Muhammad Imran RAZZAK[1,2], Muhammad Khurram KHAN[1], Khaled ALGHATHBAR[1], Rubiyah YUSOF[3]

CoEiIA, King Saud University, Saudi Arabia (1), International Islamic University, Pakistan (1), CAIRO, Universiti Teknologi Malaysia (3).

CSLDA and LDA fusion based face recognition

***Abstract**. Face recognition has great demands and become one of the most important research area of pattern recognition but there are several issues involved in it. Unsupervised statistical methods i.e. PCA, LDA, ICA are the most popular algorithms in face recognition that finds the set of basis images and represents faces as linear combination of those images. This paper presents a novel layered face recognition method based on CSLDA and LDA. The basic aim is to decrease FAR by reducing the face dataset to very small size through layered linear discriminant analysis. Although the computational complexity at the time of recognition is much higher than conventional PCA and LDA because weights are computed for small subspace at time of recognition but it provide a good results especially for large dataset. CSLDA of LDA is insensitive to large dataset and also small sample size and it provided 84% accuracy on Banca face database. The proposed approach is also applicable on other applications and recognition methods i.e. PCA, KDA, DLDA etc.*

***Streszczenie.** Rozpoznawanie twarzy jest jedną z bardziej ważnych metod graficznego rozpoznawania wzorów. Najbardziej popularnymi metodami są tu PCA, LDA, ICA gdzie twarz jest reprezentowana jako liniowa kombinacja bazowych komponentów. Artykuł prezentuje inną metodę bazującą na CSLDA i LDA. Głównym celem jest zmniejszenie FAR przez zredukowanie bazy danych do bardzo małych rozmiarów przez warstwową liniową dyskryminację. Złożoność komputerowa metody jest nieco większa ale otrzymane rezultaty, głównie zmniejszenie błędu są zachęcające. (**Rozpoznawanie twarzy przez fuzję metod CSLDA i LDA**).*

Keywords: Subspace, LDA, Fuzzy Rules, Face Recognition, Small Sample Size, SSS.
Słowa kluczowe: rozpoznawanie twarzy, grafika komputerowa.

Introduction

Face recognition is the branch of pattern recognition in which human visual perception in term of face recognition are imitated to computer. During the some last decades, biometrics recognition has been an intensive felid of research and consequently number of face recognition algorithms has been proposed computer scientists, neuroscientists and psychologist's efforts [1-2]. The computer scientists are trying to develop methods for face recognition whereas the psychologists and neuroscientists are working on biological perception of human face recognition process i.e. face recognition is done holistically or feature analysis etc [3]. It is the most popular biometrics used for security purposes due to its ease of end-user use, identification of an individual from distance and great demand for crimes and terrorism safety applications but it involved several challenges i.e. different types of variabilities of face under different environment that make it more difficult and less accurate. The variabilities which make the face recognition more complex are face illumination, face pose, expression eyeglasses and makeup etc. These variablaties has great influence for large database face images. Two issues in face recognition algorithms are: feature representation and classification based on features. This paper presents a novel technique classification side by fusing the client specific linear discriminant alaysis of LDA and LDA results. The proposed technique is intensive to both SSS and large face variation due to light or face expression by optimizing the separability criteria.

Low dimensional face feature representation with enhanced discriminatory is one of the main issue recognition. Based on feature representation; face recognition methods can be classified into two groups i.e. face and constituent. Face based method (appearance based technique) uses raw information face pixel i.e. PCA, LDA, KPCA, SVM whereas constituent based approach uses the relationships between face features i.e. nose, lips, and eyes. Compared to face based methods, the constituent based methods are more flexible but the performance is dependent on features. In other words appearance based approach works directly on images or appearance of the objects and process the image as 2D pattern where constituent based approach based on local level features. Among appearance based representation PCA and LDA based methods are the tow most power methods for dimensionality reduction and successifully applied in many complex classification problems such as speech recognition, face recognition, etc [4] . The accuracy of face recognition system is affected by small sample size problem and also by separability criteria of LDA. The separability criteria are not directly related to the classification accuracy. In order to use LDA on face recognition problem number of research has been done [5].In general LDA based methods perform better than PCA but on the other hand LDA based methods are facing problem with SSS. First Belhumeur et.al involved eigenanalysis of two inverted matrix products and uses class specific information for finding the projection that best discriminates among classes for face recognition [6]. Basically it finds the projection by maximizing the within class scatter and maximizing between class scatter [7].The aim of LDA is to find the representation of feature vector space. The accuracy of face recognition system is affected by small sample size problem and also by separability criteria of LDA. The spearability criteria are not directly related to the classification accuracy.

The conventional solution to misclassification for small sample size problem and large data set with similar faces is the use of PCA into LDA i.e. fisherfaces. PCA is used for dimensionality reduction and then LDA is performed on to the lower dimensional space [8]. However the use of LDA over PCA results in loss of significant discriminatory information. To avoid this loss, direct linear discriminate analysis (D-LDA) is used [9-10]. It performs directly on high dimensional to avoid the loss of discriminatory information. D-LDA has several issues in large variation and its performance is degraded in this case. Fractional-step linear discriminant analysis (F-LDA) used weighting function to avoid misclassification by assigning the more weight to the relevant distance for dimensionality reduction [11]. Yang et.al use PCA to reduce the dimension of feature space and then OFLD method is applied for feature extraction [12]. Penalized discriminant analyses (PDA) overcome the SSS problem and also smooth the coefficient of discriminant vector. Dia et.al presented inverse fisher discriminant ayalysis; it modifies the procedure of PCA and derives the regular and irregular information from Sw. Yang et.al presented fuzzy inverse FDA based on fuzzy FDA and inverse fisher discriminant analysis by using fuzzy K-nearest neighbor class. We present a novel technique for classification instated of feature extraction by reducing the dataset to produce better separability criteria using CSLDA over LDA results. It accepts high dimensional dataset and reduces the dataset for CSLDA by applying LDA. The proposed technique is intensive to both SSS and large face variation due to light or face expression by optimizing the separability criteria. The reset of the paper is organized as: section 2 and section 3 describes the fisher discriminant analysis and client specific linear discriminant analysis. Section 4 presents the proposed solution layered CSLDA of LDA computation and, section 5 presents the experimental results, performance evaluation and list of benefits of proposed technique, finally conclusion is presented in section 5.

Fisher Discriminant analysis

Fisher Linear Discriminant also referred as Linear Disciriminant Analysis is a classical pattern recognition method was introduces by Fisher (1934). It is very effective feature extraction method but facing issues for SSS problem. PCA express face into compact principal components through an optimal transformation which hold the maximum variance of data vector and LDA is the improved version of PCA. The conventional solution to misclassification for small sample size problem and large data set with similar faces is the use of PCA into LDA i.e. fisherfaces. PCA is used for dimensionality reduction and then LDA is performed on to the lower dimensional space [8].

The optimal projection W is matrix that maximizes the determinant of between class scatter matrix and within class scatter matrix ratio. The basis vector for LDA can be denoted as

(1) $$W = \arg \max \frac{|W^T W_{PCA} S_B W_{PCA} W|}{|W^T W_{PCA} S_w W_{PCA} W|}$$

where: $W=[w_1,w_2 \ldots w_m]$ is the set of eigen vector between class scatter matrix S_B and within class scatter matrix S_w corresponding to m largest.

Between class scatter matrix is define as

(2) $$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T$$

Within class scatter matrix is define as

(3) $$S_w = \sum_{i=1}^{C} \sum_{x_k \in X_j} (x_k - \mu_i)(x_k - \mu_i)$$

where $\mu_i$is the Xi class mean and Ni is the number of samples in ith class.

Face recognition using LDA has been discussed by many authors [1-12]

CSLDA

The PCA and LDA based approaches are based on global representation of testing and training data in feature space while client specific liner discriminant analysis (CSLDA) is a conventional LDA representation that involved multiple shared faces. Instead of multiple shared fisher face among all clients, CLSDA uses the PCA and LDA to generate a client specific template for each user. As only one fisher face is involved in authentication, thus it is more speedy than LDA and PCA. The authentication is based on comparison of claimed user's features with face images features. The claim user is either accepted or rejected based on the minimum Euclidean distance computing.

The decision is based on the combined score of distance to client and distance to imposter mean. It can be either tested against the client mean or can be tested against the imposter mean.

(4) $$\begin{aligned} & d_c = |a_i z - a_i \mu_i| \\ & d_c \le t_c \qquad Claim \quad accept \\ & d_c \ge t_c \qquad Claim \quad reject \end{aligned}$$

(5) $$\begin{aligned} & d_i = |a_i z - \frac{N_i}{N - N_i} a_i \mu_i \quad | \\ & d_i \le t_i \qquad Claim \quad reject \\ & d_i \ge t_i \qquad Claim \quad accpet \end{aligned}$$

Proposed methodology

Basically there are two issues in face recognition are: feature representation and classification based on extracted features. This paper discusses classification part by fusing the client specific linear discriminant analysis of LDA and LDA results. The proposed technique is intensive to both SSS and large face variation due to light or face expression by optimizing the separability criteria. First the face are localized and rotated by calculating the angle from eyes point. From the rotated face, normalized face is extracted and this normalized face is used for feature extraction using fisher discriminate analysis. First the close matched faces are extracted instead of one selection by LDA. Based on LDA results, CSLDA is computed for every selected face and finally results are fused with LDA results.

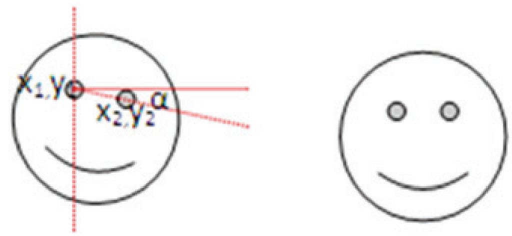

Fig. 1. Raw face rotated face

a) b) c)

Fig. 2. Face rotation along y-axis: a) raw face, b) rotated face, c) normalized extracted face

Face Normalization

The angle α is calculated from the two eye points and face is rotated by angle α along y axis. The angle is calculated as.

(6) $$d_1 = \sqrt{(x_1 - x_2)^2}$$

(7) $$d_2 = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

(8) $$\alpha = \cos^{-1}(d_1 / d_2)$$

The whole face is rotated pixel by pixel by using the following transformation

(9) $$\begin{aligned} x' &= x\cos\alpha - y\sin\alpha \\ y' &= y\cos\alpha - y\cos\alpha \end{aligned}$$

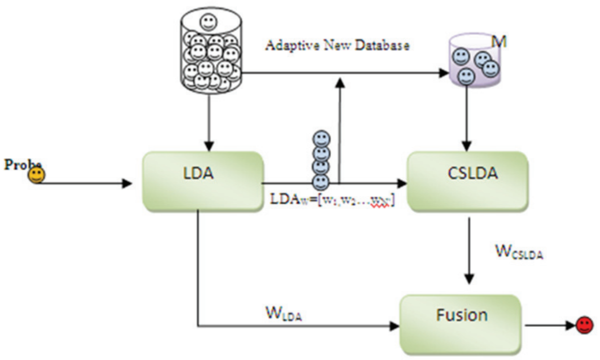

Fig. 3. Layered LDA (L-LDA)

CSLDA of LDA
Simply the problem can be stated as:

"Given a set of N classes, find M classes against a probe image P where M<<N and M are very closes to P and then identify the probe identity by using the CSLDA for each M Class"

The previous LDA based algorithm finds the optimal projection vector that maximize the between class scatter matrix and within class scatter matrix.

Suppose there are N clients face images and every client has ki samples of client. The total number of sample is given by

(10) $$K = \sum_{i=1}^{N} k_i$$

The M is the selected classes using linear discriminant analysis based on nearest neighbour approach on probe P and can be computed as

(11) $$Min[D] = | \ if \ \ d_i < \theta$$

(12) $$m_j = N_i(\underset{\theta}{Min}[D])$$

$$where \quad D = Euc\_dist\,[d_i, d_2, \dots d_N]$$

And

(13) $$M = \{m_1, \dots m_j\}$$

(14) $$where \ \ M \subseteq N \ \ and \ \ M <<< N$$

Thus this new adaptive dataset consist of K' faces.

(15) $$K' = \sum_{j=1}^{M} K_j$$

This new small adaptive subspace $LDA_{N_i'}$ consist of most similar faces of M selected clients as a result of minimum Euclidean distances less than θ by projecting the probe image. Unlike conventional LDA approaches selecting one optimized face as a recognition result, we select several faces from large data set using LDA to reduce the data set from N to M. Thus LDA is used for adaptive classification into sub classes to find the better seperablity criteria on small dataset instead of large dataset. CSLDA is performed on reduced mall data set instead of all data set and for all selected clients.

$$New \ size \ of \ traning \ users = M$$
$$where \ \ M' \subset N \ \ and \ \ M <<< N$$

Then new CSLDA is computed as

(16) $$Trainig \ \ size \ \ for \ CSLDA \quad K' = \sum_{j=1}^{M} K_j$$

(17) $$\mu' = \frac{1}{M}\sum_{j=1}^{M_i} z_j$$

$$x_j = U^T(z_j - \mu')$$

$$where \ U^T is \ M \ eigen \ vector \ and \ \ j = 1,2 \dots M$$

(18) $$\phi' = \frac{1}{M}\sum_{j=1}^{M'_i} x_j x_j^T$$

(19) $$v = \frac{1}{M}\sum_{j=1}^{N'_i} x_j \ \ client \ \ mean$$

And

(20) $$M' = \frac{M}{M - M_i}\sum_{j=1}^{N'_i} v v^T$$

(21) $$\varphi_i = \phi' - M_i'$$

(22) $$v = \varphi_i^{-1} v$$

Between class scatter matrix on new adaptive database is computed as

(23) $$S_B' = \sum_{j=1}^{M} N_j(\mu_j' - \mu')(\mu_j' - \mu')^T$$

(24) $$S_w' = \sum_{j=1}^{M} \sum_{x_k \in X_j} (x_k - \mu_j')(x_k - \mu_j')^T$$

(25) $$\mu' = \frac{1}{M}\sum_{j=1}^{M'} z_j$$

And similarly class mean

(26) $$\mu_j' = \frac{1}{M_j}\sum_{j=1}^{Kj} z_j$$

Fusion of CSLDA and LDA
We performed score level fusion by combining the LDA and CSLDA weights by using the following rules.

$$R-1 \ : \ \forall M \ \ if \ W_i < .003 \ \ then \ \ W_j = W_i$$
$$if \ \ j > 1 \ \ then \ \ Min\,(LDA) \ \ AND \ \ Min\,(CSLDA)$$
$$else \ \ M_i \ \ is \ \ recognized \quad face$$

Experiment results and discussion:

We have used BANCA face database for performance evaluation. It contains 10 images for each 40 subject with fontal view and all images are normalized. For testing we have used 5 to 8 images and for remaining for testing. The considerable performance is gained by applying layered linear discriminant analysis. The proposed scheme focuses on classification by using existing feature extraction technique and reducing the dataset to produce better separability criteria. Basically LDA is performed layered to find the new adaptive database and then CSLDA is performed on sub database and by considering each image in sub dataset as client. Three different cases are discussed. By using LLDA, FAR is almost reduces to 2.74. For training purpose we used 4, 6 and 8 images.

Algorithm: CSLDA of LDA

Input: A set of M training classes, each class contain *m* images and probe face image P

Output: Recognized Face Image

Algorithm:

Step 1: Calculate between class scatter matrix and within class scatter matrix on M classes

Step 2: Find minimum Euclidean distances D_i of Probe P by projecting on to the Feature Space on M if $D_k = D_i < \theta$

Step 3: Create new adaptive database of size M' for training where $M' \ll M$

Step 4: For each Client in M perform Step 5

Calculate new feature space on new adaptive database of size M'

Step 5: Calculate CSLDA on Small data set M by re-computing the between class and within class scatter matrix

Step 6: Fuse the two result (LDA and CSLDA) using AND

Fig. 5: Case-1: first row contain probe image, 2nd row contains the Euclidian distance computed on LDA, and row 3 contains the CSLDA results computed on adaptive new database as a result of row 2, whereas row 4 the recognized results

Fig. 6: Case-II: first row contain probe image, 2nd row contains the Euclidian distance computed on LDA, and row 3 contains CSLDA weights on small dataset, whereas row 4 contain new results after fusion.

Fig. 7: Case-III: first row contain probe image, 2nd row contains the Euclidian distance computed on LDA, and row 3 contains CSLDA weights on small dataset, whereas row 4 contain new results after fusion.

The figure 5 describes the Case-I, for probe P, the Euclidian distance computed by project probe on to the feature space of whole data, we selected six faces by using the rules. The figure shows that for probe P, the minimum Euclidian distance is .1488, thus by using conventional technique, the recognized face is different from the probe. To overcome this issue, we selected six faces having very less Euclidian distance and create new dataset and recomputed the feature space on this small dataset and CSLDA weights are computed for each image by considering each image as a client, thus it requires six times computation of CSLDA on small dataset.

The figure 6 describes the Case-II, for probe P, the 2nd row shows the Euclidian distance computed by projecting the probe on to the feature space of whole dataset, As in this case the face detected is accurate but still very difficult to decide the exact face due to small difference between other faces. Thus we selected six faces having the minimum and very close to probe image. The figure 6 shows that for probe P, the minimum Euclidian distance is 0.1266 but to find the exact face is still confusing so we created new dataset based on the LDA results and recomputed the feature space on this small dataset. Now CSLDA weighs are computed s based on small dataset and fuse the two results

Figure 7 describes the Case-III, for probe P; the Euclidian distance computed by project probe on to the feature space of whole data, we selected six faces by using the rules. The figure shows that for probe P, the minimum Euclidian distance with exact class is .4177 using LDA where as the minimum Euclidian distance is 0.0066. As $.0066>\theta$ thus the probe image is considered a imposter. The CSLDA-LDA is computational complex as compared to previous methods because creating of new adaptive database and re-computation of feature space is performed at classification time

Conclusion

We presented a novel class specific to client specific linear discriminant face recognition method based on Fisher's linear discriminant and CSLDA. The basic aim is to decrease FAR by reducing the face dataset to very small size through layered linear discriminant analysis. First the face is normalized using eye location and CSLDA is performed on selected face from LDA. Basically the selected LDA faces are more close to probe image, and the probe image may be one of them instead of minimum distance face. Although the computational complexity at the time of recognition is much higher than conventional PCA and LDA because training is required for new adaptive database at the time of classification and CSLDA weights are computed for each face in sub dataset. CSLDA-LDA provides significant performance gain especially similar face database and SSS problems with 84% accuracy and reduces FAR to 2.74 on Banca face database.

REFERENCES

[1] Zhao W., Chellappa R., Rosenfeld A., Phillips P.J., Face Recognition: A Literature Survey, ACM Computing Surveys, 2003, pp. 399-458.
[2] Scheenstra A. , Ruifrok A. , Veltkamp R. C. , A Survey of 3D Face Recognition Methods, LNCS June 2005
[3] Chellapa R., Charles L., Sirohey S., Human and Machine Recognition of Face, IEEE Proceedings, 1995.
[4] Lu J., Plataniotis K.N., Venetsanopoulos A.N., Face Recognition Using LDA-Based Algorithms, IEEE Transaction on Neural Network, 2003, vol 14.
[5] Yu H., Yang J., A Direct LDA Algorithm for High Dimensional Data with Application to Face Recognition, Pattern Recognition, 2001
[6] Oh B.J., Face Recognition using Radial Basis Function Network based on LDA, World Academy of Science and Technology 2005.
[7] Han P.Y., Jin A.T.B., Abas F.S., Neighborhood Preserving Discriminant Embedding in Face Recognition, Journal of Vis. Com. Image. R 2009
[8] Belhumeur P.N., Hespanha J.P, Kriegman D.J., "Eigenfaces vs Fisherfaces: Recognition using Class Specific Linear Projection", IEEE Transaction Pattern Analysis Machine Intelligence, 1997 vol 19.
[9] Chen L. F., Liao H.Y. M., Ko M.T., Lin J.C.,Yu G.J, A new LDA-based face recognition system which can solve the small sample size problem, Pattern Recognit., vol. 33, pp. 1713–1726, 2000.
[10] Yu H. and Yang J., A direct lda algorithm for high-dimensional data with application to face recognition, Pattern Recognit., vol. 34, pp. 2067–2070, 2001
[11] Lotlikar R., R. Kothari, Fractional-step Dimensionality Data with Application to Face Recognition IEEE Transaction Pattern Analysis Machine Intelligence, 2000 vol 22.
[12] Yang J., Yang J.Y., Why can LDA be Performed in PCA Transformed Space ?, Pattern Recognition 2003 vol 36.

***Authors**: Muhammad Imran Razzak, Dr. Muhammad Khurram Khan, Dr Khaled Alghathbar, Center of Excellence in Information Assurance, King Saud University, Saudi Arabia, E-mail: merazaq@ksu.edu.sa mkhurram@ksu.edu.sa, ksaksu@gmail.com. Prof Rubiyah Yusof, CAIRO, Universityof Technology, Malaysia*