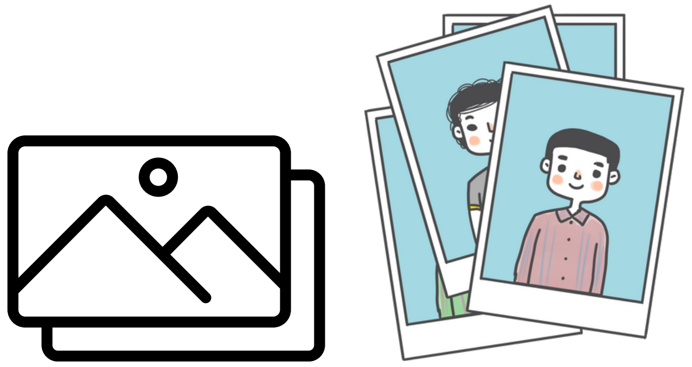
# EIGENFACES VS FISHERFACES:

Recognition using class specific Linear Projection

CS663 COURSE PROJECT

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# 1. Introduction

- We studied and implemented the paper - https://cseweb.ucsd.edu/classes/wi14/cse152-a/fisherface-pami97.pdf, which describes 4 methods for Face Recognition persisting to the various challenges faced such as lightning variations, alignment, expressions etc
- The first method involved direct correlation between all pairs of images which was computationally very expensive
- The second linear subspace method which involves the Lambertian surface assumption, but it only works well if there is no internal shadowing
- The third method was performing PCA dimension reduction. This method showed absurd results for poor lighting conditions
- The fourth method which the paper majorly proposed was performing the Fisher Linear discriminant which takes into account the inter and intra-class calculations.
- We majorly focused on 2 methods, specifically eigenfaces and fisherfaces extraction

# 2. Eigenfaces

**ALGORITHM:**

- Exploits the fact that most natural face images have a high variance in a lower dimensional subspace.
- We use PCA to determine this lower dimensional subspace.
- Compute the eigencoefficients of every training image using this PCA
- For a test image compute the eigencoefficients again using the same PCA
- Classify the image to a class using the nearest neighbor algorithm

# 2. Eigenfaces

**LIMITATIONS:**

- Much of the variation from one image to the next is due to illumination changes.
- Eigenfaces **fails on images with a variation in lighting**
- Variation in lighting dominates the variation in the facial expression, pose and the identity, of a person and hence pollutes the PCA eigenvectors
- We can remove the top 3 eigenvectors to get better results. By discarding the three most significant principal components, the variation due to lighting is reduced

# 3. Why does the top 3 eigenvectors makes such dfference?

- If PCA is presented with images of faces under varying illumination, the projection matrix *W_opt* will contain principal components (i.e., Eigenfaces) which retain, in the projected feature space, the variation due lighting
- Since the first principal components capture the variation due to lighting, then better clustering of projected samples is achieved by ignoring them. Yet, it is unlikely that the first several principal components correspond solely to variation in lighting; as a consequence, information that is useful for discrimination may be lost.

# 4. Fisherfaces

- In this method, we argue that using a class-specific linear method for dimensionality reduction and classifying images in the reduced feature space, we will get better recognition rates
- The Fischer Linear Discriminant shapes the data in such a way that the ratio of the between-class scatter and the within class scatter is maximized.
- Firstly we perform PCA to reduce dimensionality to N-c and, to ensure that the resulting within-scatter matrix (Sw) is non-singular.
- Then we perform a Fischer Linear Discriminant on the output to reduce dimensionality to c-1 to get our ideal fisher-coefficients.

- **Between-class Scatter matrix**

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

- **Within-class Scatter matrix**

$$S_W = \sum_{i=1}^{c} \sum_{\mathbf{x}_k \in X_i} (\mathbf{x}_k - \boldsymbol{\mu}_i)(\mathbf{x}_k - \boldsymbol{\mu}_i)^T$$

- The FLD optimal projection is given by

$$W_{opt} = \arg\max_W \frac{\left|W^T S_B W\right|}{\left|W^T S_W W\right|} = \left[\mathbf{w}_1 \;\; \mathbf{w}_2 \;\; \ldots \;\; \mathbf{w}_m\right]$$

- The set of generalized eigenvectors of SB and SW corresponding to the m largest generalized eigenvalues are given as -

$$S_B \mathbf{w}_i = \lambda_i S_W \mathbf{w}_i, \qquad i = 1, 2, \ldots, m$$

- Thus for for image recognition problem, we follow the following optimal projection

$$W_{opt}^T = W_{fld}^T W_{pca}^T$$

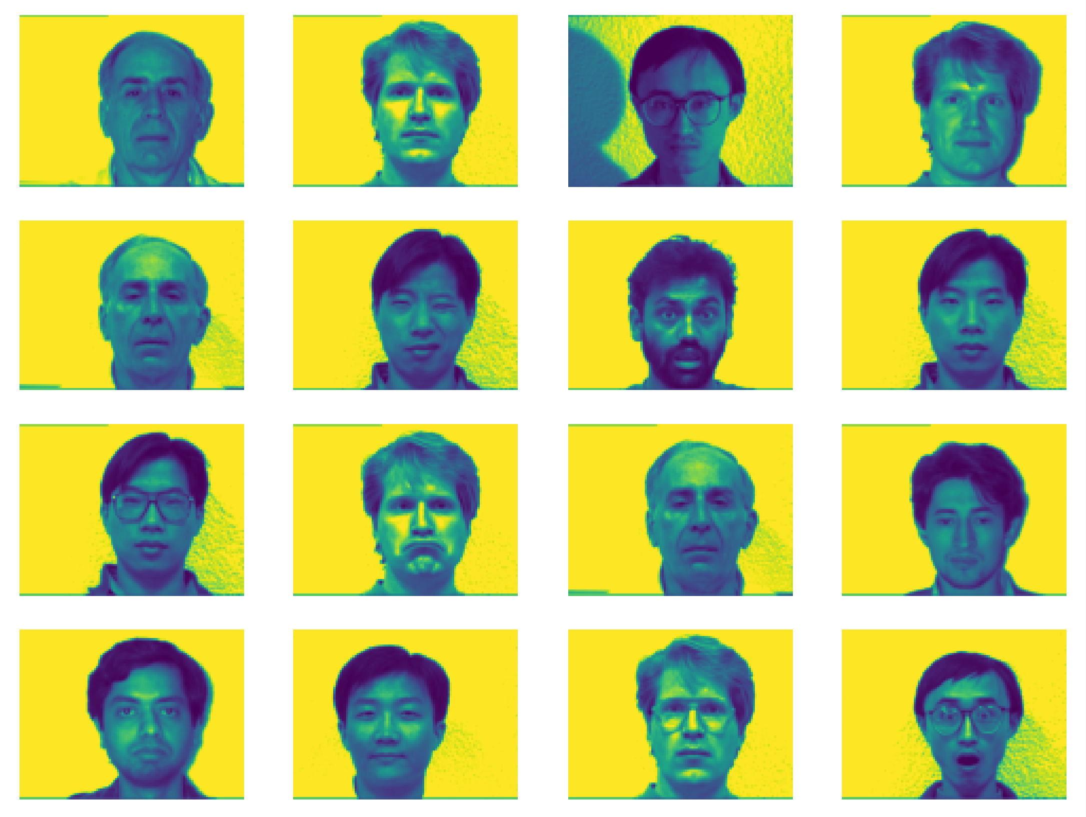
where

$$W_{pca} = \arg\max_W \left|W^T S_T W\right|$$

$$W_{fld} = \arg\max_W \frac{\left|W^T W_{pca}^T S_B W_{pca} W\right|}{\left|W^T W_{pca}^T S_W W_{pca} W\right|}$$

# 5. Datasets

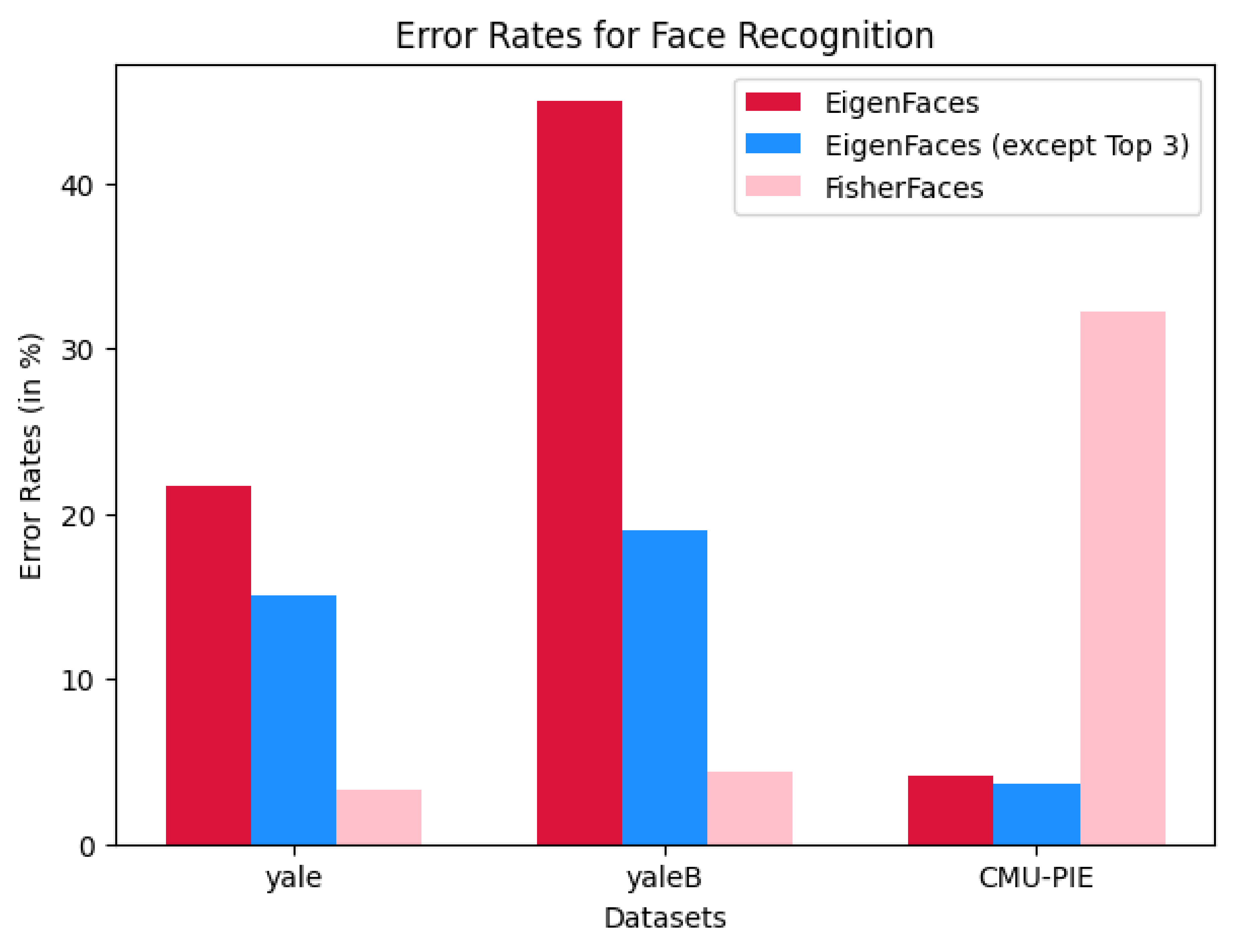
| | |
|---|---|
| **Yale** | includes 165 images (15 individuals) with different lighting, expression, and occlusion configurations. It also includes attributes like happy, sleepy, wearing **glasses** etc. We used it for glass recognition also |
| **Extended Yale (YaleB)** | contains 2412 frontal-face images with size 192×168 over 38 subjects and about 64 images per subject. The image in it are different lighting conditions and various facial expressions |
| **CMU-PIE** | This data consists of 640 black and white face images of people taken with varying pose (straight, left, right, up), expression (neutral, happy, sad, angry), eyes (wearing sunglasses or not), and size |



Some Samples from Yale

# 6. Results

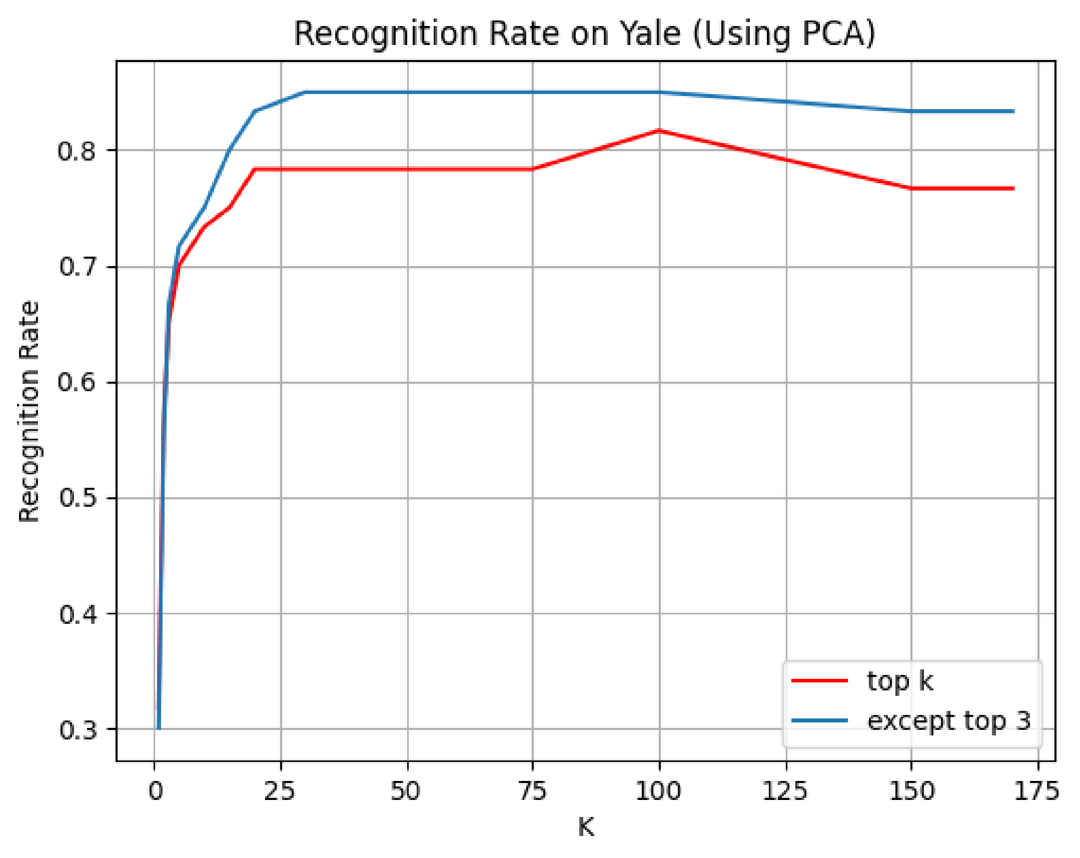
| | EigenFace | EigenFace(/top3) | FisherFace |
|---|---|---|---|
| Yale | 21.667 | 15 | 3.33 |
| Yale B | 44.964 | 19.003 | 4.361 |
| CMU-PIE | 4.091 | 3.636 | 32.273 |



# 7. Yale Dataset

| | EigenFace | EigenFace(/top3) | FisherFace |
|---|---|---|---|
| Yale | 21.667 | 15 | 3.33 |

- Splitted the dataset randomly such that 7 images of each person in train and 4 for test, totally 105 images in train and 60 in test
- Applied PCA based method with k = 50, and fisherface with 15
- As the dataset had images with varying illumination, we observe that error for eigenfaces decreases when removing top 3
- As explained before, it is because face images follow lambartian model and the top 3 eigenvectors represent most of the lighing variation
- Fisherface however performs even much better than both of them as expected
- The plot aside shows variation of recognition rate with the parameter k



# 8. Yale B

| | EigenFace | EigenFace(/top3) | FisherFace |
|---|---|---|---|
| Yale B | 44.964 | 19.003 | 4.361 |

- Here we applied fisherface with number of classes reduced to 38, and eigenface algorithm with k = 50
- Results show a similar trend here as seen in previous dataset
- Due to variations in lighting, fisherface performs the best among the three
- Number of examples were more in this dataset, which reflects the relatively poor performance of eigenfaces

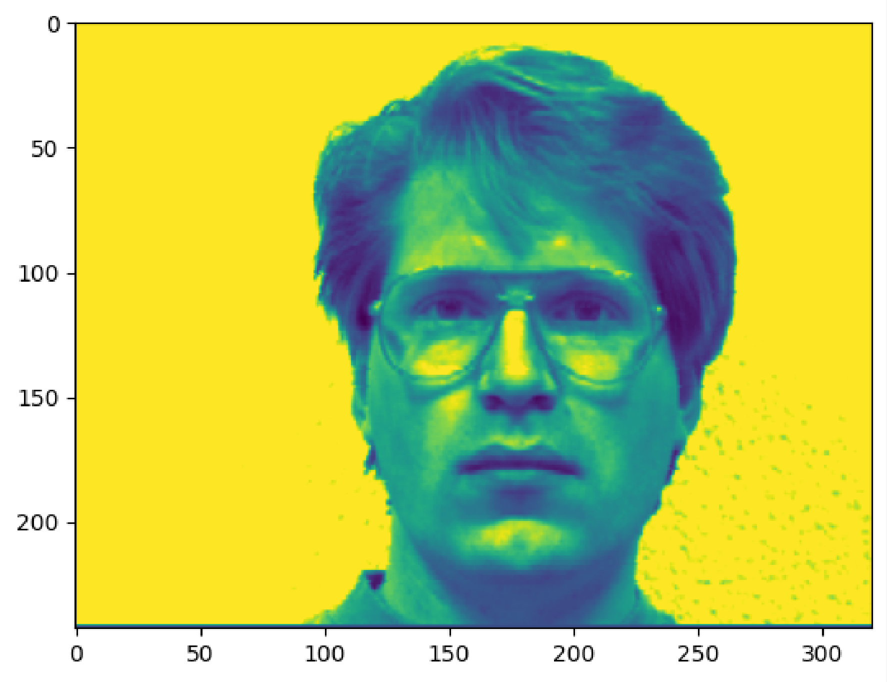
# 9. CMU

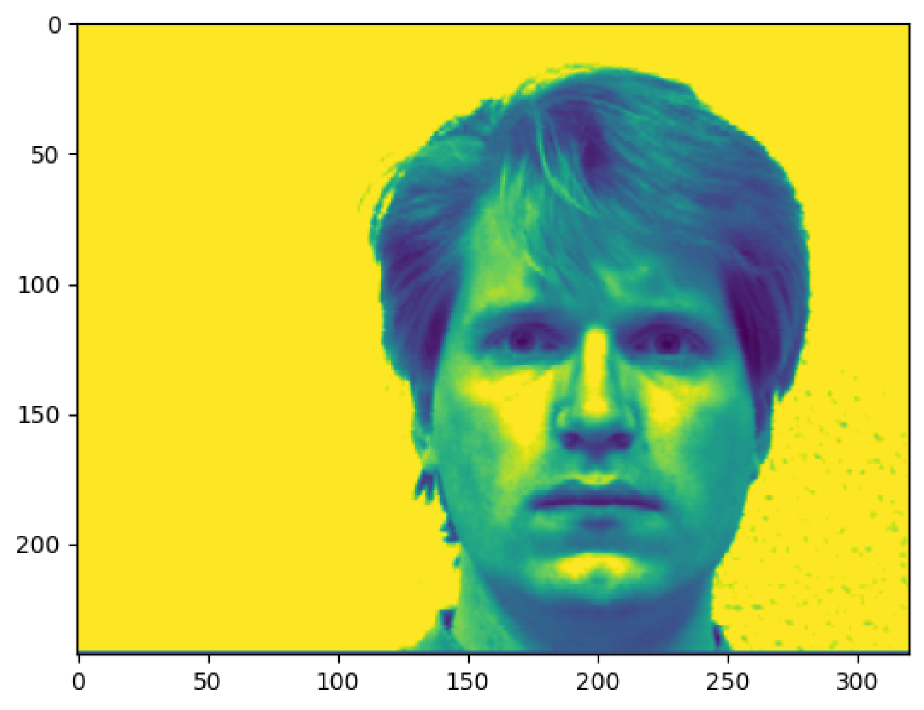
| | EigenFace | EigenFace(/top3) | FisherFace |
|---|---|---|---|
| CMU-PIE | 4.091 | 3.636 | 32.273 |

- The number of classes (persons) here are 20, each with different lighting, expressions, as well as changes in the alignment of their poses
- Although Fisherface was performing better, here Eigenface defeats it!
- The main reason for this would be that since CMU is a multi-pose dataset, and changing alignment induces excessive variations in face leading LDA to neglect the whole face, as LDA ignores highly changing variations of a face
- It was also written in the paper that it does not account for alignment variations
- According to paper, with cropped images also (better aligned) eigenfaces performs better

# 10. Glass Recognition

- The learning set was divided into 2 sets of ‘glasses’ and ‘without glasses’. Wiith these two classes, the images can be projected to a line using the Fisherface methods.
- The Yale Dataset was used which contained 36 images with equal images for both classes.
- Cross validation (k = 1) was used to determine the recognition rates. That is, before computing the projection matrix W, all pictures of each individual were taken out of the database in order to classify their images.



# 10. Glass Recognition results

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Glass Recognition Error rates (calculated using Leaving one out) -
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EigenFaces :                    43.333
Eigenfaces (Leaving Top 3) :    36.667
FisherFaces :                   30.000
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- We used the Yale dataset for performing glass recognition, since had images with labels as ‘glasses’ and ‘noglasses’ (with no variation in light)
- The errors were relatively more because of less amount of data available (only 30 images)
- That’s why we used “Leave One Out” method to train more on this data
- Even if with lesser data, we can observe that Fisherface performed better as compared to Eigenface

# 11. Conclusion

- All methods perform well when given a picture from the test set that is comparable to an image from the training set,
- The Eigenface technique performs better when the largest three principal components are removed, but it does not produce the desired error rates in the presence of lighting change.
- The Fisherface method appears to be the best at extrapolating and interpolating over variation in lighting and expressions.
- Fisherface also fares better than other methods in glasses recognition.

# 12. Work Distribution

Atishay : EigenFaces, Dataloaders, FisherFace, Glass recognition

Cheshta : FisherFace class and understanding paper

Kanad : Dataloader for CMU, FisherFace algorithm + LDA

Overall everyone contributed equally by studying various parts of the paper and implementing them

# 13. References

P. N. Belhumeur, J. P. Hespanha and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: recognition using class specific linear projection," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 711-720, July 1997, doi: 10.1109/34.598228.

Tech stack used - Numpy, Matplotlib, cv2, PIL, scipy

Datasets - Yale, Yale B, CMU

THANK YOU!