Face_Recognition-Copy1

September 2, 2021

Importing required libraries

Reading the input images and vectoring them

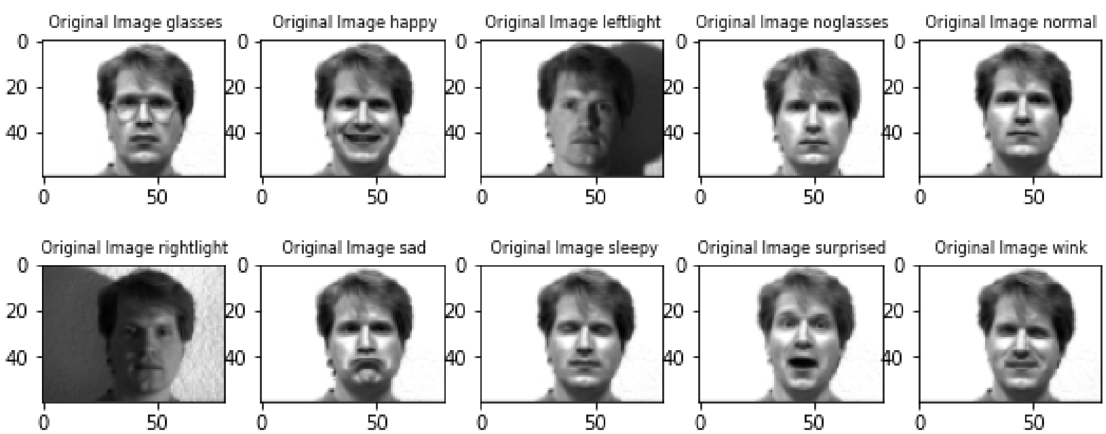
0.0.1 Analysis of Images

Below steps were followed to solve this problem. First, all the given images were analyzed. There are 10 images of the first person (Subject 1) shot at different lighting and with different face expressions. There are 9 images of the second person (Subject 2) captured the same way as Subject 1. In addition, there are 2 test images, one for each person which will be used to perform face recognition.

- After importing all the images, as mentioned, the images are down-sampled by a factor of 4.
- After down-sampling, the images are vectorized (all pixels are represented by a column vector).

```
Subject 1 matrix shape:  (10, 4800)
Subject 2 matrix shape:  (9, 4800)
```

Analysis of Subject 1

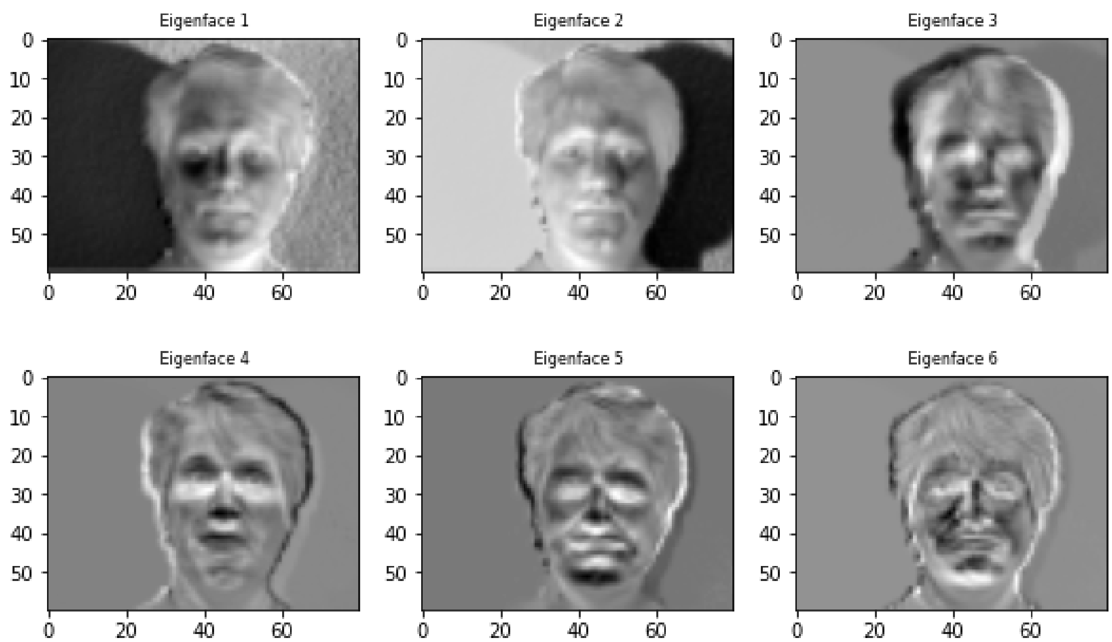


Steps to get Eigen Faces • The data matrix of subject 1 has the below dimensions Subject 1 matrix shape: (10, 4800)

There are 10 images (as we can see above), and each image has 4800 pixels.

- To compute the eigen faces for Subject 1, we calculate the Covariance matrix of the image data based on the algorithm. This captures the variability of data along different directions (i.e the covariance between the different images of Subject 1 in this case).
- We can get the Eigen faces for Subject 1 by performing eigen decomposition on the covariance matrix calculated above. We will compute the leading 6 Eigen vectors for the covariance matrix, which will represent the 6 Eigen faces that we will analyze.
- After re-shaping the Eigen vectors, below are the top 6 Eigen faces for Subject 1 (1 being the first Eigen face).

Plotting the First 6 Eigen faces For Subject 1 after Eigen Decomposition



Interpretation of Eigen Faces Interpretation of the Leading 6 Eigen Faces We observe that the first and second components (eigen faces) are clearer than the other eigen faces. These capture most of the important features of input image, and we can interpret the direction of the most important feature by comparing them with the original image. We also see that while most important features of Subject 1(facial features) are captured in the first 2 Eigen faces, the remaining eigen faces capture direction of features that are not captured by the first 2 components (glasses/ facial expressions). Eigen Face 1: This Eigenface captures the most important linear combination of features from the "RightLight" Original image. You can see the facial features like eyes, nose, mouth etc and the light captured well.

Eigen Face 2: This Eigenface captures the second most important features along the direction of the "LeftLight" Original image. You can see the facial features like eyes, nose mouth etc are captured well in this.

Eigen Face 3: This Eigenface captures the direction of the features from the "Noglasses" Original

Image, we can see that the eyes are not very clear in this image as this is captured in the first 2 eigen faces. This captures the No glasses feature, which is the area around the eyes.

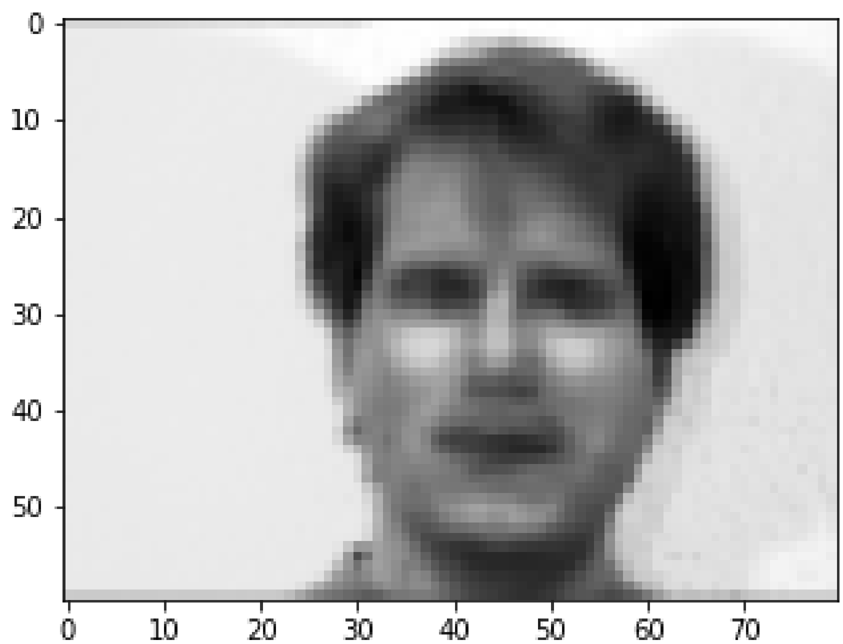
Eigen Face 4: This Eigenface captures the direction of the features from “Surprised” Original Image (the facial expression of surprise).

Eigen Face 5: This Eigenface captures the direction of the features from “Wink” Original Image (the facial expression of winking eye)

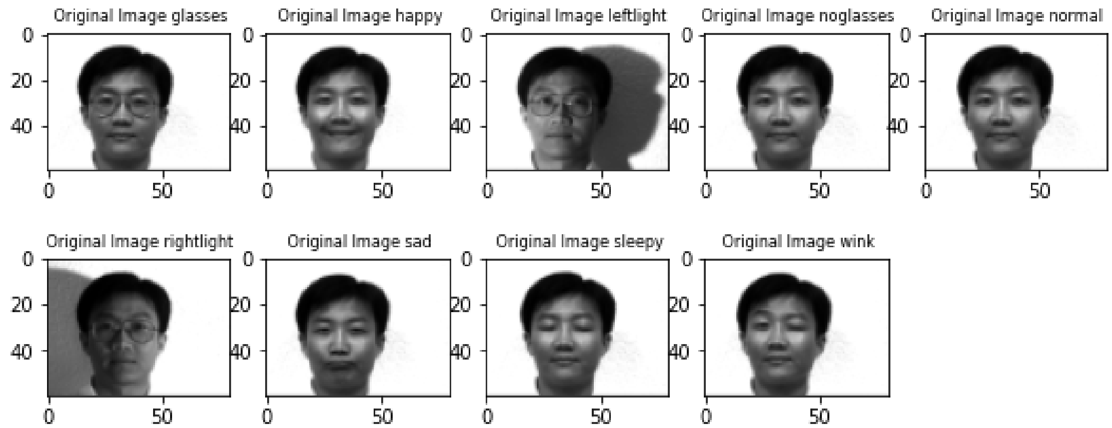
Eigen Face 6: This Eigenface captures the direction of the features from “Happy” Original Image(the facial expression of smile). However, this is the blurriest image of all since most of the important features are not part of this eigen vector.

Representation of the mean of all 10 images

```
<matplotlib.image.AxesImage at 0x21d892f6070>
```



Analysis of Subject 2



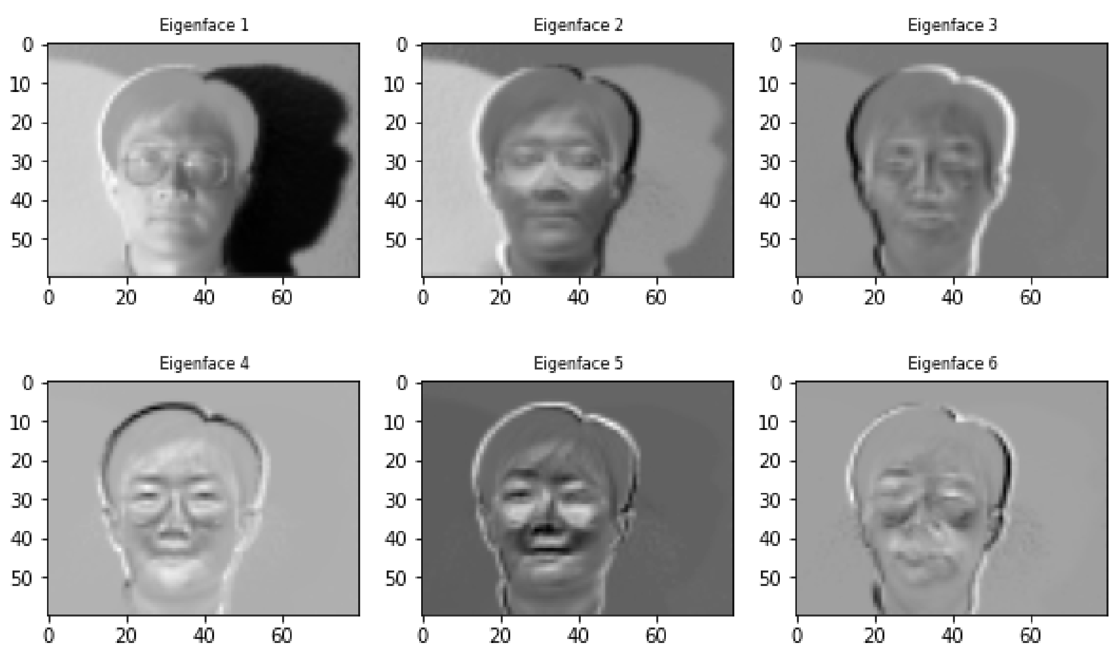
Analysis of Subject 2 • The data matrix of subject 1 has the below dimensions
Subject 2 matrix shape: (9, 4800)
There are 9 images (as we can see above), and each image has 4800 pixels.

• To compute the eigen faces for Subject 2, we calculate the Covariance matrix of the image data based on the algorithm. This captures the variability of data along different directions (i.e the covariance between the different images of Subject 2).

• We can get the Eigen faces for Subject 2 by performing eigen decomposition on the covariance matrix calculated above. We will compute the leading 6 Eigen vectors for the covariance matrix, which will represent the 6 Eigen faces that we will analyze.

• After re-shaping the Eigen vectors, below are the top 6 Eigen faces for Subject 2 (1 being the first Eigen face).

Plotting the First 6 Eigen faces For Subject 1 after Eigen Decomposition



Interpretation of Eigen Faces Interpretation of the Leading 6 Eigen Faces
We observe that the first and second components (eigen faces) are clearer than the other eigen faces. These capture most of the important features of input image, and we can interpret the direction of the most important feature by comparing them with the original image. We also see that while most important features of Subject 2(facial features) are captured in the first 2 Eigen faces, the remaining eigen faces capture direction of features that are not captured by the first 2 components (facial expressions).
Eigen Face 1: This Eigenface captures the most important linear combination of features from the "Left Light" Original image. You can see the facial features like nose, mouth, light direction etc. are captured well in this.

Eigen Face 2: This Eigenface captures the second most important features from the " RightLight" Original image. You can see the facial features like nose mouth etc are captured well in this.

Eigen Face 3: This Eigenface captures the direction of the features from the "Noglasses" Original Image, we can see that the eyes are not very clear in this image as this is captured in the first 2 eigen faces. This captures the No glasses feature predominantly.

Eigen Face 4: This Eigenface captures the direction of the features from "Glasses" Original Image (we can identify the glasses and eyes in this).

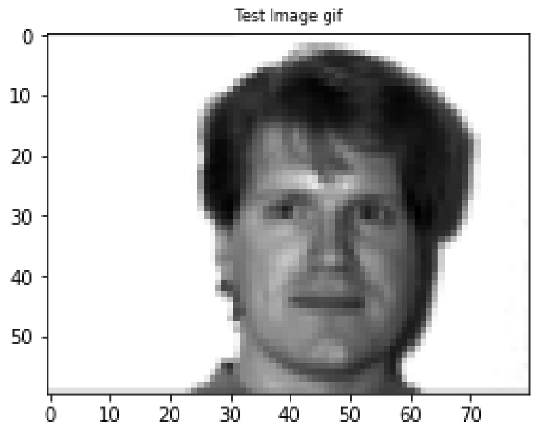
Eigen Face 5: This Eigenface captures the direction of the features from " Wink" Original Image (the facial expression)

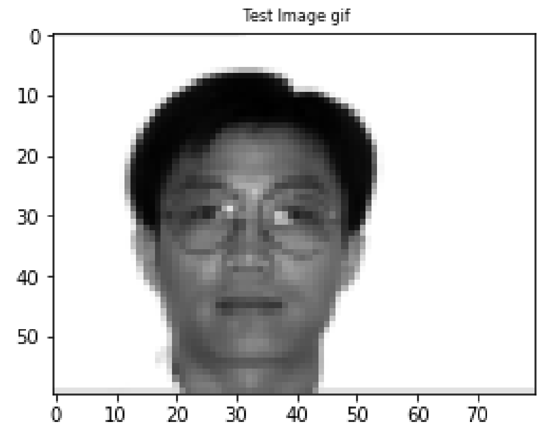
Eigen Face 6: This Eigenface captures the direction of the features from "Happy" Original Image(the facial expression of smile). However, this is the blurriest image of all since most of the important features are not part of this eigen vector.

0.0.2 Classification of Images from a test set

For this, the two test images were imported, down-sampled and vectorized the same way as the other images. After this, we will calculate the projection residual of the 2 test images with the vectorized eigen faces based on the formula provided. Since the eigen vectors are shifted to a new space, when we calculate the covariance matrix and subtract by the data mean, I have applied the same to the test images and standardized the same so that the test image data is in the same range of the eigen faces that they are being compared to.

Visualizing the images used for testing





Calculating the projection residuals s11 : Projection residual of Test Image of Subject 1 with the first Eigen face of Subject 1
s21 : Projection residual of Test Image of Subject 1 with the first Eigen face of Subject 2
s12 : Projection residual of Test Image of Subject 2 with the first Eigen face of Subject 1
s22 : Projection residual of Test Image of Subject 1 with the first Eigen face of Subject 2

```
456810484.8157536
39597766887.267166
10607273834.12047
2261626105.6724176
```

```
Projection Residual scores are:
[[4.56810485e+08 3.95977669e+10]
 [1.06072738e+10 2.26162611e+09]]
```

Classification results From these residuals, we can identify the lowest scores for each subject's test images respectively. As learnt in the lecture, when we performed Eigen decomposition with multiple training images for each subject, we extracted 6 components, which captured the direction of the most important features from the original 10 images.
When a test image is projected with the top eigen face, if the test image is of the same subject as the eigen face, the features will be in the same direction with some changes due to the compression, which is shown as the residual.
If the test image if of a different subject from the eigen face, then the features will be in different directions which will give a larger residual since they are completely different.

We can use this residual to classify the test image as Subject 1 or Subject 2. As we can see, the residual for Subject 1 when projected with Eigen face of subject 1 is 456810484.82, however when projected with the eigen face of subject 2 – it is 39597766887.27. We can classify Test Image 1 as Subject 1 since it has a lower residual which is more along the same direction as Eigen face of subject 1. Similarly, the residual for Subject 2 when projected with Eigen face of subject 1 is 10607273834.12, however when projected with the eigen face of subject 1 – it is 2261626105.67. We can classify Test 2 as Subject 2 since it has a lower residual which is more along the same direction as Eigen face of subject 2.

THE END