Single Training Sample Face Recognition Using Fusion of Classifiers

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Abstract

This paper deals with Face recognition using Single training sample which is a new challenging problem in machine vision. In the proposed method, first four different representation of face are generated using Gabor filters which vary in angle. Then a Base-classifier is assigned for each of them and also for original image. Finally EMV technique combines the Base-classifiers. EMV behaves like MV but chooses the vote of the Base-classifier assigned to original image as winner class when there is multiple winner class. Experimental results on ORL face dataset, show an improvement about 2%, 4% and 5% than 2DPCA, $(PC)^2A$ and PCA respectively.

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Keywords: *Face Recognition, Nearest Neighbor, Base-Classifier, Enhanced Majority Voting. Small Sample Size Problem*

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1. Introduction

Face Recognition is an effective pathway between human and computer, which has a lot of applications in information security, human identification, security validation, law enforcement, smart cards, access control and etc. For this reasons, industrial and academic computer vision and pattern recognition researchers have a significant attention to this task.

Almost of the face recognition systems [1-3] are related to the set of the stored image of a person, which called training data. Efficiency of these types of systems considerably falls when the size of training data sample is small (Small Sample Size Problem). For example in ID card verification and mug-shot we have only one sample per person. Several methods have done with the mentioned problem which we will introduce some of them that our idea is given from.

From the primary and most famous appearance based methods we can mention to PCA [4]. Then for one training sample per person, J. Wu et al. introduced $(PC)^2A$ [5] method. In this method, at first a preprocess on image is done to compute a projection matrix of face image and combine it with the original image, then PCA have being applied on projection combined image. S.C. Chen et al. offered $E(PC)^2A$[6] method which was the enhanced version of $(PC)^2A$. To increase the efficiency of system they could increase the set of training samples by calculating the projection matrix in different orders and combining it with the original image. In [7] J. Yang offered 2DPCA method for feature extraction. 2DPCA is a 2D extension of PCA and has less computational load compared to PCA with better efficiency than PCA for few training samples.

By another point of view we can use from different representation of face image to extract more useful information of image. In this paper, at first we have used from different Gabor filters to generate different representation of face image and assign a classifier for each of them and also for original image, then by using an enhanced version of majority voting [8], we combined the classifiers to increase the efficiency of face recognition system. Experimental results prove our claims.

2. Outline of Two Dimensional Principle Component Analysis

In the traditional PCA, two-dimensional face images are transformed into one-dimensional vectors before computing the covariance matrix. It is worth noting that the evaluation of covariance matrix became more difficult due to the big size of training samples. Moreover, computing the eigenvectors of a large covariance matrix is a very time-consuming task. Recently, a new technique called Two-Dimensional Principal Component Analysis (2DPCA) was proposed by Yang in 2004 [7] for face identification. It's a Principal idea to calculate the covariance matrix, based on two-dimensional original training image matrices. As a result, less time is required to determine the corresponding eigenvectors. Moreover, 2DPCA leads to higher recognition rates than its counterpart (PCA) [7].

2.1 Basic steps of 2DPCA

Suppose that there are M face images in the training set. Each image can be denoted by X^i ($m \times n$ matrix, (i= 1,2,...,M)). Let $V \in R^{n \times d}$ be a matrix with orthonormal columns, projecting X into V yields a $m \times d$ matrix $Y = XV$.

In 2DPCA, image covariance (scatter) matrix is used to determine a good projection matrix V and can be computed as following:

Consider M training face images, and then C is computed by:

$$\mathrm{C} = \frac{1}{M} \sum_{k=1}^{M} \left[(X_k - (\overline{X}))^T (X_k - (\overline{X})) \right] \tag{1}$$

Where $\overline{X}$ is the mean of all training images.

The following criterion can be adopted to find V_{opt} :

$$J(V) = V^T C V \tag{2}$$

where V is a unitary column vector. This criterion is called the total scatter criterion. The unitary vector V that maximizes the criterion is called the optimal projection axis. Intuitively, this means that the total scatter of the projected samples is maximized after the projection of an image matrix on to V .

It has been proved that the optimal value for the projection matrix V_{opt} is composed by the orthonormal eigenvectors $V_1, V_2, ..., V_d$ of C corresponding to the d largest eigenvalues. The size of C matrix is only n×n. Hence, computing its eigenvectors is very efficient.

3. Outline of Gabor filter

Gabor function first proposed by Dennis Gabor used as a tool for signal detection in noise. Thereafter, Gabor functions proposed by Daugman for conjoint resolution of information in the *2D* spatial and *2D* Fourier domains.

The *2D* Gabor filter $\psi_{f,\theta}(x, y)$ can be represented as a complex sinusoidal signal modulated by a Gaussian kernel function as follows:

$$\psi_{f,\theta}(x,y) = \exp\left[-\frac{1}{2}\left\{\frac{x^2_\theta}{\sigma^2_x} + \frac{y^2_\theta}{\sigma^2_x}\right\}\right]\exp(2\pi f x_\theta)$$

$$\begin{bmatrix} x_\theta \\ y_\theta \end{bmatrix} = \begin{bmatrix} \sin\theta & \cos\theta \\ -\cos\theta & \sin\theta \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} \tag{3}$$

σ_x, σ_y are the standard deviations of the Gaussian envelope along the x and y-dimensions, f is the central frequency of the sinusoidal plane wave, and θ is the orientation. The angle θ is defined by:

$$\theta = \frac{\pi}{p}(n-1) \tag{4}$$

For $n = 1, 2, ..., p$ and $p \in N$, where p denotes the number of orientations.

The Gabor representation of a face image is computed by convolving the face image with the Gabor filters [9]. Let $f(x, y)$ be the intensity at the coordinate (x, y) in a gray scale face image, its convolution with a Gabor filter $\psi_{f,\theta}(x, y)$ is defined as:

$$g_{f,\theta}(x,y) = f(x,y) \otimes \psi_{f,\theta}(x,y) \tag{5}$$

Where $\otimes$ denotes the convolution operator. Figure 1 illustrates the convolution result of a face image with a Gabor filter.

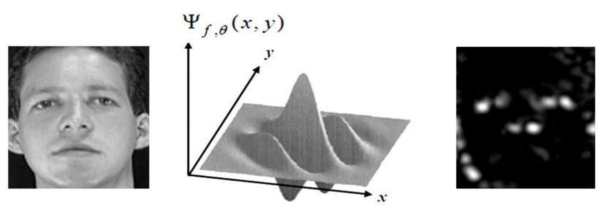

Figure 1. Convolution result of a face image with a Gabor filter; (left) Face image, (center) Gabor filter (*f*=0.165 Hz, $\theta = 0.135^\circ$, $\sigma_x, \sigma_y = 3$), (right)

4. Proposed method

Our Proposed method is organized in three steps as follows:

1. Applying a set of Gabor filters on face images to create a new representation of them
2. Extracting the informative features from samples using 2DPCA transform
3. Classifying the face images using a two-stage classifier

4.1 Applying a set of Gabor filters on face images to create a new representation of them

In order to extract more useful information of face image, we have used from different representation of image by applying Gabor filters with different angels. As a result, four Gabor responses are generated from each image sample, which are various in orientations. The orientations of used Gabor filters vary from 0° to 180° by 45° steps (0°,45°,90° and 135°).

4.2 Extracting the informative features from samples using 2DPCA transform

Feature extraction means extracting useful features. The algorithm which used for feature extraction is very important part of face recognition system for extracting the essential features of images as well as reducing the dimension of input image.

To obtain the mentioned goal, 2DPCA is applied for each Gabor responses and original face image as shown in Figure 2.

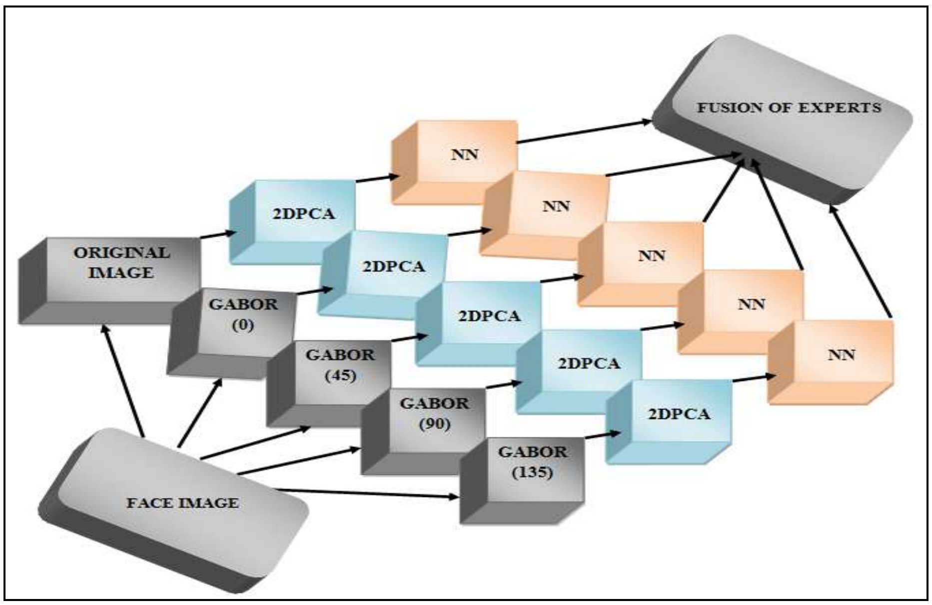

Figure 2. The schematic illustration of our proposed methods

4.3 Classifying the face images using a two-stage classifier system

As described in the previous sub-section, after acquiring image vectors using 2DPCA, we aim to classify the face images. For achieving this goal, we used a two-stage classifier, in which, the first stage consists of five Nearest Neighbor Classifiers which called Base-Classifiers (Experts) and the second stage is a combiner which combines the vote of Base-Classifiers to improve the efficiency of recognition. See the sketch of method in Figure 2.

Several methods can be used to combine the experts, such as: *Maximum*, *Minimum*, *Averaging*, *product*, *Weighted Averaging* and *Majority Voting* (MV). In the proposed method, we used a new type of Majority Voting called Enhanced Majority Voting (EMV) as the combiner.

In standard Majority Voting the winner class determines by the majority of the vote of Base-Classifiers. This type of fusion technique is useful and has an acceptable performance in many applications. But in some cases it is hard to determine the winner class. For example, when the majority vote of Base-Classifiers is same for two or more class, the traditional majority voting method randomly select one of them as winner classs. Hence, we proposed EMV method instead of MV which chooses the vote of the Base-Classifier of original image as winner class when there are two or more winner class.

As mentioned above, we have four Gabor filters which are differ from each other in orientation. One of the most important Gabor parameters is frequency of Gabor filter. Figure 3 shows the effect of different Gabor frequencies on the recognition rate when the first face image of each subject is selected as training sample. Our experiments show that the optimal show that the optimal value of Gabor frequency is0.165 Hz.

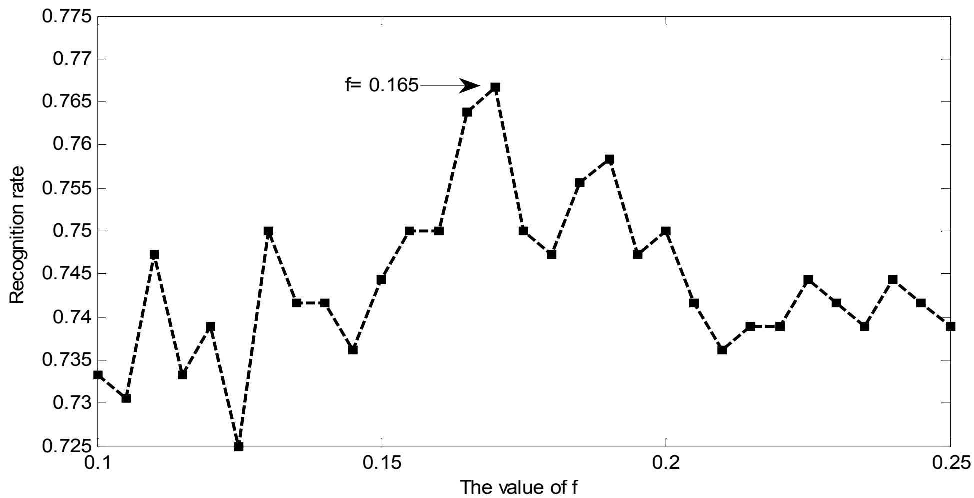

Figure 3. Effect of frequency on the recognition rate

5. Experimental results

To test the performance of our proposed method, some experiments are performed on ORL face database [10] which contains images from 40 individuals, each providing 10 different images. For some subjects, the images were taken at different times. The facial expressions and facial details (glasses or no glasses) also vary. The images were taken with a tolerance for some tilting and rotation of the face of up to 20 degrees and also some variation in the scale of up to about 10 percent. All images are grayscale and normalized to a resolution of 112×92 pixels (Figure 4).

Figure 4. Some samples of ORL database

We compared our model with single training sample face recognition using conventional 2DPCA as feature extractor and Nearest Neighbor as classifier (see Figure 5). Therefore, we can conclude that the proposed model's recognition rate is higher than the mentioned model for each selected face image of subjects.

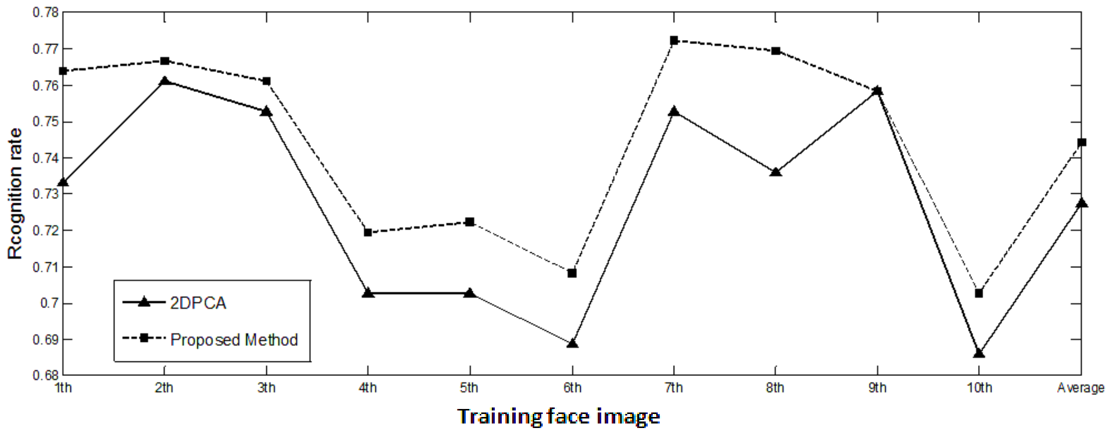

Figure 5. Comparison the recognition rate of our proposed method and conventional 2DPCA for different selected face of subjects as training sample.

As Table I shows, the recognition rate for each Gabor responses is not too high. But the correct recognition rate drastically increases when we using proposed EMV fusion scheme.

Table I. Average accuracy of our proposed method compared to different algorithms on ORL database

Method	Average Recognition rate
Gabor(0^0)	55.64%
Gabor(45^0)	56.53%
Gabor(90^0)	55.47%
Gabor(135^0)	56.72%
Original image	72.75%
Majority voting	73.10%
Enhanced majority voting	**74.44%**

We also compared our proposed method with some of the recent algorithms which used for one training image per person face recognition. The same database is used for comparison purposes. In order to have good generalization, we choose sequentially one of the samples from 1 to 10 for each person as training and the rest 9 images as testing. Table II reports the average recognition rate for different methods.

Table II. Average accuracy of our proposed method compared to different algorithms on ORL database

Method	PCA	$(PC)^2A$	2DPCA	Proposed method (MV)	Proposed method (EMV)
Average rate	69.20%	69.9%	72.75%	73.10	**74.44**

As you see, experimental results show an improvement of 5.5% in average accuracy compared to the PCA algorithm which has an average recognition rate of 69.20%.

6. Conclusion

In this paper, we proposed an effective method to make applicable face recognition task in situations where only one training sample per person is available. In our proposed method, first we generate four different representation of face image using Gabor filters which vary in angle. Then we assign a Base-classifier for each of them and also for the original image. Finally Enhanced Majority Voting technique combines the Base-classifier. EMV behaves like MV except when the majority vote of Base-classifiers is same between two or more classes (multiple winner class). In this situation EMV chooses the vote of the Base-classifier assigned to original image as winner class. Experimentation results suggest that, under the one training sample scenario, our proposed method outperforms than other algorithms such as PCA, $(PC)^2A$ and 2DPCA.

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