SVM Classification for Face Recognition

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ABSTRACT: *Human face recognition has become an active area of research over the last decade. The major problem of face recognition is the classification. In this paper, a new face recognition algorithm based on fusion of 2DPCA and Gabor features with SVM classifier is presented. The method first extracts features by employing Gabor wavelets followed by a face recognition algorithm 2DPCA and the SVM method is applied to classify image faces. The performance of the proposed algorithm is tested on the public and largely used databases of FRGCv2 face and ORL databases. Experimental results on databases show that the use of SVM can achieve promising results.*

Keywords: Biometrics, 2 D Principal components Analysis, Identification of the Face, Gabor, SVM

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1. Introduction

After more than 30 years of research, Pattern recognition and computer vision have received significant attention due to the wide range of commercial and law enforcement applications together with the availability of feasible technologies. Within the face recognition literature, debate has been centered on how human beings involve human faces and this has become an important and active research area. Face recognition is the ability to establish a subject's identity based on his facial characteristics. Automatic face recognition has been extensively studied over the past two decades due to its important role in a number of application domains, such as access control, visual surveillance [1]. A lot of methods are proposed to overcome the difficulty of face recognition.

A good face recognition methodology should consider representation as well as classification issues, and a good representation method should require minimum manual annotations [2]. Principal Component Analysis (PCA) is a classical algorithm for feature extraction, which is widely used in pattern recognition and computer vision [7]. In references [8], PCA algorithm is applied in face recognition, and the satisfied results are obtained. Recently, two-dimensional Principal Component Analysis (2DPCA) was presented and applied in face recognition [9].

In this paper, we proposed a face recognition system that combines magnitude and the phase of Gabor filter and 2DPCA.

Human face identification is performed in three steps: detection of the face, extraction of the relevant features from facial images and the classification. This paper is organized as follows. In Section 2 we explain the detection in the face. The section 3 we describe the Gabor wavelet.

Section 4 presents the 2DPCA, Section 5 present the SVM. Section 6 gives the experimental results of the proposed method tested on the 2 public and largely used databases FRGCv2 face and ORL face. Conclusions and perspective works are given in Section 7.

2. Detection face

Detecting human faces from an image is a key problem in various face-related applications such as face tracking, face recognition, facial expression recognition, etc. The purpose of face detection is to determine whether or not there are any faces in an image and, if any, the location of each face is shown. We have used Open CV to detect faces in our database FRGCv2 and ORL [2].

OpenCV is an open source computer vision library which is written in C and C++ and runs under Linux, Windows and Mac OS X[12]. The object detector of OpenCV has been initially proposed by Paul Viola and improved by Rainer Lienhart [3].

Figure 1. Detection face with open cv

3. Gabor Wavelet

The Gabor wavelet, which captures the properties of orientation selectivity, spatial localization and optimally localized in the space and frequency domains, has been extensively and successfully used in face recognition [3]. Daugman pioneered the using of the 2D Gabor wavelet representation in computer vision in 1980's [4].

Gabor wavelets (filters) characteristics of frequency and orientation representations are quite similar to those of the human visual system. These have been found appropriate for texture representation and discrimination. This Gabor-wavelet based extraction of features directly from the gray-level images is successful and widely been applied to texture segmentation, and fingerprint recognition. The commonly used Gabor filters in the face recognition area [5], [6] are defined as follows Equation (1).

$$\Psi_{\mu,v}(z) = \frac{\| k_{\mu,v} \|^2}{\sigma^2} e^{(-\|k_{\mu,v}\|^2 \| z \|^2 / 2\sigma^2)} \left[e^{ik_{\mu,v} z} - e^{-\frac{\sigma^2}{2}} \right] \quad (1)$$

Where:
μ and v define the orientation and the scale of the Gabor filters, $z = (x, y)$ and $k_{\mu,v}$ is defined as following form Equation (2):

$$k_{\mu,v} = k_v e^{i\varphi u} \quad (2)$$

$k_v = kmax/f^v$ and $\varphi u = \pi\mu/8$. kmax is the maximum frequency, and f is the spacing factor between kernels in the frequency domain. Usually, $\sigma = 2\pi$, $kmax = \pi/2$ and $f = \sqrt{2}$. In this paper, $\mu \in \{0, 1, ..., 7\}$ and $v \in \{1, 2, 3, 4\}$.

The Gabor wavelet representation of a face image is obtained by doing a convolution between the image and a family of Gabor filters as described by Equation (3). The convolution of image $I(z)$ and a Gabor filter $\Psi_{\mu,v}(z)$ can be defined as follows:

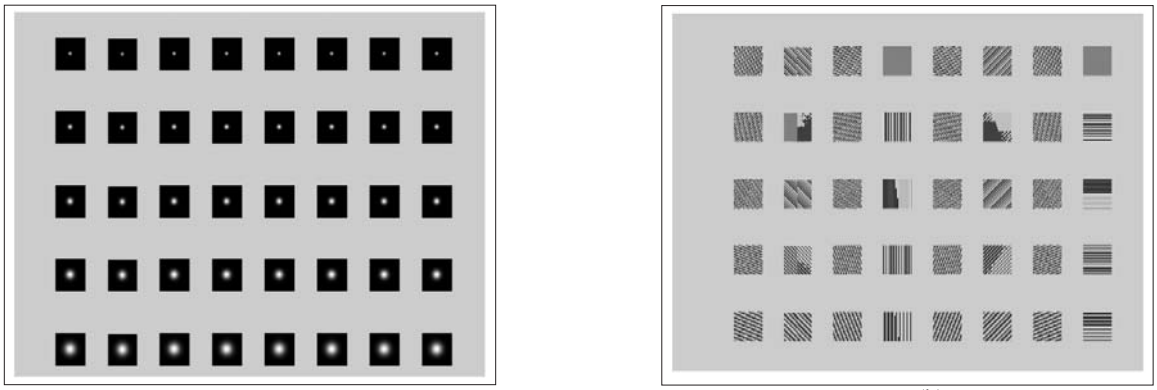
$$F_{\mu,v}(z) = I(z) \times \Psi_{\mu,v}(z) \quad (3)$$

Where $z = (x, y)$, * denotes the convolution operator, and $F_{u,v}(z)$ is the Gabor filter response of the image with orientation u and scale v.

The solutions suggested on each level of this chain resulted in a significant improvement of the performances compared to the

traditional approaches. For the recognition algorithms, we proposed to fuse the phase and the magnitude of Gabor's representations of the face as a new representation, in the place of the raster image. Although the Gabor representations were largely used, particularly in the algorithms based on global approaches, the Gabor phase was never exploited.

Convolving the image with these 40 Gabor kernels can then generate the Gabor features. The magnitude and the phase are used to form the final face representation. The input image is a facial image that is geometrically normalized and whose size is 64*64 pixels. So, the size of our vector is (64 * 64 * 40 * 2) too large to solve this problem we are going to sample it.



(a) (b)

Figure 2. (a) The magnitude part of the representation. (b) The phase part of the representation

4. Two-Dimensional Principal Component Analysis (2DPCA)

Normally, the PCA-based face recognition methods, the 2D face image samples usually have been transformed into 1D image vectors by some technique like concatenation [9]. 2DPCA model is a method that uses the 2D features, which are features obtained directly from original vector space of a face image rather than from a vectorized 1D space. The notion of 2DPCA was initially proposed by [10]. The usage of 2DPCA for face recognition is a novel idea and is discussed in this section. The steps of 2DPCA face recognition model are given below [11]:

• Acquire face images to form a training set ($X1, X2, \ldots, XN$)

• Extract features using 2DPCA for each training sample and each testing sample.

• Classify and recognize the image using Volume measure (VM)

• Give the result of recognition.

The VM is calculated using the formula given in Equation (4).

$$Vol\ A = \sqrt{det\ A^T A} \tag{4}$$

Where A is the matrix of full column rank and A^T is its transpose. The process of classification and recognition is described below. Considering a training face set $\{X1, X2, \ldots, XN\}$, 2DPCA uses all training samples to build the total sample covariance matrix C (5).

$$C = \frac{1}{N} \sum_{i=1}^{N} (X_i - \bar{X})^T (X_i - \bar{X}) \tag{5}$$

Where X_i is the ith training sample, which is a h x w matrix, $\bar{X}$ denotes the mean sample matrix of all training sample matrix, and N is the number of training samples. The crucial idea of 2DPCA is to select some good projection vectors. To choose good projection vectors, the total scatter of the projected samples is used [9], which can be denoted by the trace of the covariance matrix of the projected feature vectors. So the following criterion was adopted.

$$J(w) = tr(S_w) \tag{6}$$

Where S_w is the covariance matrix of the projected feature vectors of the training images, and $tr(S_w)$ stands for the trace of S_w.

Obviously, to maximize the criteria in Equation (6) S_w is equal to find a projection direction w, onto which the total scatter of the projected samples is maximized. The covariance matrix S_w can be written by (7):

$$S_w = E[(X - E(X))W]^T[(X - E(X))W] \tag{7}$$

From the definition of image covariance matrix in Equation (4), $J(w)$ can be obtained by using the following equation (8).

$$J(w) = W^T C_w \tag{8}$$

The optimal projection axes, $w_1, w_2, \ldots, w_d$, are the ortho-normal eigenvectors of C corresponding to the first d largest eigenvalues. It is proved by [14] that the covariance matrix in 2DPCA can be computed more accurately than that in PCA and it can also be computed easily. So a feature matrix $Y_i = [y_{i1}, y_{i2}, .., y_{id}]$ for each training face sample (or each sample in gallery set) [15] can be obtained by $y_{ik} = X_i w_k$, $k = 1, 2, \ldots, d$.

In the similar fashion, the 2DPCA model also gets a feature matrix $Y_t = [y_{t1}, y_{t2}, \ldots y_{td}]$ for each testing face sample after the transformation by 2DPCA mentioned (described) above. Then, a nearest neighbor classifier based on the matrix distance is used for classification (9).

$$C = arg\,min \sum_{k=1}^{d} \| y_{tk} - y_{ik} \|_2 \tag{9}$$

Where $C \in [1, 2, \ldots N]$, and the distance between Y_c and Y_t is minimal. Then, Y_t belongs to the class where Y_c belongs to. This classification measure is based on the matrix distance proposed by [9] and is used in 2DPCA.

5. Support vector machines

Support vector machines are learning machines that classify data by shaping a set of support vectors [16]. SVMs provide a generic mechanism to robust the surface of the hyper plane to the data through. Another benefit of SVMs is the lowest expected probability of generalization errors [17]. Moreover, once the data is classified into two classes, an appropriate optimizing algorithm can be used if needed for feature identification, depending on the application [18]. SVM creates a hyper-plane between two sets of data for classification; in our work, we separate the data into two classes: face belongs to the train database and face doesn't belong to the train database. Input data X that fall one region of the hyper-plane, (XT • W– b) > 0, are labeled as +1 and those that fall on the other area, (XT • W– b) < 0, are labeled as -1.

We seek the linear classifier that separates the data with the lowest generalization error. Intuitively, this classifier is a hyper plane that maximizes the margin error, which is the sum of the distances between the hyper plane and positive and negative examples closest to this hyper plane.

We consider the example in (a) where there are many possible linear classifiers that can separate the data, but there is only one that maximizes the margin shown in (b). This classifier is termed the optimal separating hyper-plane (OSH).

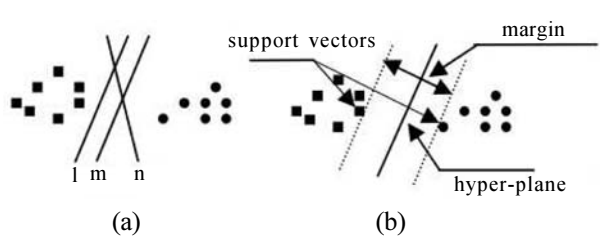


Figure 3. (a) Arbitrary hyper-planes: l, m, n; (b) Optimal hyper-plane

6. Experiment and results

The proposed 2DPCA method was used for face recognition combined with gabor and tested on two well-known face image databases (ORL, FRGC). The ORL database was used to evaluate the performance of 2DPCA under conditions where the pose and sample size are varied. The FRGC database was employed to test the performance of the system under conditions where

there is a variation over time, in facial expressions, and in lighting conditions.

The FRGC consisted of progressively difficult challenge problems. Each challenge problem consisted of a data set of facial images and a defined set of experiments. One of the impediments to developing improved face recognition is the lack of data. The FRGC challenge problems include sufficient data to overcome this impediment. The set of defined experiments assists researchers and developers in making progress in meeting the new performance goals [12].

The FRGC distribution consists of six experiments. In our work, we use two experiments 1 and 4. In experiment 1, the gallery consists of a single controlled still image of a person and each probe consists of a single controlled still image. Experiment 1 is the control experiment [12]. In experiment 4, the gallery consists of a single controlled still image, and the probe set consists of a single uncontrolled still image [12].

The ORL has ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses) [13].

Figure 4. FRGC Face

Figure 5. ORL Face

In the first part of experiment we have used the magnitude and phase of Gabor to extract the characteristic vector and the algorithm of recognition PCA.

The input image is a face image detected with Opencv and normalized geometrically so the size of the face is 64*64 pixels.

The first protocol P1 evaluates performance comparison of images (reference and tests) belonging to sessions to acquire the same semester. The second protocol P2 evaluates performance testing sessions belonging to image acquisition two consecutive semesters and one last test P3 performance of image reference and test, separated by a year.

Tables 1 and 2 list the equal error rates for the FRGC and ORL databases, respectively in the case of using GABOR et PCA.

Tables 3 and 4 list the equal error rates of the FRGC and ORL databases, respectively in the case of using GABOR et 2DPCA.

		EER
Exp 1	***P*1**	0.17
Exp 1	***P*2**	0.33
Exp 1	***P*3**	0.2
Exp 2	***P*1**	0.26
Exp 2	***P*2**	0.3
Exp 2	***P*3**	0.4

Table 1. ERR using GABOR + PCA for the FRGC database [2]

	EER
40 features	0.09

Table 2. ERR using GABOR + PCA for the ORL database[2]

		EER
Exp 1	***P*1**	0.15
Exp 1	***P*2**	0.20
Exp 1	***P*3**	0.154
Exp 2	***P*1**	0.17
Exp 2	***P*2**	0.195
Exp 2	***P*3**	0.33

Table 3. ERR using GABOR + 2DPCA for the FRGC database

	EER
40 features	0.054

Table 4. ERR using GABOR + 2DPCA for the ORL database

		EER
Exp 1	***P*1**	0.07
Exp 1	***P*2**	0.15
Exp 1	***P*3**	0.09
Exp 2	***P*1**	0.10
Exp 2	***P*2**	0.13
Exp 2	***P*3**	0.17

Table 5. Error rate for fusing magnitude et phase of Gabor, 2DPCA and SVM for the FRGC database

	EER
40 features	0.00088

Table 6. ERR for fusing magnitude et phase of Gabor, 2DPCA and SVM for the ORL database

These tables note that using the SVM to classify faces has an important influence on the performance of the application and the improvement of the error rates. The experiments we report validate our claim.

7. Conclusion

This paper presents recognition approach for face identification based on 2DPCA, Gabor wavelet and SVM classifier. The experiments carried out to investigate the performance of 2DPCA by comparing it with the performance of the PCA and the important influence on the performance of the application and the improvement of the error rates by using the SVM.

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