# *Face Recognition Challenge*

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***Abstract***— *Face recognition is an important application of Image processing owing to its use in many fields***.** *This report on face recognition challenge aims to discuss importance and motivation behind the face recognition problem. It also discusses different approaches used in face recognition and importance of feature extraction for face detection and recognition problem and challenges that are faced in it. This Paper discusses reducing the dimensions on images with PCA and then applying LDA on three different datasets to get the desired axes. Applying PCA before LDA reduces computation time for calculation of within-class and inter-class scatter matrix in LDA. Proposed algorithm gives 84.21% accuracy on class dataset, 100% accuracy on SEAS FR DB and the one generated by the authors.*

***Keywords—Face Detection, Face Recognition, PCA, LDA, Eigenfaces, KNN,Fisherfaces***

## I. Introduction to face recognition

Face detection and Face recognition have been the core problem in Computer Vision, specifically in image processing for more than over a decade. Today in this information era, we have most of our data secured by computers by incurring different security mechanisms such as passwords, encryption keys, fingerprints. The human face plays an important role in our social interaction, conveying people's identity [1]. Using the human face as a key to security, biometric face recognition technology has received significant attention in the past several years due to its potential for a wide variety of applications in both law enforcement and non-law enforcement agencies.

As compared with other biometrics systems using fingerprint/palm print and iris, face recognition has distinct advantages because of its non-contact process. Images can be captured from a distance without touching the person and face can be extracted from that image. The identification does not require interacting with the person. In addition, recognized face images can be recorded and archived can later help identify a person which can be very helpful for crime investigation, surveillance systems, video telephony, and credit card verification [2].

## II. Existing approaches in Face Recognition

### *A. Principal Component Analysis*

PCA is most efficient techniques for face recognition and image compression. It is being used for identifying the important feature in face and calculating initial face image. PCA reduces the large dimensionality of image vector and convert it to small dimensionality for feature space whose basis vectors correspond to the maximum variance direction in the original image space. This process is called eigenspace projection. It calculate eigenvector for particular facial image using covariance matrix.Sum of all eigenface represented new image [3].

### *B. Linear Discriminant Analysis*

LDA is a classification method that finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes the between-class scatter matrix $S_B$ and the within-class scatter matrix $S_W$ are defined. The goal is to maximize SB while minimizing SW, in other words, maximize the ratio $\det|S_B|/\det|S_{W|}$. Maximizing here means Fisher criterion [4].

### *C. Support Vector Machine*

Given a set of points belonging to two classes, a Support Vector Machine (SVM) finds the hyperplane that separates the largest possible fraction of points of the same class on the same side, while maximizing the distance from either class to the hyperplane. PCA is first used to extract features of face images and then discrimination functions between each pair of images are learned by SVMs.

### *D. Neural Network*

NN can be used in face detection and recognition because these models can simulate the way neurons work in the human brain. It uses unsupervised methods for extracting features and supervised methods for finding features able to reduce classification error. It uses feed-forward neural networks (FFNN) for classification. It could decrease the error rate training several neural networks and averaging over their outputs, although it is more time-consuming that the simple method [5].

## III. Proposed approach

Applying PCA followed by LDA
1. Applying PCA to reduce dimensionality
2. Applying LDA to recognize images (Novelty factor)
3. Applied k-NN algorithm to classify image

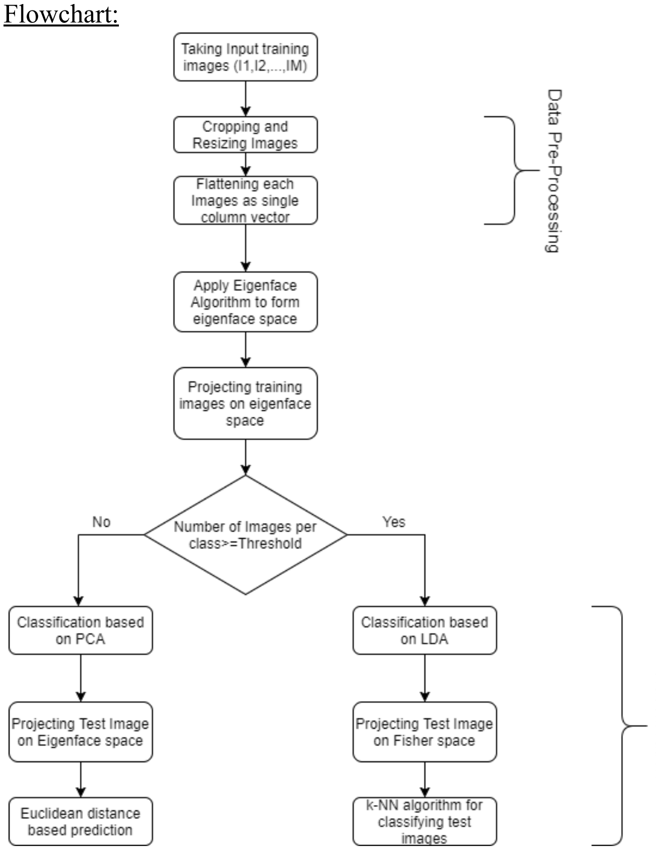
PCA focuses on giving axes which provides maximum variance of the data. Using only PCA will not focus on the interclass separation of the data [6].

LDA on the other hand gives axes which focuses on maximum interclass separation. So, we are first reducing the dimensions with PCA and then applying LDA on this dataset to get the desired axes. Applying PCA before LDA reduces computation time for calculation of within-class and inter-class scatter matrix in LDA.

In contrast, Neural network discussed in existing approach include its "black box" nature, greater computational burden, proneness to overfitting, and the empirical nature of model development. SVM has high algorithmic complexity and extensive memory requirements of the required quadratic programming in large-scale tasks as well the drawback is in the selection of the kernel function parameters.

## IV. Algorithm

Flowchart:




Pseudocode of Eigenface Algorithm

Step 1: Obtain Face images $I_1, I_2, ..., I_m$ (training faces)

Step 2: Represent every image $I_i$ as a column vector $\Gamma_i$

Step 3: Compute the average face vector $\Psi$:

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i$$

Step 4: Subtract the mean face:

$$\Phi_i = \Gamma_i - \Psi$$

Step 5: Compute the covariance matrix C:

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T = AA^T \ (N^2 x N^2 \text{ matrix})$$

where $A = [\Phi_1 \ \Phi_2 \dots \Phi_M]$ ($N^2xM$ matrix)

Step 6: Compute the eigenvectors $u_i$ of $AA^T$

The matrix $AA^T$ is very large → not practical !!

Step 6.1: Consider the matrix $A^TA$ (MxM matrix)

Step 6.2: Compute the eigenvectors $v_i$ of $A^TA$

$A^TAv_i = \mu_i v_i$

Step 6.3: Compute the M best eigenvectors of $AA^T$: $u_i = Av_i$

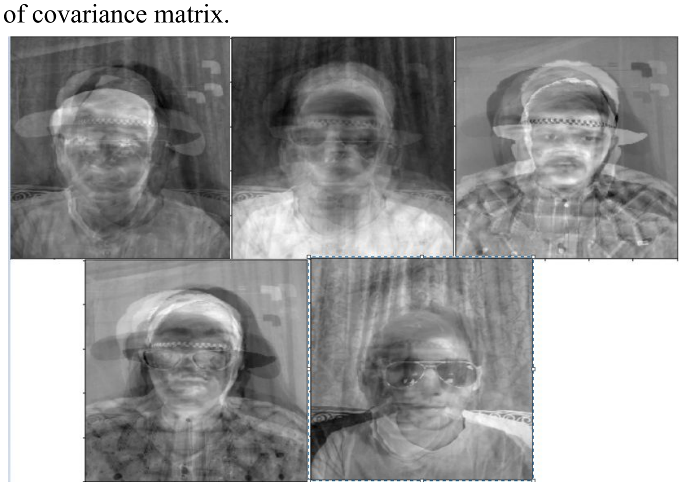
(**important**: normalize $u_i$ such that $\| u_i \| = 1$)

Step 7: Keep only K eigenvectors (corresponding to the K largest eigenvalues)

$w_j = u_j^T \Phi_i$ ($\Omega_i = [w_1^i, w_2^i, ..., w_K^i]^T$, $i = 1,2,...,M$)

(we call the $u_j$'s eigenfaces)

Below are eigenfaces computed by keeping best eigenvectors of covariance matrix.



Step 8: Classification of test Images

Step 8.1: Converting to grayscale images

Step 8.2: Flattening test image

Step 8.3: Normalize $\Gamma$: $\Phi = \Gamma - \Psi$

Step 8.4: Project on the eigenspace

$$w_i = u_i^T \Phi$$

Step 8.5: Represent $\Phi$ as: $\Omega = [\, w_1\ w_2 \dots w_K]^T$

Step 8.6: Find $e_r = \min_l \| \Omega - \Omega^l \|$

Step 8.7: $e_r$ gives nearest training image *l* so the testing image is recognized as face *l* from the training set.

<u>Pseudocode of Linear discriminant Analysis Algorithm:</u>

Input: L = Projected images computed by Eigenface algorithm

Step 1: Suppose there are C classes

Let $\mu_i$ be the mean vector of class i, i = 1,2,...,C

Let $M_i$ be the number of samples within class i, i = 1,2,...,C

Let M = $\sum_{i=0}^{C} M_i$ be the total number of samples

Step 2: <u>Within-class scatter matrix</u>:

$$S_w = \sum_{i=1}^{C} \sum_{j=1}^{Mi} (y_j - \mu_i)(y_j - \mu_i)^T$$

Step 3: <u>Between-class scatter matrix</u>:

$$S_b = \sum_{i=1}^{C} (\mu_i - \mu)(\mu_i - \mu)^T$$

$$\mu = 1/C \sum_{i=1}^{C} \mu_i$$

(mean of entire data set)

Step 4: maximize $\frac{det(Sb)}{det(Sw)}$

LDA transformation should retain class separability while reducing the variation due to sources other than identity (e.g., illumination).

Step 5: Compute eigenvalue and eigenvectors of the matrix: $S_w^{-1}S_b$, By solving the equation: $S_w^{-1}S_b u_k = \lambda_k u_k$

Step 6: Keep only K eigenvectors corresponding to the highest K eigenvalues and using those selected eigenvectors, Fisher face space is formed.

Step 7: Project L onto the Fisher face space

Step 8: Classification:

Step 8.1: Take a test image and flatten it

Step 8.2: Project onto Eigenface space

Step 8.3: Project the projected image onto the Fisher face space

Step 8.4: Use kNN algorithm for computing nearest training images to recognize images

## V. Experimental results

I. Details about the three different datasets used

*A. Class Dataset*

Size of images: 500 X 500
Resolution: 250000
Image format: JPG File
Different pose: Joy, Sad, Fear, Disgust, Surprise, Anger, Hat, Glasses/ Goggles
Pencil drawings: Same dimension, formate and pose
Dots Per Inch: 96

*B. SEAS FR DB*

Size of images: 160 X 160
Resolution: 25600
Image format: JPG File
Different pose: Front Face, Left Face, Right Face, Up Lift, Down tilt, Glasses, No Glasses, Happy, Sad, Wink, Surprise, Sleepy, Beard, No beard, Left- Right Light, Full Light, Top Light

*C. Own Dataset*

Size of images: 640 X 480
Resolution: 307200
Image format: JPG File
Different pose: Joy, Sad, Fear, Disgust, Surprise, Anger
Pencil drawings: Same dimension, formate and pose
Dots Per Inch: 96

II. Minimum dimension for which model gives best accuracy on "**Class Dataset**" : **100x100**,

- Best accuracy is 82.89%.
- Number of eigenvectors taken: 63 (90% Variance explained)
- Main reason for this accuracy is less number of training examples per class.

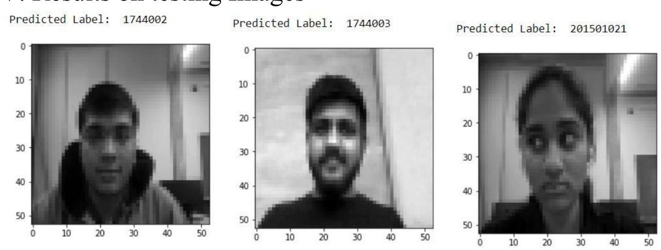
III. Minimum dimension for which model gives best accuracy on "**Own Dataset**" : **53x53**,

- Best accuracy is **100%.**
- Number of eigenvectors taken: **8** (**90% Variance** explained)
- Main contributing factor for this accuracy is large number of training examples per class.

IV. Minimum dimension for which model gives best accuracy on “**SEAS FR**” :**72x72**,

- Best accuracy is **100%.**
- Number of eigenvectors taken: **22** (**90% Variance** explained)
- Main contributing factor for this accuracy is large number of training examples per class.

V. Results on testing Images




VI. Preprocessing on dataset

- Resize Image
- Converting image into grayscale image
- Flatten Image and create column Images matrix
- Extracting Image label

## VI. Discussions

*Learning from PCA* : Lighting conditions and orientation of subject is affecting performance of PCA algorithm poorly.

*Learning from LDA* : LDA requires more number of training examples per class to give better accuracy. Directly applying LDA is computationally expensive and the inverse of within class scatter matrix may not always exist and the LDA algorithm may fail. That is why, PCA is applied before LDA to regularize the data.

*Problems faced*

1) Different naming conventions were used by students to label their image. Only roll number of the students was extracted out from the given label.
2) All images were clicked with different backgrounds. To address this issue we cropped out only the face portion out of the images.
3) For LDA, number of images per class(student) were less which resulted in less number of points in each cluster. We experimented with more images of our group members and obtained a good result in PCA_LDA_KNN by doing so.

## VII. Conclusions

1) For small number of samples Eigenface outperforms Fisher face.
2) For small size data set, applying PCA_LDA approach is not improving accuracy over Eigenface.
3) If we increase number of training examples per class, applying PCA_LDA gives better accuracy.If testing image has very different illumination conditions than training examples, than PCA algorithm is behaving poorly.

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