人脸识别中的自适应加权子方向二维线性判别分析

Adaptively Weighted Sub-Directional Two-Dimensional Linear Discriminant Analysis for Face Recognition

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摘 要 本文提出了一种新的图像分类算法，名为自适应的子方向加权二位线性判别分析方法（AWS2DLDA）。这种方法可以再频度域上提取方向特征，并以此应用在人脸识别中。文中设计了验证次方法识别效率的相关实验。从实验结果可以看出，本文所提出的方法比其他常用方法的识别率要高。

关键词 人脸识别；方向滤波器组；二维线性判别分析法

ABSTRACT A novel image classification algorithm named adaptively weighted sub-directional two-dimensional linear discriminant analysis (AWS2DLDA) is proposed in this paper. AWS2DLDA can extract the directional features of images in the frequency domain, and it is applied to face recognition. Some experiments are conducted to demonstrate the effectiveness of the proposed method. Experimental results confirm that the recognition rate of the proposed system is higher than the other popular algorithms.

KEYWORDS Face Recognition; Directional Filter Banks; Two-Dimensional Linear Discriminant Analysis

1 Introduction

Over the past 20 years, image classification have become a very popular area in pattern recognition, computer vision and machine learning [1-2]. Face recognition system is an automatic system that can identify the person using human facial features. It has received much attention because of its wide range of applications. Principal Component Analysis (PCA) [3-5] and Linear Discriminant Analysis (LDA) [6-10] are two popular approaches. However, PCA and LDA methods require that the database is a subset of the 1-dimensional vector space. When we apply these methods to images or videos, the data should be transformed to vectors. Usually, this transformation will lead to huge computational complexity, and it may also result in the lose of some geometric information.

An alternative way to handle the above problem is to extract features from the face image matrix directly. In resent years, several methods based on matrix are proposed, such as Two-Dimensional Principal Component Analysis (2DPCA) [11-13] and Two-Dimensional Linear Discriminant Analysis (2DLDA) [14-17]. 2DPCA and 2DLDA can extract the features in a straightforward manner based on the image matrix projection. And these algorithms, not only greatly reduce the computational complexity, but also enhance the recognition effectiveness.

However, 2DLDA can extract the statistical features of images only, and the specific characters of the images may be ignored. For example, the directionality of images is a crucial feature for an efficient image representation. Directional Filter bank (DFB) [18] is a powerful tool to capture the directionality of image. In this paper, a novel image classification algorithm, based on DFB and 2DLDA, named Adaptively Weighted Two-Dimensional Linear Discriminant Analysis (AW2DLDA), is proposed and the effectiveness of the proposed method is verified by some experiments on ORL database and Yale face database.

The rest of the paper is organized as follows. In section 2, a brief review of DFB is given. In section 3, we give the introduction of the proposed methods. In section 4, several experiments are implemented to justify the superiority of the proposed algorithms. And conclusions are made in section 5.

2 Review of DFB

Recently, the new 2-D image representation has become an active research topic. The DFB is a toolkit that can explore the intrinsic geometrical structure of images. It indicates that directionality is an important feature for an image representation. The DFB can split the spectrum into 2^n wedge-shaped slices by using an n-level iterated tree structured filter banks. The complete design details of this filter bank may be found in [19]. These theories include the design of the quincunx filter bank (QFB) by applying dimensionality changing transformations, and complete reconstruction filter bank by applying McClellan transformations. The more general two-dimensional directional filter bank design algorithms could also be presented in [20-21]. In addition to the two band systems, the first two stages of the filter bank are preceded by a modulator which shifts the input signal spectrum by π in the ω_1 direction. The ideal passband characteristics for the analysis/synthesis filters in the first two filter bank stages are diamond shaped and correspond to the anti-aliasing filter for quincunx downsamplers. Four different parallelogram-shaped passband characteristics are use in the remaining stages. The ideal spectral partitioning possible with the directional filter bank family is shown in Fig. 1.

3 Proposed AW2DLDA

The proposed AW2DLDA method contains three steps: Firstly, construct the new databases of each sub-direction and apply 2DLDA on each new database. Secondly, compute their discriminant power. Finally, classify the test or unknown face images.

3.1 Directional Images Sets and Feature Extraction

In AW2DLDA method, directionality feature of face images is extracted firstly. The DFB is performed on each face images. Given a training sample set $X=\{X_i^j \in R^{m\times n}\}(i=1,2,\cdots,c, j=1,2,\cdots,N_i)$, n-level DFB is performed. 2^n directional images are obtained for one training sample. Suppose that $X_i^{j,p}$ denotes the pth subband of jth sample of the ith class. Let X^p be the set which contains all directional images the pth subband, i.e. $X^p=\{X_i^{j,p}, i=1,\cdots,c, j=1,\cdots N_i\}$ .Then 2^n directional images sets are gotten. Each set contains the information of the face images in one direction. Then 2DLDA is performed on each directional images set X^p. Let $\bar{X}_i^p$ and $\bar{X}^p$ denote the mean sample of ith class and mean sample of all directional images in X^p. The within-class scatter matrix S_b^p and between-class scatter matrix S_w^p of X^p are defined as follows:

$$S_b^p=\frac{1}{N}\sum_{i=1}^{c}N_i(\bar{X}_i^p-\bar{X}^p)^T(\bar{X}_i^p-\bar{X}^p) \quad (1)$$

$$S_w^p=\frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N_i}(X_i^{j,p}-\bar{X}_i^p)^T(X_i^{j,p}-\bar{X}_i^p) \quad (2)$$

Where T denotes transpose, and $N=\sum_{i=1}^{c}N_i$ is the total number of training images. Then both S_w^p and S_b^p are $n\times n$ nonnegative definite matrices.

The 2DLDA criterion function J^p can be defined by

$$J^p(u)=(u^TS_b^pu)/(u^TS_w^pu) \quad (3)$$

The goal of 2DLDA is to find the optimal projection direction u to maximize (3). Obviously, the optimal projection u is the eigenvector corresponding to the maximum eigenvalues of the following eigen-equation:

$$S_b^pu=\lambda S_w^pu \quad (4)$$

Note that S_w^p is usually nonsingular in face recognition problems unless there is only one training sample in each class. Thus the eigen-equation (4) is easy to be solved. Usually, a set of orthogonal directions, u_1, u_2..., u_d , which maximizes the criterion function J^p, should be computed. These projection directions can be the k eigenvectors corresponding to the first k largest eigenvalues of (4). Let $U^p=(u_1\ u_2\cdots u_d)$, where $d=n$, then U^p is called optimal projection matrix. The pth directional feature of an image R is defined by

$$Y^p=R^pU^p \quad (5)$$

Then the directional feature of R is $Y=\{Y_1,\cdots Y_{2^n}\}$, which is applied in the classification.

3.2 Computation of the Discriminant Power

The goal is to find an efficient way to compute the discriminant power of each directional images set, i.e. which sets are more important for the classification task. For one directional images set, large variance between-class and small variance within-class mean large discriminant power. Thus the discriminant power can be measured by the division of the between-class variance and within-class variance. The between class variance and with-in class variance can be estimated by the trace of between-class scatter matrix and within-class scatter matrix. So the discriminant power of X^p is defined by

$$W_p=trace(S_w^p)/trace(S_b^p) \quad (6)$$

In fact, the between-class scatter matrices and within-class scatter matrices of each directional images set are computed in the last part of section 3, so the computation of discriminant power is very simple.

3.3 Classification

In this part, given a test face image T, directional images of T is computed by performing DFB on T. Then each unknown directional features of T are extracted by corresponding optimal projection matrices U^p $(p=1,2,\cdots,2^n)$. The nearest neighbor classifier using Euclidean distance is used to classify each directional images of T. We get 2^n results for the unknown image T, the probability P_c of T belong to cth class is defined by

$$P_c(T)=\sum_{p=1}^{2^n} W_p Q_c(T^p) \tag{7}$$

Where

$$Q_c(T^p)=\begin{cases}1 & T^p \text{ belong to } c\text{th} \\ 0 & \text{otherwise}\end{cases} \tag{8}$$

3.4 The Whole Procedure

Firstly, the face database should be divided into training and test sets randomly. The whole procedure of our proposed method is as follows:

(1) Training stage

i. DFB is performed on each face image to get the directional images of each face image.

ii. 2DLDA is applied on each directional images set. Optimal projection matrices U^p $(p=1,2,\cdots,2^n)$ are obtained. And the discriminant power of each directional images set is computed by (6).

iii. Extract the directional features of training images.

(2) Test stage

i. Perform DFB on test image to extract the directional images of test image.

ii. Extract the directional features of test image by optimal projection matrices U^p $(p=1,2,\cdots,2^n)$.

iii. Identify directional images in each directional images set.

iv. Compute the weighted summation to classify T.

4 Experimental Results

In the following, we assess the feasibility and performance of the proposed AWS2DLDA method for face recognition. The comparative performance is carried out against some popular face recognition algorithms such as the PCA, 2DPCA, LDA, 2DLDA. Two face databases, ORL face database [22] and Yale face database [23], are used in this study. In all the experiments, the nearest-neighbor (NN) algorithm is applied as the classifier for its simplicity. The following experiments are implemented on a PC with Athlon 2.5GHz CPU and 768MB RAM and programmed in the MATLAB platform. In the following experiments, the 3-level DFB is applied.

4.1 The Experiments on ORL Face Database

We test our algorithms on ORL face database from Olivetti-Oracle Research Lab firstly. The ORL face database contains 400 face images, 10 different face images per person for 40 individuals. Some face images are captured at different times. There are facial expressions (open or closed eyes, smiling or non-smiling) and facial details (glass or no glasses). These face images are taken with a tolerance for some tilting and rotation of the face up to 20^0. All face images are gray with 256 levels and size of 112×92.

In the following, five face images per person are randomly selected for training. The remaining five images are used for test. To evaluate the generalization power of algorithms more accurately, a cross-validation strategy is performed, and run the system 20 times. Fig. 1 shows the comparative face recognition performance of the different algorithms. The horizontal axis indicates the number of features used and the vertical axis represents the average correct recognition rate of the 20 experiments. Note that the upper bound of the dimensionality of PCA is N-1, where N is the number of individuals. Here N = 40. It also should be noted that the first 3 principal components in these methods are removed for improving the recognition performance. From Fig. 1, we can see that the proposed AWS2DLDA has the highest recognition rate in these algorithms.

4.2 The Experiments on the Yale Face Database

Yale face database contains 165 images of 15 individuals (each person has 11 different images). These images are under variations with following facial expressions or configurations: center-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleepy, surprised and wink. All images are gray with 256 levels and size of 100×100 pixels.

We randomly select five samples from each person for training and the remaining six samples are used for testing. This process is repeated 20 times and 20 different training and test sets are created. Fig. 2 shows the comparative average face recognition performance of the different methods. The horizontal axis indicates the number of features used and the vertical axis represents the average correct recognition rate of the

20 experiments. Note that the upper bound of the dimensionality of PCA is N-1, where N is the number of individuals. Here N = 15. It also should be noted that the first 3 principal components in each algorithms are removed for improving the recognition performance. Fig. 2 shows that the features extracted by AWS2DLDA have more discriminant power than other methods.

5 Conclusions

We have presented to use AWS2DLDA for face recognition. AWS2DLDA is designed based on DFB. The image features extracted by AWS2DLDA contain the directionality information of images. Experimental results reveal that the recognition rate of proposed algorithm is higher than other popular methods.

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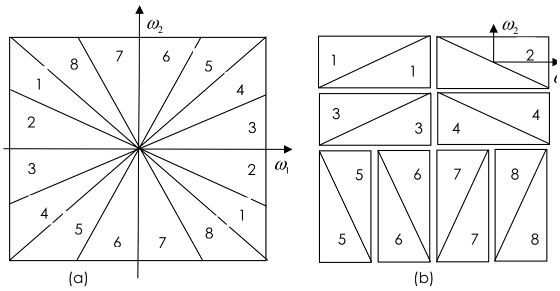

Fig. 1 The ideal frequency partition map for a 3-level DFB. (a) input. (b) outputs

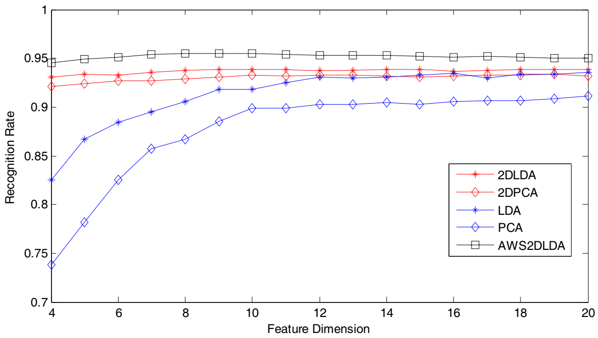

Fig. 2 The average recognition rate of several algorithms on ORL face database

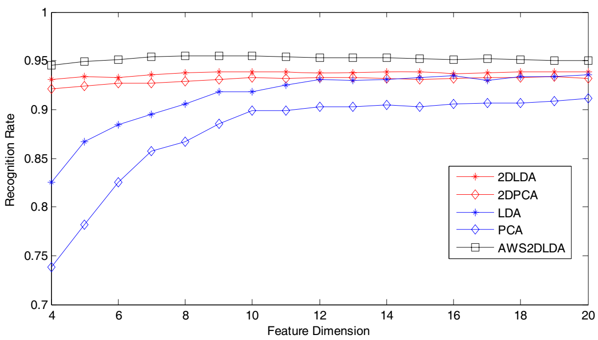

Fig. 3 The average recognition rate of several algorithms on Yale face database