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Research Article

Performance Evaluation of LDA, CCA and AAM

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Abstract: Wouldn't we love to replace passwords access control to avoid theft, forgotten passwords? Wouldn't we like to enter the security areas just in seconds? Yes the answer is face recognition. In this study we explore and compare the performance of three algorithms namely LDA, CCA, AAM. LDA (an evolution of PCA is a dimensionality reduction technique where it solves the problem of illumination to some extent, maximizing the inter class separation and minimizing the intra class variations. CCA, a measure of linear relationship between two multidimensional variables where it takes the advantage of PCA and LDA for maximizing the correlation and better performance. AAM is a model based approach where it just picks the landmarks of the images for recognition therefore reducing the error rate and producing good performance rate.

Keywords: AAM, CCA, efficiency, face recognition, landmarks, LDA, PCA, performance

INTRODUCTION

Automated method of recognizing the person using any physiological or behavioral characteristics is Biometrics. Bernd and Koshizen (2004), Priyadarsini *et al*. (2011) and Edwards *et al*. (1998) Biometrics are the replacement for other authenticating techniques like PIN, passwords. They are the basement for pattern recognition techniques of an individual directed towards his physiological characteristics. Physiological techniques include finger scan, iris scan, retina scan, hand scan and facial recognition. Among these, facial recognition is the apt one everyone prefers because it requires no physical interaction, perfect identification and it can be captured with a basic camera also. That's why in airports and other private areas, cameras are mere preferred. They are two types of comparisons for face recognition namely verification and identification where the input image is fetched, compared with the databases and gives us the matching output. The general block diagram of face recognition is.

The main function of first and second blocks (Fig. 1) are to determine whether human faces appear in a given image and where these faces are located. The expected outputs of third block are features containing each face in the input image. In order to make further face recognition system more robust and easy to design, face alignment are performed to justify the scales and orientations of these features. Besides serving as the pre-processing for face recognition, face detection could be used for region-of-interest detection, retargeting, video and image classification etc. After the face detection step, human-face features are extracted from images. Directly using these features for face recognition have some disadvantages, first, each feature usually contains over 1000 pixels, which are too large to build a robust recognition. Second, face features may be taken from different camera alignments, with different face expressions, illuminations and may suffer from occlusion and clutter. To overcome these drawbacks, feature extractions are performed to do information packing, dimension reduction, salience extraction and noise cleaning. After this step, a face patch is usually transformed into a vector with fixed dimension or a set of fiducial points and their corresponding locations. After formulizing the representation of each face, the last block is to recognize the identities of these faces. In order to achieve automatic recognition, a face database is required to build. For each person, several images are taken and their features are extracted and stored in the database. When an input face image comes in, to perform face detection and feature extraction and compare its feature to each face class stored in the database.

In this study we are evaluating the performance of three algorithms namely Linear Discriminant Analysis (LDA) Jelšovka *et al*. (2011) and Kukharev and Forczmanski (2007) Canonical Correlation Analysis (CCA), Active Appearance Model (AAM) (Cootes and Taylor, 2001; Cootes *et al*., 2001).

Linear Discriminant Analysis (LDA) is a feature extraction technique which reduces the dimensionality and preserves as much as information possible

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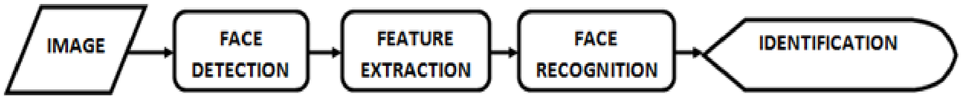


Fig. 1: General block diagram of face recognition

(Belhunmeur *et al*., 1997) Canonical Correlation Analysis (CCA) is a multidimensionality technique and takes an advantage of both PCA and LDA. Active Appearance Model in an enhancement of the above both methods where the error rate is reduced and performance is good.

LITERATURE REVIEW

Face Recognition Zhao *et al*. (2005) and Hardoon *et al*. (2004) has become an important cue for identification of individuals. They are many face recognition methods but the general classification is either holistic or feature based. Feature based is nothing but the sensory organs like eyes, nose, ears, teeth and holistic or content based is two dimensional intensity variation. Linear Discriminant Analysis (LDA) is a dimensionality reduction technique. The basic principle underlying is that it searches for the directions in the database that have largest variance and a projection matrix is defined for the data to project on it. It maximizes the ratio between classes to within class variance. Usually every face in the database is converted into vectors of weight even the input image. The weight of the input image is compared with the weight of images in the database and the nearest neighbor matches and gives us the result. Here in LDA noise is removed. The LDA is classified into two types namely class dependent and class independent. In class dependent it maximizes the ratio between class and within class; in independent it maximizes overall class variance to within class variance.

The Fig. 2 shows the plot between class dependent and class independent where the data in the original space (circles), data in transformed space (diagonal lines), test points (crosses) and the decision region obtained.

The drawback of LDA is the more reduction of an image is done the less information is obtained (more lost) and the recognition is poor.

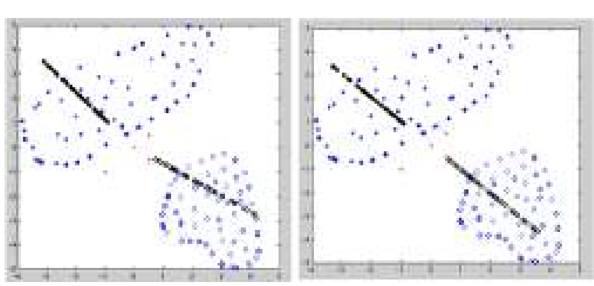


Fig. 2: Plot of class dependent and class independent

Canonical Correlation Analysis (CCA) Borga (2004) is a powerful multivariate analysis between two sets of variables. It describes linear relationship between two sets of 1-D data sequences. CCA is commonly used in signal processing, image processing etc. The drawback of CCA is it varies with magnitude and sign. Also the weights may be distorted due to multicollinearity. Thus precaution must be taken.

Active Appearance Model (AAM) Cootes *et al*. (2001) and Donner *et al*. (2006), is a powerful model of texture and joint shape with a gradient-descent fitting algorithm. Here we manually landmark the images with any values (n = 52, n = 72). In terms of pixel intensities they are non-linear parametric models. In order to minimize the error between input image and closest model instance fitting AAM is used that is non linear optimization problem is solved.

EXISTING AND PROPOSED METHODS

Linear discriminant analysis: Face Recognition using LDA Jelšovka *et al*. (2011) and Kukharev and Forczmanski (2007) are a feature extraction technique and a famous example of dimensionality reduction. LDA was evolved because PCA does not project lower dimensional data and performance was not good. And also there are many unsolved issues in PCA like how many directions one has to choose but this is not in the case of LDA. The basic principle of LDA is it tries to find the best projection direction in the databases belonging to various classes that are well separated. The block diagram of LDA is shown in Fig. 3.

In the Fig. 3 comprises of LDA block diagram where first the database images and input image is fetched into the block combined mean. Then the database images are fetched in pre-processing block where we can see the images are converted to grayscale then averaging and reshaping is done for the proper alignment of images. This is done because every single image in the database may be of different size, so in order to make it of same size reshaping is done. Mean while input image is sent to the block of feature extraction where every part of sensory organs like eyes, nose and teeth are extracted. Now the database images and input image is classified into within class and between class variance where the outcome is projected vector of weights. Using that co-variance matrix is calculated for both input and database images. Using co-variance matrices eigen values are obtained. Now the Euclidean distance is computed and finally matched image is obtained.

The algorithm of LDA in brief:

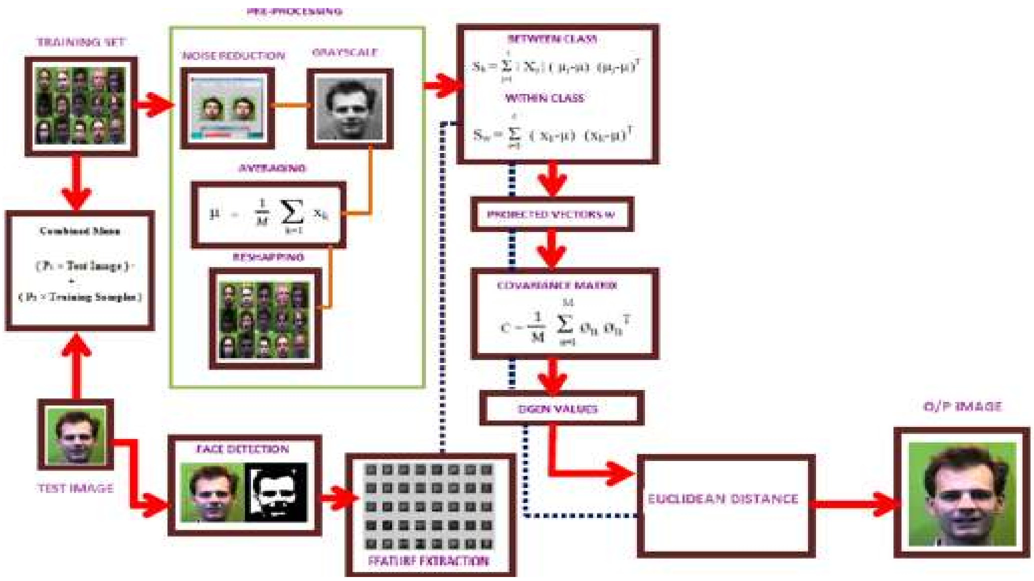


Fig. 3: Block diagram of LDA

Step 1: Both test image and training images should be taken, then convert them into a matrix form.

Step 2: Compute the mean for test image, database images and also for combined test and database images. Mean for combined test and database images is calculated as:

$$\text{Combined Mean} = (P_1 \times \text{Test imag}) + (P_2 \times \text{training samples}) \quad (1)$$

where, P_1 and P_2 are apriori probabilities of the class. For this simple class the probability factor is assumed as 0.5.

Step 3: In LDA m sample images $\{x_1, x_2, \ldots\ldots\ldots, x_n\}$ are projected face space taken with C classes $\{X_1, X_2, \ldots\ldots\ldots, X_j\}$.

where,
M = Total Number of Images
j = Total Number of Persons

Average of each class free space:

$$\mu_j = \frac{1}{M} \sum_{x_j \in X_j} x_k \quad (2)$$

Total average of Projected Free Space:

$$\mu = \frac{1}{M} \sum_{k=1} x_k \quad (3)$$

where,
x_k = Projected free space:

$$X_k = (AV_i) * (T_i - \psi) \quad (4)$$

where,
T_i = Training Images
ψ = Mean of The Training Images:

$$A = \{\o 1, \o 2, \ldots\ldots\ldots, \o n\} \text{ where } i = 1, 2, 3, \ldots\ldots, M$$

Step 4: Projected fisher image is calculated with fisher Eigen vector and projected face space.

Step 5: Fisher Eigen vector is calculated from eig (S_b, S_w) = [Eigen Vectors Eigen Value].

S_b = Between Scatter Matrix
S_w = Within Scatter Matrix:

$$S_b = \sum_{j=1}^{c} |X_j| (\mu_j - \mu)(\mu_j - \mu)^T \quad (5)$$

where,
j = 1, 2, ..., c
Xj = Number of classes or persons
µj = Calculates each person in projected face space
µ = Mean calculated for total eigen face:

$$S_w = \sum_{j=1}^{c} (x_k - \mu)(x_k - \mu)^T \quad (6)$$

Step 6: In order to find eigen face of training image, the eigen vector of the co-variance matrix is calculated. A compact less dimension (M<<N2), M-1 Eigen vectors are calculated:

$$C = \frac{1}{M} \sum_{n=1}^{M} \o_n \o_n^T \quad (7)$$

where, $\o_n$ is the individual difference of each image from mean vector:

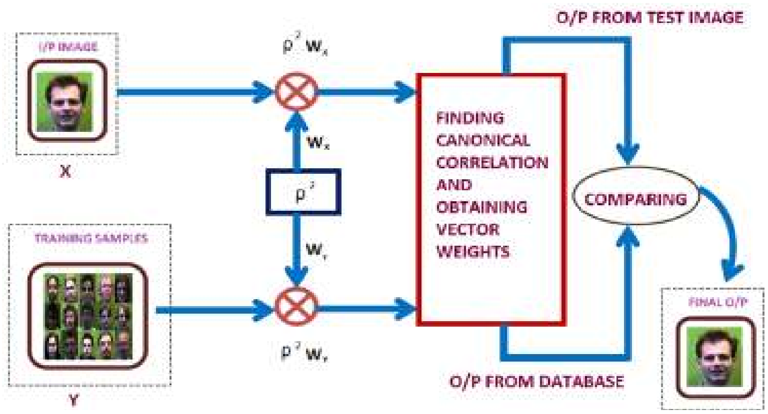


Fig. 4: Block diagram of CCA

$$A = \sum_{n=1}^{M} \text{ø}_n \tag{8}$$

where, A = {ø_1, ø_2,....., ø_n}:

$$\text{Ø}i = Ti - \psi \tag{9}$$

This is the mean calculated for M number of sample images with {T_1, T_2, T_3, ... T_n}:

$$\psi = \frac{1}{M} \sum_{n=1}^{M} T_n \tag{10}$$

where,
T_n = The number of training images

Step 7: Euclidean Distance is calculated between projected test image vector (input image) and projected fisher image (training image of database calculated fisher value).

Canonical correlation analysis: CCA evaluates the linear relationship between two multidimensional variables. It is a powerful multivariate analysis method. The principle of CCA is it finds basis the for two vectors, one for x and other for y in a such a way that it maximizes the correlation between the projections of the variables are mutually maximized. Here also dimensionality is reduced and the new basis is equal or less than smallest dimensionality of the two variables. This is highly speed transformation.
The block diagram of CCA is given in Fig. 4.

In the Fig. 4, the input X is fetched for correlation. Similarly the database images say Y is also fetched for correlation. Mean while mean squared (ρ^2) is multiplied with the sets of basis vectors W_x and W_y. The obtained result from the block of input correlation and database correlation is sent for finding the canonical correlation for X and Y (canonical variates) and we obtain vector weights. Euclidean distance is calculated for input image and the database images. The images are then compared and we obtain finally the matched result.

Considering two sets of basis vectors, one for X and another for Y:

$$S_x = (x.w_x) \text{ and } S_y = (y.w_y) \tag{11}$$

where,
x = Test Image
y = Training Samples
W_x, W_y = Normalized Co-variance Matrices
S_x, S_y = Sets Of Basis Vectors:

$$\rho = \frac{E[S_x S_y]}{\sqrt{E[S_x^2]\, E[S_y^2]}} \tag{12}$$

$$\rho = \frac{E[(x^T w_x\, y^T w_y)]}{\sqrt{E[(x^T w_x\, x^T w_x)]\, E[(y^T w_y\, y^T w_y)]}} \tag{13}$$

$$\rho = \max_{w_x w_y} \frac{E[w_x^T x\, y^T w_y]}{\sqrt{E[w_x^T x\, x^T w_x]\, E[w_y^T\, y\, y^T w_y]}} \tag{14}$$

$$\rho = \max_{w_x w_y} \frac{w_x^T C_{xy} w_y}{\sqrt{w_x^T C_{xx} w_x\, w_y^T C_{yy} w_y}} \tag{15}$$

Solving this with constraint:

$$w_x^T C_{xx} w_x = 1 \tag{16}$$

$$w_y^T C_{yy} w_y = 1 \tag{17}$$

$$C_{xx}^{-1} C_{xy} C_{yy}^{-1} C_{yx} w_x = \rho^2 w_x \tag{18}$$

$$C_{yy}^{-1} C_{yx} C_{xx}^{-1} C_{xy} w_y = \rho^2 w_y \tag{19}$$

$$C_{xy} w_y = \rho \lambda_x C_{xx} w_x \tag{20}$$

$$C_{yx} w_x = \rho \lambda_y C_{yy} w_y \tag{21}$$

$$\lambda_x = \lambda_y^{-1} = \sqrt{\frac{w_y^T C_{yy} w_y}{w_x^T C_{xx} w_x}} \tag{22}$$

Fig. 5: Flow of handling shapes and textures

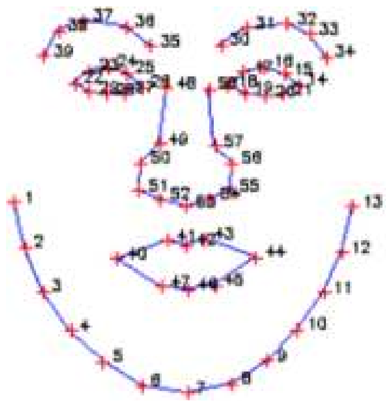


Fig. 6: An example of landmark connectivity scheme

The algorithm of CCA is given below:

Step 1: Training sets (databases) are defined. Subjects may differ 20, 40 to 400.
Step 2: Pre-Processing is done i.e., the databases and the input is converted into gray scale and reshaped. This is done mainly to reduce the noise.
Step 3: CCA tries to finds pair of projection x and y.
Step 4: It maximizes the correlation between the within set and between set co-variance matrix.
Step 5: The canonical correlation between x and y can be found by solving eigen value equations.
Step 6: An input image compares with the subjects and gives us the result.

CCA produces changes in sign and magnitude of canonical weights for each variate. Also, weights may be distorted due to multicollinearity. Therefore, caution is necessary if interpretation is based on canonical weights.

Active Appearance Model (AAM): Generally AAM is used in medical fields for segmentation. AAM Cootes *et al*. (2001), Donner *et al*. (2006) and Cootes and Taylor (2001) are defined as a template model which is deformable under an implicit/explicit optimization which deforms shape to image. The three steps involved for handling shapes and textures are.

In the Fig. 5 shows us the flow of handling shapes and textures.

Shapes: It extracts all the geometrical information from an object that remains when location, scale and rotational effects are filtered out.

Textures: The pixel intensities across the object.

After defining the shapes, we get a problem of describing the shape. Suppose we take an example that the Greek Island Crete is like a man lying, but using that we cannot construct any algorithms. So in order to obtain true shapes we have to filter out the location, scale and rotational effects. The system that proposes such coordinate reference is called pose. We can define a shape effectively by locating finite number of points in the perimeter of the shape. The method is called landmarks.

In the Fig. 6 is an example of landmark connectivity scheme where n = 58 is taken.

This land marking procedure is done using Procrustes Analysis where it aligns the images.

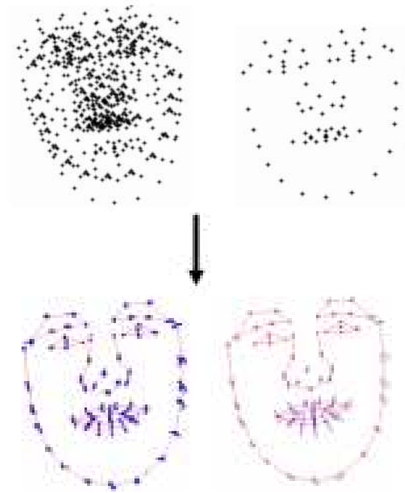
Procrustes analysis algorithm:

1. Compute the centroid of each shape: $(\bar{x}, \bar{y}) = \left(\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i\right)$
2. Align both shapes to the origin: $(x_c, y_c) \rightarrow (x - \bar{x}, y - \bar{y})$
3. Normalize each shape by isomorphic scaling: $\hat{x} = \frac{x_c}{\|x_c\|}$
4. Arrange shape matrices as $X' = [\hat{x}|\hat{y}]_{n\times 2}$
5. Perform SVD $(X_2' X_1') = USV^T$
6. The optimal rotation matrix is given by $R = UV^T$

In the Procreates analysis algorithm shows the steps to be followed for Procrustes Analysis for aligning shapes.

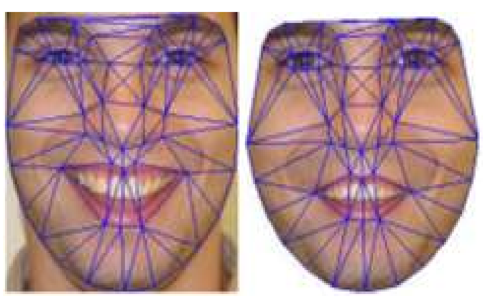
Generalized Procrustes Analysis algorithm (GPA): A GPA sequentially aligns pairs of shapes with procrustes mean and aligns it. After aligning it a new estimation is done again till it reaches the previous mean:

1. Choose the first shape as an estimate for the mean shape $\rightarrow \overline{\mathrm{X}} = \mathrm{X}_1$
2. k = 0
3. Repeat
4. for each shape x_i, i = 1. . . *n* do
5. procrustes $(\mathrm{X}_i, \overline{\mathrm{X}})$
6. End for
7. k = k+1
8. Recompute new mean from the aligned shapes $\overline{\mathrm{X}}_k = \frac{1}{n}\sum_{i=1}^{n} \mathrm{X}_i$
9. Until mean converges$\rightarrow \overline{\mathrm{X}}_{k+1} \approx \overline{\mathrm{X}}_k$



(a) (b)

Fig. 7: An example of how the Point Distribution Mean (PDM)



(a) Original (b) Warped texture

Fig. 8: Image warping of a face

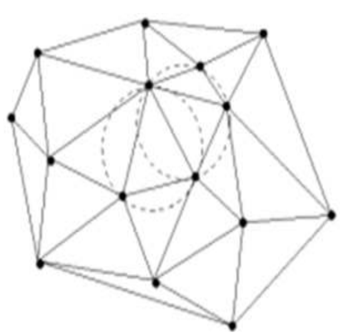


Fig. 9: The delaunay triangulation

The Generalized Procrustes Analysis algorithm (GPA) is advancement to Procrustes analysis where it takes repeated means until it reaches the desired mean.

Now we find a common shape for each person. This is achieved using Procrustes that aligns all face shapes of the same person. At start we choose an image and calculate the mean. Now all the remaining images mean is also calculated after Procrustes. We name this as Procrustes mean. If these means are superimposed they are called Point Distributed Mean (PDM):

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$
$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad (23)$$

where, x, y are the coordinates of the landmarks.

In the Fig. 7 says how the mean is re-calculated for the same person's image and PDM is obtained.

Since we are removing location, scale, rotation from the images we get a problem i.e., there is no constant intra-variation. This issue is solved by PCA. Here PCA maximize the variance and defines axes using this variance. It is used to visualize multidimensional data.

Texture modeling: One must consider the information constituted by its own pixel only shape is not enough for images. In shape the data acquisition is straight forward since the landmarks in shape constitute itself. So we need texture modeling also. In Texture it captures the pixels using Image Warping and Modeling Pixel Variations. Here a piece-wise affine is used called Delaunay triangulation.

Transformation of spatial configuration of an image into another is image warping.

In the Fig. 8, the pixel intensities changes from one to another and they also have different landmarks. This happens because of one point to one point correspondence.

Creating image warping is always an issue. To solve this we use triangulation technique where three landmarks are connected as triangle.

The delaunay triangulation: It is a triangle network whose vertexes are points and these do not intercept themselves. They follow a certain property that they do not have vertexes inside its circumference.

In the Fig. 9, the Delaunay triangle maximizes the minimum angle of every triangle in order to form equilateral triangle. For concave nature where the shapes lies outside for that the Delaunay Triangulation must be restricted.

Finally combining the shape and texture part we get the recognition perfect of the person. The generalized procedure is shown below.

In the Fig. 10 explains the block diagram of AAM where the input image is fetched to shaping, then aligning. At this stage we apply PCA to get proper aligned shapes. At the same time texture is done by image warping which creates problem and it is solved by Delaunay Triangle. Finally shape and texture is combined.

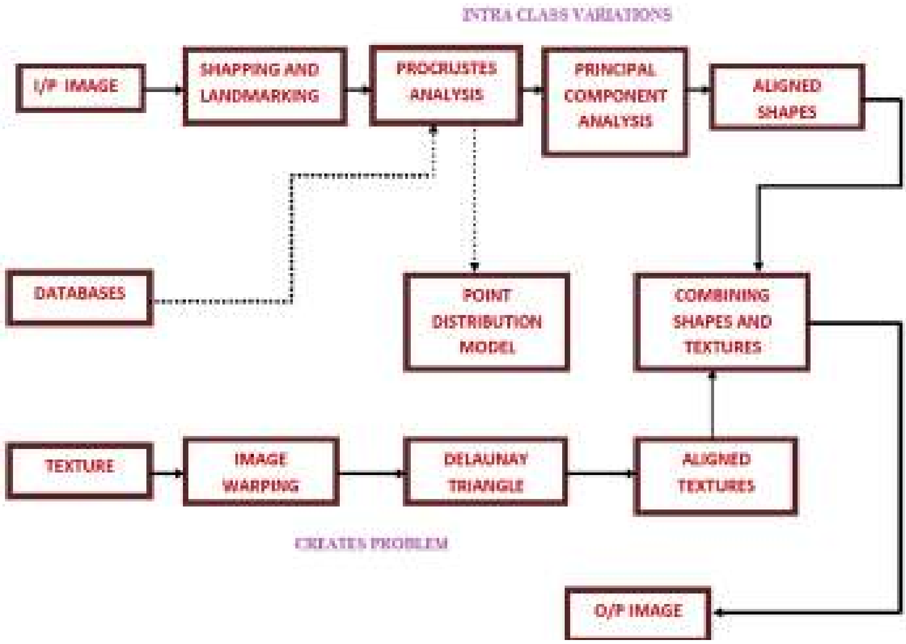


Fig. 10: Generalized AAM block diagram

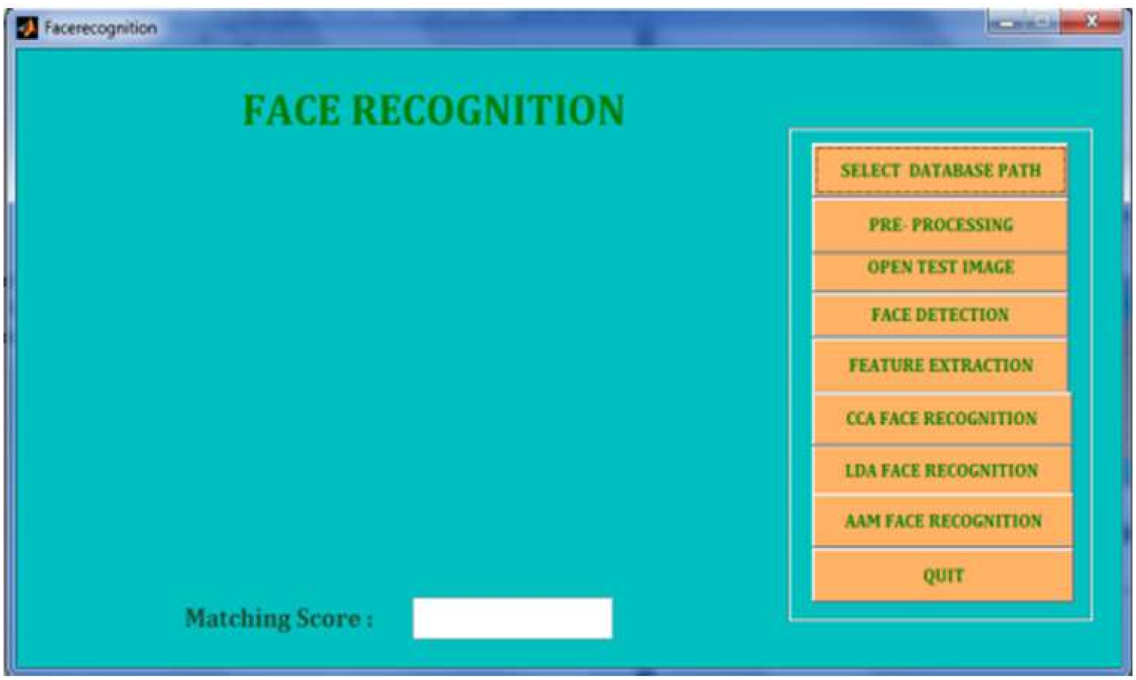


Fig. 11: GUI window

EXPERIMENTAL RESULTS

Procedure: The entire sequence of training and testing is sequential and can be broadly classified as consisting of following steps:

- Database preparation
- Training
- Testing
- Results

Databases preparation: FERET face database (Fig. 11) provided by AT&T Laboratories from Cambridge University, AT&T (Fig. 12) database and finally VIT students database (Fig. 13) were used. The images are 180×200 pixels. Lighting variations, pose variations, spectacular variations also included.

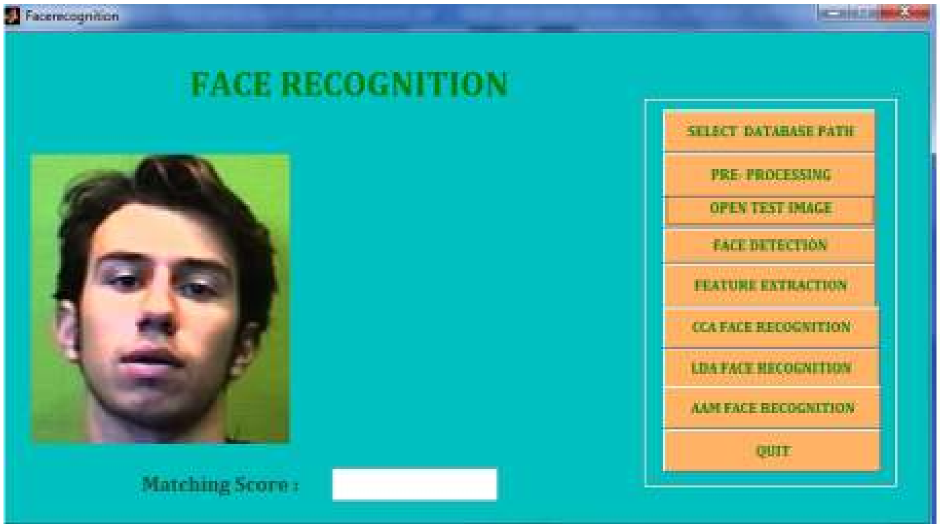


Fig. 12: Input image

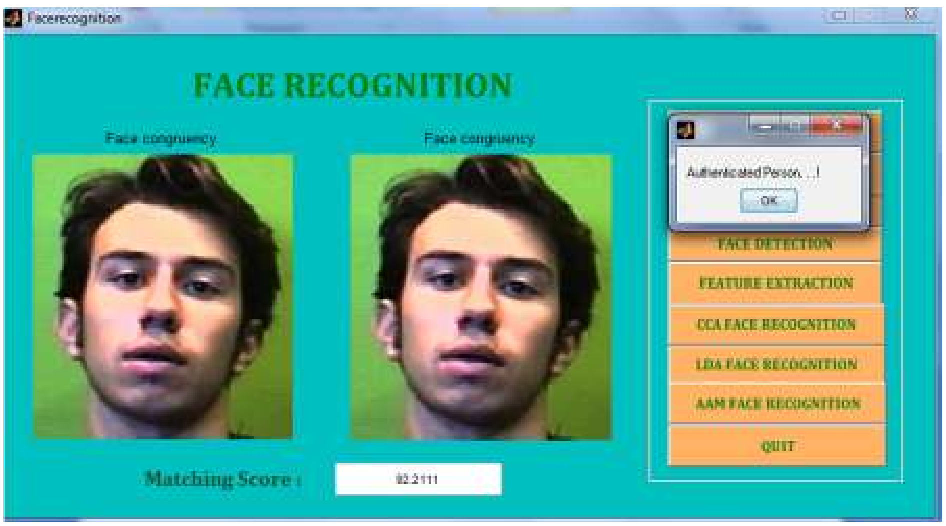


Fig. 13: LDA output

Training process: After database preparation, we have to train the images. Training the images means, converting them into grey images if they are colored, normalizing them if required and extracting the features. Since it is a feature based method, therefore features of eyes, nose and mouth are extracted. Images of same person are in the same class and Images of different persons are in different class. After creation of classes, their weight vectors are find out, these weight vectors are called training images weight vectors.

Testing process: The main aim is to recognize images. In training process to find out weight vectors of training images. Similarly to find out the weight vectors of testing images. Now to calculate an Euclidian Distance by difference of the weight vectors of training images and testing images. Now minimum Euclidian distance is find out. With the help of minimum Euclidian distance to recognized index, recognized index is the particular image in the training database.

Experiments and results: The experiments have been done with different databases. All the images in the databases are considered. LDA, CCA, AAM were done using MATLAB Gonzalez *et al*. (2000) software. LDA and CCA were existing methods and AAM was embedded with it and performance was evaluated. All these algorithms were increased in counts of 15, 20, 50, 100, 200 to see perfect variations, respectively. We got percentage Recognition Rate as 98%, False Rejection Rate as 0.03 and False Acceptance Rate as 0.02 for CCA.

The MATLAB coding was constructed using GUI (Fig. 14).

We have considered a total of 200 images comprising of 10 images/person of 20 individuals with

Fig. 14: ORL database-LDA MATLAB simulation output
(120 test images given as input and the corresponding recognized image; Here eight image wrongly recognized. Hence we get a Recognition Rate = (112/120)*100 = 93.33%) for above sample as 120 test images we got recognition rate as 93.33%

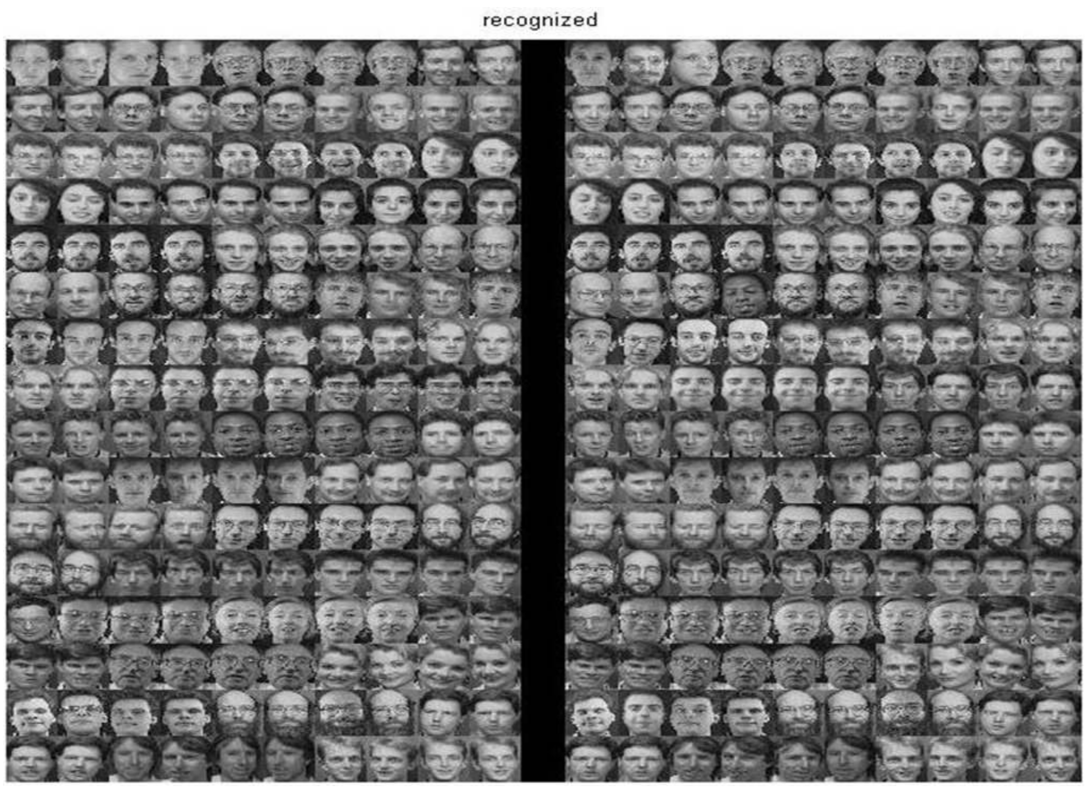


Fig. 15: ORL database-LDA MATLAB simulation output
One hundred and sixty test images given as input and the corresponding recognized image; Here thirteen image wrongly recognized; Hence we get a Recognition Rate = (147/160)*100 = 91.875%

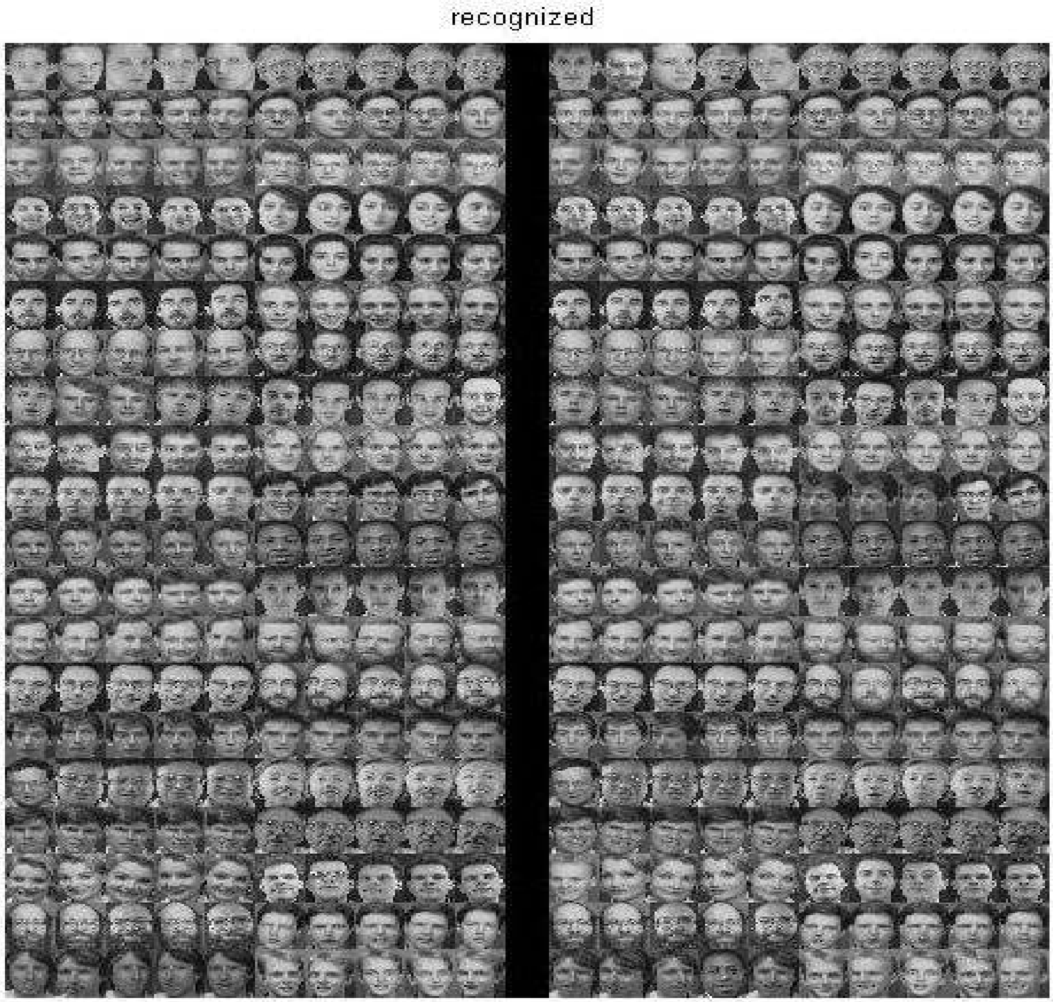


Fig. 16: ORL database-LDA MATLAB simulation output
Two hundred test images given as input and the corresponding recognized image here twelve images wrongly recognized hence we get a Recognition Rate = (190/200)*100 = 95%

Fig. 17: CCA output

Fig. 18: AAM output shown through video, initial and final of a particular image

Fig. 19: Sample of FERET database

varying different Illumination and pose condition. The training, FERET, ORL and VIT database are shown in Fig. 19, 23 and 27. The following figures (Fig. 12 and 13) shows the images recognized using LDA for the given input.

No. of test images 120: For 120 images in the Test Database and 400-120 = 280 images in the Training Database the input images and the corresponding recognized image is shown in Fig. 14.

No. of test images 160: For 160 images in the Test Database and 400-160 = 240 images in the Training Database the input images and the corresponding recognized image is shown in Fig. 15.

For above sample as 160 test images we got recognition rate as 91.875%.

No. of test images 200: For 200 images in the Test Database and 400-200 = 200 images in the Training Database the input images and the corresponding recognized image is shown in Fig. 16.

We have considered a total of 200 images comprising of 10 images per person of 20 individuals with varying condition. The training, FERET, ORL and VIT database are shown in Fig. 19, 23 and 27. The

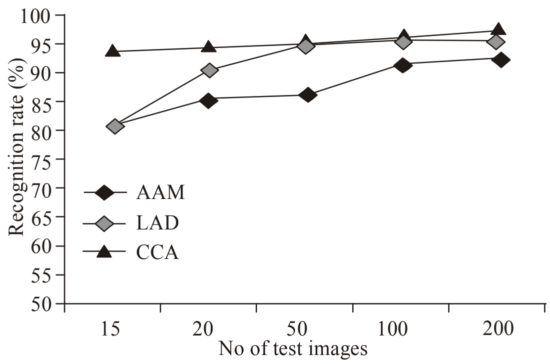


Fig. 20: Recognition rate using FERET Databases

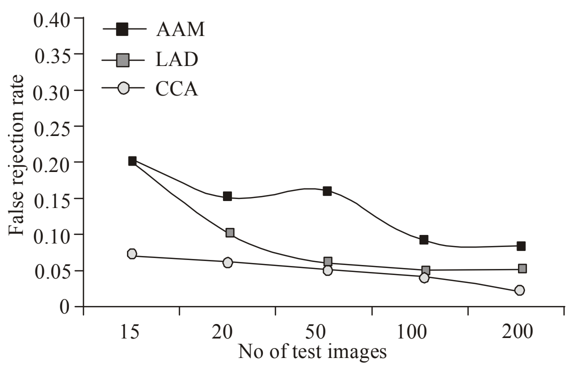


Fig. 21: False Rejection Rate using FERET Databases

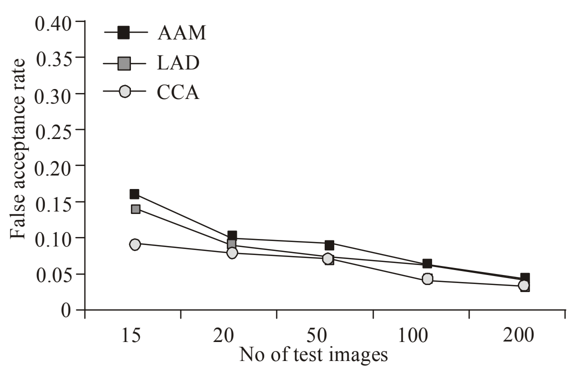


Fig. 22: False Acceptance Rate using FERET Databases

Fig. 23: Sample of VIT Students database

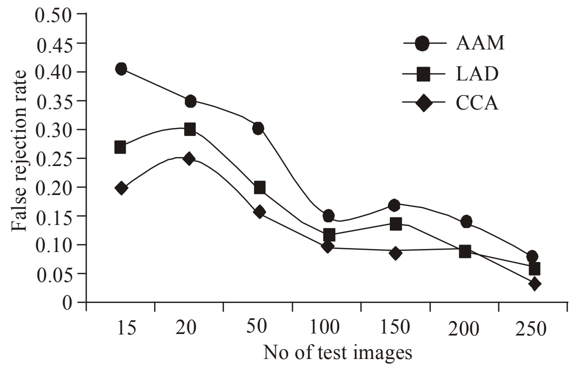


Fig. 24: Recognition rate using VIT Databases

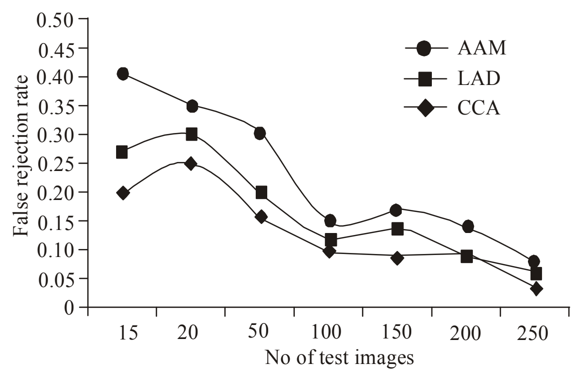


Fig. 25: False Rejection Rate using VIT Databases

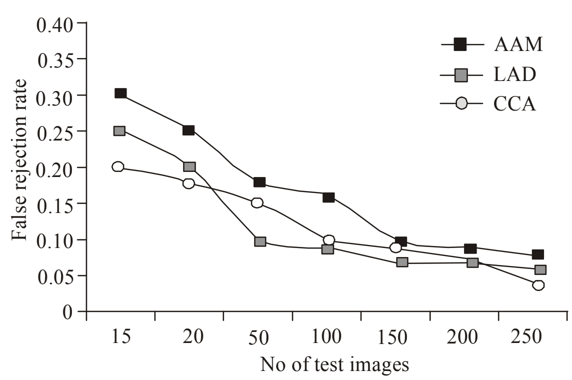


Fig. 26: False Acceptance Rate using VIT Databases

following figures and Fig. 17 and 18) shows the images recognized using CCA and AAM for the given input.

Experimental results-FERET database using LDA, CCA and AAM: It has been analyze the three post-processing LDA, CCA and AAM were performed on three public available databases FERET Database (Fig. 19 Database. With our experimental data we got percentage Recognition Rate as 92, 95 and 98% respectively (Table 1) and Fig. 20), False Rejection Rate as 0.08, 0.05 and 0.02 respectively (Fig. 21) and False Acceptance Rate as 0.04, 0.04 and 0.03 respectively (Fig. 22). The CCA has had almost

Table 1: Simulation results- LDA, CCA, AAM using FERET-database

Comparison between LDA, CCA, AAM using FERET database

	Recognition rate (%)			False acceptance rate			False rejection rate		
No. of test	AAM	LDA	CCA	AAM	LDA	CCA	AAM	LDA	CCA
15	80	80	93.33	0.16	0.14	0.09	0.20	0.20	0.07
20	85	90	94.00	0.10	0.09	0.08	0.15	0.10	0.06
50	86	94	95.00	0.09	0.07	0.07	0.16	0.06	0.05
100	91	95	95.00	0.06	0.06	0.04	0.09	0.05	0.04
200	92	95	98.00	0.04	0.04	0.03	0.08	0.05	0.02

Table 2: Simulation results-LDA, CCA, AAM using VIT-database

Comparison between LDA, CCA, AAM using VIT database

	Recognition rate (%)			False acceptance rate			False rejection rate		
No. of test	AAM	LDA	CCA	AAM	LDA	CCA	AAM	LDA	CCA
15	60.00	73.33	80.00	0.30	0.25	0.20	0.40	0.27	0.20
20	65.00	70.00	75.00	0.25	0.20	0.18	0.35	0.30	0.25
50	70.00	80.00	84.00	0.18	0.10	0.15	0.30	0.20	0.16
100	85.00	88.00	90.00	0.16	0.09	0.10	0.15	0.12	0.10
150	83.35	86.00	90.60	0.10	0.07	0.09	0.17	0.14	0.09
200	86.50	91.00	91.00	0.09	0.07	0.07	0.14	0.09	0.09
250	92.00	94.00	96.00	0.08	0.06	0.04	0.08	0.06	0.04

Table 3: Simulation results-LDA, CCA, AAM using ORL-database

Comparison between LDA, CCA, AAM using ORL database

	Recognition rate (%)			False acceptance rate			False rejection rate		
No. of test	AAM	LDA	CCA	AAM	LDA	CCA	AAM	LDA	CCA
15	80	80.00	93.33	0.16	0.14	0.09	0.20	0.20	0.06
20	85	90.00	94.00	0.10	0.09	0.08	0.15	0.10	0.05
50	86	94.00	95.00	0.09	0.07	0.07	0.16	0.06	0.04
100	91	95.00	96.00	0.06	0.06	0.04	0.08	0.05	0.04
120	92	93.33	95.00	0.05	0.05	0.04	0.08	0.07	0.05
160	92	91.87	96.00	0.05	0.04	0.04	0.08	0.09	0.04
200	92	95.00	97.00	0.04	0.04	0.03	0.08	0.05	0.03

Fig. 27: Sample of ORL database

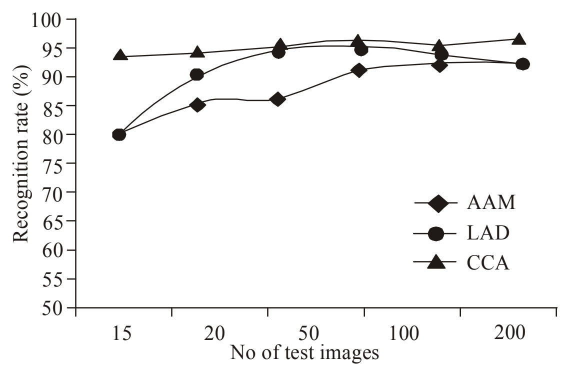


Fig. 28: Recognition Rate using ORL Databases

all the test images recognized in every iteration. It also has the highest Recognition Rate on the largest sample images.

Experimental results-VIT database using LDA, CCA and AAM: Success of a practical face recognition system with videos and images grabbed live depends on its robustness against the inadvertent and inevitable data variations. The number of images (VIT Database Fig. 15) was increased in counts of 15, 20, 50, 100, 150, 200 and 250, respectively to see the perfect variations. To combine and analyze we got percentage Recognition Rate as 92, 94 and 96%, respectively

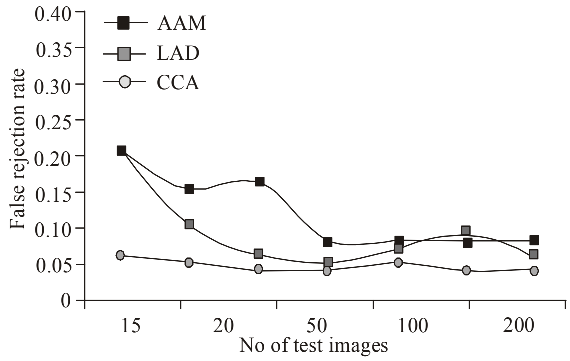


Fig. 29: False Rejection Rate using ORL Databases

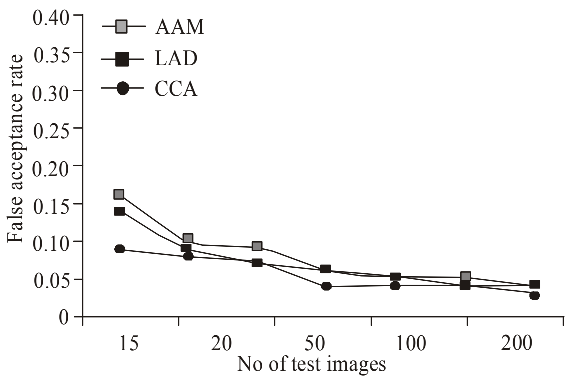


Fig. 30: False acceptance Rate using ORL Databases

(Table 2 and Fig. 24), False Rejection Rate as 0.08, 0.06 and 0.04, respectively (Fig. 25) and False Acceptance Rate as 0.08, 0.06 and 0.04, respectively (Fig. 26). The CCA has had almost all the test images recognized in every iteration. It also has the highest Recognition Rate on the largest sample images.

Experimental results-ORL database using LDA, CCA and AAM: Experiment were performed using LDA, CCA and AAM based on their ability of recognition in ORL Database and by testing these method on different number of images, found that CCA is the most efficient method in all. To test the efficiency of the system the test images were computed by a varying no. of probe images. The Recognition Rate (%RR), False Acceptance Rate (FAR) and False Rejection Rate (FRR) have been accounted in Table 3 from which we can see that the CCA out performs the other two algorithms LDA and AAM. We got percentage Recognition Rate as 92.95 and 97%, which is shown in Fig. 28, False Rejection Rate as 0.04, .0.04 and 0.03 which is shown in Fig. 29 and False Acceptance Rate as 0.08, 0.05 and 0.03, which is shown in Fig. 30, respectively.

CONCLUSION

We analyze Principal Component Analysis, Canonical Correlation Analysis and Active Appearance Model. PCA which is good for low dimensional representation for face images but it is not able to discriminate between variations due to illumination changes. So in order to solve this problem we moved to LDA. LDA solves the illumination change problem to some extent by finding the transformation such that it maximizes the inter-class separation and minimizes the intra-class variations. Here also the performance is some what good. So we move to Canonical Correlation Analysis (CCA) which combines two feature extractors to improve the performance of the system, by obtaining the advantages of both (PCA+LDA). CCA also finds the transformation for each image in the database and maximizes the correlation between them. But in CCA, canonical function can be interpreted by the sign and the magnitude of the canonical weights assigned to each variable with respect to its canonical variates. Also, these weights may be distorted due to multicollinearity. Therefore, considerable caution is necessary if interpretation is based on canonical weights. AAM which has the capability to observe the variation of different individuals in the database and correct using fitting process. The shape of the faces are varied and mean is calculated for it. Meanwhile the database images are also sent to the mean block where individual means is calculated and result is arrived till we reach the desired mean. This is called Procrustes mean. AAM calculates texture model using image warping where it removes differences in texture.

Even though CCA is better, further work needs to be done to extend this face recognition system to general pose. Moreover, it has a disadvantage in projecting in multidimensional conditions. It can be extended to 3 D Morphable where more perfect matchings can be obtained and performance can be more. In today's generation people prefer less time in security purposes, so the more development in every stage the more it becomes user feasibility.

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