International Journal of Computer Trends and Technology- volume 3 Issue2-2012

# Performance analysis of Linear appearance based algorithms for Face Recognition

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***Abstract*—Analysing the face recognition rate of various current face recognition algorithms is absolutely critical in developing new robust algorithms. In his paper we propose performance analysis of Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Locality Preserving Projections (LPP) for face recognition. This analysis was carried out on various current PCA, LDA and LPP based face recognition algorithms using standard public databases. Among various PCA algorithms analyzed, Manual face localization used on ORL and SHEFFIELD database consisting of 100 components gives the best face recognition rate of 100%, the next best was 99.70% face recognition rate using PCA based Immune Networks (PCA-IN) on ORL database. Among various LDA algorithms analyzed, Illumination Adaptive Linear Discriminant Analysis (IALDA) gives the best face recognition rate of 98.9% on CMU PIE database, the next best was 98.125% using Fuzzy Fisherface through genetic algorithm on ORL database. Among various LPP algorithms analyzed, Subspace Discriminant LPP (SDLLP) provides the best face recognition rate of 98.38% on ORL database, the next best was 97.5% using Contourlet-based Locality Preserving Projection (CLPP) on ORL database.**

***Keywords-face recognition; Principal Component Analysis; Linear Discriminant Analysis; Locality Preserving Projections; PCA-Immune Network; Illumination Adaptive LDA; Fisher Discriminant; Subspace Discriminant LPP; Contourlet-based Locality Preserving Projection.***

## I. INTRODUCTION

Facial recognition methods can be divided into appearance-based or model-based algorithms. Appearance-based methods represent a face in terms of several raw intensity images. An image is considered as a high-dimensional vector. Statistical techniques are usually used to derive a feature space from the image distribution. The sample image is compared to the training set.

Appearance methods can be classified as linear or non-linear. Linear appearance-based methods perform a linear dimension reduction. The face vectors are projected to the basis vectors, the projection coefficients are used as the feature representation of each face image, and approaches are PCA, LDA, and LPP. Non-linear appearance methods are more complicate. Linear subspace analysis is an approximation of a nonlinear manifold. Kernel PCA (KPCA) [23] is a method widely used.

Model-based approaches can be 2-Dimensional or 3-Dimensional. These algorithms try to build a model of a human face. These models are often morphable. A morphable model allows classifying faces even when pose changes are present, and approaches are Elastic Bunch Graph Matching [24] or 3D Morphable Models [25].

Important information may be contained in the high-order relationship among pixels, so Independent Component Analysis [26-27] seems feasible to be a promising face feature extraction method but ICA algorithms are iterative, time consuming and have converge difficultly.

PCA is a transformation that chooses a new coordinate system for data set that the greatest variance by any projection of the data set comes to lie on the first axis (the first principal component), the second axis corresponds to the maximum remaining variations in the dimension orthogonal to the first axis, and so on. The fundamental idea behind PCA is that if there are series of multidimensional data vectors representing objects which have similarities, it is possible to use transformation matrix to create a reduces space that accurately describes the original multidimensional vectors.

In LDA the original data is transformed into a lower dimensional space (feature space) such that the ratio of the between-class scatter matrix to within-class scatter matrix is maximized i.e. the between-class scatter matrix is maximized while the within-class scatter matrix is minimized and thus maximum discrimination is achieved.

LPP proposed by He and Niyogi is an alternative to PCA. LPP is a linear manifold learning approach. It can be viewed as a linear approximation of Laplacian eigenmaps. The first step of LPP is to generate an unsupervised neighborhood graph on training data, and then finds an optimal locality preserving projection matrix under certain criterion.

In this paper we report performance analysis of various current PCA, LDA and LPP based algorithms for face recognition. The evaluation parameter for the study is face recognition rate on various standard public databases. The remaining of the paper is organized as follows: Section II provides a brief overview of PCA, Section III presents PCA algorithms analysed, Section IV provides brief overview of LDA, Section V presents LDA algorithms analysed. Section VI provides brief overview of LPP, Section VII presents LPP algorithms analysed. Section VIII presents performance analysis of various PCA, LDA and LPP based algorithms finally Section IX draws the conclusion.

## II. PRINCIPAL COMPONENT ANALYSIS (PCA)

Consider the training sample set of face image $F = \{x_1, x_2, \dots, x_M\}$,

where $x_i, \left(x_i \in R^n, i = 1, \dots, M\right)$ corresponds to the lexicographically ordered pixels of the *ith* face image, and where there are *M* face images. PCA tries to mapp the original n-dimensional image space into an m dimensional feature space, where m<<n. The new feature vectors $y_i \in R^m$ are defined by the following linear transform:

$$y_k = W^T x_k \quad k = 1, \dots, M$$

where $W = [w_1, w_2, \dots, w_m], w_i \in R^n$, which is orthogonal with each other is the eigenvector of total scatter matrix $S_T$ corresponding to the $m^{th}$ largest eigenvalue. The total scatter matrix is defined as

$$S_T = \sum_{k=1}^{M} (x_k - \mu)(x_k - \mu)^T$$

Where $\mu$ is the mean value of all training samples.

## III. PCA ALGORITHMS ANALYZED

### *A. PCA and Support Vector Machine (SVM)*

PCA is used to extract the essential characteristics of face images, SVM as classifier. One against one classification strategy for multi-class pattern recognition is used based on 2D static face image [1].

### *B. Incremental Two-Dimensional Two-Directional Principal Component Analysis (I(2D)2PCA)*

Feature extraction method that combines advantages of Two-Directional Principal Component Analysis $(2D)^2$PCA and Incremental PCA (IPCA). $I(2D)^2$PCA consumes less computational load than IPCA as well as smaller memory waste than $(2D)^2$PCA [2].

### *C. Infrared face recognition based on the Compressive Sensing (CS) and PCA*

The facial image is normalized and then the normalized image does fast compressive sensing. PCA is used for non-adaptive linear projections from CS which then classifies the image using 3-nearest neighbor method [3].

### *D. Symmetrical Weighted Principal Component Analysis (SWPCA)*

SWPCA applies mirror transform to facial images, and gets the odd and even symmetrical images based on the odd-even decomposition theory. The Weighted Principal Component Analysis (WPCA) is performed on the odd and even symmetrical training sample sets respectively to extract facial image features and nearest neighbor classifier is employed for classification [4].

### *E. PCA based Immune Networks (PCA-IN)*

PCA is utilized to obtain eigenvalues and eigenvectors of the face images, and then the randomly selected single training sample is input into the immune networks which are optimized using genetic algorithms [5]. This experiment is repeated for 30 times and the "Average Recognition Rate" (ARR) is obtained.

### *F. Manual face localization*

Localizes the face and eliminates the background information from the image in a manner that the majority of the cropped image consists of the facial pattern. Curvelet transform is used to transform the image into a new domain and to calculate initial feature vectors. The feature vectors are then dimensionally reduced using Two Dimensional Principal Component Analysis (B2DPCA) and classified using Extreme Learning Machine (ELM) [9].

### *G. Fractional Fourier transform (FRFT) and PCA*

The face images are transformed into FRFT domain. PCA is adopted to reduce the dimension of face images and Mahalanobis distance is used for classifying [10].

### *H. Supervised learning framework for PCA-based face recognition using Genetic Network Programming (GNP) fuzzy data mining (GNP-FDM)*

Genetic based Clustering Algorithm (GCA) is used to reduce the number of classes. A Fuzzy Class Association Rules (FCARs) based classifier is applied to mine the inherent relationships between eigen-vectors [11].

### *I. PCA and minimum distance classifier*

Different facial images of a single human face are taken together as a cluster. PCA is applied for feature extraction. Minimum distance classifier is used for the recognition that avoids the exploit of threshold value which is changeable under different distance classifiers [12].

## IV. LINEAR DISCRIMANT ANALYSIS

Let us consider a set of N sample images $\{x_1, x_2, \dots, x_n\}$ taking in an n-dimensional image space, and assume that each image belongs to one of c classes $\{c_1, c_2, c_3, \dots, c_c\}$.

Let Ni be the number of the samples in class

$$c_i \ (i = 1, 2, \dots \dots, c), \mu_i = \frac{1}{N} \sum_{i=1}^{N} x_i$$

be the mean of the samples in class Ci. Then the between-class scatter matrix Sb is defined as

$$S_b = \frac{1}{N} \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T$$

The within-class matrix $S_w$ is defined as

$$S_\omega = \frac{1}{N} \sum_{i=1}^{c} \sum_{x_k \in c_i} (x_i - \mu_i)(x_i - \mu_i)^T$$

In LDA, the projection $W_{opt}$ is chosen to maximize the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of projected samples

$$W_{opt} = \arg mxw \frac{\left|W^T S_b W\right|}{\left|W^T S_\omega W\right|} = [\omega_1 \omega_2 \omega_3 \dots \omega_d]$$

where $\{w_i | i = 1, 2, \dots, d\}$ is the set of generalized eigen-vectors of $S_b$ and $S_w$ corresponding to the m largest generalized eigenvalues $\{\lambda_i = 1, 2, \dots, d\}$, i.e.,

$$S_b \omega_i = \lambda_i S_\omega \omega_i,\ i = 1, 2, \ldots\ldots, d.$$

## V. LDA ALGORITHMS ANALYZED

### A. Regularized-LDA (R-LDA)

R-LDA is used for extracting low-dimensional discriminant features from high dimensional training images and then these features are used by Probabilistic Reasoning Model (PRM) for classification [13].

### B. Multi-Feature Discriminant Analysis (MFDA)

Feature extraction method that combines advantages of Two-Directional Principal Component Analysis $(2D)^2$PCA and Incremental PCA (IPCA). I$(2D)^2$PCA consumes less computational load than IPCA as well as smaller memory waste than $(2D)^2$PCA [2].

### C. Rearranged Modular 2DLDA (Rm2DLDA)

Two-dimensional linear discriminant analysis has lower time complexity but it implicitly avoids the small sample problem encountered in classical LDA Rm2DLDA was developed. It was based on the idea of dividing an image into sub-images and then concatenating them to form a wide image matrix [15].

### D. Illumination Adaptive Linear Discriminant Analysis (IALDA)

The images of many subjects under the different lighting conditions are used to train illumination direction classifier and varieties of LDA projection matrices. Then the illumination direction of a test sample is estimated by illumination direction classifier, the corresponding LDA feature which is robust to the illumination variation between images under the standard lighting conditions and the estimated lighting conditions is extracted [16].

### E. Fuzzy Fisherface (FLDA) through genetic algorithm

Searches for optimal parameters of membership function. The optimal number of nearest neighbors to be considered during the training is also found through the use of genetic algorithms [17].

### F. Semi-supervised face recognition algorithm based on LDA self-training)

Augments a manually labeled training set with new data from an unlabeled auxiliary set to improve recognition performance [18]. Without the cost of manual labeling such auxiliary data is often easily acquired but is not normally useful for learning.

### G. Random sampling LDA

To reduce the influence of unimportant or redundant features on the variables generated by PCA, random sampling LDA was introduced. By incorporating Feature Selection for face recognition (FS_RSLDA) was introduced, in this algorithm unimportant or redundant features are removed at first, this way the obtained weak classifier is made better [19].

### H. Revised Non-negative Matrix Factorization (NMF) with LDA based color face recognition)

Block diagonal constraint is imposed on the base image matrix and coefficient matrix on the basis of the constraints of traditional NMF. And LDA is then implemented on factorization coefficients to fuse class information [20].

### I. Layered Linear Discriminant Analysis (L-LDA)

Decrease False Acceptance Rate (FAR) by reducing the face dataset to very small size through L-LDA .It is intensive to both small subspace (SSS) and large face variations due to light or facial expressions by optimizing the separability criteria. Hence it provides significant performance gain, especially on similar face database and Small Subspace (SSS) problems [21].

## VI. LOCALITY PRESERVING PROJECTIONS

LPP is an unsupervised manifold dimensionality reduction approach, which aims to find the optimal projection matrix W by minimizing the following criterion function:

$$J_1(W) = \sum_{i,j} \left\| y_i - y_j \right\|^2 S_{ij},$$

Substituting $y_i = W^T x_i$ into above objection function, it yields by direct computation that

$$J_1(W) = 2trace(W^T XLX^T W),$$

Where L=D-S is called Laplacian matrix, *D* is a diagonal matrix defined by

$$D = diag\{D_{11}, D_{22}, \cdots, D_{NN}\}$$

$$\text{where } D_{ii} = \sum_i S_{ij}.$$

Matrix *D* provides a natural measure on the data points. The bigger the value $D_{ii}$ (corresponding to $y_i$) is, the more "important" is $y_i$. Thereby, the projection matrix *W* should maximize the following constraint objective function simultaneously:

$$J_2(W) = \sum_{i=1}^{N} y_i^T D y_i = trace(Y^T DY)$$

$$= trace(W^T XDX^T W).$$

Solving problems min $J_1(W)$ and max $J_2(W)$ simultaneously is equivalent to minimizing the following criterion function:

$$J(W) = \frac{trace(W^T XLX^T W)}{trace(W^T XDX^T W)},$$

The optimal locality preserving projection matrix

$$W_{LPP} = \arg \min_{W \in R^{d \times l}} J(W)$$

can be obtained by solving the following generalized eigen-value problem:

$$XLX^T W = (XDX^T) W \Lambda.$$

where $\Lambda$ is a diagonal eigenvalue matrix. While in most cases, the number of training data is smaller than the dimension of feature vector, i.e. d << N. When this 3S problem occurs, the matrix $XDX^T$ is not full rank.

## VII. LPP ALGORITHMS ANALYZED

### A. Bilateral Two-Dimensional LPP

It is based on 2D image matrices rather than column vectors so the image matrix does not need to be transformed into a long vector before feature extraction. The advantage arising in this way is that 2D image matrices can be effectively compressed from horizontal and vertical directions and uses F-norm classification measure [30].

### B. Regularized LPP (RLPP)

Supervised graph and regularization technique which not only overcomes the singularity problem of LPP but also find optimal LPP projection matrix in the entire input space [31].

### C. Support Vector Machines (SVM) and LPP

It is combined semi-supervised face recognition, which constructs data model on video sequence to unearth the space-time information. It then uses semi-supervised LPP to build a nearest neighbour graph which models the inherent geometrical structure of the face space. SVM is applied to find a separating hyperplane for the training data set and predict the labels for the testing face data [32].

### D. Subspace Discriminant LPP (SDLLP)

Based on discriminant graph and modified LPP criterion, SDLLP method tackles the 3S issue of LPP and gives an optimal algorithm by introducing corresponding eigen-systems [33]. The projection feature vectors learned are linear independent and make modified LPP criterion function reach maximum.

### E. Discrete sine transform (DST)

DST-feature based LPP algorithm is used for face recognition and to obtain the 2D-DST facial feature. 1D-DST is performed along two directions of a facial image matrix, namely horizontal and vertical directions. A column DST-feature vector is then formed by scanning its 2D-DST coefficients along a zigzag route starting from the top left corner and subsequently LPP can be performed in DST domain directly [34].

### F. Contourlet-based Locality Preserving Projection (CLPP)

For dimensionality reduction and feature extraction CLPP is used. The main advantage of CLPP over LPP lies in the fact that the former realize dimensionality reduction effectively than later. This can reduce the complexity greatly and avoid the disadvantages of the pre-processing PCA step [35].

### G. Enhanced Supervised Locality Preserving Projections (ESLPP)

An extension to LPP named ESLPP allows both locality and class label information to be incorporated. This improves the performance of classification. ESLPP uses similarity based on robust path instead of Gaussian heat kernel similarity. It can capture the underlying geometric distribution of samples even when there are noise and outliers [36].

### H. Two-Dimensional Discriminant Locality Preserving Projection (2DDLPP)

2DDLPP is a 2D-based feature extraction method, which can directly process 2D image matrix without PCA pre-processing. Hence it can be possible to retain the valid information of human face images. 2DDLPP aims to preserve the local manifold structure information and the discriminant information [37].

### I. Fractal Locality Preserving Projections (FLPP)

FLPP calculates the fractal codes of face images, and then use LPP method to analysis the manifold structure, and do face recognition [38].

### J. Multilinear Principal Component Analysis (MPCA) and LPP

It involves preprocessing in order to improve the face image, then the feature extraction is achieved by merging MPCA along with LPP. To calculate the feature projection matrices, the test face sample is mapped onto a feature matrix with the assistance of MPCA, LPP and there by the face recognition is done by comparing the test feature matrix with the enrolled face features in the database using L2 distance [39].

### K. Regularised Generalised Discriminant Locality Preserving Projections (RGDLPP)

RGDLPP locality preserving within-class scatter is replaced in DLPP approach by locality preserving total scatter. To alleviate the problem of unreliable small and zero eigenvalues caused by noise and the limited number of training samples regularising the small and zero eigenvalues of locality preserving within-class scatter is done, this enables RGDLPP to be executed in the full sample space and alleviates the over-fitting problem [40].

### L. Tensor Locality Preserving Projections (TLLP)

TLLP is a natural extension of LPP to the multilinear case, which can take data directly in the form of tensors of arbitrary order as input hence there exist significant reduction in both space complexity and time complexity [41].

## VIII. PERFORMANCE ANALYSIS

### A. Performance analysis of various PCA based algorithms

Illumination invariant face recognition based on DCT and PCA on YALE Database B gives accuracy of 94.2% [28].

TABLE I. PERFORMANCE COMPARISON BETWEEN PCA+NN, SVM AND PCA+SVM ON ORL DATABASE

| Class Number | Training samples | Test samples | Method | Recognition rate (%) |
|---|---|---|---|---|
| 200 C | 60 | 140 | PCA+NN | 90 |
| | | | SVM | 85.71 |
| | | | PCA+SVM | 94.29 |
| 40 C | 120 | 280 | PCA+NN | 80.36 |
| | | | SVM | 78.93 |
| | | | PCA+SVM | 81.10 |

As Table I shows, face recognition rate of PCA+SVM method, under small samples circumstance, is better than PCA+NN and SVM [1].

TABLE II. PERFORMANCE COMPARISON BETWEEN PCA, 2DPCA, (2D)2PCA, IPCA, I(2D)PCA AND I(2D)2PCA ON YALE DATABASE

| Method | Recognition rate (%) |
|---|---|
| PCA | 80.80 |
| 2DPCA | 82.05 |
| $(2D)^2$PCA | 82.13 |
| IPCA | 78.47 |
| I(2D)PCA | 81.19 |
| $I(2D)^2$PCA | 81.39 |

TABLE III. PERFORMANCE COMPARISON BETWEEN PCA, 2DPCA, (2D)2PCA, IPCA, I(2D)PCA AND I(2D)2PCA ON ORL DATABASE

| Method | Recognition rate(%) |
|---|---|
| PCA | 85.14 |
| 2DPCA | 86.29 |
| $(2D)^2$PCA | 86.64 |
| IPCA | 84.75 |
| I(2D)PCA | 86.16 |
| $I(2D)^2$PCA | 86.28 |

Table II and Table III shows, face recognition rate of $I(2D)^2$PCA is better when compared to PCA, 2DPCA, $(2D)^2$PCA, IPCA, I(2D)PCA on YALE and ORL databases [2].

TABLE IV. PERFORMANCE COMPARISON BETWEEN EIGENFACE, EIGEN-GEFES AND EIGEN-GEFEW ON FRGC DATABASE

| Methods | Recognition rate (%) |
|---|---|
| Eigenface | 87.14 |
| Eigen-GEFeS | 86.67 |
| Eigen-GEFeW | 91.42 |

Table IV shows, Eigen-GEFeW is the best performing instance when compared with Eigenface and Eigen-GEFeS on Face Recognition Grand Challenge (FRGC) dataset [29].

Infrared face recognition based on the compressive sensing and PCA is invariant to variations in facial expressions and viewpoint, and is computationally efficient [3].

TABLE V. PERFORMANCE COMPARISON BETWEEN PCA, SPCA, WPCA AND SWPCA ON ORL DATABASE

| Method | Training samples/class | Recognition rate (%) |
|---|---|---|
| PCA | 6 | 92.50 |
| SPCA | 6 | 94.37 |
| WPCA | 6 | 94.37 |
| SWPCA | 6 | 96.00 |

TABLE VI. PERFORMANCE COMPARISON BETWEEN PCA, SPCA, WPCA AND SWPCA ON YALE DATABASE

| Method | Training samples/class | Recognition rate (%) |
|---|---|---|
| PCA | 4 | 85.71 |
| SPCA | 4 | 88.57 |
| WPCA | 4 | 89.52 |
| SWPCA | 4 | 93.33 |

Table V and Table VI shows, the correct recognition accuracy with SWPCA improved almost by 10% compared with PCA. The reason that the SWPCA method performs better than other conventional algorithms is that SWPCA not only utilizes the natural symmetrical property of human face to enlarge the number of training samples, but also employs the weighted PCA space to improve the robustness against variance of illumination and expression [4].

TABLE VII. PERFORMANCE COMPARISON BETWEEN 2DPCA, DDCT AND 2PCA, MODULAR WEIGHTED (2D)2PCA AND PCA-IN ON ORL DATABASE

| Methods | Recognition rate (%) |
|---|---|
| 2DPCA [6] | 76.70 |
| DDCT and 2PCA [7] | 76.22 |
| Modular Weighted $(2D)^2$PCA [8] | 72.22 |
| PCA-IN | 99.70 |

Table VII shows, best performance (99.70%) of PCA-IN classifiers was compared with the results reported in [6-8]. PCA-IN method outperformed all other methods [5]. Face recognition rate of Manual face localization on ORL and SHEFFIELD database consisting of 100 components is 100% [9].

In FRFT face images are transformed into FRFT domain, it uses several angles characters for classifying. Experiments on FERET database shows that FRFT provides new insights into the role that pre-processing methods play in dealing with images [10].

GNP-FDM successfully prevents the accuracy loss caused by a large number of classes in the Multiple Training Images per Person – Complicated Illumination Database (MTIP-CID). GCA reduces the overlaps in the PCA domain [11].

PCA and minimum distance classifier gives a recognition rate of 96.7% on ORL database [12].

### B. *Performance analysis of various LDA based algorithms*

TABLE VIII. PERFORMANCE COMPARISON BETWEEN R-LDA AND R-LDA USING PRM ON YALE DATABASE

| Number of features | Methods | Recognition rate (%) |
|---|---|---|
| 32 | R-LDA | 95 |
| 32 | R-LDA Using PRM | 97.5 |

TABLE IX. PERFORMANCE COMPARISON BETWEEN R-LDA AND R-LDA USING PRM ON UMIST DATABASE

| Number of features | Methods | Recognition rate (%) |
|---|---|---|
| 12 | R-LDA | 88.50 |
| 12 | R-LDA Using PRM | 98.48 |

Table VIII and Table IX shows, R-LDA Using PRM gives better recognition when compared to R-LDA on YALE and

UMIST databases. Further it is observed that by taking more number of features (32), the recognition rate is maximum (97.5%) for ORL database and by considering 12 number of features in case of UMIST database the recognition rate is 98.48% [13].

Compared to LDA, MFDA significantly boosts the recognition performance. The accuracy for LDA is 60% compared to the 83.9% accuracy of MFDA [14].

TABLE X. PERFORMANCE COMPARISON BETWEEN 2DLDA, RM2DLDA (2X2) AND RM2DLDA (4X4) ON ORL DATABASE

| Methods | Recognition rate (%) |
|---|---|
| 2DLDA | 95.65 |
| Rm2DLDA(2 x 2) | 96.65 |
| Rm2DLDA(4 x 4) | 97.1 |

TABLE XI. PERFORMANCE COMPARISON BETWEEN 2DLDA, RM2DLDA (2X2) AND RM2DLDA (4X4) ON YALEB DATABASE

| Methods | Recognition rate (%) |
|---|---|
| 2DLDA | 88.68 |
| Rm2DLDA(2 x 2) | 90.75 |
| Rm2DLDA(4 x 4) | 91.55 |

TABLE XII. PERFORMANCE COMPARISON BETWEEN 2DLDA, RM2DLDA (2X2) AND RM2DLDA (4X4) ON PIE DATABASE

| Methods | Recognition rate (%) |
|---|---|
| 2DLDA | 90.58 |
| Rm2DLDA(2 x 2) | 93.0 |
| Rm2DLDA(4 x 4) | 95.04 |

Table X, Table XI and Table XIII shows, Rm2DLDA gives better recognition when compared to 2DLDA on ORL, YALE and PIE databases [15].

TABLE XIII. PERFORMANCE COMPARISON BETWEEN LDA AND IALDA ON B1 DATABASE

| Method | Training samples/class | Test samples/class | Recognition rate (%) |
|---|---|---|---|
| LDA | 2 | 43 | 59.38 |
| IALDA | 1 | 44 | 85.52 |

TABLE XIV. PERFORMANCE COMPARISON BETWEEN LDA AND IALDA ON CMU PIE DATABASE

| Method | Training samples/class | Test samples/class | Recognition rate (%) |
|---|---|---|---|
| LDA | 2 | 19 | 74.25 |
| IALDA | 1 | 20 | 98.9 |

Table XIII and Table XIV show, IALDA gives better recognition when compared with LDA on B1 and CMU databases [16]. The recognition rate is increased from 94.12% using Fuzzy Fisherface (FLDA) to 98.125% using Fuzzy Fisherface through genetic algorithm on ORL database [17].

Experiments on ORL database, AR database and CMU PIE database show that Semi-supervised face recognition algorithm based on LDA is robust to variations in illumination, pose and expression and that it outperforms related approaches in both transductive and semi-supervised configurations [18].

RSLDA is an effective random sampling LDA method, the 1-NN classifier in the feature subspace obtained by RSLDA has better classification performance as compared to that induced by BaseLDA on AR, ORL, YALE, YALEB face datasets [19]. For ORL, the classification accuracy has an increase of 15.1% around.

Experimental results on CVL and CMU PIE databases prove the algorithm improves recognition rate effectively [20]. L-LDA is insensitive to large dataset and also small sample size and it provided 93% accuracy and reduced False Acceptance Rate (FAR) to 0.42 on BANCA face database [21].

### C. *Performance analysis of various LPP based algorithms*

B2DLPP can better avoid the interference of light, noise and other factors via extracting discriminate information. Also dimension reduction by two directions needs less cost of space and time than that by one side, so eigenvector space is far smaller than the original space and it can avoid a SSS [30].

TABLE XV. PERFORMANCE COMPARISON BETWEEN DLPP AND RLPP ON ORL DATABASE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| DLPP | 5 | 89.65 |
| RLPP | 5 | 96.80 |

TABLE XVI. PERFORMANCE COMPARISON BETWEEN DLPP AND RLPP ON FERET DATABSE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| DLPP | 5 | 78.17 |
| RLPP | 5 | 92.00 |

Table XV shows, the correct recognition accuracy with DLPP and RLPP is 89.65% and 96.80% with training number 5 respectively for ORL database. Table XVI shows, the correct recognition accuracy with DLPP and RLPP is 78.17% and 92.00 % with training number 5 respectively for FERET database [31].

Support Vector Machines and Locality Preserving Projections can not only discover the spatio-temporal connection between video faces, but also take advantage of the superiority of semi-supervised learning and manifolds learning [32].

TABLE XVII. PERFORMANCE COMPARISON BETWEEN DLPP, PCA+LPP AND SDLPP ON ORL DATABSE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| DLPP | 8 | 92.75 |
| PCA+LPP | 8 | 95.63 |
| SDLPP | 8 | 98.38 |

TABLE XVIII. PERFORMANCE COMPARISON BETWEEN DLPP, PCA+LPP AND SDLPP ON FERET DATABASE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| DLPP | 8 | 81.75 |
| PCA+LPP | 8 | 79.92 |
| SDLPP | 8 | 91.58 |

Table XVII and Table XVIII show, SDLPP provides better recognition when compared to DLPP and PCA+LPP on ORL and FERET databases [33].

TABLE XIX. PERFORMANCE COMPARISON BETWEEN LPP, OLPP, WPCA AND CLPP ON ORL DATABSE

| Method | Recognition rate (%) |
|---|---|
| LPP | 92.0 |
| OLPP | 95.5 |
| CLPP | 97.5 |

Table XIX shows, CLPP provide better recognition when compared to LPP and OLPP on ORL database which contains images from 40 individuals, each providing 10 different images [34].

TABLE XX. PERFORMANCE COMPARISON BETWEEN LPP, OLPP, WPCA AND CLPP ON YALE DATABSE

| Method | Recognition rate (%) |
|---|---|
| LPP | 90.5 |
| OLPP | 92.0 |
| CLPP | 94.1 |

Table XX shows, CLPP provide better recognition when compared to LPP and OLPP on YALE database which contains 165 images of 15 individuals [34].

TABLE XXI. PERFORMANCE COMPARISON BETWEEN LPP, OLPP, WPCA AND CLPP ON PIE DATABSE

| Method | Recognition rate (%) |
|---|---|
| LPP | 90.5 |
| OLPP | 90.5 |
| CLPP | 95.8 |

Table XXI shows, CLPP provide better recognition when compared to LPP and OLPP on PIE database of 41,368 images of 68 people [34].

TABLE XXII. PERFORMANCE COMPARISON BETWEEN Laplacianface AND DST-LPP ON ORL DATABSE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| Laplacianface | 5 | 96.30 |
| DST-LPP | 5 | 96.60 |

TABLE XXIII. PERFORMANCE COMPARISON BETWEEN Laplacianface AND DST-LPP ON FERET DATABSE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| Laplacianface | 5 | 89.67 |
| DST-LPP | 5 | 92.33 |

Table XXII and Table XXIII show, DST-LPP provides better recognition when compared to Laplacianface on ORL and FERET databases respectively with 5 training number [35].

TABLE XXIV. PERFORMANCE COMPARISON BETWEEN LPP, OLPP AND ESLPP ON ORL DATABSE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| LPP | 5 | 90.50 |
| OLPP | 5 | 91.00 |
| ESLPP | 5 | 92.45 |

TABLE XXV. PERFORMANCE COMPARISON BETWEEN LPP, OLPP AND ESLPP ON YALE DATABSE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| LPP | 5 | 88 |
| OLPP | 5 | 91.50 |
| ESLPP | 5 | 93.50 |

Table XXIV and Table XXV show, ESLPP provides better recognition when compared to LPP and OLPP on ORL and YALE databases respectively with 5 training number [36].

TABLE XXVI. PERFORMANCE COMPARISON BETWEEN LPP AND 2DDLDPP ON ORL DATABASE

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| LPP | 5 | 90.58 |
| 2DDLDPP | 5 | 96.45 |

Table XXVI show, 2DDLDPP provides better recognition when compared to LPP on ORL database with 5 training number [37].

TABLE XXVII. PERFORMANCE COMPARISON BETWEEN LPP AND 2DDLDPP on YALE database

| Method | Training samples | Recognition rate (%) |
|---|---|---|
| LPP | 8 | 93.33 |
| 2DDLDPP | 8 | 96.56 |

Table XXVII show, 2DDLDPP provides better recognition when compared to LPP on YALE database with 5 training number [37].

TABLE XXVIII. PERFORMANCE COMPARISON BETWEEN LPP AND FLPP ON ORL DATABASE

| Method | Recognition rate (%) |
|---|---|
| LPP | 94.3 |
| FLPP | 95.4 |

TABLE XXIX. PERFORMANCE COMPARISON BETWEEN LPP AND FLPP ON YALE DATABASE

| Method | Recognition rate (%) |
|---|---|
| LPP | 86.2 |
| FLPP | 86.5 |

Table XXVIII and Table XIX show, FLPP provides better recognition when compared to LPP and on ORL and YALE databases respectively with 5 training number [38].

TABLE XXX. PERFORMANCE COMPARISON BETWEEN MPCA+LDA AND MPCA+LPP ON FERET DATABASE

| Methods | Recognition rate (%) |
|---|---|
| MPCA+LDA | 93.75 |
| MPCA+LPP | 96.5 |

TABLE XXXI. PERFORMANCE COMPARISON BETWEEN MPCA+LDA AND MPCA+LPP ON AT&T DATABASE

| Method | Recognition rate (%) |
|---|---|
| MPCA+LDA | 95 |
| MPCA+LPP | 96.5 |

Table XXX and Table XXXI show, MPCA+LPP provides better recognition when compared to MPCA+LDA and on FERET and AT&T databases respectively [39].

RGDLPP statistically significantly outperforms LPP, DLPP algorithms on PIE database [40].

TABLE XXXII. PERFORMANCE COMPARISON BETWEEN LPP, TLPP ON ORL DATABASE

| Method | Recognition rate (%) |
|---|---|
| LPP | 96.6 |
| TLPP | 97.1 |

Table XXXII show, LPP provides better recognition when compared to TLPP on ORL database [41].

### *D. Performance comparison between PCA and LDA based algorithms*

TABLE XXXIII. PERFORMANCE COMPARISON BETWEEN EIGENFACES AND FISHERFACES ON YALE DATABASE

| Number of features | Methods | Recognition rate (%) |
|---|---|---|
| 32 | Eigenfaces | 90.5 |
| 32 | Fisherfaces | 93.5 |

Table XXXIII shows, LDA gives better recognition when compared to PCA while 32 features are considered on YALE Database [13].

TABLE XXXIV. PERFORMANCE COMPARISON BETWEEN EIGENFACES AND FISHERFACES ON UMIST DATABASE

| Number of features | Methods | Recognition rate (%) |
|---|---|---|
| 12 | Eigenfaces | 90.62 |
| 12 | Fisherfaces | 94.45 |

Table XXXIV shows, LDA gives better recognition when compared to PCA while 12 features are considered on UMIST Database [13].

TABLE XXXV. PERFORMANCE COMPARISON BETWEEN 2DPCA AND RLDA ON ORL DATABASE

| Methods | Recognition rate (%) |
|---|---|
| 2DPCA | 77.86 |
| RLDA | 73.89 |

Table XXXV shows, 2DPCA gives better recognition when compared to RLDA on ORL Database [15]

TABLE XXXVI. PERFORMANCE COMPARISON BETWEEN 2DPCA AND RLDA ON YALEB DATABASE

| Methods | Recognition rate (%) |
|---|---|
| 2DPCA | 77.86 |
| RLDA | 73.89 |

Table XXXVI shows, 2DPCA gives better recognition when compared to RLDA on YALEB Database [15].

TABLE XXXVII. PERFORMANCE COMPARISON BETWEEN 2DPCA AND RLDA ON PIE DATABASE

| Methods | Recognition rate (%) |
|---|---|
| 2DPCA | 87.74 |
| RLDA | 92.22 |

Table XXXVII shows, RLDA gives better recognition when compared to 2DPCA on PIE Database [15].

TABLE XXXVIII. PERFORMANCE COMPARISON BETWEEN PCA AND LDA ON B1 DATABASE

| Method | Training samples/class | Test samples/class | Recognition rate (%) |
|---|---|---|---|
| PCA | 1 | 44 | 57.2 |
| LDA | 2 | 43 | 59.38 |

TABLE XXXIX. PERFORMANCE COMPARISON BETWEEN PCA AND LDA ON CMU PIE DATABASE

| Method | Training samples/class | Test samples/class | Recognition rate (%) |
|---|---|---|---|
| PCA | 1 | 20 | 64.56 |
| LDA | 2 | 19 | 74.25 |

Table XXXVIII and Table XXXIX show, LDA gives better recognition when compared to PCA on B1 and CMU PIE Databases respectively [16].

TABLE XXXX. PERFORMANCE COMPARISON BETWEEN PCA AND LDA ON ATT, CROPPED YALE, FACES94, FACES95, FACES96, JAFE DATABASES

| Database Name | LDA | PCA |
|---|---|---|
| ATT | 94.40 | 91.30 |
| CROPPED YALE | 93.80 | 90.30 |
| FACES95 | 90.80 | 87.00 |
| FACES96 | 97.20 | 94.00 |

From Table XXXX, it is evident that the best algorithm to recognize image without disturbance is PCA, because in the same recognition rate, PCA takes shorter time than LDA. But to recognize image with disturbances, LDA is better to use because it has better recognition rate [22]. In term of time taken, PCA tends to be much better than LDA, especially to recognize images with background disturbance [22].

## IX. CONCLUSION

In this paper, we have analysed various current PCA, LDA and LPP based algorithms for face recognition. This analysis is vital in developing new robust algorithms for face recognition. Among various PCA algorithms analysed, the best result was found when Manual face localization was used on ORL and SHEFFIELD database consisting of 100 components. The face recognition rate in this case was 100%. The next best was 99.70% face recognition rate using PCA-IN on ORL database. Among various LDA algorithms analysed, it was found that IALDA gives the best face recognition rate of 98.9 % when 20 test samples and 1 training sample were considered on CMU PIE Database. The next best was 98.125 % using Fuzzy Fisherface through genetic algorithm on ORL database. Among various LPP algorithms analyzed, Subspace Discriminant LPP (SDLLP) provides the best face recognition rate of 98.38% on ORL database, the next best was 97.5% using Contourlet-based Locality Preserving Projection (CLPP) on ORL database.

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