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GABOR FILTER-BASED FACE RECOGNITION TECHNIQUE

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We propose a novel human face recognition approach in this paper, based on two-dimensional Gabor filtering and supervised classification. The feature extraction technique proposed in this article uses 2D Gabor filter banks and produces robust 3D face feature vectors. A supervised classifier, using minimum average distances, is developed for these vectors. The recognition process is completed by a threshold-based face verification method, also provided. A high facial recognition rate is obtained using our technique. Some experiments, whose satisfactory results prove the effectiveness of this recognition approach, are also described in the paper.

Key words: Face recognition; Face identification; Feature vector; 2D Gabor filter; Supervised classification; Face verification.

1. INTRODUCTION

This article approaches an important biometric domain, which is human face recognition. Face represents a physiological biometric identifier that is widely used in person recognition. During the past decades, face recognition has become a well-known computer vision research field [1].

A facial recognition system represents a computer-driven application for automatically authenticating a person from a digital image or a video sequence. It performs the recognition by comparing selected facial characteristics in the input image with a face database. Any recognition process is divided into two main operations: face identification and face verification. Facial identification consists in assigning the input face image to one person of a known group, while face verification consists in validating or rejecting the previously detected person identity.

Also, face recognition techniques could be divided into two categories: geometric and photometric approaches. Geometric techniques 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 approaches are statistical techniques that distill an image into values and compare these values with templates [1].

Most popular face recognition methods include Eigenfaces [2, 3], Fisherfaces [4], Hidden Markov Models [5], the neuronal model Dynamic Link Matching [6] and connectionist approaches. Face recognition technologies have a variety of application areas, such as: access control systems, surveillance systems and some law enforcement areas. Also, the facial recognition systems can be incorporated into more complex biometric systems, to achieve a better person authentication.

We approached the face recognition domain in our previous works [3]. We provided some eigenimage-based techniques, based on the influential work of M. Turk and A. Pentland [2]. Proposed in 1991, their Eigenface approach represents the first genuinely successful system for automatic recognition of human faces. Our method introduced a continuous model for facial feature extraction, representing the two-dimensional face image by a differentiable function and replacing the covariance matrix by a linear symmetric operator [3].

In this paper we propose a new face recognition system, using Gabor filtering [7,8]. The first part of the proposed recognition algorithm consists of a face feature extraction process that is described in the next section. Our featuring approach processes each facial image with a filter bank containing several 2D antisymmetrical Gabor filters, at various orientations, frequencies and standard deviations [8]. A powerful 3D face feature vector is obtained.

In the third section, we provide a supervised face feature vector classification approach. A minimum average distance classifier is proposed. The obtained face classes represent the result of the face identification process.

The recognition system is completed by a face verification procedure. An automatic threshold-based face verification approach is proposed in the fourth section. Some facial recognition experiments, performed with the described approach, are presented in the fifth section. The conclusions of this work are drawn in the sixth section.

2. FACE FEATURE EXTRACTION APPROACH

Face feature extraction represents the first part of the identification process [1]. Before describing the featuring process, we must mention another important operation related to face recognition. A proper *image face registration* is essential for a good face-recognition performance. We could perform this face registration process using some facial detection algorithms, which are mentioned in the last section.

Also, some image pre-processing operations may be necessary [9]. First, the original face images have to be converted to the grayscale form. Then, some contrast and illumination adjustment operations are performed. All face images must be processed with the same illumination and contrast. Therefore, some histogram equalization operations are performed on these images, to obtain a satisfactory contrast [9].

Also, the facial images are often corrupted by various types of noise. So, we process them with the proper low-pass filters, for noise removal and restoration [9–11]. We developed some robust image de-noising and restoration techniques in our previous works [10, 11], which could be applied here.

The enhanced face images are now ready for the featuring process. A Gabor filter-based face feature extraction is proposed in this section [7,8]. We try to obtain some feature vectors which provide optimal characterizations of the visual content of facial images. For this reason we choose the two-dimensional Gabor filtering, a widely used image processing tool, for feature extraction.

A fair amount of research papers have been published in literature for Gabor filter-based image processing [7,8]. 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.

The Gabor filter (Gabor Wavelet) 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 [8]. It achieves an optimal resolution in both spatial and frequency domains.

Our approach designs 2D odd-symmetric Gabor filters for face image recognition, having the following form:

$$G_{\theta_k, f_i, \sigma_x, \sigma_y}(x, y) = \exp\left(-\left[\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right]\right) \cdot \cos\left(2\pi f_i x_{\theta_k} + \varphi\right), \tag{1}$$

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 two axes, *x* and *y*. 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 $G_{\theta_k, f, \sigma_x, \sigma_y}$, given by relation (1), represent a group of wavelets which optimally captures both local orientation and frequency information from a digital image. Each face image is filtered with $G_{\theta_k, f, \sigma_x, \sigma_y}$ at various orientations, frequencies and standard deviations. So, the design of Gabor filters for facial recognition needs an appropriated selection of those filter parameters.

Thus, we consider some proper variance values, a set of radial frequencies and a sequence of orientations. So, let the filter's parameters be $\sigma_x = 2$, $\sigma_y = 1$, $f_i \in \{0.75,\ 1.5\}$ and n = 5, which means $\theta_k \in \left\{\frac{\pi}{5}, \frac{2\pi}{5}, \frac{3\pi}{5}, \frac{4\pi}{5}, \pi\right\}$. Therefore, we create a 2D Gabor filter bank $\left\{G_{\theta_k, f_i, 2, 1}\right\}_{f_i \in \{0.75, 1.5\}, k \in [1,5]}$, composed of 10 channels. The created filter set is applied to the input facial image, by convolving the face image with each Gabor filter from this set. The resulted Gabor responses are then concatenated into a three-dimensional feature vector.

If I represent such a face image, having a $[X \times Y]$ size, then its feature extraction can be expressed as follows:

$$V(I)[x, y, z] = V_{\theta(z), f(z), \sigma_x, \sigma_y}(I)[x, y] , \tag{2}$$

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

$$\theta(z) = \begin{cases} \theta_z, & z \in [1, n] \\ \theta_{z-n}, & z \in [n+1, 2n] \end{cases}, \qquad f(z) = \begin{cases} f_1, & z \in [1, n] \\ f_2, & z \in [n+1, 2n] \end{cases}, \tag{3}$$

and

$$V_{\theta(z), f(z), \sigma_x, \sigma_y}(I)[x, y] = I(x, y) \otimes G_{\theta(z), f(z), \sigma_x, \sigma_y}(x, y). \tag{4}$$

A fast 2D convolution could be performed using the Fast Fourier Transform [9], therefore formula (4) is equivalent with the following relation:

$$V_{\theta(z), f(z), \sigma_x, \sigma_y}(I) = FFT^{-1}[FFT(I) \cdot FFT(G_{\theta(z), f(z), \sigma_x, \sigma_y})]. \tag{5}$$

Therefore, for each facial image I we obtain a 3D face feature vector $V(I)$, having a $[X \times Y \times 2n]$ dimension. This tridimensional feature vector constitutes a robust content descriptor of the input face. A face image (marked with a red rectangle) and its 10 Gabor representations, that constitute the components of the corresponding feature vector, are displayed in Fig. 1.

Fig. 1 – Human face and its 2D Gabor representations (feature vector components).

There are various metrics which can be applied to these feature vectors. Since the size of each vector depends on the size of the corresponding face image, a resizing procedure has to be performed on the compared facial images, first.

Then, some well-known metrics, such as Euclidean distance or the *sum of absolute differences* (SAD) could be applied. We compute the distance between these facial feature vectors using a *squared Euclidean metric*, characterized by the following formula:

$$d(V(I),V(J)) = \sum_{x=1}^{X}\sum_{y=1}^{Y}\sum_{z=1}^{2n}\left|V(I)[x,y,z)] - V(J)[x,y,z)]\right|^2 , \tag{6}$$

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

3. A SUPERVISED FACE CLASSIFICATION METHOD

The next stage of the face identification process consists of feature vector classification [12]. We propose a supervised classification technique for these Gabor filter-based 3D feature vectors.

Popular supervised classifiers, including *minimum distance classifier* and *K-Nearest Neighbour* (K-NN) classifier, can be used in this case [12]. We develop an extended version of minimum distance classifier, named the *minimum average distance classifier*.

First, we create the training set of this supervised classifier. We consider N authorized (registered) persons. Each of these registered users provides a set of faces of its own, which are included in the training set. Each face image from the training set represents a *template face*. Therefore, the model of the proposed training face set can be expressed as $\left\{\left\{F_j^i\right\}_{j=1,\ldots,n(i)}\right\}_{i=1,\ldots,N}$, where F_j^i represents the j^{th} template face of the i^{th} user and $n(i)$ is the number of training faces of the i^{th} user. The classification process creates N face classes, each class corresponding to a registered person. Then, one computes the training feature vector set as $\left\{\left\{V(F_j^i)\right\}_{j=1,\ldots,n(i)}\right\}_{i=1,\ldots,N}$.

Also, we consider a set of input digital images to be recognized. Let us note them $\{I_1,\ldots,I_K\}$. Our classification approach inserts each of these input images in the class of the *closest* registered user, representing the user corresponding to the minimum *average distance*. An average distance value is computed as the mean of the distances between the feature vector of the input image and the feature vectors of the template faces corresponding to an authorized person. The minimum average distance classification process is expressed formally as follows:

$$\text{Class}(j) = \arg\min_{i\in[1,N]} \frac{\sum_{t=1}^{n(i)} d(V(I_j),V(F_t^i))}{n(i)}, \forall j \in [1,K] \tag{7}$$

where the result $\text{Class}(j) \in [1,N]$ represents the index of the face class where I_j is inserted. Let $C_1,\ldots,C_N$ be the resulted classes.

These obtained human face classes represent the face identification result. Each input image is identified as a face of a registered person. Unfortunately, some of these identified images could not really represent the persons they are associated with. Some of them could not represent human face images at all.

Therefore, a verification operation is necessary to complete the face recognition process. It is described in the next section.

4. AUTOMATIC FACE VERIFICATION TECHNIQUE

Face verification constitutes the final step of the facial recognition process. As mentioned in the introduction, the verification procedure consists in either confirming or invalidating a facial identification result.

In the identification stage, each input image is associated with a registered user of the system. In the verification stage one must decide if it really represents a face of that person. We propose an automatic threshold-based verification approach [3].

Thus, we compute a proper threshold value and compare the average distances from each face class with it. If the average distance corresponding to an image from a class is greater than threshold *T*, then that image is invalidated and rejected from the face class. The verification process is represented formally as follows:

$$\forall i \in [1, N], \quad \forall I \in C_i : \frac{\sum_{j=1}^{n(i)} d(V(I), V(F_j^i))}{n(i)} > T \Rightarrow C_i = C_i - \{I\}. \tag{8}$$

Any threshold-based recognition approach implies the difficult task of choosing an appropriate threshold value. Many facial recognition techniques set empirically this threshold value. We provide an automatic threshold detection method. Thus, one considers the overall maximum distance between any two training face feature vectors corresponding to the same registered user, as a satisfactory threshold value. So, we get:

$$T = \max_{i \le N} \left(\max_{j \ne k \in [1, n(i)]} d\left(V(F_j^i), V(F_k^i)\right)\right). \tag{9}$$

All the images that still belong to the classes $C_1, ..., C_N$ after performing the verification process modeled by (8), represent the correctly identified faces, so they are accepted by the recognition system. 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*. So, the class sequence $C_1, ..., C_{N+1}$ represent the final face recognition output.

5. EXPERIMENTS

We have performed numerous face recognition experiments, using the proposed technique. Our recognition system has been tested on various face image datasets and satisfactory 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 got high values for the performance parameters, *Precision* and *Recall*. We have used *Yale Face Database B*, containing thousands of 192×168 facial images, representing various persons, for our recognition tests [13]. The obtained results prove the effectiveness of the proposed human face authentication approach. We have got lower recognition rates for images representing rotated or non-frontal faces.

A small facial training set example, composed of faces of 3 authorized persons, is represented in Fig. 2. A small sized input image set, with *K* = 6, is displayed in Fig. 3. The computed average distance values, having the form $\frac{\sum_{t=1}^{n(i)} d(V(I_j), V(F_t^i))}{n(i)}$, are registered in Table 1. From this table, it results the face identification: User 1 => $\{I_2, I_4\}$, User 2 => $\{I_1, I_5\}$, User 3 => $\{I_3, I_6\}$. We also get *T* = 0.9759, so, the verification provides the final recognition result: User 1 => $\{I_2, I_4\}$, User 2 => $\{I_1\}$, User 3 => $\{I_3, I_6\}$, Unauthorized => $\{I_5\}$.

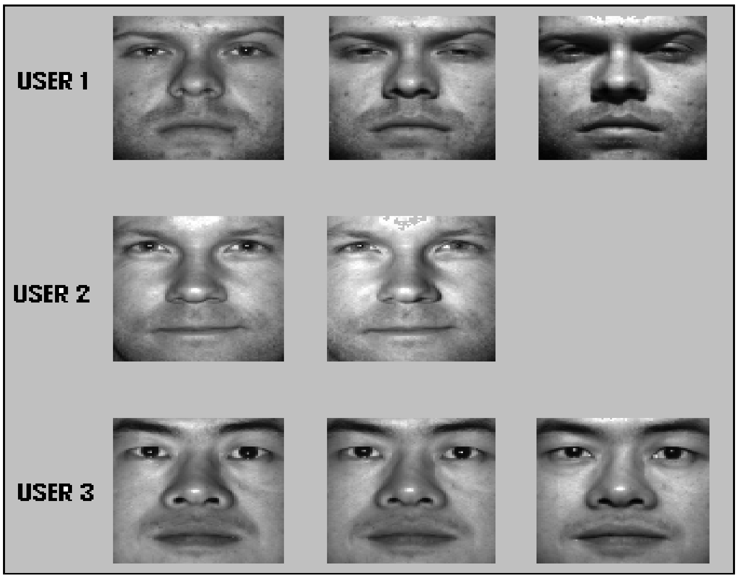

Fig. 2 – Face training set example.

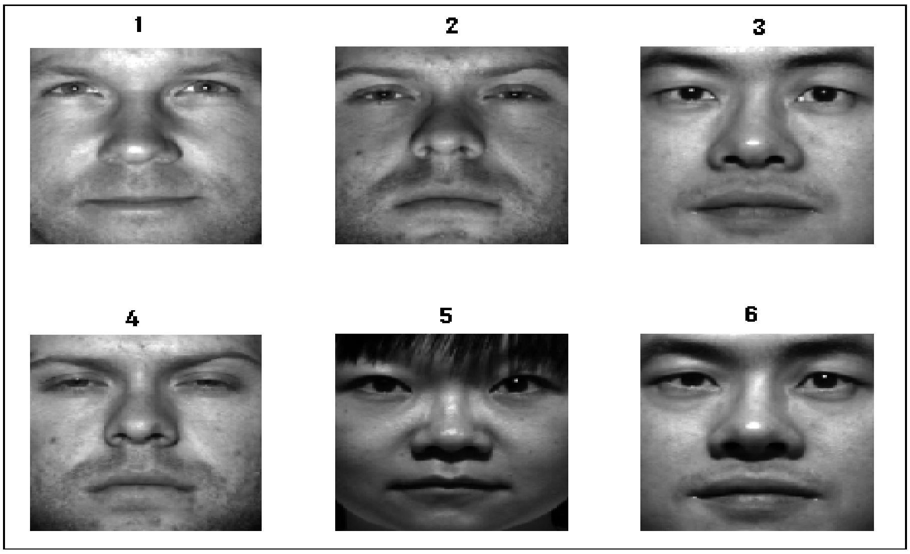

Fig. 3 – Input image set.

Table 1

Resulted average distance values

	I_1	I_2	I_3	I_4	I_5	I_6
User 1	1.0970	0.6208	1.5475	0.7779	1.6175	1.0379
User 2	0.5581	1.4291	1.7623	1.2103	1.1313	1.2551
User 3	1.2154	1.0946	0.9278	1.2548	1.3562	0.6333

6. CONCLUSIONS

A novel supervised facial recognition system has been proposed in this paper. The main contribution of this article is the proposed 2D Gabor filter-based feature extraction that produces robust three-dimensional face feature vectors.

Another contribution of this paper is the supervised classifier used for facial feature vector classification. It uses minimum average distances and the squared Euclidean metric. The proposed threshold-based verification technique, containing an automatic threshold detection procedure, represents an important novelty element of this paper, too. A high recognition rate has been achieved by our technique, as it results from the performed experiments.

The obtained results prove the effectiveness of our method. This technique provides a higher recognition rate than many other facial recognition approaches. We have compared it with our Eigenimage-based recognition technique, and found they produce similar results for identical face datasets.

Our future work will continue the research in the facial recognition domain. Since the described face recognition approach provides a satisfactory person authentication, we intend to include it into a more complex biometric system that uses more identifiers besides human face. Also, we will focus our research on face detection and face localization domains [14]. Thus, we can combine this face recognition technique with a face detection method, to obtain a system that is able to recognize faces from image scenes and video sequences.

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