

## Face Recognition: Motivation

Overview:

1. Why faces?
2. Applications for Face Analysis Technology?
3. Faces and Human Perception.

## Why Faces?

2

Technology Perspective:

- General challenge for Computer Vision
  - Faces are highly variable.
  - Geometry and appearance not too complicated, however, already difficult to describe with simple geometric basics or functions.
- Many possible commercial applications.

Human Perspective:

- Face analysis is very easy for humans! -- Can't be difficult!?
- Understanding the human visual system, might help to understand the human brain.

## Research Areas with a Focus on Faces.<sup>3</sup>

### Technology / Applications:

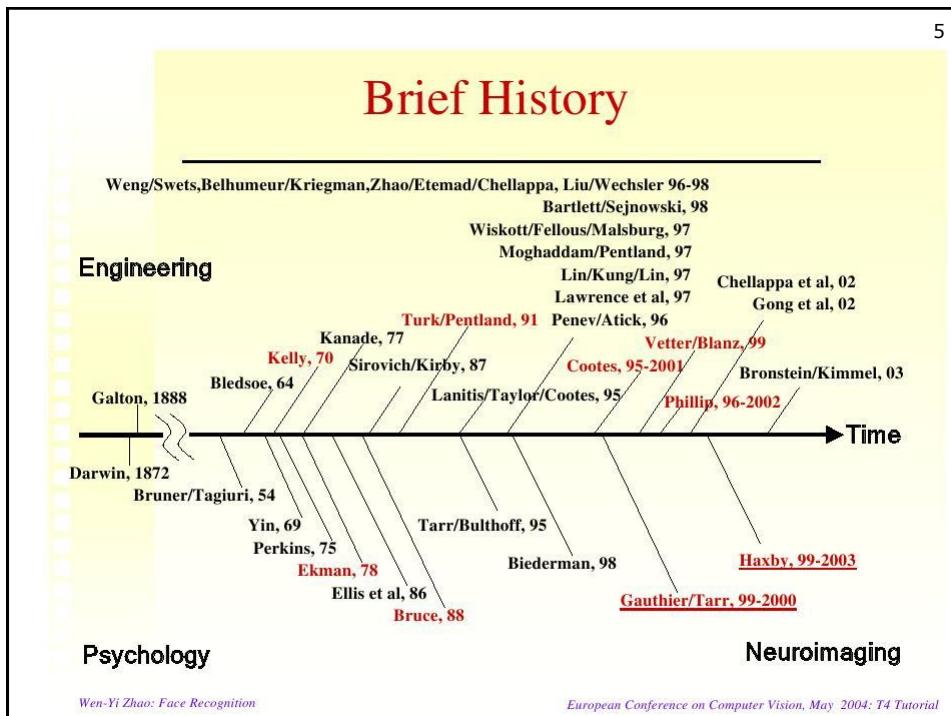
- Computer Graphics
  - Synthetic Actor, Virtual Makeup, ....
- Computer Vision
  - Biometry: Face Recognition, Face Verification,
  - Man-Machine Interface: Emotion recognition, gaze analysis, attention control, ...
- Video coding
  - MPEG-4 standard for face and emotion coding

## Research Areas II

4

### Life Sciences:

- Medicine
  - Formal description of faces / head shape variability (anthropology),
  - Surgery planning, ....
- Biology
  - Large areas of the human brain react to faces.  
Are faces special?
  - Faces are a classical stimuli for the investigation of the development of the visual system of infants.
- Psychology
  - How do humans memorize faces?
  - Do we judge personal attributes from face images?



## Face Recognition Applications

Entertainment:	Video Game / Virtual Reality / Training Programs Human-Computer-Interaction / Human-Robotics Family Photo Album / Virtual Makeup
Smart Cards:	Drivers' Licenses / Passports / Voter Registrations / Entitlement Programs / Welfare Fraud /
Information Security :	TV Parental control / Desktop Logon / Personal Device (Cell phone etc) Logon / Medical Records / Internet Access
Law Enforcement & Surveillance:	Advanced Video Surveillance / CCTV Control Shoplifting / Drug Trafficking / Portal Control

## The Face as Biometric Feature

7

Face recognition from different modalities:

- from single image.
- from two or more image, from video.
- from 3D data ( laser or structured light technology).

Face recognition covers different tasks:

- Face verification
- Face identification
- Expression and emotion recognition
- Age analysis
- Lip reading
- ....

## Face Verification versus Identification

8

### Face Verification

Is this the person,  
the person claims to be?



e.g. the '**SmartGate**' installation at Sydney's airport for crew members utilizes software from **Cognitec**. The system compares the face with stored images of the person matching the identity as claimed in the passport (passport picture not used).

### Face Identification

Who is this person?



An Example:  
Prof. Dr. Antonio Loprieno,  
Former rector of the  
University of Basel.  
The picture was taken a few  
years ago.

Face identification is the more difficult task! Current commercial systems are mostly limited to the verification task.

# The machine readable biometric Passport

Germany : mandatory

Switzerland: voluntary!?

In a machine readable part at minimum the following information is stored:

- name, family name,
- country, passport number
- gender, date of birth
- date of expiration

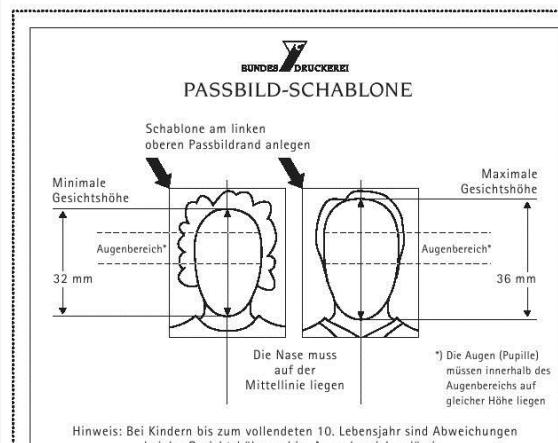
In the RFID-Chip additional biometric information is stored:

- passport photograph
- two fingerprints ( Germany since 2007 )

## How to generate a valid passport photo I

10

### SCHABLONE ZUR PRÜFUNG DER BIOMETRIETAUGLICHKEIT VON PASSBILDERN



From: "Deutsche Bundesdruckerei"

### CHECKLISTE ZUR BILDBEURTEILUNG

Bitte prüfen Sie das Passbild anhand der Fotomustertafel und der folgenden Kriterien:

- **FORMAT**  
1. Bildgröße 35 x 45 mm?  
2. Gesichtshöhe 32 - 36 mm vom Kinn bis zum Haarsatz?
- **KOPFPOSITION UND GESICHTSAUSDRAHK**  
3. Kopfhaltung gerade (nicht geneigt, gedreht oder gekippt)?  
4. Nase etwa auf der gekennzeichneten Mittellinie?  
5. Frontalaufnahme?  
6. Gesichtsausdruck neutral?  
7. Lippen geschlossen?
- **AUGEN UND BLICKRICHTUNG**  
8. Augen innerhalb des markierten Bereichs auf gleicher Höhe?  
9. Augen offen und deutlich sichtbar?
- **SCHÄRFE UND KONTRAST**  
10. Foto scharf und kontrastreich?
- **AUSLEUCHTUNG**  
11. Ausleuchtung gleichmäßig (keine Schatten)?
- **HINTERGRUND**  
12. Hintergrund einfarbig?
- **FOTOQUALITÄT**  
13. Natürliche Hauttöne?  
14. Keine Knicke und Verunreinigungen?
- **BRILLENTRÄGER**  
15. Augen erkennbar und nicht verdeckt?

BITTE BEACHTEN SIE:  
Nur wenn alle Fragen mit "JA" beantwortet wurden,  
ist das Bild biometrietauglich.

HINWEIS:  
Bei Säuglingen und Kleinkindern sind bei 3./4./6./7./8./9.  
aus altersbedingten Gründen Abweichungen zulässig.

## How to generate a valid passport photo II

11



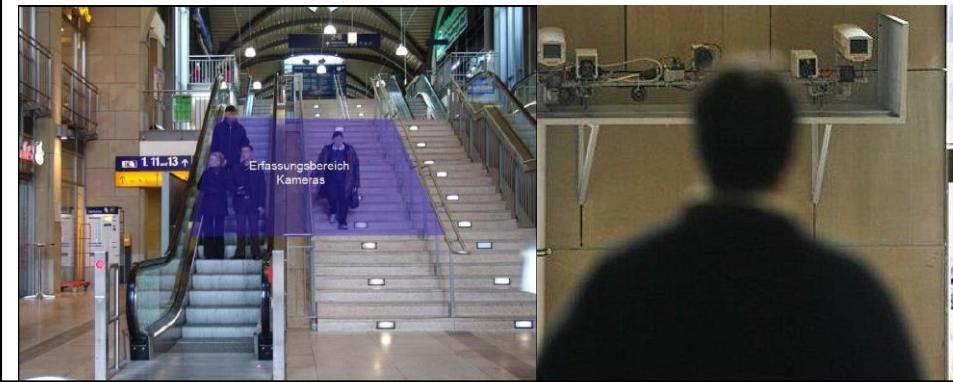
## Face Recognition at the Train Station in Mainz

12

At the main train station in Mainz the German Bundes Kriminalamt tested several commercial face recognition systems for their practicability (2006).

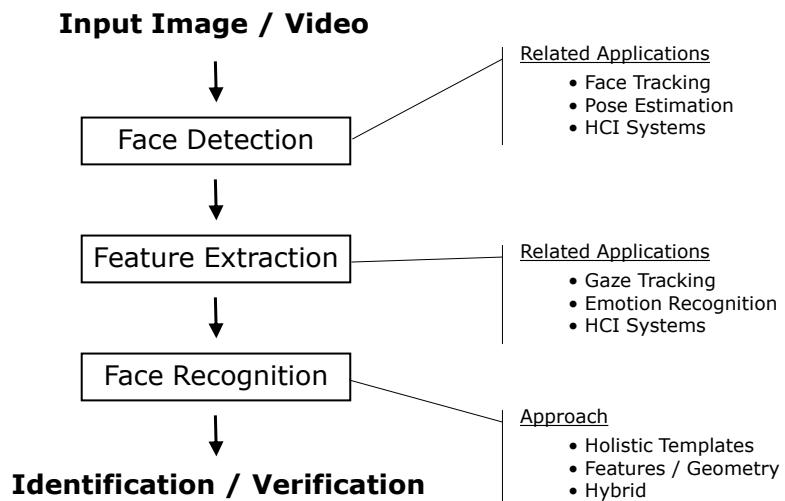
200 people equipped with an RIFD chip pass every day together with 20000 other persons the setup.

Controversial results!



## Basic Face Recognition System

13



## Face Recognition Systems: Performance

14

Since the mid 90th there are several companies on the market and sell face recognition systems.

Is face recognition solved?

How to evaluate recognition systems?

There is no general standardized test, however, a series of tests have been performed in the past.

1. FRVT Face Recognition Vendor Tests: NIST & DARPA

<http://www.frvt.org>

2. M2VTS, XM2VTS, BANCA: EU-sponsored research projects

<http://www.ee.surrey.ac.uk/Research/VSSP/xm2vtsdb>

<http://banca.ee.surrey.ac.uk>.

3. Colorado State University Web Site: DARPA

<http://www.cs.colostate.edu/evalfacerec/>



organized by Dr. Jonathon Phillips  
NIST (& DARPA)  
<http://www.frvt.org>

" Face Recognition Vendor Tests (FRVT) provide independent government evaluations of commercially available and prototype face recognition technologies. These evaluations are designed to provide U.S. Government and law enforcement agencies with information to assist them in determining where and how facial recognition technology can best be deployed. In addition, FRVT results help identify future research directions for the face recognition community."

The evaluation is open to mature prototypes or commercial systems from academia and industry.

## FRVT History

Since 1993 a series of test have been performed funded though various US government agencies ( NIST, DARPA, DoD).

1993 – 1996 FERET  
2002 FRVT  
2003 - 2006 Face Recognition Grand Challenge  
2006 FRVT

### GOAL:

- Assess performance on large scale data sets
- Identify new promising approaches
- Measure improvements on difficult tasks:
  - Pose and illumination variation
  - Moths / years between images
  - Video sequences

## FRVT 2002 : Test design

17

### A) High Computational Intense test

- 121589 still images
- 37437 individuals



### B) Medium Computational Intense test

- 7500 images
- Pose variations
- Illumination Variations
- Months / years between images



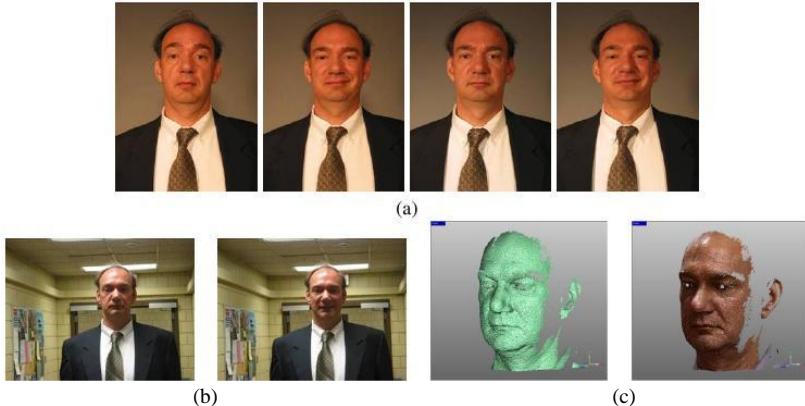
## FRVT 2002: Conclusions

18

- Indoor performance improved since 2000.
- Performance decreases approximately linearly with elapsed time.
- Better systems are not sensitive to indoor lighting changes.
- Males are easier to recognize than females.
- Older people are easier to recognize than younger people.
- Pose variations are still major problems. (3D morphable models could help to compensate pose changes.)
- Outdoor face recognition performance needs improvement.

## Face Recognition Grand Challenge

19



Exp 1: Controlled indoor still versus indoor still (a)

Exp 2: Indoor multi-still versus indoor multi-still (a)

Exp 3: Controlled indoor still versus uncontrolled (b)

Exp 4: still 3D versus 3D (c)

evaluation → [www.frvt.org](http://www.frvt.org)

## Internet Resources

20

### Face Recognition Home Pages

- <http://www.face-rec.org>
- <http://www.facedetection.com>

### Face Databases

- UT Dallas [www.utdallas.edu/dept/bbs/FACULTY\\_PAGES/otoole/database.htm](http://www.utdallas.edu/dept/bbs/FACULTY_PAGES/otoole/database.htm)
- Notre Dame database [www.nd.edu/~cvrl/HID-data.html](http://www.nd.edu/~cvrl/HID-data.html)
- MIT database [ftp://whitechapel.media.mit.edu/pub/images](http://whitechapel.media.mit.edu/pub/images)
- Edelman [ftp://ftp.wisdom.weizmann.ac.il/pub/FaceBase](http://ftp.wisdom.weizmann.ac.il/pub/FaceBase)
- CMU PIE [www.ri.cmu.edu/projects/project\\_418.htm](http://www.ri.cmu.edu/projects/project_418.htm)
- Stirling database [pics.psych.stir.ac.uk](http://pics.psych.stir.ac.uk)
- M2VTS multimodal [www.tele.ucl.ac.be/M2VTS](http://www.tele.ucl.ac.be/M2VTS)
- Yale database [cvc.yale.edu/projects/yalefaces/yalefaces.htm](http://cvc.yale.edu/projects/yalefaces/yalefaces.htm)
- Yale databaseB [cvc.yale.edu/projects/yalefacesB/yalefacesB.htm](http://cvc.yale.edu/projects/yalefacesB/yalefacesB.htm)
- Harvard database [hrl.harvard.edu/pub/faces](http://hrl.harvard.edu/pub/faces)
- Weizmann database [www.wisdom.weizmann.ac.il/~yael](http://www.wisdom.weizmann.ac.il/~yael)
- UMIST database [images.ee.umist.ac.uk/danny/database.html](http://images.ee.umist.ac.uk/danny/database.html)
- Purdue [rvl1.ecn.purdue.edu/~aleix/aleix\\_face\\_DB.html](http://rvl1.ecn.purdue.edu/~aleix/aleix_face_DB.html)
- Olivetti database [www.cam-orl.co.uk/facedatabase.html](http://www.cam-orl.co.uk/facedatabase.html)
- .....

What makes face recognition so difficult?

<sup>21</sup>



What makes face recognition so difficult?

<sup>22</sup>

Face images of a single person can vary in:

- pose
- illumination
- age
- facial expression
- make up
- perspective

already much easier ..

23



complex changes in appearance  
(pose and illumination only)



CMU-PIE database.

## Face Identification by Image Comparison

24

... done by pixel analysis



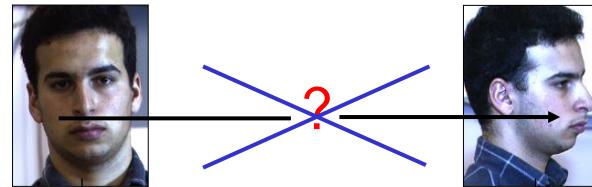
?



But which pixel to compare with which ?

Shape information tells us which pixel to compare

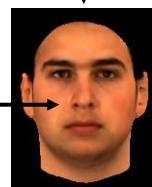
## Normalizing for pose, illumination and ...<sup>25</sup>



Shape recovery  
Illumination inversion



Shape recovery  
Illumination inversion



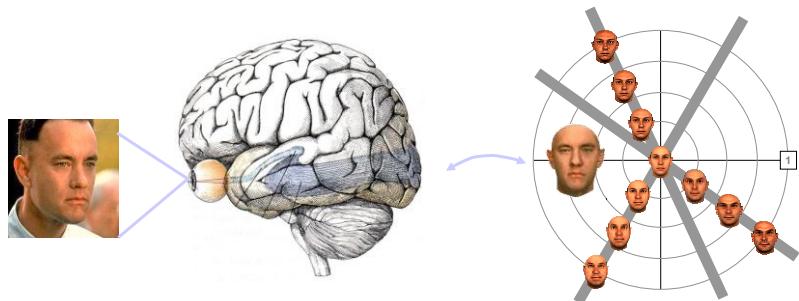
How can we do this ?

That is the topic of the remaining lectures!

## Human Face Perception: What do we know – What can we learn?

Comment: This section on “human face perception” does not try to be comprehensive, it’s a simple attempt to convey a first impression on the research done in this field.

## Human Face Perception: What do we know – What can we learn?

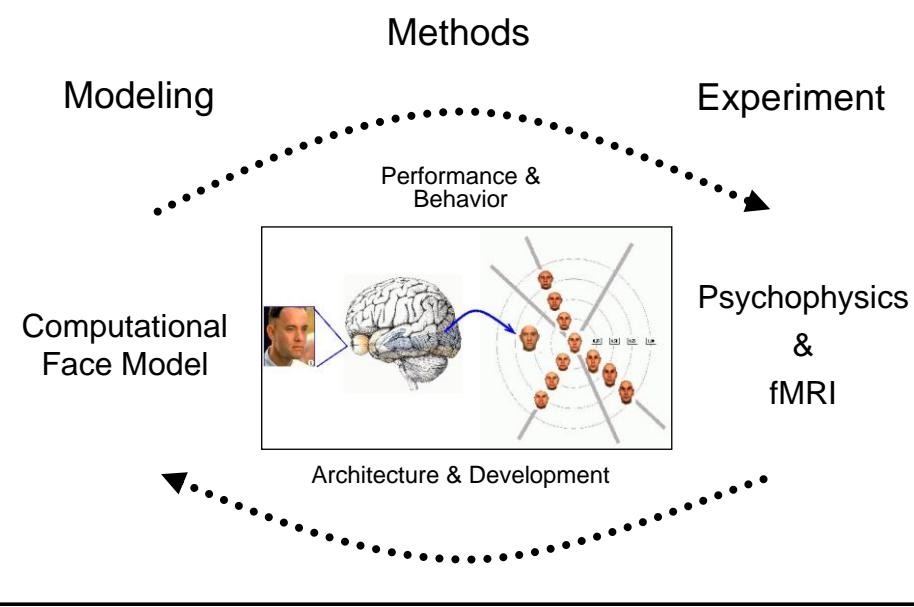


**Idea:** First, investigate how the human brain solves the face recognition task and second, transform this findings in computer algorithms!

If that is not directly possible, do it iteratively.

- 1.) Implement some first ideas
- 2.) Compare with human performance and behavior
- 3.) Implement better algorithms
- .... and so on

## Investigation of Higher Cognitive Functions!<sup>29</sup>



# Human Face Perception:

30

## An example of an experiment:

### **Prototype-referenced shape encoding revealed by high-level aftereffects.**

David Leopold, Alice J. O'Toole, Thomas Vetter, & Volker Blanz  
*Nature Neuroscience* vol.4 no.1 (2001) 89-94.

A " Facespace " was created using a morphing tool!

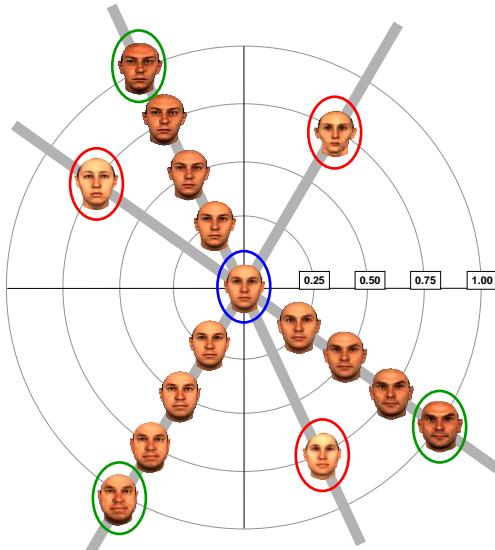
From a set of example faces the average face was computed.

Then the morphing tool was used to generate "morphs" between the original and the average and also extrapolations beyond the average. This extrapolations we call "anti-faces".

## The experiment: Stimuli

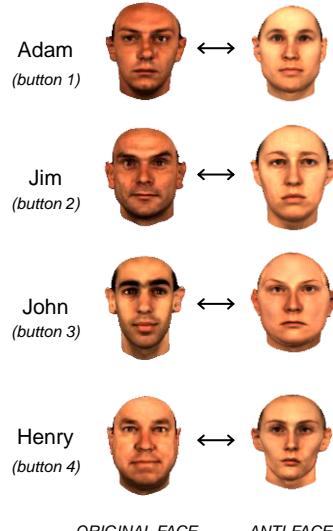
31

Face Space



## The experiment!

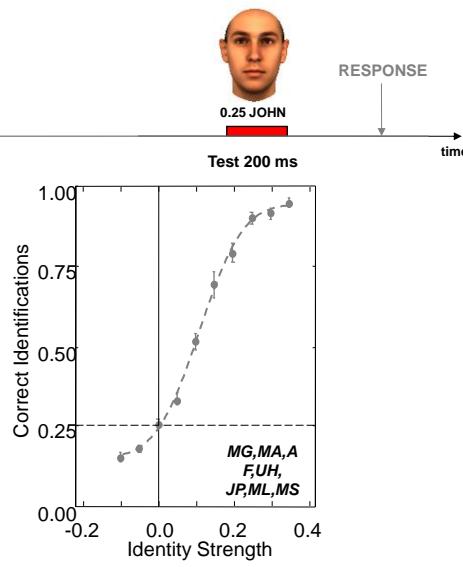
32



ORIGINAL FACE      ANTI-FACE

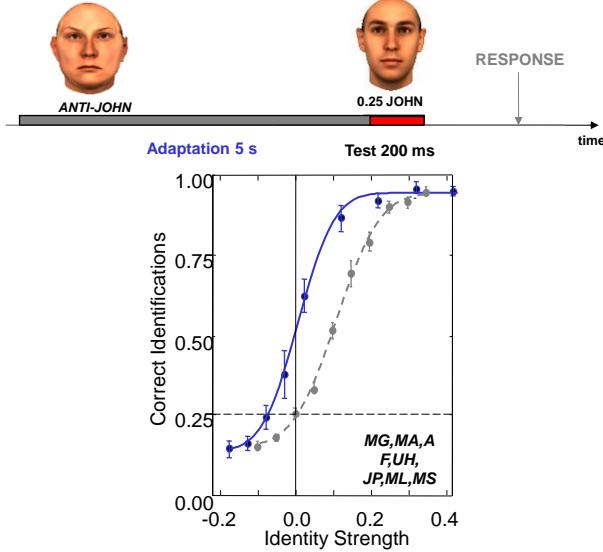
## Experiment: A 'Naming Task', one out of four!

33



## Experiment: A 'Naming Task', one out of four!

34

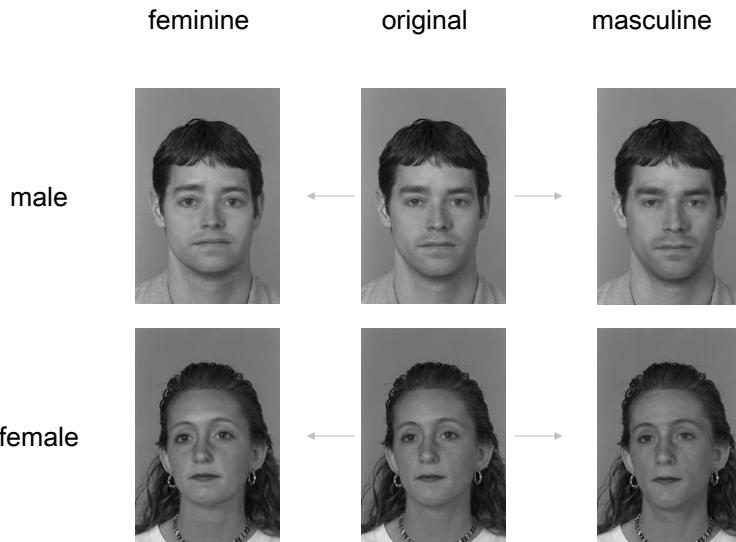


## The experiment: Conclusions

35

- Average face is special.
- The human brain is adaptive within seconds.
- “Morphs” between the average and an individual code for the same identity.
- Aftereffect not only in topographic visual areas.
- .....

## Facial Attributes I: Gender



## Experiment I: Hypotheses

Not only the gender but also the facial features of a person affect gender-stereotypic attributions.

H1 - Subjects rate the leadership aptitude of ...

- a man higher than of a woman.
- a masculine person higher than of a feminine person.

H2 - Subjects rate the social competence of...

- a woman higher than of a man.
- a feminine person higher than of a masculine person.

## Experiment I: Results

	feminine	masculine	Mean SC	Mean LA
male			4.66	4.48*
female			4.7	4.09*
Mean SC	4.77*	4.58*		
Mean LA	4.25	4.32		

## Some other findings and experiments

Examples from:

**Face Recognition by Humans: Nineteen Results Researchers Should Know About.**  
 Pawan Sinha et al., *Proceedings of the IEEE* Vol. 94, No. 11, November 2006



Example 1:

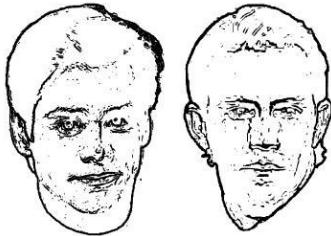


Fig. 1. Unlike current machine-based systems, human observers are able to handle significant degradations in face images. For instance, subjects are able to recognize more than half of all familiar faces shown to them at the resolution depicted here. Individuals shown in order are: Michael Jordan, Woody Allen, Goldie Hawn, Bill Clinton, Tom Hanks, Saddam Hussein, Elvis Presley, Jay Leno, Dustin Hoffman, Prince Charles, Cher, and Richard Nixon.

## some other findings .....

41

Example 2:



Example 3:

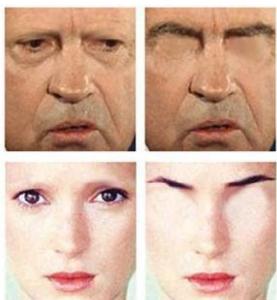


Fig. 3. Images which contain exclusively contour information are very difficult to recognize, suggesting that high-spatial frequency information, by itself, is not an adequate cue for human face recognition processes. Shown here are Jim Carrey (left) and Kevin Costner.

## more findings .....

42

Example 4:



Example 5:



Fig. 5. Sample stimuli from Sadr et al.'s [70] experiment assessing the contribution of eyebrows to face recognition: original images of President Richard M. Nixon and actor Winona Ryder, along with modified versions lacking either eyebrows or eyes.

Fig. 6. Even drastic compressions of faces do not render them unrecognizable. Here, celebrity faces have been compressed to 25% of their original width. Yet, recognition performance with this set is the same as that obtained with the original faces.

## more findings .....

43

Example 6:

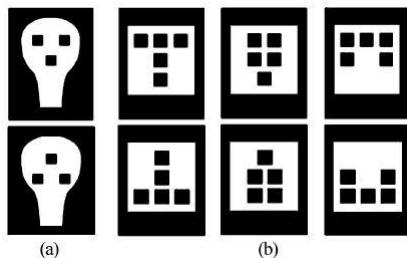


Fig. 15. (a) Newborns preferentially orient their gaze to face-like pattern on top, rather than one shown on bottom, suggesting some innately specified representation for faces (from [36]). (b) As a counterpoint to idea of innate preferences for faces, Simion et al. [73] have shown that newborns consistently prefer top-heavy patterns (left column) over bottom-heavy ones (right column). It is unclear whether this is the same preference exhibited in earlier work, and if it is, whether it is face-specific or some other general-purpose or artificial preference.

Example 7:

	Faces	Cats	Schematic Faces	Objects
				
% MR Signal	1.6	1.6	0.9	0.6

Fig. 17. Upper left, an example of FFA (fusiform face area) in one subject, showing right-hemisphere lateralization. Also included here are example stimuli from Tong et al. [80], together with amount of percent signal change observed in FFA for each type of image. Photographs of human and animal faces elicit strong responses, while schematic faces and objects do not. This response profile may place important constraints on the selectivity and generality of artificial recognition systems.

## Some Illusions: Thatcher Illusion

44

Thatcher Illusion



Rotate each image by 180 °



## Some Illusions: Mask Illusion

45



### – What can we learn?

46

We have seen some phenomena of human face perception, now how to start to implement a face recognition algorithm?

The results – an incomplete summary:

1. Human system extremely robust, however not perfect.
2. Fast adaptation but also very stable.
3. There exist top down mechanisms.
4. .....

Why are these findings so difficult to exploit for engineers?

- Mostly behavioral results.
- Only global input-output relations, difficult to isolate subsystems.
- No technology available to observe the brain on a neuronal level in a wide range simultaneously.
- No direct information on an algorithm or an architecture.
- .....