CS663: Course Project
Eigenfaces vs Fisherfaces

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1 Objective

The aim of the project is to use Fisher's linear discriminant analysis (LDA) for facial recognition and compare it with the Eigenface technique, another method based on linear projection of the image space to a lower dimensional subspace. The fisherface method produces substantially low error-rates on the Yale and Harvard face databases.

2 Variation in lightning

For this section, Harvard database has been used. The database has been divided into 5 subsets based on lighting variations.
Subset-1 : (0-15)°, Subset-2 : (15-30)°, Subset-3 : (30-45)°, Subset-4 : (45-75)°, Subset-5 : (85-130)° (angles mentioned are maximum of longitudinal and latitudinal lighting angles).Size of images = 192x168.

2.1 Extrapolation

For this part, the training data consists of images from subset-1 (30 images), data has been tested from subsets 2 (45 images),3 (65 images) using three methods - eigenfaces, eigenfaces w/o first 3 components, fisherfaces. Classification has been done using simple minimum euclidean distance classifier on reduced subspace. The results clearly show that fisherface method outperforms them both. The results have been summarized below.

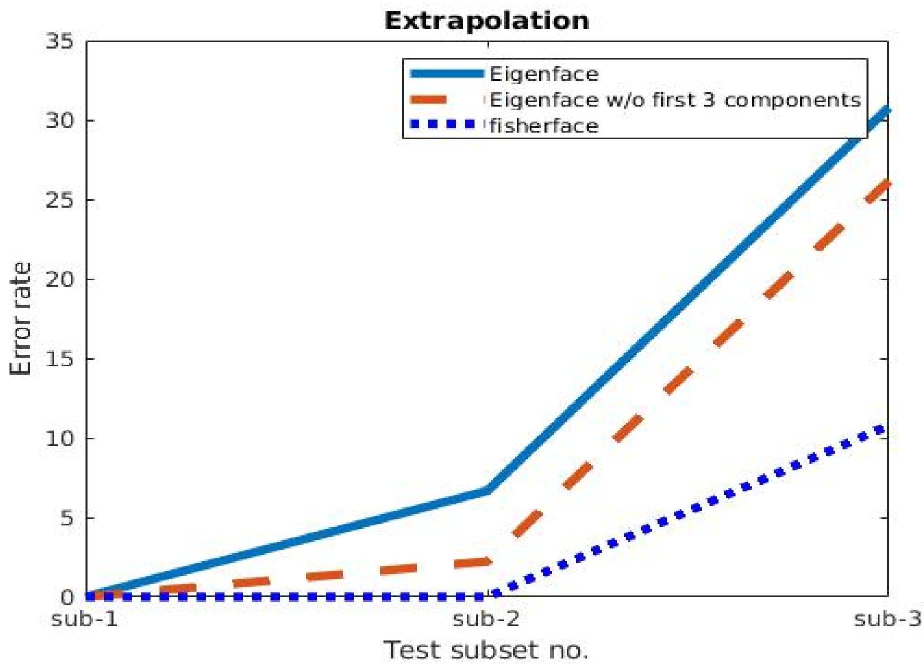

Figure 1: Performance on Harvard database

Method	Reduced Space	Error subset-2	Error subset-3
eigenface	4 10	31.11 6.66	44.61 30.76
eigenface (w/o first 3)	4 10	15.55 2.22	32.31 26.15
fisherface	4	0	10.77

Table 1: Extrapolation on Harvard

2.2 Interpolation

For this part, the training data consists of images from subset-1 and 4 (85 images), data has been tested from subsets 2,3,5 (95 images) using three methods - eigenfaces, eigenfaces w/o first 3 components, fisherfaces. Classification has been done using simple minimum euclidean distance classifier on reduced subspace. The results clearly show that fisherface method outperforms them both. The results have been summarized below.

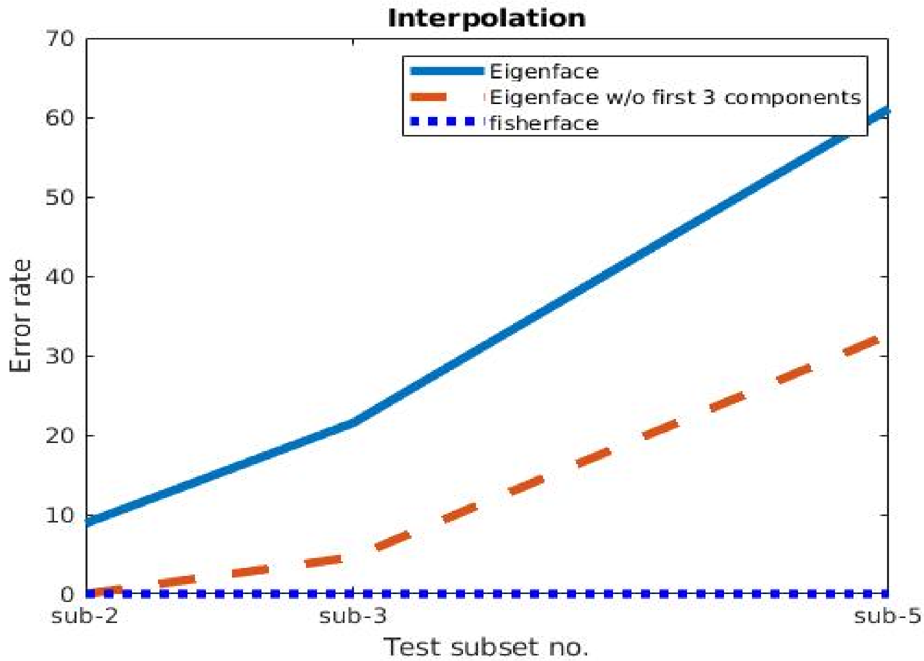

Figure 2: Interpolation on Harvard

Method	Reduced Space	Error subset-2	Error subset-3	Error subset-5
eigenface	4	15.55	49.23	67.36
	10	8.88	21.53	61.05
eigenface (w/o first 3)	4	8.88	18.46	57.89
	10	0	4.61	32.63
fisherface	4	0	0	0

Table 2: Interpolation on Harvard

2.3 Inferences

1. The eigenface method fails at high variations in illumination in images.

2. Removing the first 3 eigenvectors does increase the performance but still has high error-rates.

3. The fisherface method performs way better than the eigenface technique for any illumination levels, both in accuracy and computation time.

3 Variation in Facial Expression, Eye Wear, and Lighting

This part uses the Yale facial database (cropped and full-face) consisting of 165 images each from 15 different persons (11 images per person). Different images of the same person have different expressions, eye wear (glasses or not) and also different lighting angles. Size of images : cropped = (100x100), full-face = (243x320). Classification has been done using 'leaving one out' classifier.

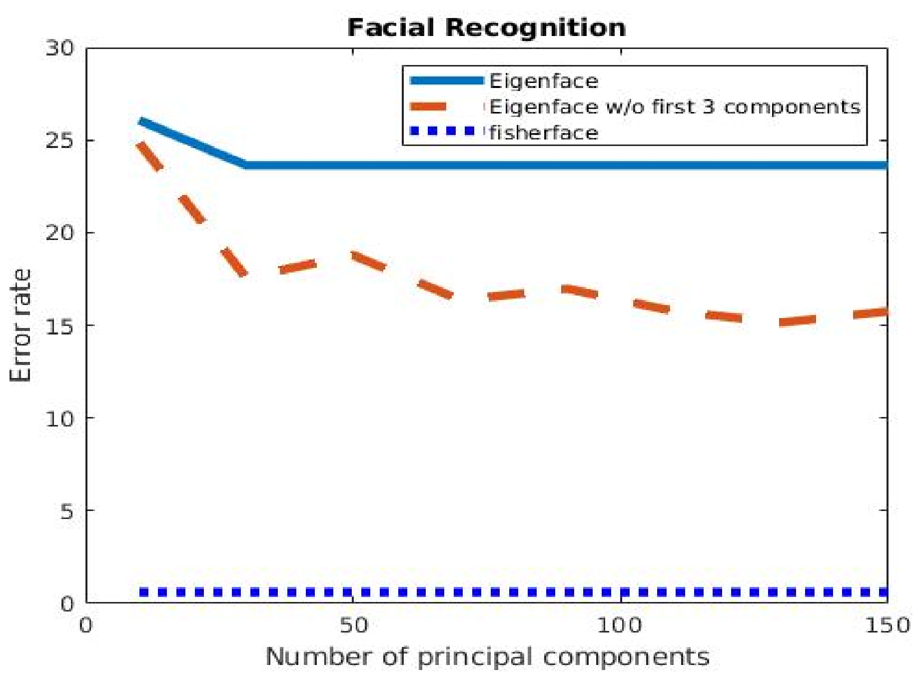

Figure 3: Performance on Yale database

Method	Reduced Space	Error (Crop face)	Error (Full face)
eigenface	30	23.63	22.42
eigenface (w/o first 3)	30	18.78	18.78
fisherface	15	0.60	0

Table 3: Performance on Yale database

3.1 Inferences

1. Both eigenface and fisherface techniques perform better on full-face images than on cropped images.

2. Fisherface method again outperforms eigenfaces, both in accuracy and computation time.

3. Fisherface method performs great on full-face images, probably due to face contours, but if we have background variations present in the image, then the error rates could be high.

4. Since we can divide data into classes (for fisherface) by any category (like eye-wear), we can use this technique in many other ways (detecting facial accessories).

4 Fisherfaces

The fisherfaces capture data very differently than the eigenfaces. It masks the features which are highly variable (mouth, here) and shows the features important for recognition (nose, brows).

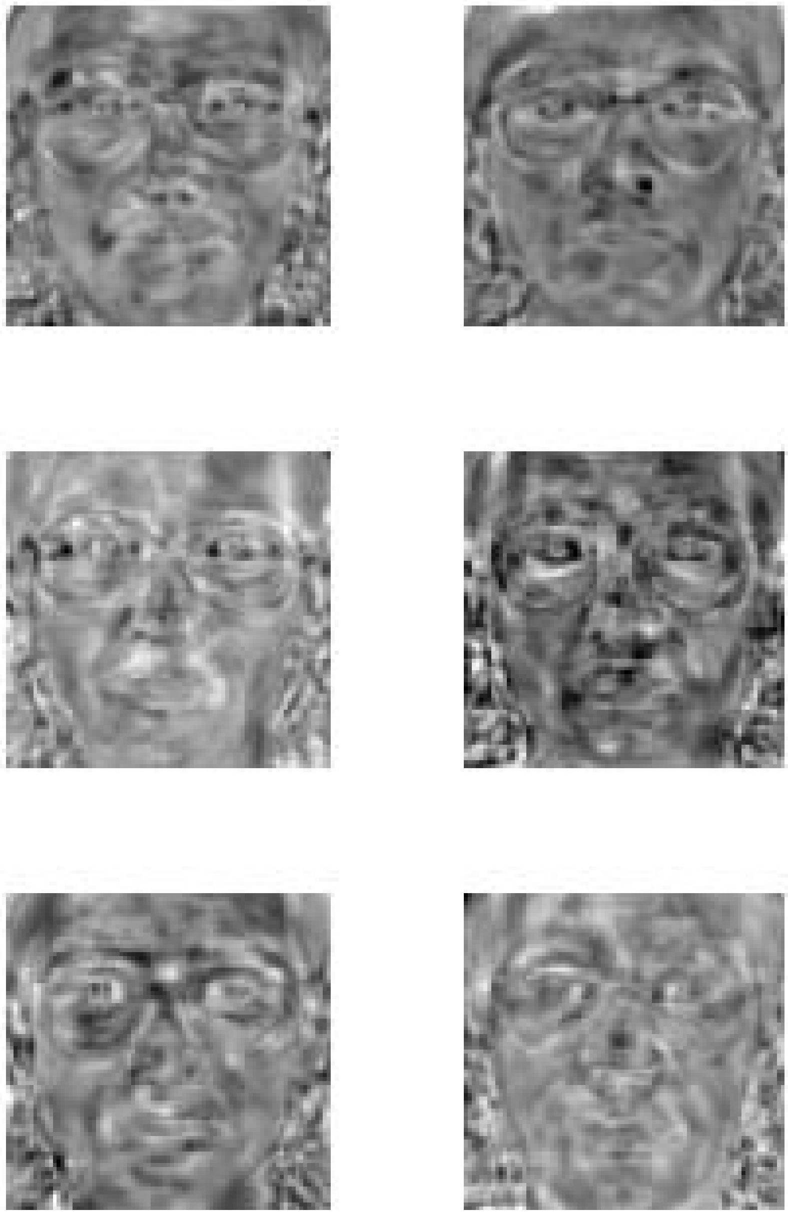

Figure 4: Fisherfaces

5 Eigenfaces

For the eigen-faces below (for Yale database), notice the first 3 eigenfaces which clearly represent the illumination problem in facial recognition through this method.

Figure 5: Eigenfaces

6 References

[1] Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection - Joao P. Hespanha, David J. Kriegman, Peter N. Belhumeur