Eigenfaces vs Fisherfaces: Recognition Using Class Specific Linear Projection

CS663 Digital Image Processing Project

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Chapter 1

Introduction

1.1 Problem Statement

Given a set of face images labeled with the person's identity (the learning set) and an unlabeled set of face images from the same group of people (the test set), identify each person in the test images.

We are going to implement an algorithm that uses Fisherfaces which helps in countering following two major problems in face recognition : variation in lighting direction and variation in facial expression. Similar to Eigenfaces method, this method is also based on linearly projecting the image space to a low dimensional feature space which is insensitive to variation in lighting direction and facial expression. Fisherfaces method tries to maximize [1] the ratio of inter-class scatter to that of intra-class scatter in order to maintain discriminability.

Let the inter-class scatter matrix be defined as

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

the intra-class scatter matrix be defined as

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

and it's ratio is maximized which is given by :

$$W_{opt} = \arg\max_{W} \frac{\left|W^T S_B W\right|}{\left|W^T S_W W\right|}$$
$$= \begin{bmatrix} \mathbf{w}_1 & \mathbf{w}_2 & \ldots & \mathbf{w}_m \end{bmatrix}$$

W : It is a tranformation matrix (nXm) that linearly transforms a vector from n-dimension to m-dimension. In this case, we are trying to do dimensionality reduction, so $m < n$. Here, w's are set of eigenvectors of inter-class and intra-class matrix corresdponding to m largest eigenvalues. From now on, simlar to PCA, eigen coefficients are calculated using these eigenvectors. In testing phase, eigen coefficient of test image is calculated and closest eigen coefficient from the database is identified. This eigen coefficient tells the identity of the person.

Chapter 2

Methods Used

2.1 EigenFaces

Eigenfaces is the name given to a set of eigenvectors when they are used in the computer vision problem of human face recognition.The eigenvectors are derived from the covariance matrix of the probability distribution over the high-dimensional vector space of face images. The eigenfaces themselves form a basis set of all images used to construct the covariance matrix. This produces dimension reduction by allowing the smaller set of basis images to represent the original training images. Classification can be achieved by comparing how faces are represented by the basis set.

2.2 FisherFaces

When one wishes to find a subspace that maps the sample vectors of the same class in a single spot of the feature representation and those of different classes as far apart from each other as possible. The techniques derived to achieve this goal are known as discriminant analysis (DA).

The most known DA is Linear Discriminant Analysis (LDA), which can be derived from an idea suggested by R.A. Fisher in 1936. When LDA is used to find the subspace representation of a set of face images, the resulting basis vectors defining that space are known as Fisherfaces.

Chapter 3

Experiments

We tested our algorithm for fisherfaces and eigenfaces on two databases: AT&T and Yale.

3.1 AT&T

In this database , there are 32 folders containing images of 32 different persons. Each individual has been photographed for 10 different times, under varying lighting, facial expressions and facial details. Size of each image is 92x112 pixels with 256 grey level per pixel.

3.2 Yale

In this database, there are 38 different folders containing images of 38 different persons. Each individual has been photographed for 60 different times under varying illumination conditions. Size of each image is 168x192 pixels with 256 grey level per pixel.

Chapter 4

Observations

4.1 Accuracy Plots

We plotted Prediction Rate vs Values of K on AT&T database.(No. of Eigenvectors taken corresponding to k largest eigenvalues) for both eigenfaces and fisherfaces.

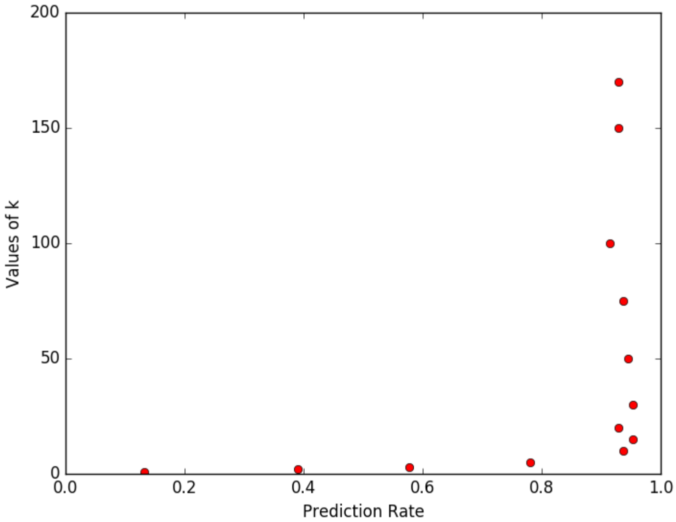

Figure 4.1: Prediction accuracy with k-eigenfaces

For AT&T database, We trained eigenfaces and fisherfaces both on 192 images having 6 images of 32 different persons. We tested on 128 images having 4 images of 32 different persons.

For Eigenfaces, the highest no. of images that we classified correctly was 122/128.

For Fisherfaces, the highest no. of images that we classified correctly

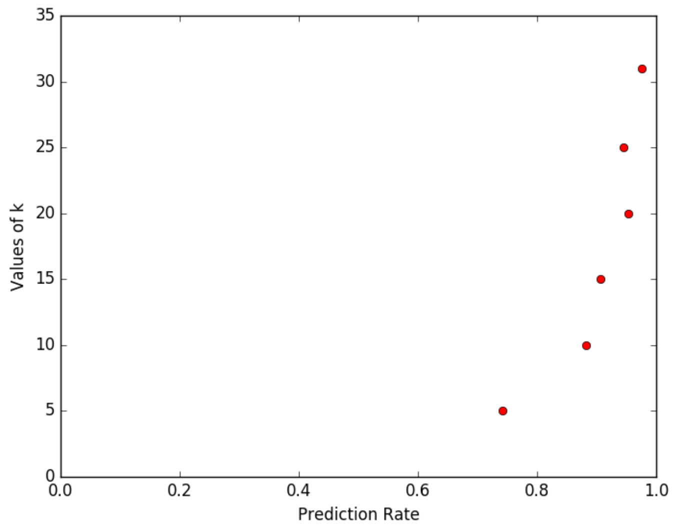

Figure 4.2: Prediction accuracy with k-fisherfaces

was 125/128.

For YALE database, We trained eigenfaces and fisherfaces both on 1520 images having 40 images of 38 different persons. We tested on 760 images having 20 images of 38 different persons.

For Eigenfaces, the highest no. of images that we classified correctly was 615/760.

For Fisherfaces, the highest no. of images that we classified correctly was 709/760.

4.2 K-Eigenfaces/FisherFaces

We plotted K eigenvectors and fisherfaces with K largest eigenvalues for Yale Database. Each eigenvector has been reshaped to 168x192 pixel. These are shown below:

Eigenfaces capture illumination and facial features both. In contrast, Fisherfaces do not encode illumination feature. It focusses on features for distinguishing the persons and hence illumination is not captured.

Figure 4.3: 20 eigenfaces for YALE

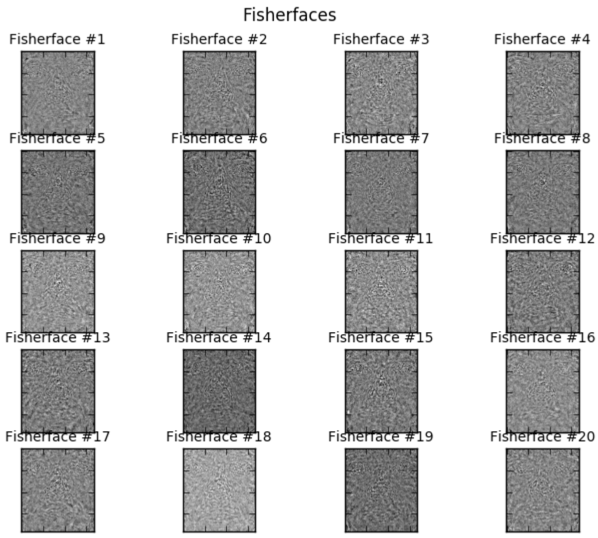

Figure 4.4: 20 fisherfaces for YALE

4.3 Reconstruction of Image

As we saw in the previous section, that any image can be approximated using a linear combination of k-eigenfaces/fisherfaces. The coefficients for linear combination are found by projecting the image onto those k-eigenvectors.

We took one image from AT&T database and tried to reconstruct it using eigenfaces and fisherfaces. The results are shown below:

Figure 4.5: Reconstructed Image using eigenfaces

Figure 4.6: Reconstructed Image using fisherfaces

As we can see, the image reconstructed from Eigenfaces is better than Fisherfaces. This is because Fisherface does not encode the features for reconstruction but the features for distintion between classes.

Chapter 5

Conclusion

We can conclude from the observations that eigenfaces are better for representation of face if the goal is reconstruction of images and fisherfaces are better for recognition since it does a class specific linear projection.

Chapter 6

References

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