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Appearance Global and Local Structure Fusion for Face Image Recognition

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Abstrak

Analisis komponen utama (PCA) dan analisis deskriminan linear (LDA) merupakan metode ekstraksi berbasis penampakan yang menghasilkan fitur-fitur dengan struktur global. Fitur-fitur dengan struktur global mempunyai kelemahan, yaitu fitur-fitur dengan struktur lokal tidak dapat dicirikan. Proyeksi pelestarian lokalitas (LPP) dan wajah-Laplacian orthogonal (OLF) merupakan metode ekstraksi model penampakan yang menghasilkan fitur-fitur dengan struktur lokal, namun fitur struktur global diabaikan. Baik fitur dengan struktur lokal maupun global adalah sama-sama penting. Sehingga ekstraksi menggunakan fitur struktur lokal atau global saja tidak cukup. Pada penelitian ini, diusulkan metode ekstraksi berbasis penampakan yang menggabungkan fitur-fitur dengan struktur global dan lokal. Hasil ekstraksi untuk metode penampakan PCA dan LDA digabungkan dengan hasil ekstraksi dari proyeksi pelestarian lokalitas. Hasil pemodelan telah diuji dengan citra wajah basisdata Olivetty Research Laboratory. Hasil eksperimen menunjukkan bahwa metode yang diusulkan telah mencapai akurasi pengenalan yang lebih tinggi dibandingkan metode PCA, LDA, LPP dan OLF.

***Kata kunci**: LDA, PCA, pengenalan wajah, penyatuan fitur, struktur lokal dan global*

Abstract

Principal component analysis (PCA) and linear descriminant analysis (LDA) are an extraction method based on appearance with the global structure features. The global structure features have a weakness; that is the local structure features can not be characterized. Whereas locality preserving projection (LPP) and orthogonal laplacianfaces (OLF) methods are an appearance extraction with the local structure features, but the global structure features are ignored. For both the global and the local structure features are very important. Feature extraction by using the global or the local structures is not enough. In this research, it is proposed to fuse the global and the local structure features based on appearance. The extraction results of PCA and LDA methods are fused to the extraction results of LPP. Modelling results were tested on the Olivetty Research Laboratory database face images. The experimental results show that our proposed method has achieved higher recognation rate than PCA, LDA, LPP and OLF Methods.

***Keywords**: face recognition, feature fusion, global and local structure, LDA, PCA*

1. Introduction

Development of personal identification technology has shifted from the text based method into the image and the signal methods. Face recognition is part of biometrics field [1-4], [6], [7], [9]. It is the most widely used to office security system. Crusial problem on face recognition is feature extraction [9]. The result of feature extraction is used to recognize face, such as Principal Component Analysis (PCA) [10], [11], [17]. Main idea of PCA is to discover feature vectors based on the best value on image subspace, these vectors are well known *"Eigenfaces"* as image features. PCA has conducted dimension reduction so that number of dimensions used equal or less than number of training set used. [12]. Location and shape data generated by PCA change when transformed into different sub space. Linear Descriminant Analysis (LDA) doest not change data set and try to provide a separate class. LDA is extraction method to bring the data sets in one class and the distance between classes of data sets [5], [8]. However, for both PCA and LDA has a weaknes, extraction result obtained is global stucture, in fact local sctructure is also very important to characterize an object [14] such as Locality Preserving Projection [2] and orthogonal laplacianfaces [1], [4]. In this research, we propose a new approach to select and to fuse the extracted features that have global and

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local structures. These features are sorted in descending order and fused from the most to the least dominant feature.

2. Proposed Method

In this research, we devide two main processes, which are the training and the testing processes. On the training process, training sets are extracted by PCA, LDA and locality preserving projection (LPP). The results of feature extraction are projected and selected. The selection results of the training process are re-fused into a whole feature. Whereas on the testing process, testing set is projected on each of the projection results of the training sets and selected according to the number of results in the the training sets selection. Similarly, the features on the testing set can be achieved by re-fusing of the feature selection. To recognize face images, similarity measurement is conducted by comparing to features on each the training and the testing sets resulted as shown in Figure 1.

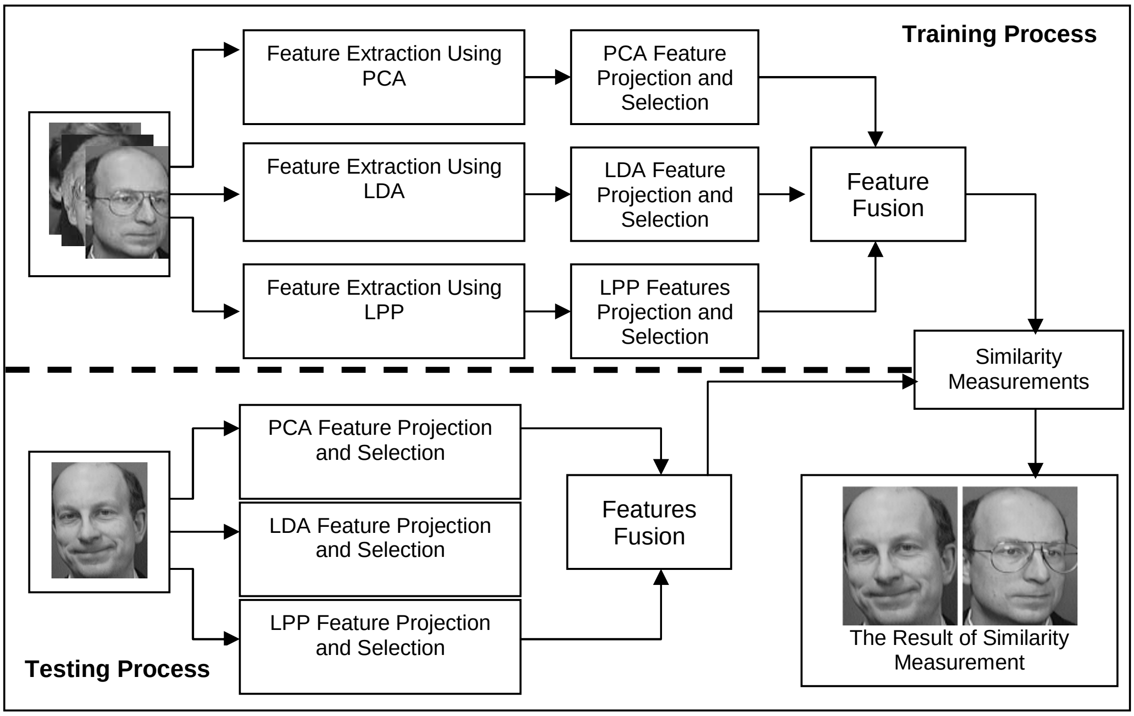

Figure 1. The Proposed Method System

2.1. Feature Extraction by Using Principal Component Analysis

Kurhunen-Loeve is linear technique used to project the higher into the lower dimension data. It is called as Principal Component Analysis (PCA) [10], [11], [17]. If an image dimension is represented by using *n* (image row x coloumn) and number of training set used is *m*, in this case *m*<<*n*, then it can be expressed by using the following

$$\begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ \ldots\ldots \\ X_m \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \ldots\ldots & x_{1,n} \\ x_{2,1} & x_{2,2} & x_{2,3} & & x_{2,n} \\ x_{3,1} & x_{3,2} & x_{3,3} & & x_{3,n} \\ \ldots\ldots & & & & \ldots\ldots \\ x_{m,1} & x_{m,2} & x_{m,3} & \ldots\ldots & x_{m,n} \end{bmatrix} \quad (1)$$

The average of all training set can be written by using the following equation

$$\mu_i = \frac{\sum_{j=1}^{m} x_{j,i}}{m} = [\mu_1, \mu_2, \ldots\ldots\ldots\ldots\ldots\ldots\ldots, \mu_n] \quad (2)$$

Based on the face image average, the matrix covariance can be reprsented by using the following equation

$$C = \frac{1}{m-1}\phi_{j,i}\phi_{j,i}^T$$

$$C = \frac{1}{m-1}(x_{j,i} - \mu_i)(x_{j,i} - \mu_i)^T \quad (3)$$

The eigenvalue and the eigenvector of Equation (3) can be calculated by using the following equation

$$\begin{aligned} C\Lambda &= \lambda I\Lambda \\ (\lambda I - C)\Lambda &= 0 \\ Det\ (\lambda I - C) &= 0 \end{aligned} \quad (4)$$

The result of Equation (4) has *m* dimension, where $m<<n$, so the minimum number of dimension reduction obtained is $n - m$ [10], [11].

2.2. Feature extraction by using Linear Descriminat Analysis

Linear Descriminant Analysis (LDA) is improvement of PCA process, LDA is used to maximize the difference of between-class ratio and minimize within-class ratio [5], [8]. The largest between-class ratio and the smallest within-class ratio obtained, the feature extraction resulted is the better. The difference of LDA ratio can be expressed by using the following equation

$$W_{LDA} = \underset{W}{\arg\max} \frac{W^T.S_B.W}{W^T.S_W.W} \quad (5)$$

and

$$S_B = \sum_{i=1}^{n} n_i.(X_i - \mu)(X_i - \mu)^T \quad (6)$$

$$S_W = \sum_{i=1}^{n} \sum_{x_k \in X_i} .(X_k - \mu_i).(X_k - \mu_i)^T \quad (7)$$

The eigenvalue and the eigenvector of the LDA can be calculated by using the following equation

$$S_B W_i = \lambda S_w W_i \quad (8)$$

2.3. Feature Extraction by Using Locality Preserving Projection

PCA and LDA aim to preserve the global structures. However, in many real world applications, the local structures are more important. Locality Preserving Projection (LPP) is new algorithm for learning with local structures. The local structure features are more important than global structure features [2]. LPP seeks to preserve the intrinsic geometry of the data and the local structures. Objective function of LPP can be expressed by using the following equation

$$\min \sum_{ij} (f_i - f_j)^2 W_{ij} \tag{9}$$

W is similarity matrix and it can be written by using the following equation

$$W_{ij} = \begin{cases} e^{-\frac{(x_i - x_j)^2}{t}} & \text{if } x_i \text{ is among k nearest neighbors of and } x_j \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

This function can be reduced in the form $a^T XLX^T a$, where $X = [x_1, x_2, \ldots, x_M]$. $D_{ii} = \Sigma_j W_{ij}$ and $L = D - W$ (*Laplacian* matrix). *D* can give natural measurement on the data points. Whereas LPP vector can be achieved by solving minimization of the following equation

$$a_{opt} = \arg\min a^T XLX^T a \tag{11}$$

with $a^T XDX^T a = 1$

Vector transformation of *a*, which minimize objective function of the eigenvalue and the eigenvector can be formulated by using the following equation

$$XLX^T a = \lambda XDX^T a \tag{12}$$

2.4. Feature Selection and Fusion of the Extraction Result by Using PCA, LDA and LPP

Fusion of feature extraction results is usually conducted on an appearance global structure only, such as PCA+LDA [15], PCA+LDA+ICA [16]. In fact, the local structure is also very imorptant to characterize an object. In this research, we propose an appearance feature selection and fusion of the global and the local structures. An appearance feature extraction with the global structures is resulted by PCA and LDA. Whereas for the local structures are resulted by LPP. Feature extraction results for PCA, LDA and LPP respectively can be expressed by using the following equation

$$\Lambda PCA = [\Lambda 1,1; \Lambda 1,2; ...; \Lambda 1,m] \tag{13}$$

$$\Lambda LDA = [\Lambda 2,1; \Lambda 2,2; ...; \Lambda 2,m] \tag{14}$$

$$\Lambda LPP = [\Lambda 3,2; \Lambda 3,2; ....; \Lambda 3,m] \tag{15}$$

If number of features extracted for each the feature extraction method is *m*, whereas the number of feature selection is *S* and *S*<*m*, than number of features fusion of PCA+LDA+LPP can be represented by 3*S*. Feature selection and fusion modelling can be shown in Figure 2. The result of feature fusion can be written in the following matrix

$$\Lambda^{fusion} = \begin{bmatrix} \Lambda_{1,1} & \Lambda_{1,2} & \Lambda_{1,3} & \ldots & \Lambda_{1,S} \\ \Lambda_{2,1} & \Lambda_{2,2} & \Lambda_{2,3} & \ldots & \Lambda_{2,S} \\ \Lambda_{3,1} & \Lambda_{3,2} & \Lambda_{3,3} & & \Lambda_{3,S} \end{bmatrix} \tag{16}$$

To simplify calculation, Equation (16) can be written in the row vector as shown in the following equation

$$\Lambda^{fusion} = [\Lambda_{1,1}; \Lambda_{1,2}; \ldots, \Lambda_{1,S}; \Lambda_{1,S+1}; \Lambda_{1,S+2}; \ldots, \Lambda_{1,2S}; \Lambda_{1,S2+1}; \Lambda_{1,2S+,2}; \ldots, \Lambda_{1,3S}] \tag{17}$$

Equation (17) is fusion feature of PCA, LDA as the global structures and LPP as the local structures.

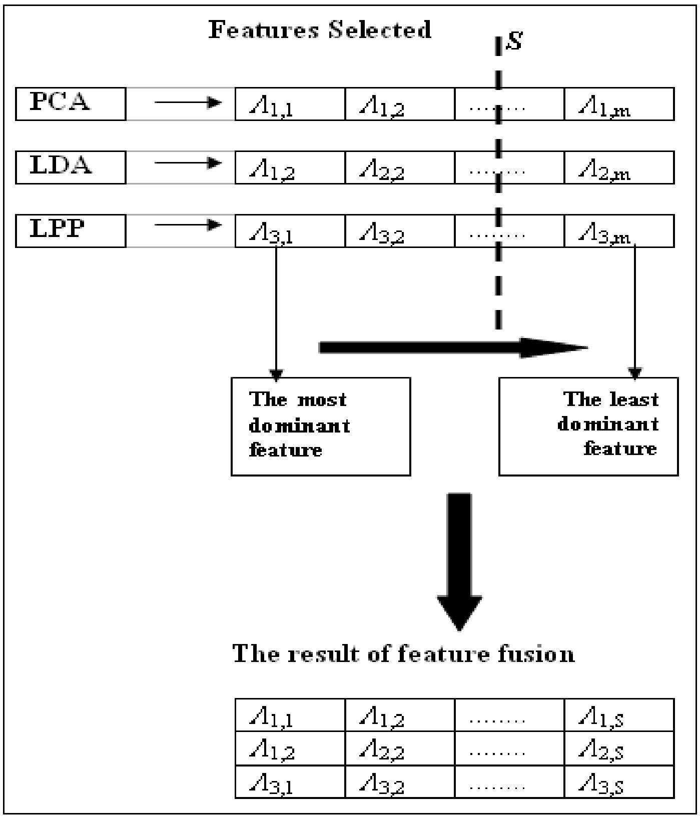

Figure 2. Selection and Fusion Features of the Extraction Results

3. Similarity Measurement

To deterimine the classification results, it is necessary to be conducted similarity measurement based on feature fusion. It can be written in the following equation

$$d\left(\Lambda_{Training}, \Lambda_{Testing}\right) = \frac{|\Lambda_{Training} - \Lambda_{Testing}|}{|\Lambda_{Training}| + |\Lambda_{Testing}|} \quad (18)$$

Recognition rate percentage resulted can be calculated by dividing number of true recognition results to number of the testing sets as written in the following equation

$$\mathrm{Re}cognition\_Rate = \frac{TrueClassification}{NumberOfTestingSets} x100\% \quad (19)$$

4. Experimental Results and Analysis

In this research, we utilize the Olivetty Research Laboratory (ORL) face image to test proposed method. The ORL face image consists of 40 persons and for each person has 10 poses, so number of face images used is 400 face images [13]. For some persons, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / without glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement). Figure 3 is sample of ORL face image

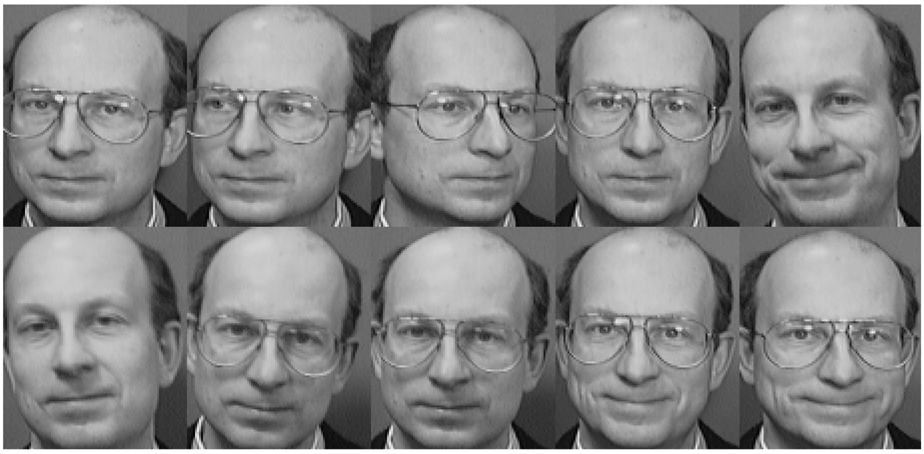

Figure 3. Sample of Olivetty Research Laboratory Face Image

4.1. Experimental Scenarios

To compare the experimental results, we perform 3 scenarios. The first scenario, number of training sets used was 5 poses for each person and the remaining 5 poses were used as testing set. The second scenario, number of training sets was increased to 6 poses for each person and the remaining 4 poses were used for testing set. And the last scenario, number of training sets used was 7 poses and the remaining 3 poses were used as testing set. Whereas number of features used to measure the similairity is 5 to 50 features for each method

4.2. Results and Analysis

The experimental results of the first scenario can be shown in Figure 4. The more number of dimensions used, the higher recognition rate percentage achieved. This phenemonen also appeared on the second and the last scenarios. The more number of training sets used, the higher recognition rate percentage obtained.

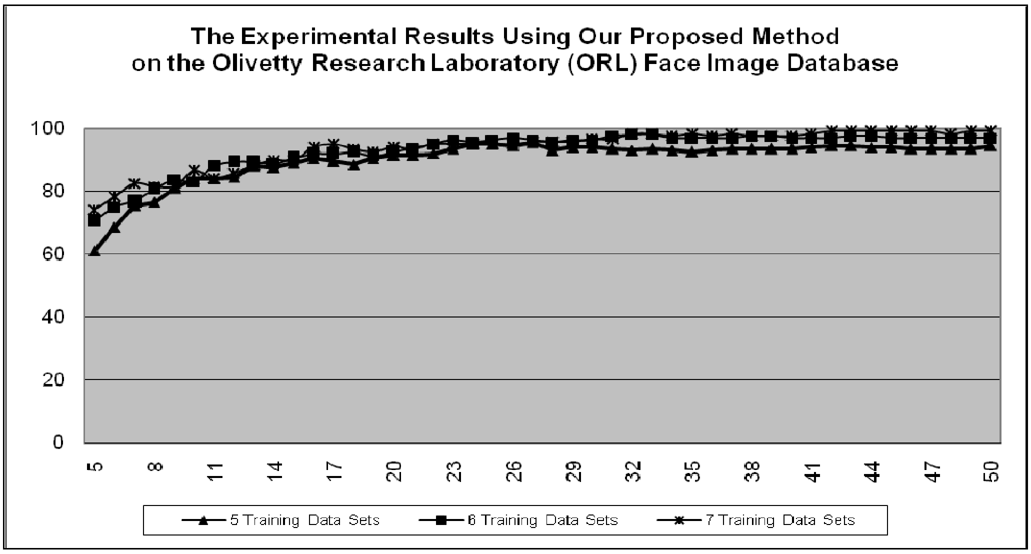

Figure 4. The Experimental Results Using Our Proposed Method
On The Olivetty Research Laboratory (ORL) Face Image Database

On the high dimension, recognition rate percentage has stable tendency, whereas on the low dimension has upward trend. Some errors occurred when using the features in small quantities due to the number of dominant features that are not used as a measurement of similarity. It can be prooved by increasing in the recognition rate percentage when the features used to measure similarity were increased. Maximum recognition rate for each scenario can be shown in Table 1. The maximum recognition also tends to rise in accordance with the amount of training data used. The experimental results have also compared to other methods, such as PCA, LDA, LPP and OLF as shown in Table 2. We have compared our proposed method with other method such as PCA, LDA, LPP and OLF on the ORL face image database. Comparison results show that the proposed method has obtained higher recognition rate than other method the maximum recognition also tends to rise in accordance with the number of training sets used.

Table 1. The maximum Recognition Rate on the Olivetty Research Laboratory Face Image Database by Using Our Proposed Method

Scenario	Number of the training Sets	The order of the training Set	The order of the testing Set	The maximum experimental results achieved (%)	Dimension Used
1	5	1,3,5,7,9	2,4,6,8,10	95.50	27
2	6	1,3,5,7,9,2	4, 6, 8,10	98.13	32
3	7	1,3,5,7,9,2,4	6,8,10	99.17	42

Table 2. Comparison of the Recognition Rate on the Olivetty Research Laboratory Face Image

Number of Training Sets	PCA	LDA	LPP	Orthogonal Laplacianfaces	Our Proposed Method
5	76,50%	94,44%	83,00%	91,50%	95,50%
6	81,25%	95,62%	90,63%	97,50%	98,13%
7	87,50%	98,83%	92,50%	99,17%	99,17%

5. Conclusion

Based on the experimental results on the ORL face database can be concluded Our proposed method “the Gobal (PCA and LDA) and the local structure features (LPP) fusion” of the extraction results based on appearance have increased the percentage rate for face image recognition. Fusion of appearance global and local structure dominant features can achieve higher recognition rate than PCA, LDA, Locality Preserving Projection and Orthogonal Laplacianfaces. The recognition results of our proposed method were influenced by number of training sets and dimensions used. The more number of training sets and dimensions used, the higher recognition rate achieved.

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