Assignment 1 Report

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Abstract

This paper mainly introduces a face recognition system based on principal component analysis (PCA) and eigenfaces. The experiment consisted of collecting and vectorizing a set of representative facial images, standardizing the data, and applying PCA methods to extract the most feature surfaces. A face recognition system is constructed by using feature surfaces to generate new faces. In the follow-up experiment, factors such as component number k were adjusted constantly, and their effects on the accuracy of face recognition were analyzed.

1 Introduction

This report examines the application of Principal Component Analysis (PCA) and Eigenfaces in facial recognition. The process begins with vectorizing facial images into one-dimensional vectors of grayscale pixel values. The dataset is normalized by centering each image vector, achieved by subtracting the mean across all images. PCA is applied to the training data, retaining a specified number of principal components, k. This involves calculating the covariance matrix of the centered data, performing eigenvalue decomposition to extract eigenvectors, and constructing Eigenfaces. These Eigenfaces are visualized to analyze their role in capturing key facial features.

New faces are generated by combining random weight vectors with the Eigenfaces, providing insights into the face generation process. A recognition system is built based on the Euclidean distance between facial feature vectors. The impact of varying k on recognition accuracy is evaluated to understand its influence on system performance.

2 METHODOLOGY

This section outlines the methodology used to implement the facial recognition system based on Principal Component Analysis (PCA) and Eigenfaces. The process involves several key steps: data preprocessing, feature extraction through PCA, eigenface generation, and the construction of a face recognition system.

2.1 Data Preprocessing

The Face Dataset was loaded and stored in a dictionary, where each image was represented as a matrix of grayscale pixel values. These images were then vectorized by flattening each image into a one-dimensional vector. The flattening process converts each 2D face image (112x92 pixels) into a 1D array of size 10304.

The dataset was normalized by centering each vector. This was done by subtracting the mean vector of all images from each individual image vector. This normalization step ensures that the features are centered around zero, which is crucial for PCA to perform effectively.

2.2 Principal Component Analysis (PCA)

After data normalization, PCA was applied to extract the most significant features (principal components) from the dataset. Using the PCA function from the sklearn.decomposition module, we computed the principal components of the training dataset. We specified the number of components, k, which defines the dimensionality of the new feature space.

PCA works by calculating the data's covariance matrix, followed by eigenvalue decomposition. The eigenvectors corresponding to the largest eigenvalues represent the dataset's most important features. These eigenvectors are then combined into a new matrix, called the Eigenfaces, which captures the dataset's primary facial features.

2.3 Face Recognition System

A face recognition system was built using the Eigenfaces. The system works by comparing the feature vectors of a test face to those of the known faces in the training set. The Euclidean distance between these feature vectors is computed. The equation to calculate the Euclidean distance is:

$$\text{Euclidean Distance} = \|W - query\_weight\| = \sqrt{\sum_{i=1}^{n}(W_i - query\_weight_i)^2}$$

The face with the smallest distance to the test face is considered the closest match. This recognition system uses the weights obtained from the projection of test faces onto the Eigenface space.

3 Experimental Setup

This section outlines the methodology used in the experiment, which involves four main stages: data loading and preprocessing, feature extraction using PCA, face generation, and face recognition. The ORL face dataset was used, with images vectorized and normalized for PCA. Eigenfaces were generated by computing the covariance matrix and selecting the principal components. A face recognition system was then built by comparing feature vectors using Euclidean distance. The effect of the number of components, k, on recognition accuracy was also analyzed.

3.1 DATA LOADING AND PREPROCESSING

The experiment was conducted using the ORL face dataset, which consists of 40 individuals, with each individual having 10 images. The images were resized and preprocessed to standardize their dimensions before applying any further analysis. The dataset was split into a training set and a test set using an 80/20 ratio, meaning 80% of the images were used for training and 20% for testing.

Figure 1: Visualization with gray scale values.

3.2 FEATURE EXTRACTION (PCA)

The experiment utilized Principal Component Analysis (PCA) for feature extraction. Facial images were first vectorized into pixel vectors, forming a matrix where each row represented an image and each column represented a pixel intensity. The pixel vectors were then normalized by centering the data and subtracting the mean vector from each vector. PCA was applied to the normalized data by computing the covariance matrix, eigenvalues, and eigenvectors. The top k eigenvectors, corresponding to the largest eigenvalues, were retained to form the basis for generating eigenfaces. Three typical values of k were selected for analysis: 10, 60, and 320. The retained eigenvectors were combined into a matrix, forming the eigenface space. Each facial image vector was projected onto this space, resulting in feature vectors that represent the faces. Thirty eigenfaces were visualized and presented in Figure 2.

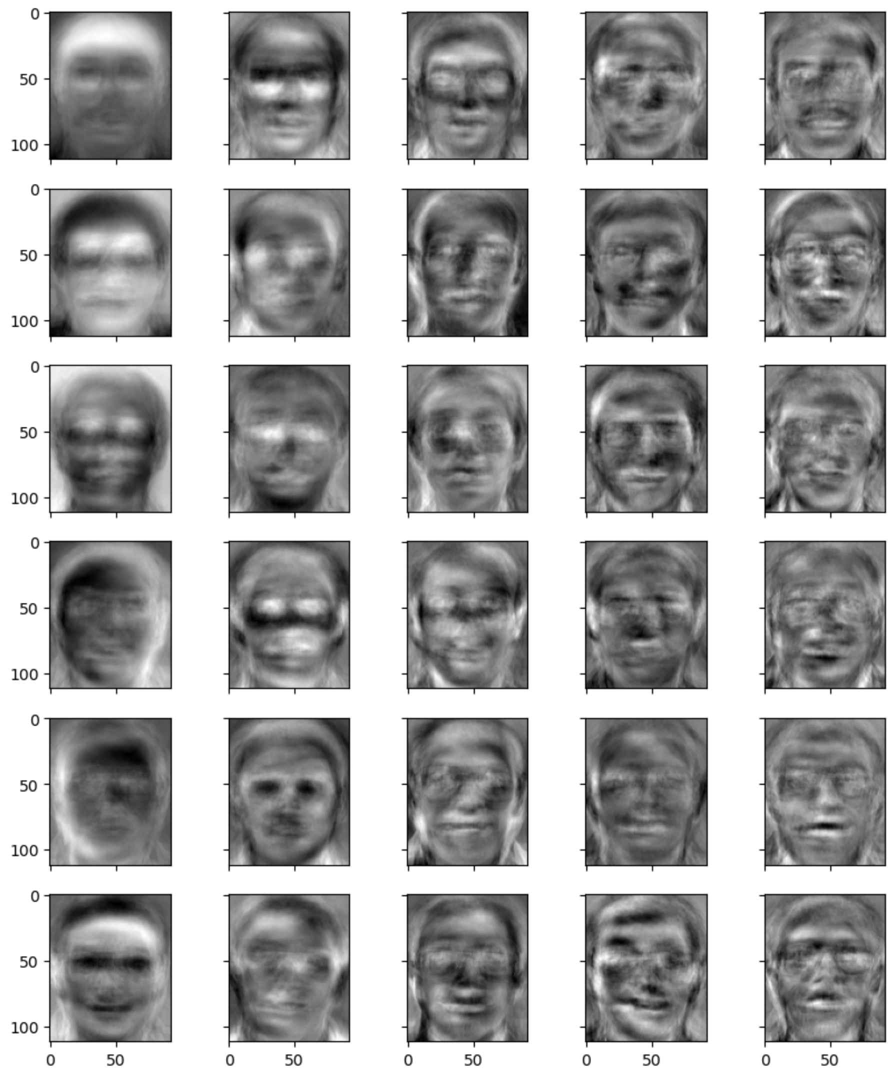

Figure 2: Visualize eigenfaces.

3.3 FACE GENERATION

The experiment generated new faces by applying random weight vectors and visualized both the mean face and a randomly generated face using eigenfaces. The number of principal components, k, was varied to observe its effect on the generated faces.

For k=10 (Figure 3), the generated faces appeared blurred and lacked fine details. With fewer components, the system captured only the most dominant facial features, resulting in a coarse representation of the face.

For k=60 (Figure 4), the faces were more detailed compared to k=10. More components allowed the system to capture additional facial variations, resulting in clearer images, though still lacking fine details.

For k=320 (Figure 5), the generated faces displayed high realism and detailed features. Using all available components enabled the system to capture the most subtle variations in facial structure, producing faces that closely resemble real human faces.

This experiment demonstrated the trade-off between computational efficiency and detail captured. Increasing k improved face generation quality but also increased computational complexity, confirming the role of PCA in balancing detail and efficiency.

Figure 3: The mean face and random face generated with eigenfaces(k=10).

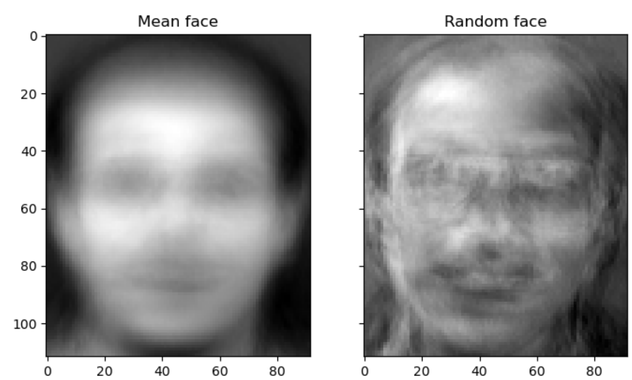

Figure 4: The mean face and random face generated with eigenfaces(k=60).

3.4 FACE RECOGNITION

The experiment implemented a face recognition system based on eigenfaces. This process involved calculating the Euclidean distance between the feature vectors of facial images to assess their similarity and perform recognition. The system identifies the best matching face by comparing the query image with all faces in the training set. Figure 6 illustrates an example of the face recognition process, showing the query image (left) and the best-matching face (right) for two different queries. In both cases, the recognition system successfully identifies the most similar face based on the extracted features.

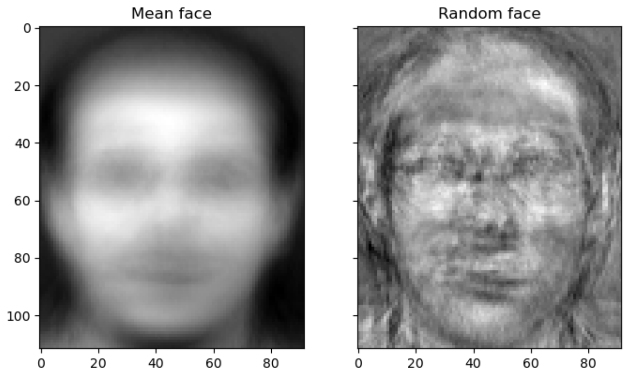

Figure 5: The mean face and random face generated with eigenfaces(k=320).

Figure 6: Face recognition example.

4 RESULTS

Experiments were conducted to assess the impact of varying the number of principal components k in PCA on the accuracy of the face recognition system. The results demonstrated that increasing k generally improved recognition performance. However, a point of diminishing returns was observed, where further increases in k led to little or no improvement in accuracy. Table 1 presents the recognition accuracy corresponding to different values of k, highlighting the effect of component selection on system performance.

Table 1: Accuracy with different value of k

k	accuracy
5	0.80
10	0.95
15	0.95
20	0.95
60	0.96
100	0.95
200	0.95
320	0.95

5 OBSERVATIONS

This study establishes a multidimensional experimental framework integrating Principal Component Analysis (PCA) and Eigenface methodology. The benchmark dataset comprises 400 facial images across 40 distinct categories, ensuring demographic diversity and sample representativeness. Through systematic parameter optimization, we quantitatively demonstrate the critical role of principal component dimensions (k=10, 60, 320) in governing recognition accuracy. Empirical results reveal a significant positive correlation between k-values and classification performance, with accuracy reaching saturation thresholds when k exceeds 200.

Visual analytics of the first 30 Eigenfaces elucidates their capacity to encode essential facial patterns. These orthogonal bases not only reconstruct facial morphologies but also enhance discriminative feature representation through variance maximization. The experimental paradigm validates the efficacy of dimension reduction in balancing computational efficiency with recognition robustness.