Práctica: Eigenfaces

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***Abstract*—This work investigates the use of Principal Component Analysis (PCA) and the Eigenfaces approach for face recognition and morphing on the Olivetti faces dataset. We first describe the PCA pipeline—mean centering, covariance computation, and singular value decomposition—and its application to extract principal components (Eigenfaces). Reconstruction experiments demonstrate how image fidelity improves as the number of components increases, with full-component reconstructions yielding smoother, denoised images. We then perform two morphing experiments in the reduced feature space—linear interpolation and linear combination of PCA-reconstructed faces—and analyze their smoothness and detail preservation. We conclude that although modern diffusion-based models outperform PCA in accuracy and realism, PCA still offers a simple, interpretable, and efficient baseline for exploratory analysis and lightweight face-recognition systems and dimensionality reduction.**

***Index Terms*—Data Exploration, Machine Learning, Eigenfaces, UNAM**

I. INTRODUCTION

Face recognition has long been a key area of research in biometrics due to the non-intrusive nature of facial identification and its familiarity to humans, who naturally recognize faces throughout their lives. Facial recognition systems offer several benefits, such as ease of integration with other biometric methods, straightforward implementation, and the widespread availability of facial image databases.

Although automatic face recognition under controlled conditions—especially with 2D images—is largely considered a solved problem, developing a reliable system remains a complex challenge. It requires careful selection of preprocessing, feature extraction, and classification techniques. Significant hurdles persist, including face recognition in uncontrolled environments (with changes in lighting, pose, or facial expression), dealing with occlusions, non-frontal faces, and ensuring real-time performance. Additionally, open research areas include video-based recognition, recognition from a single image, 3D face recognition, and the integration of face data into multimodal biometric systems. These ongoing challenges continue to drive research in the field. [1]

A. Principal Component Analysis

Principal Component Analysis (PCA) is a widely adopted statistical technique for reducing the dimensionality of datasets while preserving the most relevant information. It identifies underlying patterns and correlations in data by computing the principal components new variables that represent directions of maximum variance. PCA is commonly used in fields such as high-dimensional data analysis, noise filtering, and feature selection [2].

The PCA procedure consists of several sequential steps. The first step is data standardization, which adjusts each feature to have a mean of zero and unit variance. Then, the covariance matrix of the standardized data is computed to measure the relationship between variables. This is followed by the eigen decomposition of the covariance matrix, yielding eigenvalues and eigenvectors. Eigenvectors are then sorted according to their eigenvalues in descending order, indicating the amount of variance each principal component contributes. Finally, the original data is projected onto the space formed by the most significant eigenvectors to achieve dimensionality reduction [3].

Data Standardization

Standardization ensures all features contribute equally. It is done by subtracting the mean of each feature from every data point:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{1}$$

$$X_i' = X_i - \bar{X} \tag{2}$$

Covariance Matrix

The covariance matrix expresses how features vary with respect to each other. Its diagonal elements represent the variance of individual features, while the off-diagonal elements represent covariances between feature pairs:

$$\mathrm{cov}(X,Y) = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y}) \tag{3}$$

$$\text{cov} = \frac{X'^T X'}{n-1} \tag{4}$$

Eigenvalues and Eigenvectors

To find the principal components, we solve the eigenvalue equation of the covariance matrix. The eigenvalues indicate the significance of each component:

$$\det(\text{cov} - \lambda I) = 0 \tag{5}$$

where λ is an eigenvalue and I is the identity matrix of the same size as the covariance matrix.

Each eigenvector corresponds to an eigenvalue and defines a direction in the data space:

$$(\text{cov} - \lambda I)v = 0 \tag{6}$$

In practice, instead of computing the eigen decomposition of the covariance matrix directly, many implementations of PCA, especially in image analysis and Eigenfaces rely on Singular Value Decomposition (SVD) due to its numerical stability and computational efficiency. SVD factorizes a given data matrix X (typically the mean-centered data matrix) into three components:

$$X = U\Sigma V^T \tag{7}$$

Here, U and V are orthogonal matrices containing the left and right singular vectors, respectively, while Σ is a diagonal matrix of singular values. The columns of V correspond to the principal directions (analogous to eigenvectors), and the squared singular values in Σ represent the variance explained by each component. SVD is particularly useful when dealing with high dimensional data, such as facial images, where the number of features exceeds the number of samples. Moreover, it avoids the explicit computation of the covariance matrix, making it more efficient and less prone to numerical errors. In the context of Eigenfaces, the principal components derived from SVD are used to form a low dimensional face space, allowing effective face recognition with reduced computational cost. [4]

Dimensionality Reduction

Finally, the data is projected onto the subspace defined by the most significant eigenvectors:

$$X_{\text{red}} = X' \cdot v \tag{8}$$

This transformation enables the representation of the original data in a lower-dimensional space, retaining its most discriminative features. In the context of Eigenfaces, PCA is applied to facial image data, allowing efficient facial recognition based on the reduced feature set.

B. Dataset

The Olivetti faces dataset as seen in 1 and originally collected by AT&T Laboratories Cambridge, consists of 400 grayscale images of size 64×64 pixels [5]. These images depict 40 distinct subjects, with exactly 10 different images per subject. All faces are captured under controlled conditions—nearly frontal pose, uniform background—and include mild variations in lighting, facial expression (e.g., smiling or neutral), and accessories such as glasses.

Each image in the dataset is aligned and cropped so that the facial region occupies the majority of the frame. In this report, we load the dataset via the scikit-learn function `fetch_olivetti_faces`, which returns a data matrix of shape 400×4096, where each row corresponds to one flattened 64×64 image [6]. Prior to applying PCA, we standardize this matrix by subtracting the global mean face (computed over all 400 images) from each sample.

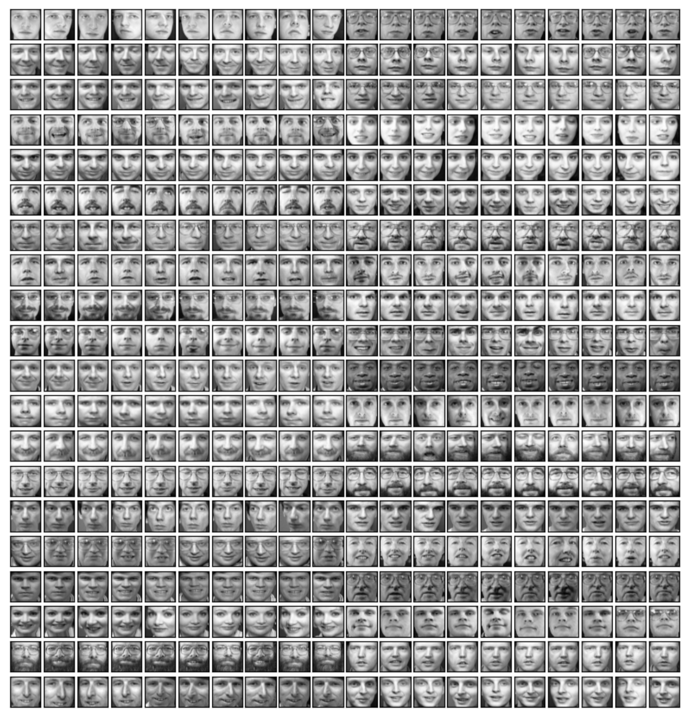

Fig. 1: The Olivetti dataset.

The Olivetti faces dataset is widely used as a benchmark for PCA and Eigenfaces because its moderate size and controlled variations allow clear analysis of dimensionality reduction and reconstruction quality. In our experiments, this dataset enables us to assess how the number of principal components affects both the fidelity of reconstructed images and the discriminative power of the reduced feature space.

II. Methodology

This work utilized the Olivetti Faces dataset provided by the fetch_olivetti_faces function from the scikit-learn library. The dataset contains 400 grayscale facial images of size

64×64 pixels, representing 40 distinct individuals, each with 10 different facial expressions.

First, the mean face 2 was computed by averaging all images across the dataset. This average face was then subtracted from each image to center the data, effectively eliminating overall brightness variations and emphasizing facial features with higher variability. This centering is essential for the subsequent application of Principal Component Analysis (PCA), as it ensures that the first principal component corresponds to the direction of maximum variance in the data.

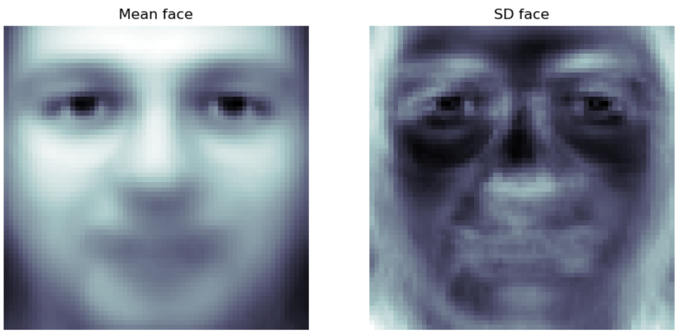

Fig. 2: Mean face (left) and standard deviation face (right)

To extract the principal components, Singular Value Decomposition (SVD) was applied to the centered dataset. This decomposition yields a set of orthonormal vectors—commonly referred to as Eigenfaces—that form a new basis representing the most significant variations among the facial images. These Eigenfaces were stored in the rows of the matrix V^T, obtained from the decomposition.

Using the computed Eigenfaces, a random image from the dataset was selected and reconstructed by projecting it onto varying numbers of principal components. This allowed an analysis of how image quality and detail were affected as the dimensionality of the face representation was reduced.

To further evaluate the generalization of the model, the same reconstruction procedure was applied to two facial images of team members not present in the original dataset. This helped assess the model's ability to represent previously unseen faces using the learned face space.

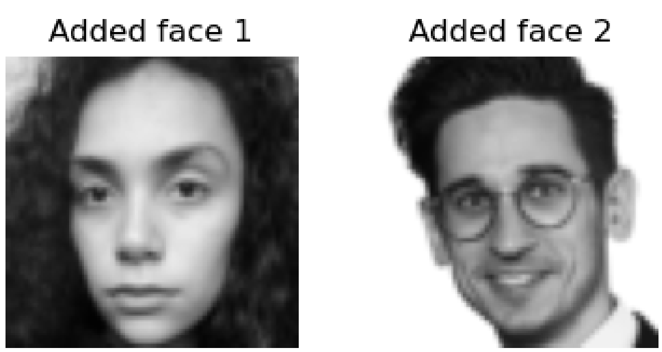

Fig. 3: Added faces

Finally, two face morphing experiments were conducted. The first used a linear combination of two faces which were added to the dataset as vectors in the reduced feature space to create a gradual transition between them. The second involved feature space interpolation, where intermediate representations were generated by interpolating between the principal component projections of two images. Both techniques demonstrate how facial features can be blended or transformed smoothly within the PCA-reduced space.

III. Results and Discussion

Firstly, a reconstruction experiment was performed on a randomly selected face from the Olivetti dataset. The goal was to observe how the quality and fidelity of the reconstructed image evolve as the number of principal components eigenfacesincreases. The original image is displayed in Fig. 4 alongside its reconstructions using 5, 10, 25, 50, 100, 200, and 400 components.

With only 5 eigenfaces, the reconstructed image appears blurry and lacks distinctive facial features, though it still captures the clear structure of a face. As the number of eigenfaces increases, the reconstruction progressively resembles the original image more closely. At 25 components, the angle of the original face starts to show correctly, and with 100 or more, the reconstruction becomes visually closer to the original.

Interestingly, the image rebuilt with all 400 components actually looks a bit sharper than the original. That's probably because PCA tends to smooth things out, a real photo might have some noise, but the reconstructed version, made from the main patterns in the data, skips over that high-frequency noise.

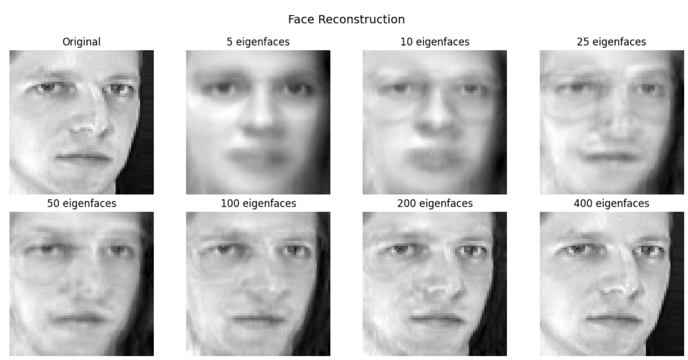

Fig. 4: Reconstruction of a randomly selected face from the Olivetti dataset using varying numbers of principal components

In the second experiment, face morphing was performed by interpolating between two facial images in the PCA-reduced feature space. Both input images were external to the training dataset. A total of ten intermediate faces were generated, gradually blending the characteristics of the first face into those of the second.

The morphing process produced a smooth and continuous transition between the two individuals. However, the starting image (corresponding to interpolation factor α = 0) appeared noticeably blurry and lacked detail, particularly in the eye region. This deficiency persisted throughout the interpolated sequence—although facial features transitioned gradually and convincingly from one identity to the other, the eye details remained poorly defined, even in the final image (α = 1).

This outcome may be attributed to the nature of the training dataset, which contains only grayscale facial images of 40 male subjects. Since the input images for morphing were from individuals not represented in the dataset specifically, one female face, the model may lack the necessary variance in its learned components to accurately represent features that deviate significantly from the training distribution.

As a second approach, we tried morphing through a linear combination of the two pictures reconstructed from the full 400 eigenfaces. Although the results seem rather good, this may be due to a similar head position and image crops of the two pictures.

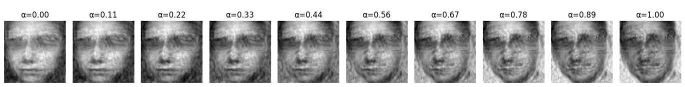

Fig. 5: Face morphing through linear interpolation in the PCA-reduced feature space.

Fig. 6: Face morphing through linear combination of the two pictures.

IV. Conclusion

In recent years, deep learning–based methods—particularly diffusion models—have demonstrated remarkable success in both face recognition and image morphing, achieving higher accuracy and generating more photorealistic transitions than classical approaches. These models learn complex, non-linear mappings from data and can handle variations in pose, lighting, and expression far more robustly than linear techniques.

Nonetheless, PCA remains an important foundational tool. Its simplicity and computational efficiency make it ideal for exploratory data analysis, educational purposes, and scenarios with limited computational resources. By projecting high-dimensional face images onto a lower-dimensional subspace, PCA provides clear insights into the main modes of variation within a dataset. Moreover, the Eigenfaces framework offers a transparent, interpretable basis that can serve as a fast baseline or preprocessing step for more sophisticated pipelines. Therefore, while modern methods set new performance benchmarks, PCA continues to hold its worth as a reliable, understandable, and lightweight technique in the face-recognition toolbox.

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