An Improved Face Recognition Technique Based on Modular Multi-directional Two-dimensional Principle Component Analysis Approach

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Abstract—**In this paper, a new method named modular multi-directional two-dimensional principle component analysis (M^2D2DPCA) is proposed for face recognition. First, the original images are rotated at some predetermined angles so that we may extract features from the images in any direction. Then we divide the rotated images into smaller sub-images and apply 2DPCA approach to each of these sub-images. Finally we propose a fusion method named modular multi-directional 2DPCA (M^2D2DPCA) to combine a bank of preliminary results in different directions. Compared with conventional 2DPCA based algorithms, the advantage of the proposed method is that it can extract significant features from the images in any direction and avoid the effects of varying illumination and facial expression. The results of the experiments on ORL and Yale datasets show that the proposed M^2D2DPCA method can obtain a higher recognition rate than the conventional 2DPCA based methods.**

Index Terms—**face recognition, feature extraction, 2DPCA, MD2DPCA, M^2D2DPCA, feature fusion**

I. INTRODUTION

Face recognition[1~4] is a hot topic in computer vision and pattern recognition. Yet,it is still a challenging task because the image of a face varies with facial expression, age, viewpoint, illumination conditions, noise etc. How to effectively extract informative features from training images is the key point of face recognition.

The methods based on principle component analysis (PCA)[5] are recognized as one of the most important feature extraction[6~8] instruments and still widely used in face image recognition. Sirovich and Kirby [9] first used PCA algorithm to represent the human face, while Turk and Pentland [10,11] proposed a famous " eigenface " method. The disadvantage of the traditional eigenface method based on PCA is that the 2D face image matrix must be previously transformed into a high-dimensional 1-D image vector. This transformation leads to some important issues such as small sample size problem and a high-dimensional image vectors space, where it is difficult to evaluate the covariance matrix accurately due to its large size [12].

To overcome this shortcoming, two-dimensional principle component analysis (2DPCA) [12] was proposed. The 2DPCA projects the image matrix onto the projection axis directly to extract the features from the image matrix, and the projected result is the so-called feature matrix[13]. 2DPCA is computationally more efficient than PCA because the total scatter matrix of 2DPCA has the lower dimensionality than that of PCA. Nevertheless, 2DPCA just extracts the information between the rows of the images and ignores the correlation between the columns. To alleviate this problem, two-directional two-dimensional PCA($(2D)^2$PCA) was proposed by Zhang et al.[14]. $(2D)^2$PCA shows that 2DPCA essentially works in the row direction of images and Zhang et al. proposed the alternative-2DPCA that works in the column direction of images . The alternative-2DPCA extracts feature in the column direction, which also can be viewed as the 2DPCA working in row direction. But, features extracted in one or two directions are always not sufficient for achieving high recognition rate. In Ref. [15], the authors first indicated that features extracted in different directions have different influences for accurate classification, and then proposed a method called multi-directional two-dimensional PCA (MD2DPCA). The MD2DPCA consists of two consecutive stages: First, using the directional 2DPCA(D2DPCA)[15] to extract features in different directions.In the second stage, using a matching score level fusion method to fuse several results of D2DPCA in different directions for face recognition.

A problem faced by all the methods which have been mentioned above is that they extract the most informative features all in a global manner. Consequently, some useful local information might be ignored. Also, it is difficult to avoid the influence of variations in illumination and facial expression when we extract features in a global manner. So, some researchers

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propose modular based algorithms to solve this problem.

Modular PCA(MPCA) [16] divides images into smaller sub-images and uses PCA to extract features on each sub-image. MPCA considers each sub-image as a sample and projects all of the sub-images onto a single projection matrix.Thus, variations in facial expression or illumination will affect only some of the sub-images. It has been shown that 2DPCA is a special case of BPCA[17]. Also, modular 2DPCA and block-wise two-directional 2DPCA employ a block-wise approach in feature extraction for reducing the computational complexity and obtain a higher recognition rate accuracy under the conditions of varying facial expression, illumination and pose[18,19]. But these modular based methods just extract features only in one or two directions, and some useful information in other directions might be lost.

In this paper, we propose a new algorithm called modular multi-directional two-dimensional PCA(M^2D2DPCA), which is an extension of the MD2DPCA method. In the M^2D2DPCA method, first,the original images are rotated in some predetermined directions(degrees). Then, we divide the rotated images into smaller sub-images and apply 2DPCA approach to each of the sub-images. Finally, we develop a fusion method to fuse the recognition results in different directions. The proposed method not only extracts significant features in any direction, but also extracts many more informative local features. Further more, variations in facial expression and illumination may affect only some of the sub-images. Hence, we expect the proposed method to have a better recognition rate. In the paper, we used two face databases to evaluate the performance of the M^2D2DPCA, 2DPCA, $(2D)^2$PCA, M2DPCA ,M$(2D)^2$PCA and MD2DPCA.

The rest of this paper is organized as follows: Section II describes the D2DPCA and MD2DPCA method. Section III explains the proposed method modular MD2DPCA (M^2D2DPCA) . The experiments on two public face datasets are given to compare the proposed method with several relevant methods in section IV. Finally, a conclusion is drawn in section V.

II. MULTI-DIRECTIONAL 2DPCA

A. 2DPCA

Consider an m by n random image matrix A. Let $X \in R^{n\times d} (d \le n)$ be a projecting matrix with orthonormal columns. Projecting A onto X by the linear transformation $Y = AX$ yields an m by d matrix Y.Y is the feature matrix and X is the projection matrix. The idea of 2DPCA is to find the optimal projection matrix X_{opt}.

Suppose that there are N training image samples in total and $A_k (k = 1,2....N)$ represents the kth image of training samples. $\bar{A}$ is the mean of all training samples.

$$\bar{A} = \frac{1}{N}\sum_{K=1}^{N} A_K \qquad (1)$$

The total scatter matrix of the training images is defined as

$$G = \frac{1}{N}\sum_{K=1}^{N} (A_K - \bar{A})^T (A_K - \bar{A}) \qquad (2)$$

Then,calculating the eigenvalues and eigenvectors of G, and the eigenvector of G corresponding to the largest eigenvalue is the best projection axis[20]. In general, it is not enough to have only one optimal projection axis. We usually need to select a set of projection axes, $X_1, X_2, \ldots X_d$ [15].In fact, these optimal projection axes are the orthonormal eigenvectors of G corresponding to the first d largest eigenvalues, and the $X_{opt} = [X_1, X_2, \ldots X_d]$ is the optimal projection matrix.

B. Directional 2DPCA

In Ref [15], the authors indicated that features extracted only in one or two directions are not enough, and then proposed the directional 2DPCA(D2DPCA) that can extract features from the sample image in any direction. The D2DPCA is implemented by performing the 2DPCA on the rotated sample images which are obtained by using original image multiplying the rotation matrix $R(\alpha)$ in Euclidean space[15]. The rotation matrix $R(\alpha)$ is as follow:

$$R(\alpha) = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} \qquad (3)$$

D2DPCA rotates sample images in a certain angle α and denotes the rotated sample images as $r_\alpha(A_1), r_\alpha(A_2), \ldots r_\alpha(A_N)$ .Since the rotated images will not be matrix form, they fill its four corners with 0 pixel values[15]. Fig.1 shows the image rotated with $\alpha = \frac{\pi}{6}$.

(a) (b)

Fig.1 (a)The original image,(b) the image rotated with $\alpha = \frac{\pi}{6}$.

Similarly to 2DPCA, D2DPCA projects the rotated images $r_\alpha(A_1), r_\alpha(A_2), \ldots r_\alpha(A_N)$ onto the projection matrix X by linear transformation as follow:

$$Y = r_\alpha(A_k)X \quad (k = 1, 2, ...N) \qquad (4)$$

Where Y is the feature matrix of the rotated image. The idea of D2DPCA is to find the optimal projection matrix X_{opt}^{D2DPCA}.

Let $\overline{r_\alpha(A_k)}$ denote the mean of all the rotated training images and the total scatter matrix of the rotated image is defined as:

$$G_{D2DPCA} = \frac{1}{N}\sum_{K=1}^{N}(r_\alpha(A_k) - \overline{r_\alpha(A_k)})^T(r_\alpha(A_k) - \overline{r_\alpha(A_k)}) \quad (5)$$

Then solving for eigenvalues and eigenvectors of the total scatter matrix G_{D2DPCA} ,and selecting d' orthonormal eigenvectors as projection axes, i.e. $X_1^{D2DPCA}, X_2^{D2DPCA}, \dots X_{d'}^{D2DPCA}$,corresponding to the d' largest eigenvalues. The $X_{opt}^{D2DPCA} = [X_1^{D2DPCA}, X_2^{D2DPCA}, \dots X_{d'}^{D2DPCA}]$ is the optimal projection matrix of D2DPCA. As we can see from above, the 2DPCA and the alternative-2DPCA are two special cases of D2DPCA for $\alpha = 0, \pi/2$ respectively[15].

C. Multi-directional 2DPCA

In Ref [15], the authors have proposed an effective fusion method named multi-directional 2DPCA(MD2DPCA) to fuse the features extracted by the D2DPCA in different directions for classification. The flowchart of MD2DPCA is shown in Fig.2 and its process[15] is implemented as follows:

Step1. Obtaining the projection matrix. It rotates all the training images with certain predetermined angles: $\{0, \pi/l, 2\pi/l, ..., (l-1)\pi/l\}$, where l is the number of the feature extraction directions. Then apply 2DPCA to the rotated images to obtain the projection matrix. Now we have l projection matrixes.

Step2. Calculating the matching score of D2DPCA in one direction. Projecting all the rotated training and testing samples onto the corresponding projection matrixs to obtain their feature matrixes and then calculating the matching score between each testing sample and training sample[15] using:

$$s_{\alpha,i,j} = \sum_{p=1}^{d'} \left\| Y_i^p - Y_j^p \right\| \quad (6)$$

Where Y_i^p and Y_j^p represent the *pth* feature vector of the feature matrix from sample A_i and A_j, respectively. $\left\| Y_i^p - Y_j^p \right\|$ denotes the Euclideandistance between the two vector Y_i^p and Y_j^p .Hence $s_{\alpha,i,j}$ is Euclideandistance between the two feature matrixes from sample A_i and A_j rotated with α [15].

Step3. Adding up all the matching scores of D2DPCA in all directions by:

$$s_{i,j} = \sum s_{\alpha,i,j} \quad (7)$$

Step4. Recognition using nearest neighbor classifier .

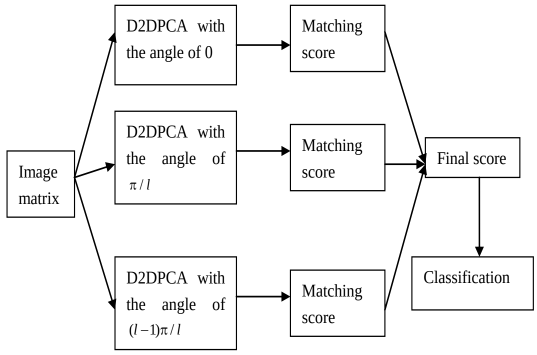


Fig. 2 The framework of MD2DPCA[15]

III. M²D2DPCA:MODULAR MULTI-DIRECTIONAL 2DPCA

Under the conditions of varying facial expression and illumination, the methods(including PCA, 2DPCA, $(2D)^2$PCA, MD2DPCA) are not very effective since the features would vary considerably from the features of the face images with normal facial expression and illumination[16]. If the face images are divided into smaller sub-images , only some of the sub-images may vary and rest of the sub-images will remain the same. Therefore it is expected that the proposed method modular multi-directional 2DPCA(M^2D2DPCA) not only extracts more informative features from different directions and local regions, but also has a higher recognition rate under the conditions of varying facial expression and illumination

In this section, we present the details of the proposed M^2D2DPCA method. The flowchart of M^2D2DPCA is shown in Fig. 3.

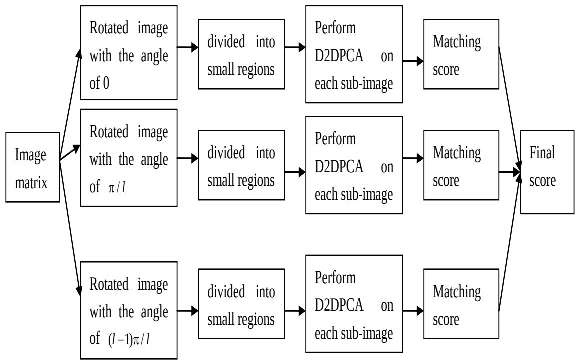


Fig. 3 The flowchart of M^2D2DPCA

As shown in Fig.3, the process of the M^2D2DPCA is implemented by the following steps:

Step1. Rotating the sample images with the angles $\{0, \pi/l, 2\pi/l, ..., (l-1)\pi/l\}$, where l is the number of the features extraction directions. Let image A be an m by n image matrix and A_i denotes the *ith* sample image. The image matrix rotated with angle α is shown as follow:

$$r_\alpha(A_i) = \begin{bmatrix} r_\alpha(A_k)_{11} & r_\alpha(A_k)_{12} & \cdots & r_\alpha(A_k)_{1n} \\ r_\alpha(A_k)_{21} & r_\alpha(A_k)_{22} & \cdots & r_\alpha(A_k)_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_\alpha(A_k)_{m1} & r_\alpha(A_k)_{m2} & \cdots & r_\alpha(A_k)_{mn} \end{bmatrix} \quad (8)$$

The new position of each pixel in the rotated image matrix is obtained by using original position multiplication of the rotation matrix $R(\alpha)$ ((3)) in Euclidean space[15].

Step2. The rotated image matrix of A_i is divided into $N = p*q$ sub-images, where p and q are the numbers of the blocks in vertical and horizontal directions, as given in (9).

$$r_\alpha(A_i) = \begin{bmatrix} r_\alpha(B_k)_{11} & r_\alpha(B_k)_{12} & \cdots & r_\alpha(B_k)_{1q} \\ r_\alpha(B_k)_{21} & r_\alpha(B_k)_{22} & \cdots & r_\alpha(B_k)_{2q} \\ \vdots & \vdots & \vdots & \vdots \\ r_\alpha(B_k)_{p1} & r_\alpha(B_k)_{p2} & \cdots & r_\alpha(B_k)_{pq} \end{bmatrix} \quad (9)$$

Where $r_\alpha(B_i)_{xy}$ denotes each sub-image of the rotated image matrix. The width and height of each sub-image can be calculated as $m_1 = m/p$ and $n_1 = n/p$, respectively.

It is expected that the image divided into smaller sub-images is helpful for extracting more local information and reducing the influence of varying facial expression and illumination. Nevertheless, the face images can not be divided into very small regions, because most of the global information of the face may be lost. The optimal block size ultimately depends on the characteristics of each particular database[16].

Step3. After dividing the images, performing D2DPCA on the sub-image, the size of each block is reduced.

The total scatter matrix of all the rotated sub-image is defined as:

$$G_{M^2D2DPCA} = \frac{1}{M}\sum_{k=1}^{N}\sum_{x=1}^{p}\sum_{y=1}^{q}(r_\alpha(B_k)_{xy} - \overline{r_\alpha(B_k)})^T(r_\alpha(B_k)_{xy} - \overline{r_\alpha(B_k)}) \quad (10)$$

Where $M = Npq$ denotes the total number of all the training sub-images rotated with a certain angle. The average image $\overline{r_\alpha(B_k)}$ of all the training sub-images rotated with a certain angle is computed as:

$$\overline{r_\alpha(B_k)} = \frac{1}{M}\sum_{k=1}^{N}\sum_{x=1}^{p}\sum_{y=1}^{q} r_\alpha(B_k)_{xy} \quad (11)$$

Next, we calculate the eigenvalues and eigenvectors of the total scatter matrix $G_{M^2D2DPCA}$, and select d' orthonormal eigenvectors as projection axes, i.e. $X_1^{M^2D2DPCA}, X_2^{M^2D2DPCA}, \ldots X_{d'}^{M^2D2DPCA}$,corresponding to the d' largest eigenvalues. The $X_{opt}^{M^2D2DPCA} = [X_1^{M^2D2DPCA}, X_2^{M^2D2DPCA}, \ldots X_{d'}^{M^2D2DPCA}]$ is the optimal projection matrix of M^2D2DPCA.

In this way, a feature matrix with the same number of blocks as before but with reduced size is obtained as given in (12):

$$Y_k = \begin{bmatrix} r_\alpha(B_k)_{11}^T X_{opt}^{M^2D2DPCA} & r_\alpha(B_k)_{12}^T X_{opt}^{M^2D2DPCA} & \cdots & r_\alpha(B_k)_{1q}^T X_{opt}^{M^2D2DPCA} \\ r_\alpha(B_k)_{21}^T X_{opt}^{M^2D2DPCA} & r_\alpha(B_k)_{22}^T X_{opt}^{M^2D2DPCA} & \cdots & r_\alpha(B_k)_{2q}^T X_{opt}^{M^2D2DPCA} \\ \vdots & \vdots & \vdots & \vdots \\ r_\alpha(B_k)_{p1}^T X_{opt}^{M^2D2DPCA} & r_\alpha(B_k)_{p2}^T X_{opt}^{M^2D2DPCA} & \cdots & r_\alpha(B_k)_{pq}^T X_{opt}^{M^2D2DPCA} \end{bmatrix} \quad (12)$$

Let a testing face image matrix C rotated with the same angle and divided into the same number of blocks with the training sample.The rotated matrix C is as follow:

$$r_\alpha(C) = \begin{bmatrix} r_\alpha(B)_{11} & r_\alpha(B)_{12} & \cdots & r_\alpha(B)_{q1} \\ r_\alpha(B)_{21} & r_\alpha(B)_{22} & \cdots & r_\alpha(B)_{q2} \\ \vdots & \vdots & \vdots & \vdots \\ r_\alpha(B)_{p2} & r_\alpha(B)_{p2} & \cdots & r_\alpha(B)_{pq} \end{bmatrix} \quad (13)$$

Projecting $r_\alpha(C)$ onto the optimal projection matrix $X_{opt}^{M^2D2DPCA}$ by the linear transformation $Y = AX$ yields a feature matrix for the testing image as given in (14):

$$Y' = \begin{bmatrix} r_\alpha(B)_{11}^T X_{opt}^{M^2D2DPCA} & r_\alpha(B)_{12}^T X_{opt}^{M^2D2DPCA} & \cdots & r_\alpha(B)_{1q}^T X_{opt}^{M^2D2DPCA} \\ r_\alpha(B)_{21}^T X_{opt}^{M^2D2DPCA} & r_\alpha(B)_{22}^T X_{opt}^{M^2D2DPCA} & \cdots & r_\alpha(B)_{2q}^T X_{opt}^{M^2D2DPCA} \\ \vdots & \vdots & \vdots & \vdots \\ r_\alpha(B)_{p1}^T X_{opt}^{M^2D2DPCA} & r_\alpha(B)_{p2}^T X_{opt}^{M^2D2DPCA} & \cdots & r_\alpha(B)_{pq}^T X_{opt}^{M^2D2DPCA} \end{bmatrix} \quad (14)$$

Step 4. After obtaining feature matrixes of all the rotated training and testing images, we calculate the matching score between each testing sample and training sample, Similarly to MD2DPCA in section II.C.

$$s_{\alpha,i,j} = \sum_{p=1}^{d'} \left\| Y_i^p - Y_j^p \right\| \quad (15)$$

The Y_i^p and Y_j^p represent the *pth* feature vector of the feature matrix and $\left\| Y_i^p - Y_j^p \right\|$ denotes the Euclidean distance between Y_i^p and Y_j^p.

Then we calculate the final matching score of D2DPCA in all directions as following:

$$s_{i,j} = \sum s_{\alpha,i,j} \quad (16)$$

Step5. Classification using the nearest neighbor classifier.

IV. Experiments And Analysis

The performance of conventional algorithms (including 2DPCA, M2DPCA,$(2D)^2$PCA, M$(2D)^2$PCA and MD2DPCA) and the proposed method M^2D2DPCA were evaluated with two image databases, ORL and Yale[21].The ORL database was employed to examine the performance of mentioned algorithms for varying number of eigenvectors and sample size. The Yale database was used to test the performance of the system under the conditions of varying facial expression and illumination. We used MATLAB2010 for all of our experiments and performed on a PC with Pentium(R) Dual-Core E5800 3.20GHz CPU ,2GB memory and windows XP operating system.

A. Experiments on the ORL Database

The ORL database includes 400 gray-scale images of 40 individuals, each providing 10 different images. The images of each subject vary with facial expressions, facial details, scale and limited rotation. Moreover, there is also some tilting and rotation of the face of up to 20 degrees. All images are normalized to a resolution of 112 *92 pixels. Five sample images of one subject in the ORL database are shown in Fig. 4. In the experiment, the first five images in each subject were used for training and the remaining images were used to test the recognition rates. Thus, the total number of training samples and testing samples were both 200. The D2DPCA can extract features in any direction and this paper proposed a framework to fuse multi-direction features.We tested the proposed method using three directions and five directions(denoted as 3d and 5d) in the experiments respectively. The face images were divided into 4*4 blocks for testing the performance of the modular based algorithms(including modular 2DPCA, modular $(2D)^2$PCA and the proposed method). Hence the size of each sub-image is 56*46,the total scatter matrix is 56*56.The feature matrixs of M2DPCA,MD2DPCA and M^2D2DPCA are all 112*4V(V denotes the number of eigenvectors).But for the 2DPCA, $(2D)^2$PCA and $M(2D)^2$PCA ,the sizes of feature matrixs are 112*V,V*V ,4V*4V, respectively. Fig.5 shows the result of dividing a face image into 4*4 blocks..

Fig. 4 Five images of one person from ORL face database

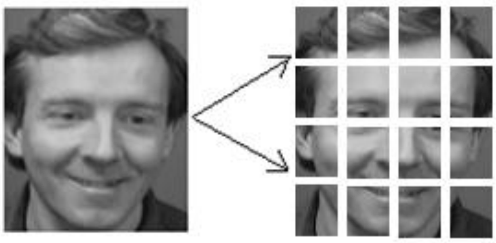


Fig.5 A face image divided into 4*4 blocks.

In the experiment, for the proposed method, we first rotated the training samples and divided them into smaller sub-images according to (8) and (9).Then we computerd the feature matrix of each training sample as given in (12). Similar to training sample, we calculated the feature matrix of the testing sample as given in (14). After obtaining feature matrixes of the rotated training and testing images, we calculated the matching score between each testing sample and training sample according to (15) and (16). Finally, we classified the test sample by using the nearest neighbor classifier.

In the first experiment, we tested the performance of the proposed method and the related methods for varying number of eigenvectors(V from 1 to 20). It can be observed from Fig. 6 that the recognition rates are increasing in all methods as we increase the number of eigenvectors, and the recognition rates tend to be stable for number>7 . Fig. 6 also shows that modular based methods have better recognition rates than the other methods (includ 2DPCA, $(2D)^2$PCA and MD2DPCA) in different number of eigenvectors and the proposed M^2D2DPCA method always outperforms the other methods for the number varying from 1 to 20. However, the proposed M^2D2DPCA method using five directions also obtains the highest recognition rate of 97%.

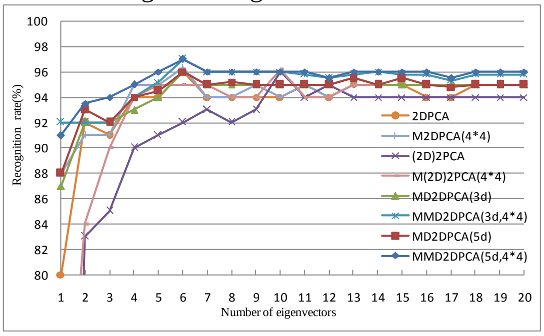


Fig.6 Recognition rates of the mentioned methods with varying number of eigenvectors.

Then, we conducted the next experiment at V=10, i.e. eigenvectors corresponding to the ten maximum eigenvalues of the covariance matrix. This experiment was used to examine the performance of the related methods with varying sample size and varying V would have the same effect on the related algorithms as shown in Fig. 6. Thus,we only considered the first ten eigenvectors for the experiment. As shown in Fig.7, the recognition rates are increasing in all methods as the increasing of S(S denotes samples size) and the recognition rates grow fast when S<5, but grow slowly when S>5. It can also be observed from Fig.7 that the proposed method(M^2D2DPCA using three and five directions) has the higher recognition rates than that of the other methods at most of S and the highest recognition rate of 97.3% was obtained by the proposed method at S=9.

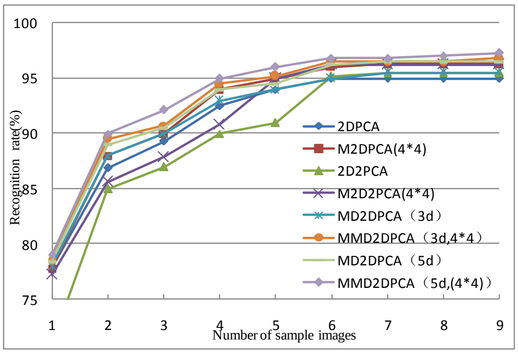


Fig.7 Recognition rates of the mentioned methods with varying sample size.

From the results we note that the proposed M^2D2DPCA method always has a slightly better recognition rates than the traditional methods with varying number of eigenvectors and sample size, since it not only extracts many more significant information from different directions,but also extracts local information from smaller regions, while the minor and insignificant variations are eliminated.

Furthermore, we varied M(number of sub-images) from 2 to 64 to observe the effect of varying M on recognition rate. The number of eigenvectors is 10 and sample size is 5. Here, we only compared the proposed method in different number of directions. We can observe from Fig.8 that the recognition rates are increasing as the increasing number of sub-images when M<16, because many more significant local information has been extracted from smaller regions and variations affect only some of the sub-images. But the recognition rates fall fast when M>16, because the global information of the face may be lost when the image is divided into very small regions. Also, it can be observed from Fig.8 that the recognition rates of the method in five directions are slightly better than the other numbers of directions, since it can extract much more significant information from the more directions.

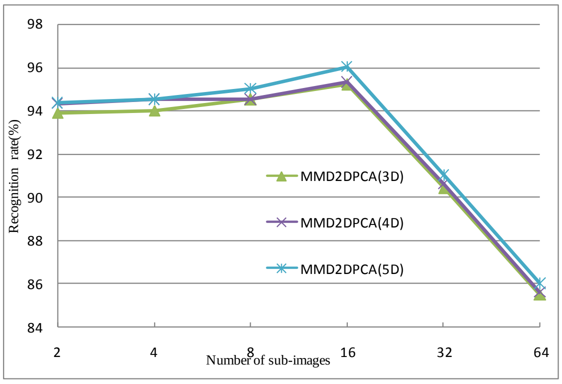
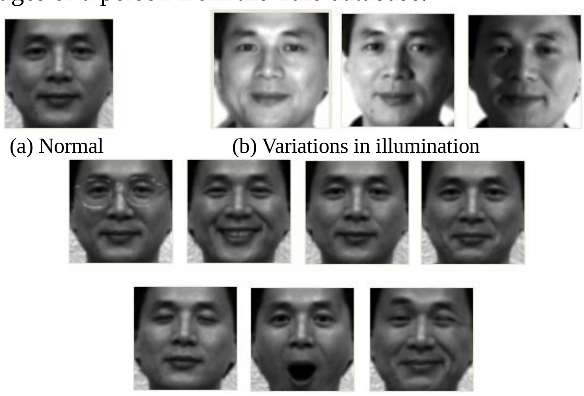


Fig.8 Recognition rates of the proposed methods with varying number of sub-images.

B. Experiments on the Yale Database

The Yale database has 165 images of 15 adults(each person has 11 images). The face images are with variations in facial expression (including normal, sad, happy and surprised expressions)and Variations in illumination. There are also images with and without glasses. Each image was manually cropped and resized to 100*100 pixels in this experiment. Figs.9 shows the images of a person from the Yale database.



(a) Normal (b) Variations in illumination

(c) Variations in facial expression

Fig.9 Images of one person in the Yale database.(a) normal image, (b)images with variations in illumination, and (c) images with variations in facial expression.

In order to compare the performance of related methods for facial expression and illumination variations, we designed two sub-experiments: the normal face image of each person is chosen as training sample for both two sub-experiments. Three face images with variations in illumination of each person are chosen as the testing samples for sub-experiment 1 and seven face images with variations in facial expression of each person are chosen as the testing samples for sub-experiment 2. Thus the total number of training samples for both two sub-experiments is 15. The total number of testing samples in sub-experiment 1 and 2 are 45 and 105,respectively. In these two sub-experiments, we used the case of the 4*4 blocks for the modular based methods(including M2DPCA, $M(2D)^2PCA$ and $M^2D2DPCA$). Hence the size of each sub-image is 25*25,the total scatter matrix is 25*25. The number of eigenvectors V varys from 1 to 20.The feature matrixs of M2DPCA,MD2DPCA and $M^2D2DPCA$ are all 100*4V.But for the 2DPCA, $(2D)^2PCA$ and $M(2D)^2PCA$,the size of the feature matrixs are 100*V,V*V ,4V*4V ,respectively.

In these two sub-experiments, for the proposed method, we conducted the experiments similarly to the experiment mentioned in section IV.A. We first rotated the training samples and divided them into smaller sub-images according to (8) and (9).Then we culculated the feature matrix of each training sample and testing sample as given in (12) and (14),respetively.. After obtaining feature matrixes of the rotated training and testing sample, we calculated the matching score between each testing sample and training sample according to (15) and (16). Finally, we classified the test sample by using the nearest neighbor classifier.

Tab.I shows the top recognition rates under the conditions of varying illumination and facial expression for all methods. It can be observed from Tab.I that modular based methods effectively reduce the influence of variations in illumination and improve the recognition performance. The proposed $M^2D2DPCA$ method using five directions obtains the best recognition rate of 86.21%. Under the conditions of varying facial expression, compared with 2DPCA,$(2D)^2PCA$ and MD2DPCA,modular based methods also have better recognition rates, because the influence of variations in facial expression is reduced by dividing the image into smaller regions. In all the related methods, the performance of the proposed method using five directions is the most excellent and obtains the best recognition rate of 98.12%.

TABLE I.
EXPERIMENTAL ON YALE FACE DATSBASE

Method	Top recognition rate(%)	Top recognition rate(%) (Variations in facial
2DPCA	80.20	95.16
M2DPCA	84.42	96.50
$(2D)^2PCA$	80.20	95.16
$M(2D)^2PCA$	84.42	96.50
MD2DPCA(3d)	81.00	96.10
M2D2DPCA (3d)	85.50	97.50
MD2DPCA(4d)	81.20	96.33
M2D2DPCA (4d)	85.82	97.80
MD2DPCA(5d)	81.55	96.60
M2D2DPCA (5d)	86.21	98.12

From all the results we note that improvement is obtained in the case of modular based methods and the proposed method always has the best recognition performance. Since the face images were divided into smaller regions,the variations in illumination and facial expression would be more representative of the local information of the face, so the modular based methods can avoid the effects of varying illumination and facial expression. However, because of extracting information from many more directions, the proposed M^2D2DPCA method can obtain much more significant information from not only the horizontal and vertical directions. These are helpful for obtaining higher recognition rates as observed in the experimental results. 2DPCA, $(2D)^2$PCA and MD2DPCA methods were not very effective when the face images have variations in illumination and facial expression, because they consider the global information of each face image and under these conditions the eigenvectors of the test image and the training image with normal illumination and facial expression may have a big difference, so it is difficult to recognize them correctly.

V. Conclusion

In this paper, a modular multi-directional 2DPCA(M^2D2DPCA)method, which is an extension of the multi-directional 2DPCA(MD2DPCA) method for face recognition has been proposed. The advantages of the method can be briefly expressed as follows: First, the proposed method can extract significant information from the images in any direction, and its implementation is very simple. Second, since the face images are divided into smaller regions, the variations in illumination and facial expression will be more representative of the local information of the face, hence the method can reduce the effects of varying illumination and facial expression. The experimental results on ORL and Yale database show that the proposed M^2D2DPCA method is more powerful for classifying human face images than the conventional 2DPCA based methods.

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