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A Review of PCA and LDA Face Recognition Techniques

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Abstract**—** The security of information is becoming very significant and difficult. Face and facial feature detection plays an important role in various applications. Face Recognition system is used in security. In the field of image analysis and computer vision, face recognition presents a challenging problem due to distinct variation in facial expression, occlusion and illumination. A large number of face recognition algorithms have been developed in last decades. In this paper an attempt is made to review the two techniques i.e. PCA and LDA.

Keywords**—**Principal component analysis; linear discriminant analysis; face recognition; image processing; fisherface; eigenface.

I. INTRODUCTION

To recognize individuals humans often use faces. Early face recognition algorithms used simple geometric models, but now the recognition process has now matured into a science of mathematical representations and matching processes as there is a need to optimize both hardware and software component of a system especially when images are involved. Therefore, mathematically huge image database needs to be processed in such a manner that it gives results within seconds. This can only be achieved if some dimension reduction technique like PCA is applied which works on a principle of variance and linearity of data. However sometimes, data processed after dimension reduction still needs to be supplemented with another discriminant techniques which would help to process the data more efficiently as well as accurately. The current existing systems are still needs to be improved. Face recognition can be used for both verification and Identification.

There are several challenges [1] associated with face and facial feature detection due to the following factors.

a) *Intensity*: There are three types of intensity- color, gray, and binary.
b) *Pose*: Face images vary due to the relative camera-face pose, and some facial features such as an eye may become partially or fully occluded.
c) *Structural components*: Facial features such as beards, mustaches, and glasses may or may not be presented.
d) *Image rotation*: Face images directly vary by different rotations.
e) *Poor quality*: Image intensity in poor-quality images, such as blurred images, distorted images, and images with noise.
f) *Facial expression*: The appearance of faces depends on a personal facial expression.
g) *Unnatural intensity*: Cartoon faces and rendered faces from 3D model have unnatural intensity.
h) *Occlusion*: Faces may be partially occluded by other objects such as hand, scarf, etc.
i) *Illumination*: Face images may vary due to the position of light source.

Principal Component Analysis (PCA)

The PCA is one of the most successful techniques that have been used in image recognition and compression described by Turk and Pentland in 1991 [2]. It is also known as Eigenspace Projection or Karhunen-Loeve Transformation The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically, while retaining as much as possible of the variation present in the original dataset. This is the case when there is a strong correlation between observed variables. The jobs which PCA can do are prediction, redundancy removal, feature extraction, data compression, etc.

The main purpose of using PCA for face recognition is to construct the large 1-D vector of pixels from 2-D facial image and express it into the compact principal components of the feature space. This can be called eigenspace projection. Eigenspace is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images (vectors). PCA Method uses Eigenvectors and Eigenvalues for representing face images. These Eigenvectors can be thought of as a set of features which together characterize the variation between face images [2]. Each image location contributes more or less to each Eigenvector, so that we can display the Eigenvector as a sort of ghostly face which is called as an Eigen face.

Step 1: A set of M images (I_1, I_2, $I_3 \ldots I_M$) with size N*N can be represented by column or row vector of size N^2

Step 2: The average (μ) of the training set image is defined by

$$\mu = \frac{1}{M}\sum_{n=1}^{M} I_n \qquad (1)$$

Step3: Each trainee image differs from the average image by vector (Φ)

$$\Phi_i = I_i - \mu \qquad (2)$$

Step4: Total Scatter Matrix or Covariance Matrix is calculated from Φ as follows:

$$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T \qquad (3)$$

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$= AA^T$, where $A= [\Phi_1\Phi_2\Phi_3\ldots\ldots\Phi_n]$
Step5: Calculate the eigenvalues of the C, $\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_N$ (not practical since C is very large)
Step 6: Calculate eigenvectors of the C, $\mu_1, \mu_2, \mu_3, \ldots, \mu_N$
Step 7: Dimensionality Reduction step: The covariance matrix is very large, calculation of eigenvectors takes lots of time and increases the cost of recognition. So, another matrix L is formed, whose size is MxM, to make the computations mathematically manageable. So, the M eigenvalues and eigenvectors are calculated.
$L= A^TA$
Eigenvectors of C and L are equivalent. AA^T can have N^2 eigenvalues and eigenvectors. A^TA can have M eigenvalues and eigenvectors.
Step 8: The magnitude of eigenvalue describes the amount of variation contributed by an eigenface along the eigenvector direction.

The eigenvectors are arranged in descending order with respect to their corresponding eigenvalues and we can ignore the components of less significance.
So, the eigenface with small eigenvalues are neglected.
Instead of using all the M numbers of the eigenfaces, M' ≤ M numbers of the eigenfaces is sufficient to show its effect as maximum variance is contained in the first 5% to 10% of the dimensions.
Step 9: To classify an image, it can be projected into this feature space. Calculate the vectors of weights

$$\Omega^T= [\omega_1, \omega_2 \ldots \omega_{M'}] \quad (4)$$

where $\omega_k = \mu_k^T(I - \mu)$

$$k = 1,2,\ldots\ldots, M' \quad (5)$$

where M' represents not the total eigenfaces, but the ones with greater values.
Step 10: Compute the threshold.

In Recognition Procedure, to recognize a face, subtract the average face from it. Then, compute its projection onto the face space. Compute the distance in the face space between the face and all known faces. Reconstruct the face from eigenfaces. Compute the distance between the face and its reconstruction. If the distance between the face and its reconstruction is larger than threshold, then it is not a face, else if the distance in the face space between the face and all known faces is smaller than threshold, then it's a new face. If the distance in the face space between the face and all known faces is larger than threshold, then it's a new face
There are various limitations of this technique:
Illumination conditions: performance degrades with light changes.
Problems with eigenfaces: Different head pose, Different alignment, Different facial expressions.
Orientation: plane rotations can be handled, out-of-plane rotations are more difficult to handle.

Linear Discriminant Analysis (LDA)

LDA is a data separation and dimensionality reduction technique which is used for classification problems. LDA is also known as Fisher's Discriminant Analysis and it searches for those vectors that have directions that can best discriminate different classes [3]. It was first developed by Robert Fisher in 1936 for taxonomic classification [4]. Linear Discriminant group images of the same class and separate images of different class. This criterion tries to maximize the between-class scatter matrix measure while minimizing the within-class scatter matrix measure [5]. LDA works when the measurements made on independent variables for each observation are continuous quantities. When dealing with categorical independent variables, the equivalent technique is discriminant correspondence analysis.

For the same person, the within class scatter matrix (intrapersonal) is used which shows the variations due to the different lighting and face. For the different persons, between-class scatter matrix (extrapersonal) is used, which shows the variations due to difference in identity.

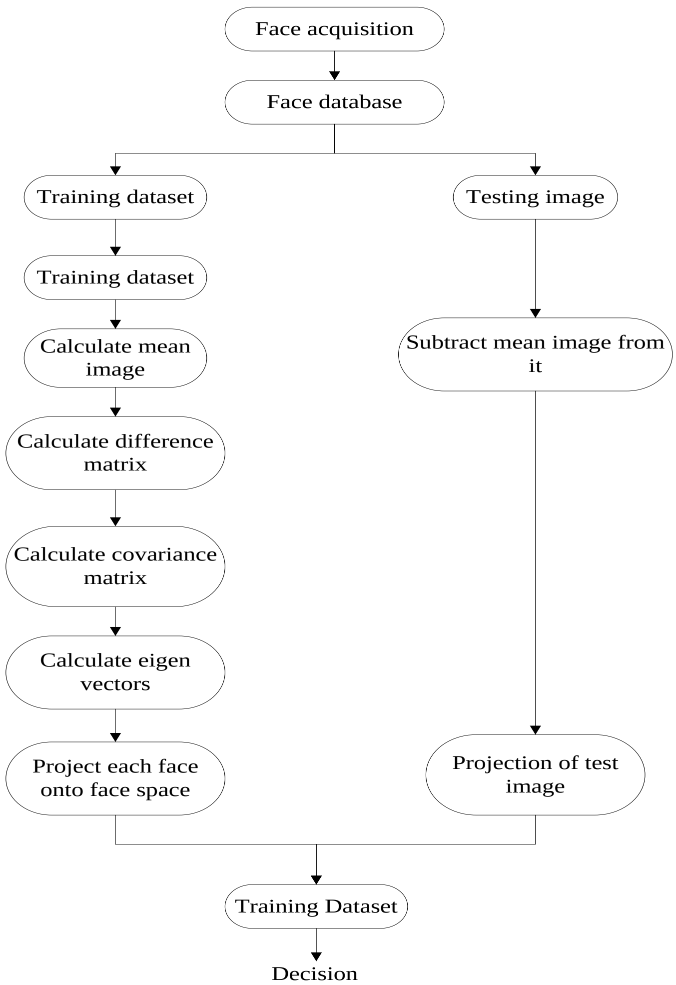

Fig. 1. PCA approach for face recognition.

Between -class scatter matrix, S_B

$$S_B = \sum_{i=1}^{c} M_i (x_i - \mu)(x_i - \mu)^T \quad (6)$$

Within -class scatter matrix, S_W

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

where M_i is the number of training samples in class i, c is the number of distinct classes, μ_i is the mean vector of samples

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belonging to class i and X_i represents the set of samples belonging to class I with x_k being the k-th image of that class. LDA finds a set of vectors W maximizing

$$W_{LDA} = \left|\frac{W^T S_B W}{W^T S_W W}\right| = [w_1\ w_2\ \dots\ w_m]$$

where $\{w_i \mid i = 1, 2, \dots, m\}$ is is the set of generalized eigenvectors of S_B and SW corresponding to the m largest generalized eigenvalues $\{\lambda_i \mid i = 1, 2, \dots, m\}$. W is the optimal projection matrix, which can be obtained via solving the generalized eigenvalue problem: $S_B W = \lambda\ S_W W$. This ratio is maximized when the column vectors of the projection matrix (W_{LDA}) are the eigenvectors of $S_W{}^{-1} S_B$[6].

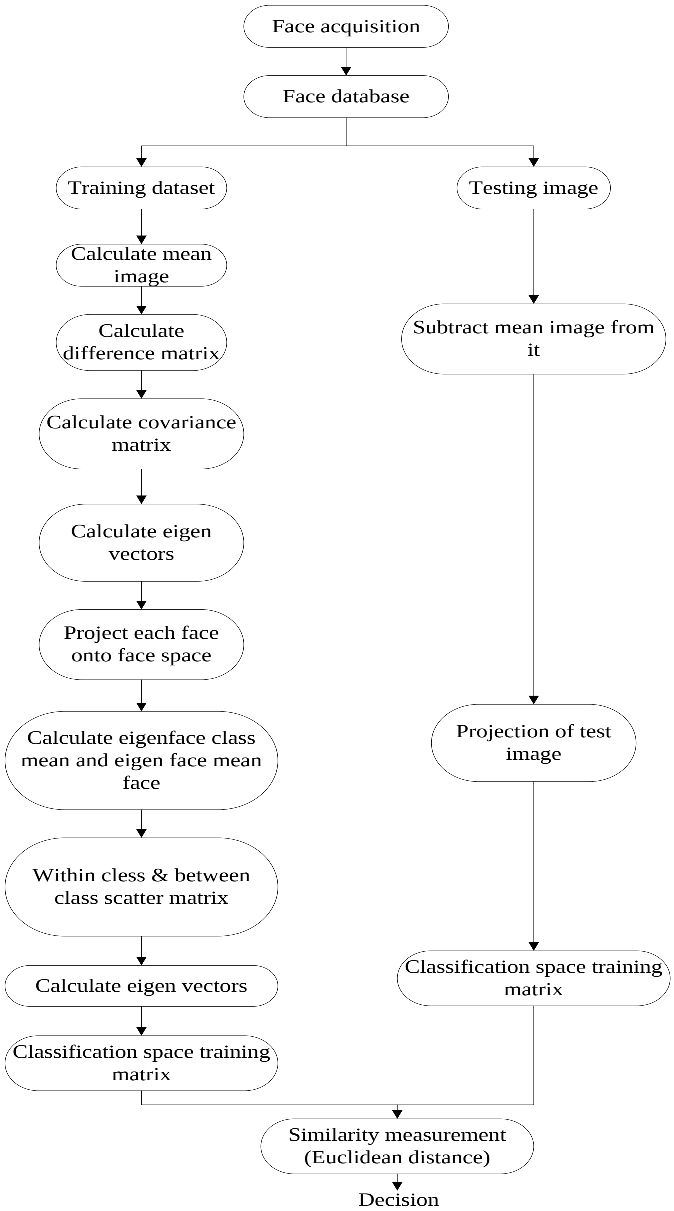

Fig. 2. LDA approach for face recognition.

In Recognition Procedure, to recognize a face, compare the test image's projection matrix with the projection matrix of each training image by using a similarity measure. The result is the training image which is the closest to the test image.

II. Comparison

In PCA, there is no distinction between inter- and intra-class variabilities. It project faces onto a lower dimensional sub-space. It is optimal for representation but not for discrimination. LDA find a sub-space which maximizes the ratio of inter-class and intra-class variability. It has same intra-class variability for all classes. In some cases, it is faster than PCA. It has lower error rates. It works well even if different illumination or in different facial expression. PCA is unsupervised whereas LDA is supervised. When the training set is small, PCA can outperform LDA. When the number of samples is large and representative for each class, LDA outperforms PCA.

To recognize image without disturbance, PCA takes shorter time than LDA. But to recognize image with disturbances, LDA is better to use because it has better recognition rate [9]. In terms of time taken, PCA tends to be much better than LDA, especially to recognize images with background disturbance [9].

III. Conclusion

In this paper, the two face recognition techniques i.e. PCA and LDA are presented. This study is important for developing new robust algorithms for face recognition. By combining both these techniques, the recognition rate can be improved.

IV. Future Scope

By combining PCA and LDA with Object Tracking, we can implement it to recognize moving individuals. The object tracking program will track the individual and capture images. The Face Detection program can then detect faces from these images and create the facial image for the individual. Finally, the face Recognition program can recognize the individual from these facial images.

References

[1] M. Yang, D. J. Kriegman, and N. Ahuja, "Detecting faces in images: a survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24 no 1, pp. 34–58, 2002.

[2] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal Cognitive Neuroscience*, vol. 3, no. 1, pp. 71-86, 1991.

[3] W. S. Yambor, "Analysis of PCA-based and fisher discriminant-based image recognition algorithms," Technical Report CS-00-103, Computer Science Department, Colorado State University, July 2000.

[4] R. A. Fisher, "The use of multiple measures in taxonomic problems," *Ann. Eugenics*, vol. 7, pp. 179-188, 1936.

[5] A. M. Martinez and A. C.Kak, "PCA versus LDA," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no.2, pp. 228-233, 2001.

[6] P. N Belhumeur, J. P Hespanha, and D. J. Kriegman, "Eigen faces vs. fisher faces: recognition using class specific linear projection," *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 19, pp. 711-720, 1997.

[7] K. Etemad and R. Chellappa, "Face recognition using discriminant eigenvectors," *IEEE Transaction for Pattern Recognition*, pp. 2148-2151, 1996.

[8] U. k. Jaliya, K. Brahmbhatt, S. A Patel, P. J. Patel, "A comparative study of PCA & LDA human face recognition methods," *IEEE Transactions on Neural Networks*, vol. 8, no. 1, 2011.

Rupish Arora, "A review of PCA and LDA face recognition techniques", *Journal of Scientific and Technical Advancements*, Volume 1, Issue 3, pp. 293-296, 2015.

[9] E. Hidayat, F. Nur, A. Muda, C. Huoy, and S. Ahmad, "A comparative study of feature extraction using PCA and LDA for face recognition," *in Proceeding 7th International Conf. on Information Assurance and Security*, pp. 354 - 359, 2011.

[10] K. S. Sodhi and M. Lal, "Comparative analysis of PCA-based face recognition system using different distance classifiers," *International Journal of Application or Innovation in Engineering & Management*, vol. 2, issue 7, 2013.

[11] S. G. Bhele and V. H. Mankar, "A review paper on face recognition technique," *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)*, vol. 1, issue 8, 2012.

[12] S. K. Hese and M. R. Banwaskar, "Performance evaluation of PCA and LDA for face recognition," *International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)*, vol. 2, issue 2, 2013.

[13] H. Rady, "Face recognition using principle component analysis with different distance classifiers," *International Journal of Computer Science and Network Security (IJCSNS)*, vol.11, no.10, 2011.

Rupish Arora, "A review of PCA and LDA face recognition techniques", *Journal of Scientific and Technical Advancements*, Volume 1, Issue 3, pp. 293-296, 2015.