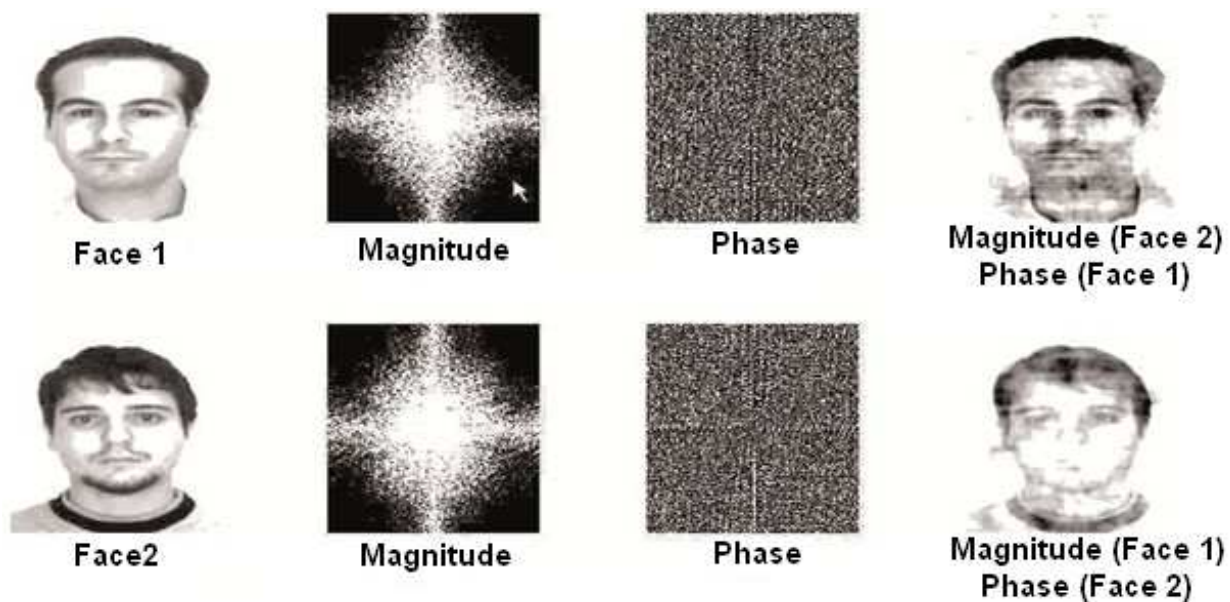


Fig. 12. Oppenheim's experiment.

To perform the face classification task, a PCA (Smith, 2002) is used to obtain the main characteristics of the faces training. Figure 13 shows the process:

Image 1, Image 2...Image N in Figure 13 are the phase spectrum of the training faces. In training phase, basis vectors are obtained by PCA. In the testing phase, the basis vectors obtained in training phase are used to extract the features for a classifier.

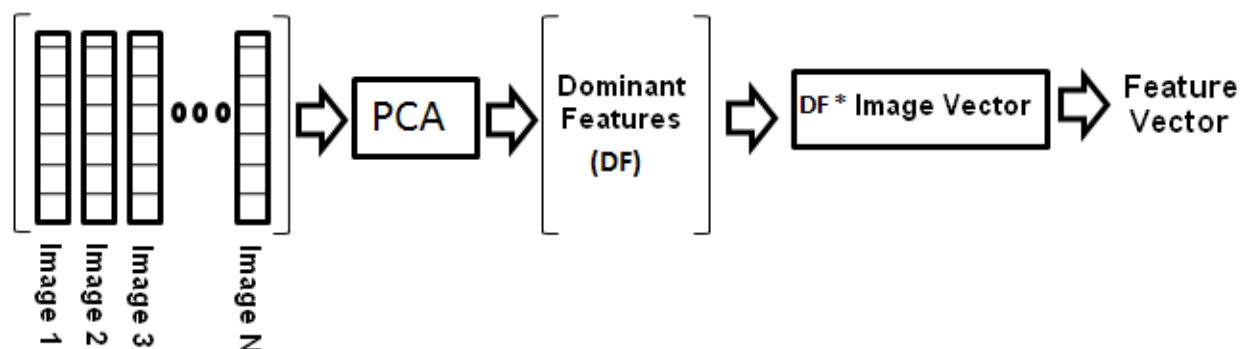


Fig. 13. Feature extraction by PCA

This method performs well although the recognition performance can be degraded in the presence of illumination variations and partial face occlusions.

Figure 14 shows the features vector obtained using Eigenphases. The vectors of the same person with different illumination show similitude.

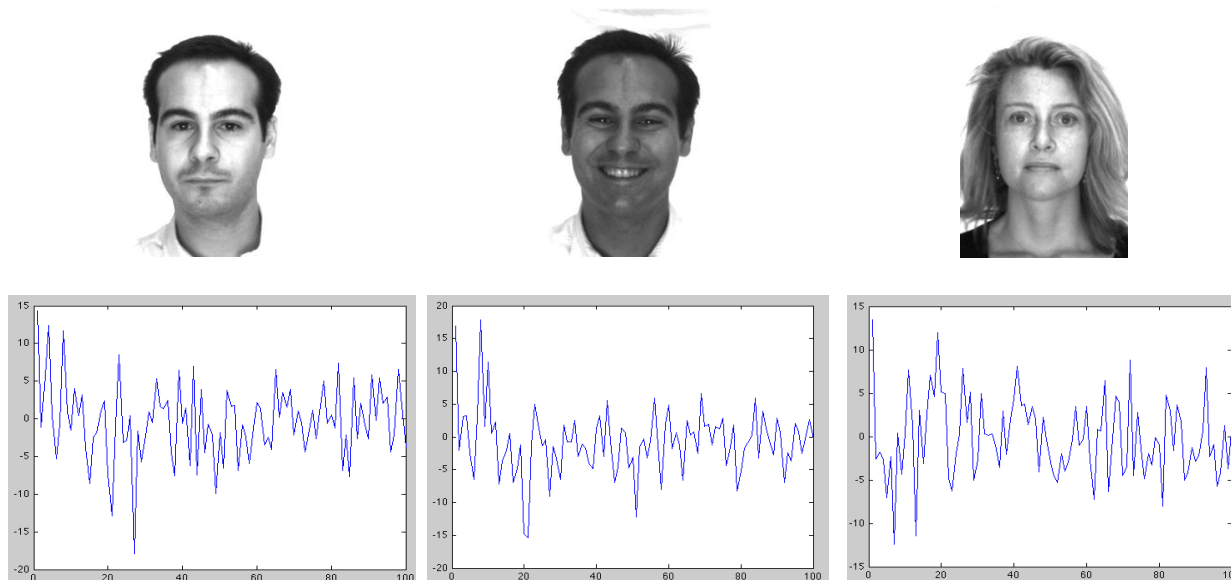


Fig. 14. Features vectors.

In this method a histogram equalization stage was proposed. Histogram equalization is a method in image processing for contrast adjustment. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. The method is useful in images with backgrounds and foregrounds that are both bright and dark.

Histogram equalization was performed in 5 different ways:

Global equalization of the image and obtain the phase spectrum of the complete image (Global EQ)

Perform a local equalization of the image using windows of size 3×3 and obtain the phase spectrum of the complete image (Local 3)

Perform a local equalization of the image using windows of size 6×6 and obtain the phase spectrum of the complete image (Local 6)

Equalization of the image and estimate the phase spectrum locally using windows of size 3×3 (Local Fourier 3)

Equalization of the image and estimate the phase spectrum locally using windows of size 6×6 (Local Fourier 6)

The histogram equalization is obtained by:

$$p_r = (r_k) = \frac{n_k}{MN} \quad k = 0, 1, 2, \dots, L-1 \quad (26)$$

where p_r is the probability that an intensity occurs r_k , n_k is the number of times the pixel with intensity k appearing in the picture and M and N is the number of rows and columns in the original image. To compute the output of the histogram equalization, the following equation is used:

$$s_k = (L-1) \sum_{j=0}^k p_r(r_j) \quad k = 0, 1, 2, \dots, L-1 \quad (27)$$

where L is the gray scale.

2.6.1 Results

To evaluate this method were used the same conditions mentioned for Wavelet's method. The results are shown in table 6.

Identification Percentage	Verification Percentage
87.5 %	99%

Table 6. Results using Eigenphases

Method	Identification Percentage	False acceptance	False reject
E.G	87.24 %	0.07%	4.66%
Local 3	87.58 %	0.03%	7.65%
Local 6	86.95 %	0.01%	8.93%
Local Fourier 3	89.57%	0.29%	0.8%
Local Fourier 6	89.37%	0.68%	0.52%

Table 7. Results using Histogram equalization

3. Conclusion

In this chapter several frequency domain feature extraction methods were analyzed. The feature vectors are then fed into a classifier, for example a multilayer neural network (ANN), Gaussian Mixture Models (GMM) or Support vector machines (SVM) to recognize the face image.

A modification to the Eigenphases algorithm was proposed based on the Histogram Equalization and the Phase Spectrum of an image. Also a method that allows that the features vector size can be independent of the captured image size was proposed for Gabor method.

The evaluation of some methods for feature extraction show that the some vectors are robust against changes in illumination, wardrobe, facial expressions and additive noise, blurred images (filters), resizing, shifting and even with some age changes. Therefore, the identity verification system could 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).

The combination of methods to obtain the feature vector, such as Gabor and Eigenfaces, could deliver a higher percentage of recognition. Finally, we can emphasize some advantages of the Frequency Domain Feature Extraction Methods: Compact extraction of the face information, easy implementation, robustness against several condition changes and fast processing.

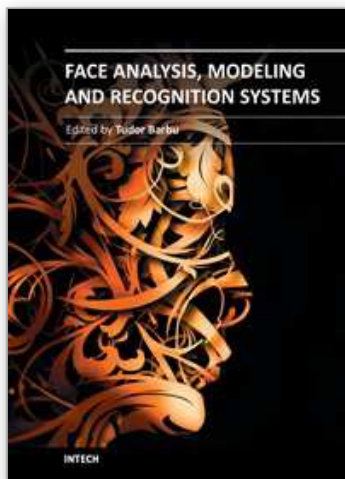
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5. References

- P. Reid. (2004). *Biometrics for Networks Security*. Prentice Hall, New Jersey.
- R. Chellappa; C. Wilson, and S. Sirohey. (1995). Human and Machine Recognition of Faces: A Survey. *Proc. IEEE*, vol. 83, No. 5, pp. 705- 740.
- R. J. Baron. (1981). Mechanisms of human facial recognition, *International Journal of Man-Machine Studies*, pp. 137-178.
- L. Sirovich and M. Kirby. (March 1987). Low-dimensional procedure for the characterization of human faces," *J. Opt. Soc. Am. A.*, Vol. 4, No. 3, pp. 519-524.
- Brunelli R., Poggio T. (1993). Face recognition: Features vs. Templates. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 15, No. 10.
- M. Turk and A. Pentland. (1991). Eigenfaces for Recognition. *J. Cognitive Neuroscience*, vol. 3, no.1.
- M. Turk and A. Pentland. (1991). Face Recognition using Eigenfaces. *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 586-591.
- Moghaddam B.; Wahid W. & Pentland A. (1998). Beyond eigenfaces: Probabilistic matching for face recognition. *Proceedings of the Second International Conference on Automatic Face and Gesture Recognition*, Nara, pp. 30-35.
- I. Smith. (February 2002). A tutorial on Principal Components Analysis.
- Tanaka H.T., Ikeda M and Chiaki H. (1998). Curvature-based face surface recognition using spherical correlation - Principal directions for curved object recognition. *Proceedings of the Second International Conference on Automatic Face and Gesture Recognition*, Nara, pp. 372-377.
- M. Yoshida, T. Kamio and H. Asai. (2003). Face Image Recognition by 2- Dimensional Discrete Walsh Transform and Multi-Layer Neural Network. *IEICE Trans. Fundamentals*, Vol. E86-A, no.10, pp. 2623- 2627.

- Shanks, J. L. (1969). Computation of the Fast Walsh-Fourier Transform," IEEE Trans. Comput., Vol. 18, No. 5, pp. 457-459.
- Lanitis A., Taylor C.J. and Cootes T.F. (1995). A unified approach to coding and interpreting face images. Proceedings of the International Conference on Computer Vision ICCV'95, Cambridge.
- Kirby M. and Sirovich L. (1990). Application of the Karhunen-Loeve procedure for the characterization of human faces. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 12, No. 1.
- P. Hallinan, G. Gordon, A. Yullie, P. Gabiland and D.Mumford. (USA 1999). Two and Three Dimensional Patterns of Face.
- I. Hong, Y. Wan and A. Jain. (August 1998). Fingerprint image enhancement algorithm and performance evaluation," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 20, No.8, pp. 777-789.
- C. Cruz, R. Reyes, M. Nakano-Miyatake and H. Perez-Meana. (June 2004). Verificacion de firmas usando la transformada de Gabor," Revista Internacional Informacion Tecnologica, Vol. 15, No. 3, pp. 53-60.
- J. G. Daugman. (July 1988). Complete discrete 2D Gabor transform by neural networks for image analysis and compression", IEEE Trans. on Acoustic Speech and Signal Proc., vol. 36, No. 7, pp. 1169-1179.
- Scott E. (1999). Computer Vision and Image Processing. Prentice Hall PTR, Prentice Hall, Inc, Upper Saddle River, NJ 07458, ISBN :0-13-264-599-8.
- Conrad S. and Kuldip K. (2003). Fast Features for Face Authentication Under Illumination Direction Changes. Pattern Recognition Letters 2, 2409-2419.
- H. Feichtinger, T. Strohmer. (USA 1998). Gabor Analysis Algorithms. Ed. Birkhauser, Boston, Ma.
- T. Kamio, H. Ninomiya, and H. Asai. (Nov. 1994). A neural net approach to discrete Walsh transform. IEICE Trans. Fundamentals, vol.E77-A, no.11. pp.1882-1886.
- H.T.L. Mar and C.L. Sheng. (1973). Fast Hadamard transform using the H diagram. IEEE Trans. Comput., vol.C-22, No.10, pp.957-960.
- A. V. Oppenheim and J. S. Lim. (May 1981). The importance of phase in signals. Proc. IEEE, vol 69, No°5, pp. 529-541.
- Lindsay I Smith. (February 2002). A tutorial on Principal Components Analysis.



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The purpose of this book, entitled Face Analysis, Modeling and Recognition Systems is to provide a concise and comprehensive coverage of artificial face recognition domain across four major areas of interest: biometrics, robotics, image databases and cognitive models. Our book aims to provide the reader with current state-of-the-art in these domains. The book is composed of 12 chapters which are grouped in four sections. The chapters in this book describe numerous novel face analysis techniques and approach many unsolved issues. The authors who contributed to this book work as professors and researchers at important institutions across the globe, and are recognized experts in the scientific fields approached here. The topics in this book cover a wide range of issues related to face analysis and here are offered many solutions to open issues. We anticipate that this book will be of special interest to researchers and academics interested in computer vision, biometrics, image processing, pattern recognition and medical diagnosis.

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