Vision Lab

Face Recognition: Past, Present and Future

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APPENDIX 1

DATASETS

Face databases

The appearance of a face is affected by many factors

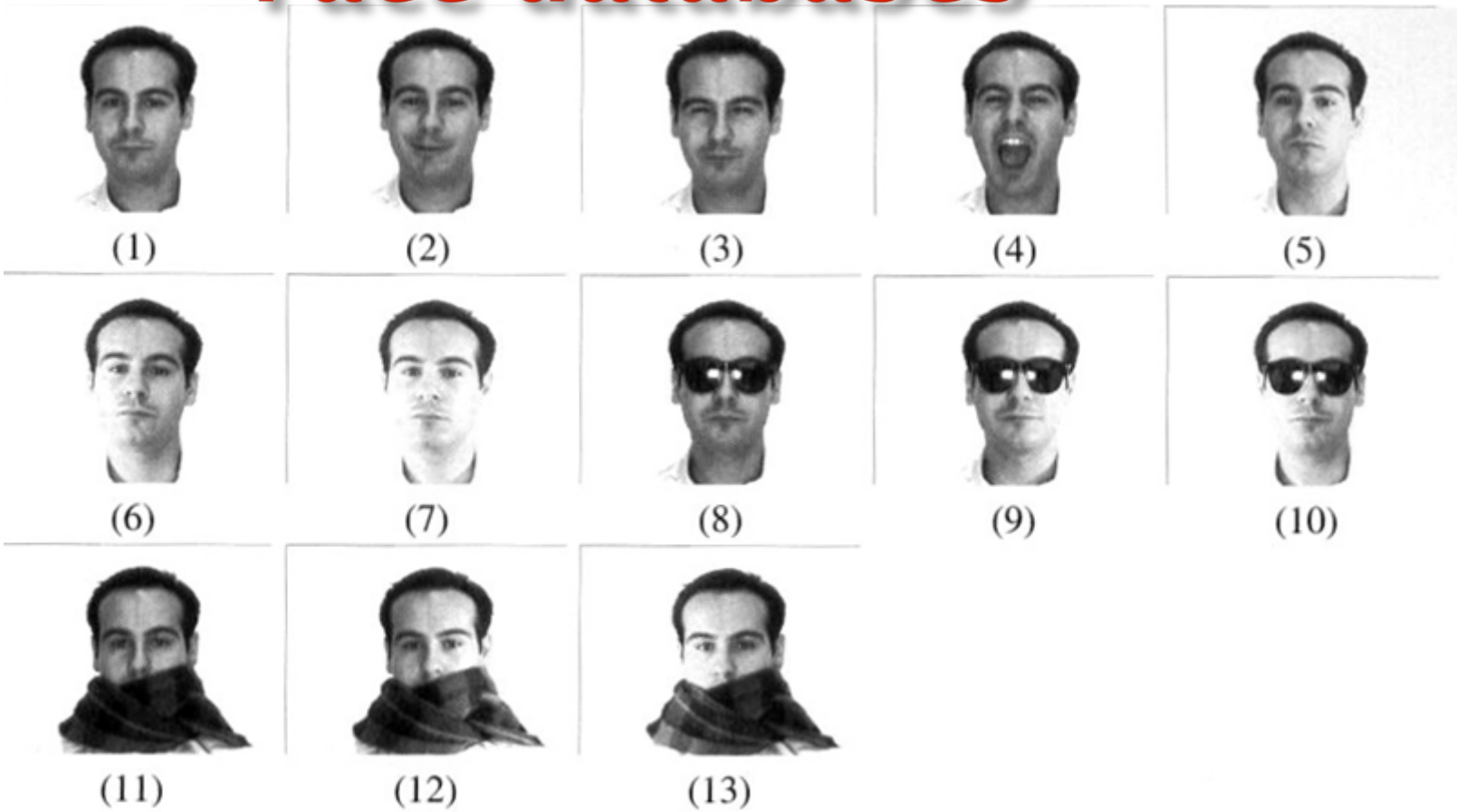
- Identity
- Face pose
- Illumination
- Facial expression
- Age
- Occlusion
- Facial hair

The development of algorithms robust to these variations requires databases of sufficient size that include carefully controlled variations of these factors.

Common databases to comparatively evaluate algorithms.

Collecting a high quality database is a resource-intensive task.

Face databases



AR database. The conditions are (1) neutral, (2) smile, (3) anger, (4) scream, (5) left light on, (6) right light on, (7) both lights on, (8) sun glasses, (9) sun glasses/left light (10) sun glasses/right light, (11) scarf, (12) scarf/left light, (13) scarf/right light

Face databases

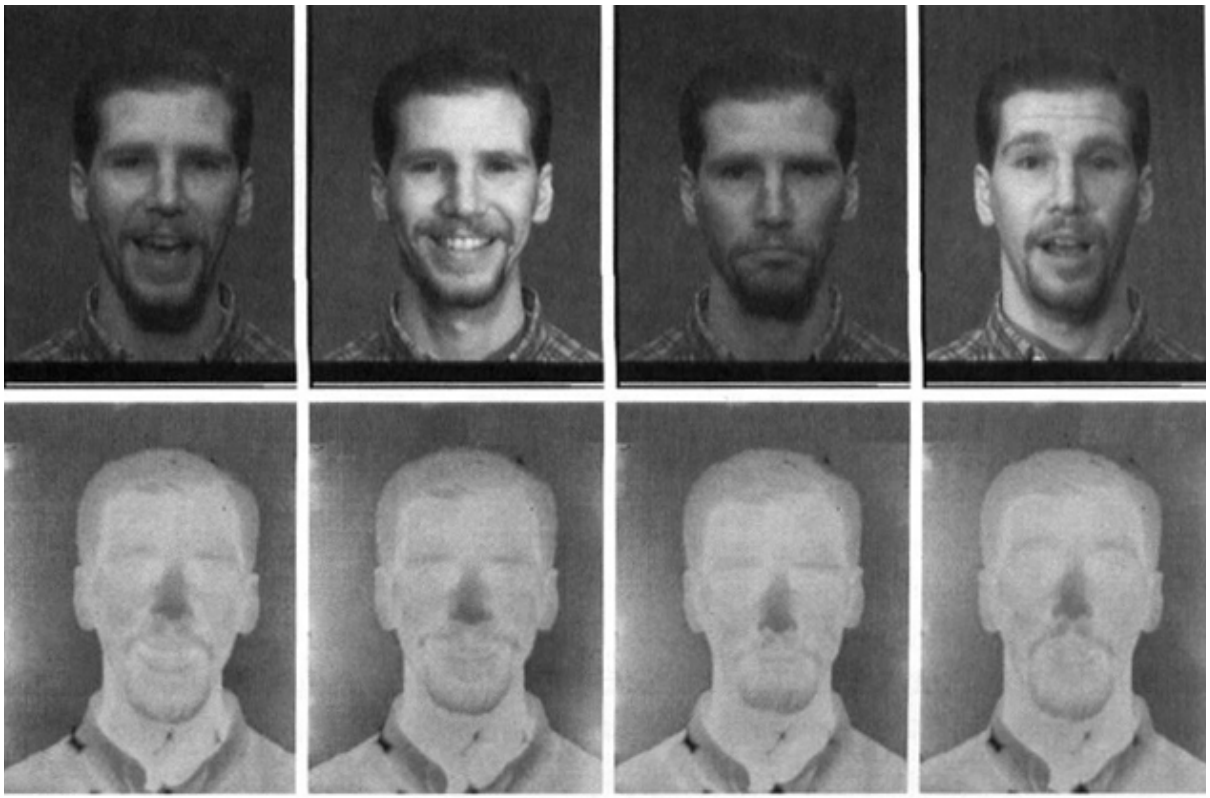
CAS-PEAL database. The images were recorded using separate cameras triggered in close succession. The cameras are about 22.5^0 apart. Subjects were asked to look up, to look straight ahead, and to look down. Shown here are seven of the nine poses currently being distributed.

Face databases

Illumination variation in the CAS-PEAL database. The images were recorded with constant ambient illumination and manually triggered fluorescent lamps.

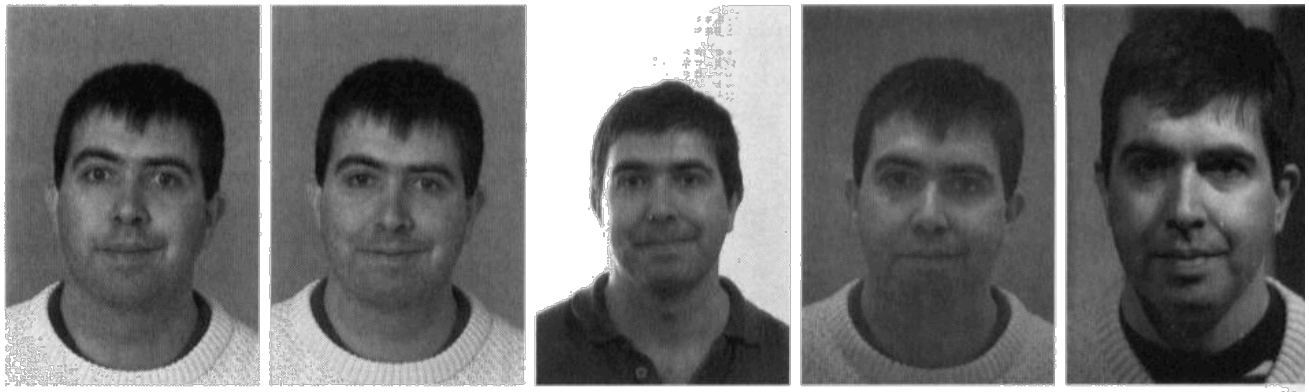
Also the **CMU PIE database** has been designed to include illumination variations

Face databases



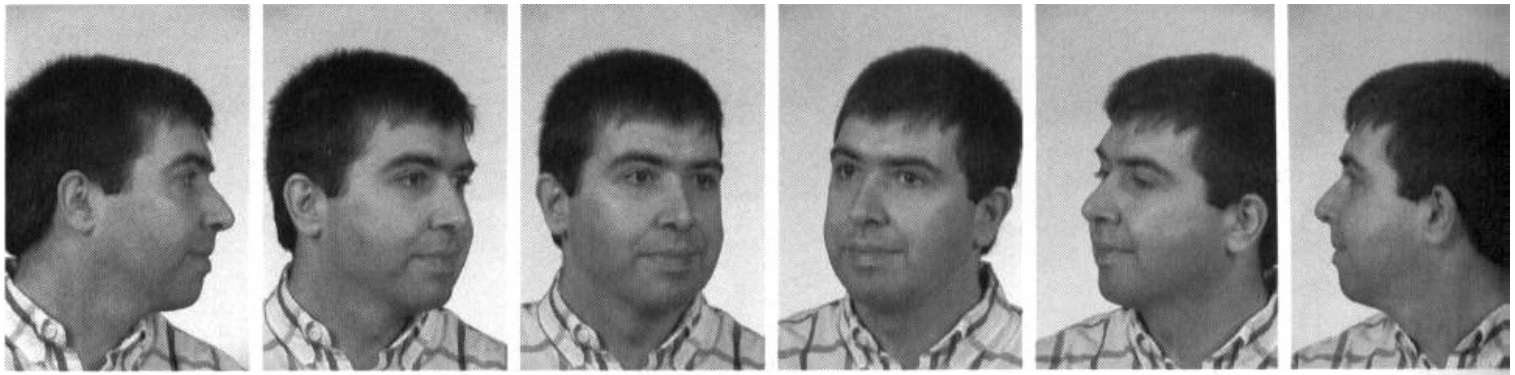
Equinox IR database. The upper row contains visible images and the lower row long-wave infrared images. The categories are (a) vowel (frontal illumination), (b) "smile" (right illumination), (c) "frown" (frontal illumination), (d) "surprise" (left illumination).

Face databases



fa fb duplicate I fc duplicate II

Frontal image categories used in the FERET evaluations. For images in the fb category, a different facial expression was requested. The fc images were recorded with a different camera and under different lighting conditions. The duplicate images were recorded in a later session, with 0 and 1031 days (duplicate I) or 540 to 1031 days (duplicate II) between recordings.



pr +90° hr +67.5° qr +22.5° ql −22.5° hl −67.5° pl −90°

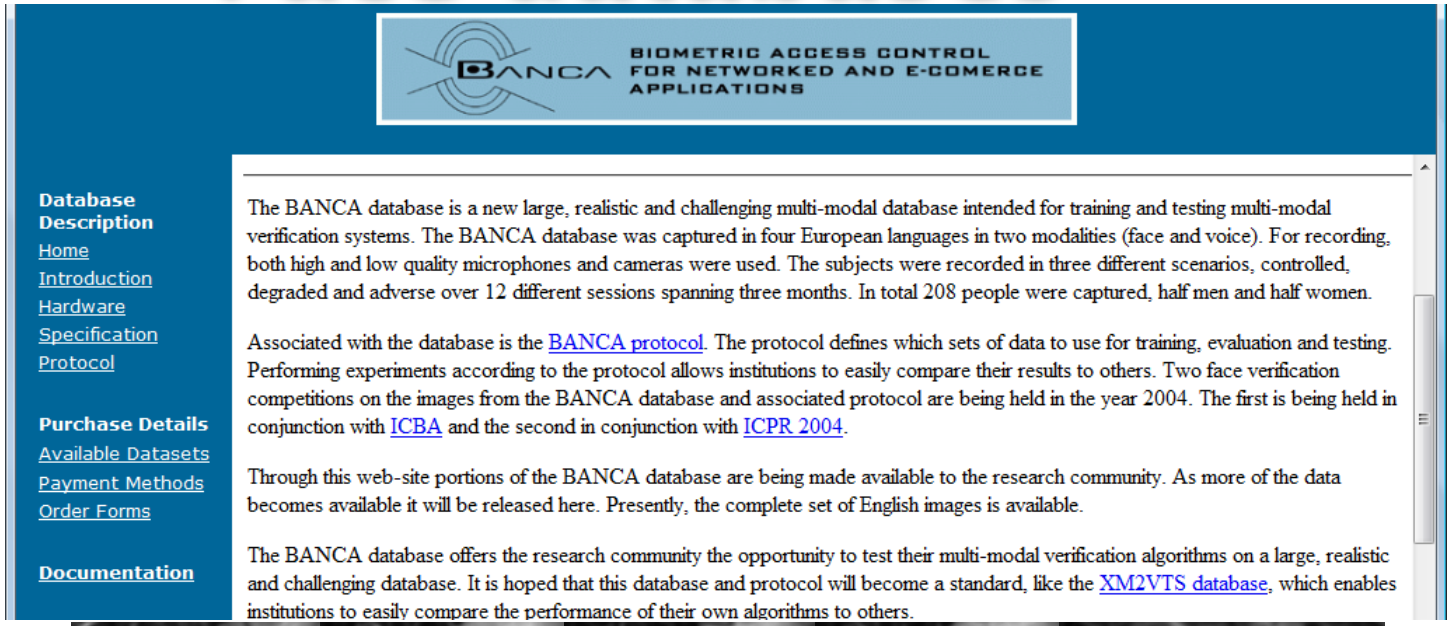
Additional set of pose images from the FERET database: right and left profile (labeled pr and pl), right and left quarter profile (qr, ql), and right and left half profile (hr, hl).

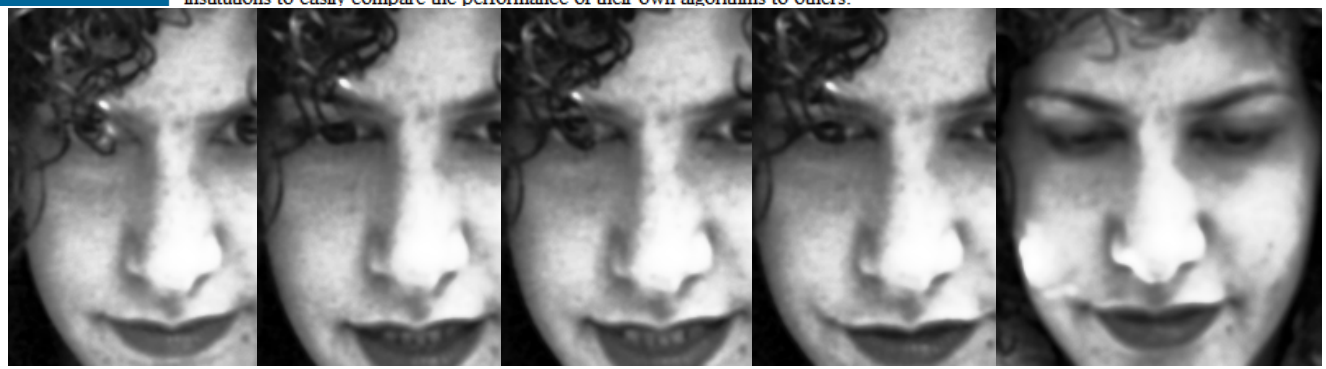
Face databases

Notre Dame HumanID database. Example images of the "unstructured" lighting condition recorded in the hallway outside of the laboratory.

University of Texas Video Database. Example images for the different recording conditions of the database. First row: Facial speech. Second row: Laughter. Third row: Disgust.

Face databases





The BANCA and XM2VTS video databases distributed by the University of Surrey

Face databases

The BANCA Protocol

An evaluation protocol defines a set of data, how it should be used by a system to perform a set of experiments and how the system performance should be computed.

In verification, two types of protocols exist; closed-set and open-set. In closed-set verification the population of clients is fixed. This means that the system design can be tuned to the clients in the set. Thus both the adopted representation (features) and the verification algorithm applied in the feature space are based on some training data collected for this set of clients. Anyone who is not in the training set is considered an impostor. The XM2VTS protocol is an example of this type of verification problem formulation.

In open-set verification we wish to add new clients to the list without having to redesign the verification system. In particular, we want to use the same feature space and the same design parameters such as thresholds. In such a scenario the feature space and the verification system parameters must be trained using completely independent data from that used for specifying client models. The BANCA protocol is an example of an open-set verification protocol.

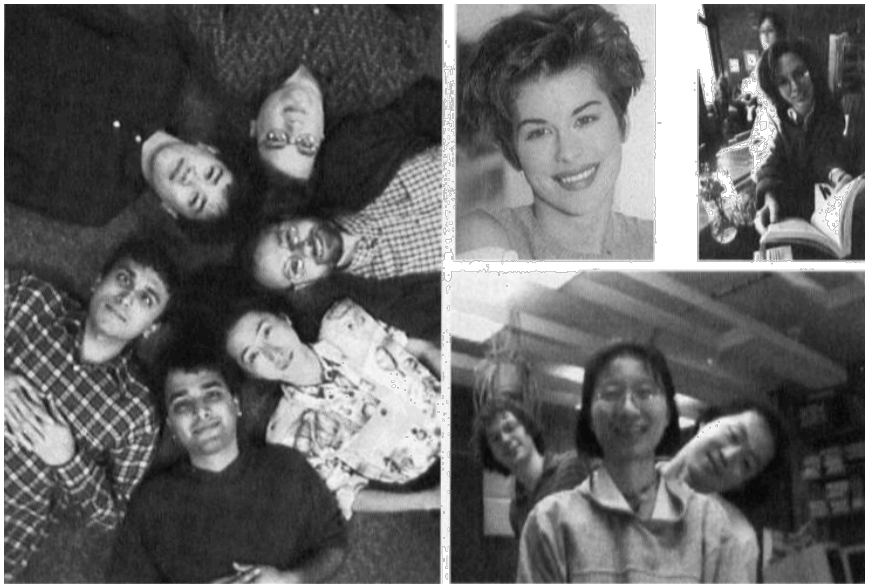
Face detection databases

- Face detection algorithms typically have to be trained on face and non-faces images to build up an internal representation of the human face.
- Popular choices are the FERET, MIT, ORL, Harvard, and AR public databases. Nonpublic databases are often also employed.
- These data sets should be representative of real-world data containing faces of various orientations against a complex background.
- In recent years two public data sets emerged as quasi-standard evaluation test sets:
  - The combined MIT/CMU test set for frontal face detection
  - The CMU test set II for frontal and non-frontal face detection

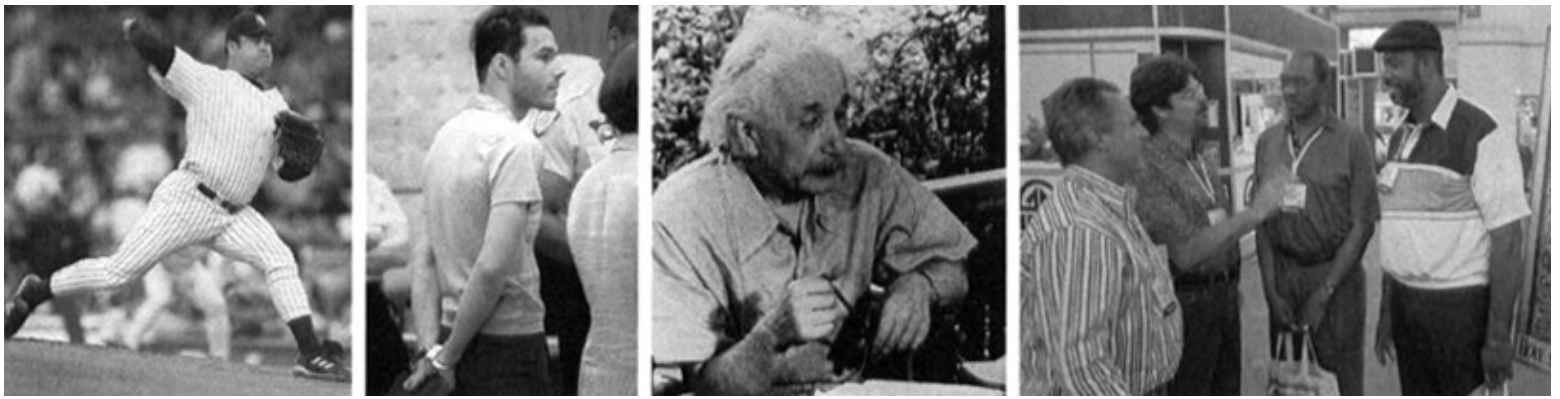
Face detection databases

Example images from the Upright Test Set portion of the MIT/CMU test set.

Face detection databases



Example images from the Tilted Test Set portion of the MIT/CMU test set.

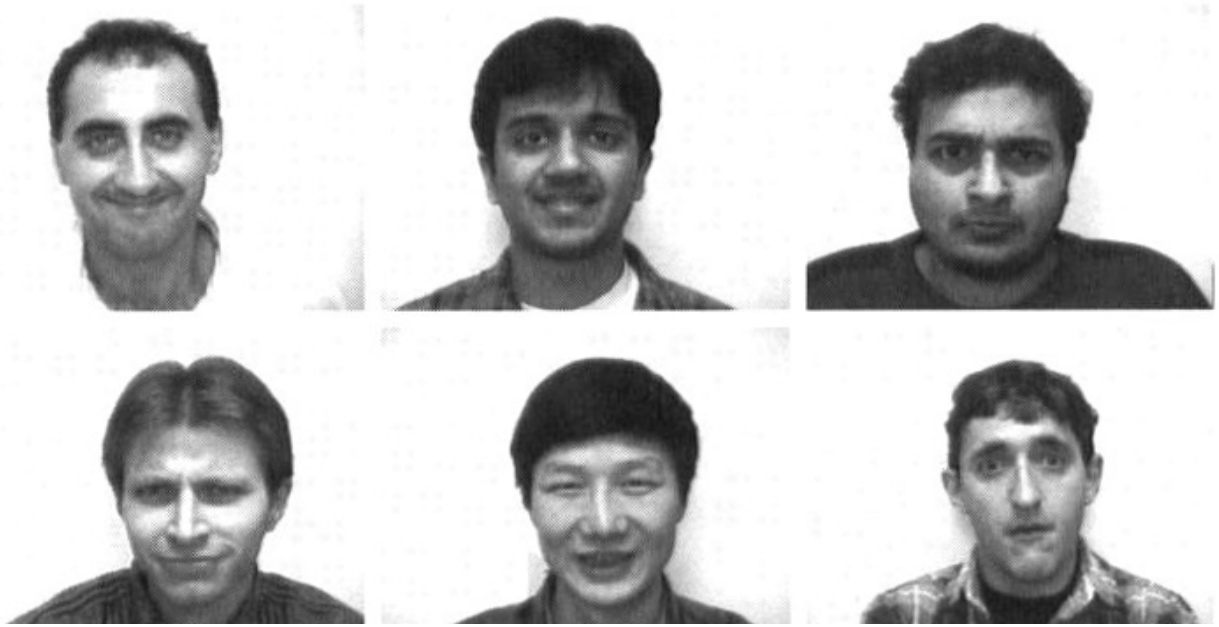


CMU Test Set II. Most of the faces in this test set are in profile view.

Face actions databases

Cohn-Kanade AU-Coded Facial Expression database. Examples of emotion-specified expressions from image sequences.

University of Maryland database. The images show peak frames taken from an image sequence in which the subjects display a set of facial expressions of their choice.



References	Elicitation method	Size	A/V	Emotion description	Labeling	Accessibility
Cohn-Kanade (CK) '00 [71]	Posed	210 adults, 3 races; Available: 480 videos	V	Category: 6 basic emotions, and AUs	FACS	Y
Sebe et al. (SD) '04 [123]	Natural: Subjects watched emotion-inducing videos	28 adults	V	Category: Neutral, happy, surprise, disgust	Self-report	N
MMI '05[3] [106], [98]	Posed: static images, videos recorded simultaneously in frontal and profile view; Natural: Children interacted with a comedian. Adults watched emotion-inducing videos	Posed: 61 adults Natural: 11 children and 18 adults. Overall: 3 races Available: 1250 videos, 600 static images	V	Category: 6 basic emotions, single AU and multiple AUs activation	FACS, Observers' judgment	Y
UT Dallas '06 [95]	Natural: Subjects watched emotion-inducing videos	229 adults	V	Category: 6 basic emotions, puzzle, laughter, boredom, disbelief	Observers' judgment	Y
BU-3DFE (BU)'06 [148]	Posed: 3D range data by using 3DMD digitizer.	100 adults Mixed races	V	Category: 6 basic emotions. Four levels of intensity	N/A	Y
FABO face and body gesture [63]	Posed: two cameras to record facial expressions and body gestures respectively	23 adults Mixed races Available: 210 videos	V	Category: 6 basic emotions, neutral, uncertainty, anxiety, boredom	N/A	Y
Banse-Scherer '96 [8]	Posed	6 actors & 6 actresses Available: 1344 audio samples	A	Category: hot/cold anger, panic fear, anxiety, despair, sadness, elation, happiness, interest, boredom, shame, pride, disgust, contempt.	Listeners' judgment	Y
Danish Emotional Speech Database '96[5]	Posed	2 actors & 2 actresses; 2 words, 9 sentences, 2 passages; 10 min of audio data.	A	Category: neutral, surprise, happiness, sadness, anger	Listeners' judgment	Y
ISL meeting corpus '02 [15]	Natural: meeting corpus	18 meetings; Available: data of 5 participants per meeting averagely	A	Category: Positive, neutral, negative [3], [90]	Listeners' judgment	Y
CSC corpus [65]	Natural: subject was motivated to tell the truth and deceive the interviewers in different tasks	32 adults, 15.2 h, 3882 speaking turns, 9687 SUs	A	Deceptive, non-deceptive speech	Self-report	N
Automatic call center (ACC)'05 [83]	Natural: Human-computer dialogue at a commercial call system	1187 calls 7200 utterances	A	Category: Negative, non-negative	listeners' judgment	N
Bank and Stock Service 04 [34]	Natural: human-human dialogue at call center	350 dialogues, 10000 speaking turns	A	Category: fear, anger, stress	Listeners' judgment	N
AIBO database '04 [13]	Natural: children and robot interaction	110 dialogues, 29200 words	A	Category: joyful, emphatic, surprised, ironic, helpless, touchy, angry, bored, motherese, reprimanding, rest	Listeners' judgment	N
Chen-Huang (CH) '00 [21]	Posed	100 adults, 9900 visual and AV expressions	AV	Category: 6 basic emotions, and 4 cognitive states (interest, puzzle, bore, frustration)	N/A	N
Adult Attachment Interview (AAI)'04[111]	Natural: subjects were interviewed to describe the childhood experience	60 adults Each interview last 30-60min	AV	Category: 6 basic emotions, embarrassment, contempt, shame, general positive and negative.	FACS	N
RU-FACS (RU) '05 [10]	Natural: subjects were tried to convince the interviewers they were telling the truth	100 adults	AV	Category: 33 AUs	FACS	N
SAL '05[7]	Induced: subjects interacted with artificial listener with different personalities	24 adults 10h	AV	Dimensional labeling/categorical labeling	FEEL-TRACE	Y
Belfast database (BE) '03 [38]	Natural: clips taken from television and realistic interviews with research team	125 subjects. 209 sequences from TV, 30 from interview	AV	Dimensional labeling/categorical labeling	FEEL-TRACE	Y

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Vision Lab

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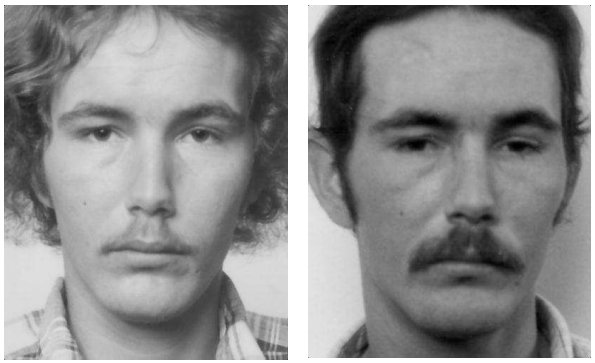
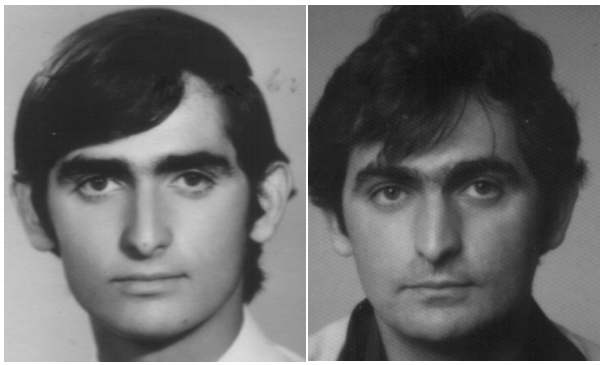
Face aging databases



FG-NET dataset:
images of about 100 individuals with ages varying from 5 to 69 years of age



MORPH dataset:
images of 13,000 individuals collected over four years

Face aging databases

IIIT-Delhi face aging database:2,618 images from 49 female and 53 male Indian celebrities

3D Face Databases

- Features:
  - Full 3D / 2.5D
  - Single view / Multi-view
  - Illumination changes
  - Expressions changes
  - Only shape or shape + texture
  - Pre-processing
  - Quality of data (sensors)

3D Face Databases

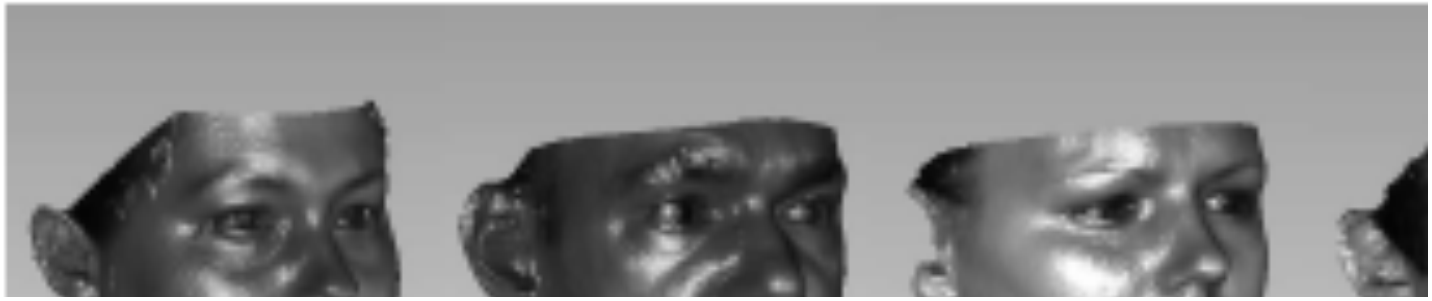
- UND database (University of Notre Dame)
  - 953 facial scans (277 subjects)
  - frontal scans (neutral expression)
  - 2.5D shape + texture

3D Face Databases

- FRGC database (NIST)
  - 4007 scans (465 subjects)
  - nearly frontal
  - different expressions
  - 2.5D shape + texture

3D Face Databases

- USF database (University of South Florida)
  - 100 scans
  - full-view models
  - neutral expression



3D Face Databases

- 3D_RMA database (Royal Military Academy of Belgium)
  - 120 subjects (2 sessions, 3 scans each)
  - different (but limited) orientations
  - 3D points

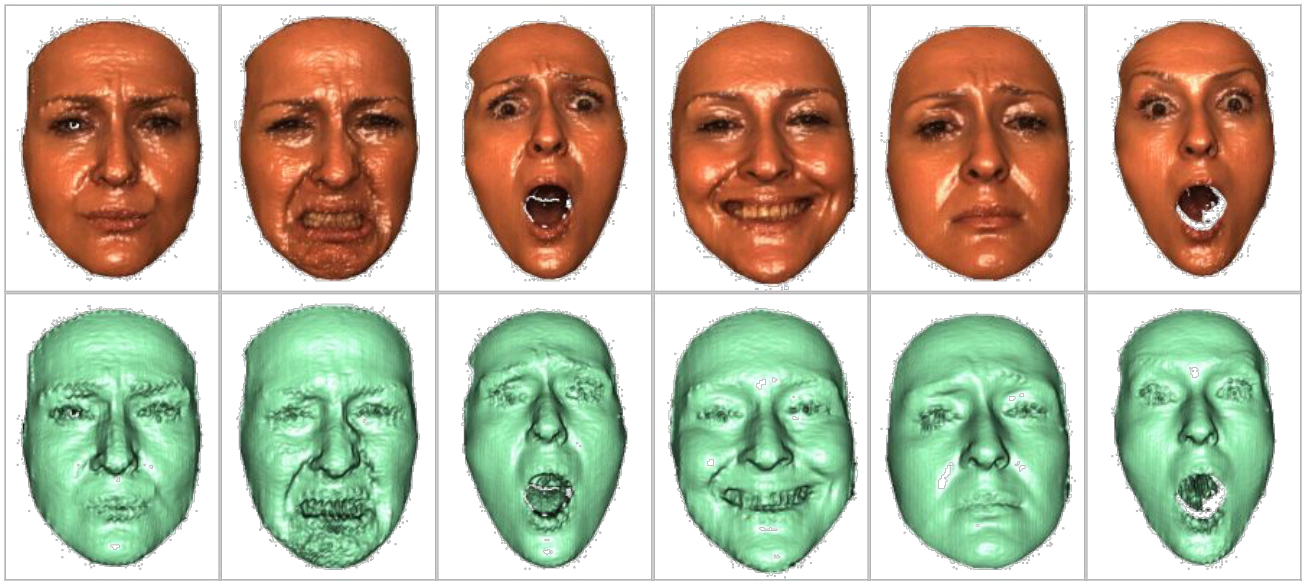
3D Face Databases

- GavabDB database (University Rey Juan Carlos – Madrid)
  - different orientations and expressions
  - 61 subjects (9 scans)
  - Shape only

3D Face Databases

The Bosphorus database contains scans of 105 individuals: 61 male; 44 female

About 50 scans/subject. Each scan either presents a diffent facial expression (anger, happiness, disgust), or a head rotation along different axes.



A.Savran, N. Alyüz, H. Dibeklioğlu, O. Çeliktutan, B. Gökberk, B. Sankur, L. Akarun,
Bosphorus Database for 3D Face Analysis, The First COST 2101 Workshop on Biometrics and Identity Management (BIOID 2008) Roskilde University, Denmark, May 2008.

3D Mask Attack Dataset

Vision Lab

76500 frames of 17 persons, recorded using Kinect for both real-access and spoofing attacks. https://www.idiap.ch/dataset/3dmad

Face recognition challenges

After

- **FERET**
- **FRVT**
- **FRGC**
- **…**

Face recognition challenges

Labeled Faces in the Wild

Menu
- LFW Home
  - Mailing
  - Explore
  - Download
  - Train/Test
  - Results
  - Information
  - Errata
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  - Changes
- UMass Vision

LFW Home

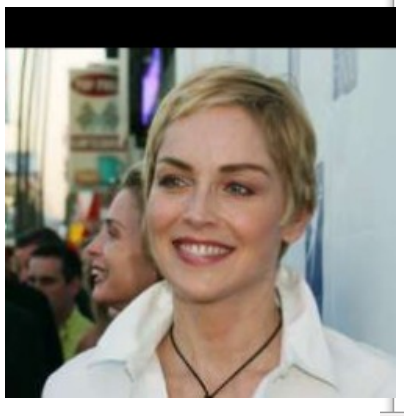
New: Professor Learned-Miller will be running a workshop titled Faces in Real-Life Images at the European Conference on Computer Vision with co-organizers Andras Ferencz and Frederic Jurie.

Welcome to Labeled Faces in the Wild, a database of face photographs designed for studying the problem of unconstrained face recognition. The database 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 database. The only constraint on these faces is that they were detected by the Viola-Jones face detector. More details can be found in the technical report below.

last updated: 2007/11/21 1:30 PM EST
change log

Mailing list:
If you wish to receive announcements regarding any changes made to the LFW database, please send email to majordomo@cs.umass.edu with the message body: "subscribe lfw" on a single line.

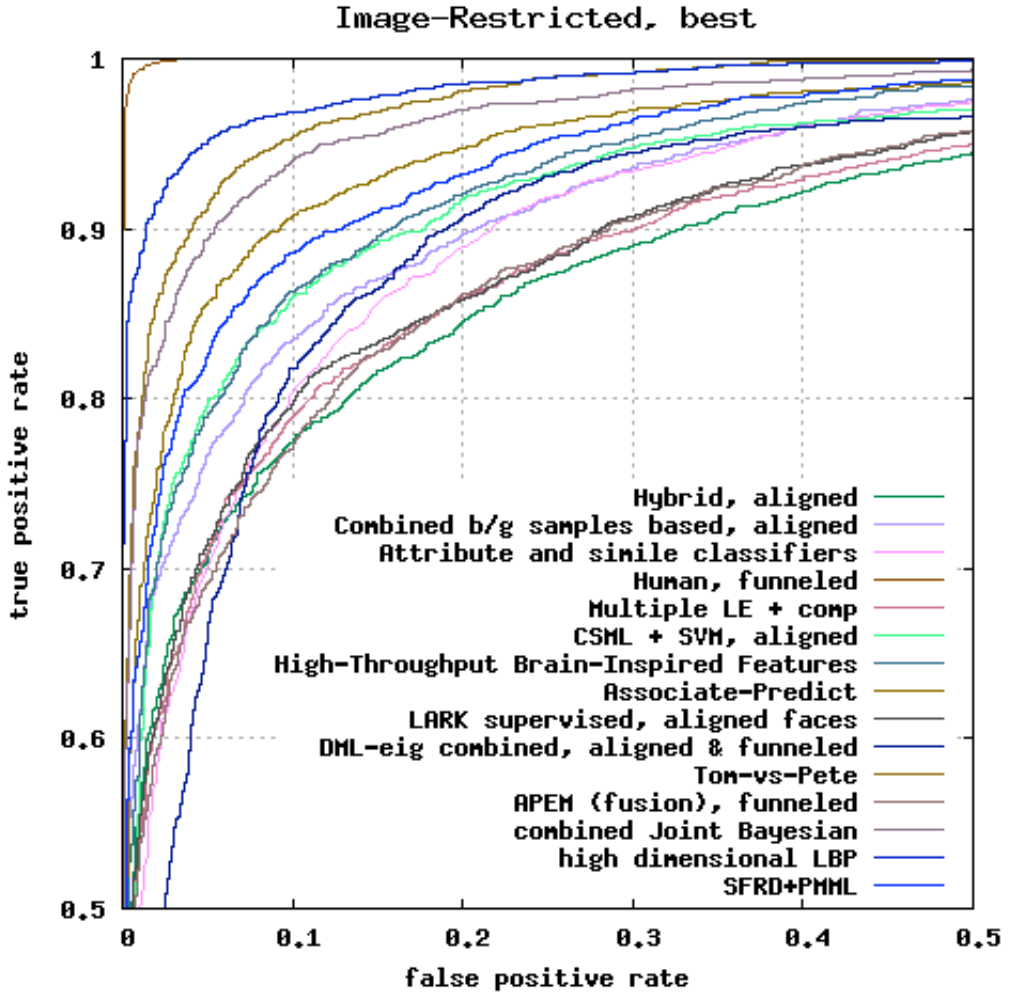
Explore the database:
- Alphabetically by first name:
  [A][Alf][Ang][B][Bin][C][Che][Col][D][Daw][Don][E][Eri][F][G][Goe][H] [I][J]
  [Jav][Jes][Joh][Jos][K][Kim][L][Lil][M][Mark][Mel][Mik][N][O][P] [Per][Q][R][Ric]
  [Rog][S][Sha][Ste][T][Tim][U][V][W][X][Y][Z]
- Alphabetically by first name, only people with more than one image:
  [A][B][C][D][E][F][G][H][I][J][K][L][M][N][O][P][Q][R][S][T][U][V][W][X][Y][Z]
- Alphabetically by last name:
  [A][B][C][D][E][F][G][H][I][J][K][L][M][N][O][P][Q][R][S][T][U][V][W][X][Y][Z]
- By number of images per person:



Face recognition challenges

Vision Lab

Labeled Faces in the Wild



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

Biometrics challenges

ICB 2009

The 3rd IAPR/IEEE International Conference on Biometrics

- Home
- Call for Papers
- Committee
- Competitions
- Keynote Speakers
- Paper Submission
- Demo Submission
- Awards
- Call for Tutorials
- Conference Venue
- Sponsors
- Travel Information
- Poster

ICB2009 Competitions

Competitions Chairs

Bernadette Dorizzi	Biosecure Foundation, France
Jonathon Phillips	NIST, USA

Face recognition from stills and video

This competition is performed under the supervision of Norman Poh from the University of Surrey

Fingerprint

This competition is performed under the supervision of Raffaele Cappelli from the University of Bologna

Multimodal Biometric Feature Selection Challenge

This competition is performed under the supervision of Krzysztof Kryszczuk from the Ecole Politechnique Federale de Lausanne

Multiple Biometrics Grand Challenge

The Multiple Biometrics Grand Challenge is organized and supported by the National Institute of Standards and Technology (NIST). The MBGC is sponsored by multiple U.S. Government Agencies. Dr Jonathon Phillips is the responsible for the NIST MBGC evaluation. Within the framework of ICB program, submissions are encouraged to the MBGC evaluation. The results of the MBGC, together with the other competitions, will be presented at a special conference session.

Signature verification

This competition is performed under the supervision of Sonia Garcia-Salicetti from the institute TELECOM SudParis

Biometrics challenges

ICB-2013

The 6th IAPR International Conference on Biometrics

June 4 - 7, 2013 Madrid, Spain

Competitions

The availability of common benchmark databases, together with evaluation protocols has been partly responsible for the significant gains made in biometrics in recent years. We believe that such evaluations should be continued. Databases and, more importantly, unbiased evaluation mechanisms should be spread across the scientific community, making it possible for scientists to evaluate their progress.

The 6th IAPR International Conference on Biometrics (ICB 2013) is supporting the organization of the following 8 evaluations:

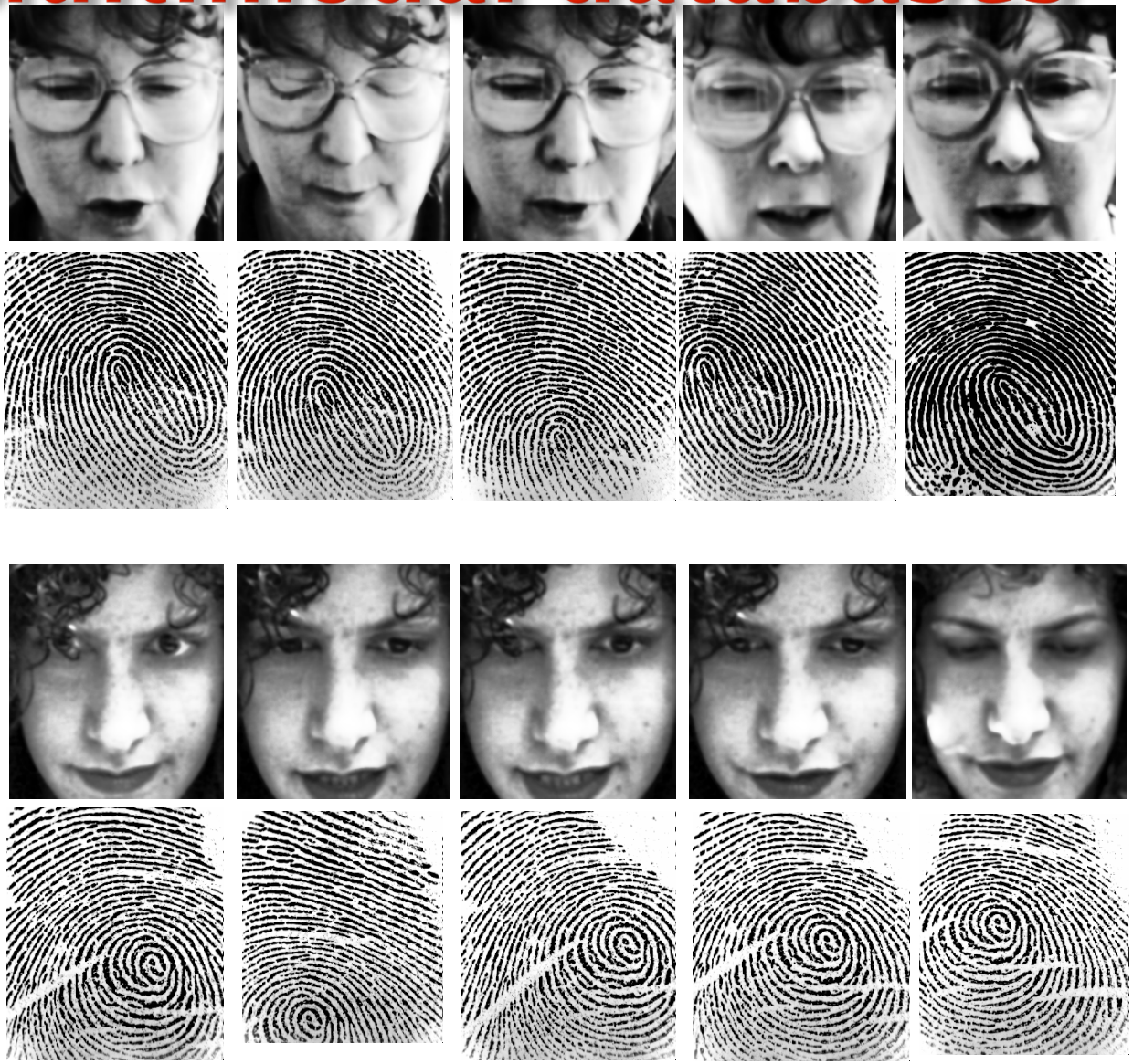
» The 2nd competition on counter measures to 2D facial spoofing attacks
» Competition on face recognition in mobile environment using the MOBIO database
» Competition on speaker recognition in mobile environment using the MOBIO database
» The First ICB Competition on Face Recognition (ICFR2013)
» The First ICB Competition on Iris Recognition (ICIR2013)
» Competition on Secure Template Fingerprint Verification (STFV@ICB-2013)
» Competition on Fingerprint Indexing (FIDX@ICB-2013)
» Competition on Fingerprint Liveness Detection

Competitions will be running from January 7, 2013 to March 22, 2013, but database and instructions will be available in late 2012. Each competition will have the opportunity to submit for review a competition summary paper for possible publication into the official proceedings.

Together with these 8 evaluations, an on-site spoofing challenge intended to evaluate operational vulnerabilities of various biometric systems will be conducted:

» TABULA RASA Spoofing Challenge. [NEW!]

Multimodal databases

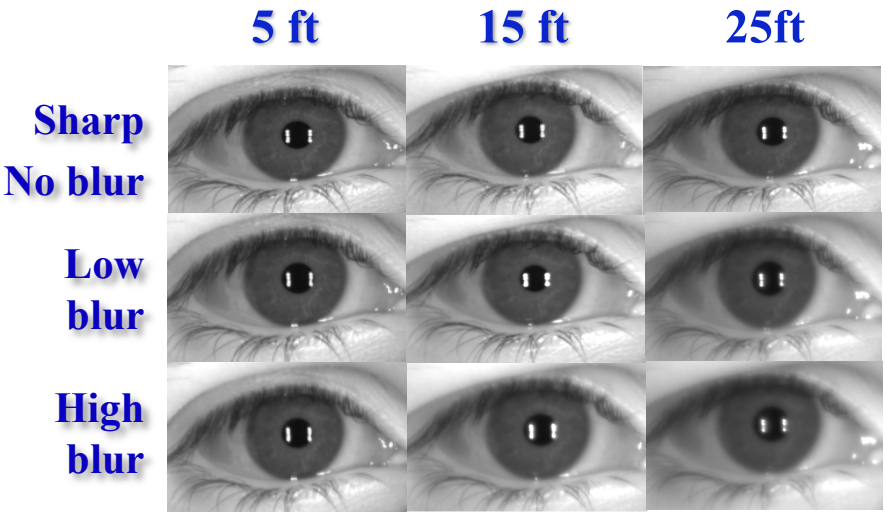


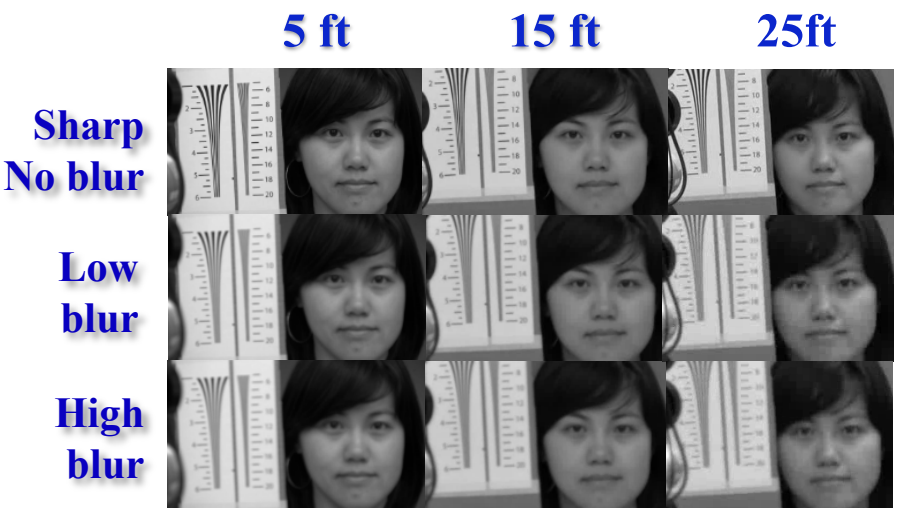
Quality in Face and Iris Research Ensemble (Q-FIRE)

Vision Lab

- **Release 1**
  - 4TB of visible face and NIR face/iris video for 90 subjects
  - Multiple distance up to 8.3 meters with controlled quality degradation
- **Release 2**
  - An additional 83 subjects (*currently sequestered*)
- Available by Request to CITeR *http://www.clarkson.edu/citer/research/collections*

Out-of Focus Blur





S. Schuckers, Clarkson University, sschucke@clarkson.edu

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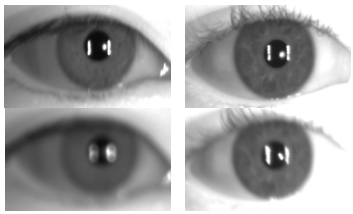
Motion Blur



Illumination

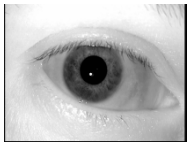
Angle

Multiple Faces

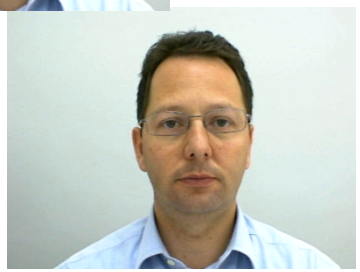
S. Schuckers, Clarkson University, sschucke@clarkson.edu

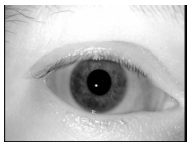
Multimodal databases

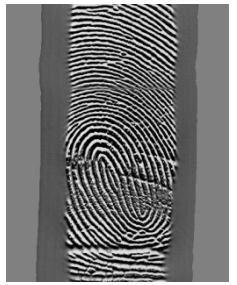










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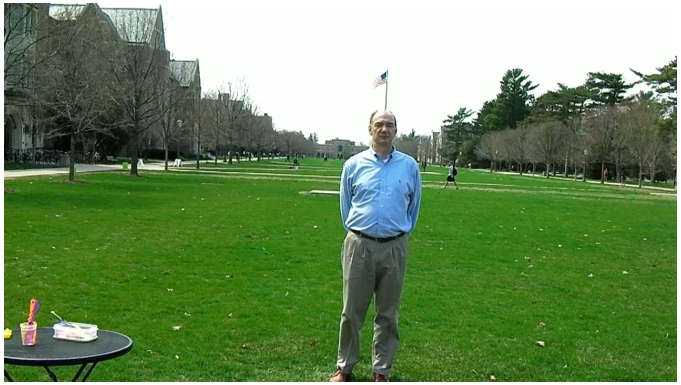
VIDEO DATASETS

Natural Viewing Environment Video

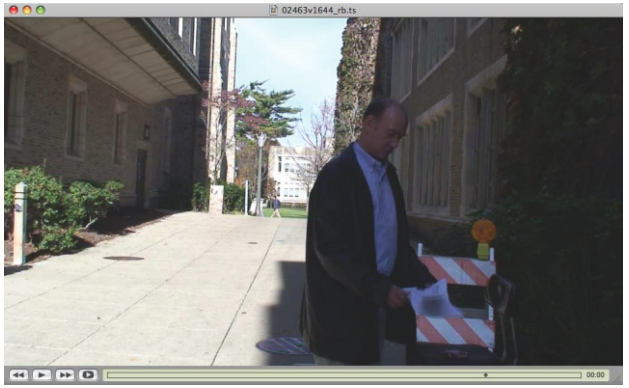
Courtesy of Jonathon Phillips, NIST

Point & Shoot Challenge—Video



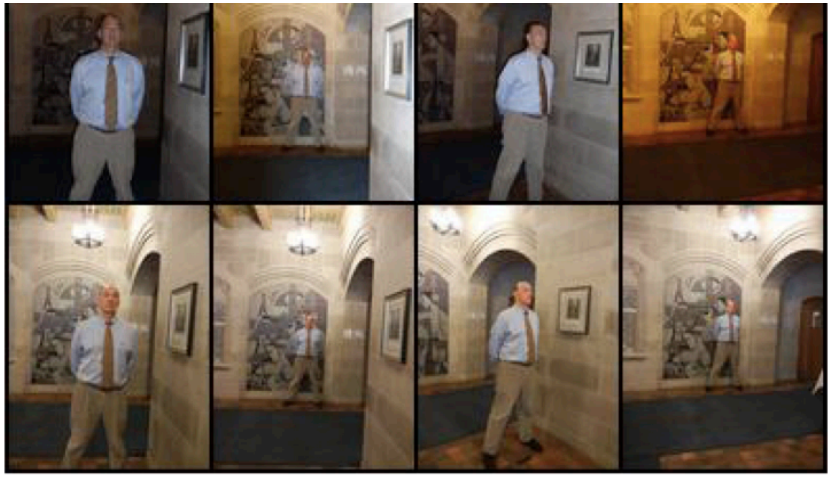
Multiple Biometric Grand Challenge MBGC

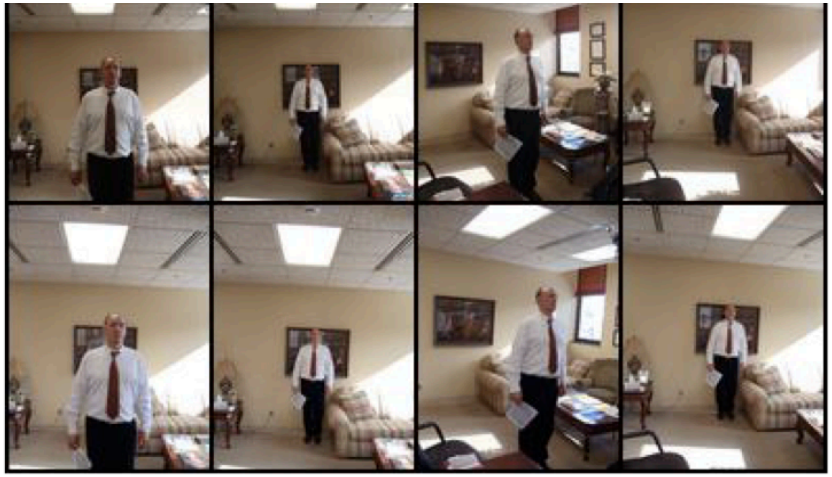
- Walking footage: Subject walks towards camera.
- Activity/Conversation footage: Non-frontal footage of subject performing an A/C.



U of Texas at Dallas & U of Notre Dame

Examples PaSC—Stills





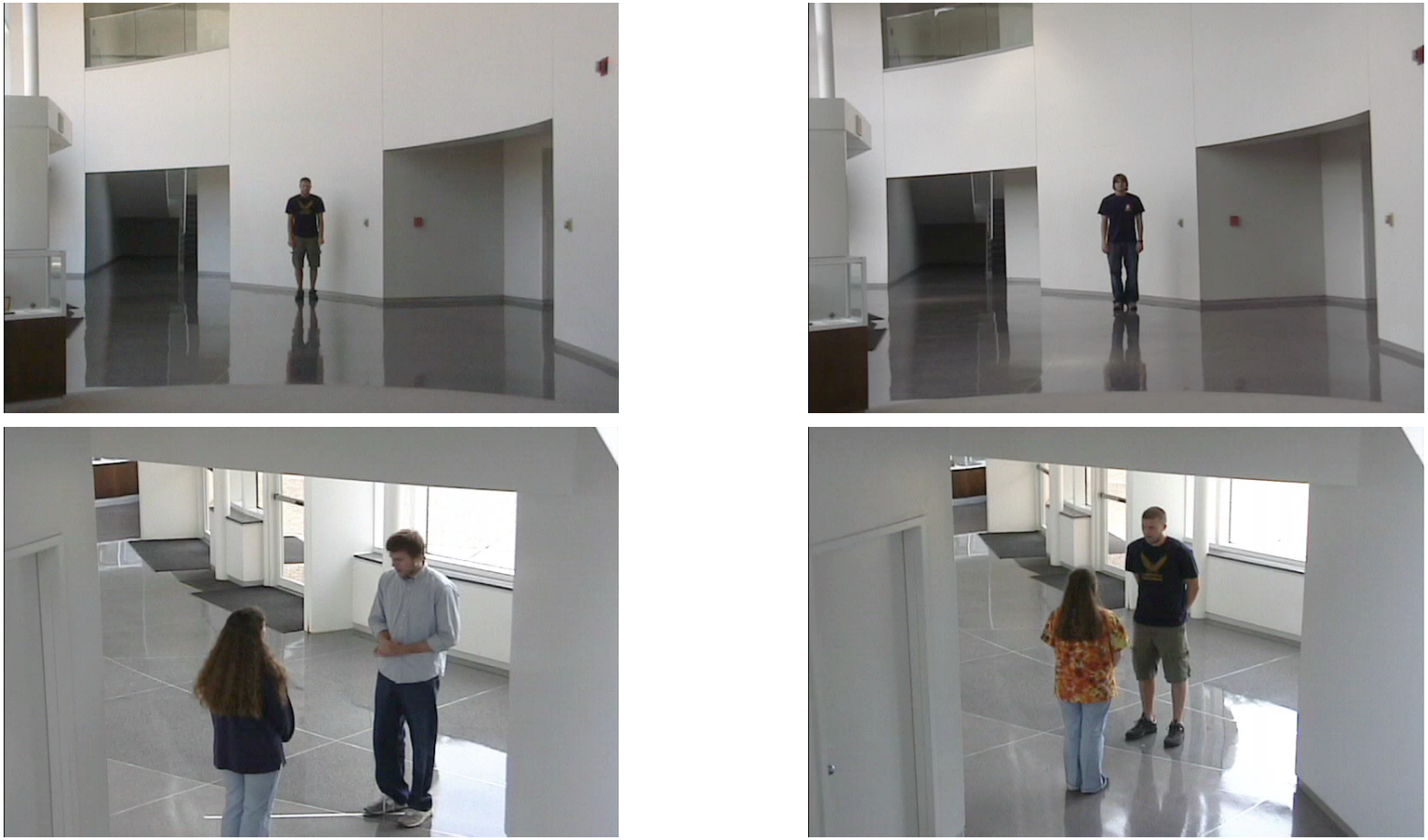
PaSC

- Problem Defined
  - 9,376 stills; 293 subjects
  - 2,802 videos; 265 subjects
  - Video-to-video
  - Still-to-video
  - Still-to-still
- http://face.nist.gov
- Release 11 June 2013

- Design: Colorado State (CSU) and NIST
- Data collection: Notre Dame, NIST, and CSU

FOCUS UT-Dallas Dataset

FOCS videos: 510 walking (frontal face) and 506 activity (profile face) videos



J. O'Toole, P. J. Phillips, S. Weimer, D. A. Roark, J. Ayyad, R. Barwick, and J.Dunlop, “Recognizing people fromdynamicandstatic faces and bodies:Dissectingidentity with a fusion approach,” *Vision Research, vol.51, no.1, pp.74-83, 2011.*

National Institute of Standards and Technology, "Face and Ocular Challenge Series (FOCS)”.

Face in Video Evaluation

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Face In Video Evaluation (FIVE)

2014-07-16 Program Announcement

Scope: The Face in Video Evaluation (FIVE) is being conducted to assess the capability of face recognition algorithms to correctly identify or ignore persons appearing in video sequences – i.e. the open-set identification problem. Both comparative and absolute accuracy measures are of interest, given the goals to determine which algorithms are most effective and whether any are viable for the following primary operational use-cases: 1. High volume screening of persons in the crowded spaces (e.g. an airport); 2. Low volume forensic examination of footage from a crime scene (e.g. a convenience store); 3. Persons in business meetings (e.g. for video-conferencing); and 4. Persons appearing in television footage. These applications differ in their tolerance of false positives, whether a human examiner will review outputs, the prior probabilities of mate vs. non-mate presence, and the cost of recognition errors.

Out of scope: Gait, iris and voice recognition; Recognition across multiple views (e.g. via stereoscopic techniques); Tracking across sequential cameras (re-identification); anomaly detection; detection of evasion.

Relationship to FRVT: The Face Recognition Vendor Tests of 2000, 2002, 2006, 2010, and 2013 gave quantitative statements of accuracy and speed of mostly still-image face recognition algorithms. The last test included a video track (FRVT class V) – results from that work are being provided to participants. Our new FIVE program supersedes the FRVT work but proceeds in an almost identical manner.

Test progression: Software submitted to NIST will be evaluated on sequestered sets to quantify accuracy and speed. Algorithms must be implemented behind the formal C++ API to be published by NIST. This will be very similar to the API used in the prior FRVT evaluation. The test will be conducted over at least three iterative cooperative test-report-test phases engaging algorithm developers.This process will culminate in the publication of reports on this website and in the open literature.

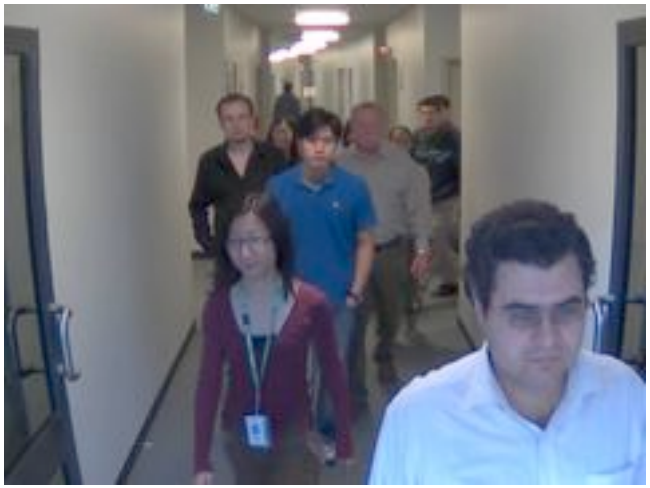
Test data: This program will leverage several archival video corpora that are sequestered at NIST. Each includes subjects who are generally neither cooperative nor actively uncooperative. The datasets have in-common that several subjects are usually present in

Other Links

- FRVT Homepage
- face.nist.gov
- Image Group Publications Archive Homepage
- Fingerprint Homepage
- Image Group Homepage
- Biometrics Evaluations Homepage
- ITL Biometrics Overview
- iris.nist.gov

http://www.nist.gov/itl/iad/ig/five.cfm

…and Beyond



- **Female makeup Datasets**
- **Plastic Surgery Face Database**
- **YouTube Faces Database**
- **ChokePoint**
- **SCface - Surveillance Cameras Face Database**
- **Long Distance Heterogeneous Face Database (LDHF-DB)**
- **VADANA: Vims Appearance Dataset for facial ANAlysis**
- **MOBIO - Mobile Biometry Face and Speech Database**

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APPENDIX 2

KINSHIP

Lorusso L., Brelstaff G., Brodo L., Lagorio A., Grosso E., “Visual judgments of kinship: an alternative perspective”, Perception 40(11):1282-9, 2011

Faces and Kinship

Faces and Kinship

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1 Kings 3:16-27

Raphael's oil painting *The Judgement of Solomon* – 1518

Face-based Kinship analysis: the literature

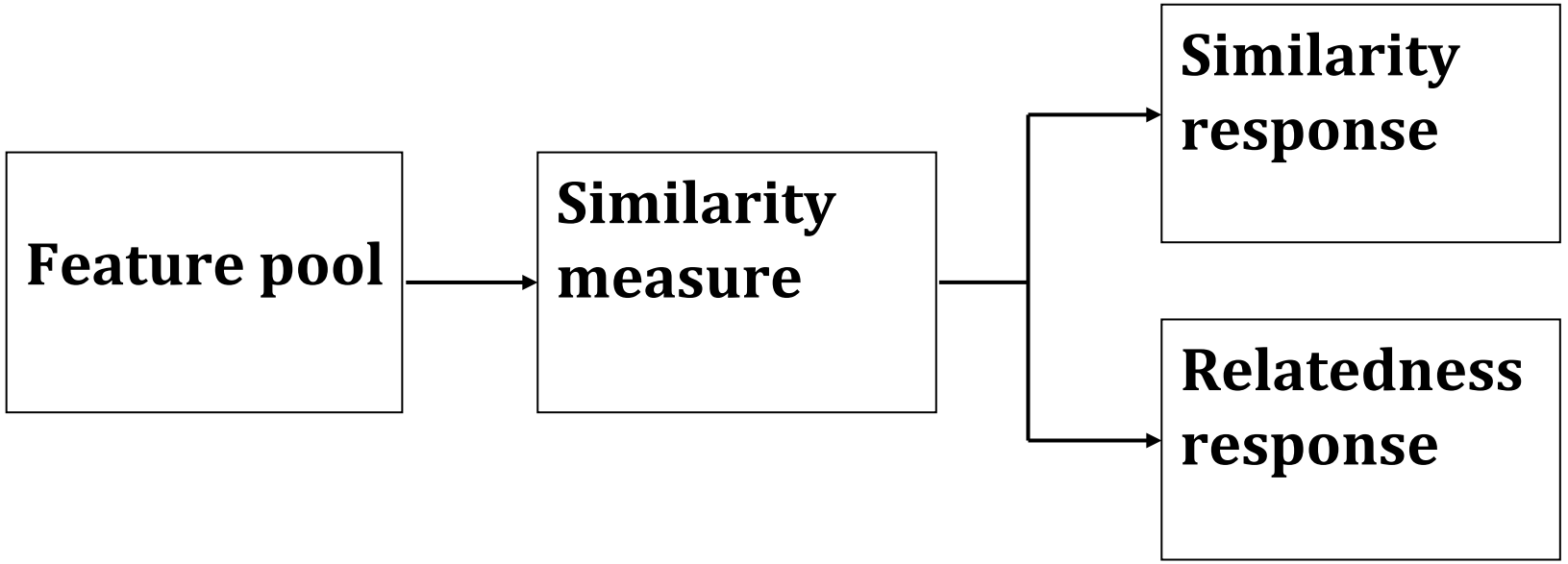
Studies of kin recognition investigated the relationship between **KINSHIP** and **SIMILARITY**:

- Maloney & Dal Martello , 2006, "Kin recognition and the perceived facial similarity of children" *Journal of Vision* 6, pp. 1047-1056.
- Dal Martello & Maloney, 2006, "Where are kin recognition signals in the human face?", *Journal of Vision* 6, pp. 1356-1366.
- DeBruine et al., 2009, "Kin recognition signals in adult faces" *Vision Research* 49, pp. 38-43.
- Alvergne et al., 2010, "Are parents' perceptions of offspring facial resemblance consistent with actual resemblance? Effects on parental investment" *Evolution and Human Behaviour* 31, pp.7-15.

Face-based Kinship analysis: the literature

Maloney and Dal Martello (2006) have introduced a model for kin recognition - ***Thresholded Similarity Observer (TSO) model*** - in which kin recognition is reduced to a similarity measure of similarity cues.

The TSO Model



The flow of visual information (visual pathway) in similarity and kinship judgments
(Maloney and Dal Martello 2006).

The TSO Assumptions

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1. Genetically-related people manifest in their faces "Kin signals".
2. "Kin signals" are represented by similarity features.
3. Kin recognition is a signal detection task.
4. Perception of similarity and kin recognition are based on a common measure of similarity of features.
5. Kinship and similarity judgments are based on a common flow of visual information from the stimulus to the observer.
6. The model of perceived similarity between faces is a "generalized" (*vs* an "individualized") model.

The TSO Model Expanded

The TSO Assumptions

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- From such assumptions it follows that judgments of similarity and kinship do not require any kind of cognitive modulation, but a visual flow of similarity information is sufficient for the observer to make the judgments.

- In other words, **bottom-up mechanisms are sufficient** to make kinship judgments.

Not considered in TSO

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- **Top-down mechanisms**: task-driven and context-dependent strategies. Different tasks and visual contexts may induce the observer to follow different observational strategies.

- **Relations between concepts,** may enhance or undermine the belief that two persons are ***similar*** or ***genetically related*** (i.e. *priming* effects of a judgment over another).

Not considered in TSO

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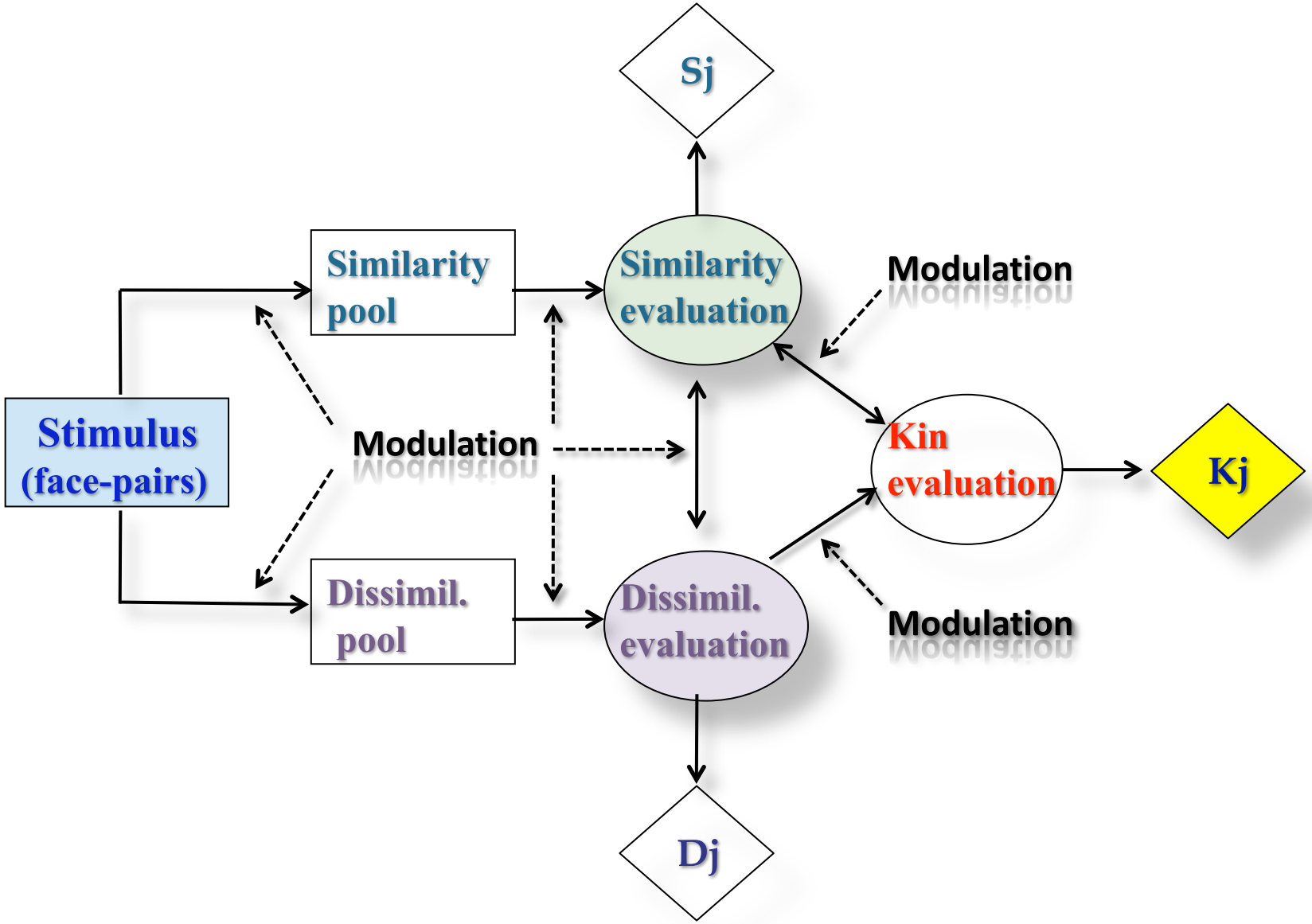
- Our past study on this topic (Lorusso et al., *Perception* 2011) investigates the possibility that a **judgment of kinship may not be just a judgment of similarity** and that different strategies may be involved in those judgments modulated by the ***task***, ***relations*** between concepts, and different ***stimulus contexts***.

Lorusso L., Brelstaff G., Brodo L., Lagorio A., Grosso E., "Visual judgments of kinship: an alternative perspective", *Perception* 40(11):1282-9, 2011

The TSO Model Expanded



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APPENDIX 3

INDUSTRY DEPLOYED FACE RECOGNITION SYSTEMS

Commercial FR systems

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From: ***www.face-rec.org***

- 3M/Cogent *(2D + 3D rectification)*
- A4Vision, Inc. *(3D scanner)*
- AcSys Biometrics Corp.
- Animetrics Inc. *(3D shape)*
- Ayonix Inc. *(2D ???)*
- Betaface *(2D + hair & variable features)*
- Cognitec Systems GmbH *(LFA)*
- Crossmatch Tech. *(2D face capture)*
- Cybula Ltd. *(3D shape/2D texture)*
- Face.com *(2D mugshots)*
- DreamMirh Co., Ltd. *(2D ???)*
- Geometrix, Inc. *(3D shape)*
- Iconquest *(2D Fractal-based ???)*
- L-1/Identix Inc. / Safran-Morpho *(2D Templates +LFA)*
- KeeSquare Srl *(2D landmark-based)*
- Luxand *(2D facial landmarks)*
- NeuroTechnology *(2D ???)*
- Omniperception *(2D + Quality measurements)*
- PittPatt/Google *(Hi-Tech algorithms ???)*
- SensibleVision *(2D Template matching ???)*

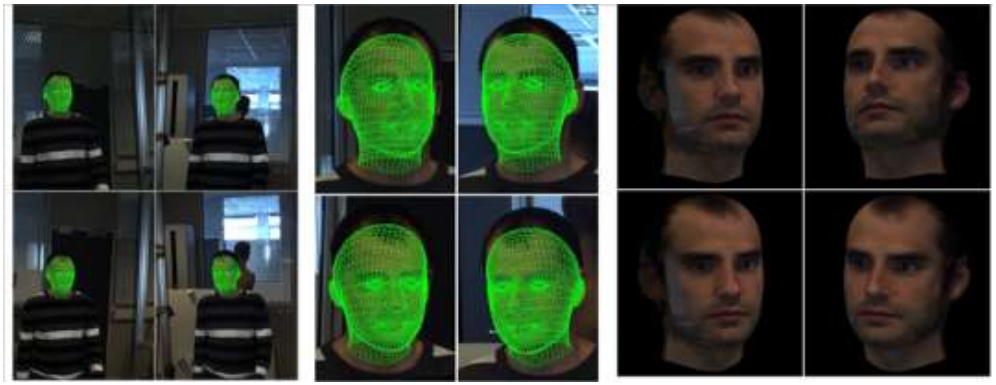
MORPHOWAY V : WORKFLOW

Face detection and tracking

3D pose and shape estimation

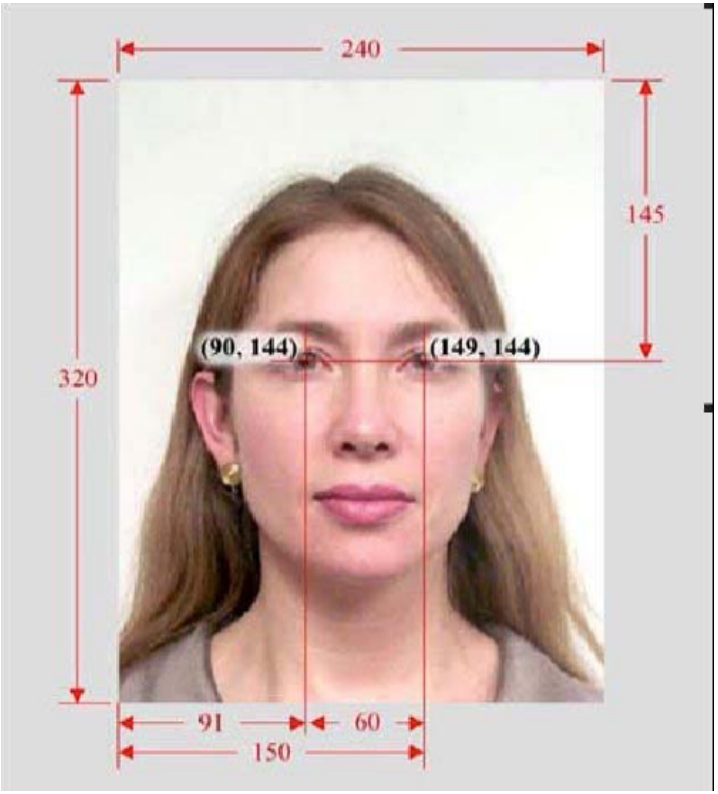
Frontal view synthesis

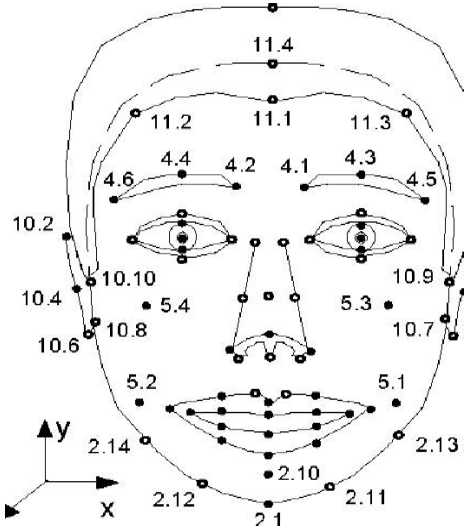
Matching algorithm

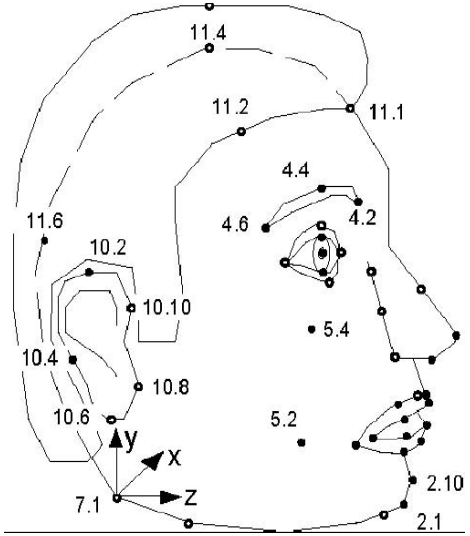


SAFRAN Morpho

The *standard* face







Width(pixels)	Distance from Eye to Eye (Inclusive)
240(min)	**60**
480	120
720	180

Templates and standards

Eurosmart white paper 2003

Figure 2: Biometric Template Size
Source: Frost & Sullivan

Biometric	Bytes Required
Finger-scan	300-1200
Finger geometry	14
Hand geometry	9
Iris recognition	512
Voice verification	1500
Face recognition	500-1000
Signature verification	500-1000
Retina recognition	96

- *It is generally anticipated that any single biometric template would fit within 10 Kbytes of data memory in the storage device (That includes the template itself, the signature or encryption overhead and any additional data required to fulfill the data file structure).*