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Fusion of PCA and LDA Based Face Recognition System

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Abstract.Face recognition is an important biometric because of its potential applications in many fields, such as access control, surveillance, and human-computer interface. In this paper, a system that fuses the output of a PCA and LDA based system is presented. The fusion is based on a set of rules. Both PCA and LDA based systems were trained using the same training data and tuned to give the highest equal error rate. It was found out that the fusion of both systems increases the recognition rate by 8% and 3% from the performance of the PCA and LDA systems respectively.

Keywords:PCA, LDA, biometric, face, recognition, fusion

1. Introduction

Face recognition approaches can be divided into three groups [1]; global, local, and hybrid approaches.Two of the widely used representations of the face region are Eigenfaces [2], which are based on principal component analysis (PCA), and Fisherfaces [3], which are based on linear discriminant analysis (LDA).Yoo et al. [4] presented a PCA based face recognition system. The system was tested on face images represented in various colour spaces such as RGB, HSV, YC_bC_r, and $YC_g{}^{,}C_r{}^{,}$ from the colour FERET database. Euclidean distance is used as matching criteria. They reported that YC_bC_r colour space give the best recognition rate of 92.3%. Perronnin et al. [5] proposed a face recognition system that uses Gabor features as face features. LDA is used to reduce the Gabor representation dimension. Various distance metrics were tested and they reported that Mahalanobis metric give the best result which is 93.2% on the FERET database. Yong and Aleix[6] use multiple FERET still images for training and video sequences for testing their face recognition system. PCA, ICA, and LDA are used for face recognition and their results are compared using a weighted probabilistic as matching criteria. For expression changes experiment, PCA, ICA, and LDA achieved 94%, 94% and 98% recognition rate respectively. For occlusion experiment, they found out that LDA performedworse than PCA and ICA when the face image occlusion is large. ICA achieved the highest score on largest occlusion size tested (80 by 80) with 91% recognition rate. On experiment with various pose, all three systems give same recognition rate of 94%. In this paper, a system that fuses the output of PCA and LDA based systems is presented. This paper is organised as follows; Section 2 outlines the proposed system while in section 3 the results and discussions are presented before the paper concludes in section 4.

2. Proposed System

Fig. 1 shows the proposed rule-based face recognition system. A set of training and testing images were projected to a lower dimensional feature space. The projection will produce two new set of feature vectors; training and testing feature vectors with much smaller dimension compared to the original image dimension. These feature vectors, representing the images, are then used in matching task between test image and training images. The individual recognition result from PCA and LDA based system are used as input for the data fusion stage which gives the final recognition result.

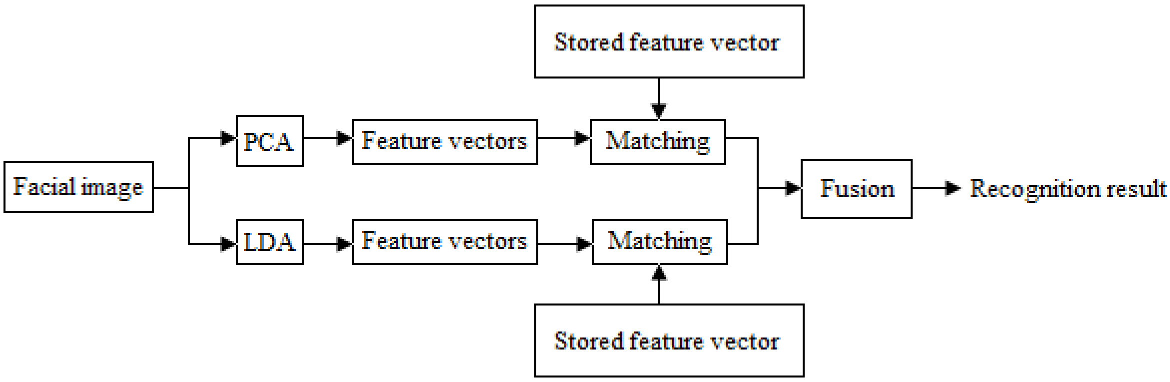

Fig. 1: Block diagram of the proposed rule-based face recognition system

2.1. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a statistical linear transform method often used for data compression by reducing the number dimensions without much loss of information.The Eigenface method uses PCA to linearly project the image space to a low dimensional feature space.Consider a set of M sample data, $\mathbf{X} = [\ \mathbf{x_1}\ \mathbf{x_2} \dots \mathbf{x_M}\ ]$, where $\mathbf{x_i}$ is a 1-D vector image and each data with n-dimensional space. The total scatter matrix $\mathbf{S_t}$ of $\mathbf{X}$ defined as,

$$S_t = \sum_{i=0}^{M} (x_i - \mu)(x_i - \mu)^T \tag{1}$$

where$\mu \in \Re^n$ is the mean image of all samples. Next, a set of n-dimensional eigenvectors, $\mathbf{V} = [\ \mathbf{V_1 V_2} \dots \mathbf{V_k}]$ of$\mathbf{S_t}$ are obtained such as: $\mathbf{S_t V_j} = \lambda_j \mathbf{V_j}$where j = 1, 2, …, k and k < M. The eigenvectors $\mathbf{V} = [\ \mathbf{V_1 V_2} \dots \mathbf{V_k}]$ corresponds to first k largest eigenvalues $[\ \lambda_1 \lambda_2 \dots \lambda_k]of\mathbf{S_t}$.The eigenvectors $\mathbf{V}$were then normalized so that $\|\mathbf{V}_j\| = 1$. Since $\mathbf{V}_j$ has the same dimension as the original image, they are referred as eigenfaces.The linear transformation mapping the original n-dimensional image to k-dimensional feature space defined as:$\mathbf{Y_i} = \mathbf{V}^T \times \mathbf{X_i}$. $\mathbf{Y_i} \in \Re^k$,$\mathbf{X_i} \in \Re^n$, where k <n and $\mathbf{V} \in \Re^{nxk}$. In this system, the number of training images,M, used is 300 which the same number of eigenvalues used.

2.2. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis is a popular technique for dimensionality reduction and simple classifiers in the reduced feature vector. Let P_1, P_2 … P_C be the face classes in the training database with C is total class in the training database. In this case, the term “class” indicates a “person”. Let each face class P_i has n facial images $\mathbf{x_j}$, with j=1, 2 … n. The mean image $\boldsymbol{\mu_i}$ of each class $P_i$can be computed as,

$$\boldsymbol{\mu_i} = \frac{1}{n} \sum_{j=1}^{n} \boldsymbol{x_j} \tag{2}$$

wheren= total number of imagesfor a given class.Then the mean image (mean face),$\boldsymbol{\mu}$ of all the classes in the databaseis calculated as,

$$\boldsymbol{\mu} = \frac{1}{c} \sum_{i=1}^{c} \boldsymbol{\mu_i} \tag{3}$$

Then the within-class scatter matrix is calculated as,

$$S_w = \sum_{i=1}^{C} \sum_{j=1, x_j \epsilon X_i}^{n} \left(x_j - \mu_i\right)\left(x_j - \mu_i\right)^T \quad (4)$$

And the between-class scatter matrix is calculated as,

$$S_B = \sum_{i=1}^{C} k_i\left(\mu_i - \mu\right)\left(\mu_i - \mu\right)^T \quad (5)$$

Then the eigenvector $v_k$that satisfy the Equation 6 below need to be calculated.

$$S_B v_k = \lambda S_w v_k \quad (6)$$

wherek = 1, 2, …, m. v_k is the eigenvector, λ is the eigenvalue, and m is the number of eigenvectors.

Note that there are at most C - 1 non zero generalized eigenvalues, and so an upper boundary of m is C - 1. In face recognition problem, the within-class scatter matrix S_W is always singular; thus, the Fisherface method can overcome this problem by using PCA to reduce the dimension of the feature space to M – C and then applying the standard LDA as defined by equation (6) to reduce the dimension to C - 1. In this LDA system, the total number of classes, C, (number of persons in the training database)is 100. And the number of training images per person, n, 3. Thus, the total images in training database,M, is300.

2.3. Matching

For the matching task of both systems, the Euclidean distance measureis used.If the Euclidean distance*d(x,y)*between test image *y* and an image *x* in the training database is smaller than a given threshold *t*, then images *y* and *x* are assumed to be of the same person. The threshold *t* is selected as the largest Euclidean distance between any two face images in the training database, divided by a threshold tuning value (*Tcpara*) as given in equation (7).

$$t = \frac{\left\lfloor \max\left\{\left\|\Omega_j - \Omega_k\right\|\right\}\right\rfloor}{Tcpara} \quad (7)$$

where j, k = 1, 2, …, M and Ω is the reduced dimension images.

To measure the performance of both systems, several performance metrics are used. These are:

For Recall

- ***Correct Classification***. If a test image $\mathbf{y}_i$is correctly matched to an image $\mathbf{x}_i$ of the same person in the training database.
- ***False Acceptance.*** If test image $\mathbf{y}_i$ is incorrectly matched with image $\mathbf{x}_j$, where ***i*** and ***j*** are not the same person
- ***False Rejection.*** If image $\mathbf{y}_i$is of a person***i*** in the training database but rejected by the system.

For Reject

- ***Correct Classification***. If $\mathbf{y}_i$, from the unknown test database is rejected by the program
- ***False Acceptance***. If image $\mathbf{y}_i$is accepted by the program.

2.4. Data Fusion Stage

As shown in Fig. 1, the recognition result of the PCA and LDA systems will serve as input for the fusion decision stage. The fusion decision stage is a module that consists of several rules [7]. The rules are:

For Recall

- If both systems give correct matching, then correct match is found

- If one system give correct matching and the other system give wrong matching or not found, then correct match is found
- If both systems give wrong matching, then the fusion system give wrong matching
- If one system gives wrong matching and the other system give not found, then the fusion system give wrong matching
- If both system give not found, then the fusion system give not found

For Reject

- If both system correctly reject image from unknown test database, then the fusion system give correct reject
- If one system correctly reject image from unknown test database and the other system accept unknown test image, then the fusion system give correct reject
- If both system accept image from unknown test database, then the fusion system give false acceptance

The fusion decisionrules can be summarize as an OR operator as shown in Table 1.

TABLE 1: Fusion Decision Rules

PCA output	LDA output	Fusion System output
0	0	0
1	0	1
0	1	1
1	1	1

3. Results and Discussion

3.1. Face Database

A total of 500 images with frontal face of a person were selected from the FERET database. They represent 200 different individuals. 100 individuals are used for training & testing, and the other 100 different individualsare used for testing only. All the 500 selected FERET images were cropped to get only the desired face part of a person (from forehead to the chin). All images are adjusted so that both eyes coordinates of an individual are aligned in the same horizontal line and the dimension for each image is set to60 x 60 pixels.Three images per individual will be used for training.Two testing databases were created. The first database, Known Test Database, has 100 images of the 100 persons in the training database. This database will be used to test the recall capability of the face recognition system. The second database, Unknown Test Database, has also 100 images of 100 different persons. This database will be used to test the rejection capability of the system.

3.2. Setting The Threshold Tuning Parameter

The value of the threshold tuning parameter can be used to tune the performance of the system to have either high correct recall with high false acceptance rate for application such as boarder monitoring or high correct rejection rate for unknown persons for application such as access control. For this work, the threshold tuning parameter was set so that the system has equal correct recall and rejection rate. Fig. 2 shows how the correct recall and reject rates changes as the value of the threshold tuning parameter changes. When the correct recall and reject rates are the same, this is called equal error rate. As can be seen from Figure 2, both PCA and LDA systems have the same highest recall rateof 98% and reject rateof 100%. However the LDA system giveshigher equal correct rateof 94%compared with the equal correct rate of 89%given by thePCA system

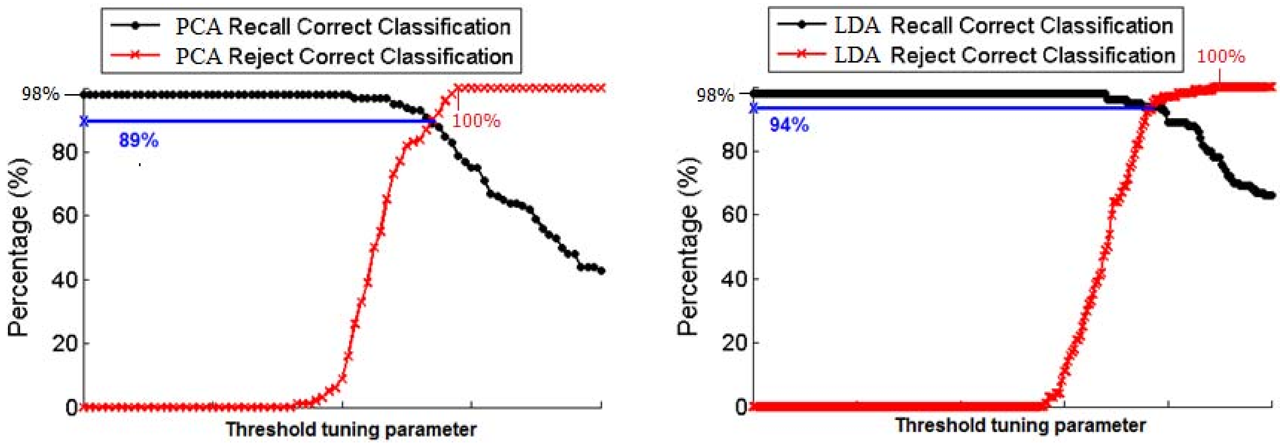

Fig. 2. Comparison of PCA and LDA based face recognition rate

3.3. Comparison Between Individual and Fused Systems

Experiments are performed using the fusion decision rule mentioned above. Both PCA and LDA systems are using the same training image database, and fed with the same test input image at same time. Fig. 3 shows that fusion system gives better performance than either of the single systems individually. The PCA and LDA systems give 89% and 94% equal correct ratesrespectively; however, the fused system gave a correct recall and reject rates of 97% each. Thus, the fusion of both systems increases the recognition rate by 8% and 3% from the performance of the PCA and LDA systems respectively.

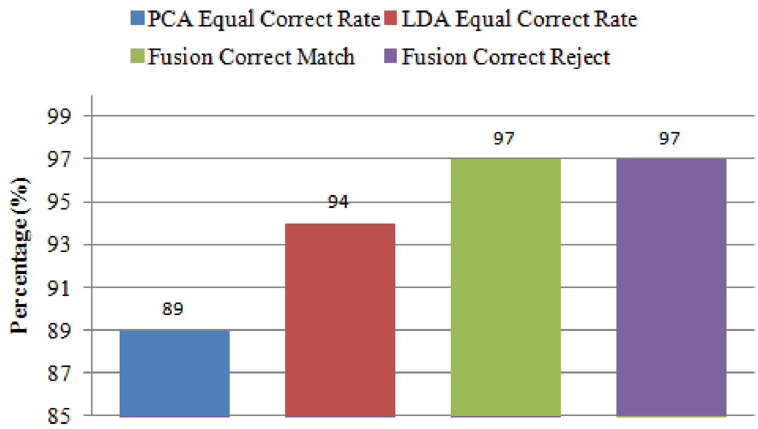

Fig.3:Comparison of recognition results.

4. Conclusion

In this paper, a system that fuses that outputs of PCA and LDA based system is presented.The proposed system fuses both systems using a set of rules. Experimental results on the FERET database have shown that the proposed system outperforms each of the individual system when used separately.

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