Jurnal Teknologi

Full paper

The Comparison of Laplacianfaces QR Decomposition and Linear Discriminant Analysis QR Decomposition Algorithm for Face Recognition System on Orthogonal Subspace

Purbandini*

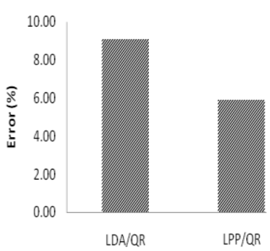
Program Study of Information System, Department of Mathematic, Faculty of Science and Technology, Airlangga University Indonesia

*Corresponding author: purbandini@fst.unair.ac.id

Article history

Received :2 February 2014
Received in revised form :
3 August 2014
Accepted :15 October 2014

Graphical abstract



Abstract

Development of an optimal face recognition system will greatly depend on the characteristics of the selection process are as a basis to pattern recognition. In the characteristic selection process, there are 2 aspects that will be of mutual influence such the reduction of the amount of data used in the classification aspects and increasing discrimination ability aspects. Linear Discriminat Analysis method helps presenting the global structure while Laplacianfaces method is one method that is based on appearance (appearance-based method) in face recognition, in which the local manifold structure presented in the adjacency graph mapped from the training data points. Linear Discriminant Analysis QR decomposition has a computationally low cost because it has small dimensions so that the efficiency and scalability are very high when compared with algorithms of other Linear Discriminant Analysis methods. Laplacianfaces QR decomposition was a algorithm to obtain highly speed and accuracy, and tiny space to keep data on the face recognition. This algorithm consists of 2 stages. The first stage maximizes the distance of between-class scatter matrices by using QR decomposition and the second stage to minimize the distance of within-class scatter matrices. Therefore, it is obtained an optimal discriminant in the data. In this research, classification using the Euclidean distance method. In these experiments using face databases of the Olivetti-Att-ORL, Bern and Yale. The minimum error was achieved with the Laplacianfaces QR decomposition and Linear Discriminant Analysis QR decomposition are 5.88% and 9.08% respectively.

Keywords: Laplacianfaces; Linear Discriminant Analysis; QR decomposition; dimension reduction; classification

Abstrak

Pengembangan sistem pengenalan wajah yang optimal akan sangat bergantung pada proses seleksi ciri yang digunakan sebagai basis pada pengenalan pola. Dalam proses seleksi ciri tersebut akan terdapat 2 aspek yang saling berpengaruh yaitu aspek reduksi terhadap jumlah data yang digunakan pada klasifikasi serta peningkatan kemampuan pendiskriminannya. Metode Linear Discriminant Analysis membantu penyajian struktur global sedangkan metode Laplacianfaces merupakan salah satu metode yang berdasarkan penampakan (appearance-based method) dalam pengenalan wajah, dimana struktur lokal manifold yang disajikan dipetakan dalam adjacency graph dari titik-titik data pelatihan. Linear Dicriminant Analysis dekomposisi QR memiliki biaya komputasi rendah karena memiliki dimensi yang kecil sehingga efisiensi dan skalabilitas yang tinggi bila dibandingkan dengan algoritma metode Linear Discriminant Analysis lainnya. Laplacianfaces dekomposisi QR merupakan algoritma untuk memperoleh kecepatan dan keakuratan yang tinggi serta ruang yang dibutuhkan untuk menyimpan data lebih kecil dalam pengenalan wajah. Algoritma ini terdiri dari 2 tahap. Tahap pertama memaksimalkan jarak within-class scatter matrices dengan menggunakan dekomposisi QR dan tahap kedua meminimalkan jarak between-class scatter matrices. Sehingga didapatkan diskriminan yang optimal pada data tersebut. Dalam penelitian ini, pengklasifikasiannya menggunakan metode jarak Euclidean. Dalam eksperimen ini menggunakan basis data wajah Olivetti-Att-ORL, Bern dan Yale. Kesalahan minimum dicapai dengan Laplacianfaces dekomposisi QR dan Linear Discriminant Analysis dekomposisi QR masing-masing adalah 5.88% dan 9.08%.

Kata kunci: Laplacianfaces; Linear Discriminant Analysis; dekomposisi QR; reduksi dimensi; klasifikasi

1.0 INTRODUCTION

At the end of today, the development of information technology has many and varied applications using face images as a source of information. In general, a facial image can provide specific information relating to personal identification based on face recognition that can be used in an electronic security system. Advantages possessed of a security system based on face recognition was the ability of its security which were relatively difficult to penetrate.

Face recognition was one of the pattern recognition approach for personal identification purposes as well as other approaches such as the introduction of biometric fingerprint, signature, retina of the eye and so on. Facial image identification in relation to the object that is never the same because of the parts that can be changed. These changes can be caused by facial expressions, light intensity and angle shooting or change accessories in the face. In this connection, the object of the same with a few differences should be recognized as an object of the same.

The method is based on the appearance of a very successful technique for face recognition in recent years. When using methods based on appearance, size n x m pixel image is described as a vector in the space dimension n x m (R^{nxm}). In practice, this n x m dimensional space is too large to do a quick face recognition. To solve the problem of space dimension reduction done this. The technique is very well known for this purpose was Linear Discriminant Analysis (LDA). LDA is among the most optimal dimension reduction methods for classification, which provides a high degree of class separability for numerous applications from science and engineering [3][15].This method aims to present a global structure of the image space origin [1]. In many real-world applications, the local structure was more important. Therefore, Locality Preserving Projection (LPP) was a linear technique that can provide local manifold structure modeled by an adjacency graph from the training data points [12][14].

There are several methods of face recognition are now developing such Eigenfaces, Fisherfaces and Laplacianfaces. In Eigenfaces method using Principal Component Analysis (PCA) [5][6], Fisherfaces using PCA [2][7] and LDA while Laplacianfaces using LPP [12]. Laplacianfaces a basis vector that is generated by LPP. Some researchers have made improvements including face recognition system that Fisherfaces QR decomposition method known LDA/QR algorithm [1][16] and Lapalacianfaces QR decomposition method known LPP/QR algorithm [11]. This algorithm consists of 2 stages. The first stage algorithm maximize the distance of between-class scatter matrices by using QR decomposition and following with the second stage algorithm minimizing the distance of within-class scatter matrices. Because the algorithms are equally using QR decomposition, the purpose of this study was to compare the two algorithms to determine the advantages of each algorithm.

2.0 EXPRIMENTAL

2.1 Face Database

In this testing to evaluate the performance of the algorithm using three standard face databases, (1) Olivetti face database-Att-ORL [19], which includes 40 people each person has 10 frontal face images that have a size of 320x243 which has the characteristics of the variation change the face position and lighting variations absence with minimum changes in facial expressions, the face image is used first normalized by reducing the size of a 65x67; (2) database University of Bern (UB) [18], which includes 30 people each person has a 10 frontal face images that have a size of 512x342, have characteristics that relatively small changes in facial expression and changes in the position of the head to the left, right, top and bottom of ± 30 degrees, the face image is used first normalized by reducing the size of a size of 120x139 normalized; and (3) Yale database [17], which contains 15 images each person has 11 variations that have a size of 320x243, the subject varies with gender, facial expression, lighting and accessories face, the face image is used first to reduce the size to be normalized 104x136. In Table 1 shows the statistics of the data base used in the test faces.

Table 1 Statistics of the face database used in testing

Face Database	Size	Dimension
ORL	400	4355
UB	300	16680
Yale	165	14144

2.2 Linear Discriminant Analysis QR Decomposition (LDA/QR)

The LDA/QR algorithm consists of 2 levels. The first level aims to maximize the between-class scatter of distance matrix (S_b) by applying the QR decomposition to a small matrix size up on the first floor with an algorithm named pre-LDA/QR algorithm. On the second floor designed to minimize the within-class scatter of distance matrix (S_w) and combine the information from the results of the first floor. After obtaining between-class scatter matrix ($\tilde{S}_b$) and in a reduced class ($\tilde{S}_w$), then do find the eigenvalues and eigenvectors of the matrix $\tilde{S}_w^{-1}\tilde{S}_b$ if non-singular, or vice versa. The conclusion of a non-singular form.

Suppose the data matrix A $\in \Re^{dxn}$ R_{dxn} where each a_i is a vector field in *d*-dimensional space. The assumption that A consists of the *c* class $\{\Pi_i\}_{i=1}^{c}$ and size of the *i-th* class $|\Pi_i| = n_i$. Definition of between-class distribution matrix (S_b), the within-class distribution matrix (S_w) and total distribution matrix (S_t) is as follows [1][2][14]: $S_b = H_b H_b^t$, $S_w = H_w H_w^t$ and $S_t = H_t H_t^t$

where $H_b = \left[\sqrt{N_1}(m_1 - m), \ldots, \sqrt{N_c}(m_c - m)\right] \in \Re^{dxn}$,

$H_w = A\left[m_1 e_1^t, \ldots, m_c e_c^t\right] \in \Re^{dxn}$ and $H_t = A - me^t \in \Re^{dxn}$,

$e_t = (1\ldots,1)^t \in \Re^{dxn}$, m_1 is the average value of the i^{th} class and m is the overall average value of the data matrix. Where $S_t = S_b + S_w$ is the first level of the LDA / QR algorithm helping to solve optimization problems.

$$G = \arg\max \text{trace}\left(G^t S_b G\right) \quad (1)$$

This optimization is used for between-class to maximize distance matrix (S_b). The solution can be obtained by solving the eigen value problem on S_b. Besides, it also can be solved via QR decomposition of the centroid matrix C where $C = (m_1, m_2, \ldots, m_c)$ which consists of a centroid *c*. $C = QR$ is QR decomposition of C, which $Q \in \Re^{nxc}$ is a matrix of orthonormal columns and $R \in \Re^{nxc}$ is upper triangular. And $G = QV$ to get an orthogonal matrix V by solving the optimization problem at

Equation (1). Thus $\mathrm{trace}\left(G^t S_b G\right) = \mathrm{trace}\left(V^t Q^t S_b Q V\right)$ for the orthogonal matrix V.

2.3 Laplacianfaces QR Decomposition (LPP/QR)

In this algorithm to learn the structure of face manifold using Laplacianfaces method, which is a function of base Laplacianfaces obtained by LPP method. LPP looking for direction to present the intrinsic geometry of the data training of local structures. Objective function of LPP was as follows:

$$\min \sum_{ij} \left(y_i - y_j\right)^2 W_{ij} \tag{2}$$

where y_i is the one-dimensional depiction of the x_i and the matrix W is a similarity matrix. Laplacianfaces is a function of the base with the LPP solution the minimum eigen value for the purpose of minimizing the objective function of LPP.

To analyze theoretically from the LPP associated with the PCA and LDA to obtain the covariance matrix XLX^T, if L was the Laplacian matrix $\frac{1}{n}I - \frac{1}{n^2}ee^t$ where n is the number of data, I is the identity matrix and e is a column vector at each data. Weighting matrix S gives $\frac{1}{n^2}$ of any data that was $S_{ij} = \frac{1}{n^2}$ for every i and j. $D_{ij} = \sum_j S_{ji} = \frac{1}{n}$. So Laplacian matrix $L = D - s = \frac{1}{n}I - \frac{1}{n^2}ee^T$

$$XLX^T = \frac{1}{n}X\left(I - \frac{1}{n}ee^T\right)X^T = E\left[\left(x_i - m\right)\left(x_i - m\right)^T\right] \tag{3}$$

LPP analysis associated with LDA. To solve the problem in LDA eigenvalues then used $S_b w = \lambda S_w w$. The class c and each class consists of the *i-th* sample of n_i points. Assume that m_i is a vector average of the class-i and x_i indicates the sample point *i-th* class. To calculate the matrix S_w and S_b:

$$S_w = \sum_{i=1}^{l}\left(\sum_{j=1}^{n_i}\left(x_j - m_i\right)\left(x_j - m_i\right)^T\right) = \sum_{i=1}^{l}\left(X_i L_i X_i^T\right) \tag{4}$$

$$S_b = \sum_{i=1}^{k} n_i \left(m_i - m\right)\left(m_i - m\right)^T = C - XLX^T \tag{5}$$

LPP algorithm :

Step 1: PCA projection.

The set of the original image $\{x_i\}$ is projected into the PCA subspace by removing the smallest principal component. They only use 98% of information in the error terms of re-construction. Furthermore the results of the transformation matrix PCA, W, denoted by W_{PCA}

Step 2: Build the nearest adjacency graph.

Let G denote a graph with n nodes. Node-i describes face image x_i. Edge will be placed between nodes i and j if x_i and x_j is located adjacent to the x_i are among the k nearest neighbors of x_j or x_j is among $_k$ nearest neighbors of x_i. Adjacency graph up nearby are estimates of local manifold structure. In this case it is said that the use of k nearest neighborhoods resulted in an increase in the complexity of the calculations.

Step 3: Perform the selection of weights.

The weightings used are heatkernel:

$$W_{ij} = e^{\frac{-\left\|x_i - x_j\right\|^2}{t}} \tag{6}$$

if nodes i and j are connected, it will put equality above weights W_{ij} in others will be put $W_{ij} = 0$, t is a constant parameter. Weight matrix W in graph G to model the structure of the face manifold with the presentation of the local structure.

Step 4: Get eigen map.

To obtain a value eigen vectors and eigen values, and eigen vector calculation of eigen values eigen vectors common problems

3.0 RESULTS AND DISCUSSION

3.1 Classification Accuracy

In this test aims to evaluate and compare the algorithms LDA/QR and LPP/QR in terms of studying the classification accuracy of face recognition. In Table 2 presents the results of testing the classification accuracy of face recognition algorithm between LDA/QR and LPP/QR on ORL, UB and Yale face database.

Table 2 The results of measurements of classification accuracy of face recognition on ORL, UB and Yale database

Dataset	Train Data	LDA/QR (%)	LPP/QR (%)
ORL	ORL 5	86.50	94.00
	ORL 6	91.25	94.38
	ORL 7	92.50	95.83
UB	UB 5	88.67	94.67
	UB 6	89.17	95.00
	UB 7	91.11	97.78
Yale	Yale 5	84.44	86.67
	Yale 6	86.67	94.67
	Yale 7	95.00	96.67

In Figure 1 shows the classification accuracy measurements on ORL face database, UB and Yale by using LDA and LPP/QR. In this test, using the term train which states the amount of data poses as training data. Train 5 means 5 poses as training data and the rest as test data. Train 6 means 6 poses as training data and the rest as test data. Train 7 means 7 poses as training data and the rest as test data.

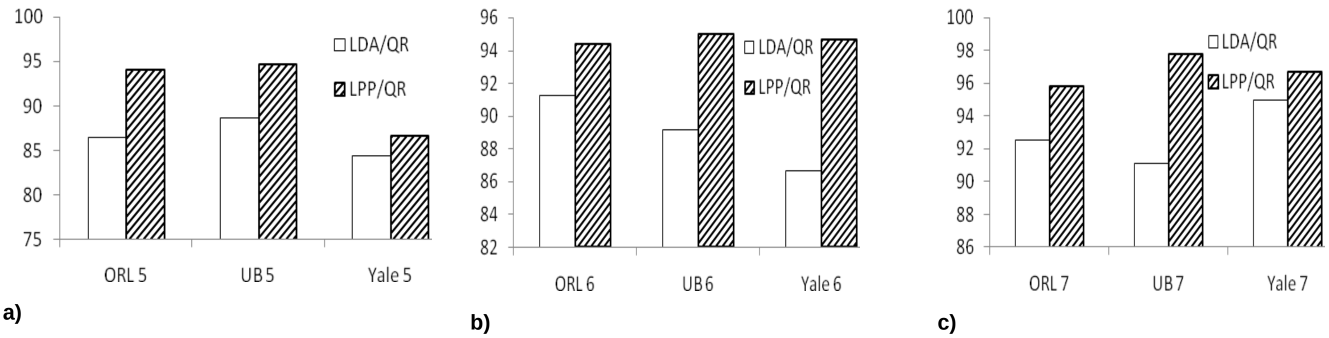


Figure 1 Measurement of classification accuracy on ORL, UB and Yale face recognition Train5, Train6 and Train7

3.2 Efficiency

In this study the efficiency of the testing LDA/QR and LPP/QR algorithm, with the help of the CPU time. Measurement results can be seen in Figure 2. In this test using data Train5, data Train6 and data Train7 for each of the ORL, UB and Yale face database.

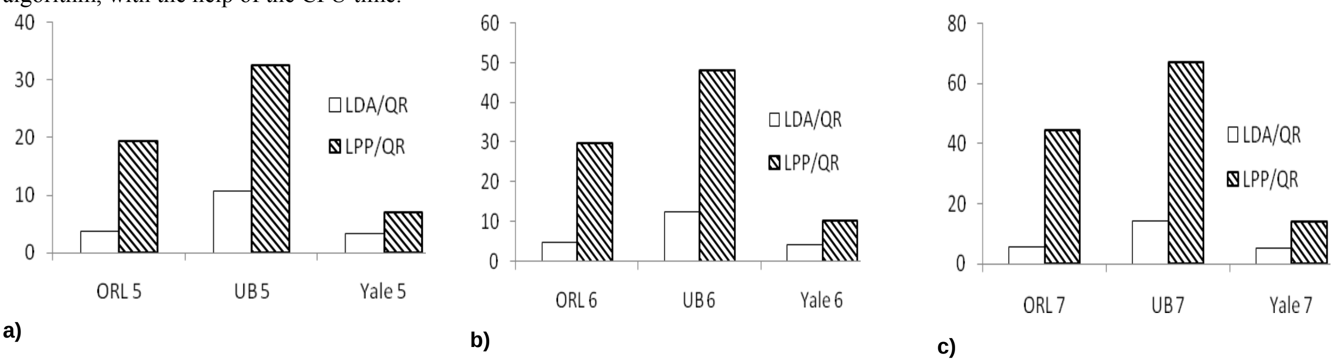


Figure 2 Measurement time face recognition Train5, Train6 and Train7

3.3 Scalability

Scalability is a measurable amount of space required in the algorithm, scalability to very high dimensional reduction algorithms are needed for large data. Some algorithms including PCA, PCA + LDA, LDA / GSVD and RLDA need all the data in main memory for computing SVD or GSVD and this can not be measured (scalable) [5][6]. LPP/QR has high scalability for the number of classes is small enough stored in the main memory.

Scalability of the algorithm can be analyzed as follows: first calculate the average value of the m_i class on c-class, and the average value of the total m of the data, save matrix H_b in main memory. Then the matrix QR decomposition applied to H_b. The data stored in the main memory can be called in to work on matrix multiplication $Z = (H_w)^T Q$, where the matrix $Z \in \Re^{t \times t}$. So at matrix $S_b = RR^T$ and $S_w = Z^T Z$ were called $\tilde{S}_b$, $\tilde{S}_w$ and $\tilde{S}_b^{-1}\tilde{S}_w$, and has the size txt, where $t = N$-k-2. The data have been mapped in the PCA space eigenvalues form will be called upon to do so has the size of matrix multiplication nxN. Table 3 shows the comparison of the time complexity and space on the algorithm of LDA/QR and LPP/QR

Table 3 The comparison of the time complexity and space on the algorithm of LDA/QR and LPP/QR

Algorithm	Time Complexity	Space Complexity
LDA/QR	O(nNk)	O(nk)
LPP/QR	O(nNk)	O(nN)

In this study the scalability testing of LDA/QR and LPP/QR algorithms, measurement results can be seen in Figure 3. At this scalability measurements using one UB face database. In Figure 3 shows the comparison of the measurement of scalability to the number of training data in the LDA/QR and LPP/QR algorithms. Results of this test indicate the increase in the amount of training data increases linearly scalability.

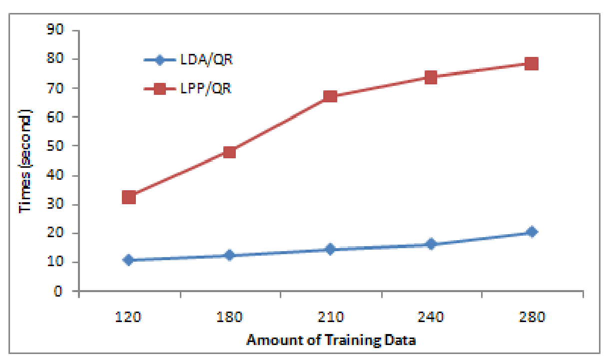


Figure 3 Measurement of scalability to the number of training data in the UB face database

The results of this test indicate an increase in the amount of training data increases linearly scalable methods such as LDA/QR. This means that the LPP / QR is a linear technique that can provide local manifold structure is mapped in the adjacency graph of the training data points.

■4.0 CONCLUSION

Algorithm LPP/QR has almost the same efficiency LDA/QR algorithm. LPP/QR algorithms has high classification accuracy. In this case shows that the appearance-based method is a very successful technique for face recognition algorithms which has the ability to recognize faces up to 94.12%. This means that the LPP/QR was a linear technique that can provide local manifold structure mapped in the adjacency graph of the training data points. The efficiency and scalability of the training data from LPP/QR algorithms show that the same shape with the LDA/QR algorithm was linear. The time required to process LPP/QR algorithm was higher than the LDA/QR algorithm for LPP/QR influenced by weighting the effect size Nk, while the algorithm LDA/QR just need time to process the data for $k-1$, where N = the number of training data points and k = number of classes. Classification accuracy of face recognition LPP/QR higher than the LDA/QR algorithm.

References

[1] Jieping Ye and Qi Li. 2005. A Two-Stage Linear Discriminant Analysis via QR-Decomposition. *IEEE Transaction on Pattern Analysis and Machine Intelligence.* 27(6): 929–941

[2] P. N. Belhumemour, J. P. Hespanha, and D. J. Kreigman. 1990. Eigenfaces vs. Fisherfaces: Recognation Using Specific Linear Projection. *IEEE Trans. Pattern Analysis and Machine Intelligence.* 19(7): 711–720.

[3] Fukunaga. *Introduction to Statistical Pattern Classification.* San Diego, California.

[4] Shakhnarovich and Moghaddam. 2004. *Face Recognation in Subspaces, Handbook of Face Recognation*. Spriger-Verlag

[5] Turk, M. and Pentlant, A. 1991. Face Recognition Using Eigenfaces. *Proc. IEEE Conf. of Computer Vision and Pattern Recognition*. 586–591

[6] Lindsay, I. Smith. 2002. *A Tutorial on Principal Component Analysis*.

[7] S. Balakrishnama, A. Ganapathiraju, *Linear Discriminant Analysis–A Breif Tutorial*. Institute for Signal and Information Processing.

[8] Howard Anton. 2000. *Elementary Linear Algebra*. 7thEdition. John Wiley & Sons Inc., New York.

[9] Shapira, L. G., and Stockman, G. C. 2001. *Computer Vision*. Prentice Hall, Upper Saddle River.

[10] Rully, S. 2004. *Sistem Pengenalan Wajah dengan Penerapan Algoritma Genetika pada Optimasi Basis Eigenface dan Proyeksi Fisherface*. Master Theses of Computer Science, Universitas Indonesia.

[11] Purbandini. 2006. *Sistem Pengenalan Wajah pada Subruang Orthogonal dengan Menggunakan Laplacianfaces Terdekomposisi QR*, Master Theses of Informatics Engineering, Institut Teknologi Sepuluh Nopember Surabaya Indonesia.

[12] Xiaofei He, Shuicheng Yan, Yuxiao Hu, Partha N and Hong-Jiang Z. 2005. Face Recognation Using Laplacianfaces. IEEE *Transactions on Pattern Analysis and Machine Intelligence, Col*. 27(3): 328–340.

[13] Tao Xioing, Jieping Ye, Qi Li, Vladimir, C. and Ravi, J. 2004. *Efficient Kernel Discriminant Analysis via QR Decomposition*. NIPS.

[14] Xiaofei He and Partha N. 2000. *Locality Preserving Projections (LPP)*. University of Chicago.

[15] Haesun Park, Barry L. Drake, Sangmin Lee, Cheong Hee Park. 2007. *Fast Linear Discriminant Analysis using QR Decomposition and Regularization*. Georgia Institute of Technology.

[16] Jianqiang Gao, Liya Fan, Lizhong Xu. 2012. Solving the Face Recognition Problem Using QR Factorization. *WSEAS Transactions On Mathematics*. 8(11): 712–721.

[17] Yale Center for Computational Vision and Control. 2006. *Yale Face Database*. http://cvc.yale.edu/ projects/yalefaces/yalefaces.html.

[18] University of Bern, Bern, Switzerland. 2006. *University of Bern Face Database*. ftp://iamftp.unibe.ch/pub/Images/FaceImages/.

[19] Research Center of Att, UK, *Olivetti–Att–ORL Face Database,* http://www.uk.research.att.com/ facedatabase.html.