

Face Recognition Using Eigenfaces

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Problem Definition

- Recognize faces vs. non-faces
- Recognize faces of a particular person vs. faces of other people

- Do it fast

Basic Idea

- PCA on face images
 - Face images lie in a low dimensional space
 - Images of the same person are close to each other
 - Images of different people are farther away

Recognition

- Given a new image, project onto face space
 - If the residual is too high, it's not a face
 - If the projection is close to one of the "prototypes", assign it to that class
 - Otherwise, it's a new face

Illustration of Face Space

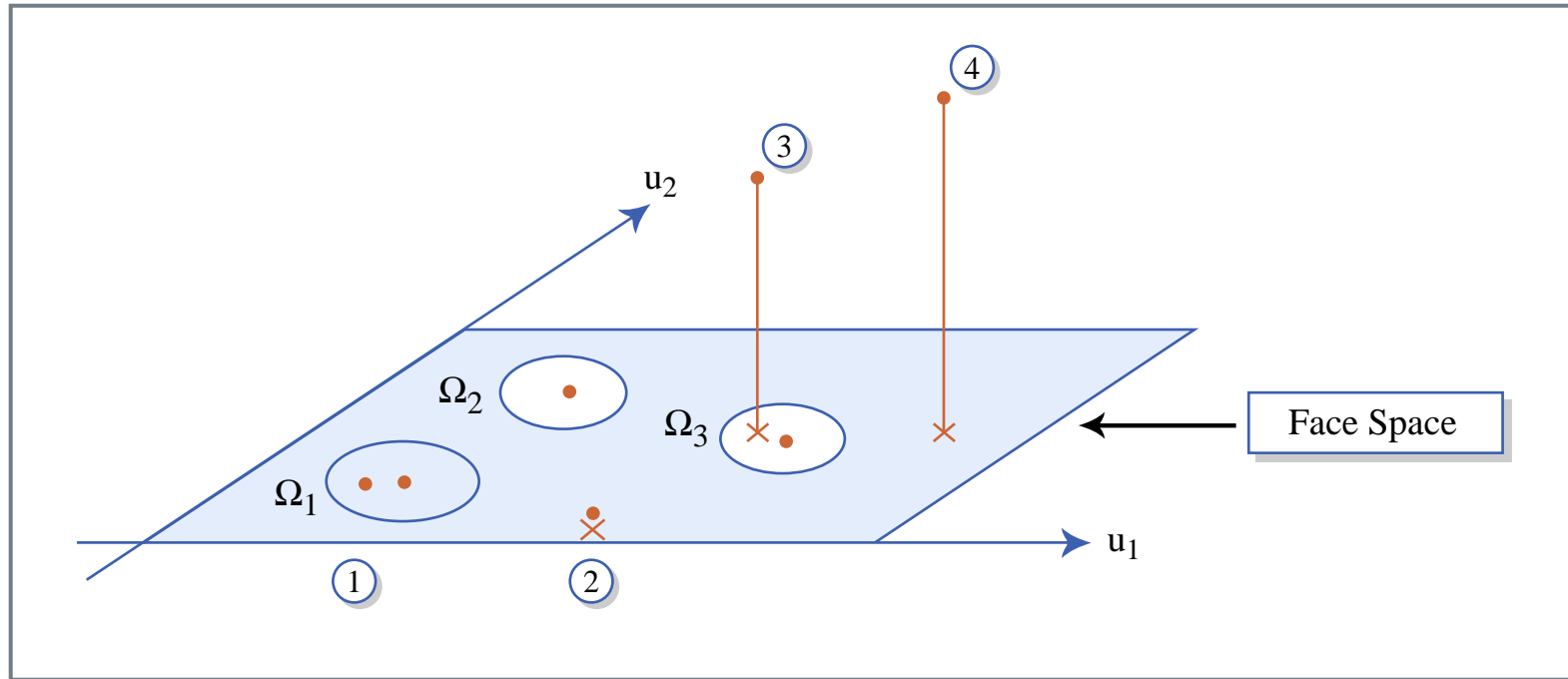


Figure by MIT OCW.

Training

- Input: M input images in a vector form Γ_i
- Mean face $\Psi = M^{-1} \sum \Gamma_i$
- Zero-mean data $\Phi_i = \Gamma_i - \Psi$
- Zero-mean data matrix $A = [\Phi_1 \Phi_2 \dots \Phi_M]$

- Covariance matrix $C = M^{-1} \sum \Phi_i \Phi_i^T = AA^T$

Training cont'd

- Eigenfaces \mathbf{u}_k are the eigenvectors of C
- Keep a small number (M') of eigenfaces
 - In the experiments, $M = 16$, $M' = 7$
- Resulting model:
 - Mean face Ψ
 - M' eigenfaces \mathbf{u}_k ($k = 1, \dots, M'$)

Detection

- Given a new image Γ , compute its weights

$$\omega_k = \mathbf{u}_k^\top (\Gamma - \Psi)$$

- The face is represented by the weight vector

$$\Omega = [\omega_1 \ \omega_2 \ \dots \ \omega_{M'}]^\top$$

- If $\| \Gamma - \Psi - \sum \omega_k \mathbf{u}_k \| < \theta_\varepsilon$, this is a face image.
- If $\| \Omega - \Omega_n \| < \theta_\delta$, this is a face from class n .

Illustration of Face Space

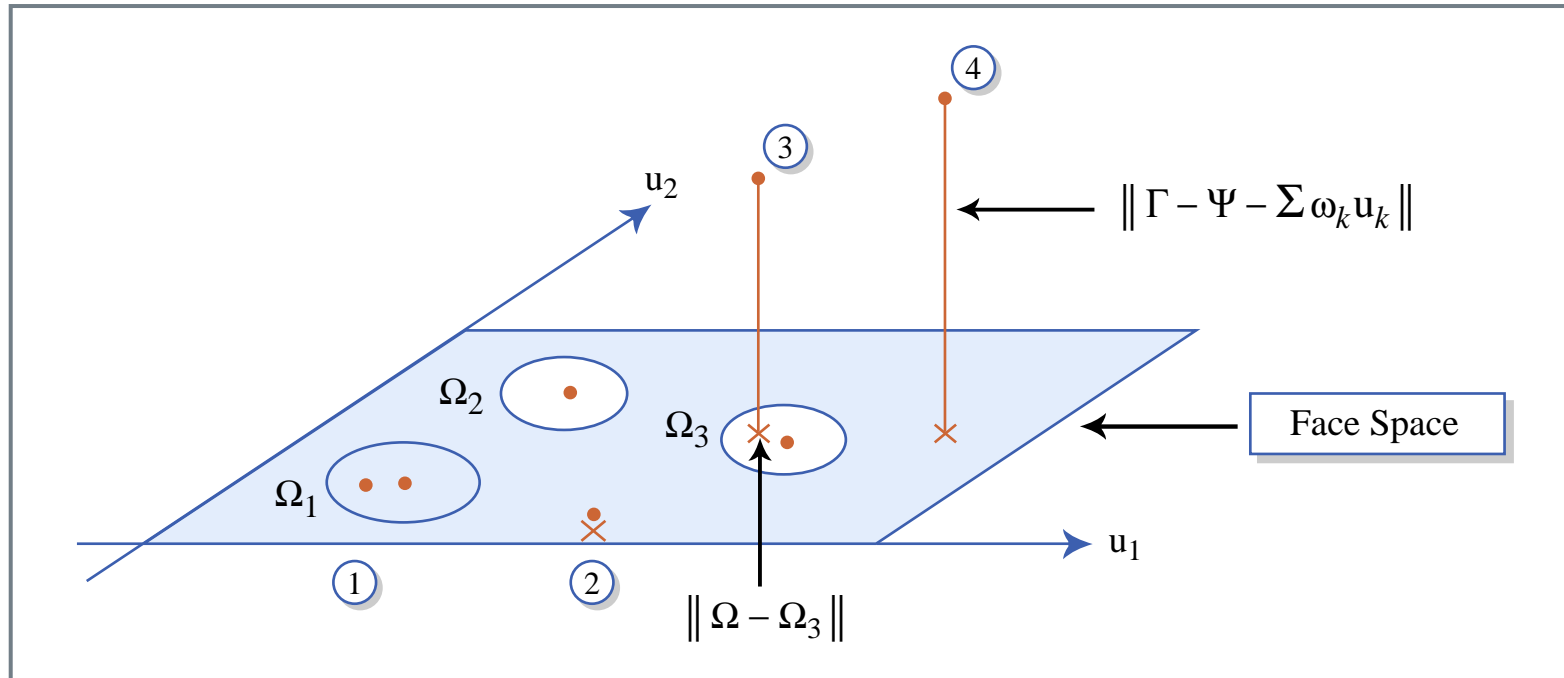


Figure by MIT OCW.

Examples of projections

Image removed due to copyright considerations. Please see Figure 3 in:

M.E. Leventon, E.L. Grimson, and O. Faugeras, "Statistical Shape Influence in Geodesic Active Contours," Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 316-323, 2000.

Notes

- Use Euclidean distance
 - not Mahalanobis distance
- Not clear how the classes Ω_k are constructed
 - here used just one image per person
- Free parameters:
 - number of eigenfaces M' and thresholds
 - in the experiments, $M' = 7$, and the thresholds varied
- Eigenfaces look like faces

Eigenfaces

Image removed due to copyright considerations. Please see Figure 2 in:

M.E. Leventon, E.L. Grimson, and O. Faugeras, "Statistical Shape Influence in Geodesic Active Contours," Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 316-323, 2000.

“Faceness” Map

- For each window location, evaluate its distance from the face space
- Slow, faster algorithms exist

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Experimental Results

- Image Database
 - Controlled experiment

- Real-time face recognition
 - Unconstrained recognition, closer to the real-world

Image Database Results

- Image Database
 - 16 people
 - 3 illuminations, 3 angles, 3 head sizes
- Use one image per person to train
 - $M = 16, M' = 7$
 - all at the same illumination, angle, size.
- Test on all other images, forcing recognition
 - 96% across illuminations
 - 85% across orientations
 - 64% across sizes

Image Database Results cont'd

- Vary the threshold (ROC, precision/recall)
 - 100% accuracy, check for “unknown” labels
 - » 19% across illuminations
 - » 39% across orientations
 - » 60% across sizes
 - 20% “unknown”, check the accuracy
 - » 100% across illuminations
 - » 94% across orientations
 - » 74% across sizes

Real-time face recognition

- Motion detection, plus head localization: small blob on top of a bigger blob
- Run the recognizer on the head window
- 2-3 times/second (long time ago, so might actually be really fast on a modern computer)
- No accuracy/precision reported

Notes on Performance

- More sensitive to head size than other factors
 - Normalization, windowing
 - Related to the “faceness” map
- Should be sensitive to orientation, as parts of the face get occluded
 - Maybe the projection is helping it
- What happens when we vary all factors at once?

Summary

- Faces have a lot of structure, let's try to capture it automatically.
- Prior work focused on crafted templates
 - This paper learns the structure through PCA
- Strong assumptions on the structure
 - Face images can be approximated by a linear low dimensional space
 - They cluster in that space w.r.t. the person
- Fairly naïve classification

Since Then

- More explicit models of the object shape
 - Active Shape/Appearance Models
- Non-linear subspace/manifold modeling
 - Mixture of Gaussians
 - Kernel PCA
 - Locally Linear Embedding, Isomaps
 - non-negative decomposition, etc.
- Classification
 - Fisher faces (Fisher Linear Discriminant)
 - Other classification methods