LaTeX Classical Face Recognition Under Real-World Variations

Fotios Kapotos, Jean, Ayoub
CentraleSupélec

1. Motivation and Problem Definition

Face recognition is a fundamental problem in computer vision with applications in security, identity verification, and human - computer interaction.

In this project, we focus on appearance-based face recognition techniques developed prior to deep learning. These methods rely on explicit feature extraction and linear subspace modeling.

The objective of this project is to compare three classical face recognition methods:

- Eigenfaces (PCA-based)[5]
- Fisherfaces (LDA-based)[2]
- Local Binary Pattern Histograms (LBPH) [1]

and to analyze their robustness under realistic image degradations such as illumination changes, noise, blur, and partial occlusions.

Problem statement: Given a labeled face image dataset, how do different classical face recognition algorithms perform under varying acquisition conditions, and what do their successes and failures reveal about global versus local visual representations?

2. Related Work

The Eigenfaces method introduced by Turk and Pentland applies Principal Component Analysis (PCA) to project face images into a low-dimensional subspace that captures the main modes of variation. While effective in controlled settings, Eigenfaces are highly sensitive to illumination changes.

Fisherfaces extend this approach by using Linear Discriminant Analysis (LDA) to maximize class separability, leading to improved robustness under varying lighting conditions, provided that sufficient training samples are available.

Local Binary Pattern Histograms (LBPH) represent faces using local texture descriptors computed over small neighborhoods. This local representation has been shown to be more robust to lighting variations and partial occlusions, at the expense of increased sensitivity to noise.

3. Methodology

3.1. Algorithms

We will implement and evaluate the following methods:

- **Eigenfaces**: PCA-based dimensionality reduction followed by nearest-neighbor classification.
- **Fisherfaces**: LDA applied after PCA to improve class discrimination.
- **LBPH**: Local Binary Pattern feature extraction with histogram-based comparison.

3.2. Datasets

We conduct our experiments on two standard face recognition datasets that are widely used in the evaluation of classical appearance-based methods.

ORL (AT&T) Face Dataset. The ORL face dataset [4] contains images of 40 individuals, with 10 grayscale images per subject. The images exhibit moderate variations in facial expression, pose, and the presence of accessories such as glasses. Due to its controlled nature and limited variability, this dataset is well suited for analyzing baseline performance and the impact of training set size on recognition accuracy.

Yale Face Dataset. The Yale face dataset [3] includes frontal face images captured under systematically varying illumination conditions. This dataset is particularly challenging for global appearance-based methods and is therefore well suited for studying robustness to lighting changes. It provides a classical benchmark for evaluating the effectiveness of discriminative subspace methods and local texture-based representations.

4. Evaluation

The proposed methods are evaluated using a combination of quantitative and qualitative analyses, with an emphasis on robustness and interpretability rather than raw performance alone.

Experimental Protocol. For each dataset, we vary the number of training images per subject in order to study sample efficiency and sensitivity to limited supervision. Test images are kept fixed across experiments to ensure fair comparison between methods.

To assess robustness, controlled degradations are applied to the test images, including changes in illumination, additive Gaussian noise, image blur, and partial occlusions. These degradations are applied at increasing levels of severity to produce robustness curves.

Evaluation Metrics. Performance is primarily measured using recognition accuracy and confusion matrices. In addition, robustness curves are used to visualize performance degradation as a function of noise, blur, or occlusion strength.

Qualitative Analysis. Beyond quantitative metrics, we perform qualitative analysis by visualizing learned Eigenfaces and Fisherfaces, as well as representative failure cases. This analysis provides insight into the differences between global subspace representations and local texture-based descriptors, and helps explain the observed performance trends.

5. Expected Contributions

The project aims to deliver:

- A reproducible experimental comparison of classical face recognition methods
- An analysis of global versus local visual representations
- Clean, well-documented code and experimental protocols

References

[1] T. Ahonen, A. Hadid, and M. Pietikäinen. Face recognition with local binary patterns. In *European Conference on Computer Vision (ECCV)*, pages 469–481, 2004.

[2] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman. Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(7):711–720, 1997.

[3] A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman. From few to many: Illumination cone models for face recognition under variable lighting and pose. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(6):643–660, 2001.

[4] F. Samaria and A. Harter. Parameterisation of a stochastic model for human face identification. In *Proceedings of the Second IEEE Workshop on Applications of Computer Vision*, pages 138–142, 1994.

[5] M. A. Turk and A. P. Pentland. Face recognition using eigenfaces. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 586–591, 1991.