



Principal component analysis on images

Rasmus R. Paulsen

DTU Compute

Based on

M. Turk and A. Pentland. *Face recognition using eigenfaces*. Computer Vision and Pattern Recognition, 1991.

<http://compute.dtu.dk/courses/02503>

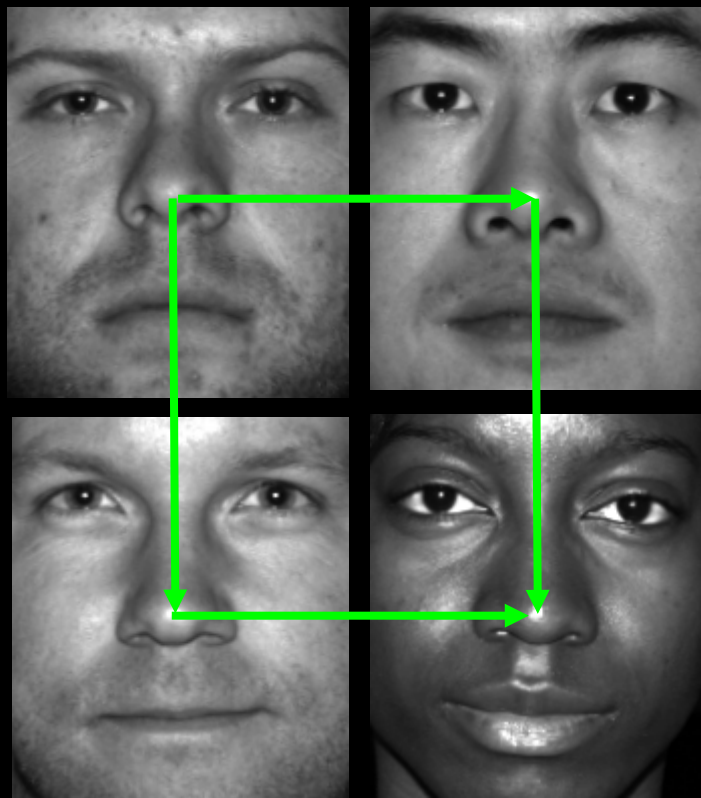


Principal Component Analysis on images

learning objectives

- Construct a column matrix from a single gray scale image
- Construct a data matrix from a set of gray scale images
- Compute and visualize an average image from a set of images
- Compute the principal components of a set of images
- Visualize the principal components computed from a set of images
- Synthesize an image by combining the average image and a linear combination of principal components

Face data



- 38 face images
 - 168 x 192 grayscale
- Aligned
 - The anatomy is placed “in the same position in all image”
- Same illumination conditions on the images we use

The Extended Yale Face Database B

<http://vision.ucsd.edu/~leekc/ExtYaleDatabase/ExtYaleB.html>



Principal component analysis on face images



- What is the main variation in face images?
 - The variation of appearance
 - Not the position in the image
 - Not the light conditions
 - Not the direction of the head

Putting images into matrices

- An image can be made into a column matrix
 - Stack all image columns into one column

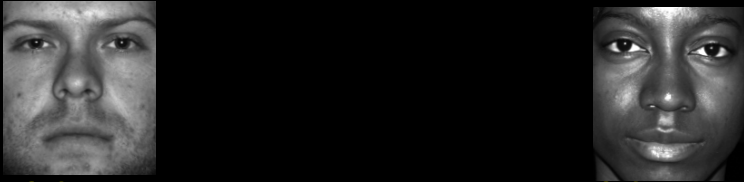


$$I = \begin{bmatrix} p_1 \\ p_2 \\ \dots \\ p_m \end{bmatrix}$$

...

Face images in matrix form

- One column is one face
- $n=38$ faces
- $m=168 \times 192 = 32256$ pixel values per image


$$X = \begin{bmatrix} p_{1,1} & \cdots & p_{1,n} \\ \vdots & \ddots & \vdots \\ p_{m,1} & \cdots & p_{m,n} \end{bmatrix}$$

The average face



$$X = \begin{bmatrix} p_{1,1} & \cdots & p_{1,n} \\ \vdots & \ddots & \vdots \\ p_{m,1} & \cdots & p_{m,n} \end{bmatrix}$$



- The average face
 - Average of each row
 - One column
 - Put it back into image shape
- Blurry around the eyes
 - Not perfectly aligned

Subtracting the mean face

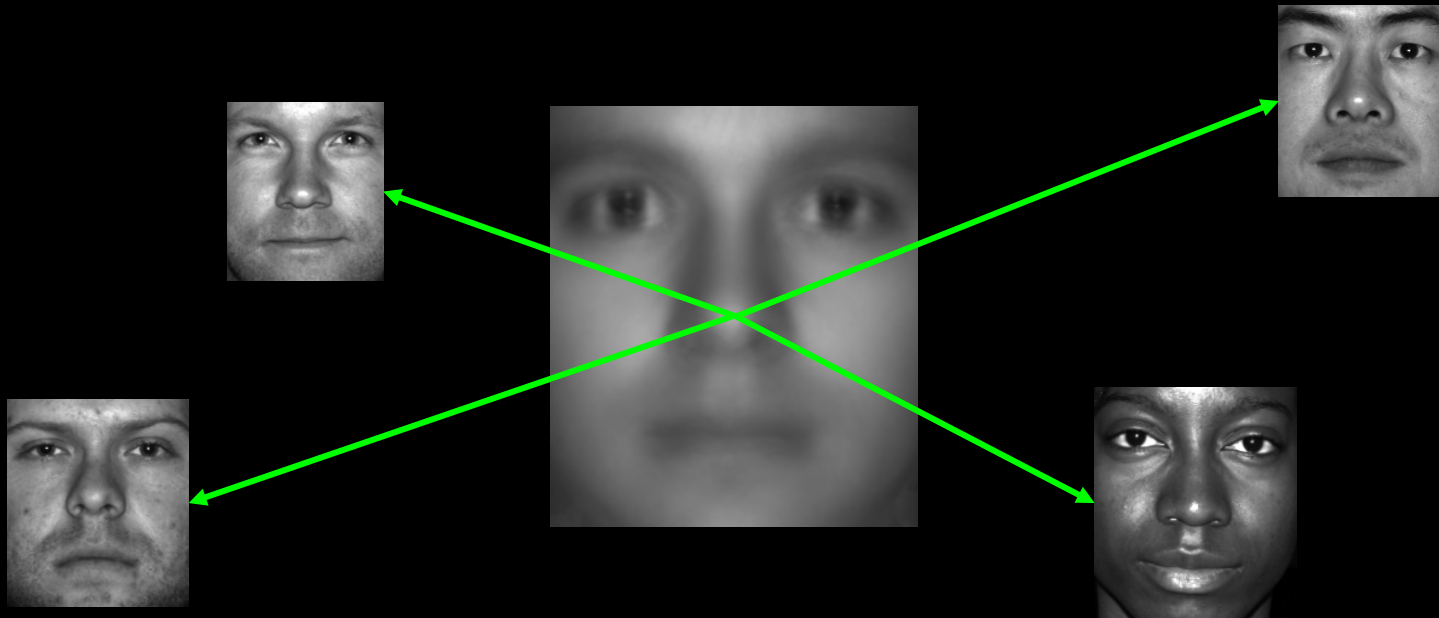
$$X' = \begin{bmatrix} p_{1,1} & \cdots & p_{1,n} \\ \vdots & \ddots & \vdots \\ p_{m,1} & \cdots & p_{m,n} \end{bmatrix} - \bar{X}$$

- We subtract the mean face from all faces



Analyzing the deviation from the mean face

- We want to do the principal component analysis on the *deviations from the average face*



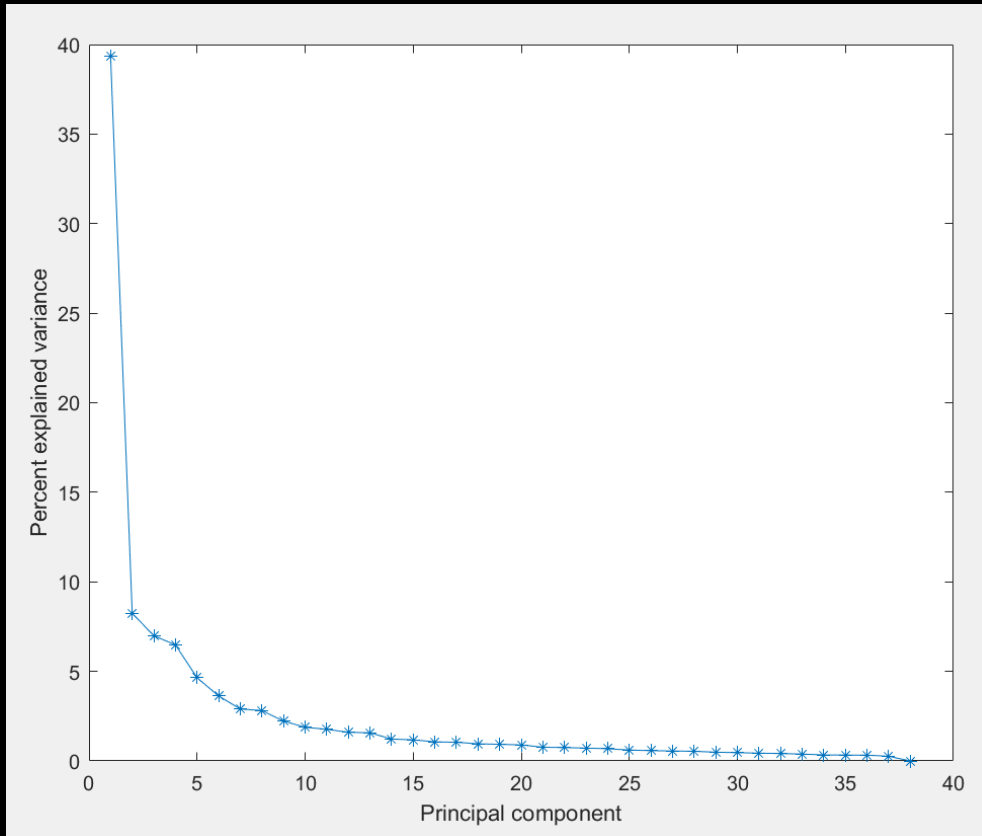


PCA Analysis on face data

$$X' = \begin{bmatrix} p_{1,1} & \cdots & p_{1,n} \\ \vdots & \ddots & \vdots \\ p_{m,1} & \cdots & p_{m,n} \end{bmatrix} - \bar{X}$$

- We do the PCA analysis on the X' matrix
- X' is 32256×38
- Standard covariance matrix is 32256×32256
- Turk and Pentland found a trick:
 - Compute the PCA on the 38×38 matrix instead of the 32256×32256 matrix
 - Details in the paper
 - Beyond the scope here

PCA on faces



- First eigenvector explains 40% of variation
- Second eigenvector explains 8% of variation

Visualizing the PCA faces

Main deviations from the average face



First PC – 40% of variation



Second PC – 8% of variation

A tool to see major variations –
brow lifting

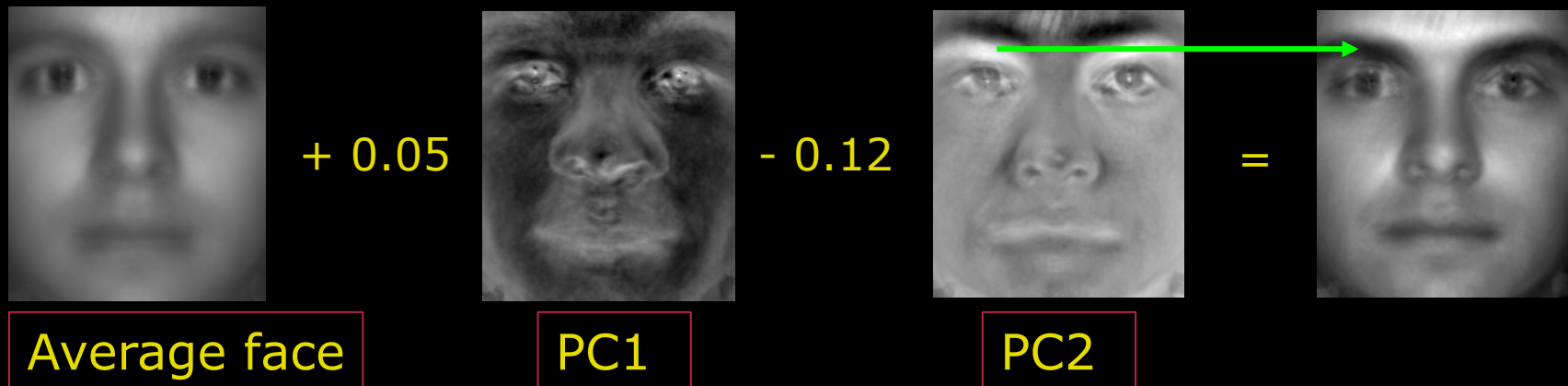
-PC

Average face

+PC

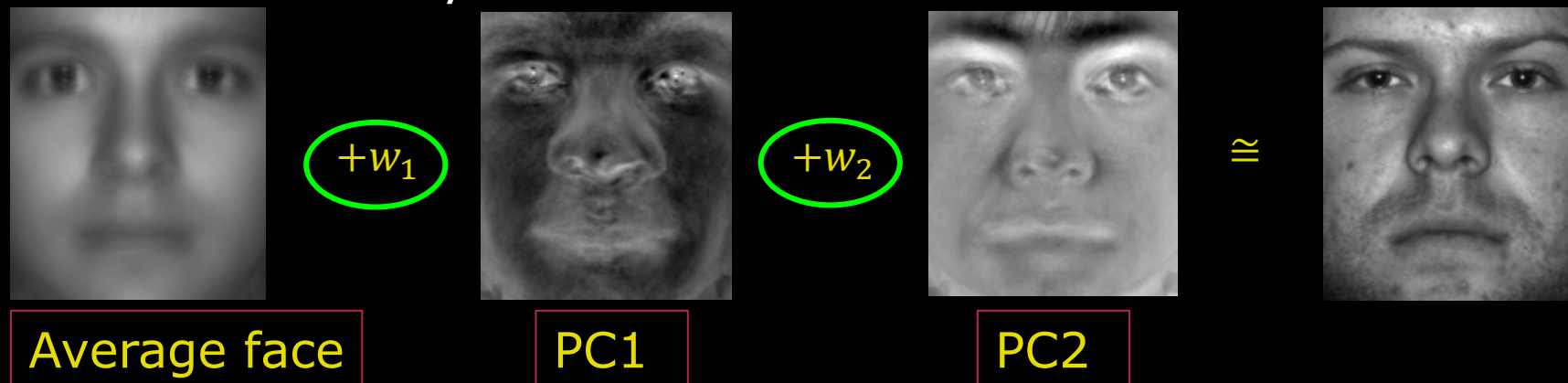
Synthesizing faces

- A new face can be created by combining
 - Average face
 - Linear combination of principal components



Decomposing faces

- A given face can be reconstructed using
 - The average face
 - Linear combination of principal components
- Found by projecting the face on the principal components
- The weights can then be used for classification/identification



Face analysis plus plus?

- More examples later in the course

