FACE IMAGE RETRIEVAL BY PROJECTION-BASED FEATURES

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ABSTRACT

Face and fingerprint images have been used as an access control for the entry and exit of countries such as in Japan and America. The issues of storage space and computation are as important as the accuracy of verification or identification. This paper reviews five existing projection-based face recognition methods, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), 2DPCA, 2DLDA, and Singular Value Decomposition (SVD). We give a mathematical review of the aforementioned approaches, discuss the usage of storage space, practicality of computation. Experimental results of comparison on ORL, UMIST, and NTHU face databases demonstrate that the 2-dimensional projection methods such as 2DPCA, 2DLDA, and SVD perform better than PCA and LDA.

1. INTRODUCTION

For the homeland security, face and fingerprint images are the two most popular biometrics adopted as an access control for the entry and exit of countries such as in Japan since November 20, 2007 [11] and in the United States of America since January 4, 2004 [16]. Moreover, the funding of the US-Visit project is over 3 million US dollars since 2004 [16]. An accurate face retrieval or recognition method becomes more and more important. Whereas, the issues of storage space and computation are as important as the accuracy of face retrieval and verification.

This paper reviews five existing projection-based face recognition methods, including Eigenface based on Principal Component Analysis (PCA) [7], Fisherface based on Linear Discriminant Analysis (LDA) [1], 2DPCA [8], which does PCA face feature extraction using the right-projected vectors, the 2DLDA [4] which does traditional LDA face feature extraction using right-projected vectors, SVD-based face recognition [3] which extracts face image features by the partial sum of products of projection onto the left singular vectors and their corresponding right singular vectors obtained from the mean image of training face images. We give a mathematical review of the aforementioned approaches: PCA, LDA, 2DPCA, 2DLDA, and SVD, discusses the usage of storage space for training images, and practicality of computation using MATLAB [12], and shows experimental results of comparison on three databases, ORL [14], NTHU [13], and UMIST [15].

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2. REVIEW OF PROJECTION-BASED METHODS

Suppose that $F_1, F_2, \cdots, F_N \in R^{m\times n}$ are N gray level face images of m rows and n columns such that $F_k(i,j) \in \{0,1,\cdots,255\}, 1 \le k \le N, 0 \le i \le m-1, 0 \le j \le n-1$. Let $\Gamma_k \in R^{mn}$ be a column-vector representation of F_k such that

$$\Gamma_k(j + m * i) = F_k(i,j) \tag{1}$$

Denote the mean vector Ψ of $\{\Gamma_k\}$ as

$$\Psi = \frac{1}{N}\sum_{k=1}^{N}\Gamma_k \tag{2}$$

Define $\Phi_k = \Gamma_k - \Psi$ and $B = [\Phi_1, \Phi_2, \cdots, \Phi_N]$, then $B \in R^{mn\times N}$, and the covariance matrix C of $\{\Gamma_k\}$ can be computed by

$$C = \frac{1}{N}BB^t = \frac{1}{N}\sum_{k=1}^{N}\Phi_k\Phi_k^t \tag{3}$$

2.1. EIGENFACE BASED ON PCA

The eigenfaces are defined as the eigenvectors of the covariance matrix C. In practical applications, the image size mn is huge (e.g., $112\times 92 = 10304$) such that a traditional computation for these eigenvectors is intractable. An alternative computation is utilized according to the following description.

It can be easily proved that $BB^t \in R^{mn\times mn}$ and $B^tB \in R^{N\times N}$ share the same eigenvalues. Furthermore, if $\mathbf{v}$ is an eigenvector of B^tB corresponding to the eigenvalue λ, then $B^tB\mathbf{v} = \lambda\mathbf{v}$ and thus $(BB^t)(B\mathbf{v}) = \lambda(B\mathbf{v})$, which implies that $B\mathbf{v}$ is an eigenvector of BB^t corresponding to the same eigenvalue λ. Note that the number of subjects $N << mn$ so that the computation of eigenvalues and eigenvectors for $B^tB \in R^{N\times N}$ is much simpler and can be done by using traditional algorithms such as $Givens$ rotations.

2.1.1. *A Training Process*

Based on the aforementioned analysis, we can select d eigenvectors $\{\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_d\}$ corresponding to the largest eigenvalues $\{\lambda_1, \lambda_2, \cdots, \lambda_d\}$ of matrix $B^tB \in R^{N\times N}$. The normalized column vectors $\{\mathbf{u}_i \in R^{mn} : 1 \le i \le d\}$, where $\mathbf{u}_i = B\mathbf{v}_i/\|B\mathbf{v}_i\|_2$ for $1 \le i \le d$, corresponding to eigenfaces can then be used for projection such that a training face image $\Gamma_k \in R^{mn}$ can be converted into a $d - dimensional$ vector $\mathbf{f}_k \in R^d$ by

$$\mathbf{f}_k = U^t\Gamma_k, \;\; where\, U = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_d] \qquad (4)$$

2.1.2. *A Testing Process*

Let $X \in R^{m\times n}$ be a test face image which is represented as a column vector $Z \in R^{mn}$, we then convert this test image into a $d - dimensional$ feature vector **z** by

$$\mathbf{z} = U^t(Z - \Psi), \;\; where\, U = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_d] \qquad (5)$$

A standard pattern recognition method such as the nearest neighbor method, Bayesian method, and Fisher's linear discriminant method can be applied to classifying the test face image X. We adopt the nearest decision rule in this paper.

2.2. Fisherface BASED ON LDA

Let the gray level face images of m rows and n columns from the jth person out of *K* persons be denoted as $F_1^{(j)}, F_2^{(j)}, \cdots, F_{N_j}^{(j)} \in R^{m\times n}$ with $1 \le j \le K$ and $N_1 + N_2 + \cdots + N_K = N$, such that $F_i^{(j)}(s,t) \in \{0, 1, \cdots, 255\}$, $1 \le i \le N_j$, $0 \le s \le m-1$, $0 \le t \le n-1$. Let $\Gamma_i^{(j)} \in R^{mn}$ be a column-vector representation of $F_i^{(j)}$ such that

$$\Gamma_i^{(j)}(t + m * s) = F_i^{(j)}(s,t) \qquad (6)$$

Denote the mean face (vector) of the *jth* person as

$$\Psi_j = \frac{1}{N_j}\sum_{i=1}^{N_j}\Gamma_i^{(j)}, \;\; 1 \le j \le K, \qquad (7)$$

and the sample mean face of $\{\Gamma_i^{(j)} \in R^{mn} | \; 1 \le i \le N_j, \; 1 \le j \le K\}$ as

$$\Psi = \frac{1}{N}\sum_{j=1}^{K}\sum_{i=1}^{N_j}\Gamma_i^{(j)}. \qquad (8)$$

Define $\Phi_i^{(j)} = \Gamma_i^{(j)} - \Psi$ and

$$W = [\Phi_1^{(1)}, \cdots, \Phi_{N_1}^{(1)}, \cdots, \cdots, \Phi_1^{(K)}, \cdots, \Phi_{N_K}^{(K)}] \qquad (9)$$

Then $W \in R^{mn\times N}$, and the covariance matrix C of $\{\Gamma_i^{(j)}\}$ can be computed by

$$C = \frac{1}{N}WW^t = \frac{1}{N}\sum_{j=1}^{K}\sum_{i=1}^{N_j}\Phi_i^{(j)}\Phi_i^{(j)t} \qquad (10)$$

The within-class scatter matrix S_W, the between-class scatter S_B matrix, and the total scatter matrix S_T based on Linear Discriminant Analysis (LDA) can be acquired by the following computations, respectively.

$$S_W = \sum_{j=1}^{K}\sum_{i=1}^{N_j}(\Gamma_i^{(j)} - \Psi_j)(\Gamma_i^{(j)} - \Psi_j)^t \qquad (11)$$

$$S_B = \sum_{j=1}^{K}N_j(\Psi_j - \Psi)(\Psi_j - \Psi)^t \qquad (12)$$

$$S_T = \sum_{j=1}^{K}\sum_{i=1}^{N_j}(\Gamma_i^{(j)} - \Psi)(\Gamma_i^{(j)} - \Psi)^t \qquad (13)$$

It is well-known that $S_T = S_W + S_B$ and $S_T = N \times C$.

Fisherfaces are defined as the images corresponding to the discriminant vectors in V_0 obtained by solving

$$V_0 = arg\; max_V \left\{\frac{|V^tS_BV|}{|V^tS_WV|}\right\} \qquad (14)$$

or is equivalent to finding the eigenvectors corresponding to the first M largest generalized eigenvalues of the following eigensystem.

$$S_B\mathbf{v} = \lambda S_W\mathbf{v} \qquad (15)$$

Again, both of the matrices of S_B and S_W are $mn \times mn$ which is huge in practical applications so that a traditional algorithm for computing the eigenvalues/eigenvectors is infeasible. An alternative way similar to the computation of eigenfaces is adopted. Fisherfaces can be computed according to the following steps to avoid computing a matrix inverse of huge size.

(1) Acquire the d optimal projection vectors in V_{pca} by the method as introduced in the eigenface computation, where $d \leq N - K$.

$$V_{pca} = arg\, max_V\{|V^t CV|\},\ where\, V_{pca} \in R^{mn\times d} \tag{16}$$

(2) Find the optimal set of vectors by maximizing Fisher's linear discriminant criterion

$$W_{fld} = arg\ max_W \left\{ \frac{|W^t(V_{pca}^t S_B V_{pca})W|}{|W^t(V_{pca}^t S_W V_{pca})W|} \right\}, \tag{17}$$

where $W_{fld} \in R^{d\times d}$ which is equivalent to solving the generalized eigensystem

$$(V_{pca}^t S_B V_{pca})\mathbf{w} = \lambda(V_{pca}^t S_W V_{pca})\mathbf{w} \tag{18}$$

(3) The optimal Fisherfaces are the column vectors of W_{ff} which are obtained by

$$W_{ff} = V_{pca} W_{fld} \tag{19}$$

2.3. 2DPCA Method BASED ON 2D PCA

2DPCA face recognition method was proposed by Yang and Zhang in 2004 [8], which is similar to eigenface method except that the matrix inverse of huge image size is reduced.

Let the gray level face images of m rows and n columns from the jth person out of K persons be denoted as $F_1^{(j)}$, $F_2^{(j)}, \cdots, F_{N_j}^{(j)} \in R^{m\times n}$ with $1 \leq j \leq K$ and $N_1 + N_2 + \cdots + N_K = N$, such that $F_i^{(j)}(s,t) \in \{0, 1, \cdots, 255\}$, $1 \leq i \leq N_j, 0 \leq s \leq m-1, 0 \leq t \leq n-1$. We search for a unit vector $X \in R^n$ such that $Y = AX$ for any given image A from the training set. The goal is to maximize the scatter of the projection vector Y given X which is equivalent to maximizing $J(X) = tr(S_X)$, where

$$\begin{aligned} S_X &= E[(Y - E(Y))(Y - E(Y))^t] \\ &= E[(AX - E(AX))(AX - E(AX))^t] \\ &= E[((A - \bar{A})X)((A - \bar{A})X)^t] \end{aligned} \tag{20}$$

$$tr(S_X) = X^t E[(A - \bar{A})^t(A - \bar{A})]X = X^t G_X X \tag{21}$$

where $G_X \in R^{n\times n}$ can be computed by

$$G_X = \frac{1}{N}\sum_{j=1}^{K}\sum_{i=1}^{N_j}(F_i^{(j)} - \Psi)^t(F_i^{(j)} - \Psi) \tag{22}$$

where

$$\Psi = \frac{1}{N}\sum_{j=1}^{K}\sum_{i=1}^{N_j} F_i^{(j)} \tag{23}$$

The optimal projection vectors $X_1,\ X_2,\ \cdots,\ X_d \in R^n$ corresponding to the $d \leq min\{m, n\}$ largest eigenvalues of matrix G_X are selected as vectors for projection.

2.3.1. A Training Phase

Each training image $A \in \{F_i^{(j)} |\ 1 \leq i \leq N_j,\ 1 \leq j \leq K\}$ can be represented as *d* feature vectors of dimension m according to the following projections (transformations).

$$U_k = AX_k,\ \ 1 \leq k \leq d \tag{24}$$

or

$$U = [U_1, U_2, \cdots, U_d] = A[X_1, X_2, \cdots, X_d] \tag{25}$$

For a reconstruction,

$$\widehat{A} = [U_1, U_2, \cdots,\ U_d]\, [X_1, X_2, \cdots,\ X_d]^t \tag{26}$$

2.3.2. A Testing Phase

Each test image $Z \in R^{m\times n}$ can be converted into $W \in R^{m\times d}$ by projections as done in the training phase.

$$W_k = ZX_k,\ \ 1 \leq k \leq d \tag{27}$$

or

$$W = [W_1, W_2, \cdots, W_d] = Z[X_1, X_2, \cdots, X_d] \tag{28}$$

The distance between the test image Z and the training image A can be measured by

$$\delta(Z, A) = \|W - U\|_F^2 = \sum_{j=1}^{d}\|W_j - U_j\|_2^2 \tag{29}$$

Finally, a pattern recognition strategy can be applied for evaluating the performance of face recognition.

2.4. 2DLDA Method BASED ON 2D LDA

2DLDA face recognition method was simultaneously proposed by Li and Yuan [4] and Yang et al. [9]. which is similar to fisherface and 2DPCAface methods except that the singularity of a matrix may be further reduced compared with the 2DPCA method, and the huge matrix inverse in the fisherface method could be avoided.

Let the gray level face images of m rows and n columns from the jth person out of K persons be denoted as $F_1^{(j)}$, $F_2^{(j)}, \cdots, F_{N_j}^{(j)} \in R^{m\times n}$ with $1 \leq j \leq K$ and $N_1 + N_2 +$

$\cdots + N_K = N$, such that $F_i^{(j)}(s,t) \in \{0,1,\cdots,255\}$, $1 \le i \le N_j$, $0 \le s \le m-1$, $0 \le t \le n-1$. We search for a unit vector $X \in R^n$ such that $Y = AX$ for any given image A from the training set. The goal is to maximize a criterion similar to a Fisher's discriminant ratio as described below.

$$J(X) = \frac{X^t S_b X}{X^t S_w X} \tag{30}$$

where the between-class scatter matrix S_b and the within-class scatter matrix S_w can be defined as follows.

$$\Psi_j = \frac{1}{N_j}\sum_{i=1}^{N_j} F_i^{(j)},\ \ 1 \le j \le K \tag{31}$$

$$\Psi = \frac{1}{N}\sum_{j=1}^{K}\sum_{i=1}^{N_j} F_i^{(j)} \tag{32}$$

$$S_b = \sum_{j=1}^{K} N_j(\Psi_j - \Psi)^t(\Psi_j - \Psi) \tag{33}$$

$$S_w = \sum_{j=1}^{K}\sum_{i=1}^{N_j}(F_i^{(j)} - \Psi_j)^t(F_i^{(j)} - \Psi_j) \tag{34}$$

Then, the optimal projection vectors $X_1,\ X_2,\ \cdots,\ X_d \in R^n$ corresponding to the $d << min\{m,n\}$ largest eigenvalues $\{\lambda_1,\ \lambda_2,\ \cdots,\ \lambda_d\}$ of the generalized eigensystem

$$S_b X = \lambda S_w X \tag{35}$$

are selected as vectors for projection. Thus, each image $A \in \{F_i^{(j)} |\ 1 \le i \le N_j,\ 1 \le j \le K\}$ can be represented as d feature vectors $\{U_k \in R^m :\ 1 \le k \le d\}$ according to the following projections (transformations).

$$U_k = AX_k,\ \ 1 \le k \le d \tag{36}$$

or

$$U = [U_1, U_2, \cdots, U_d] = A[X_1, X_2, \cdots, X_d] \tag{37}$$

For a reconstruction,

$$\widehat{A} = \widehat{F_i^{(j)}} = [U_1, U_2, \cdots,\ U_d]\,[X_1, X_2, \cdots,\ X_d]^t \tag{38}$$

A pattern recognition strategy used for 2DPCA face recognition can be applied for performance evaluation on a face image database.

2.5. SVD-Based Representation and Recognition

SVD-based face recognition method was proposed by Hsu and Chen [3] which applies singular value decomposition for face image reconstruction and recognition. It could be viewed as a two-sided 2DPCA method [4]. The matrix inverse of huge image size is also reduced. The face features are stored in the matrix composed of left and right singular vectors of the face image under study.

Let the gray level face images of m rows and n columns from the jth person out of K persons be denoted as $F_1^{(j)}$, $F_2^{(j)}, \cdots, F_{N_j}^{(j)} \in R^{m\times n}$ with $1 \le j \le K$ and $N_1 + N_2 + \cdots + N_K = N$, such that $F_i^{(j)}(s,t) \in \{0,1,\cdots,255\}$, $1 \le i \le N_j$, $0 \le s \le m-1$, $0 \le t \le n-1$. We search for unit vectors $\mathbf{y} \in R^m$ and $\mathbf{x} \in R^n$ such that $\alpha = \mathbf{y}^t A\mathbf{x}$ for an image A from the training set to maximize

$$J(\mathbf{y},\mathbf{x}) = E[(\alpha - E[\alpha])^2] = E[(\alpha - \bar{\alpha})(\alpha - \bar{\alpha})^t] \tag{39}$$

Simple derivations lead to

$$J(\mathbf{y},\mathbf{x}) = [\mathbf{y}^t E(A - \overline{A})\mathbf{x}][\mathbf{y}^t E(A - \overline{A})\mathbf{x}]^t \tag{40}$$

Therefore, the vectors $\mathbf{y}$ and $\mathbf{x}$ are the left and right singular vectors corresponding to the largest singular values.

In practical applications, we first compute the mean image.

$$\Psi = \frac{1}{N}\sum_{j=1}^{K}\sum_{i=1}^{N_j} F_i^{(j)} \tag{41}$$

For each image $A \in R^{m\times n}$, we obtain the left singular vectors $\{\mathbf{y}_i :\ 1 \le i \le r \le m\}$ and the right singular vectors $\{\mathbf{x}_j :\ 1 \le j \le c \le n\}$ with the singular values $\sigma_1 \ge \sigma_2 \ge \cdots \ge \sigma_h \ge 0$, $h = min\{m,n\}$.

The face features are stored in the matrix $F \in R^{r\times c}$ acquired by

$$F = [\mathbf{y_1}, \mathbf{y_2}, \cdots, \mathbf{y_r}]^t\, A\, [\mathbf{x_1}, \mathbf{x_2}, \cdots, \mathbf{x_c}] \tag{42}$$

For reconstruction,

$$\widehat{A} = \sum_{i=1}^{k} \sigma_i \mathbf{y}_i \mathbf{x}_i^t,\ \ k \le min\{r,c\} \tag{43}$$

SVD face recognition can proceed according to the following steps.

(1) Compute mean face image: $\Psi = \frac{1}{N}\sum_{j=1}^{K}\sum_{i=1}^{N_j} F_i^{(j)}$

(2) Apply SVD on Ψ such that $\Psi = USV^t = \sum_{i=1}^{h}\sigma_i \mathbf{u}_i\mathbf{v}_i^t$, where $h = min\{m,n\}$. Denote that
$U = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_m],$, $V = [\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_n]$.

(3) Each training face image $F_i^{(j)}$ is transformed into a face feature matrix $X_i^{(j)} \in R^{r \times c}$ by $X_i^{(j)} = U_r^t F_i^{(j)} V_c$, where *r* and *c* are user-specified and

$U_r = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_r], \;\; V_c = [\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_c].$

(4) A test face image $T \in R^{m \times n}$ is transformed into a face feature matrix $Y \in R^{r \times c}$ by $Y = U_r^t T V_c$.

(5) Compute the distance between a test face image T and a traning face images $X_i^{(j)}$ by $\delta(Y, X_i^{(j)}) = \|Y - X_i^{(j)}\|_F, \;\; a\ Frobenius\ norm.$

(6) Classify T as the *k*th person if

$k = arg\ min_j \{\delta(Y, X_i^{(j)}), \;\; 1 \le i \le N_j\}$

3. THREE FACE DATABASES

We use three databases: ORL [14], UMIST [15], NTHU [13] to test the the five projection-based face retrieval methods.

3.1. ORL Face Image Database

The ORL face database contains 400 8-bit gray level images of 112 rows and 92 columns in PGM file format. The images were taken between April 1992 and April 1994 at the Olivetti Research Laboratory in Cambridge, UK. There are 40 persons, each contributed 10 images at different times, lightings, facial expressions (open or closed eyes, smiling or non-smiling), and some details on face (with eyeglasses or no eyeglasses). All images are taken in up-right, frontal positions with a slight tilt and rotation against a dark homogeneous background. We used the first 5 images from each subject for training and the next 5 images of each person for testing. The 10 images of subject s8 are shown below.

Fig. 1. Face images of subject s8 from ORL.

3.2. UMIST Face Image Database

The UMIST [15] face database consists of 564 images of 20 people. Each covers a range of poses from profile to frontal views. Subjects cover a range of race/sex/appearance [15]. Each image has an original size of appropriately 220×220 pixels. A set of cropped size 112×92 provided by Graham and Allinson [15] are used in this paper. Each subject contains 19∼48 images in the set of cropped size. We used the first 5 images from each subject for training and the next 5 images of each subject for testing. The 10 images of subject 1t are shown below.

Fig. 2. Face images of subject 1t from UMIST.

3.3. NTHU Face Image Database

The NTHU face database is established by PRIP Lab at NTHU in the years 2005 and 2006. It contains 40 persons, 4 images for each person. Images were taken in a frontal view, as well as with a slight tilt and rotation to the right and to the left against a homogeneous light background. We used the first 3 images from each subject for training and the last image of each subject for testing. The 4 images of subject s26 are shown below.

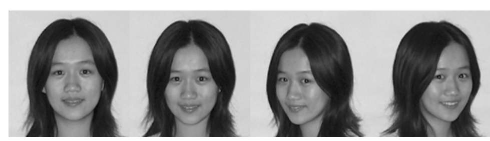

Fig. 3. Face images of subject s26 from NTHU.

4. EXPERIMENTAL RESULTS

We run each projection-based method to test 3 databases: ORL [14], UMIST [15], and NTHU [13], respectively. Only the training time as well as the testing time performed on NTHU face database are reported for reference, where the testing time includes the feature selection and retrieval rank matching for all of the 40 test images but not a single test image. Recall that the image size is 128×128 while the image size for the other two databases are both 112×92.

We plot the retrieval rates according to the following definitions. Suppose that a test image **y** is given, we want to retrieve the images $\{\mathbf{x} : \;\; 1 \le i \le M\}$, from the given database with M images. We say that a correct retrieval at rank k is achieved if there is at least one image, in the top k nearest images, which matches the test image, that is, they are obtained from the same subject.

The retrieval rates of five methods on both ORL database and UMIST database are illustrated in the following figures. The training time and testing time (in seconds) of 40 images, the theoretical storage space required, and the actual memory space used in the MATLAB programs, are summarized in Table 1. Note that the parameters d,e,k,r,c, appeared in each method need not be the same to achieve the optimal performance. The statistics regarding to the memory space actually used in our experiments are also listed for reference. The retrieval rate in Table 1 is the correct retrieval rate of matching the top 5 images. The experimental results suggest that SVD is a very competitive method since it runs fast without requesting too huge memory space for a moderate size of database such as 40 persons.

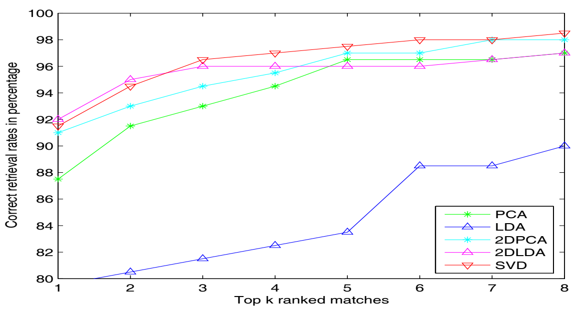

Fig. 4. Retrieval Rates on ORL Face Database.

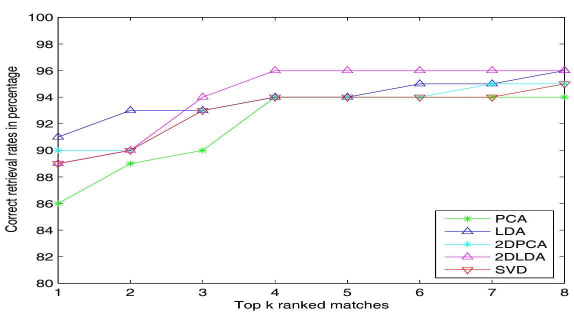

Fig. 5. Retrieval Rates on UMIST Face Database.

5. CONCLUSION

Face retrieval and recognition is one of the most popular applications in an access control of entry and exit to a country [11][16]. We have reviewed and compared five commonly used projection-based feature extraction methods: PCA [5][7], LDA [1], 2DPCA [8], 2DLDA [4][9], and SVD [3][6]. We discussed the theoretical usage of storage space and the practical usage of actual implementation using Matlab programs

	PCA	LDA	2DPCA	2DLDA	SVD
(1)	16.08	20.36	6.68	11.05	2.92
(2)	3.47	5.22	3.44	15.33	0.83
(3)	d*m*n	d*m*n	e*m+d*n	e*m+d*n	k*r*c
(4)	5465	7238	2046	4951	226
(5)	0.75	0.75	0.80	0.80	0.80

(1) Training time (sec.), (2) Testing time (sec.), (3) Floating-point numbers requested per each image, (4) Kbytes used, (5) Retrieval rate.

Table 1. **Statistics on NTHU face database.**

[12]. We also reported the training time and testing time of running the Matlab algorithms for the aforementioned five methods on NTHU face database with retrieval rates.

The experimental results indicate that the retrieval rates of the 2D projection-based methods like 2DPCA, 2DLDA, and SVD, achieve 95% by considering retrieving the top 5 matched face images from ORL with 200 candidates and UMIST with 100 candidates. The retrieval rates of 80% are relatively lower on NTHU face image database because the background pixels occupy a large portion of a face image.

We conclude that the retrieval rates of face images vary with the quality of the face images, in particular, the background pixels of a face image should be as low as possible, the 2D projection-based methods like 2DPCA, 2DLDA, and SVD, generally perform better than PCA and LDA, the SVD-based one is more competitive since it runs fast without requesting too huge memory space for a moderate size of database, for example, 50 persons.

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