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Face Recognition Using Linear Discriminant Analysis

Abstract

Linear Discriminant Analysis and Principal Component Analysis are well known linear transformation techniques that have been applied to facial recognition for many decades. In this paper, both PCA and LDA are applied to a combination of "The ORL Database of Faces" and photos of our own faces. Using PCA alone, we were able to achieve a facial recognition rate of 95.23%. LDA was also able to achieve a 95.23% facial recognition rate on our test data.

1. Introduction

Human beings tend to do well at visually recognizing patterns, with other human's faces being a very common pattern that people observe. The more interactions a person has with others create another observed instance of that person's face, helping to reinforce the memory of the person's face.

Although people are very good at recognizing faces, it is also useful, for a variety of applications, for computers to be able to recognize faces as well. There are a number of techniques currently in use that allow a computer to recognize faces as well, including techniques like elastic matching and neural nets (Zhang, Yan, & Lades, 1997). In PCA, the goal is to find the directions that maximize the variance in the data while reducing the dimensionality of the data set. LDA is a related linear transformation technique that also reduces the dimensionality of the data. LDA computes the directions that maximize the separation between different classes. Both techniques have been applied for decades now in facial recognition.

Dimensionality reduction of face data is important for quick but accurate identification of subjects in a large database (Belhumeur, Hespanha, & Kriegman, 1997), which is why PCA and LDA have become popular techniques for facial recognition. PCA is one of the original linear transformation techniques for facial recognition. It transforms the data set of faces into a feature space made up of the principal components, known as Eigenfaces (Turk & Pentland, 1991). While PCA is very accurate under certain conditions for facial recognition, its accuracy begins to decline when users have different facial expressions and especially when photos are taken under vastly different lighting conditions (Belhumeur, Hespanha, & Kriegman, 1997). LDA however goes one step further and uses a combination of the within and between-class scatter of the subjects to compute a separation matrix (Etemad & Chellappa, 1997). LDA performs eigenvalues analysis on the separation matrix instead of the covariance matrix as in PCA. This method uses class information so that "variations of the same face that are due to illumination conditions, facial expression, orientation etc., are de-emphasized" (Etemad & Chellappa, 1997).

In our implementation, we will investigate the accuracy of both PCA and LDA in facial recognition. We will be using "The ORL Database of Faces" as well as our own faces in the training and testing sets. To test the robustness of the algorithm, our photos will be taken from different angles and we will occlude our faces with eyeglasses and sunglasses.

2. Related Work

In this project, we are going to present two feature extraction approaches in face recognition system; PCA and LDA. Using eigenfaces and fisherfaces, we retrieve important features from face images while retaining as much variance as we can. Here are some other techniques for face recognition that we explored.

2-1. Latent Dirichlet Allocation (LaDiAl)

Dhamecha et al. proposed a modeling technique for face recognition using Latent Dirichlet Allocation. After dividing face images into several patches, the LaDiAl based face recognition algorithm converts the patches into patch-document, and extracts the latent Face Topic features. The model provided by LaDiAl describes a face patch is represented using the latent Face Topics. This method is meaningful due to the applicability of text analytics inspired approach for face recognition.

2-2. Classification of different sex using Linear Discriminant Analysis (LDA)

Etemad et al. suggested a classification technique in face recognition to distinguish different sex using discriminant template after LDA feature extraction. The authors compared the eigen template and the distribution coefficients for images of 20 males and 20 females of different races. This face recognition algorithm to identify a person's sex gives 95% of accuracy.

2-3. Normalized Principal Component Analysis (N-PCA)

Tripathi et al. compared accuracy for face recognition based on PCA and N-PCA in their research paper. N-PCA normalizes images to remove the lightening variations and background effects, and conduct singular value decomposition (SVD) instead of eigenvalue decomposition (EVD). The test results show that N-PCA based face recognition gives better accuracy over PCA based.

2-4. Elastic Matching and Neural Nets

In their paper, Zhang et al. do a comparison of PCA's eigenfaces, neural networks, and elastic matching. The authors create two networks; one that operates in autoassociation mode, and one that operates in classification mode. The autoassociation network extracts features for the second network. Eigenfaces and the autoassociation network both use Euclidean distance to compute the distance between the observed face and the template. Zhang et al. propose elastic matching as an aspect graph matching technique that is invariant to common face transformations and doesn't require the input and testing images to have the same dimensions. Elastic matching performed well on nearly all data sets tested, and across various lightings and expressions. The Neural network approach in the paper performed poorly and was upper bounded by the eigenface results.

2-5. Locality Preserving Projection (LPP) using Laplacianfaces

Xiaofei et al. suggested an appearance-based face recognition approach using laplacianfaces. Laplacianfaces are the optimal linear approximations to the eigenfuctions of the Laplace Beltrami operator on the face manifold. LPP is a feature extraction techniques to map face images into subspace while reducing unwanted variations resulting from illumination and facial expression.

3. Methodology

3-1 Facial Image Database

The data set in this project comes from the AT&T Laboratories Cambridge's "The ORL Database of Faces" (AT&T Laboratories Cambridge, 2002). The dataset consists of ten different images of 40 distinct people. The images are 256 level grayscales and formatted as PGM files. All images in the dataset are 92x112 pixels. The photos were taken over a period of time between April 1992 and April 1994.

Figure 1: Morton with Glasses

All images are closely cropped around the head and are directly or near directly looking at the camera. The subjects are mostly white males, but the data set also contains females and people of other races. Many of the subjects are also wearing glasses.

In combination with this data set, we also took ten pictures from each of ourselves. Our photos consist of a head on shot, a head on shot with glasses, and various photos from different angles of our heads and various facial expressions. Our photos were scaled and converted to grayscale to be consistent with the other photos in the data set. In total the full data set consists of 420 images.

3-2. Feature Extraction through Principal Component Analysis (PCA)

PCA is commonly used in face recognition applications to reduce dimension without losing significant information of the image data. Such significant features extracted through PCA are called eigenfaces. We selected the optimal number of eigenfaces by analyzing accumulated variance across the number of eigenvalues used. We used these eigenfaces to find new features for classification.

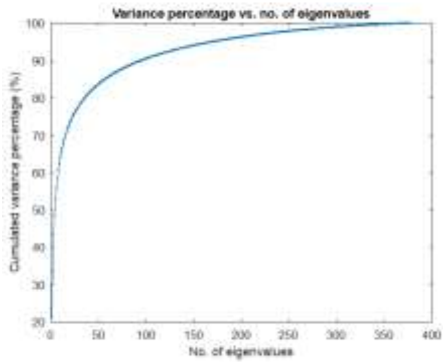

Figure 2: graph of cumulated variance

3-3. Feature Extraction through Linear Discriminant Analysis (LDA)

According to Etemad and Chellappa, each of the facial features has different discriminant power for not only identifying an individual, but also recognizing his/her gender, sex, race, and age. Since human face has a lot in common, low discriminant features may not be captured in eigenfaces. So LDA-based feature extraction is often used as an appropriate substitute of PCA to extract significant features with discriminant power. Such extracted features are called fisherfaces, and they are more capable of distinguishing image variations such as illumination and facial expression.

3-4. Implementation methodology for face recognition

Preprocessing

The facial image database used in this paper contains 420 images of 42 different individuals. These images are converted into a column vector space with size 10304x420. Then we splitted the column vector space into 10% of test data and 90% of training data. One facial image from each person is selected as a test image, thus test data contains 42 images and training data has 378 images.

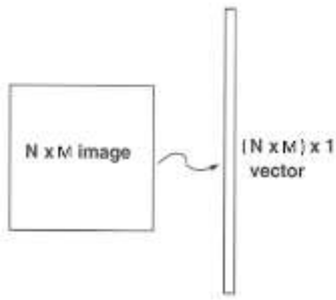

Figure 3: column vector space

Training steps

We used the proposed feature extraction methods to get eigenfaces and fisherfaces. First, we computed the mean face from the training column vector space, and normalized the training images by subtracting the mean face. The example result of this process is shown in figure 4. Second, we computed covariance matrix to calculate eigenvectors and eigenspaces, and selected 170 eigenfaces that can capture 95% of total variance in the data. Third, we projected normalized

Figure 4: image normalization process

training images onto eigenspace and calculated the mean of the projected images. Fourth, we computed between and within scatter matrices. LDA allows us to retain discriminant power by maximizing the between-class scatter and minimizing the within-class scatter matrix. Lastly, using the equation 1, we computed eigenvalues and fisherfaces.

Equation 1

$$S^{(V)} = S_w^{-1} S_b$$

Table 1: the first 16 example images of eigenfaces and fisher faces

Eigenfaces	Fisherfaces
	

4. Evaluation Results

The full data set of 420 images was split into 90% training and 10% testing, using the first image of each subject as the testing image. A photo of Son with large sunglasses and a photo of Morton with eyeglasses, were specifically chosen to be in the testing set to test the overall robustness of the implementation of the algorithm.

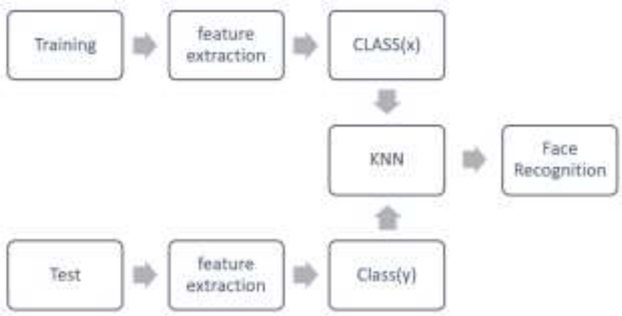

Figure 5: flow chart of evaluation method

In our experiment, the images from the training set were averaged together to create the mean face that was used in both the implementation of PCA and the implementation of LDA. The test image vectors were then normalized by subtracting the mean face. The test image vectors were then projected on to the calculated eigenspaces. The Euclidean distance was used as the similarity and the distances between the test image vector and the training image vectors was calculated. The training image with the least amount of distance, or nearest neighbor, to the test image was chosen as the most similar and the likely facial match.

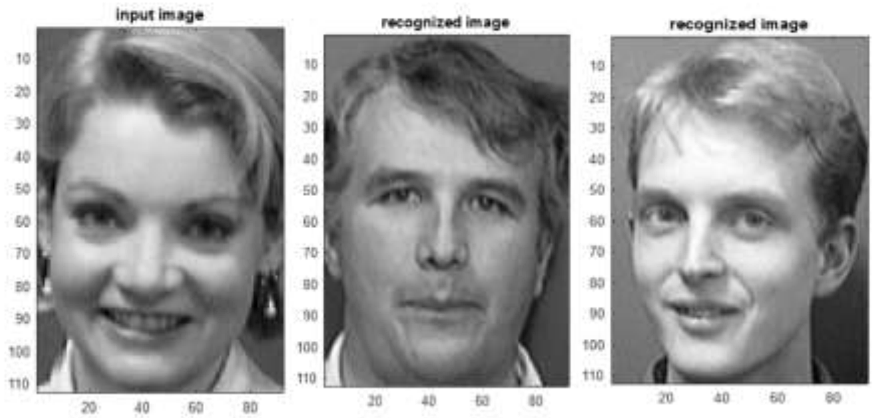

Figure 6: Left is test image, center is PCA most similar, right is LDA most similar

According to the evaluation of recognition results, Both Principal Component Analysis and Linear Discriminant Analysis achieved a recognition accuracy of 95.23%. Among 42 testing images, we got two mismatching problems. Figure 6 describes one of the mismatched cases. We found that the face recognition algorithm based on two different feature extraction methods may return different misidentified images. The results of distance measures from PCA-based and LDA-based face recognition algorithm were different.

The algorithm successfully identified Son with sunglasses as shown in Figure 7 and Morton with eyeglasses as shown in **Error! Reference source not found.**. Even with partial blocks or modifications of an image such as eyeglasses, the face recognition algorithm returned correct class image.

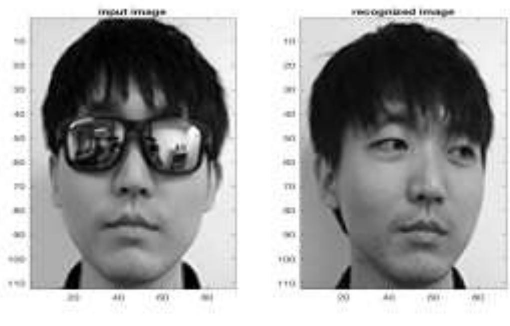

Figure 7: Left is test image, right is most similar training image

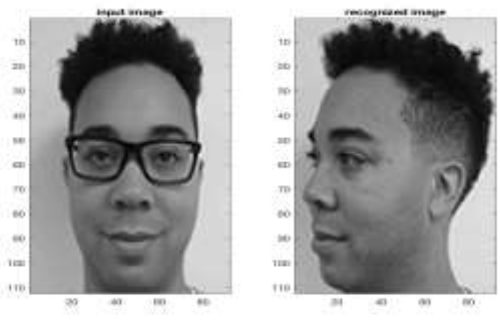

Figure 8: Morton results with glasses

Interpretation, Conclusion, Future Work

The results are consistent with previous research using PCA and LDA. Etemad et al. were able to achieve 99.2% accuracy facial recognition with LDA using a set of 2000 images. PCA was also shown to be able to achieve 96% recognition by Turk Et Al. Although we included various facial expression, angles, and wore glasses in our photos, the majority of the photos came from the ORL database and as such were mostly front on face photos with similar lighting conditions. Our included photos also appear to be taken under similar indoor lighting conditions as the ORL database. This most likely accounts for the accuracy being the same between PCA and LDA in our testing. To further test the robustness of our implementation, photos taken under a variety of lighting conditions, with different facial expressions, and various facial occlusions should be including in the testing and training data sets.

Works Cited

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