
얼굴 인식 시스템을 위한 C2DPCA & R2DLDA

C2DPCA & R2DLDA for Face Recognition

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요약

본 논문에서는 열방향 2차원 PCA(Column-directional 2 Dimensional PCA, C2DPCA) 와 행방향 2차원 LDA(Row-directional 2 Dimensional LDA, R2DLDA)를 사용하여 얻은 각각의 투영 행렬을 동시에 사용하는 방법을 제안하였다. 제안 방법은 얼굴의 가로 특징과 세로 특징을 모두 포함한 저 차원의 특징 행렬을 얻음으로써, 훈련 영상의 수에 관계없이 안정적이고 높은 인식률을 얻을 수 있다. 또한, 같은 알고리즘으로 가로 방향과 세로 방향에 PCA와 LDA를 각각 달리 적용한 실험(C2DPCA & R2DLDA, C2DLDA & R2DPCA)에서 가로 방향의 특징에 2차원 LDA를 적용한 시스템(C2DPCA & R2DLDA)이 그 반대의 경우보다 저차원으로 높은 인식률을 얻을 수 있음을 확인할 수 있었다. 실험 결과 제안한 방법이 2DPCA와 2DLDA 등 의 기존 방법보다 인식율이 높은 99.4%를 얻었다. 또한 제안 방법의 인식 처리 속도도 기존의 2DPCA와 2DLDA 방법보다 3배 이상 빠름을 확인하였다.

■ 중심어 : | 2DPCA | 2DLDA | LDA | PCA | 얼굴인식 |

Abstract

The study has proposed a method that simultaneously takes advantage of each projection matrix acquired by using column-directional two-dimensional PCA(C2DPCA) and row-directional two-dimensional LDA(R2DLDA). The proposed method can acquire a great secure recognition rate, with no relation to the number of training images, with acquired low-dimensional feature matrixes including both the horizontal and the vertical features of a face. Besides, in the alternate experiment of PCA and LDA to row-direction and column-direction respectively(C2DPCA & R2DLDA, C2DLDA & R2DPCA), we could make sure the system of 2 dimensional LDA with row-directional feature(C2DPCA & R2DLDA) obtain higher recognition rate with low dimension than opposite case. As a result of experimenting that, the proposed method has showed a greater recognition rate of 99.4% than the existing methods such as 2DPCA and 2DLDA, etc. Also, it was proved that its recognition processing is over three times as fast as that of 2DPCA or 2DLDA.

■ keyword : | 2DPCA | 2DLDA | LDA | PCA | Face Recognition |

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I. Introduction

During the last thirty years, there have been a lot of methods for putting face recognition into practical use. In 1973, Kanade made a face recognition system, for the first time, based on the geometric features of a face[1]. In 1991, there was Turk's method which used morphological features by applying PCA to face recognition[2]. A small number of training images give PCA a greater recognition rate than LDA; however, a good number of training images give LDA greater distinction performance than PCA. But a peculiar matrix from the process of acquiring a projection matrix makes direct application of LDA difficult. Because of that, in 1997, Belhumeur, etc proposed a method of face recognition that could raise between-class distinction performance by using PCA+LDA[3].

The newly proposed idea of this study is combining row-directional 2DPCA and column-directional 2DLDA at the same time. That could reduce the complexity of operation, as a result of using two-dimensional image covariance matrix. Also, compared with the existing methods, despite its own low-dimensional feature matrix, it has its great secure recognition rate with no relation to the number of training images.

The study has the following contents: Chapter 2 has explained an existing method of face recognition, Chapter 3 has described the directional two-dimensional covariance matrix method proposed here by the study. And Chapter 4 has explained the system of face recognition that takes advantage of the method proposed here, and has evaluated its performance. Last, Chapter 5 has put forward the conclusion of the study and future tasks.

II. Related Works

In case of one-dimensional method, a big-sized covariance matrix takes a long time to find a projection vector. So in 2004 Yang, etc. proposed 2DPCA that applied PCA to image covariance matrix to lessen the amount of calculation and raise a recognition rate[4]. By the way, image covariance matrix is so low in its dimension that a peculiar matrix has a small possibility of generation. Therefore, LDA can be directly applied to image covariance matrix, different from any other one-dimensional method. In 2005, with this as the base of their idea, Li, etc. proposed 2DLDA applying LDA to image covariance matrix, and could make a recognition rate greater than 2DPCA[5].

The two-dimensional method using image covariance matrix took much less time to find projection matrix and enhanced a recognition rate. But its last feature matrix is high in dimension, which enlarges a storage space and lengthens recognition time. On the other hand, in 2005, Zhang, etc. put forward 2D²PCA that considers row-directional and column-directional Block PCA at the same time[6]. It respectively used column-directional and row-directional image covariance matrix for acquiring projection matrix, and then made feature matrix. The method kept a recognition rate as high as 2DPCA and remarkably reduced the dimension of feature matrix. And Nagabhushan proposed 2D²FLD by applying such an idea to LDA in 2006[7].

2DLDA has a great recognition rate, compared with PCA or FLD which takes advantage of one-dimensional vector. However, because its feature matrix is as big as that of 2DPCA, it requires a big storage space and takes a long time when similarity is measured. Therefore, to lessen the size of 2DLDA feature matrix, a lot of researches have been being

performed. Motivated by 2DPCA and 2DLDA, P. Sanguansat et al. proposed 2DPCA plus 2DLDA method which consists of two steps: first a feature matrix is obtained by 2DPCA-based technique, second the feature matrix is projected onto the classification space via 2DLDA-based technique[8].

Noushath, etc. made a proposal for Diagonal FLD[9], where 2DLDA was executed by just taking pixels of the same number from one column, just like DiaPCA[10]. Yang proposed a method that 2DLDA is executed first horizontally, then vertically[11]. Like this, a sequence of two executions could lessen the size of feature matrix. On the other hand, Wang proved that 2DLDA is the same as Block LDA, which has column as a unit of execution like 2DPCA[12]. Based on what is mentioned above, 2D²LDA was proposed a method which acquires 2DLDA projection vector horizontally and vertically, respectively, and then projects them at the same time[13].

III. A directional two-dimensional covariance matrix method for face recognition system

PCA and LDA, typical statistical methods using morphological features transformed each face image into one-dimensional vector, and then made covariance matrix. So when N $m \times n$ -sized face images are used, the size of covariance matrix is $(m \cdot n) \times (m \cdot n)$, very big. Accordingly, as it is very hard to acquire projection vector itself, an irregular method could be used for acquiring, maximally, N projection vectors. But with two-dimensional image itself as matrix, because image covariance matrix directly acquire the covariance matrix of image, the size of column-directional image covariance matrix is $n \times n$ and the size of row-directional image covariance

matrix is $m \times m$, relatively small, and can acquire n or m the maximum number of projection vectors. Therefore, use of image covariance matrix is quite helpful to calculation and analysis of projection vectors.

As the study has acquired low-dimensional feature matrix by simultaneously using feature matrixes, ones from use of row-directional 2DPCA and ones from use of column-directional 2DLDA, it includes both the horizontal and the vertical features of a face, and has proposed a method of low-dimensional feature representation, for face recognition, that has a great secure recognition rate, with no relation to the number of training images.

Above all, equation (1) expresses row-directional covariance matrix C_t , C_b , C_ω for applying to row-directional 2DPCA.

$$\begin{aligned} C_t &= \frac{1}{N} \sum_{k=1}^N (A_k - \bar{A})(A_k - \bar{A})^t \\ &= \frac{1}{N} \sum_{k=1}^N \sum_{i=1}^n (b_{ki} - \bar{b}_i)(b_{ki} - \bar{b}_i)^t \end{aligned} \quad (1a)$$

$$\begin{aligned} C_b &= \sum_{i=1}^c N_i (\bar{A}_i - \bar{A})(\bar{A}_i - \bar{A})^t \\ &= \sum_{i=1}^c N_i \left(\sum_{j=1}^n (\bar{b}_{ij} - \bar{b}_j)(\bar{b}_{ij} - \bar{b}_j)^t \right) \end{aligned} \quad (1b)$$

$$\begin{aligned} C_\omega &= \sum_{i=1}^c \sum_{A'_k \in c_i} (A_k - \bar{A}_i)(A_k - \bar{A}_i)^t \\ &= \sum_{i=1}^c \sum_{A'_k \in c_i} \sum_{j=1}^n (b_{kj} - \bar{b}_{ij})(b_{kj} - \bar{b}_{ij})^t \end{aligned} \quad (1c)$$

Here, \bar{b}_i is the i -th column of \bar{A}^t the total mean image, \bar{b}_{ij} is the j -th column of the i -th class mean image. Next, equation (2) expresses column-directional image covariance matrix R_t , R_b , R_ω for

applying to column-directional 2DLDA.

$$\begin{aligned} R_t &= \frac{1}{N} \sum_{k=1}^N (A_k - \bar{A})' (A_k - \bar{A}) \\ &= \frac{1}{N} \sum_{k=1}^N \sum_{i=1}^m (a_{ki} - \bar{a}_i) (a_{ki} - \bar{a}_i)' \end{aligned} \quad (2a)$$

$$\begin{aligned} R_b &= \sum_{i=1}^c N_i (\bar{A}_i - \bar{A})' (\bar{A}_i - \bar{A}) \\ &= \sum_{i=1}^c N_i \left(\sum_{j=1}^m (\bar{a}_{ij} - \bar{a}_j) (\bar{a}_{ij} - \bar{a}_j)' \right) \end{aligned} \quad (2b)$$

$$\begin{aligned} R_o &= \sum_{i=1}^c \sum_{A_k \in c_i} (A_k - \bar{A}_i)' (A_k - \bar{A}_i) \\ &= \sum_{i=1}^c \sum_{A_k \in c_i} \sum_{j=1}^n (a_{kj} - \bar{a}_{ij}) (a_{kj} - \bar{a}_{ij})' \end{aligned} \quad (2c)$$

Here, \bar{a}_i is the i -th column of \bar{A} the total mean image, and \bar{a}_{ij} means the j -th column of \bar{A}_i the i -th class mean image.

Column-directional 2DPCA means the process that row-directional application of 2DPCA acquires PFk feature matrix, and is abbreviated as C2DPCA, which is expressed in equation (3).

$$PF_k = A_k' W_{PCA} \quad (3)$$

WPCA is projection matrix, and \bar{A}_k' is the transposition of $m \times n$ input image.

Row-directional 2DLDA means the process that column-directional application of 2DLDA acquires LFk feature matrix, and is abbreviated as R2DLDA, which is expressed in equation (4).

$$LF_k = A_k W_{LDA} \quad (4)$$

WLDA is projection matrix, and \bar{A}_k is $m \times n$ input image. C2DPCA & R2DLDA is a result of applying PCA to row-directional two-dimensional covariance matrix and LDA to column-directional two-dimensional covariance matrix. As for A_k input image, $n \times p$ is the dimension of C2DPCA feature matrix, PFk, and $m \times q$ is that of R2DLDA feature matrix, The dimension of such a feature matrix is bigger than one-dimensional PCA or LDA. Considering column-directional and row-directional feature matrix at the same time reduces the number of dimension efficiently. Accordingly, as in equation (5), projecting A_k to W_{PCA}' and WLDA at the same time lowers the dimension of feature matrix and $p \times q$ is the dimension of Ft the derived feature matrix.

$$F_k = W_{PCA}' A_k W_{LDA} \quad (5)$$

[Fig. 1] shows a process of generating C2DPCA & R2DLDA projection matrix and feature matrix. Generally, p and q is 10 or so, a small value.

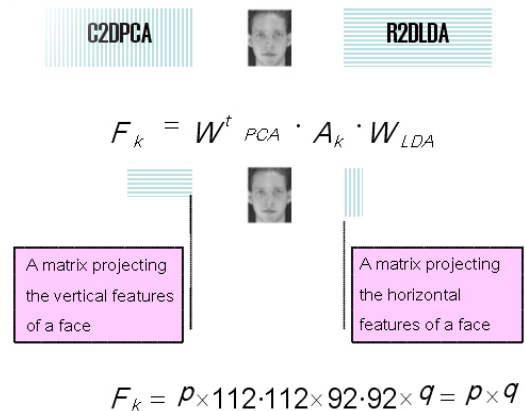


Fig. 1 Projection and feature matrix of C2DPCA & R2DLDA

IV. A face recognition system using the method of directional two-dimensional covariance matrix

[Fig. 2] describes the composition of the method proposed here. First, each face recognition system selects projection vectors and their projection matrix suitable for each of them by using all training images. Projection of each and every training image by using the selected projection matrix can finally make feature matrixes corresponded to each training image. When test image comes in, the feature matrixes acquired like this are all stored in database for comparison with a new feature matrix derived from this test image. The new test image selects projection matrix by having already used training images in each face recognition system. The projection matrix newly projected gets to make a new feature matrix with smaller dimension. The feature matrix derived like this passes through the process of comparison with every feature matrix stored in database, and is used to distinguish the last level where the test image belongs.

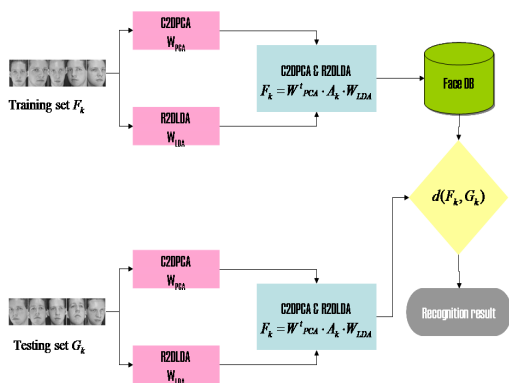


Fig. 2 Recognition procedure of C2DPCA & R2DLDA

Confirming the recognition rate of the proposed face recognition system requires a method that recognition

rate is calculated by comparing similarities between feature matrixes. When there are two feature matrixes, $F=(f_{ij})_{p \times q}$ and $G=(g_{ij})_{p \times q}$, their similarity was calculated by equation (6).

$$d(F, G) = \sum_{j=1}^q \left(\sum_{i=1}^p (f_{ij} - g_{ij})^2 \right)^{1/2} \quad (6)$$

A test image A_t is transformed into feature matrix F_t , and then the similarity with every training image is calculated by equation (6). Next, as in equation (7), feature matrix F_k with the minimum similarity is found, and the class where F_k is fixed as the class of test image. The recognition rate of a face recognition system, as in equation (8), is fixed as the rate of T_s the number of accurately recognized test images against T the number of the total test images.

$$\min(d(F_t, F_k)), \quad (k=1, \dots, N) \quad (7)$$

$$\text{Recognition rate} = \frac{T_s}{T} \times 100(\%) \quad (8)$$

AT&T face database was used for an experiment of conforming the recognition performance of the proposed face recognition system[14]. From the forty classes of AT&T face database, the basic experiment take advantage of the first five pieces of image, according to each class, as training image for finding projection matrix, and used the other five pieces as test image for comparing the feature and the recognition rate of each algorithm. All of our experiments are carried out on a PC with Pentium 2GHz CPU and 1GB memory under Matlab 7.0 platform.

The study experimented for evaluating the recognition rate of face recognition algorithms, the

existing algorithms like 2DPCA, 2DLDA, 2D²PCA, 2D²LDA, and the proposed algorithm, C2DPCA & R2DLDA. Table 1 shows the results of comparing the top recognition rate and the dimension while the number of training images varies from two pieces to eight, according to each class. 2DPCA and 2DLDA have a big dimension for the top recognition rate, whereas the other three methods have a small dimension for the top recognition rate as the three consider the row direction and the column direction at the same time. Particularly, the proposed method has almost as small a dimension as 2D²PCA and 2D²LDA, and it enhances a recognition rate with no relation to the number of training images. All the five methods, when training images are six, have the maximum recognition rate; the recognition rate of the proposed one is higher than that of any of the other four methods, and its dimension is smaller.

Table 1. Comparison of the top recognition rate

The number of training images methods		2	3	4	5	6	7	8
Proposed method	Recog. rate	89.1	91.8	93.3	95	99.4	99.17	98.8
	Dimension	14×9	13×3	7×5	8×5	7×6	6×7	3×10
2D ² LDA	Recog. rate	87.5	90.7	93.8	93.5	98.8	98.3	98.8
	Dimension	16×8	8×12	8×10	8×3	6×9	5×4	5×7
2D ² PCA	Recog. rate	87.8	89.3	92.1	94.5	97.5	97.5	97.5
	Dimension	11×5	15×6	9×6	16×6	6×7	4×5	3×8
2DLDA	Recog. rate	87.2	90	95	94	98.1	96.7	96
	Dimension	112×9	112×18	112×6	112×6	112×6	112×3	112×12
2DPCA	Recog. rate	86.9	88.6	91.7	93	97.5	96.7	96.3
	Dimension	112×4	112×6	112×6	112×7	112×7	112×3	112×3

[Table 2] has compared the training time and the recognition time of each method. 2D²PCA and 2D²LDA and the proposed method, for comparing them in the time of extracting feature matrix, all selected 8×5 feature matrix, and 2DPCA and 2DLDA selected 112×6 feature matrix. That was because these methods, when their feature matrix has such

size, recorded the maximum recognition rate in the experiment that took advantage of five pieces of training image and five pieces of test image. The mean time was measured by five times of repetition in each experiment. Here, the proposed method was 2.77 seconds, and 2DLDA was 2.29 seconds, and 2D²PCA 2.50 seconds; the proposed one has a difference of under 0.5 second with the other two. 2DPCA has the shortest feature matrix extraction time, but it has the lowest recognition rate. But the proposed one takes just 1.66 seconds to recognize 200 pieces of test image, and has been found to be over three times as fast as 2DPCA or 2DLDA.

Table 2. Comparison of the processing time

Methods	The time of feature matrix extraction	The time of test image recognition
Proposed method	2.77	1.66
2D ² LDA	2.50	1.79
2D ² PCA	3.24	1.56
2DLDA	2.29	6.04
2DPCA	1.34	6.34

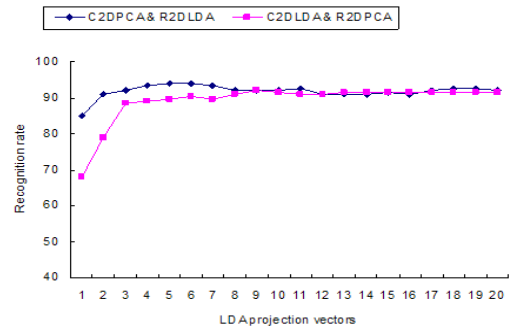


Fig. 3 The C2DPCA&R2DLDA and the C2DLDA&R2DPCA

[Fig. 3] has compared the C2DPCA&R2DLDA and the C2DLDA&R2DPCA. in the alternate experiment of PCA and LDA to row-direction and column-direction respectively(C2DPCA & R2DLDA,

C2DLDA & R2DPCA), we could make sure the system of 2 dimensional LDA with row-directional feature(C2DPCA & R2DLDA) obtain higher recognition rate with low dimension than opposite case.

V. Conclusion

The face recognition method that this study has proposed reduces a dimension efficiently so that the amount of calculation and the space of storage can be lessened for application to the ubiquitous computing environment and the mobile hand-held devices. The proposed method acquires low-dimensional feature matrix by simultaneously using a row-directional and a column-directional projection matrix, so it can reduce the complexity of operation and prevent a peculiar matrix. Also, it minimizes a feature matrix, which makes recognition faster and storage space smaller. When AT&T database was experimented with five pieces of training image and five pieces of test image as a condition, 112×92 input image was reduced into 8×5 feature matrix. At this time, the proposed method was 95% in recognition rate, was about 2.77 seconds in the time of feature matrix extraction; and it took about 1.66 seconds to recognize 200 pieces, over three times as fast as 2DPCA and 2DLDA. As for the dimension of storage space, compared with the size of 2DLDA feature matrix, the proposed method can store 200 classes as the size of 2,048,000 byte (8×5×200×256), and 2DLDA as the size of 34,406,400 byte (122×6×200×256). As increase in the number of classes makes the difference in recognition time much bigger, a face recognition system that can process a vast number of classes will have great efficiency.

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