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Two Novel Face Recognition Approaches

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1. Introduction

Face recognition represents a very important biometric domain, the human face being a psychological biometric identifier that is widely used in person authentication. Also, it constitutes a popular computer vision domain, facial recognition being the most successful application of object recognition. Recognizing of faces is a task performed easily by humans but it remains a difficult problem in the computer vision area. Automated face recognition constitutes a relatively new concept, having a history of some 20 years of research. Major initiatives and achievements in the past decades have propelled facial recognition technology into the spotlight (Zhao et. al, 2003).

A facial recognition system represents a computer-driven application for automatically authenticating a person from a digital image, using the characteristics of its face. As any biometric recognition system, it performs two essential processes: identification and verification. Facial identification consists in assigning an input face image to a known person, while face verification consists in accepting or rejecting the previously detected identity. Also, facial identification is composed of a feature extraction stage and a classification step.

Face recognition technologies have a variety of application areas, such as: access control systems for various services, surveillance systems and law enforcement (Zhao et. al, 2003).. Also, these technologies can be incorporated into more complex biometric systems, to obtain a better human recognition. Facial recognition techniques are divided into two major categories: geometric and photometric methods. Geometric approaches represent feature-based techniques and look at distinguishing individual features, such as eyes, nose, mouth and head outline, and developing a face model based on position and size of these characteristics. Photometric techniques are view-based recognition methods. They distill an image into values and compare these values with templates. Many face recognition algorithms have been developed in the last decades. The most popular techniques include Eigenfaces (Turk & Pentland, 1991, Barbu, 2007), Fisherfaces (Yin et. al, 2005), Linear Discriminant Analysis (LDA), Elastic Bunch Graph Matching (EBGM), Hidden Markov Models (HMM) (Samaria et. al, 1994) and the neuronal model Dynamic Link Matching (DLM) (Wiskott et. al, 1996).

In this chapter we present two facial recognition approaches. The first one is an Eigenface-based recognition technique, based on the influential work of Turk and Pentland (Turk & Pentland, 1991). Proposed in 1991 by M. Turk and A. Pentland, the Eigenface approach was the first genuinely successful system for automatic recognition of human faces, representing

a breakaway from contemporary research trend on facial recognition. The second technique, described in the third section, uses Gabor filtering in the feature extraction stage (Barbu, 2010). It applies a set of 2D Gabor filters, at various frequencies, orientations and standard deviations, on the facial images. A supervised classifier is used in the classification stage.

2. Eigenimage-based facial recognition approach

We have proposed an eigenimage-based face recognition technique based on the well-known approach of Turk and Pentland (Turk & Pentland, 1991). Their recognition method considers a large set of facial images that works as a training set.

Thus, each of these images is represented as a vector $\Gamma_i,\ i = 1,...,M$, then one computes the average vector Ψ. The covariance matrix is computed next as $C = A \cdot A^T$, where $A = [\Phi_1,...,\Phi_M]$ and $\Phi_i = \Gamma_i - \psi$. The matrix C is a very large one and its eigenvectors and eigenvalues are obtained from those of $A^T \cdot A$. Thus, $A \cdot A^T$ and $A^T \cdot A$ have the same eigenvalues and their eigenvectors are related as follows: $u_i = Av_i$. One keeps only M' eigenvectors, corresponding to the largest eigenvalues. Each of these eigenvectors represents an eigenimage (eigenface). Each face image is projected onto each of these eigenfaces, its feature vector, containing M' coefficients, being obtained. Any new input face image is identified by computing the Euclidean distance between its feature vector and each feature training vector. Next, some verification procedures may be necessary to determine if the input image represents a face at all or if it represents a registered person.

We have developed a derived version of this Eigenface approach. Thus, we propose a continuous mathematical model for face feature extraction in the first subsection (Barbu, 2007). Then we discretize this model, the discretized version being presented in the second subsection (Barbu, 2007). A supervised face classification system, that produces the identification results, is described in the third subsection. Facial verification is the last recognition process. In the fourth section we present a threshold-based verification approach. Some experiments performed by using our facial recognition method are presented in the fifth section.

2.1 A continuous model for face feature extraction

We develop a continuous differential model for facial feature extraction. Thus, our approach replaces the 2D face image Ω by a differentiable function $u = u(x,y)$ and the covariance matrix by a linear symmetric operator on the space $L^2(\Omega)$ involving the image vector u and its gradient ∇u. We determine a finite number of eigenfunctions, the identification process being developed on this finite dimensional space (Barbu, 2007).

Therefore, the continuous facial image become $u : \Omega \to R$ and we denote by $L^2(\Omega)$ the space of all L^2 - integrable functions u with the norm $|u|_2 = \left(\int_\Omega u^2(x,y) dx dy \right)^{1/2}$, and by $H^1(\Omega)$ the Sobolev space of all functions $u \in L^2(\Omega)$ with the distributional derivatives $D_x u = \dfrac{\partial u}{\partial x}$ and $D_y u = \dfrac{\partial u}{\partial y}$ respectively (Barbu V., 1998). Also, we denote by

$\nabla u(x,y) = (D_x u(x,y), D_y u(x,y))$ the gradient of $u = u(x,y)$. The Euclidean L^2 - norm $\int_\Omega u^2(x,y)dxdy$ is replaced in this new approach by the $H^1(\Omega)$ - energetic norm $\int_\Omega |u|^2 + |\nabla u|^2 dxdy$, that is sharper and more appropriate to describe the feature variations of the human faces. This technique is inspired by the diffusion models for image denoising, representing our main contribution (Barbu, 2007). Thus, the norm of $H^1(\Omega)$ is computed as:

$$|u|_{H^1(\Omega)} = \int_\Omega (u^2(x,y) + (D_x u(x,y))^2 + (D_y u(x,y))^2)dxdy = \int_\Omega (u^2(x,y) + |\nabla u(x,y)|^2)dxdy \quad (1)$$

We are given an initial set of facial images, $\{u_1,...,u_M\} \subset (H^1(\Omega))^M$, representing the training set. Therefore, its average value is computed as:

$$\mu(x,y) = \frac{1}{M}\sum_{i=1}^M u_i(x,y), \quad x,y \in \Omega \quad (2)$$

Next, we compute the differences:

$$\Phi_i(x,y) = u_i(x,y) - \mu(x,y), \quad i = 1,...,M \quad (3)$$

Then, we set

$$W_i = \nabla u_i = \{D_x u_i, D_y u_i\}, \quad i = 1,...,M \quad (4)$$

and consider the covariance operator $Q \in L((L^2(\Omega))^3, (L^2(\Omega))^3)$ associated with the vectorial process $\{\Phi_i, W_i\}_{i=1}^M$. If $h = \{h_1, h_2, h_3\} \in L^2(\Omega) \times L^2(\Omega) \times L^2(\Omega)$, then we have:

$$(Qh)(x,y) = \left\{\sum_{i=1}^M \Phi_i(x,y)\int_\Omega \Phi_i(\xi)h_1(\xi)d\xi + \sum_{i=1}^M W_i^1(x,y)\int_\Omega W_i^1(\xi)h_2(\xi)d\xi + \right.$$
$$\left. + \sum_{i=1}^M W_i^2(x,y)\int_\Omega W_i^2(\xi)h_3(\xi)d\xi, \right\}, \forall h_k \in L^2(\Omega), k = 1,2,3 \quad (5)$$

where $W_i = \{W_i^1, W_i^2\}$, $W_i^1(x,y) = D_x U_i(x,y)$, $W_i^2(x,y) = D_y U_i(x,y)$, $i = 1,...,M$. Equivalently we may view Q as covariance operator of the process $\Phi = \{\Phi_i\}_{i=1}^M$ in the space $H^1(\Omega)$ endowed with norm $|\bullet|_{H^1}$. Indeed, for $h_1 = z, h_2 = D_x z, h_3 = D_y z$, the equation (5) becomes:

$$(Qh)(x,y) = \{\Phi \cdot (\Phi,z)_{L^2(\Omega)}, \nabla\Phi \cdot (\nabla\Phi, \nabla z)_{L^2(\Omega)}\} = \{\Phi, \nabla\Phi\} <\Phi, z>_{H^1(\Omega)}, \forall z \in H^1(\Omega) \quad (6)$$

This means Q is just the covariance operator of the $H^1(\Omega)$ - variable Φ. We may consider Φ to be a random variable. The operator Q is self-adjoint in $(L^2(\Omega))^3$ and has an orthonormal complet system of eigenfunctions $\{\varphi_j\}$, i.e., $Q\varphi_j = \lambda_j \varphi_j$, $\lambda_j > 0$ (Barbu V., 1998).

Moreover, $\varphi_j \in (H^1(\Omega))^3$, $\forall j$. Let us associate with Q the $[3M \times 3M]$ matrix $\tilde{Q} = A^T A$, where $A : R^{3M} \to (L^2(\Omega))^3$ is given by $AY = \left[\sum_{i=1}^{M} \Phi_i y_1^i, \sum_{i=1}^{M} W_i^1 y_2^i, \sum_{i=1}^{M} W_i^1 y_3^i \right]$, $Y = \{y_1^i, y_2^i, y_3^i\}_{i=1}^{M}$, and $A^T : (L^2(\Omega))^3 \to R^{3M}$, that represents the adjoint operator, is given by

$$A^T h = \left[\int_{\Omega} \Phi_1(\xi)h_1 d\xi, ..., \int_{\Omega} \Phi_M h_1 d\xi, \int_{\Omega} W_1^1(\xi)h_2 d\xi, ..., \int_{\Omega} W_M^1(\xi)h_2 d\xi, \int_{\Omega} W_1^2(\xi)h_3 d\xi, ..., \int_{\Omega} W_M^2(\xi)h_3 d\xi \right]$$

where $h = (h_1, h_2, h_3) \in (L^2(\Omega))^3$. One results:

$$A^T A = \left\| \begin{array}{ccc} \int_{\Omega} \Phi_i \Phi_j d\xi & 0 & 0 \\ 0 & \int_{\Omega} \Phi_i \Phi_j d\xi & 0 \\ 0 & 0 & \int_{\Omega} \Phi_i \Phi_j d\xi \end{array} \right\|_{i,j=1}^{M} \tag{7}$$

We consider $\{\lambda_j\}_{j=1}^{3M}$ and $\{\psi_j\}_{j=1}^{3M} \subset R^{3M}$ a linear independent system of eigenvectors for $\tilde{Q}$, therefore $\tilde{Q}\psi_j = \lambda_j \psi_j$, $j = 1, ..., 3M$. One can see that the sequence $\{\varphi_j\}_{j=1}^{3M}$, defined by $\varphi_j = \psi_j \Phi_j$, for $1 \le j \le M$, $\varphi_j = \psi_j W_j^1$, for $M+1 \le j \le 2M$, and $\varphi_j = \psi_j W_j^2$, for $2M+1 \le j \le 3M$, represent the eigenfunctions of operator Q, i.e., $Q\varphi_j = \lambda_j \varphi_j$, $j = 1, ..., 3M$. The eigenfunctions of the covariance operator Q maximizes the variance of projected samples:

$$\varphi_j = arg\{max < Qh, h >_{(L^2(\Omega))^3}; |h|_{(L^2(\Omega))^3} = 1\} \tag{8}$$

In this way the eigenfunctions $\{\varphi_j\}_{j=1}^{3M}$ capture the essential features of images from the initial training set. From $\{\varphi_j\}$ we keep a smaller number of eigenfaces $\{\varphi_j\}_{j=1}^{3M'}$, with $M' < M$ corresponding to largest eigenvalues λ_j and consider the space

$$X = lin\{\varphi_j\}_{j=1}^{3M'} \subset (L^2(\Omega))^3 \tag{9}$$

Assuming that systems $\{\varphi_j\}$ is normalized (orthonormal in $(L^2(\Omega))^3$) one can project any initial image $\{\Phi_i, W_i^1, W_i^2\} \in (L^2(\Omega))^3$ on X by formula

$$\Psi_i(x, y) = \sum_{j=1}^{3M'} \varphi_j(x, y) < \varphi_j, T_i >_{(L^2(\Omega))^3}, i = 1, ..., 3M \tag{10}$$

where $T_i = \{\Phi_i, W_i^1, W_i^2\}$, $i = 1, ..., 3M$ and $< \cdot, \cdot >_{(L^2(\Omega))^3}$ is the scalar product in $L^2(\Omega) \times L^2(\Omega) \times L^2(\Omega)$. We denote the weights $w_i^j = < \varphi_j, T_i >_{(L^2(\Omega))^3}$, $i = 1, ..., 3M$, and the resulted feature vector will be

$$V(u_i) = (w_i^1, ..., w_i^{3M'}), \ \ i = 1, ..., 3M \tag{11}$$

2.2 Discretization of the feature extraction approach

We discretize the continuous model described in the last section. Let us assume that $\Omega = [0, L_1] \times [0, L_2]$ and let us set $x_i = i\varepsilon$, $i = 1, ... N_2$ and $y_j = j\varepsilon$, $j = 1, ... N_1$, $\varepsilon > 0$ (Barbu, 2007).

Therefore, we obtain M matrices of size $N_1 \times N_2$, which represent the discrete images. We denote their corresponding $N_1 \cdot N_2 \times 1$ image vectors as $I_1, ..., I_M$. Now, we have $\tilde{Q} = A^T \cdot A$, where

$$A = \left\| \begin{matrix} \Phi_1, ..., \Phi_M & 0 & 0 \\ 0 & W_1^1, ..., W_M^1 & 0 \\ 0 & 0 & W_1^2, ..., W_M^2 \end{matrix} \right\| \tag{12}$$

and

$$\begin{cases} \Phi_k = \left\| \Phi_k(x_i, y_j) \right\|_{i,j=1}^{N_2, N_1} \\ W_k^1 = \left\| \Phi_k(x_{i+1}, y_j) - \Phi_k(x_i, y_j) \right\|_{i,j=1}^{N_2, N_1} \\ W_k^2 = \left\| \Phi_k(x_i, y_{j+1}) - \Phi_k(x_i, y_j) \right\|_{i,j=1}^{N_2, N_1} \end{cases} \tag{13}$$

The obtained matrix has a $3M \times 3M$ dimension. Thus, we determine the eigenvectors ψ_i of the matrix $\tilde{Q}$. Then, the eigenvectors of the discretized covariance operator Q are computed as following:

$$\tilde{\varphi}_i = A \cdot \psi_i, \ \ i = 1, ..., M \tag{14}$$

We keep only $M' < M$ eigenimages corresponding to the largest eigenvalues and consider the space $X = linspan\{\tilde{\varphi}_i\}_{i=1}^{3M'}$. Then, the projection of $[\Phi_i, W_i^1, W_i^2]$ on X is given by the discrete version of Ψ_i, that is computed as:

$$P_X([\Phi_i, W_i^1, W_i^2]) = \sum_{j=1}^{3M'} w_i^j \cdot \varphi_j, \ \ i = 1, ..., 3M \tag{15}$$

where $w_i^j = \tilde{\varphi}_j^T \cdot [\Phi_i, W_i^1, W_i^2]^T$. So, for each facial image I_i a corresponding training feature vector is extracted as the sequence of all these weights:

$$V(I_i) = [w_i^1, ..., w_i^{3M'}]^T, \ \ i = 1, ..., 3M \tag{16}$$

Therefore, the feature training set of the face recognition system is obtained as $\{V(I_1),...,V(I_M)\}$, each feature vector being given by (16). The Euclidean metric could be used to measure the distance between these vectors.

2.3 Facial feature vector classification and verification

The next step of face recognition is the classification task (Duda et. al, 2000). We provide a supervised classification technique for facial authentication. Thus, we consider an unknown input image I to be recognized using the face training set $\{I_1,...,I_M\}$. The feature training set of our classifier is $\{V(I_1),...,V(I_M)\}$ and its metric is the Euclidean distance for vectors. We normalize the input image, first. So, we get $\Phi = I - \Psi$, where $\Psi = \frac{1}{M}\sum_{i=1}^{M} I_i$. The vectors W^1 and W^2 are computed from Φ using formula (13). Then it is projected on the eigenspace, using the formula $P(\Phi) = \sum_{i=1}^{M'} w^i \varphi_i$, where $w^i = \tilde{\varphi}_i^T \cdot [\Phi, W^1, W^2]^T$. Obviously, its feature vector is computed as $V(I) = [w^1,...,w^{M'}]^T$ (Barbu, 2007).

A threshold-based facial test could be performed to determine if the given image represents a real face or not. Thus, if $\|P(\Phi) - \Phi\| \le T$, where T is a properly chosen threshold value, then I represents a face, otherwise it is a non-facial image. We consider K registered (authorized) persons whose faces are represented in the training set $\{I_1,...,I_M\}$. We redenote this set as $\{I_1^1,...,I_1^{n(1)},...,I_i^1,...,I_i^{n(i)},...,I_K^1,...,I_K^{n(K)}\}$, where $K < M$ and $\{I_i^1,...,I_i^{n(i)}\}$ represents the training subset provided by the ith authorized person, $n(i)$ being the number of its registered faces.

A minimum average distance classifier, representing an extension of the classical variant of minimum distance classifier (Duda et. al, 2000), is used for feature vector classification. So, for each registered user, one calculates the average distance between its feature training subset and the feature vector of the input face. The input image is associated to the user corresponding to the minimum distance value. That user is the kth registered person, where

$$k = \arg\min_i \frac{\sum_{j=1}^{n(i)} d(V(I), V(I_i^j))}{n(i)} \tag{17}$$

where d is the Euclidean metric. Thus, each input face I is identified as a registered person by this formula. However, the face identification procedure has to be completed by a facial verification step, to determine if that face really represents the associated person. We propose a threshold-based verification approach.

First, we provide a novel threshold detection solution, considering the overall maximum distance between any two feature vectors belonging to the same training feature sub-set as a threshold value (Barbu, 2007). Therefore, the input face I may represent the kth registered user if the following condition is fulfilled:

$$\min_i \frac{\sum_{j=1}^{n(i)} d(V(I), V(I_i^j))}{n(i)} \le T \tag{18}$$

where k is computed by (17) and the threshold is given by formula:

$$T = \max_{i} \max_{j \neq t} d(V(I_i^j), V(I_i^t)) \tag{19}$$

If the condition (18) is not satisfied, then the input face is rejected by our recognition system and labeled as *unregistered*.

2.4 Experiments

The proposed Eigenface-based recognition system has been tested on numerous face datasets. We have performed many experiments and achieved satisfactory facial recognition results. Our technique produces a high recognition rate, of approximately 90%. We have used "Yale Face Database B", containing thousands of 192×168 face images corresponding to many persons, in our research (Georghiades et. al, 2001). In the next figures, there is represented such a face recognition example. In Fig. 1 one can see a set of 10 input faces to be recognized.
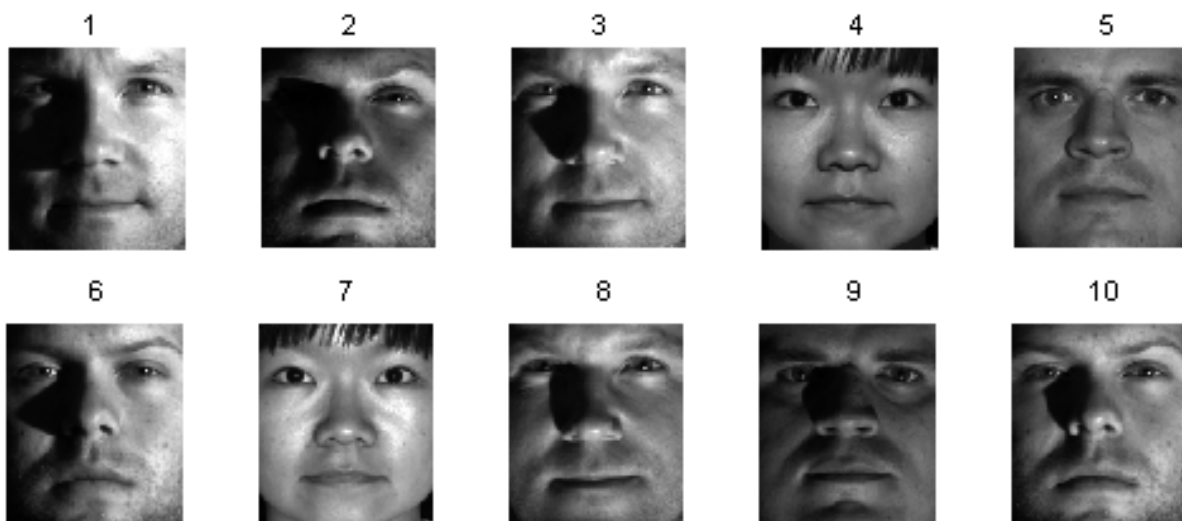

Fig. 1. Input face images

This example uses a training set containing 30 facial images belonging to 3 persons. The face set is illustrated in Fig. 2, where each registered individual has 10 photos positioned on two consecutive rows.

Therefore, one computes 90 eigenfaces for this training set but only the most important 27 ($M^{'} = 9$) of them are necessary. The most significant eigenfaces are represented in Fig. 3. Thus, the feature training set, containing face feature vectors, is obtained on the basis of these eigenimages.

The mean distances between these feature vectors are computed and the identification process provided by (17) is applied. Faces 2, 6 and 10 are identified as belonging to the first person, faces 4 and 7 are identified to the second person. Also, the faces 5 and 9 are associated to the first registered individual but their distance values, 5.795 and 5.101, are greater than the threshold value provided by (19), computed as $T = 2.568$, so the verification procedure labels them as unregistered.
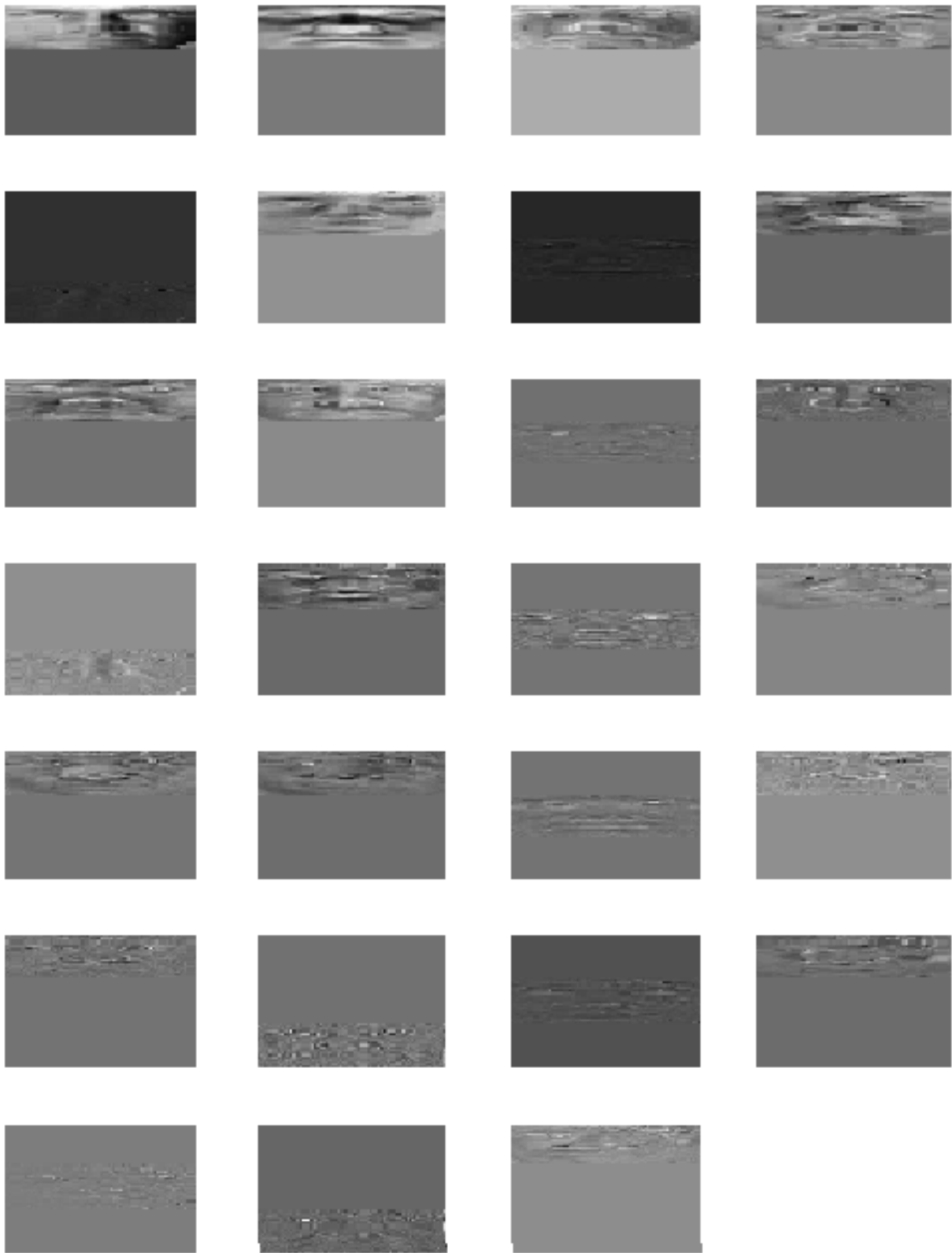
Fig. 2. Facial training set

Fig. 3. The main eigenfaces

3. Face recognition technique using two-dimensional Gabor filtering

The second face authentication approach is based on two-dimensional Gabor filtering. As one knows, a great amount of research papers have been published in literature for Gabor filter-based image processing (Movellan, 2008). Besides face recognition, Gabor filters are successfully used in many other image processing and analysis domains, such as: image smoothing, image coding, texture analysis, shape analysis, edge detection, fingerprint and iris recognition.

We use the Gabor filters in the feature extraction process, that is described in the next subsection. Then, we use a feature vector classification approach that is similar to the supervised method proposed in the previous section. A threshold-based face verification is also described in the second subsection. Some facial recognition experiments are presented in the last subsection.

3.1 A Gabor filter based facial feature extraction

We intend to obtain some feature vectors which provide proper characterizations of the visual content of face images. For this reason we use the two-dimensional Gabor filtering as a feature extraction tool (Barbu, 2010).

The Gabor filter represents a band-pass linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Thus, a bidimensional Gabor filter constitutes a complex sinusoidal plane of particular frequency and orientation modulated by a Gaussian envelope. It achieves optimal resolutions in both spatial and frequency domains (Movellan, 2008, Barbu, 2010). Our approach designs 2D odd-symmetric Gabor filters for face image recognition, having the following form:

$$G_{\theta_k, f_i, \sigma_x, \sigma_y}(x,y) = exp\left(-\left[\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right]\right) \cdot cos\left(2\pi f_i x_{\theta_k} + \varphi\right) \tag{20}$$

where $x_{\theta_k} = x\cos\theta_k + y\sin\theta_k$, $y_{\theta_k} = y\cos\theta_k - x\sin\theta_k$, f_i provides the central frequency of the sinusoidal plane wave at an angle θ_k with the x – axis, σ_x and σ_y represent the standard deviations of the Gaussian envelope along the axes x and y.

Then, we set the phase $\varphi = \pi/2$ and compute each orientation as $\theta_k = \frac{k\pi}{n}$, where $k = \{1,...,n\}$. The 2D filters $G_{\theta_k, f, \sigma_x, \sigma_y}$ computed by (20) represent a group of wavelets which optimally captures both local orientation and frequency information from a digital image (Barbu, 2010).

Each facial image has to be filtered by applying $G_{\theta_k, f, \sigma_x, \sigma_y}$ at various orientations, frequencies and standard deviations. A proper design of Gabor filters for face authentication requires an appropriated selection of those parameters. Therefore, we consider some proper variance values, a set of radial frequencies and a sequence of orientations, respectively.

The settings for the filter parameters are: $\sigma_x = 2$, $\sigma_y = 1$, $f_i \in \{0.75, 1.5\}$ and $n = 5$, which means $\theta_k \in \left\{\frac{\pi}{5}, \frac{2\pi}{5}, \frac{3\pi}{5}, \frac{4\pi}{5}, \pi\right\}$. One results the filter bank $\left\{G_{\theta_k, f_i, 2, 1}\right\}_{f_i \in \{0.75, 1.5\}, k \in [1, 5]}$, that is

composed of 10 channels. The current face image is convolved with each 2D Gabor filter from this set. The resulted Gabor responses are then concatenated into a three-dimensional feature vector. So, if I represents a $[X \times Y]$ face image, then the feature extraction is modeled as:

$$V(I)[x,y,z] = V_{\theta(z),f(z),\sigma_x,\sigma_y}(I)[x,y] \tag{21}$$

where $x \in [1,X]$, $y \in [1,Y]$ and

$$\theta(z) = \begin{cases} \theta_z, & z \in [1,n] \\ \theta_{z-n}, & z \in [n+1,2n] \end{cases}, \quad f(z) = \begin{cases} f_1, & z \in [1,n] \\ f_2, & z \in [n+1,2n] \end{cases} \tag{22}$$

and

$$V_{\theta(z),f(z),\sigma_x,\sigma_y}(I)[x,y] = I(x,y) \otimes G_{\theta(z),f(z),\sigma_x,\sigma_y}(x,y) \tag{23}$$

A fast 2D convolution is performed using Fast Fourier Transform, so, the face feature vector is computed as $V_{\theta(z),f(z),\sigma_x,\sigma_y}(I) = FFT^{-1}[FFT(I) \cdot FFT(G_{\theta(z),f(z),\sigma_x,\sigma_y})]$. For each face I one obtains a 3D face feature vector $V(I)$, that has a $[X \times Y \times 2n]$ dimension.

This feature vector proves to be a satisfactory content descriptor of the input face. In Fig. 4 one depicts a facial image and its 10 Gabor representations, representing the components of its feature vector.

Fig. 4. Feature vector components of a face image

The distance between these feature vectors must be computed using a proper metric. Since the size of each vector depends on the dimension of the featured image, a resizing procedure has to be performed on the face images, first. Then, we compute the distance between these 3D feature vectors using a *squared Euclidean metric*, which is characterized by formula:

$$d(V(I),V(J)) = \sum_{x=1}^{X} \sum_{y=1}^{Y} \sum_{z=1}^{2n} \left| V(I)[x,y,z] - V(J)[x,y,z] \right|^2 \tag{24}$$

where I and J are two face images, resized to the same $[X \times Y]$ dimension.

3.2 Face feature vector classification and verification

Feature vector classification represents the second step of the face identification process. We provide a similar supervised classification approach for these Gabor filter-based 3D feature vectors. Some well-known supervised classifiers (Duda et. al, 2000), such as minimum distance classifier or the *K-Nearest Neighbour* (*K-NN*) classifier, could be also used in this case.

The training set of this classifier is created first. Therefore, one considers N authorized system users. Each of them provides a set of faces of its own, named templates, which are included in the training set. Thus, the training face set can be modeled as $\left\{\left\{F_j^i\right\}_{j=1,...,n(i)}\right\}_{i=1,...,N}$, where F_j^i represents the jth template face of the ith user and $n(i)$ is the number of training faces of the ith user. The classification algorithm produces N face classes, each one corresponding to a registered person. Next, one computes the training vector set as $\left\{\left\{V(F_j^i)\right\}_{j=1,...,n(i)}\right\}_{i=1,...,N}$.

If the input faces to be recognized are $\left\{I_1,...,I_K\right\}$, the classification procedure inserts each of them in the class of the *closest* registered person, representing the user corresponding to the minimum *average distance*. The minimum average distance classification process is described by a formula that is similarly to (17):

$$Class(j) = \arg \min_{i \in [1,N]} \frac{\sum_{t=1}^{n(i)} d(V(I_j), V(F_t^i))}{n(i)}, \forall j \in [1,K] \tag{25}$$

where the obtained $Class(j) \in [1,N]$ represents the index of the face class where I_j is introduced. Let $C_1,...,C_N$ be the resulted classes, representing the facial identification result. Next, a verification procedure is performed, to complete the face recognition task. We use a similar automatic threshold-based verification approach (Barbu, 2010). Therefore, one computes a proper threshold value as the overall maximum distance between any two training face feature vectors corresponding to the same registered user, that is:

$$T = \max_{i \leq N} \left(\max_{j \neq k \in [1,n(i)]} d\left(V(F_j^i), V(F_k^i)\right) \right) \tag{26}$$

If the average distance corresponding to an image from a class is greater than threshold T, then that image has to be rejected from the face class. The verification process is represented formally as follows:

$$\forall i \in [1,N], \forall I \in C_i : \frac{\sum_{j=1}^{n(i)} d(V(I), V(F_j^i))}{n(i)} > T \Rightarrow C_i = C_i - \{I\} \tag{27}$$

The rejected images, that could represent non-facial images or faces of unregistered users, are included in a new class C_{N+1}, labeled as *Unauthorized*.

3.3 Experiments and method comparisons

We have performed many facial recognition experiments, using the proposed Gabor filter based approach. Our recognition system has been tested on various large face image datasets and good results have been obtained.

A high face recognition rate, of approximately 90%, has been reached by our recognition system in the experiments involving hundreds frontal images. We have obtained high values (almost 1) for the performance parameters, *Precision* and *Recall*, and for the combined measure F_1. That means our approach produce a small number of false positives and false negatives (missed hits).

We have used the same database as in the previous case, *Yale Face Database B*, containing thousands of 192×168 faces at different illumination conditions, representing various persons, for our authentication tests (Georghiades et. al, 2001). The obtained results prove the effectiveness of the proposed human face authentication approach. We have obtained lower recognition rates for images representing rotated or non-frontal faces, and higher authentication rates for frontal images.

We have performed some comparisons between the two proposed facial recognition techniques. Also, we have compared them with other face authentication methods. Thus, we have compared the performance of our approaches with the performances of Eigenface-based systems, which are the most popular in the facial recognition area.

Therefore, we have tested the Eigenface algorithm of Turk & Pentland, our Eigenface technique and the Gabor filter based method on the same facial dataset. One have computed the statistical parameters *Precision* and *Recall*, using the number of correctly recognized faces and the number of correctly rejected faces, for these approaches, the values registered in Table 1 being obtained.

	Eigenface (T&P)	Eigenface (TB)	Gabor filter based
Precision	0.95	0.85	0.88
Recall	0.94	0.85	0.90

Table 1. Performance parameter comparison

As one can see in this table, the three face recognition techniques produce comparable performance results. The original Eigenface technique performs slightly better than our two methods.

4. Conclusions

We have proposed two automatic supervised facial recognition approaches in this chapter. As one can observe, the two face authentication techniques performs the same sequence of recognition related processes: feature extraction, feature vector classification and verification of the face identity.

While the two recognition methods differ substantially in the feature extraction stage, they use quite similar classification and verification techniques. In both cases, the feature vector classification process is supervised and based on a facial training set. We propose a

minimum average distance classifier that produces proper face identification. Also, both methods use a threshold-based verification technique. We have provided a threshold value detection approach for face verification.

The main contributions of this work are brought in the feature extraction stages of the proposed recognition techniques. The most important contribution is the continuous model for the Eigenface-based feature extraction. Then, the discretized version of this model represents another important originality element of this chapter.

The proposed Gabor filtering based feature extraction procedure represents another contribution to face recognition domain. We have performed a proper selection of the Gabor 2D filter parameters and obtained a powerful Gabor filter set which is successfully applied to facial images.

We have compared the two recognition methods, based on the results of our experiments, and found they have quite similar performances. Also, both of them are characterized by high face recognition rates. The facial authentication techniques described here work for cooperative human subjects only. Our future research in the face recognition domain will focus on developing some recognition approaches for non-cooperative individuals.

The recognition techniques of this type can be applied successfully in surveillance systems and law enforcement domains. A facial authentication approach that works for non-cooperative persons could be obtained by combining one of the recognition techniques proposed in this chapter with a face detection method (Barbu, 2011).

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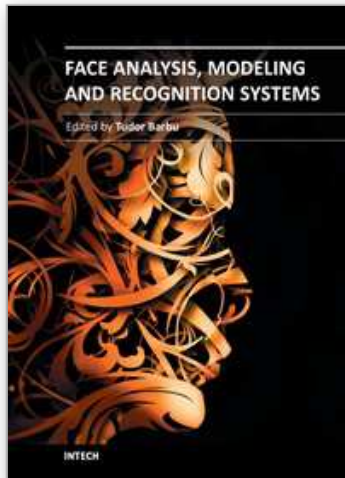
Face Analysis, Modeling and Recognition Systems

Edited by Dr. Tudor Barbu

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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