CS663 : Digital Image Processing
Fisher faces vs. Other face recognition techniques

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1 Group details

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2 Methods

2.1 Correlation method

In this method we will assign the label of the training image that has the least euclidean distance to the test image as the output label. This is equivalent to doing Eigen faces method using all the eigen vectors.

2.2 Eigen Faces Method

In this method we perform the PCA decomposition on the training images and store the top K eigen vectors and the mean vector of the training images. For a given Test image, we subtract the mean vector and project it onto the K eigen vectors to compute its eigen coefficients. We will assign the label of that training image for which the distance between its eigen coefficient vector and the eigen coefficient vector of the test image is the minimum as the output label. PCA maximises the total scatter between the images.

2.3 Linear Subspace Method

In this method, for every person, we will store the top 3 eigen vectors of the Training images of that person computed using Eigen value decomposition. For a given test image we will reconstruct it by projecting it on to the 3 eigen vectors stored for every person. We will give the label to that person for which the reconstruction error is minimum. In our implementation, for this method, we didn't use mean subtraction anywhere as it was decreasing the accuracy. This was also suggested by the paper

2.4 Fisher Faces

Fisher faces tries to project the data in the directions which maximizes the ratio between 'between class scatter' to 'within class scatter'. It tries to minimize 'within class scatter' and maximize 'between class scatter'. One difficulty is that, the within class scatter has a maximum rank of N-c, where c is the number classes. As zero in the denominator is undefined, we will first use PCA to reduce to a N-c dimension and then use the Fisher linear discriminant method. once we got the optimal directions, for a given Test image we will find that training image for which the distance between the coefficient vectors is the minimum and assign its label as the output label.

3 Experiment 1

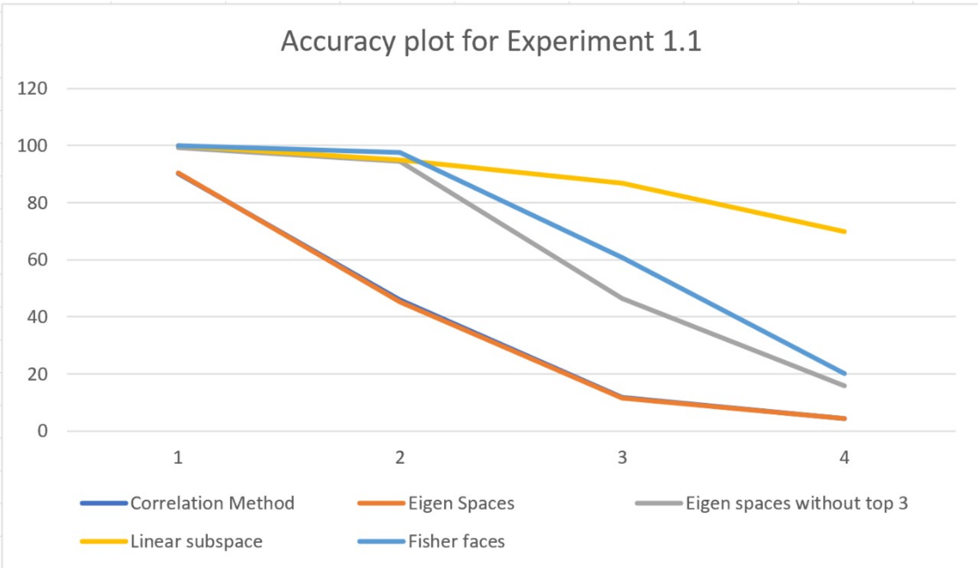
This experiment was designed to see the effect of variable illumination.
For this experiment, we used the "CroppedYale" database that was provided to us for doing HW4. This dataset contains images of 38 persons with 60 to 64 images each. Each image has different azimuthal and elevation angles of illumination. We divided this whole dataset into 5 subsets based on these angles.

- **Set1:** Contains images for which both the longitudinal and latitudinal angles of light source direction are within $15°$ of the camera axis.
- **Set2:** Contains images for which the greater of the longitudinal and latitudinal angles of the light source directions is between $15°$ and $30°$ from the camera axis.
- **Set3:** Contains images for which the greater of the longitudinal and latitudinal angles of the light source directions is between $30°$ and $45°$ from the camera axis.
- **Set4:** Contains images for which the greater of the longitudinal and latitudinal angles of the light source directions is between $45°$ and $60°$ from the camera axis.
- **Set5:** Contains images for which the greater of the longitudinal and latitudinal angles of the light source directions is between $60°$ and $75°$ from the camera axis.

3.1 Experiment 1.1

Here we trained on Set1 and tested on Set2, Set3, Set4 and Set5 using all the four methods. Note that is quite different from the method used in the paper because we didn't wanted to do "leaving-one-out" strategy for Set1 as the dataset being used here is much bigger that what is used in the paper and will take a lot of time. The results are

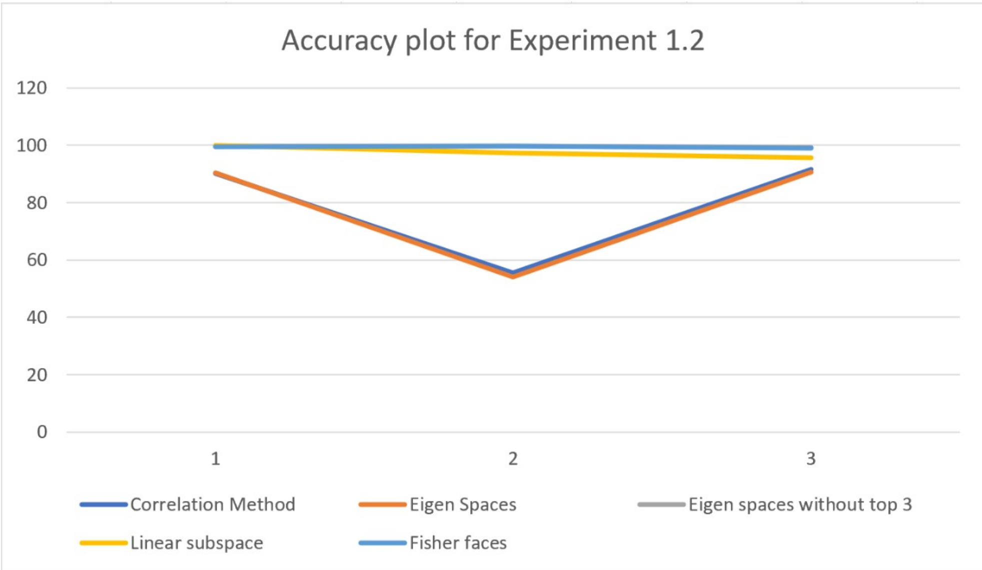
Method	Accuracy			
	Set 2	Set 3	Set 4	Set 5
Correlation	90.15%	45.91%	11.74%	4.28%
Eigen faces K = 140	90.37%	45.12%	11.41%	4.28%
Eigen faces excluding top 3	99.34%	94.46%	46.31%	15.79%
Linear Subpaces	100%	94.99%	86.91%	69.74%
Fisher faces	100%	97.63%	60.74%	20.07%



3.2 Experiment 1.2

Here, we trained on Set1 and Set5 and then tested on Set2, Set3 and Set4 using all four methods. The results are:

Method	Accuracy		
	Set 2	Set 3	Set 4
Correlation	90.15%	55.41%	91.61%
Eigen faces K = 250	90.37%	54.09%	90.60%
Eigen faces excluding top 3	99.78%	99.74%	99.33%
Linear Subpaces	100%	97.36%	95.64%
Fisher faces	99.56%	99.74%	98.99%



3.3 Conclusion

1. From **Experiment 1.1**, we observe that Linear Subspaces performed far better at generalising to images with different angles of illumination. We believe that this is due to the fact that it focuses on the top three eigenvectors, which correspond to the lighting patterns. Giving importance to these properties enabled them to distinguish different lighting cinditions and perform better.

2. We see that Fisher Faces performs better than simple Eigen Faces (even better than excluding top 3 approach) which shows that they are indeed more resilient to Lighting changes. As is also explained later we believe that combining the idea of dropping top 3 eigenvalues and fisher faces may result in better values.

3. from **Experiment 1.2**, we see that Fisher Faces and Eigen Spaces excluding top 3 generalised really well when exposed to a little more variety. But since three of the approaches did really well (above 95%), we could not draw any concrete conclusions from the observations.

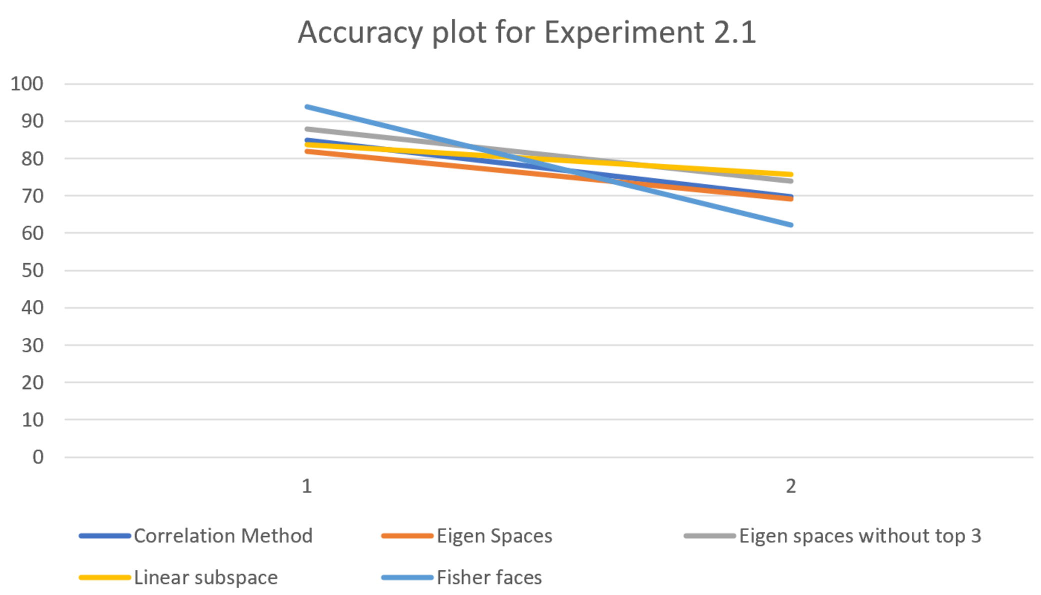
4 Experiment 2

In this experiment we used the 'Yale_Datebase' dataset and 'yaleExpCropped' dataset each of which contains images of 15 persons with 11 images each. Each of the eleven images corresponded to one type illumination of one type of facial reaction. i,e.,center-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleepy, surprised, and wink. The first dataset had full faces wheras in the second dataset the images are cropped to only include internal structures like brow, eyes, nose, mouth, and chin.

4.1 Experiment 2.1

In this experiment, we used "Leaving one out strategy". i.e., For testing an image, we removed that image from the training set, trained the model and used this model for evaluation. So, since we have 165 images, we needed to train the model 165 times. The results are:

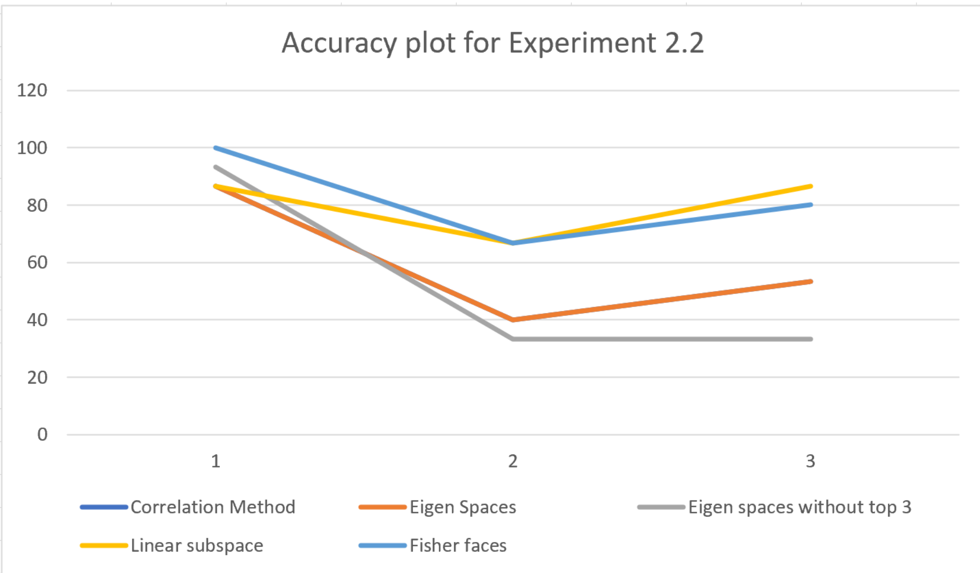
Method	Accuracy	
	Full Faces	Cropped Faces
Correlation	84.85%	69.70%
Eigen faces K = 30	81.82%	69.09%
Eigen faces excluding top 3	87.88%	73.94%
Linear Subpaces	83.64%	75.76%
Fisher faces	93.90%	62.20%



4.2 Experiment 2.2

This experiment is not present in the paper. For each of the 11 categories, we removed the all the 15 images corresponding to that category from the training set and used only these 15 images as the testing set for the learned model. We did this experiment only with the Full faces dataset. The results are:

Method	Accuracy		
	center-light	left-light	right-light
Correlation	86.67 %	40%	53.3%
Eigen faces K = 30	86.67 %	40%	53.3%
Eigen faces excluding top 3	93.33%	33.33%	33.33%
Linear Subpaces	86.67%	66.67%	86.67%
Fisher faces	100%	66.67%	80%



4.3 Conclusion

1. From **Experiment 2.1** we see that Fisher Faces don't perform as well on cropped faces when compared to other techniques. This goes to show that fisher faces need the contours of an entire face to perform well on the dataset.

2. On full faces, Fisher Faces performs really well and can be attributed to the property of trying to distinguish among different classes using S_B and S_W matrices.

3. For **Experiment 2.2**, we see that Fisher Faces perform really well on center-light classification but not as well on Left or right light classification. This shows that fisher faces do not handle asymmetric lighting very well, and this lighting difference starts playing a big role in between class scatter resulting in wrong predictions.

4. We can clearly see that lighting effects do create a problem in Fisher Faces, evident from **Experiment 1.1** as well as **Experiment 2.2**. Since we use PCA on the dataset as a preprocessing for LDA to make S_W nonsingular, we came up with the hypothesis that PCA excluding the top three eigenvalues (which hopefully correspond to lighting patterns) may result in better statistics but we did not have enough time to test the hypothesis.