Biometric Systems
Lesson 4 - Face recognition: introduction and face localization

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Why face

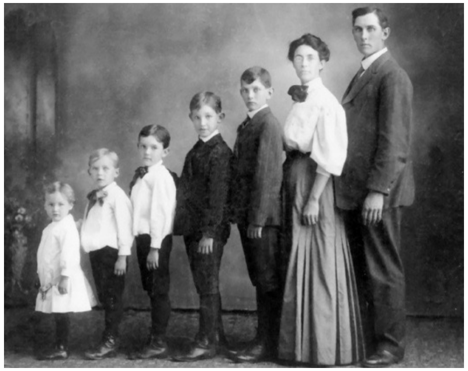
- The most important factors influencing the feasibility of a biometrics are Accuracy/Reliability and Acceptability

- DNA recognition is the most accurate trait, but also one of those requiring the most intrusive procedures. Fingerprints are accurate and more easily accepted, but require an aware and collaborating user. Moreover in some cases they might be of low quality (e.g., hard workers).

- Face has a high acceptability, the user may be unaware of image capture, but accuracy is still to be improved.

Further advantages …

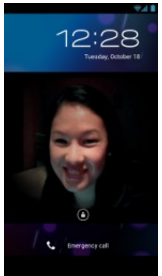
It is natural to recognize a person from face and it is usual for people to be photographed (e.g., fingerprints may be associated with the bad feeling to be suspected to be a criminal)



High recognition rate in controlled conditions

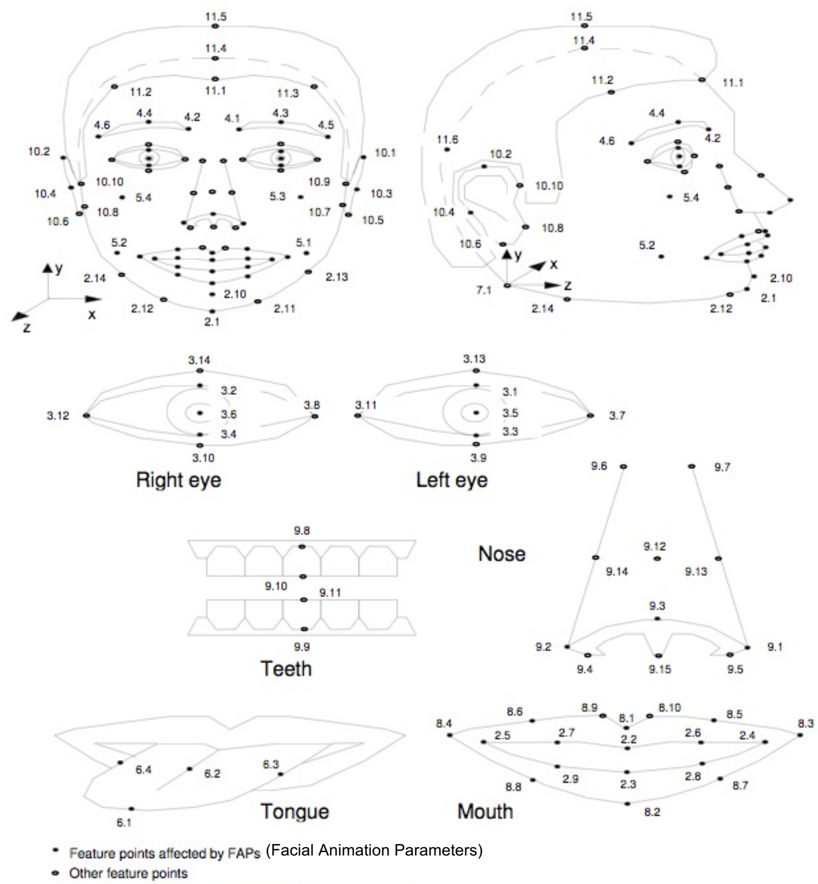
Acquisition devices are easy to deploy in the operation environment

It is possible to integrate it in logical access (login)



It is possible to integrate it in remote control applications

… but face is a complex object!



MPEG-4 feature points

Comparisons

Biometrics	Univer-sality	Unique-ness	Perma-nence	Collect-ability	Perfor-mance	Accept-ability	Circum-vention
Face	H	L	M	H	L	H	L
Fingerprint	M	H	H	M	H	M	H
Hand Geometry	M	M	M	H	M	M	M
Keystroke Dynamics	L	L	L	M	L	M	M
Hand vein	M	M	M	M	M	M	H
Iris	H	H	H	M	H	L	H
Retina	H	H	M	L	H	L	H
Signature	L	L	L	H	L	H	L
Voice	M	L	L	M	L	H	L
Facial Thermogram	H	H	L	H	M	H	H
DNA	H	H	H	L	H	L	L

H=High, M=Medium, L=Low

Classical properties

From http://www.cs.bham.ac.uk/~mdr/teaching/module/security/lectures/biometric.html

Comparisons

Biometric Comparison Chart

Sr. No	Characteristics	Fingerprint	Iris	Face	Palm Print	Voice Recognition
1	Speed	Medium/Low	Medium	Medium	Medium	Medium
2	FTE Rate	Medium/Low	Low	Low	Low/Medium	Medium
3	Standards	High	Medium	High	High	Low
4	Uniqueness	High	High	Medium	High	Medium
5	Maturity	High	Medium	Medium	Medium	Low
6	Durability	High	High	Medium	High	Low
7	Invasiveness	High	Medium	Low	High	Low
8	Overtness	High	Medium	High	Low	Low
9	Range	Low	Low	Medium	Low	High
10	Template Size	Medium (250-1,000 bytes) (per finger)	Medium (688 bytes)	High (84-2,000 bytes)	Medium (250-1000 bytes)	High (1,500-3,000 bytes)
11	Age Range	High	High	High	High	Medium
12	Universality	High	Medium	High	High	High
13	Stability	High	High	Medium	High	Low
14	Skill	Medium	Medium	Low	High	Low
15	Accuracy	Medium-High	High	Medium	High	Low
16	Hygienic Level	Low	High	High	Low	High
17	Performance	High	High	Low	High	Low
18	Cost	Low	High	Low	High	Low

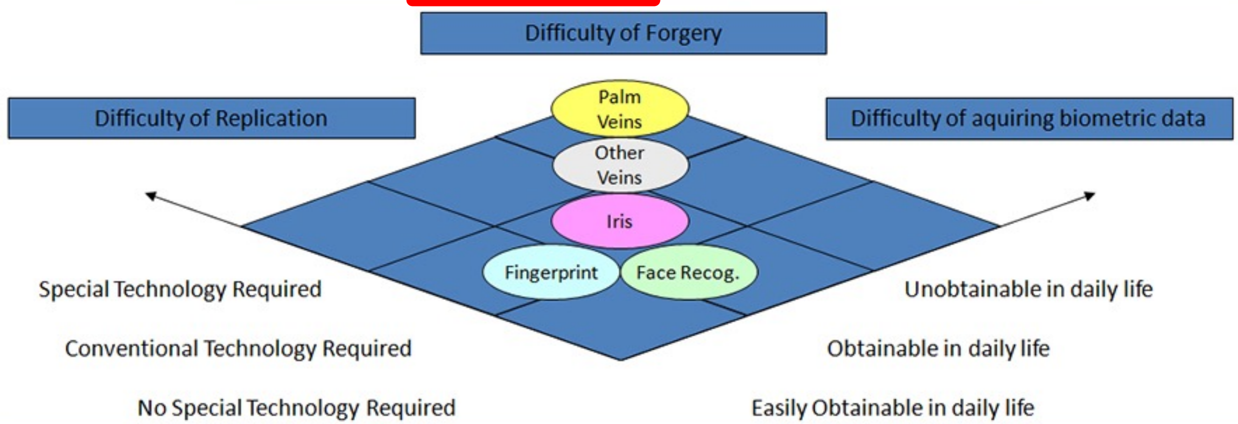
Further properties
Notice Hygienic level!

refers to possibility to acquire

From http://www.biometricsintegrated.com/biometric-types-comparison.html/biometric-comparison-chart

Comparisons

	Fingerprint	Face Recognition	Iris	Palm Veins	Other Veins
Hygienic	low	high	high	high	low
Applicability	medium	high	medium	high	medium
Security Level	medium	medium	high	high	high
Convenience Level	high	medium	low	high	medium
Accuracy	medium	low	medium	high	medium
Social acceptance	low	low	medium	high	medium
Costs	low	medium	high	medium	medium

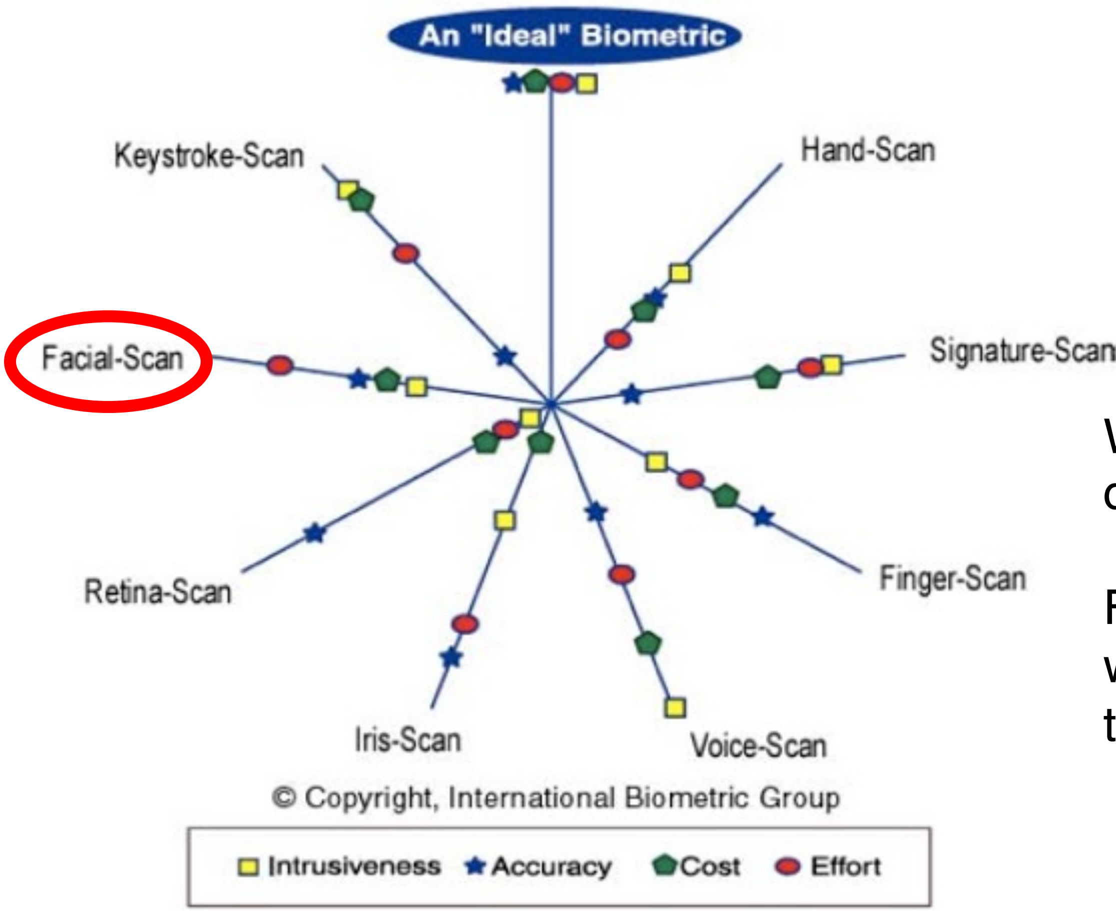


Palm Vein is the leading technology for security, convenience to be adopted to be a standard of the future

Interesting to notice the position of face which shares «good» properties with fingerprints

From http://www.ssbs.com/sasolutions/medical-solution/sproducts-client-secure.aspx

Comparisons

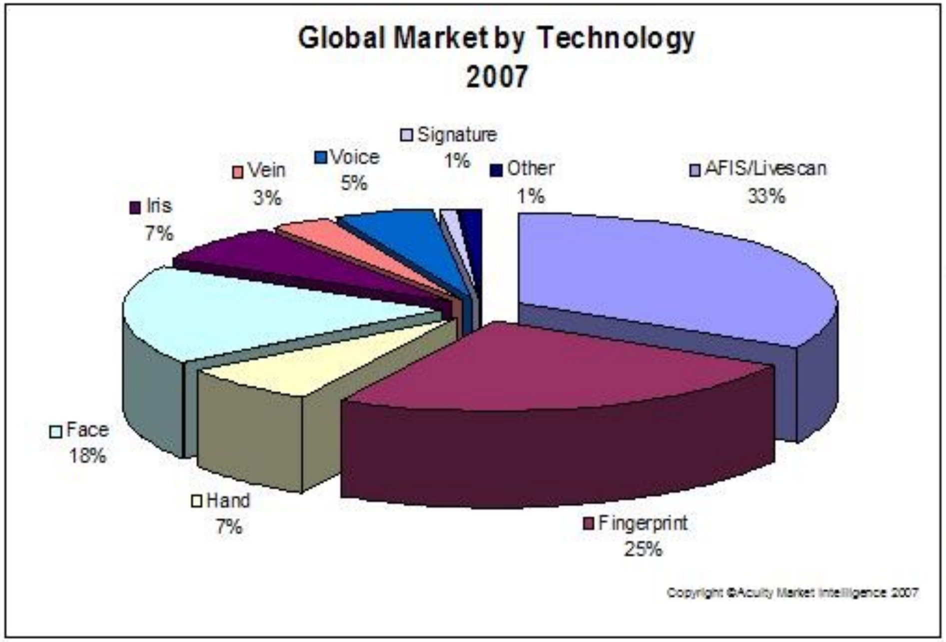


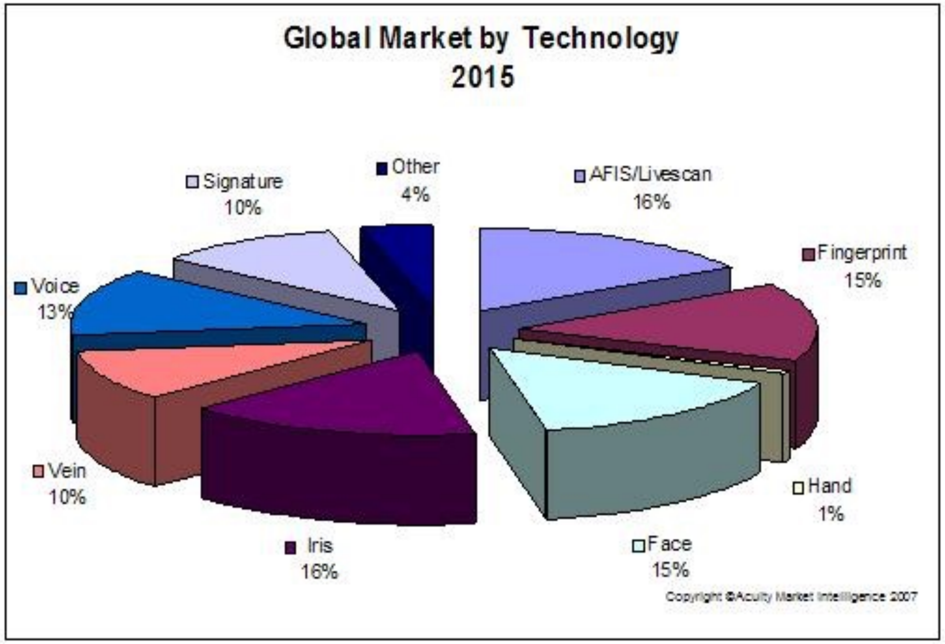
Source: Zephyr Analysis

Which is the most important dimensions?

Face is in acceptable position when compared with other traits

Market





By Acuity Market Intelligence
(can you guess what is their product?)

Applications

Forensics

iOS face recognition app – FaceVault

Border control

In a crowd!

Problems

Intra-personal variations.
Piero Fornasetti's template of Cavalieri's face gave birth to hundreds of variations.

http://www.artistdaily.com/blogs/artistdaily/archive/2013/04/22/350-ways-of-drawing-faces.aspx

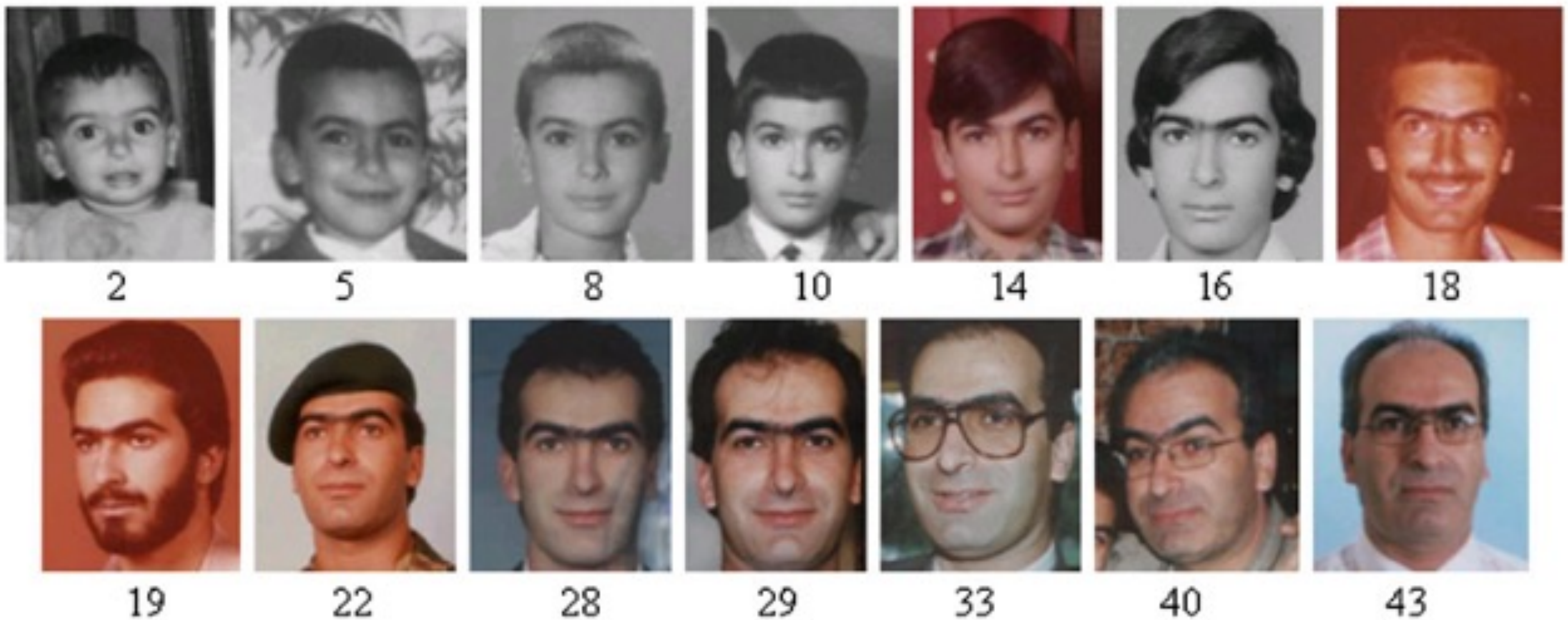
Inter-personal similarities.
Bradley Cooper & Hrithik Roshan

http://www.mensxp.com/entertainment/gossip/7356-have-we-met-before-bollywoodhollywood-lookalikes.html

In detail: PIE (Pose, Illumination, Expression) variations

http://www.csee.wvu.edu/~gidoretto/courses/2011-fall-cp/assignments/final_project/results/cao_chen/index.html

In detail: PIE (Pose, Illumination, Expression) variations + Ageing = A-PIE



(a) FG-NET

(b) MORPH

Popular databases

Very popular public face databases:

- AR-Faces
- FERET
- MIT
- ORL
- Harward
- MIT/CMU
- CMU test set II
- …

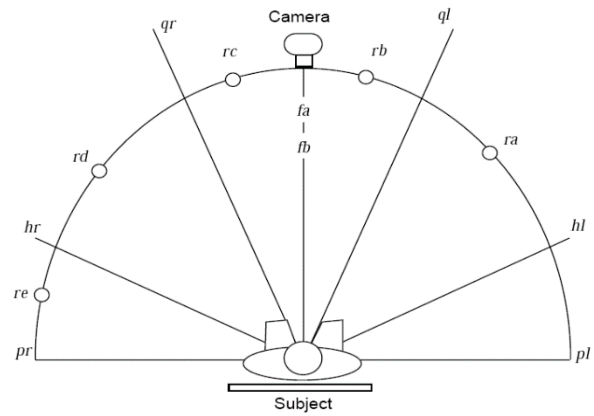
Controlled variations in PIE (difference with **uncontrolled** settings: we KNOW which is the distortion … memento Torralba!)

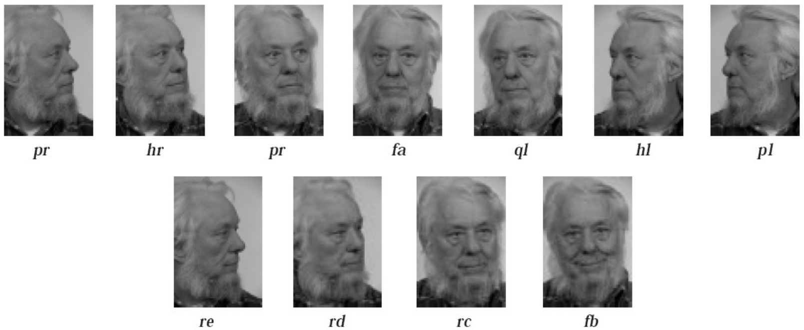
Popular databases

Name	RGB/Gray	Image Size	Number of people	Pictures / person	Number of conditions	Available	Web Address
AR Face Database*	RGB	576 × 768	126 70 Male 56 Female	26	i, e, o, t	yes	http://rvl1.ecn.purdue.edu/~aleix/aleix_face_DB.html
Richard's MIT database	RGB	480 × 640	154 82 Male 74 Female	6	p, o	yes	
CVL Database	RGB	640 × 480	114 108 Male 6 Female	7	p, e	yes	http://www.lrv.fri.uni-lj.si/facedb.html
The Yale Face Database B*	Gray Scale	640 × 480	10	576	p, i	yes	http://cvc.yale.edu/projects/yalefacesB/yalefacesB.html
The Yale Face Database*	Gray Scale	320 × 243	15 14 Male 1 Female	11	i, e	yes	http://cvc.yale.edu/projects/yalefaces/yalefaces.html
PIE Database*	RGB	640 × 486	68	~ 608	p, i, e	yes	http://www.ri.cmu.edu/projects/project_418.html
The UMIST Face Database	Gray	220 × 220	20	19 to 36	p	yes	http://images.ee.umist.ac.uk/danny/database.html
Olivetti Att - ORL*	Gray	92 × 112	40	10		yes	http://www.uk.research.att.com/facedatabase.html
(JAFFE) Database	Gray	256 × 256	10	7	e	yes	http://www.mis.atr.co.jp/~mlyons/jaffe.html
The Human Scan Database	Gray	384 × 286	23	~66		yes	http://www.humanscan.de/support/downloads/facedb.php
The University of Oulu Physics-Based Face Database	Gray	428 × 569	125	16	i	Cost $50	http://www.ee.oulu.fi/research/imag/color/pbfd.html
XM2VTSDB	RGB	576 × 720	295		p	Frontal $153 Side $229.5	http://www.ee.surrey.ac.uk/Research/VSSP/xm2vtsdb/
FERET*	Gray RGB	256 × 384	30.000		p, i, e, i/o, t	yes	http://www.itl.nist.gov/iad/humanid/feret/

Popular databases: FERET (1996)

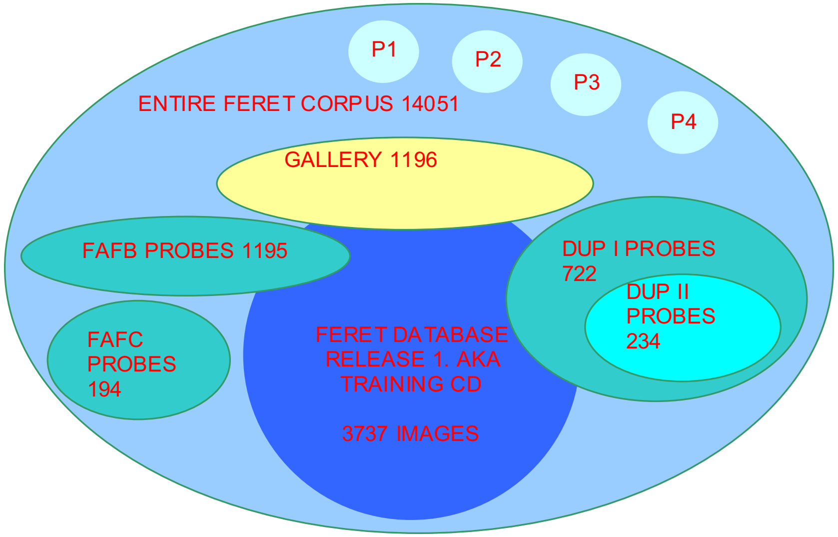
- The database contains:
  - Pose variations: the subject is captured under different orientations, each denoted by a pair of letters in the image name.
  - Illumination variations: variations are not available for all subjects and are not underlined in image names.
  - Time variations: subjects are captured at different times in different sessions.





Popular databases: FERET

- The database contains a total of 14051 images divided in different categories.
- The authors provide is a set of lists related to the names of the images for each category.
- A set of files contains the positions of eyes and mouth for each image.



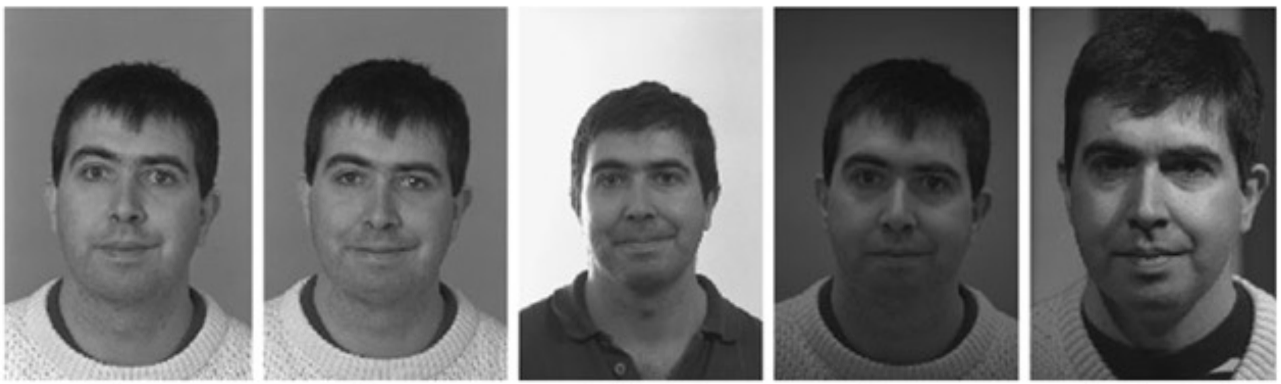
Popular databases: FERET

Two letter code	*Pose Angle (degrees)*	*Description*	*Number in Database*	*Number of Subjects*
Fa	0 = frontal	Regular facial expression	1762	1010
Fb	0	Alternative facial expression	1518	1009
ba	0	Frontal "b" series	200	200
bj	0	Alternative expression to ba	200	200
bk	0	Different illumination to ba	200	200
bb	+60	Subject faces to his left which is the photographer's right	200	200
bc	+40		200	200
bd	+25		200	200
be	+15		200	200
bf	-15	Subject faces to his right which is the photographer's left	200	200
bg	-25		200	200
Bh	-40		200	200
bi	-60		200	200
ql	-22.5	Quarter left and right	763	508
qr	+22.5		763	508
hl	-67.5	Half left and right	1246	904
hr	+67.5		1298	939
pl	-90	Profile left and right	1318	974
pr	+90		1342	980
Ra	+45	Random images. See note below. Positive angles indicate subject faces to photographer's right	322	264
Rb	+10		322	264
Rc	-10		613	429
Rd	-45		292	238
Re	-80		292	238

Notes:

1. fa indicates a regular frontal image
2. fb indicates an alternative frontal image, taken seconds after the corresponding fa
3. ba is a frontal images which is entirely analogous to the fa series
4. bj is an alternative frontal image, corresponding to a ba image, and analogous to the fb image
5. bk is also a frontal image corresponding to ba, but taken under different lighting
6. bb through bi is a series of images taken with the express intention of investigating pose angle effects (see below). Specfically, bf - bi are symmetric analogues of bb - be.
7. ra through re are "random" orientations. Their precise angle is unknown. It appears that the pose angles are random but consistent. The pose angles in the table were derived by manual measurement of inter-eye distances in the image, and in their corresponding frontal image.

Popular databases: FERET

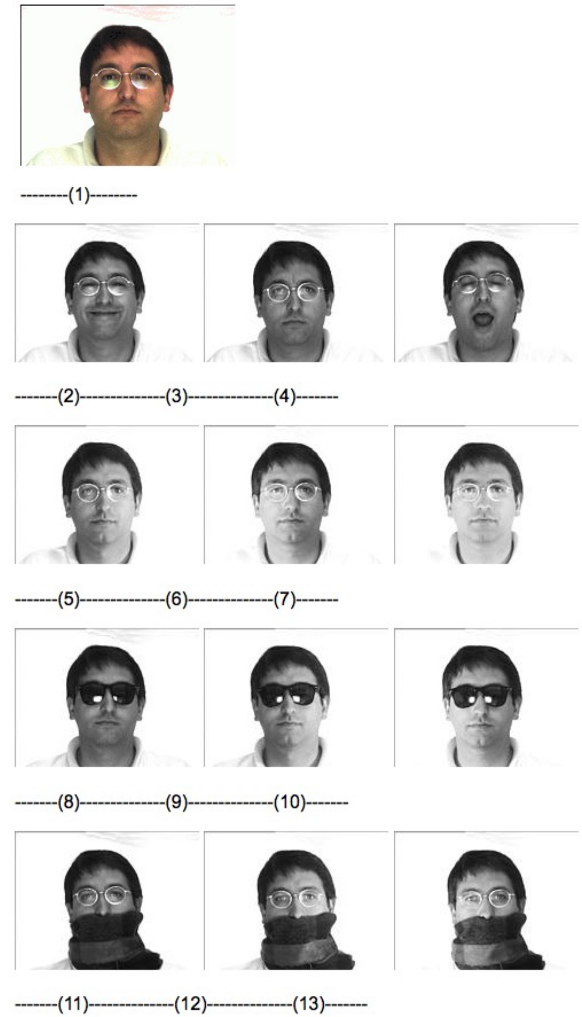


fa fb duplicate I fc duplicate II

Images from the FERET dataset. The fa and fb were taken with the same lighting condition with different expressions. The fc image has a different lighting condition than the fa and fb images. The duplicate I image was taken within one year of the fa image and the duplicate II and fa image were taken at least one year apart

Popular databases: AR-Faces (1998)

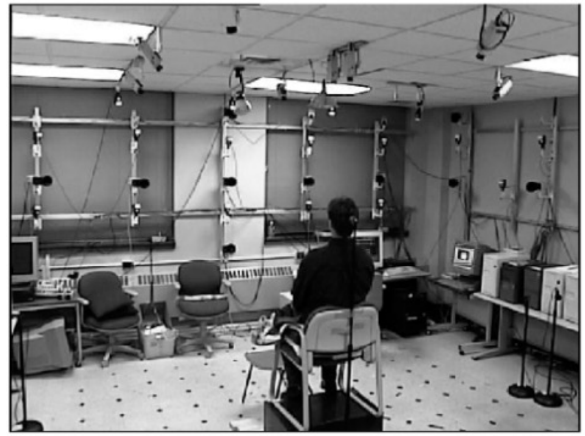
1 : Neutral expression
2 : Smile
3 : Anger
4 : Scream
5 : left light on
6 : right light on
7 : all side lights on
8 : wearing sun glasses
9 : wearing sun glasses and left light on
10 : wearing sun glasses and right light on
11 : wearing scarf
12 : wearing scarf and left light on
13 : wearing scarf and right light on
14 to 26 : second session (same as 1 to 13)

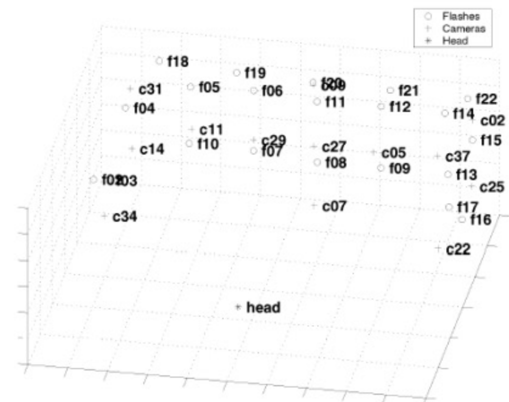


126 people (over 4,000 color images).
Different facial expressions, illumination conditions and occlusions.
Two sessions per person (2 different days).

Popular databases : CMU-PIE (2000)

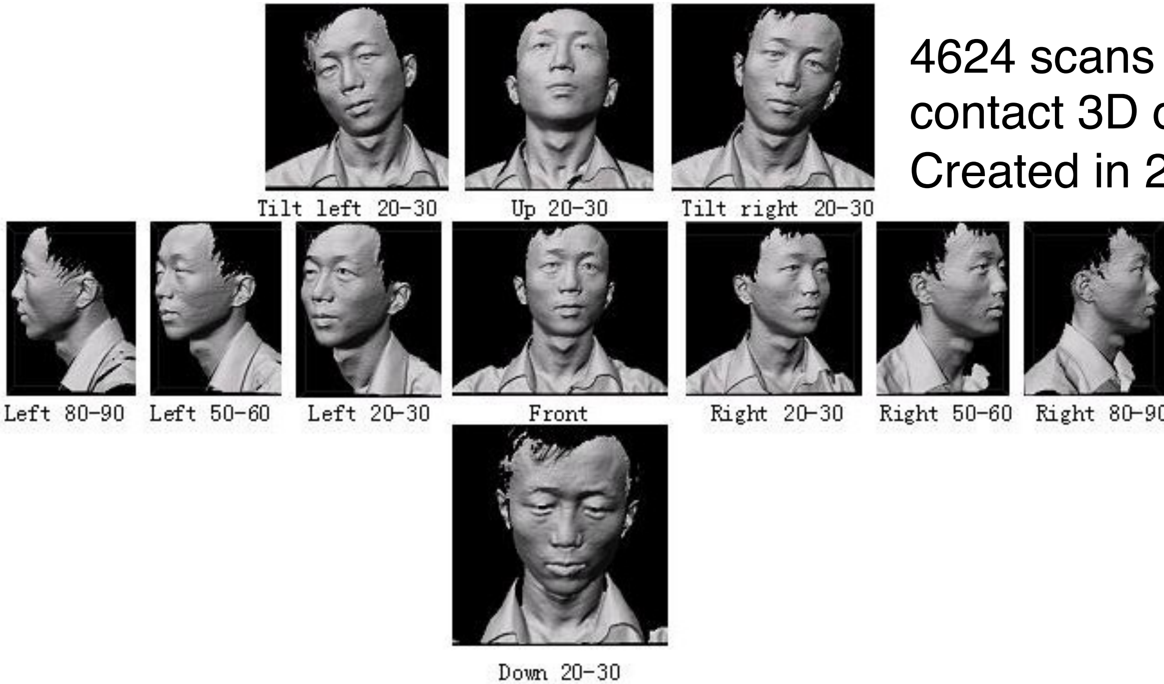
- CMU Pose, Illumination, and Expression (PIE) database.
- 68 subjects
- About 608 color pictures per subject (resolution 640×486 pixels) =41,368 images
- Each person is imaged under 13 different poses, 43 different illumination conditions, and with 4 different expressions.

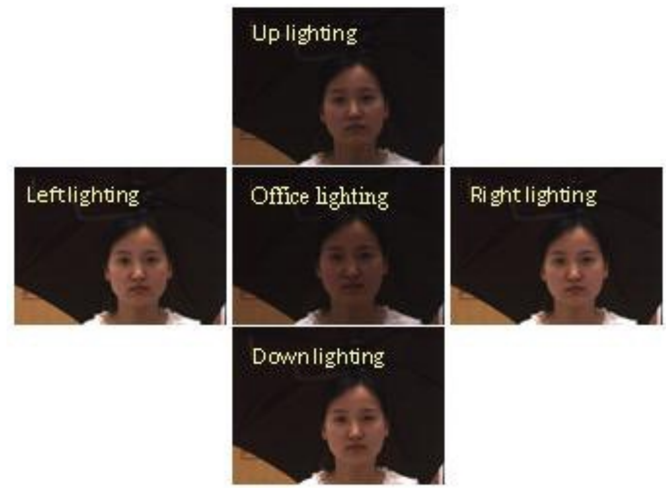




Popular databases: CASIA 3D Face V1 (2004)

4624 scans of 123 persons using the non-contact 3D digitizer, Minolta Vivid 910
Created in 2004

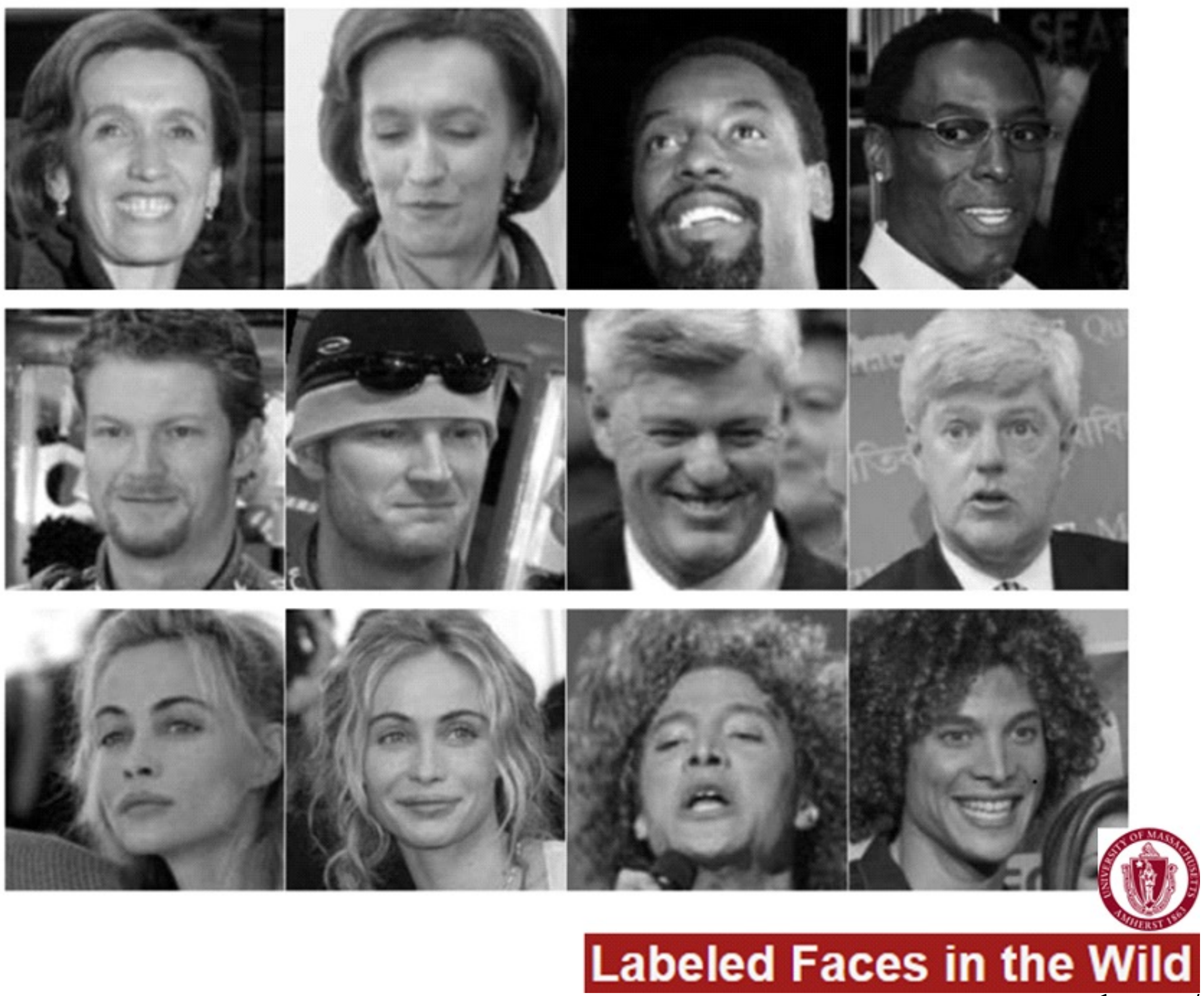




http://biometrics.idealtest.org/dbDetailForUser.do?id=8

Popular databases: LFW (Labeled Faces in the Wild)(2007)

Face images taken under *Unconstrained Conditions*



The data set contains more than 13,000 images of faces collected from the web. Each face has been labeled with the name of the person pictured. 1680 of the people pictured have two or more distinct photos in the data set. The only constraint on these faces is that they were detected by the Viola-Jones face detector.

http://vis-www.cs.umass.edu/lfw/

Popular databases: YouTube faces (2011)

The data set contains **3,425** videos of **1,595** different people. All the videos were downloaded from YouTube. An average of 2.15 videos are available for each subject. The shortest clip duration is 48 frames, the longest clip is 6,070 frames, and the average length of a video clip is 181.3 frames.
The creation started by using the 5,749 names of subjects included in the LFW data set to search YouTube for videos of these same individuals. The top six results for each query were downloaded.

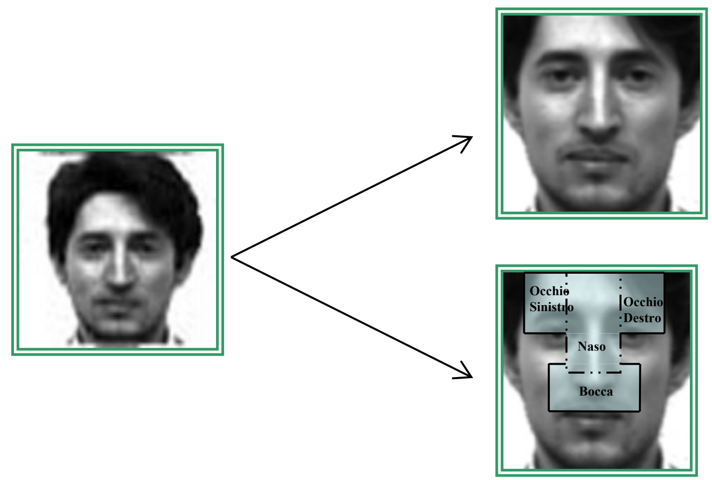
Number of videos per person:

#videos	1	2	3	4	5	6
#people	591	471	307	167	51	8

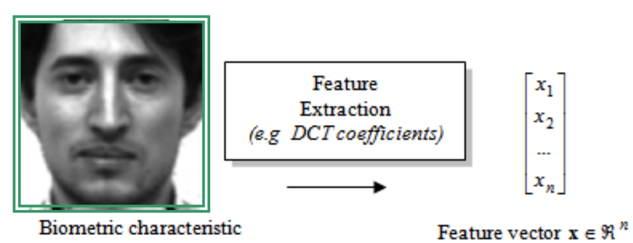
Structure of a face recognizer

- The first steps of an automatic recognition system are face capture and possible image enhancement.

- Further steps are localization -possible cropping of one or more regions of interest (ROIs) containing the whole face or its components (eyes, nose, mouth) - normalization.

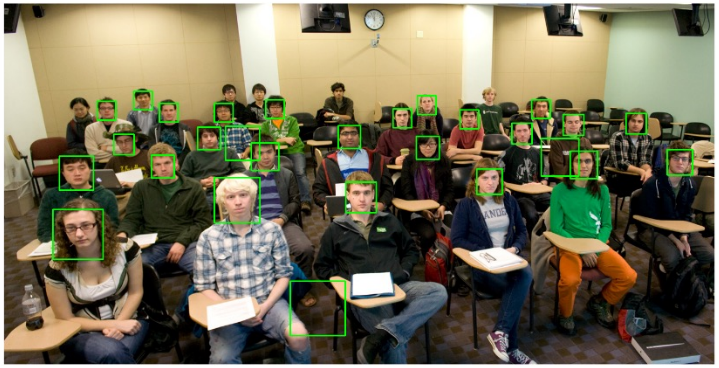


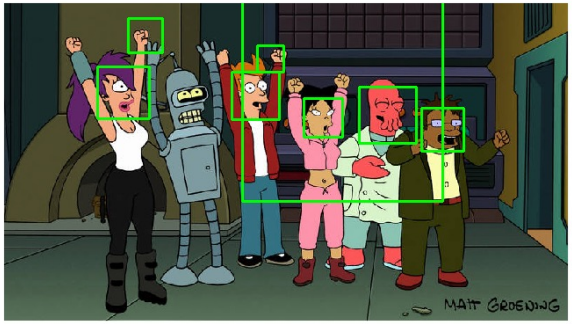
- Finally, we have feature extraction and template construction (biometric key).



Face localization

- **Problem**: given a single image or a video sequence, detect the presence of one or more faces and locate their position within the single image.
- **Requirements**: it is necessary to be independent with respect to position, orientation (pose), scale, expression, possibly DIFFERENT for different subjects in the image, as well as to illumination or cluttered background.



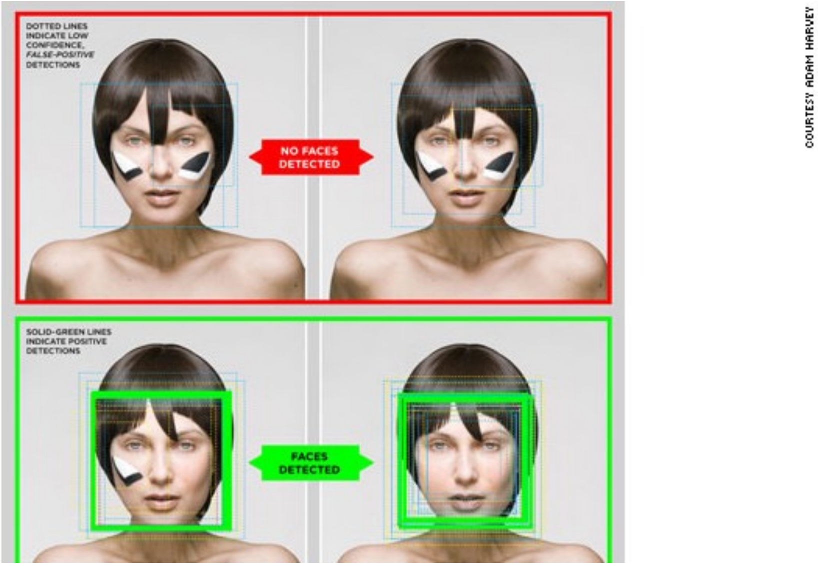


What to do here???

Face localization … possible to hide from it?

- “According to Adam Harvey, the key part of the face that computers can read is the "nose bridge," or the area between the eyes. If you can obscure that, you have a good chance of tricking computers into thinking you don't have a face, he said. Another technique is to create an "anit-face," which is less terrifying than it sounds since it just means inverting your face's color scheme. So the black-and-white triangles on the cheeks aim to achieve this effect.” (from CNN - http://whatsnext.blogs.cnn.com/2012/04/29/how-to-hide-from-face-detection-technology/)

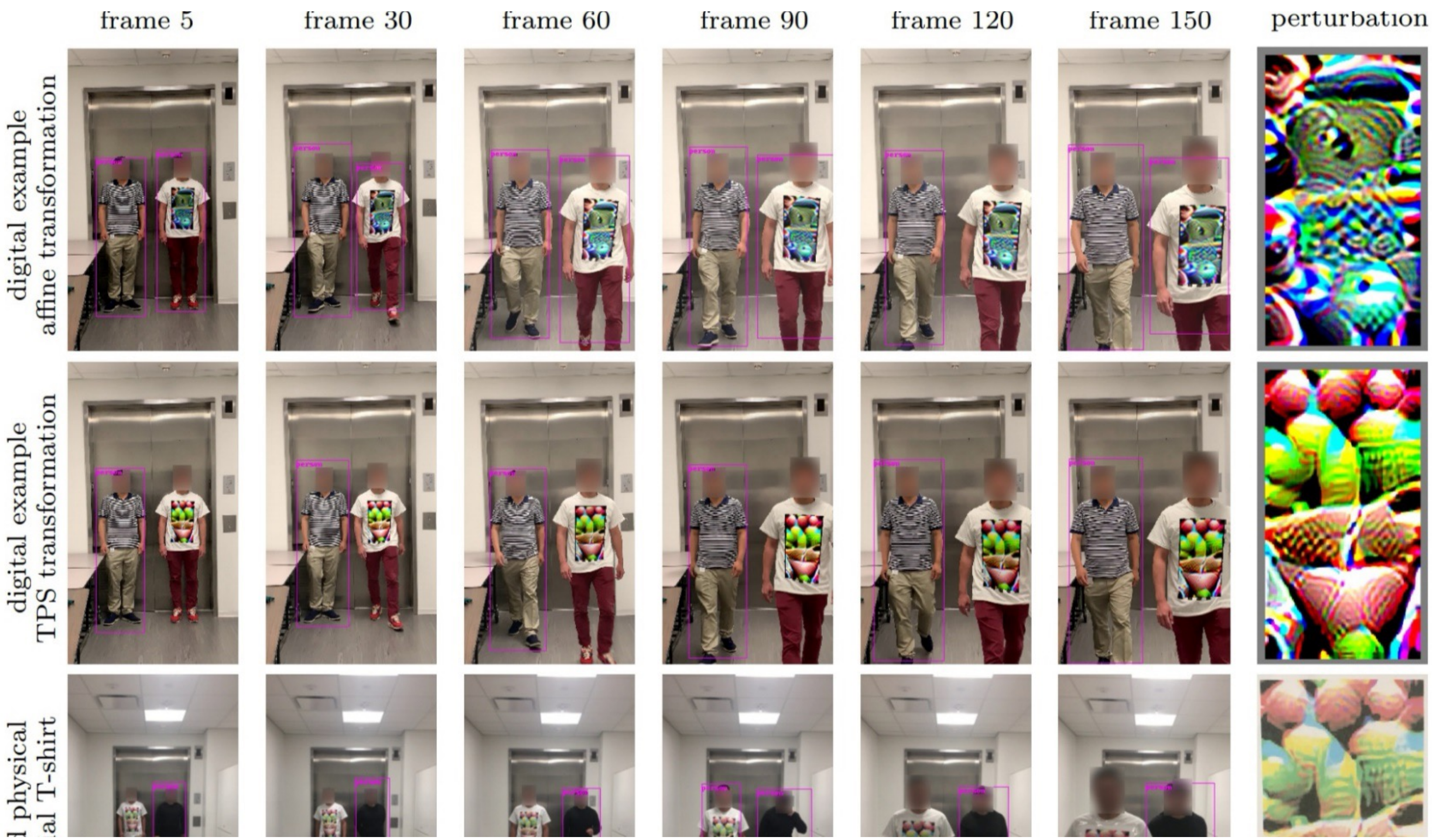
Adam Harvey proposes CV Dazzle (Computer vision Dazzle) to avoid one’s face detection (http://ahprojects.com/projects/)



Not that difficult after all!

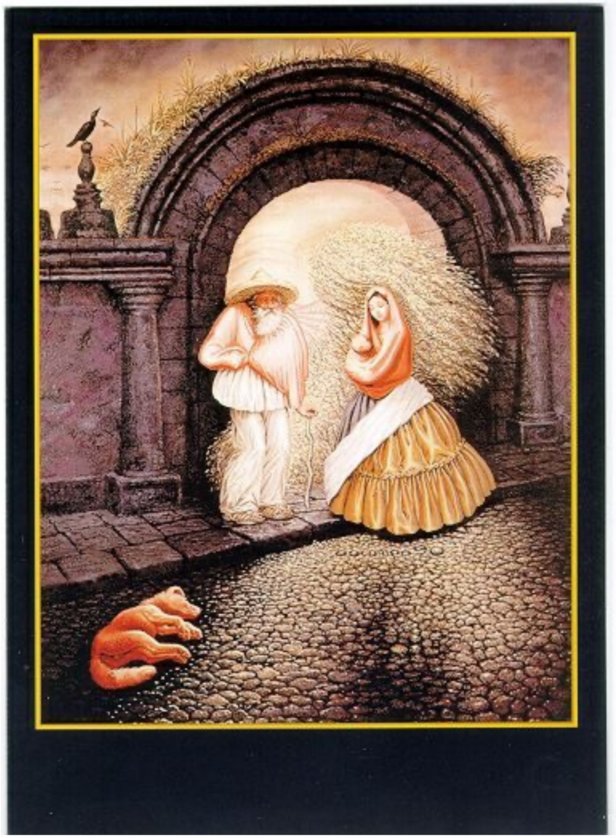
Face localization … possible to hide from it?

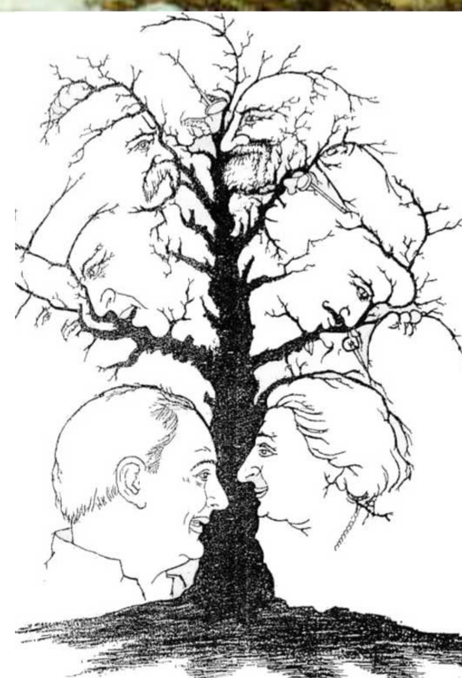
A team of researchers from Northeastern University, IBM, and MIT developed a T-shirt design that hides the wearer from image recognition systems by confusing the algorithms trying to spot people into thinking they're invisible.



From https://www.wired.it/attualita/tech/2019/11/19/t-shirt-rende-invisibile-riconoscimento-facciale/?refresh_ce=

Face localization … how many faces?

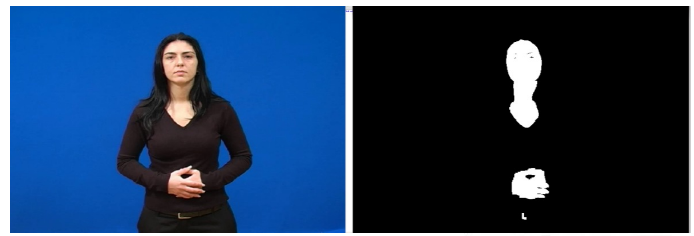




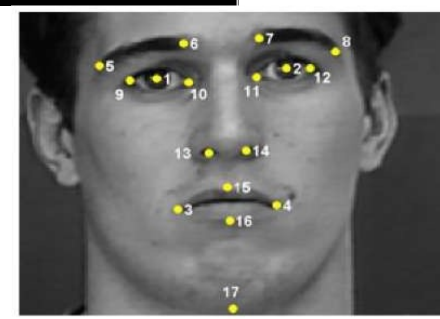
Face localization: some approaches

Feature-based techniques

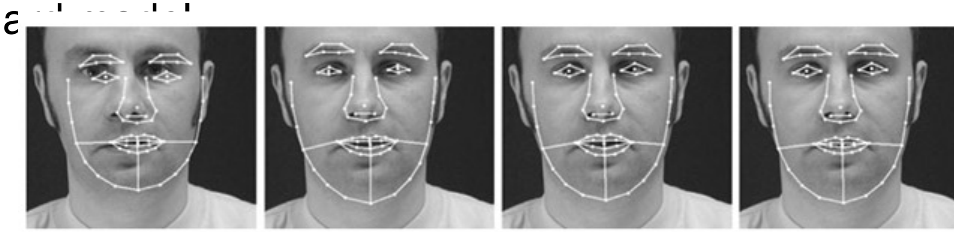
These techniques make explicit use of the knowledge about the expected face appearance, which is characterized by a set of features at different levels (below, they are from lower to higher)



- Pixel properties:
  - Edges
  - Skin color



- Face geometry properties:
  - Constellation
  - Feature searching
- Template matching against a standard model
  - Correlation
  - Snakes
  - Active Shape Models



Initial After 5 it.s 10 it.s Converged (18 it.s)

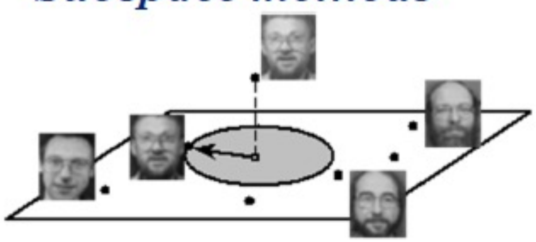
Face localization: some approaches

Image-based techniques

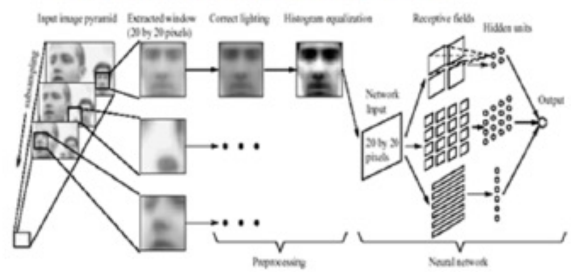
These techniques address the localization problem as a generic pattern recognition problem (class of faces).

The goal is to learn to recognize a face image according to a number of examples.

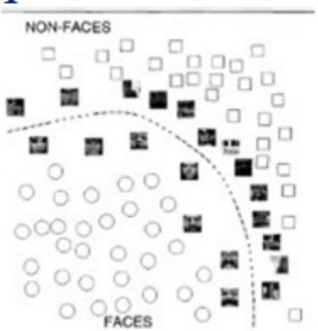
Subspace methods



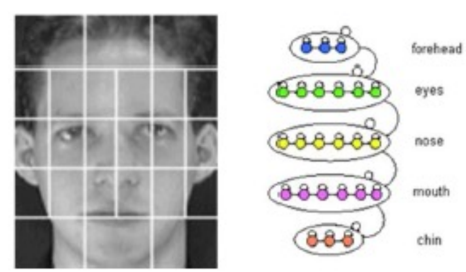
Neural networks



Support Vector Machine



Hidden Markov Model



Face localization: recent advances

Localizing Parts of Faces Using a Consensus of Exemplars
from: http://neerajkumar.org/projects/face-parts/

Some references

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