A NOVEL FACE RECOGNITION METHOD BASED ON LINEAR DISCRIMINANT ANALYSIS

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Abstract A novel face recognition approach based on the DCT and the LDA is proposed. First the DCT is used for dimension reduction, then LDA transform is performed on the lower space to extract feature. The ORL face database and the SJTU-IPPR face database are used to test our approach and the correct recognition rates of 97.5% and 92.6% are obtained respectively, which shows that our approach is comparable with other approaches.
Key words face recognition, linear discriminant analysis, discrete cosine transform, principal component analysis.

一种新颖的基于LDA的人脸识别方法

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摘要 提出一种基于离散余弦变换(DCT)与.LDA相结合的人脸识别方法,首先利用DCT将图像进行降维,然后在低维空间中利用LDA进行特征提取.利用ORL人脸数据库和我们上海交通大学图像处理与模式识别研究所的人脸数据库进行测试,实验结果分别得到了97.5%和92.6%的正确识别率,表明它可以和其他方法相比较.
关键词 人脸识别,线性判别分析,离散余弦变换,主元分析.

Introduction

Face recognition has been of great interest in recent years because its wide range of application such as surveillance and security, identity authentication and access control, etc[1]. Numerous methods have been proposed for face recognition in the last decade. Among all these approaches, a technique based on linear discriminant analysis (LDA), which was also called fisherfaces, has been proved to be a promising approach[2].

However, due to the high dimensionality image space and the number of images in the training set is much smaller than the number of pixels in each image as usual, the implementation of standard LDA will result in numerical unstable. So many approaches based on LDA, often use the principal component analysis (PCA) approach to project an image into a lower dimensional space at the first step, and then perform the LDA to extract discriminant features. But the first PCA step potentially loses useful discriminant information that is important for the following LDA [2]. Another drawback of the PCA is its computational complexity [3].

To overcome the drawbacks of the traditional PCA + LDA approach, we propose a novel LDA algorithm for face recognition in this paper. The new algorithm uses the discrete cosine transformation (DCT) to replace the PCA for the dimension reduction at the first step, and then perform the LDA to maximize the discriminant power. We conduct the experiment on ORL database and SJTU face database. The results show that our approach is effective.

1 LDA for Face Recognition

The basic idea of LDA is to find a linear transform W_{opt} in such a way that the ratio of the between-class scatter and the within-class scatter is maximized[2]. For the M-class problem, the between-and within-class scatter matrices S_b and S_w are defined as :

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$$S_b = \sum_{i=1}^{M} M_i(\mu_i - \mu)(\mu_i - \mu)^T, \quad (1)$$

$$S_w = \sum_{i=1}^{M} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T. \quad (2)$$

Where μ_i is the mean vector of class X_i:

$$\mu_i = \frac{1}{M_i} \sum_{x \in X_i} x \quad i = 1,2,\cdots M.$$

M_i is the number of sample in class X_i, μ is over all mean vector.

The optimal projection W_{opt} is:

$$W_{opt} = \arg\max_W \frac{|W^T S_b W|}{|W^T S_w W|} = [w_1, w_2, \cdots, w_n] \quad (3)$$

Where $\{w_i \mid i = 1,2,\cdots,n\}$ is satisfied

$$S_b w_i = \lambda_i S_w w_i \quad i = 1,2,\cdots,n \quad (4)$$

A solution to Equation (4) is to compute the inverse of S_w and solve an eigen problem for matrix $S_w^{-1}S_b$. However, in face recognition problem, the number of training samples is much smaller than the dimension of the sample vector. The within-class scatter matrix S_w is always singular. So many LDA based approaches, first use the PCA to project an image into a lower dimensional sub-space, and then perform discriminat projection using LDA. As Yu et al. in [2] pointed out: the PCA step helps to remove null spaces from both S_b and S_w. But the null space of S_w contains the most discriminant information for recognition. In addition to this, the PCA is computational expensive for face recognition. So here we dont use PCA for dimension reduction at the step, but use the DCT.

2 DCT for Dimension Reduction

The discrete cosine transform (DCT) is a popular image compression method. As is known, its information packing ability closely approaches PCA. Another merit of the DCT is it can be implemented efficiently using the Fast Fourier Transform (FFT). DCT has been widely used in image coding and face recognition[3].

Given an input $M \times N$ image $f(x,y)$, its DCT, $C(u,v)$ is obtained by the following equation:

$$C(u,v) = \frac{2}{\sqrt{MN}} \cdot \alpha(u)\alpha(v)$$

$$\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \cdot \cos\left[\frac{(2x+1)u\pi}{2M}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

for $u = 0,1,2,\cdots,M-1, v = 0,1,2,\cdots,N-1$.

The inverse transform is defined by:

$$f(x,y) = \frac{2}{\sqrt{MN}} \cdot \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} \cdot \alpha(u)\alpha(v) \cdot C(u,v)$$

$$\cdot \cos\left[\frac{(2x+1)u\pi}{2M} \cdot\right] \cos\left[\frac{(2v+1)v\pi}{2N}\right]$$

for $x = 0,1,2,\cdots,M-1, y = 0,1,2,\cdots,N-1$.

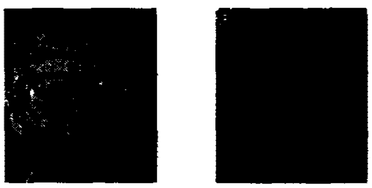
The $\alpha(\cdot)$ is defined by:

$$\alpha(w) = \begin{cases} \frac{1}{\sqrt{2}}, & w = 0 \\ 1, & \text{otherwise} \end{cases} .$$

Figure 1 shows a 92 × 112 8-bit face image (a) and its DCT coefficients (b): From (b), it can be observed that a large amount of information about the original image is stored in a fairly small number of coefficients (in the upper-left corner, corresponding to low spatial frequency DCT components in the image). We preserve these coefficients (suppose the size is $n \times n$) and set the others to zero. We use these $n \times n$ coefficients (other coefficients set to zero) to reconstructed the original image. Figure 2 shows the reconstructed images as $n = 7$, 15, 25, 40; $n = 7$; $n = 15$; $n = 25$ $n = 40$.

Obviously more coefficients will improve the effect of the reconstructed images. But for the case of face recognition, accurate reconstruction is not necessary, just as in the PCA approach[4,5]. Actually, more coefficients do not imply better recognition results, because by adding them, they may be representing more irrelevant information which is bad for recognition[6].

The number of the DCT coefficients for recognition can be determined by the mean square reconstruction error, just as the PCA approach in face recognition. It is well know that in PCA approach, large variances are stored in the eigenvectors corresponding to the large eigenvalue of covariance matrix. So we can select the fraction of eigenvector by the eigenvalue[4,5]. For DCT, large variances distribution associated with a small group of transform coefficients. The relationship



(a) (b)

Fig. 1 (a) 92 × 112 face image, (b) its DCT coefficients
图1 (a) 92 × 112 的人脸图像和(b)它的DCT变换系数

Fig. 2 The reconstructed images as coefficients $n = 7, 15, 25, 40$
图 2 利用不同的系数 $n=7,15,25,40$ 的重建图像

between PCA with DCT was discussed in details in [3].

After reduce the dimension of the original face image by using the DCT, we perform the LDA on the low dimension space to extract the discriminant feature.

3 The Proposed Face Recognition System

The proposed face recognition system based on DCT and LDA consists of two stages: training stage and recognition stage. Training stage represents a set of reference images as feature vectors that obtained by using the DCT and the LDA described above. The feature vectors are stored into a database. At recongition stage, for a given face image, the system performs the DCT and the LDA on it to get a feature vector, and then matches it with those referent images stored in the database to identify the facial image. For our system, the nearest neighbor classifier is employed as classifier. The system block diagram is shown in the Figure 3. The preprocessing includes two steps, namely (1) extract face from the input image and (2) illumination enhancement by applying graylevel histogram. As many face detection algorithm have been developed. This system assumes that the face region has been extracted from images.

4 Experimental Results

We use two face databases to test our algorithm. One is from Olivetti research laboratory (ORL), the other is from the Institute of Image Processing and Pattern Recognition of Shanghai Jiaotong University.

4.1 Experiment on ORL Database

The ORL face image database is made up of 400 images of 40 individuals, 10 images of each person with various in pose, illumination, facial expression. They are grayscale images and the resolution of each image is 92×112.

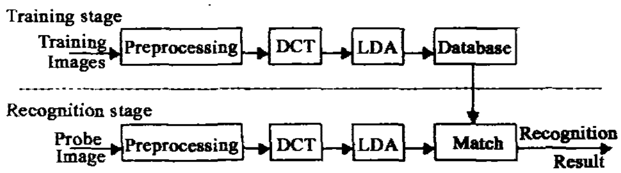


Fig. 3 Diagram of the proposed face recognition system
图 3 所提出的系统流图

In order to compare with other algorithm in literature, the first five images are for training and the other five images are for test per class so that there are 200 training images and 200 test images in total. Each image is down-sampled to 46×56 to reduce some computational time.

4.2 Number of coefficients

Figure 5 shows on the ORL database, the recognition performance versus different number of DCT coefficients.

From figure 4, we can see that only 49 DCT coefficients (about 90% total variance) are enough to obtained high recognition accuracy. Using 49 DCT coefficients, the best recognition rate for our new algorithm is 97.5%. We compare our approach with others based on ORL database. We list the recognition rate in table 1.

From table 1, we can see that the recognition rate achieved by our approach is better than most of other approaches in literature. In order to compare the speed of our approach with Fisherfaces, We use the same computer and the same programming language (Matlab6).

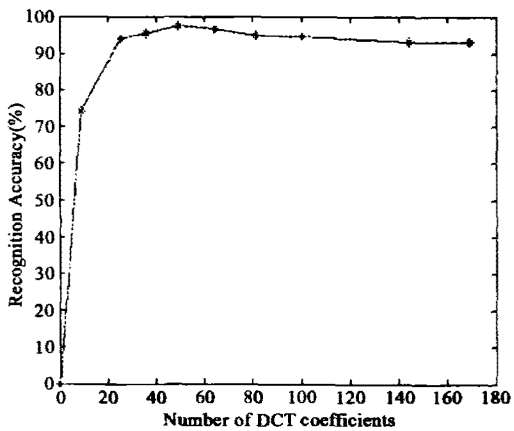


Fig. 4 Recognition accuracy versus different number of DCT coefficients
图 4 不同数目的 DCT 系数和识别率的关系

Table 1 Comparison with some other methodsusing ORL database

表1 ORL人脸数据库上不同算法的比较

Approaches	Recognition Rate
Eigenfaces [7]	90.5%
Fisherfaces [3]	95%
HMM + DCT [7]	100%
DCT [4]	91%
DCT + LDA	97.5%

For the whole process (training and testing), the Fisherfaces approach costs about 4min, but our approach less than 2min.. For recognition rate, the recognition rate of Fisherfaces is 94.5%, which is close to the result (95%) obtained by Yu[3]. Our approach, however, is 97.5%, about 3% higher than Fisherfaces approach.

S. Eickeler et al[7] use Pseudo 2D HMM + DCT for face recognition, they report 100% corrected recognition rate on the ORL face database (see table 1). Unlike our method, they didn't perform DCT on the whole image directly, but on the overlapping adjacent 8 ×8 sample windows top to down and left to right. The DCT decorrelates the subimages and allows the use of diagonal covariance matrices for the probability density function of the HMMs. As the author pointed this may has advantage for the recognition of a person tilting the head. In other words, their method may be insensitive to the change of pose.

4.3 Experiment on SJTU-IPPR Face Database

SJTU-IPPR face database is a large database compared with ORL database. There are about 1000 ~ 1500 different images of 100 individuals. The normalized images are greyscale with a resolution of 92 × 112. We select 10 images for each person, 5 for training and 5 for test.

As the same conducted on ORL database, we use only 49 DCT coefficients for our task. In table 2, we list the recognition rates conducted on our database by Eigenfaces approach, DCT approach, Fisherfaces approach and our approach.

Table 2 Comparison with some methods using our database

表2 SJTU-IPPR人脸数据库上不同算法的实验结果比较

Approaches	Recognition Rate
Eigenfaces [PCA]	85.8%
DCT	87.4%
Fisherfaces	89.0%
DCT + LDA	92.6%

From table 2, we can see that our approach also outperforms Eigenfaces approach, DCT approach and Fisherfaces approach on large database.

5 Conclusion

We have proposed a new face recognition approach based on the DCT and LDA. Our approach exploits the merit of the DCT for dimension reduction and for its fast computational speed. By using the DCT replace the PCA in the traditional Fisherfaces approach for dimension reduction, our approach can overcome the drawbacks of the PCA in the traditional Fisherfaces approach. We use two face database to test our approach. The experimental result shows that our approach is effective.

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