Project 5: Face Recognition Using Principal Component Analysis and Eigenfaces in MATLAB

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*Abstract* — Abstract.

Keywords — Keywords

# Introduction

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# Theory

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# Methodology

This project implements a face recognition system using the eigenfaces technique based on Principal Component Analysis (PCA). The purpose is to identify the provided images as either known faces, unknown faces, or non-faces. The methodology is divided into five parts: data pre-processing, PCA and eigenface computation, feature projection, classification, and evaluation.

## Data Preparation and Pre-Processing

The facial images were categorized into training and testing datasets, with the testing images divided into two sets, T1 (known faces) and T2 (unknown faces or non-faces). All the images were resized to a fixed resolution of 112x92 pixels for standardization. Color images were converted to grayscale, and each image was vectorized into a column vector using a custom pre-processing function. The resulting matrices trainData, testDataT1, and testDataT2 contained the flattened image vectors as columns.

## Eigenface Generation via PCA

PCA was applied to the mean-centered training data. The mean face vector was computed and subtracted from each of the training image vectors. Afterward, Singular Value Decomposition (SVD) was used to compute the eigenfaces from the training data. Furthermore, the top k eigenfaces corresponding to the largest eigenvalues were selected, where k varied to analyze the performance trends. Each of the training images were projected into the reduced-dimensional eigenspace to obtain the PCA coefficients, and which helped as feature representations.

## Feature Projection and Classification

The test images were also mean-centered and projected into the eigenface space using the selected eigenfaces. Furthermore, the Euclidean distance was calculated between each test image’s projection and the training projections for classification purposes. If the minimum distance was below an empirically selected threshold of three thousand, the images were classified as faces. Otherwise, they were not considered a match. Moreover, for the T2 images, the distances exceeding the threshold were classified as non-faces.

## Performance Evaluation

The accuracy of this project was assessed by computing the recognition rate for T1 (true positives) and the rejection rate for T2 (true negatives) across multiple k values. Furthermore, the accuracy information was plotted as a function of the number of eigenfaces to help with identifying the optimal dimensionality for balancing recognition and rejection performance.

## Analysis of Failure Cases

The failure cases from the T1 test set were visualized to assist with understanding misclassifications. The visualization provided the test faces that were classified as non-faces incorrectly due to the large distances from the training samples in the reduced eigenspace. Moreover, the analysis of these cases provided information on improvements for the threshold selection and overall model robustness.

# Results

Results.

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# Conclusion

Conclusion.

##### References

1. References.