Archives of Business Research – Vol. 9, No.1
Publication Date: January 25, 2021
DOI: 10.14738/abr.91.9612.
Lu, C., Ren, Y., & Han, L. (2021). Face and Ethnical Group Recognition with Images of Different Resolutions. Archives of Business Research, 9(1). 140-147.

Face and Ethnical Group Recognition with Images of Different Resolutions

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ABSTRACT

In this paper, a dataset for Xinjiang minority ethnical groups is introduced, and implementation of two dimensional Linear Discriminant Analysis (2DLDA) and two-dimensional Partial Least Squares (2DPLS) is investigated. Two important topics for face recognition and the ethnicity recognition are investigated for database with different image resolutions. Experiments show that 2DLDA performances better than 2DPLS on our face database.

Key Words: face recognition, ethnical group recognition, different resolution image

INTRODUCTION

Face recognition has been a very popular research topic in computer vision community. A complete face recognition system includes six steps, data capture [1,2], Image preprocessing [3], face detection [4], face feature extraction [5], face database comparison [6] and face recognition [7,8]. The existing facial features include three categories, holistic feature description such as PCA, LDA, ICA[9,10,11],etc. local feature description such as Gabor, LBP[12,13],etc. and some fusion features which are obtained by combining holistic feature and local feature Holistic features[14]. The criterion function of two-dimension LDA (2DLDA) and two-dimension PLS (2DPLS) have many advantages that can be established with original image covariance matrix directly instead of undergoing reshaping them to vector, and due to the importance of face recognition, ethnicity recognition is attracting more attention with broad applications [15,16,17]. In this paper, we will consider both problems with our new dataset created in our lab.

The remainder of this paper is organized as follows: after reviewing existing techniques 2DPLA and 2DPLS in Section 2, we briefly describe our face database in Section 3, and then discuss

experimental results in Section 4. In Section 5 experimental evaluations of ethnic identification has done by 2DLDA algorithm. Last but most importantly, we conclude in Section 6.

2DLDA AND 2DPLS

In this section, we will briefly outline 2DLDA and 2DPLS in order to present the contribution of this paper clearly.

2DLDA

Let $\{A_i\}_{i=1}^{N}$ be training images set, where A_i denotes ith an $m \times n$ training sample. N is the total number of training samples, containing C classes, and the ith class C_i has n_i samples, with $\sum_{i=1}^{C} n_i = N$. 2DLDA method tries to find a projected vector x that maximize the following objective function [17].

$$J(x) = \frac{x^T S_b x}{x^T S_w x} \qquad (1)$$

Where T denotes transpose, S_b and S_w are the between-class scatter matrix and the within-class scatter matrix, respectively defined as follows.

$$S_b = \sum_{i=1}^{C} N_i (\overline{A}_i - \overline{A})^T (\overline{A}_i - \overline{A}) \qquad (2)$$

$$S_w = \sum_{i=1}^{C} \sum_{j \in C_i} (A_j - \overline{A}_i)^T (A_j - A_i) \qquad (3)$$

In witch $\overline{A}$ and $\overline{A}_i$ represent the global and the ith class means defined as follows.

$$\overline{A} = \frac{1}{N} \sum_{i=1}^{C} \sum_{j \in C_i} A_j \qquad (4)$$

$$\overline{A}_i = \frac{1}{n_i} \sum_{j \in C_i} A_j \qquad (5)$$

2DLDA aims to find the optimal projection direction x in order to maximize $J(x)$.

2DPLS

M.L. Yang et al. [18] proposed 2DPLS algorithm for face recognition and we briefly describe this technique here. Let $\{A_i\}_{i=1}^{N}$ be training images set, where A_i denotes ith an $m \times n$ training sample. N is the total number of training samples, containing C classes, and the ith class C_i has n_i samples, with $\sum_{i=1}^{C} n_i = N$. Thus, we can obtain the mean matrix of samples matrix.

$$\overline{A} = \frac{1}{N} \sum_{i=1}^{C} \sum_{j \in C_i} A_j \qquad (6)$$

To finish image recognition task, sample images can be considered as a variable set in 2DPLS, called sample matrix. Another variable set is class membership matrix, which represents the relationship between samples and classes. It is similar to the definition in traditional CCA and in PLS, the class membership matrix can be coded as follow [19]

$$Z = \begin{bmatrix} P_1 & 0_2 & \dots & 0_C \\ 0_1 & P_2 & \dots & 0_C \\ \vdots & \dots & \ddots & \vdots \\ 0_1 & 0_2 & \dots & P_C \end{bmatrix}_{(m\times C)\times(n\times N)} \quad (7)$$

Where P_i means there are n_i samples in the *i*th class, but each sample here is corresponding to a matrix $Q_{m\times n}$ as large as the size of sample image. So the matrix P_i can be denoted as $P_i = [Q, Q, \dots Q]_{m\times(n\times n_C),} i = 1 \dots . C$. For obtaining the mean of class membership matrix in the sense of two dimensional sample representation, the matrix Y is rewritten as $Y = [y_{1,1}, \dots, y_{1,n_C}]$, then the covariance matrices of A and Y are denoted as

$$G_x = \frac{1}{N}\sum_{i=1}^{C}\sum_{j\in C_i}(A_{i,j} - \overline{A})\,(A_{i,j} - \overline{A})^T \quad (8)$$

$$G_y = \frac{1}{N}\sum_{i=1}^{C}\sum_{j\in C_i}(y_{i,j} - \overline{Y})\,(y_{i,j} - \overline{Y})^T \quad (9)$$

$G_{xy} = G_{yx}^T = \frac{1}{N}\sum_{i=1}^{C}\sum_{j\in C_i}(A_{i,j} - \overline{A})\,(y_{i,j} - \overline{Y})^T$ (10) respectively.

FACE DATABASE CREATION

In this section, we present our face database creation. We captured face images for six different minority nationality groups which are Kazak, Uygur, Kirgiz, Mongolian, Sibbo and Hui with different pixel resolution cameras, i.e., Hasu, Nikon D90, Nikon S60 and Kinect. Face Database contains eight different images of each of 48 distinct subjects. For some subjects, the images were different with varying the lighting, facial expressions and facial details with glasses. All the images were taken against a light homogeneous background with the subjects in an upright, frontal position. they are shown below.

The size of Each Image in the Original Face Database captured with Hasu camera is about 41M with12840 × 10550 pixel, Nikon D90 is about 5.4M with4280 × 2580 pixel, Nikon S60 is about 3.1M with30100 × 2100 pixel and Kinect is about 8K with200 × 160 pixel.

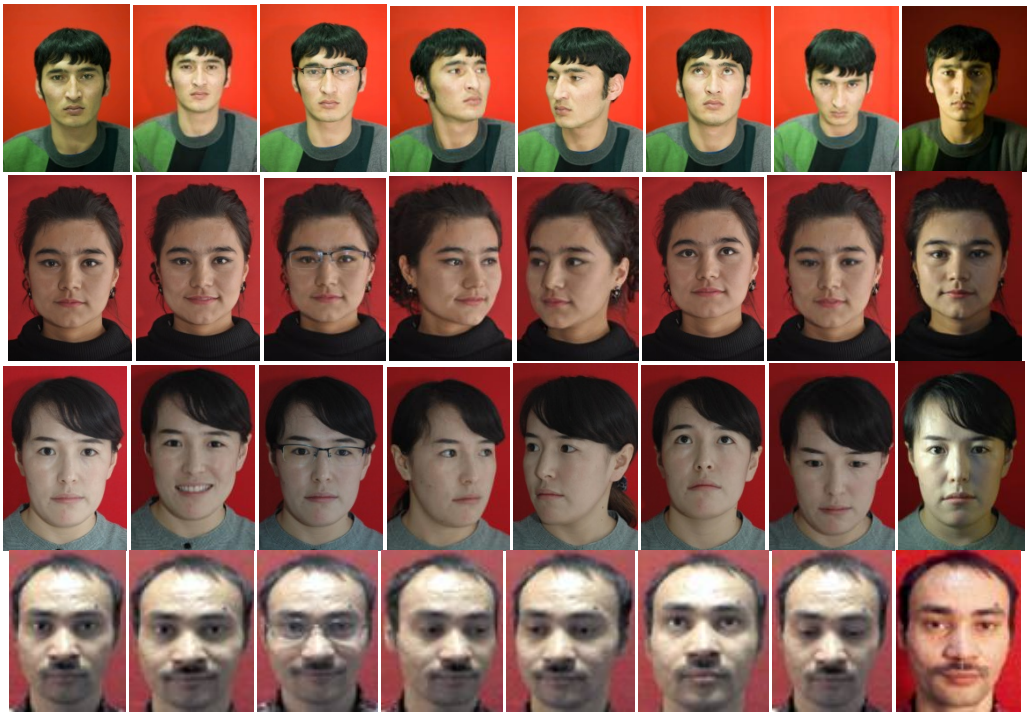


Fig. 1. The Original Image of Face Database

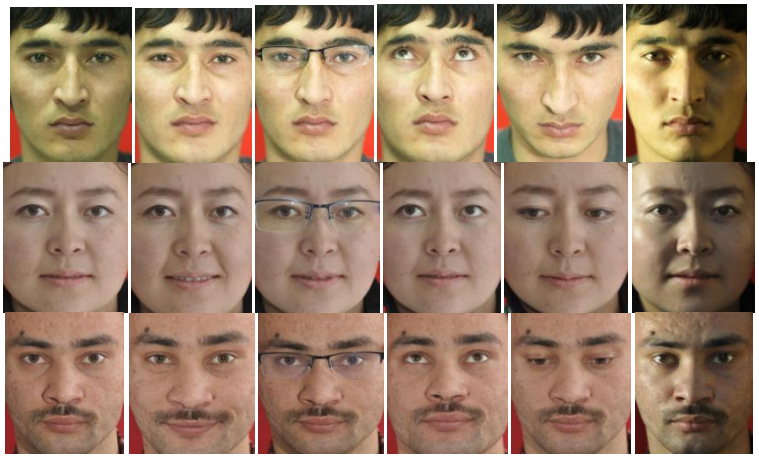


Fig. 2. The Cropped Image of Face Database



Fig. 3. The Cropped Images with three color overlay of Face Database

EXPERIMENTAL EVALUATIONS OF FACE RECOGNITION

In this section, we will carry out several experiments to demonstrate the performance of the 2DLDA algorithm and 2DPLS algorithm in our dataset with different pixel resolutions, each images being cropped and resized to 128 × 96 pixels by matlab with resize command. They are shown in figure3 shown. We select the feature dimension d=15, Each group was selected with1,2,3⋯6 as the training sample. For the chosen database, we use Hasu images as training sample and Nikon D90 and Kinect images as testing images in 2DLDA algorithm, and the face recognition rate as shown in table 1.

Then, we use Nikon D90 as training sample and Kinect images as testing images in 2DLDA algorithm, the face recognition rate as shown in table 2.

Also we have done all the experiments by 2DPLS algorithm respectively, the face recognition rate as shown in table 3 and table 4.

Table 1. Hasu images as training sample Nikon D90 and Kinect as testing sample by 2DLDA algorithm

Training Number	1	2	3	4	5	6
D90		30.7%	36.7%	43.7%	47.1%	48.7%
Kinect		36.7%	37.4%	43.7%	45.6%	48.4%

We test the face recognition rate using different pixel face database. According to table 1, we can find the lowest pixel of Kinect images as testing sample is better than D90 images when training sample is less. This deserves further investigation as better quality of testing samples may not achieve better performance. However, when training samples are large enough, high quality testing samples from D90 can achieve better results.

Table 2. Nikon D90 images as training sample and Kinect as testing sample by 2DLDA algorithm

Training Number	1	2	3	4	5	6
Kinect		36.7%	37.4%	43.7%	45.6%	49.3%

Table 3. Hasu images as training sample Nikon D90 and Kinect as testing sample by 2DPLS algorithm

Training Number	1	2	3	4	5	6
D90	23.6%	30.4%	37%	42.2%	45.2%	48.1%
Kinect	27.8%	34.1%	37.4%	42.6%	45.1%	47.9%

In table 3 we can see that the performance of the Kinect images as testing sample achieve better performance as evidenced previously.

Table 4. Nikon D90 images as training sample and Kinect as testing sample by 2DPLS algorithm

Training Number	1	2	3	4	5	6
Kinect	30%	35.1%	37.8%	43.2%	45.4%	49.1%

In table 4 we can see that the performance of the D90 images as training sample and Kinect images as testing sample achieve better performance as training sample increase.

EXPERIMENTAL EVALUATIONS OF ETHNIC IDENTIFICATION

In this section, we will carry out some experiments to demonstrate the performance of the 2DLDA algorithm in our face database for ethnical group recognition. Each images being cropped and resized to 128 × 96 pixels by matlab resize command as shown in figure 3. We also take the feature dimension d=15, there are 270 individuals of six groups was selected, they are Kazak with eight individuals having forty eight images, Uygur with eight individuals having forty eight images, Kirgiz with six individuals having thirty six images, Mongolian with seven individuals having forty two images, Sibbo with eight individuals having forty eight images and Hui with eight individuals having forty eight images .We also use Hasu images of frontage as training sample and Nikon D90 and Kinect images as testing images in 2DLDA algorithm, the face recognition rates of the best as shown in figure 4.

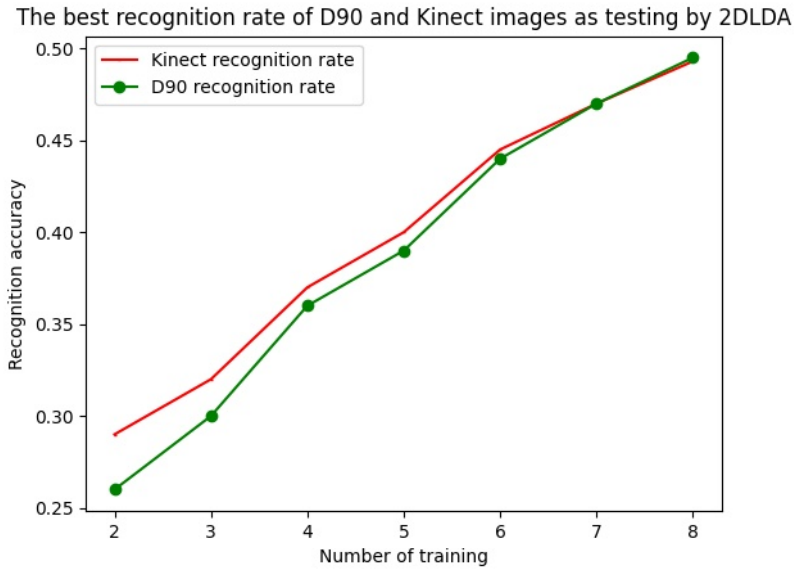


Fig. 4 The best recognition rate of D90 and Kinect images as testing by 2DLDA

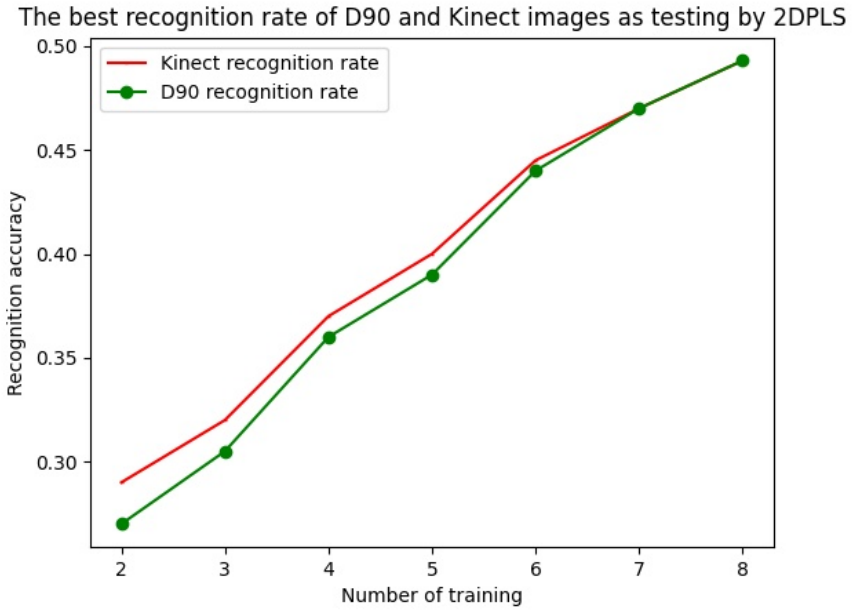


Fig. 5 The best recognition rate of D90 and Kinect images as testing by 2DPLS

According to figure 4 and figure 5, we can find the lowest pixel of Kinect images as testing sample is better than D90 images when training sample is less. However, when training samples are large enough, high quality testing samples from D90 can achieve better results with 2DLDA approach. With the training sample increasing, the best recognition rates are almost the same. The both best recognition rate reached 49.3% when all Hasu frontage images as training sample with 2DPLS algorithm.

CONCLUSIONS

In this paper, we investigated the different pixel images face database of our captured in Xinjiang by 2DLDA and 2DPLS. We have demonstrated that 2DLDA algorithm is better than 2DPLS in our face database. We can also find lower pixel of Kinect images as testing sample is better than D90 images when training sample is less.

ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (NSFC) under grant no. 61363066.

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