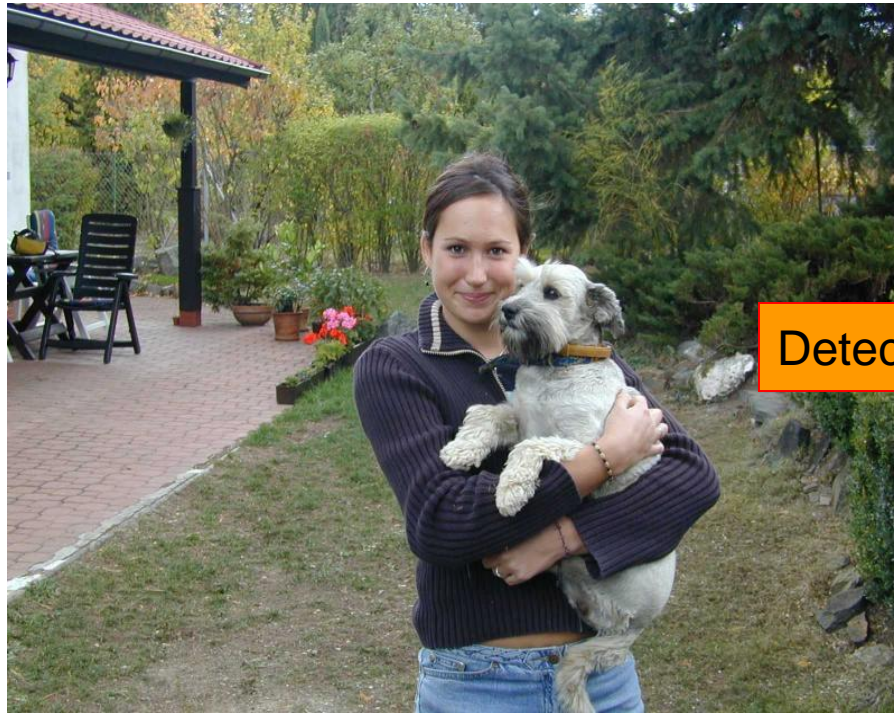


Understanding Faces

Computational Photography
Derek Hoiem, University of Illinois
Lecture by Amin Sadeghi

Some slides from Lana Lazebnik, Silvio Savarese, Fei-Fei Li

Face detection and recognition



Detection



Recognition

“Sally”

Applications of Face Recognition



Album organization



Digital photography

Face Detection

How to find faces anywhere in an image?

- Filter Image with a face?

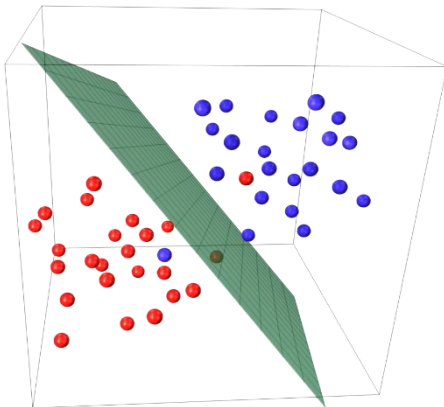


Train a Filter

Positive Training Images



Negative Training Images



SVM



Face detection: sliding windows

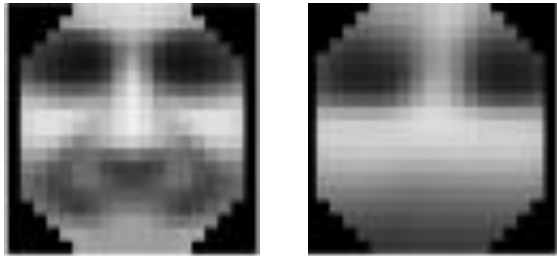


Filter/Template

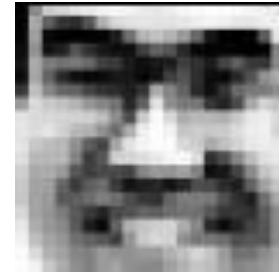


Multiple scales

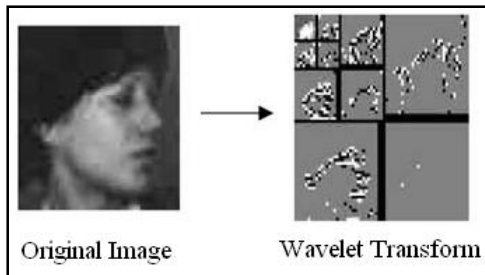
What features?



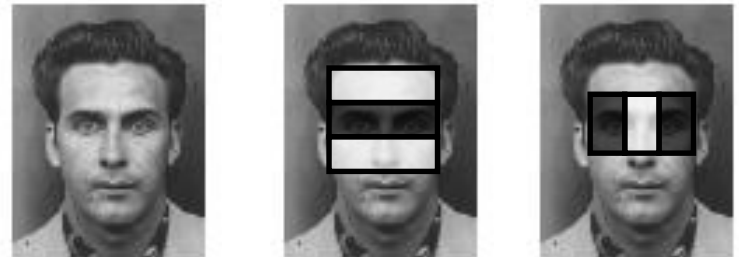
Exemplars
(Sung Poggio 1994)



Intensity Patterns (with NNs)
(Rowely Baluja Kanade 1996)



Edge (Wavelet) Pyramids
(Schneiderman Kanade 1998)



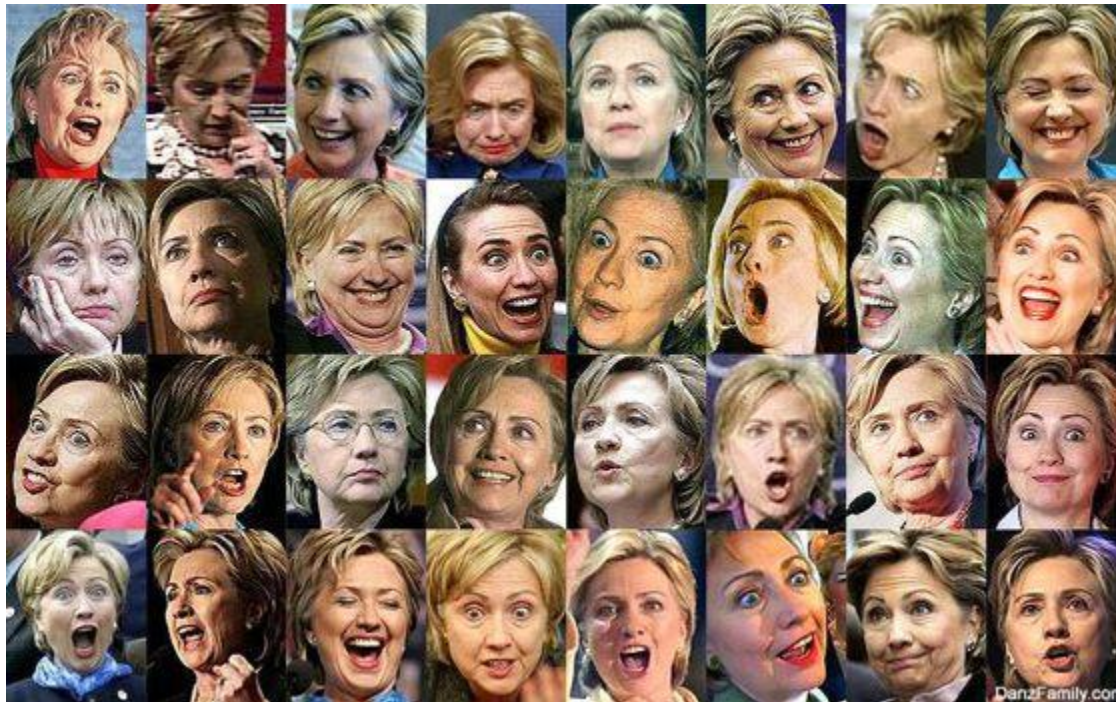
Haar Filters
(Viola Jones 2000)

How to classify?

- Many ways
 - Neural networks
 - Adaboost
 - SVMs
 - Nearest neighbor

What makes face detection hard?

Expression



What makes face detection hard?

Viewpoint



What makes face detection hard?

Occlusion



Consumer application: iPhoto 2009



<http://www.apple.com/ilife/iphoto/>

Consumer application: iPhoto 2009

- Things iPhoto thinks are faces

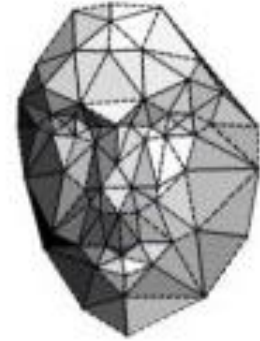


Face Recognition

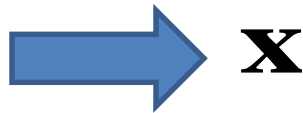
Face recognition



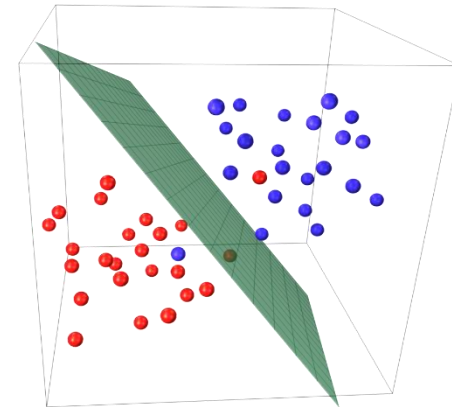
1. Detect



2. Align



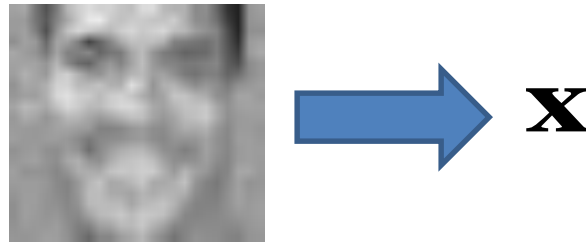
3. Represent



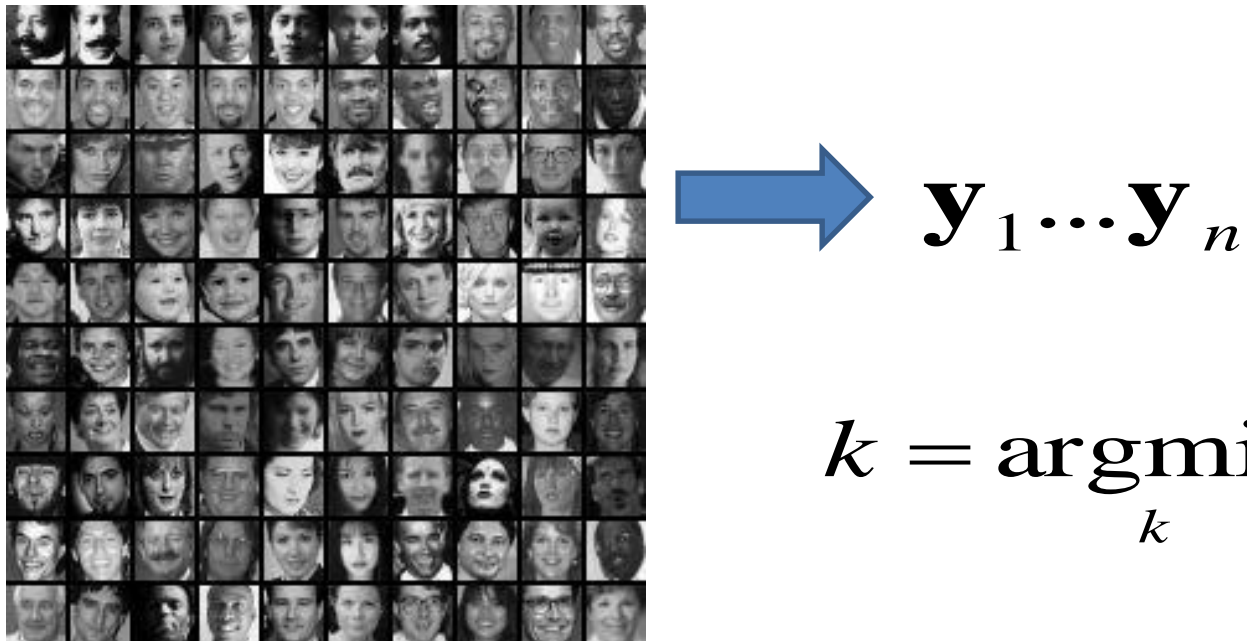
4. Classify

Simple technique

1. Treat pixels as a vector



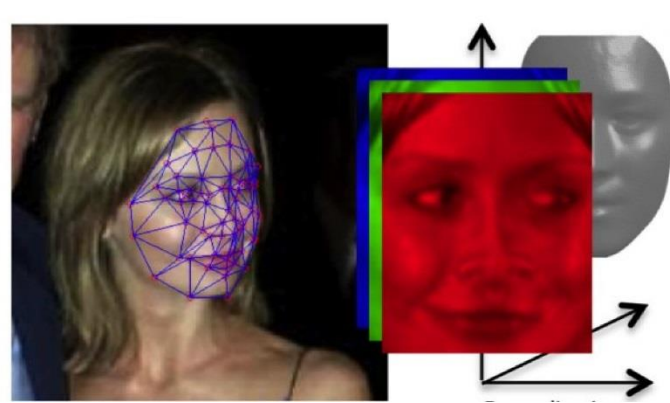
2. Recognize face by nearest neighbor



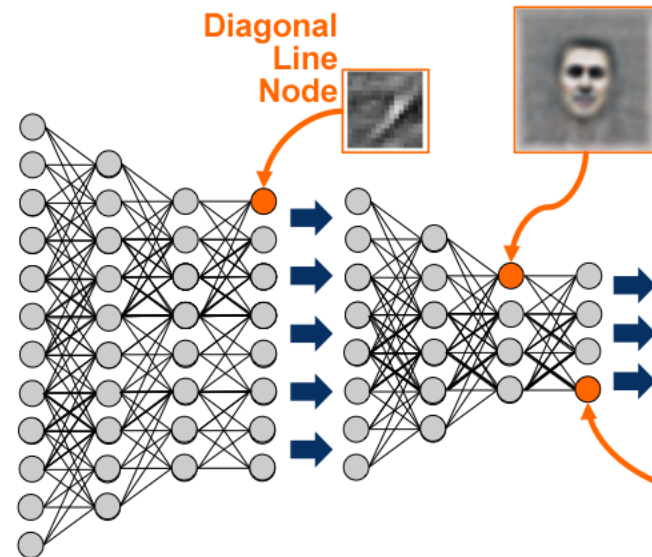
$$k = \operatorname{argmin}_k \left\| \mathbf{y}_k^T - \mathbf{x} \right\|$$

DeepFace

- 3D Alignment



- Deep Learning



Morphing and Alignment

Figure-centric averages

- Need to Align
 - Position
 - Scale
 - Orientation



Antonio Torralba & Aude Oliva (2002)

Averages: Hundreds of images containing a person are averaged to reveal regularities in the intensity patterns across all the images.

How do we average faces?



<http://www2.imm.dtu.dk/~aam/datasets/datasets.html>

Morphing

image #1



image #2

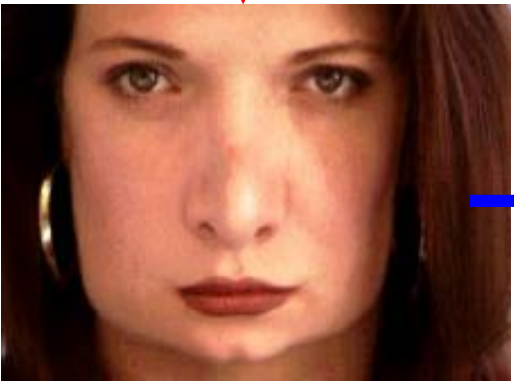


warp

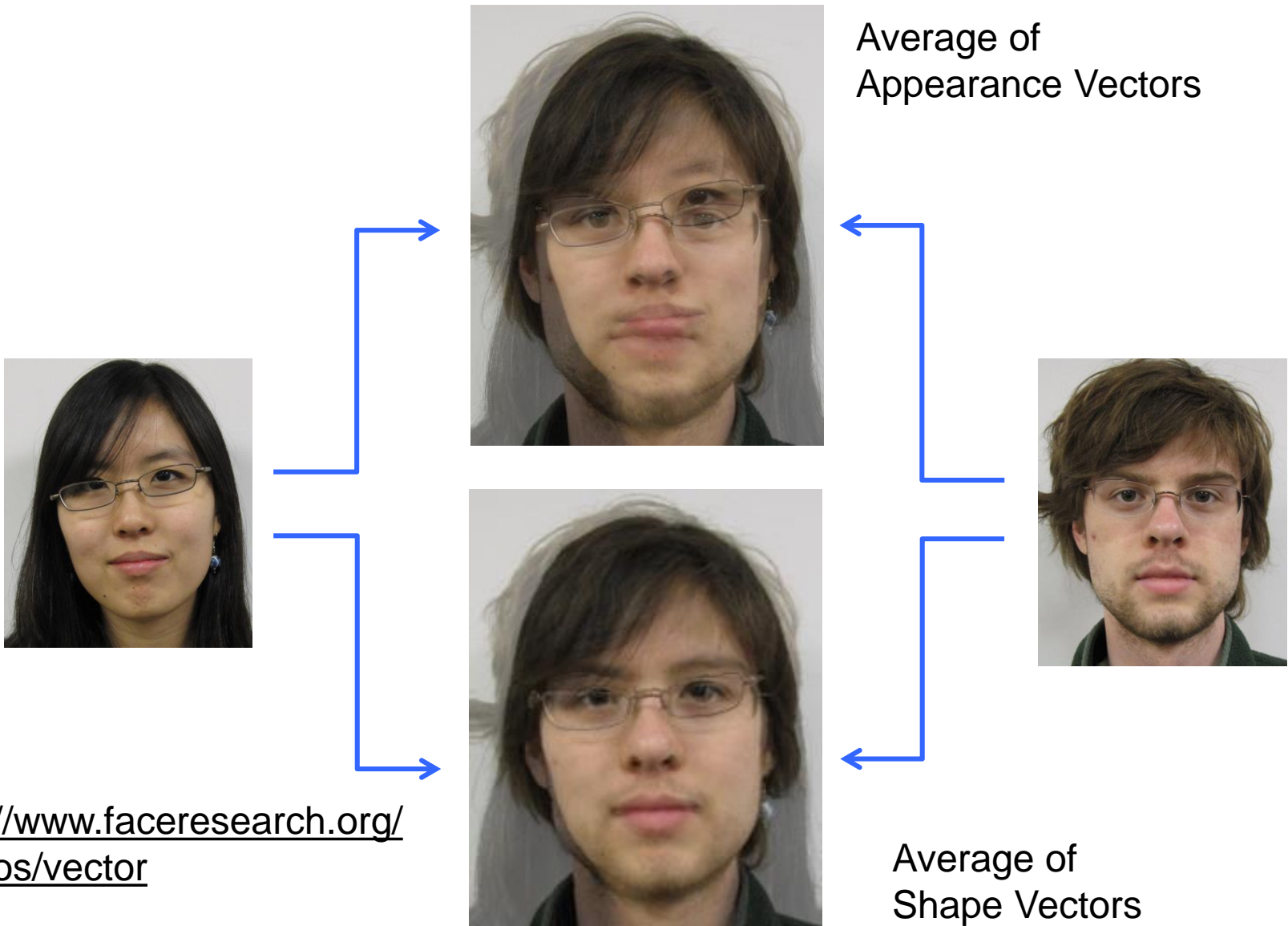


morphing

warp

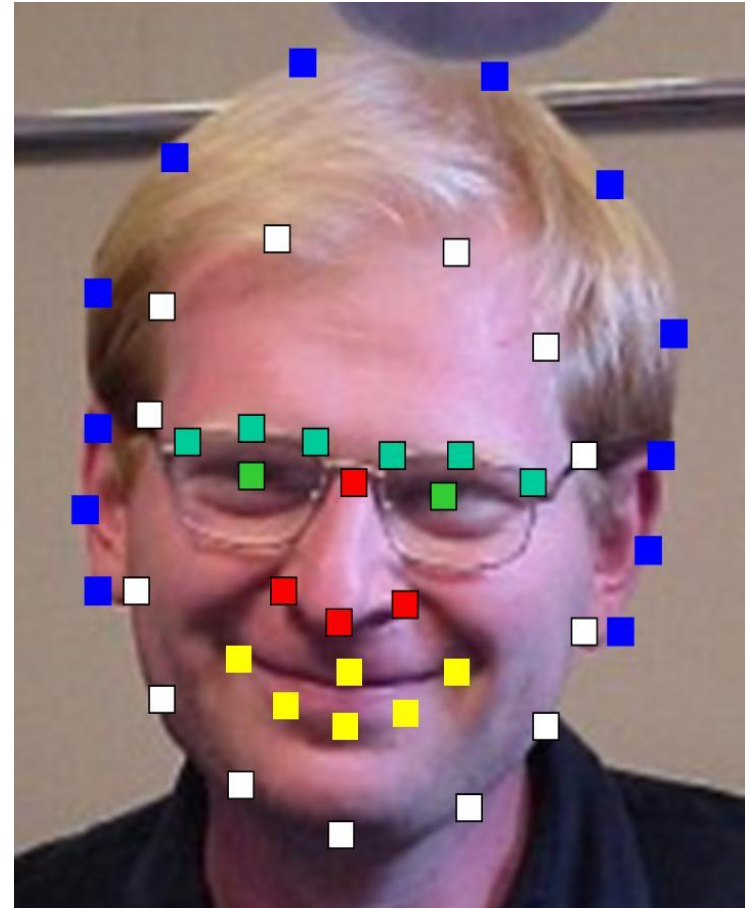
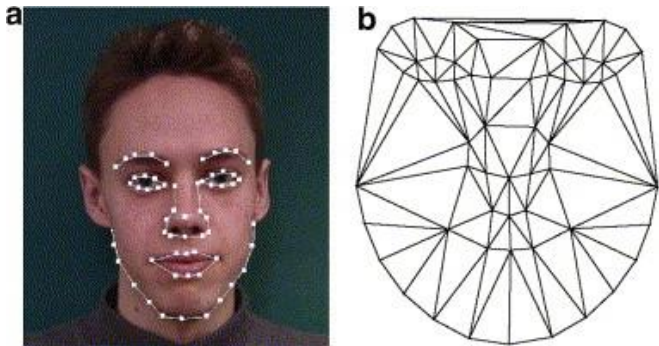


Cross-Dissolve vs. Morphing



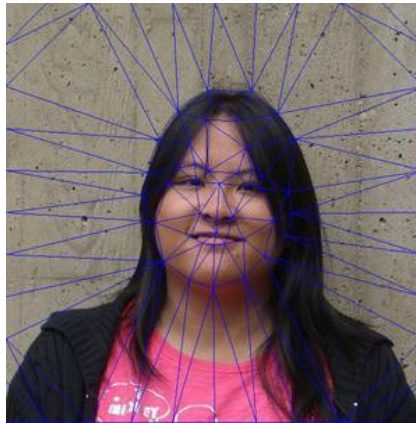
Aligning Faces

- Need to Align
 - Position
 - Scale
 - Orientation
 - **Key-points**
- The more key-points the finer alignment



Average of two Faces

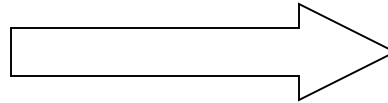
1. Input face key-points
2. Pairwise Average key-point co-ordinates
3. Triangulate the faces
4. Warp: Transform every face triangle
5. Average The pixels



Average of multiple Face



1. Warp to mean shape
2. Average pixels



<http://www.faceresearch.org/demos/average>

Appearance Vectors vs. Shape Vectors

Appearance
Vector



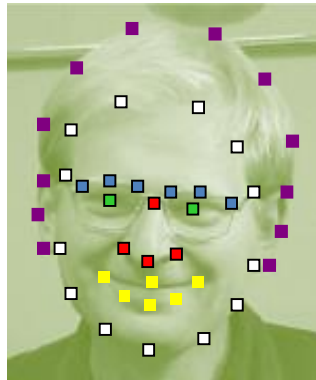
200*150 pixels (RGB)



Vector of
200*150*3
Dimensions

- Requires Annotation
- Provides alignment!

Shape
Vector



43 coordinates (x,y)



Vector of
43*2
Dimensions

Complements

Average Men of the world



AUSTRIA



AFGHANISTAN



ARGENTINA



BURMA (MYANMAR)



GERMANY



GREECE



CAMBODIA



ENGLAND



ETHIOPIA



FRANCE



IRAQ



IRELAND



MONGOLIA



PERU



POLAND



PUERTO RICO



UZBEKISTAN



AFRICAN AMERICAN

Average Women of the world



Central African

Burmese

Cambodian

English

Ethiopian

Filipino



Greek

Indian

Iranian

Irish

Israeli

Italian



Peruvian

Polish

Romanian

Russian

Samoan

South African

Subpopulation means

- Other Examples:

- Average Kids
- Happy Males
- Etc.
- <http://www.faceresearch.org>



Average female



Average kid



Average happy male



Average male

Eigen-face

Eigenfaces example

- Training images
- $\mathbf{x}_1, \dots, \mathbf{x}_N$

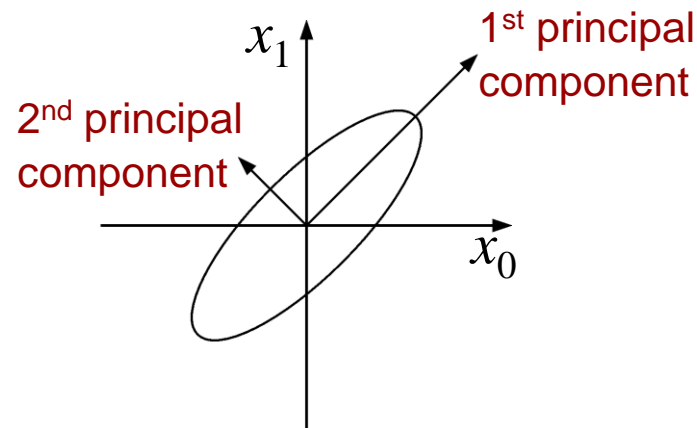
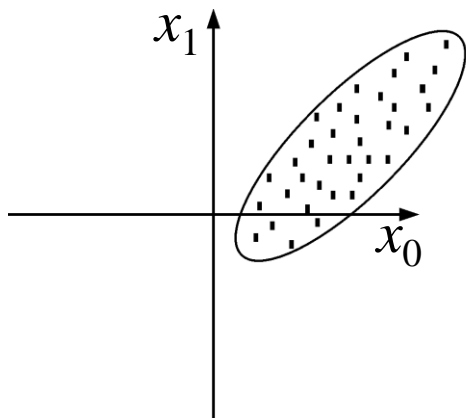


PCA

- General dimensionality reduction technique
- Preserves most of variance with a much more compact representation
 - Lower storage requirements (eigenvectors + a few numbers per face)
 - Faster matching
- What are the problems for face recognition?

Principal Component Analysis

- Given a point set $\{\vec{p}_j\}_{j=1\dots P}$, in an M -dim space, PCA finds a basis such that
 - coefficients of the point set in that basis are uncorrelated
 - The most variation is in the first basis vector, then second, ...



PCA in MATLAB

- `x=rand(3,10); %10 3D examples`
-
- `M=mean(x,2);`
- `x2=x-repmat(M,[1 n]);`
- `covariance=x2*x2';`
- `[U E] = eig(covariance)`

U =

0.74	0.07	-0.66
0.65	0.10	0.74
-0.12	0.99	-0.02

E =

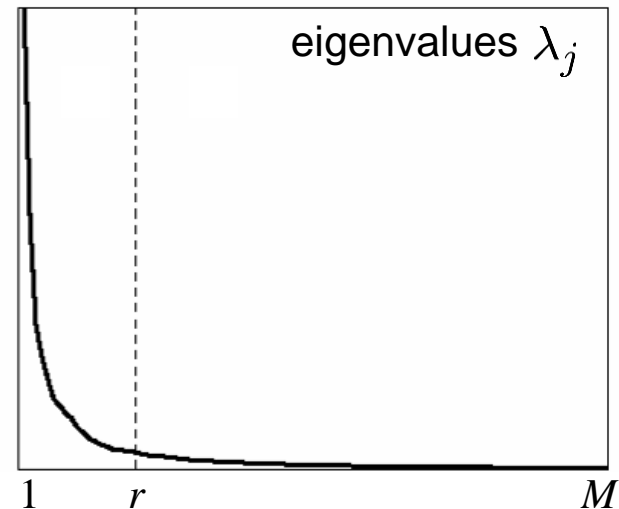
0.27	0	0
0	0.63	0
0	0	0.94

Principal Component Analysis

- Continued...
 - first $r < M$ basis vectors provide an approximate basis that minimizes the mean-squared-error (MSE) in the approximation (over all bases with dimension r)

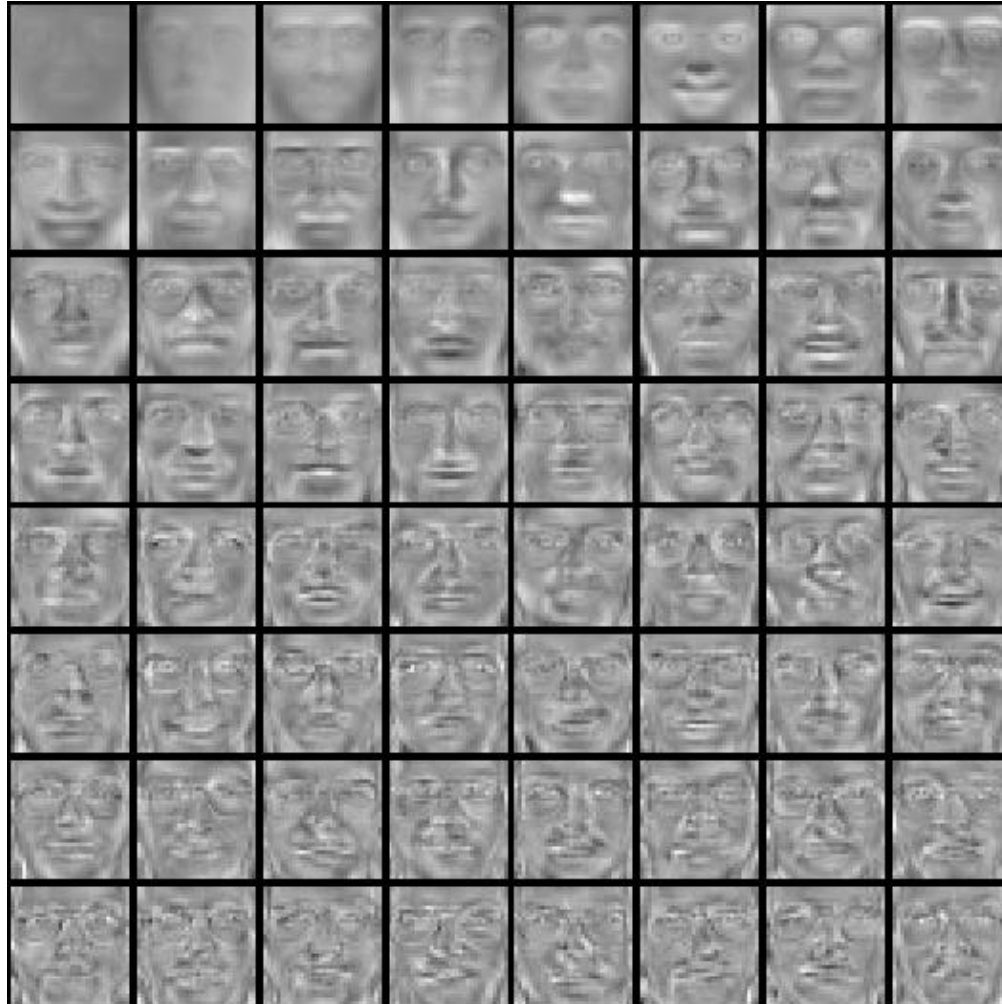
Choosing subspace dimension r :

- look at decay of the eigenvalues as a function of r
- Larger r means lower expected error in the subspace data approximation



Eigenfaces example

Top eigenvectors: u_1, \dots, u_k



Face Space

-
- How to find a set of directions to cover all space?
- We call these directions **Basis**
- If number of basis faces is large enough to span the face subspace:
- Any new face can be represented as a linear combination of basis vectors.

$$s = \alpha_1 \cdot \text{face}_1 + \alpha_2 \cdot \text{face}_2 + \alpha_3 \cdot \text{face}_3 + \alpha_4 \cdot \text{face}_4 + \dots = \mathbf{S} \cdot \mathbf{a}$$

Limitations

Global appearance method: not robust to misalignment, background variation



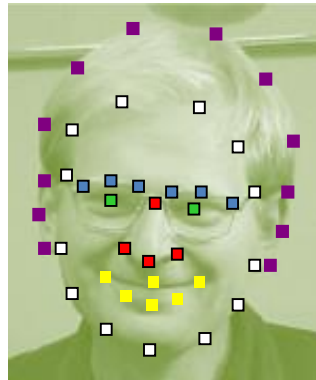
Use Shape information

Appearance
Vector



200*150 pixels (RGB)

Shape
Vector

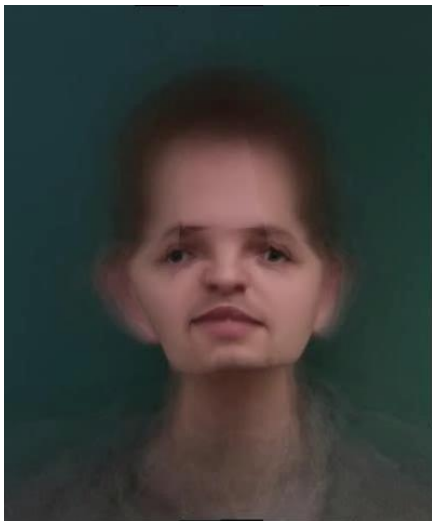


43 coordinates (x,y)

First 3 Shape Basis

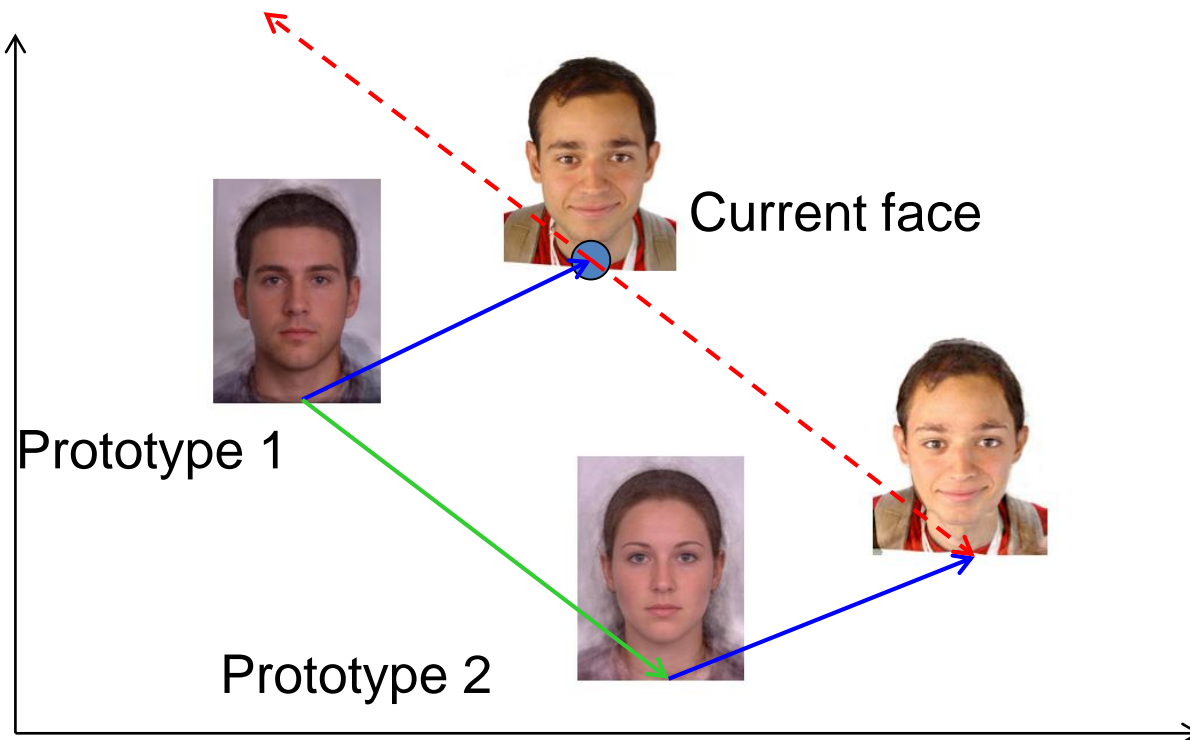


Mean appearance



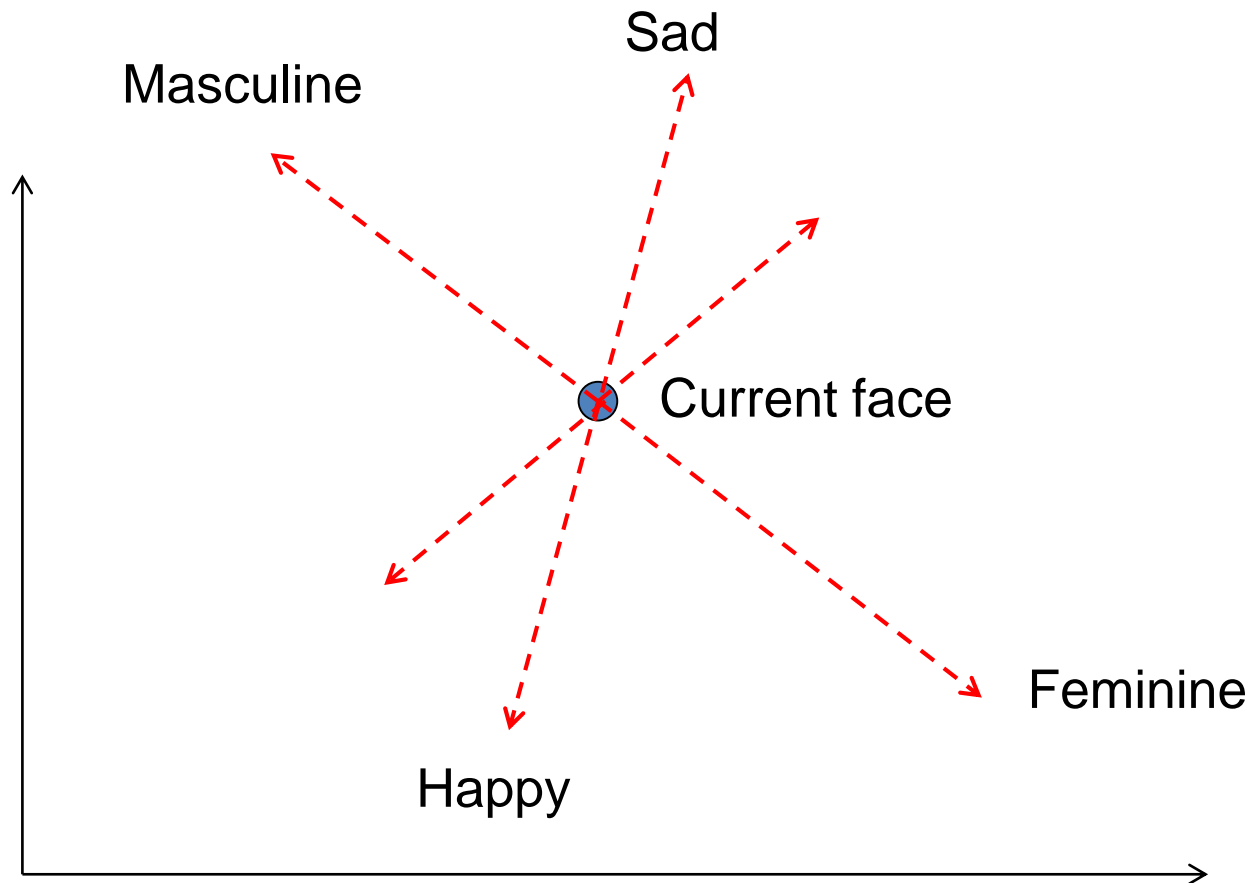
Manipulating faces

- How can we make a face look more female/male, young/old, happy/sad, etc.?
- <http://www.faceresearch.org/demos/transform>



Manipulating faces

- We can imagine various meaningful directions.



Psychological Attributes



Unreliable



Trustworthy



Incompetent



Competent



Introverted

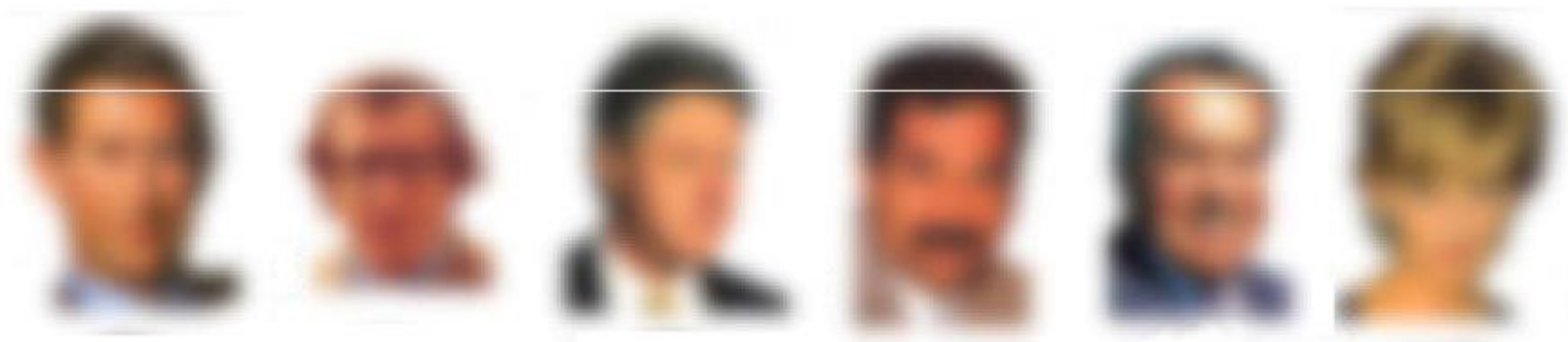


Extroverted

Human Perception

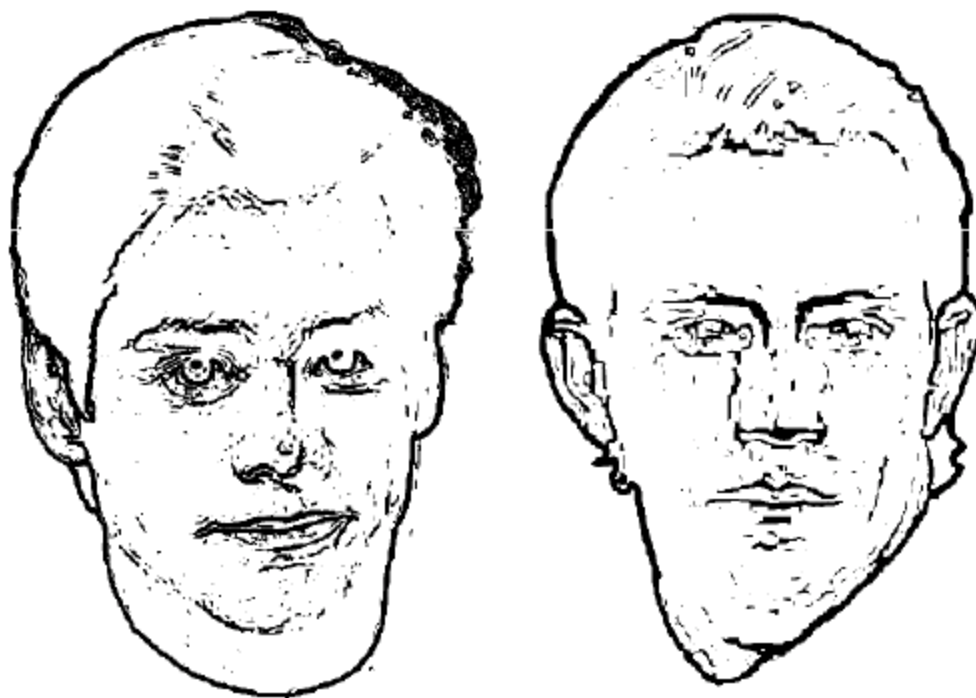
Result 1

- ▶ Humans can recognize faces in extremely low resolution images.



Result 3

- ▶ High-frequency information by itself does not lead to good face recognition performance



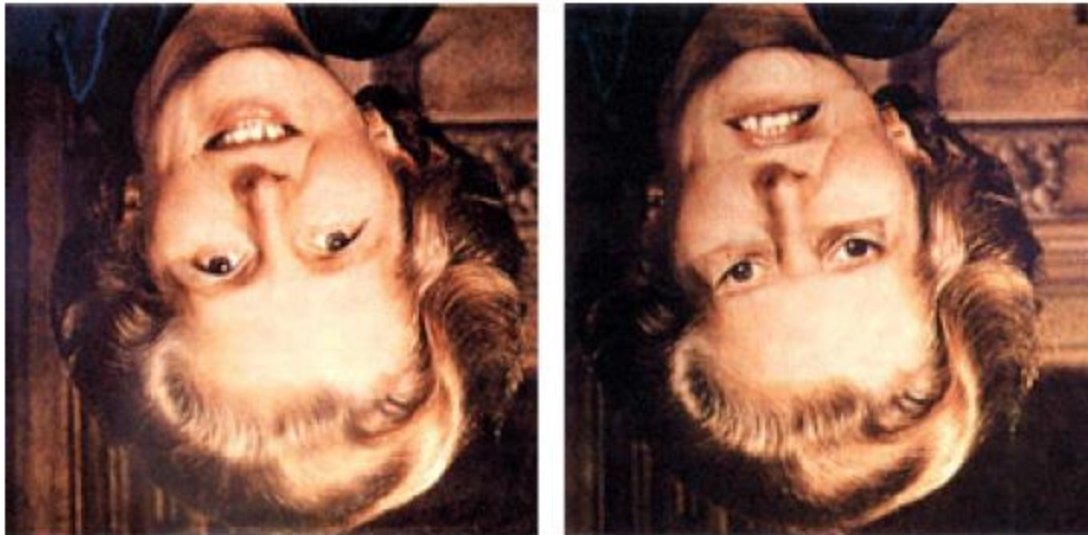
Result 5

- ▶ Eyebrows are among the most important for recognition



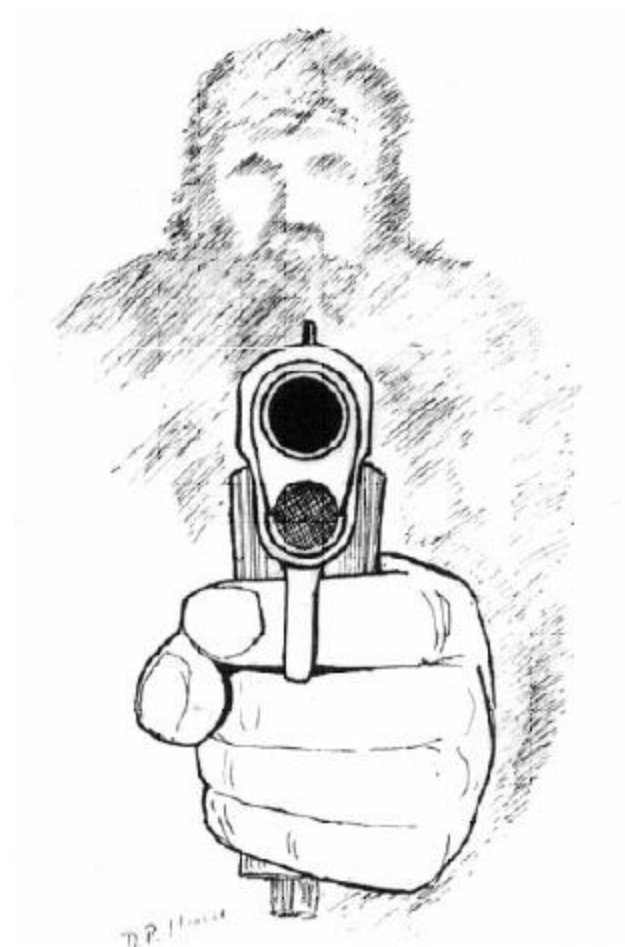
Result 8

- ▶ Vertical inversion dramatically reduces recognition performance



Result 20

- ▶ Human memory for briefly seen faces is rather poor



Which face is more attractive?

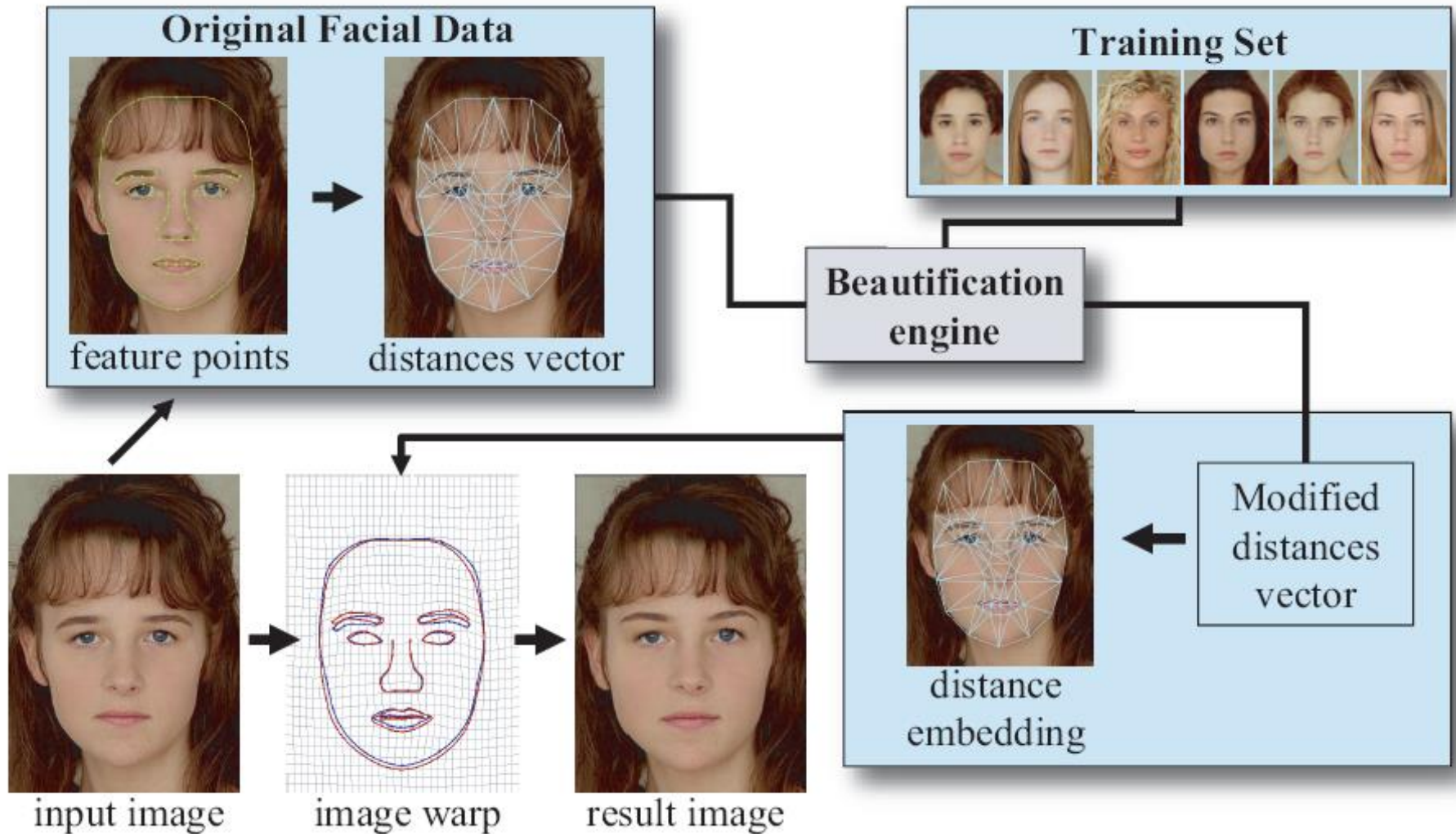


beautified



original

System Overview



Things to remember

- Face Detection
- Face Recognition
- Appearance Vector
- Shape Vector
- Face Transformation
- Principal Component Analysis