Face Recognition: Long-Range and Surveillance

(http://www.cs.uccs.edu/~asapkota/fg11/)

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In this tutorial, you will learn about:

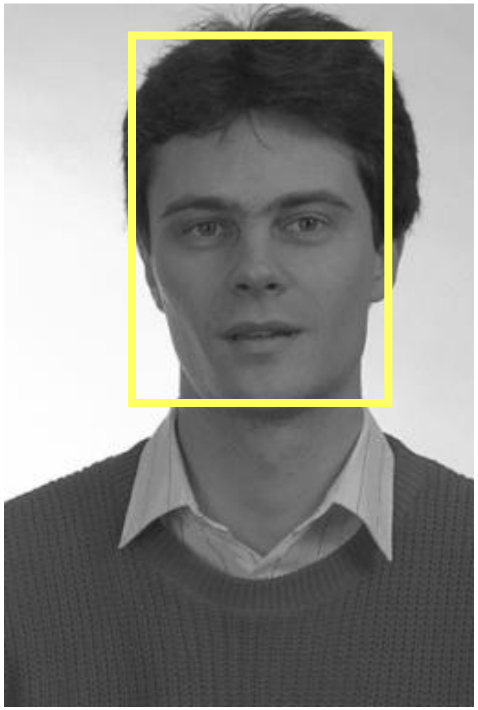
1. Motivating Concerns over Surveillance with Biometrics in Difficult Environments
2. Lighting Considerations
3. Optics Considerations
4. Sensor Considerations
5. Weather and Atmospheric Impacts
6. Data Sets for Evaluations
7. Controlled Experiments for Large Scale Collections
8. Challenges for Image Quality Assessment
9. Advanced Feature Detection
10. Mitigating the Effect of Blur

In this tutorial, you will learn about:

11. Features for Recognition
12. 3D Approaches
13. Video Based Approaches
14. Pose & Occlusion Invariance
15. Biologically Inspired Methods
16. Image Quality
17. Meta-Recognition for Post Recognition Score Analysis

Motivating Concerns

Motivating Concerns



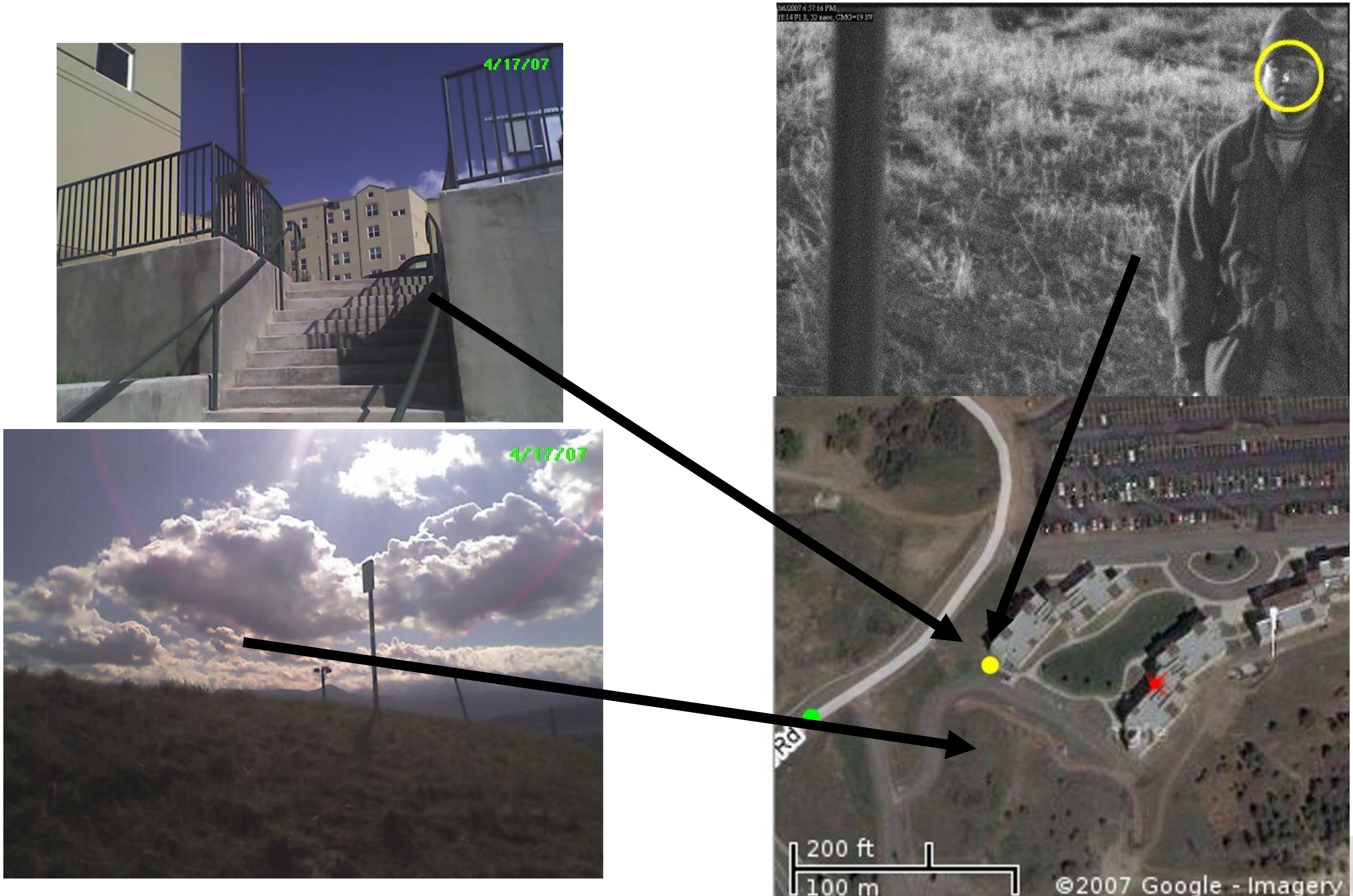
Cooperative Face

- Controlled pose
- Controlled position
- Controlled lighting

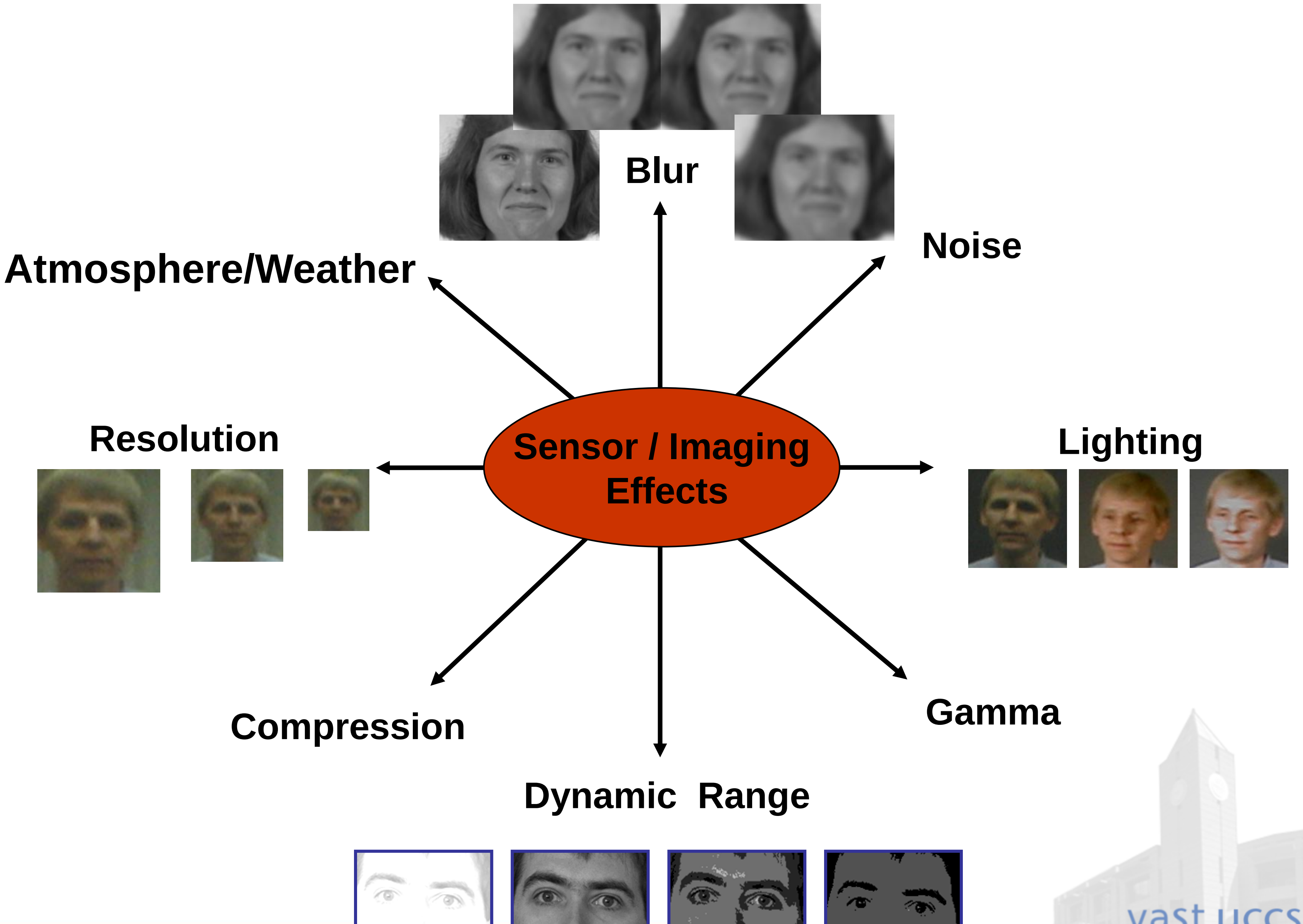
Non-Cooperative Face

- No control over subject
- Outdoors?
- Nighttime?

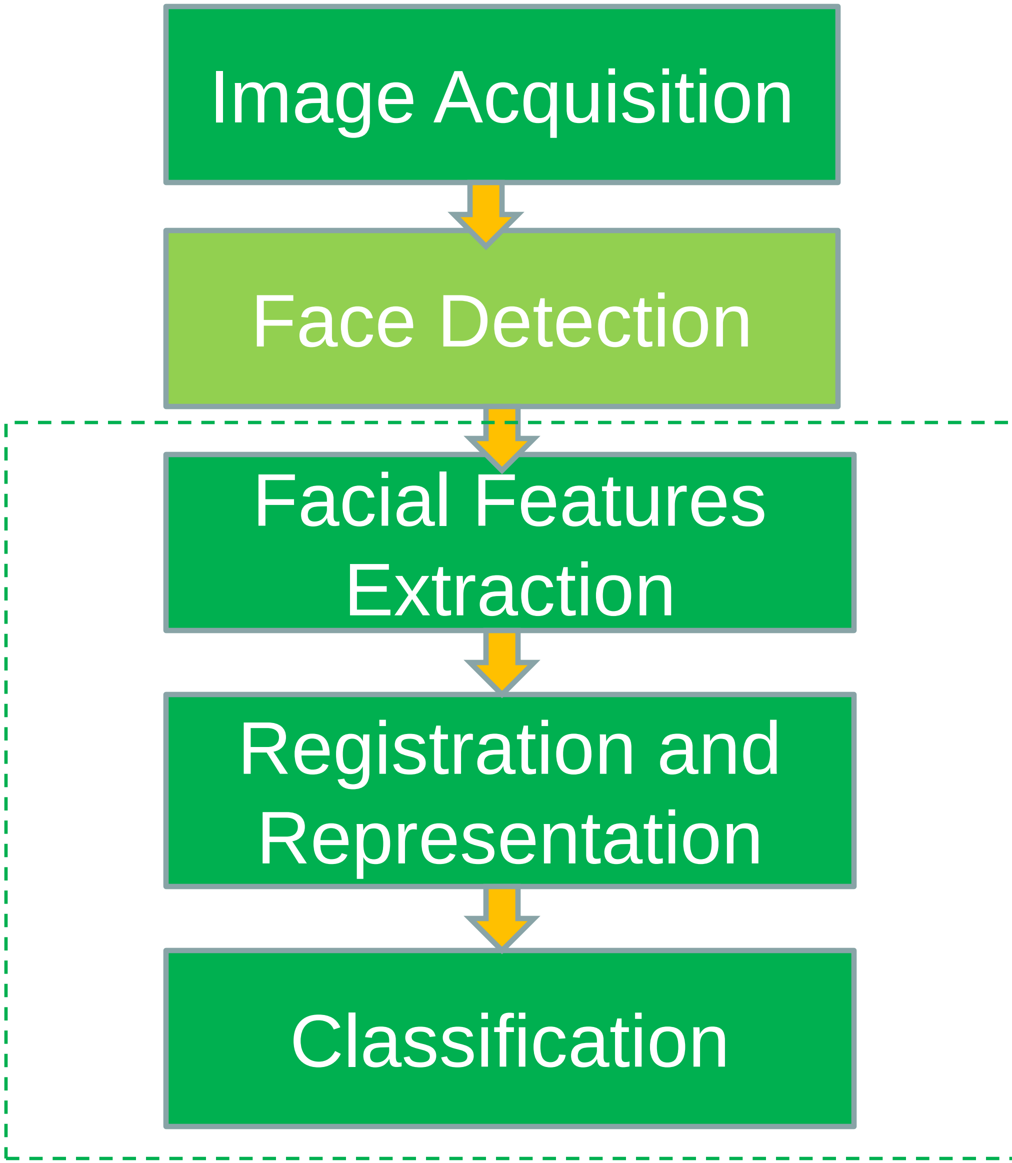
Motivating Concerns



Motivating Concerns



Face Recognition System



Face Recognition in our daily life

- Google’s picasa
- Apples iPhoto
- Facebook Face Recognition
- Windows Live Photo gallery
- Lots of face recognition login software
- Face recognition mobile apps

How is surveillance different?

Face Recognition Biometrics Deployments

Project Description	Location	Vendor	Vertical Sector	Horizontal Application	Application Description	Additional Description
Manchester, NH Viisage	US-NH	Viisage	Travel and Transportation	Surveillance/ Screening	Screening	4th US airport to adopt solution
Cognitec 'SmartGate' Sydney Airport	Australia	Cognitec	Travel and Transportation	Phys Acc/T&A	Physical Access	6k Qantas aircrew, based on passport read
Virginia Beach Surveillance	US-VA	Identix	Law Enforcement	Criminal ID	Surveillance	600 image database, 10 subjects, alarm rate met with deployer approval
Berlin Airport	Germany	ZN	Travel and Transportation	Phys Acc/T&A	Physical Access	Face recognition terminal; template stored on SC
Diversity Visa Program	US-MA	Viisage	Government	Civil ID	Immig ID	Image first entered into system at time of green card registration to prevent duplicate apps, later used for security screening
CO DL	US-CO	Identix	Government	Civil ID	DL	duplicate enrollment detection
Zurich Airport Face	Switzerland	C-VIS	Travel and Transportation	Surveillance/ Screening	Screening	Zurich Airport Police running system; targeting illegal immigrants from W. Africa, M.East and Asia
City of Brentwood Police Dept.	US-CA	Imagis	Law Enforcement	Criminal ID	Forensic	ID-2000 and CABS system integrated into the Records Management System (RMS) of Data911

http://www.biometricsinfo.org/facerecognition.htm

Face Recognition Vendors

Face Recognition SDK Vendors

- Animetrics Inc.
- Ayonix, Inc.
- Betaface.com
- Cognitec Systems GmbH
- Cross Match Technologies, Inc.
- Cybula Ltd.
- Face.com
- L-1 Identity Solutions, Inc.
- Luxand, Inc.
- Neurotechnologija
- OmniPerception, Ltd.
- Pittsburgh Pattern Recognition
- Sensible Vision, Inc.

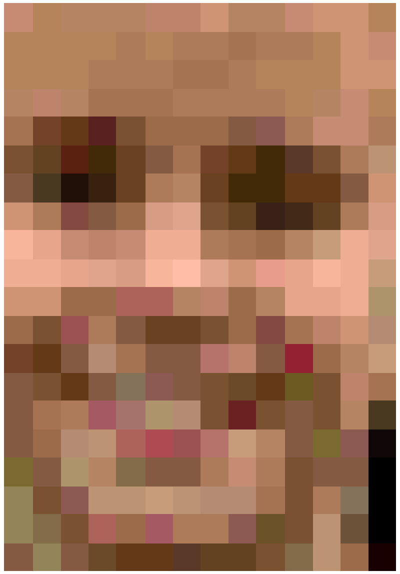
Face Recognition Application Vendors

- Airborne Biometrics Group, Inc.
- Avalon Biometrics
- Csystems Advanced Biometrics
- Face.com developers
- ID One, Inc.
- IITS, S.L.
- Kee Square S.r.l.
- Morpho
- TAB Systems
- XID Technologies Pte Ltd.

http://www.facerec.org/vendors/

Data Complexity

How many pixels are needed to reliably perceive a face? (Human Perspective?)



... Not many ... *(20x14)*

It's more a question of <u>spatial distribution</u> and …

proper <u>frequency tuning</u>

*Massimo Tistarelli, Advanced Techniques for Face Based Biometrics, June 2009

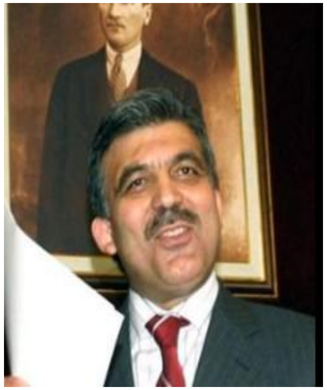
The classification problem

- Intra Class and Inter Class variations

Intra- Class Variation

Same people might appear different=> Leads to false Reject

Two different might appear same=> Leads to false Accept



Inter-Class Variation

Measures and Tools

The hardest problem is the asymmetric aspect of the problem ....

Suppose a security system that detects threatening individuals is 99.99% accurate. That is, if someone is a threat, there is a 99.99% chance that the software indicates threat," and if someone is not a threat, there is a 99.99% chance that the software indicates “non-threat.”

Assume that 1 in every 100 million border crossings brings a serious threat into the US. (i.e. 5 “terrorists” enter the US per year)

Would it be an effective security system to deploy?

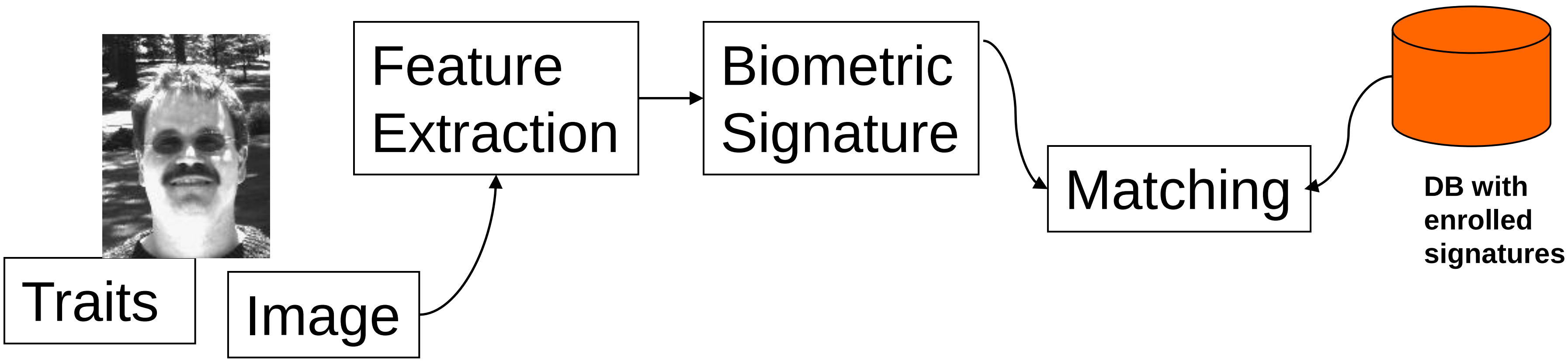
Measures and Tools

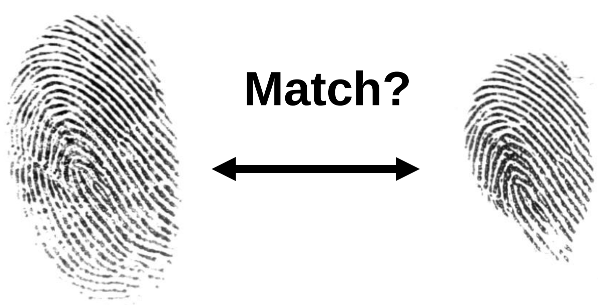
Probably not effective. These parameters will generate 10000 false alarms for every 1 real threat. That is 30 times a day, every day. And every false alarm means that all the security people go through all of their security procedures. How many false alarm before they stop taking it seriously?

Because the population of non-terrorists is so much larger than the population of "terrorists", the test is practically useless as active security. Its only real value is as a deterrent.

And of course we don't have a biometric list for most threats, let alone one that is 99.99% accurate

Measures and Terminology





Similar images, different features

PCA: 19.1, 4.7, –2.8 PCA: 18.9 4.8 –2.7

For biometrics, we need inexact matching, thresholding on a “distance” between signatures/features.

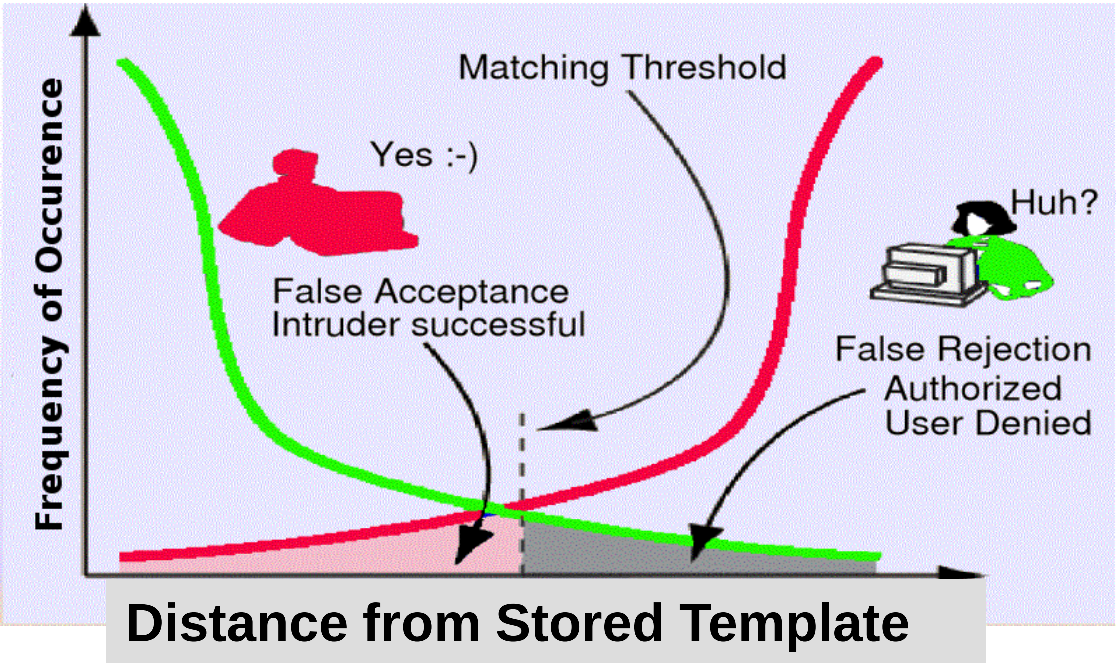
Accuracy Tradeoff

Inter-subject variations from different people and intruder attacks

Intra-subject variations from normal behavior (e.g. head pose, finger pressure, etc.)

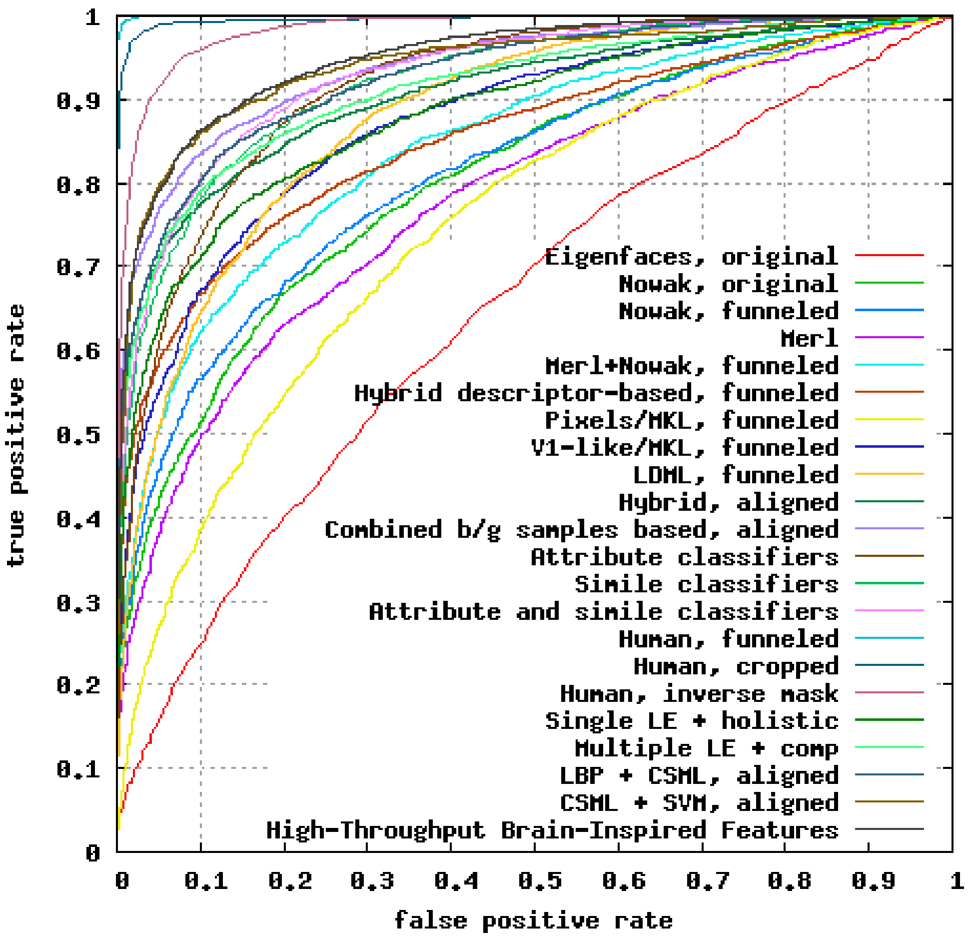
FAR = False Accept Rate=accept wrong person
FRR=False Reject Rate = doesn't accept a user as themselves

Security= low **F**alse **A**ccept **R**ate



Usability= low **F**alse **R**eject **R**ate

Accuracy Tradeoff



Probability that a person’s claim of identity is verified, showing tradeoff between False Reject and False Accept rate. This is a Verification ROC (Data from LFW Test)

Accuracy Trade-Offs

- Lower FAR = Fewer successful attacks and increased FRR
  - Less tolerant of close matches by attackers; also less tolerant of authentic matches
- Lower FRR = Ease of use and increased FAR
  - Recognizes a legitimate user the first time; more tolerant of poor matches but also more tolerant of matches by attackers
- Also important to consider Failure to Enroll (FTE) and Failure to Acquire (FTA), as the system cannot handle people it cannot enroll or data it cannot acquire. Often companies use these to “boost performance” since they remove hard cases.

Measurement Terms

- False Accept Rate, False Match Rate, True accept Rate, Genuine Accept Rate

$$FMR = FAR = 1\text{-}TAR = 1\text{-}GAR \; .$$

- False Reject Rate, False Non-Match Rate

$$FRR \neq FNMR$$

- Detection and Identification Rate (DIR)
- Failure to Enroll
- Failure to Acquire (or Failure to Capture)

Measurement Terms

- Receiver Operator Characteristic Curve (ROC)Curve (TAR vs FAR, FRR vs FAR or DIR vs FAR)
- Detection Error Tradeoff Curve (Similar to ROC but log or semi-log)
- Cumulative Match Curve (CMC) (for closed-world recognition system)
- Precision/Recall Curves

Accuracy Trade-Offs

FAR = False Accept Rate

FRR = False Reject Rate

FTE = Failure To Enroll

Biometric	FAR	FNMR	FTE
Face	1.00%	1%	0.1%
	0.10%	2%	0.1%
1-Finger	1.00%	0.01%	2.5%
	0.01%	0.6%	2.5%
2-Finger	1.00%	0.01%	1.5%
	0.01%	0.1%	1.5%
4-Finger	0.10%	0.01%	0.8%
	0.01%	<0.01%	0.8%
10-Finger	0.10%	<0.01%	0.2%
	<0.01%	0.01%	0.2%
1-Iris	0.10%	1.2%	2.5%
	0.01%	1.5%	2.5%
	0.001%	1.9%	2.5%
	0.0001%	2.0%	2.5%
2-Iris	0.10%	0.5%	4%
	0.01%	0.6%	4%
	0.001%	0.8%	2.5%
	0.0001%	1.2%	2.5%

Face has a low FTE but high non-match rate when pushed to FAR of .1%

Fingerprints achieve good accuracy and low FTE only when multiple fingers are enrolled

Iris has a high FTE rate with up to 2.25 Million in a 45 Million person population, but given that an extremely low False Accept rate

Measurement Trade-Off Impacts

How well do biometrics work?

Verification

	False Reject	False Accept
Fingerprint*	20-60 in 1000	1 in 1000
Face**	100-350 in 1000	10 in 1000
Voice***	100-200 in 1000	20-50 in 1000
Hand****	80-200 in 1000	50-150 in 1000

*Source: NIST Single fingerSDK test, top 10 vendor, April 2005, n=6000

**Source: FRVT 2002, NIST, n=35K indoor/visa images, Top 5 vendor results

***Source: Speaker ’99, NIST, n=233, telephone quality, best vendor results

****Source Kumar-et-al AVBPA n=500 in **Verification mode only**

Measurement Trade-Offs

Issue 1: Biometric Verification – Why does it reject me?

Large throughput volume is a problem.

- **Example**: <frequent flyer smart card with face image>
- Assume a system where each person is 1-1 verified to a smartcard or a networked database with 5000 people per hour (14hr/day) requesting access
  (Newark airport hourly passenger volume):

  100-400 people per hour will fail to be verified

  1400-4200 people per day will fail to be verified

Strong impetus to run at lower security than a .001 FAR

Measurement Trade-Offs

How often do biometrics match the wrong person on watch list?

	False Reject	False Accept
Fingerprint*	20-60 in 1000	1 in 1000
Face**	100-350 in 1000	10 in 1000
Voice***	100-200 in 1000	20-50 in 1000

*Source: NIST Single fingerSDK test, top 10 vendor , April 2005 n=6000

**Source: FRVT 2002, NIST, n=35K indoor/visa images , Top 5 vendor results

***Source: Speaker '99, NIST, n=233, telephone quality, best vendor results

Measurement Trade-Offs

Issue 2: Biometric (Mis)Identification – Why am I delayed as a "suspect"?

Large watchlists exasperate the problem.

Example: <face check vs. government database>

- Assume a system that checks each person's face against a watch-list database of 1,000 suspects. Assume Newark Airport: 5,000 people per hour/14hr day

  Over *70,000 false matches will occur per day from 1K watchlist:*

  Let's say individual chance of match is roughly 1 per 1,000;

  *5,000 * 14 = 70,000 people*

  *70,000 * 1,000 = 70,000,000 match attempts*

  *0.001 * 70,000,000 = 70,000 false matches!*

- What happens with a watchlist of 10K people? (Note: current US TSC TSDB list is > 450K)

Measurement Trade-Offs

Issue 3: Biometric Identification – "**Who can I be today"**

Stored biometric databases are a security problem.

Example 3: <face check vs. government database>

- A group somehow gains access to a large face database, and starts looking for someone their "gang" can use to steal an identity.
- With a face match at high accuracy levels (FAR=.1%) a single face will match .001 * 6,000,000 = 6,000 people in the DC area. With a "gang" of 10 or 100 what can they do?
- Since biometric databases often contain lots of other info (for example, CO DMV records have fingerprint, photo and all driving information), the gang would have strong potential to find the ideal new identity.

Measurement Trade-Offs

Why this puts biometric databases at risk:

Imagine… Alice uses her biometric for access to the local public library system, which by 2009 has 1.2 Million users.

In 2012, the library's computers are compromised. The attackers, who are part of an organized crime syndicate, add it to their database of over 5 million identity records with biometric data increasing the value of their "identity theft" service - providing a new identity where the purchaser's own biometrics will match.

With systems operating at FAR of 1 in 1000 a buyer may be given a choice from approximately 5000 identities! At 1 in million, they still get 5 choices!

We call this the doppelganger attack, and it's a security concern many overlook.

Measurement Trade-Offs

False Matches During Duplicate Checks Require Additional Processing.

Number of False Hits ***Per Search (i.e. each person being checked)***

FAR	50 Million	500 Million
1%	500,000	5M
0.1%	50,000	500,000
0.01%	5,000	50,000
0.001%	500	5,000
0.0001%	50	500

Total of *false matches* that must be resolved in determining if there are any duplicates

FAR	50 Million	500 Million
1%	25Trillion	25000Trillon
0.1%	2.5Trillion	2500Tillion
0.01%	250Billion	250Trillion
0.001%	25Billon	2.5Trillion
0.0001%	2.5Billion	250Billion

Two ways to address these false hits are:

- **Manually? (Note:** 2.5 Billion minutes is about 4750 years!)
- ***Automatically use another biometric and hope to reduce FAR significantly***

Types of Biometric Problems

- We differentiate between biometrics for:
  - Cooperative applications: user convenience or limited security (e.g. login) and
  - Security applications that address fraud and national issues (e.g. borders, welfare card).
- For personal applications, users want to make it work, for security applications some want to make it fail.
- For security applications you must consider what is your adversary's motivation, and what they can do to defeat the system.

Types of Biometric Problems

- Types of Biometric “subjects”
  - Cooperative: aware of system and trying to make the system work
  - Non-cooperative: not trying to help, or break the system - generally unaware of system being used.
  - Adversarial (Uncooperative): aware of the system and trying to defeat it.
  - Challenged: Probably trying to be cooperative but with physical/mental challenges.

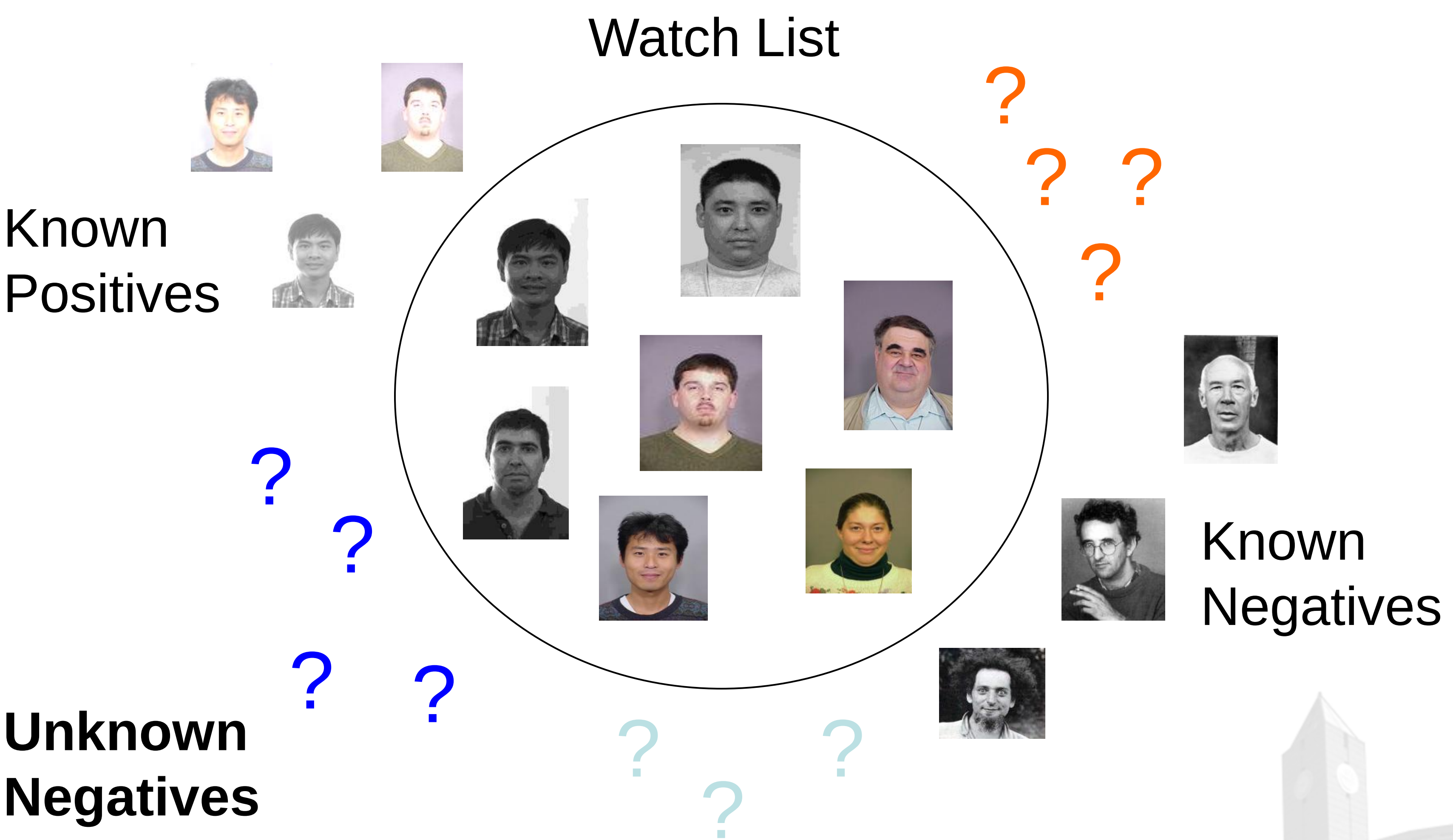
Traditional Biometric Testing

Known Positives

Watch List

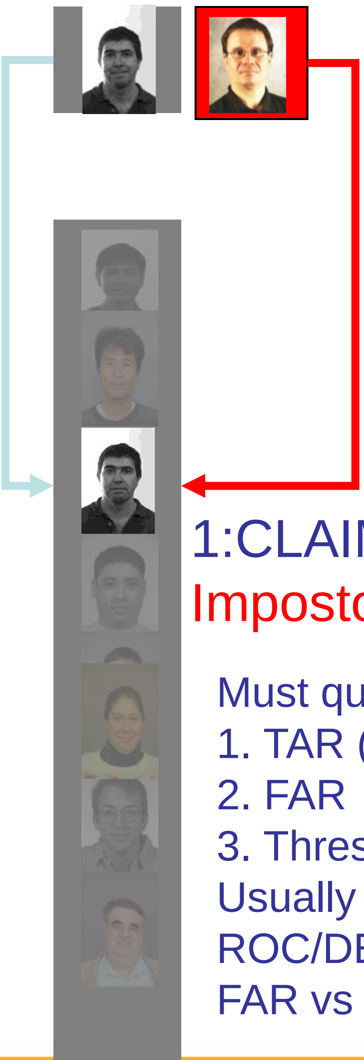
Known Negatives

The Open Set World



Types of Biometric Problems

Verification or Authentication 1:1 (Closed)



1:CLAIM
Impostor

Must quote:
1. TAR (FRR)
2. FAR
3. Thresholds

Usually show ROC/DET FAR vs FRR

Identification or Recognition 1:N Closed Set

Gallery Of Enrolled Users. Size G=8

Rank=3

Must quote:
1. Ident. Rate
2. Gallery Size
3. Rank

Usually show CMC with FRR vs Rank

Watchlist De-duplication Open Set 1:N

1:ANY
Impostor

Must quote:
1. Detect/Ident. Rate
2. FAR
3. Gallery Size
4. Rank/Thresholds

Usually show ROC/DET of FAR vs DIR

Types of Biometric Problems

- Watch-list of Open-set 1:*N*
  - Common mode for most security applications, including Border and passport, and is probably the most important to Governments
  - Is a hard problem for large *N* with cooperating subjects. Very hard with adversial subjects.
  - Performance on this problem is not frequently reported.
  - 1:*N* is not successfully modeled.

Addressing the Problem of Unknown Negatives*

- A probe p_j is recognized if the correct match score is above an operating threshold τ
  - $\mathrm{Rank}(p_j) = 1$
  - $\mathrm{s}_{*j} \geq \tau$ for the similarity match where $\mathrm{id}(p_j) = \mathrm{id}(g^*)$
- A false alarm occurs when the top match score for an impostor is above the operating threshold
  - $\max s_{ij} \geq \tau$

*P. Phillips, P. Grother, R. Micheals, "Evaluation Methods in Face Recognition," 2005.

Acquisition Considerations

Lighting Considerations

- How much light, and how to measure it?
  - Illuminance vs luminance
    - Illuminance (lux) varies significantly across the population, is impacted by directional reflection, and, in general, can only be measured to .01lux
    - Luminance (candela per m^2, or nit) describes the "brightness" of the source, and does not vary with distance

Lighting Considerations

A different approach to measuring luminance:

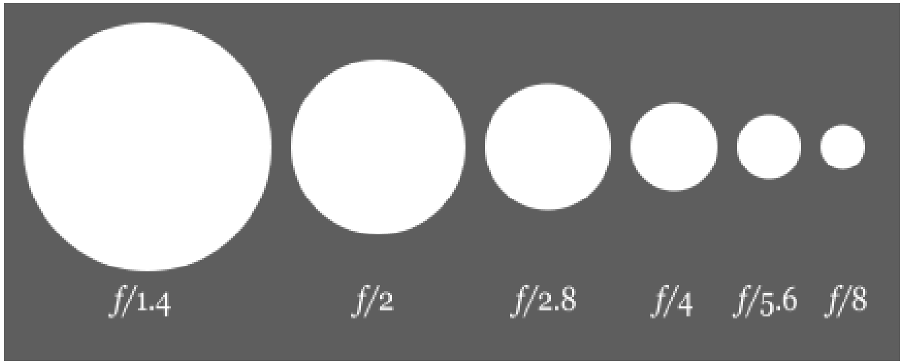
• "Sky Quality" meter - measurements in Magnitudes/arcsecond.

Conversion to nits: $\frac{cd}{m^2} = 108000 \times 10^{-0.4*s}$

s is value produced by sky quality meter

Lighting Considerations

- Low levels of light aren't just a problem at night!
  - Long-range face needs very long focal lengths, often in the 800-3200mm range
  - Combining distance with optical limits results in high F-numbers (diameter of the entrance pupil)
    - Each F-number represents a 50% loss of light



Decreasing Apertures

Lighting Considerations

0.089 nits 0.0768 nits 0.015 nits

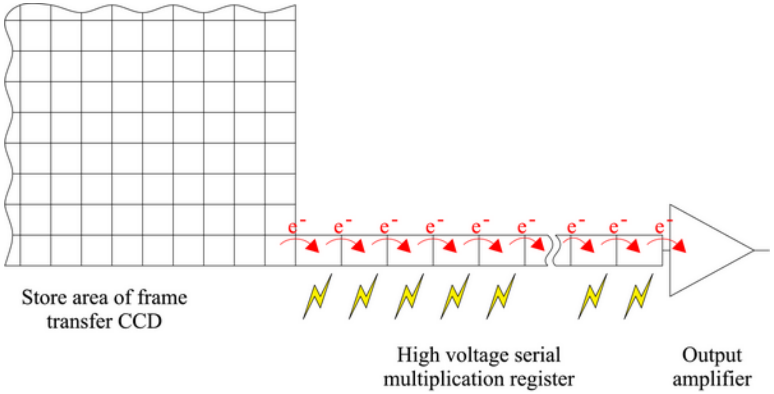
- Images from TC-285 EMCCD
- No external illumination required

Normal GenIII+ Intensifier LWIR Thermal

- LWIR lacks necessary resolution at long distances
- LWIR requires special enrollment

EMCCD Technology

- Sensor can operate from full sunlight down to starlight conditions
- How does it work?
  - Gain register is placed between the shift register and the output amplifier
  - Electrons are multiplied by impact ionization
  - Overall gain can be quite high, with a single electron yielding thousands of output electrons



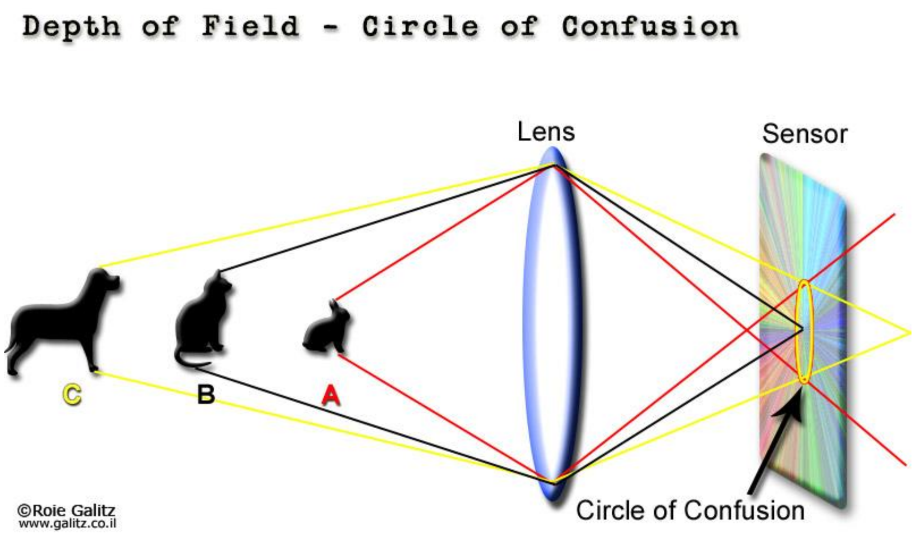
EMCCD at Quarter Moonlight Conditions

Sensor/Optics Considerations

- *Effective* resolution is more than just the number of pixels
- Modulation Transfer Function
  - Accounts for blur and contrast loss
  - Optical MTF x Sensor Geometry MTF x Diffusion MTF
  - MTF values above 0.6 are considered satisfactory
- Examples
  - Canon EF 400mm f2.8 IS USM: MTF above 9.0 over the whole field of view
  - Same setup with Canon 2xII extender: MTF above 7.0

Lens Considerations

- The ability of a lens to resolve detail is usually determined by the quality of the lens
  - High quality lenses are diffraction limited
  - If a lens is not diffraction limited, artifacts can occur



• Different rays leaving a single scene point do not arrive at single point on the sensor

• Ideally, the circle of confusion will be smaller than a sensor pixel

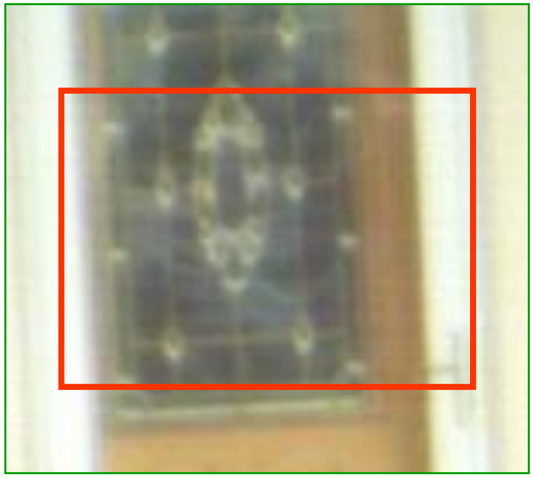
Optics / Sensor Matching

- Lenses are multiple-element multi-coated designs optimized for particular sensors and wavelengths
  - Watch out for vignetting, spatially varying blur, and color “fringe” artifacts

Sensor Considerations

Maximum FOV for face recognition is INDEPENDENT of distance.

2048x1520
Usable 1888x1320
5.85’ x 4.3’
1.65 sec cross time



1280x1024
Usable 1120x824
3.6’ x 2.6’, 1.03 sec

640x480
480x280
1.5’ x 0.9’
.35 sec

320x240
160x40
0.5’ x .1’
0.05 sec

Sensor Considerations

Depth of Field

- Depth of Field (DOF) defines the ranges around the focus distance where the subject will be in sharp focus

- DOF increases with decreasing lens aperture and decreases with focal length

Depth of Field

Front depth of field = $$\frac{d * F * a^2}{f^2 + d * F * a}$$

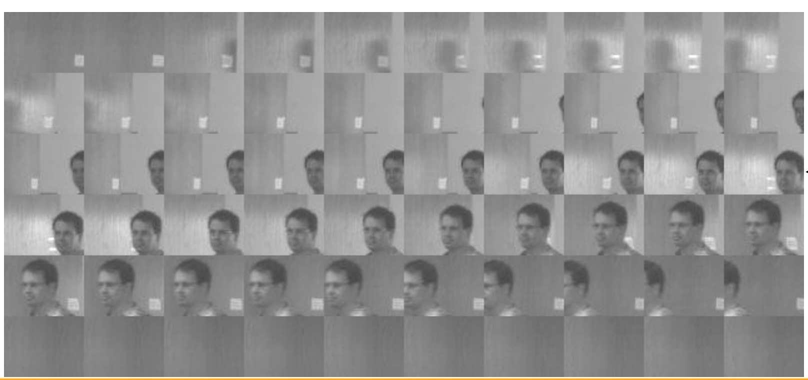
Rear depth of field = $$\frac{d * F * a^2}{f^2 - d * F * a}$$

where f is the focal length, F is the F-number, d is the diameter of the circle of confusion, and a is the subject distance

Sensor Considerations

1280

Choke-Point FOV and timing



640

320

Building a System

Sensor Considerations

Typical motion blur

(~0.4 lux, yielding face lumens of 0.115 nits)

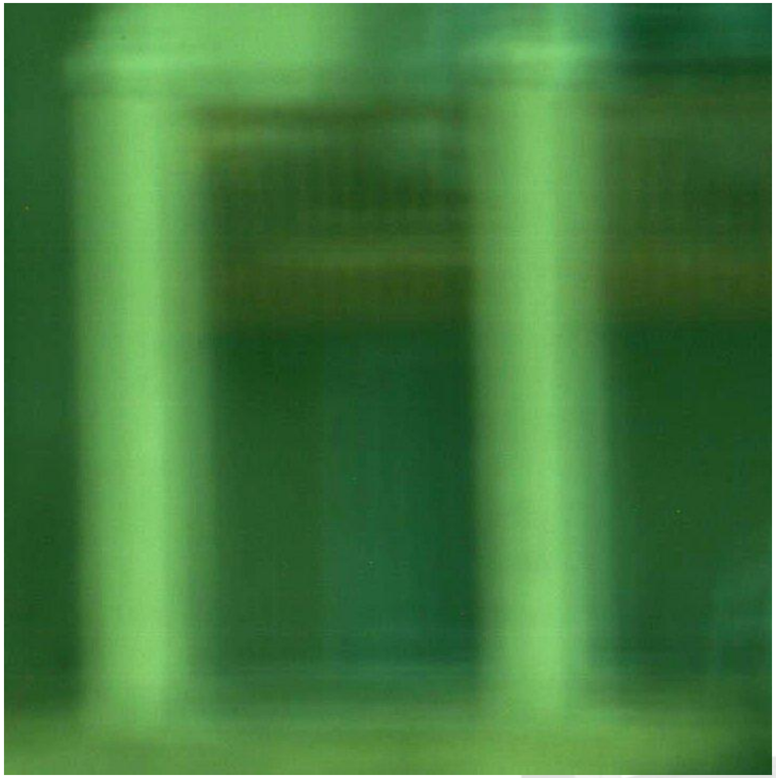
- Images taken approximately 100M from the EMCCD camera at dusk
- Top of the walking stride produces minimal blur

Sensor Considerations

On stable mount we can get sufficient image quality.
Small vibrations can cause significant blurring.

Imaging at 800m F8,
no motion around camera
All images are 700x720 region from 2048x1520

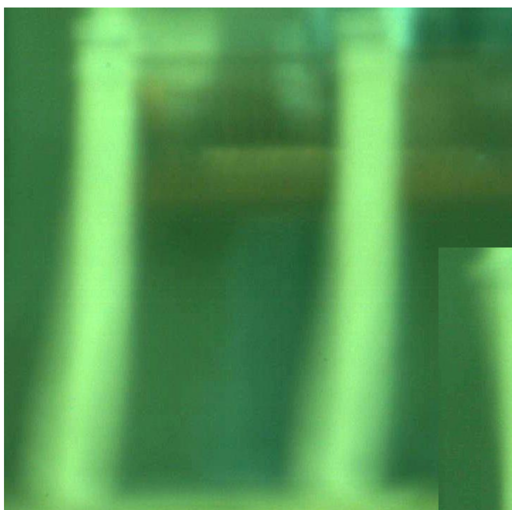
Imaging at 800m F8,
Walking near tripod

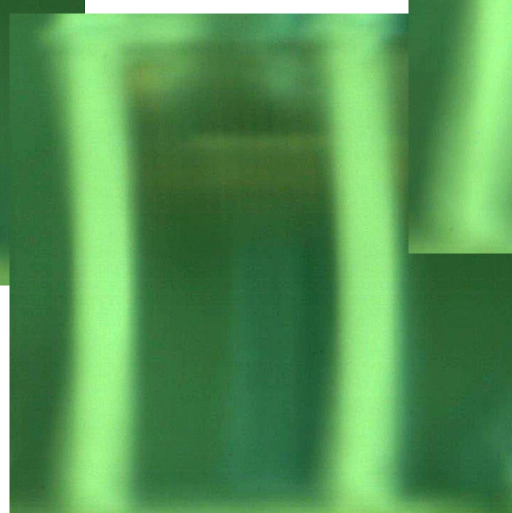


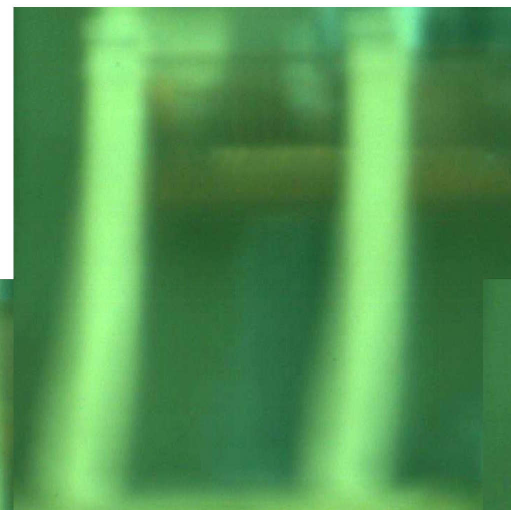
Sensor Considerations

Walking around tripod sometimes caused very significant non-linear distortions, especially with aperture wide open. Concern is that wind-loading on field-mounted sensor would have similar effect.

Results show we need optically stabilized imager for these ranges as even tripod mounting was not always stable enough.

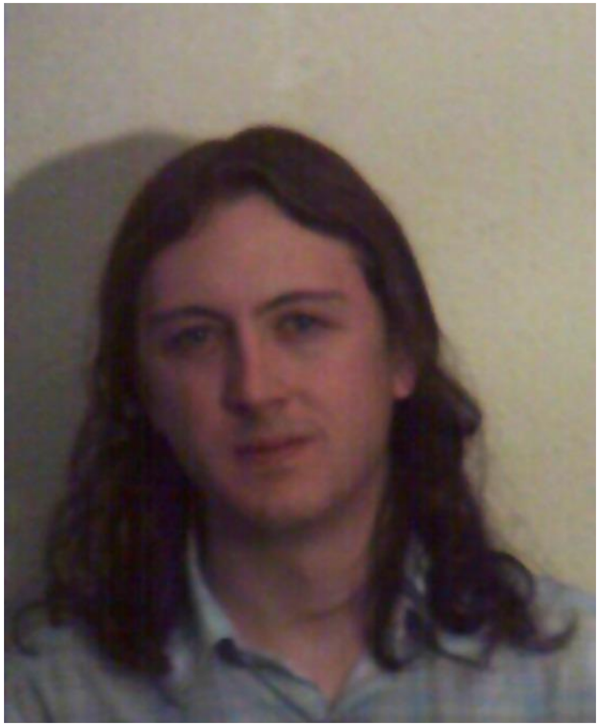






Imaging at 800m F5.6. Heavy walking near tripod

Sensor Considerations



- Rolling Shutter motion artifacts affect CMOS sensors
- Even with a short integration time, the shutter is capturing data at different times for the top and bottom of the images

Rolling Shutter

- Prevalent with Low-Cost CMOS sensors
- Each frame is acquired by scanning across the frame either vertically or horizontally
  - Not all parts of the image are recorded at exactly the same time

Mitigating the Effects of Rolling Shutter

- Baker et al. 2010*
  - Compute optical flow, compute corrected video without the non-rigid wobble artifacts, then stabilize

*S. Baker, E. Bennett, S. Kang, and R. Szeliski, "Removing Rolling Shutter Wobble," CVPR 2010.

Mitigating the Effects of Rolling Shutter

- Forssen and Ringaby 2010*
  - Parameterize camera motion as a continuous curve, with knots at the last row of each frame. Solve for curve parameters using non-linear least squares over inter-frame correspondences from a KLT tracker

Original Frame from iPhone 3GS

Rectified Image

Rectification with Global Affine Method

Rectification with Global Shift Method

P. Forssen and E. Ringaby, "Rectifying Rolling Shutter Video from Hand-held Devices," CVPR 2010.

How well do these techniques work for face recognition?

An Open Question…

ROLLING SHUTTER SENSOR DISTORTION MODEL

- Assume constant velocity, shear transformation parallel to the x-axis

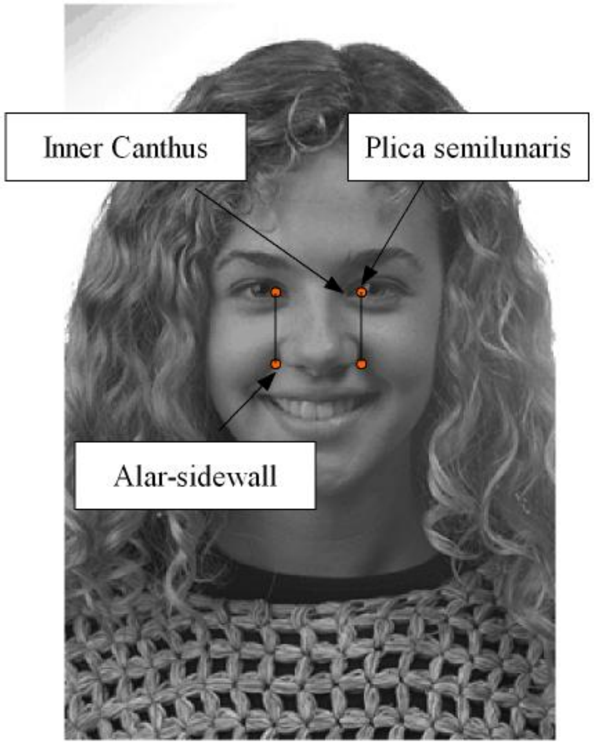
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & k \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \qquad \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & -k \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x' \\ y' \end{bmatrix}$$

Skewed Image

Recovered Image

$$k = shearing\ parameter$$

ROLLING SHUTTER DISTORTION COMPENSATION



$$k = x_{displacement(pt1\&pt2)} / y_{difference(pt1\&pt2)}$$

*B. Heflin, W. Scheirer and T. Boult, “Correcting Rolling-Shutter Distortion of CMOS Sensors using Facial Feature Detection,”

- Determine the shearing parameter (k), and then apply an affine transformation to the image to remove the image distortion from the image.

- Our approach* is based on using the coordinates of specific facial features and then determining the horizontal geometric distortion based on the average offset between these points on both sides of the face.

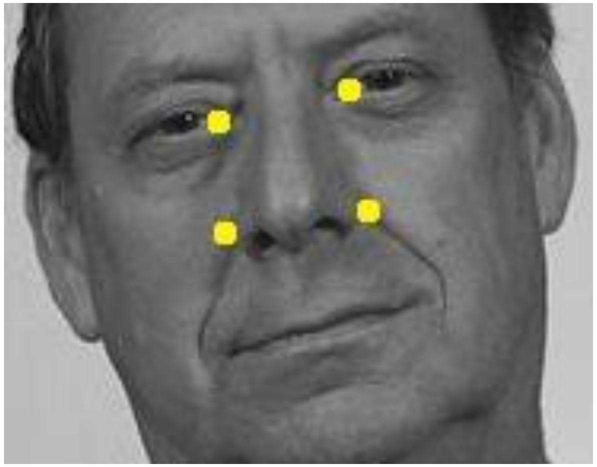
- The 1st feature point we have chosen is the x; y coordinates of the center of the eye slightly offset to in-between the **Plica semilunaris** and the **Inner Canthus** of the eye.

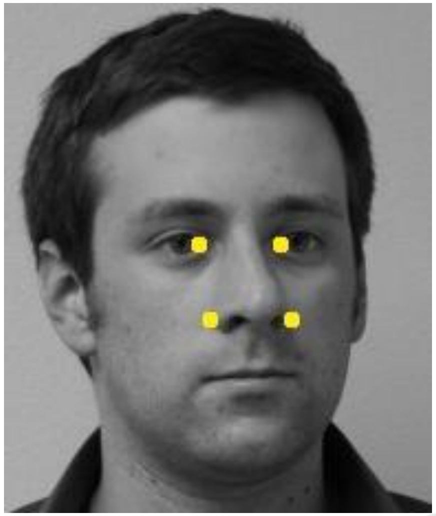
- The 2nd feature point is slightly offset from **Nostril** to the **Alar-sidewall** located on the side of the nose.

ROLLING SHUTTER DISTORTION COMPENSATION

- Due to the symmetry of the face even when there is some facial roll face the average offset between the two points in an image with no shear distortion is minimal.

- Our algorithm can handle some facial roll and pose variation up to 20 degrees with minimal initial error. Both of the images shown have an initial error of less than 1 pixel.





Qualitative Results

Skewed Image

Recovered Image

Experimental Evaluation

FERET240 subset.

- 3 gallery images per subject for training (720 for multiclass SVM)
- 1 image for testing
- 4 shearing parameters (k)
- V1-Like Features + Multiclass SVM Recognition Algorithm

RANK 1 RECOGNITION RESULTS FOR BASELINE AND ROLLING SHUTTER CORRECTED FERET 240.

k	Raw Images	Corrected Images	Median Estimate (k)
0.14	87.9%	90.7%	0.15
0.20	80.7%	90.8%	0.19
0.33	52.3%	83.8%	0.30
0.40	25.7%	83.6%	0.37

Qualitative Results

Skewed Image

Recovered Image

Experimental Evaluation

- 3 Images in gallery per subject for training (150 samples for multiclass SVM)

- ~100 frames per subject all containing rolling shutter distortion for testing

RANK 1 RECOGNITION RESULTS FOR FRAMES FROM VIDEOS FOR 4 DIFFERENT SUBJECTS. THE GALLERY WAS A SIMULATED SURVEILLANCE WATCHLIST OF 50 SUBJECTS

Subject	Range (K)	Raw Images	Corrected Images
1	0.35-0.54	56%	75%
2	0.19-0.35	59%	69%
3	0.21-0.29	25%	32%
4	0.25-0.32	48%	52%

Data for Evaluation

Face Databases

The appearance of a face is affected by many factors

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

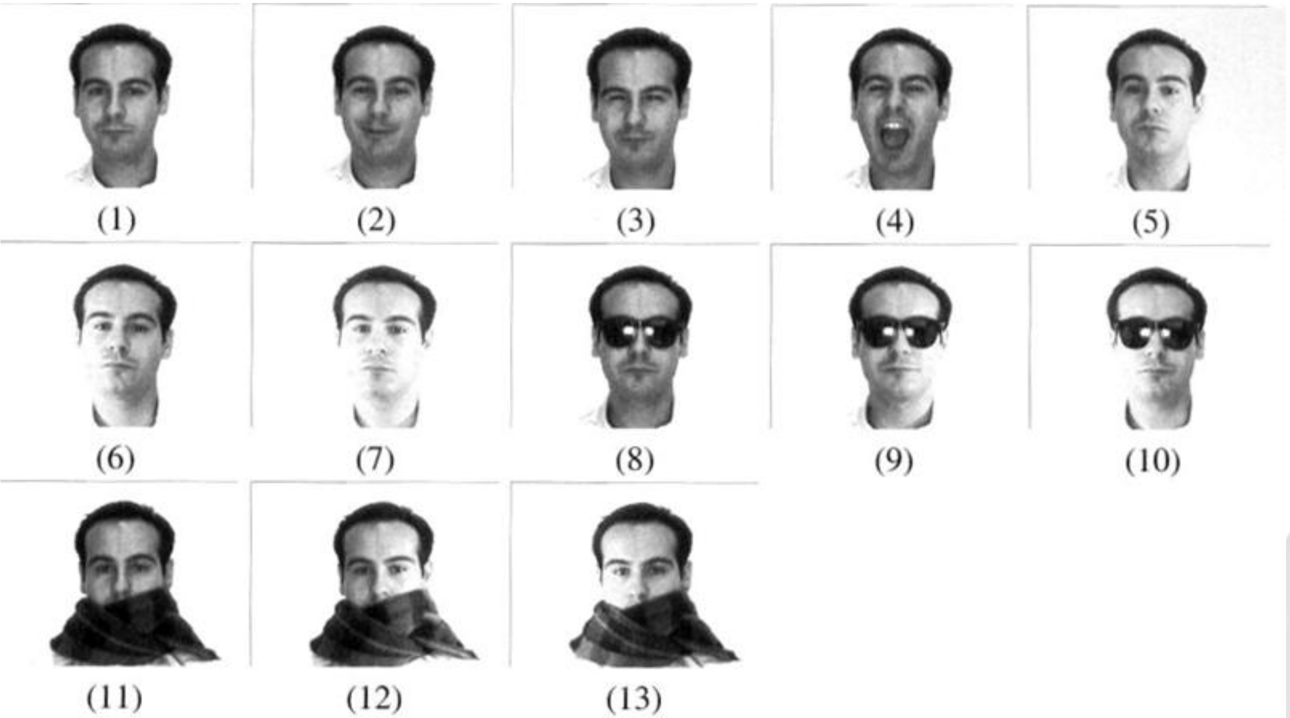
The development of algorithms robust to these variations requires databases of sufficient size that include carefully controlled variations of these factors.

Common databases are necessary to comparatively evaluate algorithms.

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

Face Databases:AR

- 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



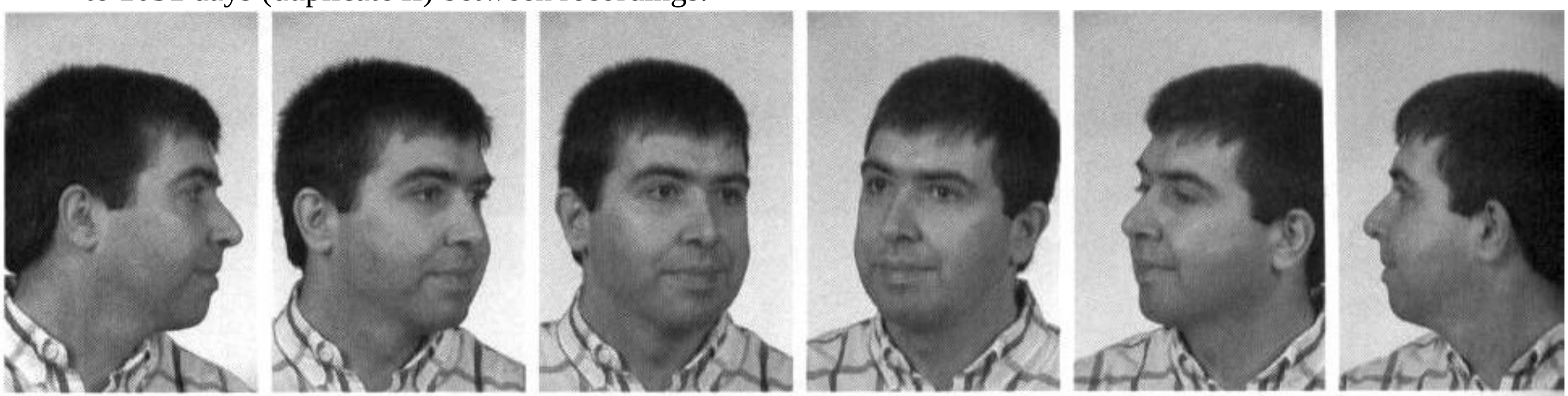
Face Databases: CAS-PEAL

- 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: FERET

fa fb duplicate I fc duplicate II

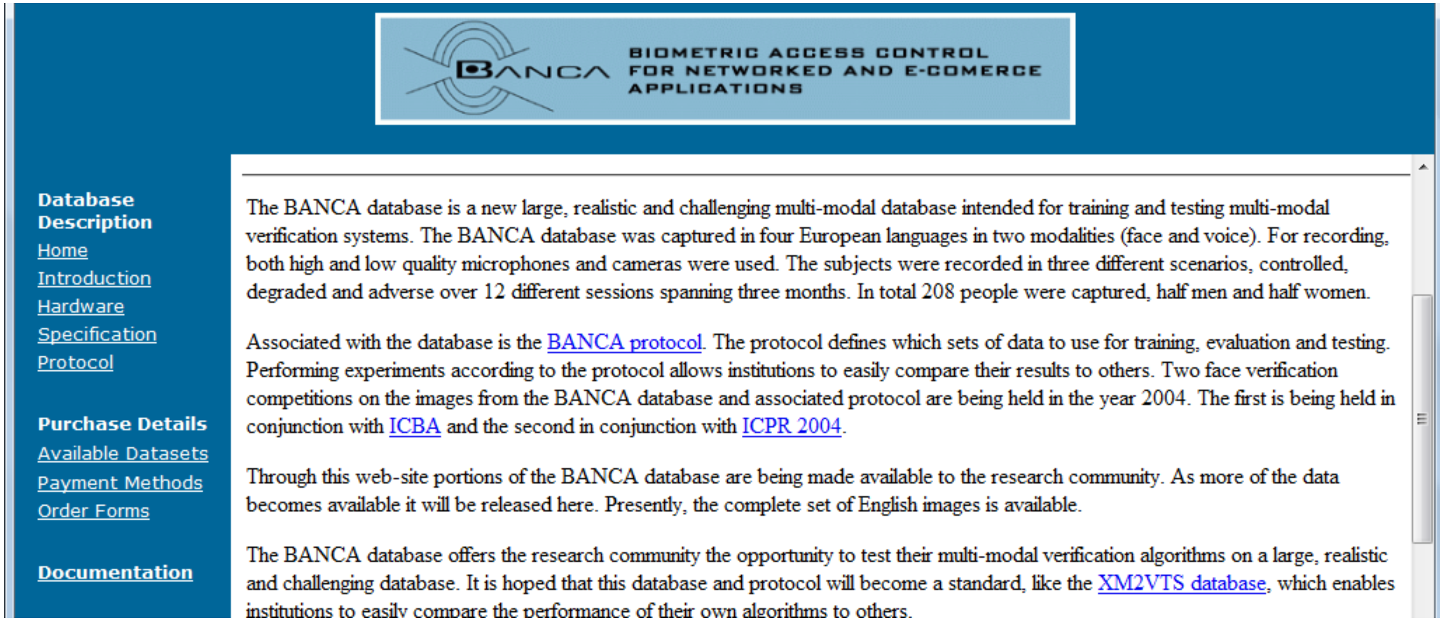
Frontal image categories used in the FERET evaluations. For images in the fb category, a different facial expression was requested. The fc images were recorded with a different camera and under different lighting conditions. The duplicate images were recorded in a later session, with 0 and 1031 days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



pr	hr	qr	ql	hl	pl
$+90°$	$+67.5°$	$+22.5°$	$-22.5°$	$-67.5°$	$-90°$

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: BANCA



BANCA BIOMETRIC ACCESS CONTROL FOR NETWORKED AND E-COMERCE APPLICATIONS

Database Description
Home
Introduction
Hardware
Specification
Protocol

Purchase Details
Available Datasets
Payment Methods
Order Forms

Documentation

The BANCA database is a new large, realistic and challenging multi-modal database intended for training and testing multi-modal verification systems. The BANCA database was captured in four European languages in two modalities (face and voice). For recording, both high and low quality microphones and cameras were used. The subjects were recorded in three different scenarios, controlled, degraded and adverse over 12 different sessions spanning three months. In total 208 people were captured, half men and half women.

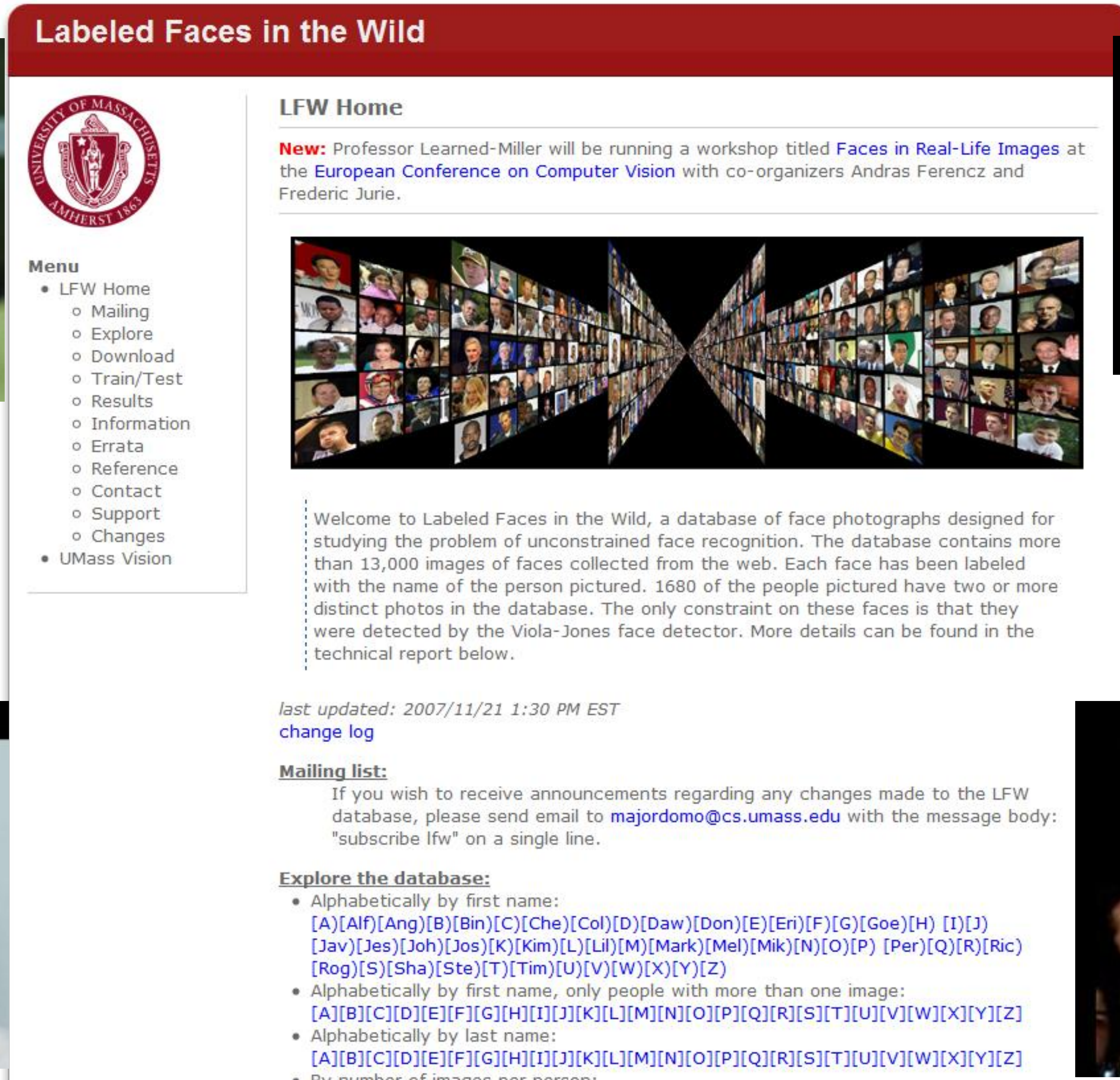
Associated with the database is the BANCA protocol. The protocol defines which sets of data to use for training, evaluation and testing. Performing experiments according to the protocol allows institutions to easily compare their results to others. Two face verification competitions on the images from the BANCA database and associated protocol are being held in the year 2004. The first is being held in conjunction with ICBA and the second in conjunction with ICPR 2004.

Through this web-site portions of the BANCA database are being made available to the research community. As more of the data becomes available it will be released here. Presently, the complete set of English images is available.

The BANCA database offers the research community the opportunity to test their multi-modal verification algorithms on a large, realistic and challenging database. It is hoped that this database and protocol will become a standard, like the XM2VTS database, which enables institutions to easily compare the performance of their own algorithms to others.

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

Labeled Faces in the Wild


Labeled Faces in the Wild

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.

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

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 Database: PubFig

PubFig: Public Figures Face Database

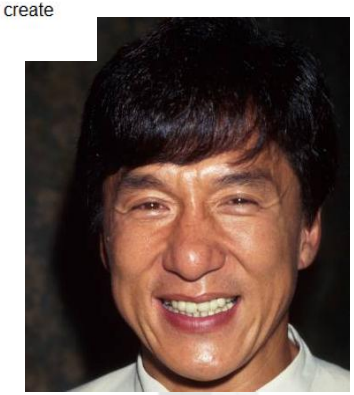
Explore Download Results

Introduction

The PubFig database is a large, real-world face dataset consisting of **58,797** images of **200** people collected from the internet. Unlike most other existing face datasets, these images are taken in completely uncontrolled situations with non-cooperative subjects. Thus, there is large variation in pose, lighting, expression, scene, camera, imaging conditions and parameters, etc. The PubFig dataset is similar in spirit to the Labeled Faces in the Wild (LFW) dataset created at UMass-Amherst, although there are some significant differences in the two:

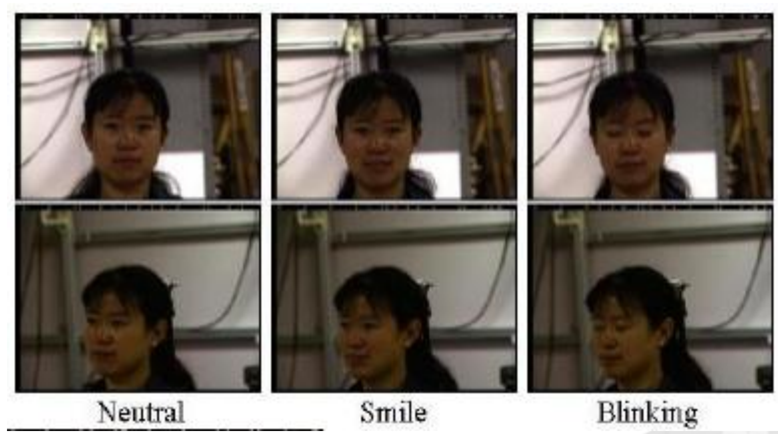
- LFW contains **13,233 images** of **5,749 people**, and is thus much broader than PubFig. However, it's also smaller and much shallower (many fewer images per person on average).
- LFW is derived from the Names and Faces in the News work of T. Berg, et al. These images were originally collected using news sources online. For many people, there are often several images taken at the same event, with the person wearing similar clothing and in the same environment. Our paper at ICCV 2009 showed that this can often be exploited by algorithms to give unrealistics boosts in performance.
- Of course, the PubFig dataset no doubt has biases of its own, and we welcome any attempts to categorize these.

We have created a face verification benchmark on this dataset that test the abilities of algorithms to classify a pair of images as being of the same person or not. Importantly, these two people should have **never** been seen by the algorithm during training. In the future, we hope to create recognition benchmarks as well.



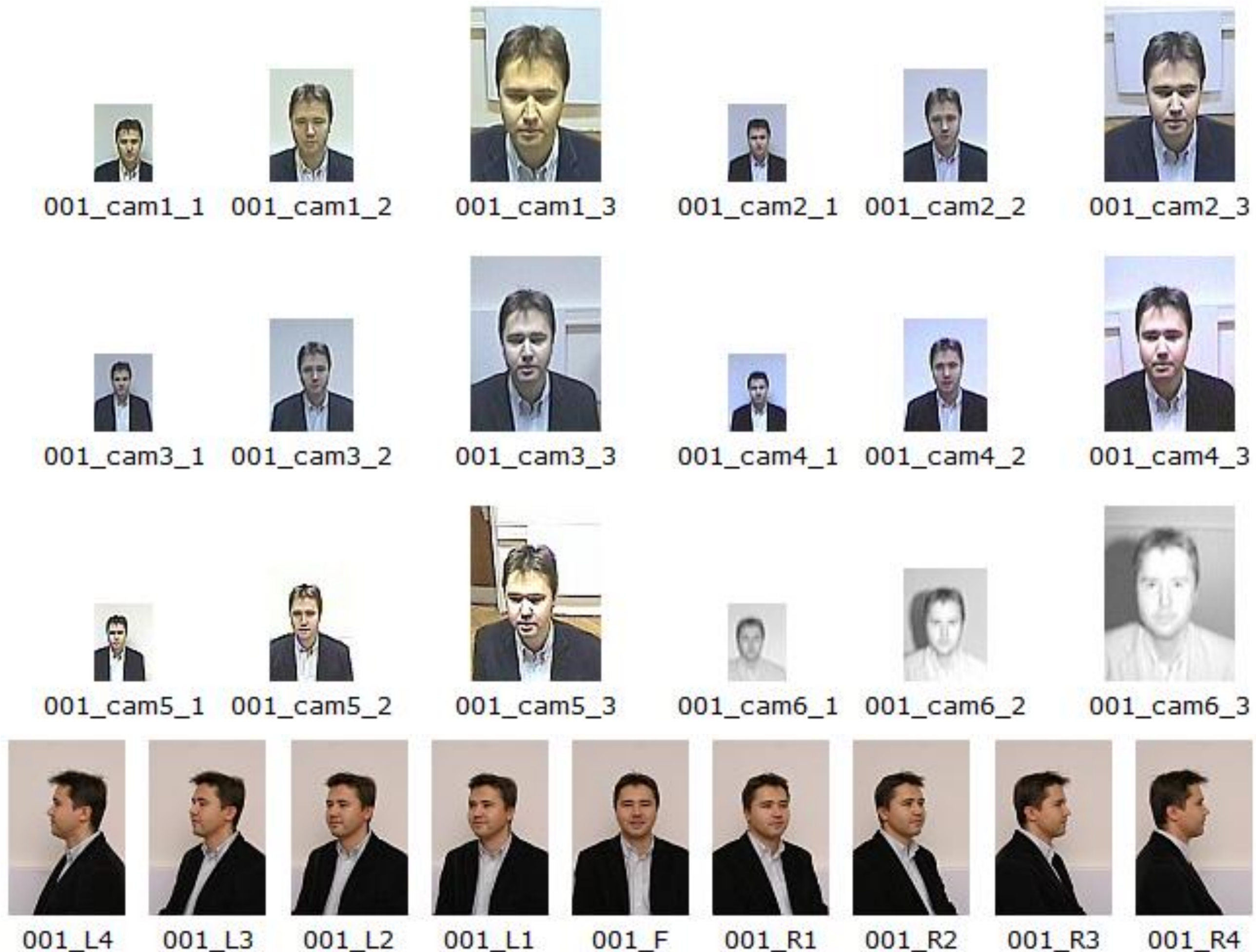
CMU PIE

- A database of 41,368 images of 68 people, each person under 13 different poses, 43 different illumination conditions, and with 4 different expressions.



ScFace Database

- 4160 static images (in visible and infrared spectrum) of 130 subjects
- 3 distances
- 5 cameras



Video Face Databases

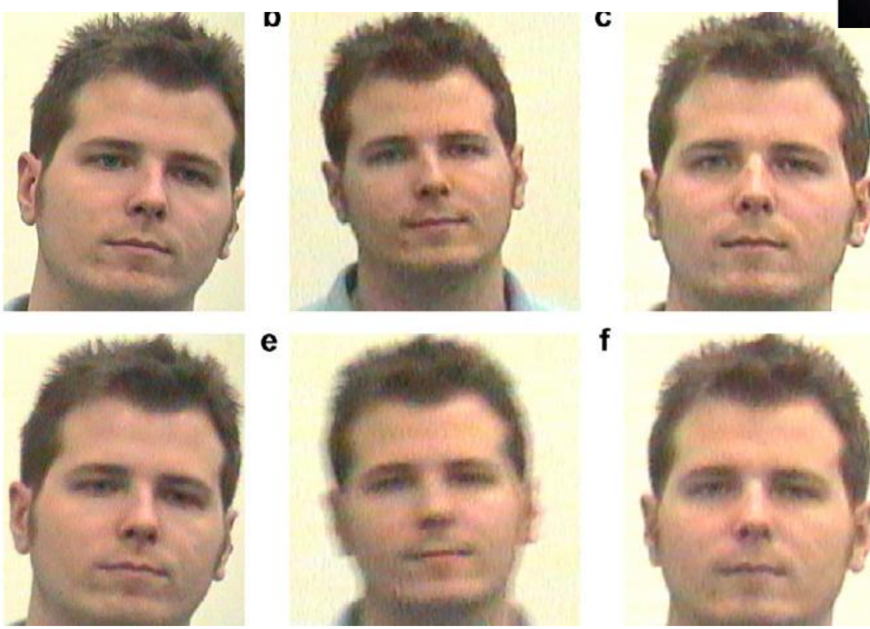
- **MoBo(Motion of Body)**
- 25 individuals walking on a treadmill
- Each subjects perform four different walk patterns: slow walk, fast walk, incline walk and walking with a ball
- Taken from 5 high resolution cameras
- All 6 views

The Honda/UCSD Database

- Each video sequence is recorded in an indoor environment at 15 frames per second, and each lasted for at least 15 seconds.
- The resolution of each video sequence is 640x480
- Set 1: Training, testing and occlusion subsets contains 20, 42, 13 videos respectively from 20 human subjects.
- Set 2: Training and Testing of 30 videos from another 15 different human subjects

UTK-LRHM

- Distances: indoor: 10–16 m and outdoor: 50–300 m



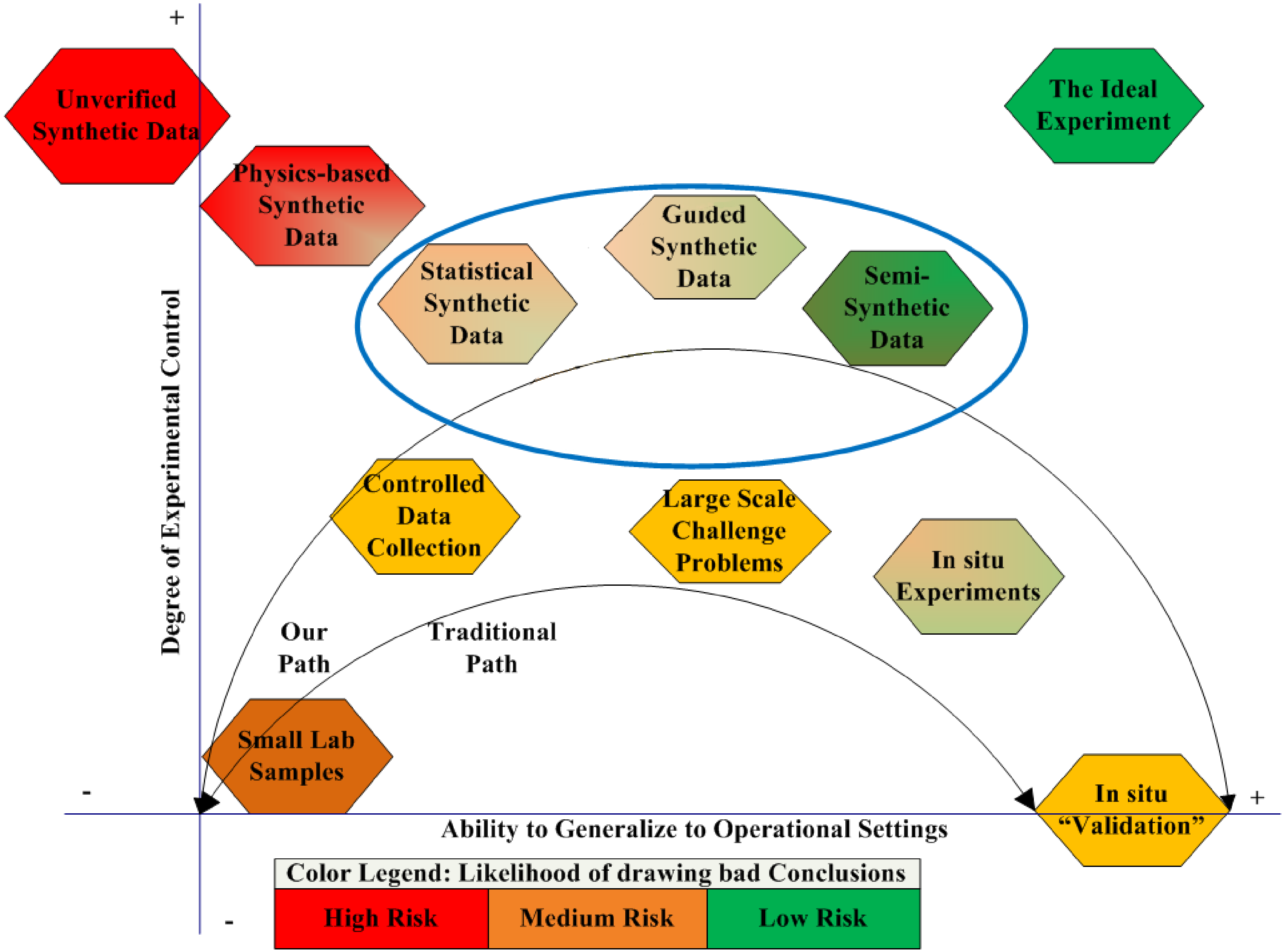
*Not public?

Lots of Available databases

- The Yale Database
- Project - Face In Action (FIA) Face Video Database, AMP, CMU
- AT&T "The Database of Faces" (formerly "The ORL Database of Faces")
- Cohn-Kanade AU Coded Facial Expression Database
- MIT-CBCL Face Recognition Database
- Image Database of Facial Actions and Expressions - Expression Image Database
- Face Recognition Data, University of Essex, UK
- NIST Mugshot Identification Database
- NLPR Face Database
- The University of Oulu Physics-Based Face Database
- Face Video Database of the Max Planck Institute for Biological Cybernetics
- Caltech Faces
- …….
- …….

Requirements of database/evaluation methods

Controlled Experiments for Large Scale Collections



Types of Face Models

- Unverified Synthetic Models
  - Artistic or simple mathematical models; have no underlying physical or statistical basis
- Physics-based Models
  - Based on structure and materials combined with properties formally modeled in physics
  - Only as good as their underlying assumptions
- Statistical Models
  - Use estimates of parameters to supplement or enhance synthetic models or physical models
  - Have greater predictive power for operational relevance for the population of the data

Types of Face Models

- Guided Models
  - Individual models based on individual people
  - No attempt to capture properties of large groups or actual physics across models
- Semi-synthetic Models
  - Use measured data, such as 2D images or 3D facial scans as the model
  - The models are used for a re-rendering of measured data

Controlled Experiments for Large Scale Collections

Sensor : **FOV 0.5° and 0.25° imaging (equivalent to 1600mm and 3200mm focal lengths).**
Inter-pupil distance in resulting images is approx 120 pixels

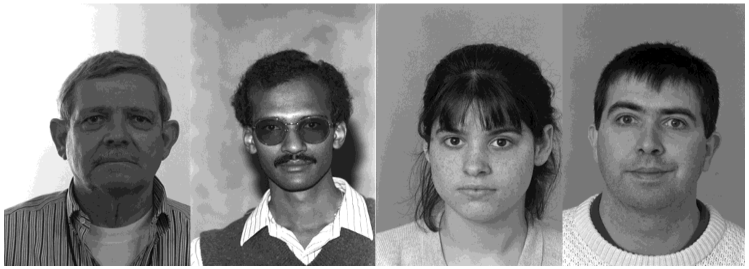
Experiment Setup :

91 ft (28m)

181ft (55m)

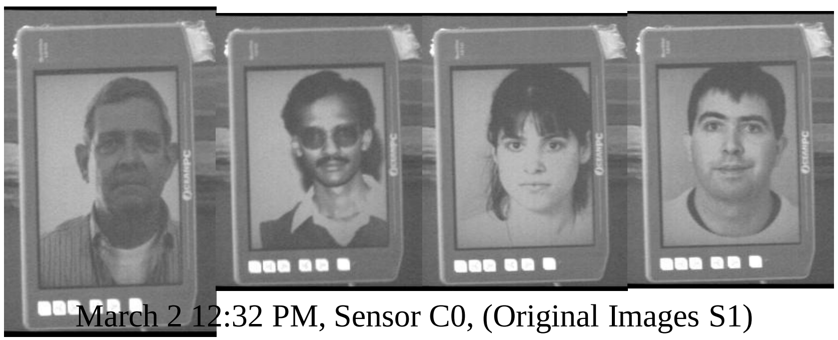
Photo-head Data Acquisition

Controlled Experiments for Large Scale Collections



S1 Gallery

S2 Gallery

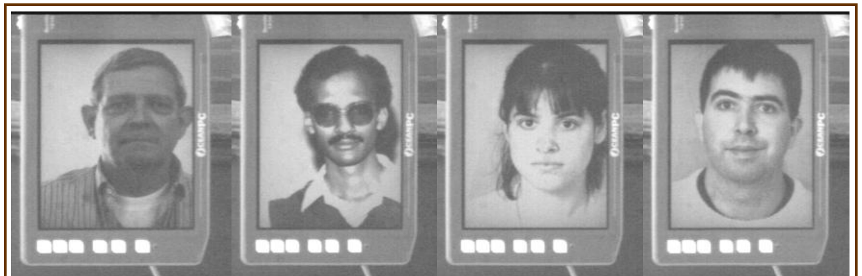


March 2 12:32 PM, Sensor C0, (Original Images S1)

(C0,S1) Probe Set

March 2 12:32 PM, Sensor C0, (Original Images S2)

(C0,S2) Probe Set



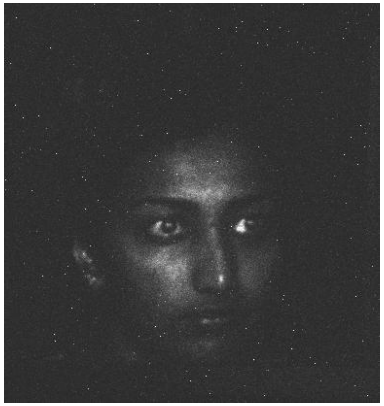
March 2 12:32 PM, Sensor C1, (Original Images S1)

(C1,S1) Probe Set

March 2 12:32 PM, Sensor C1, (Original Images S2)

(C1,S2) Probe Set

Controlled Experiments for Large Scale Collections



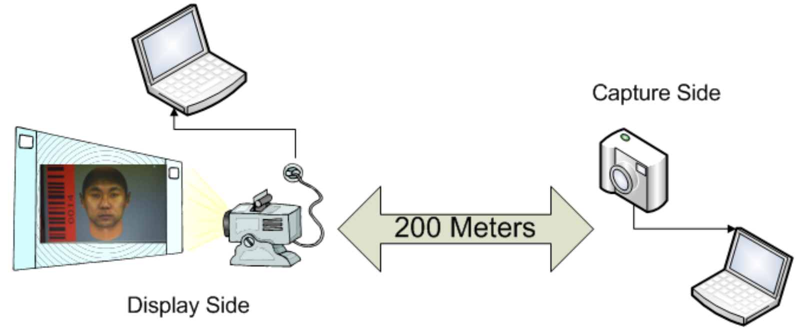
Lighting:
1/4 Moonlight
0.043 - 0.017 nits

Blur length 15 pixels, 122°

Blur length 17 pixels, 59°

Blur length 20 pixels, 52°

Controlled Experiments for Large Scale Collections

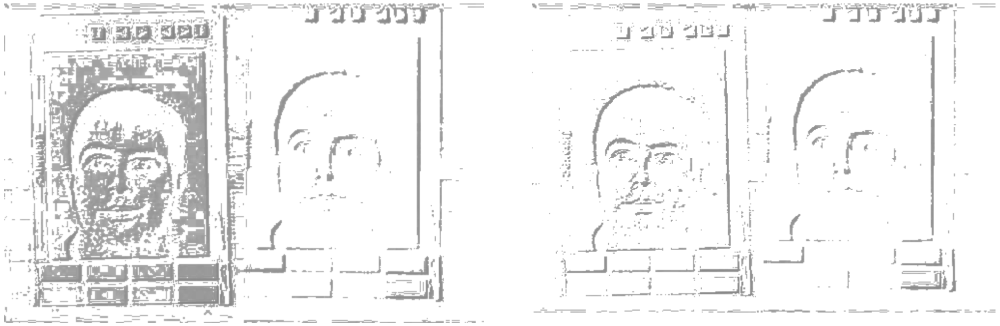


- ➢**Semi-Synthetic Data Examples**
- ➢**We match semi-synthetic data to real data to evaluate algorithms.**

Weather and Atmospheric Impacts

Atmospherics

Far camera on left

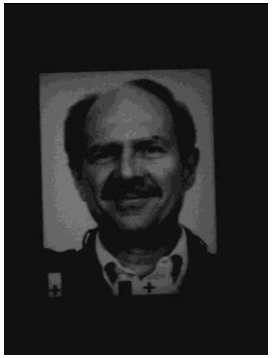


Near camera on right

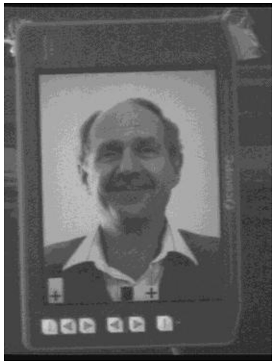
Weather and Atmospheric Impacts

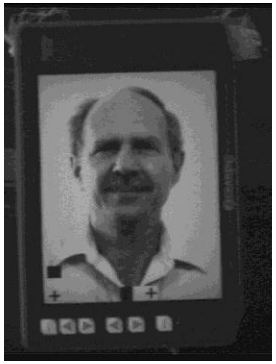
Variation over the day

Morning Twilight

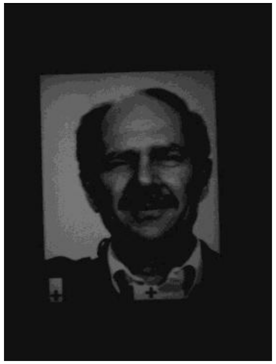


Morning

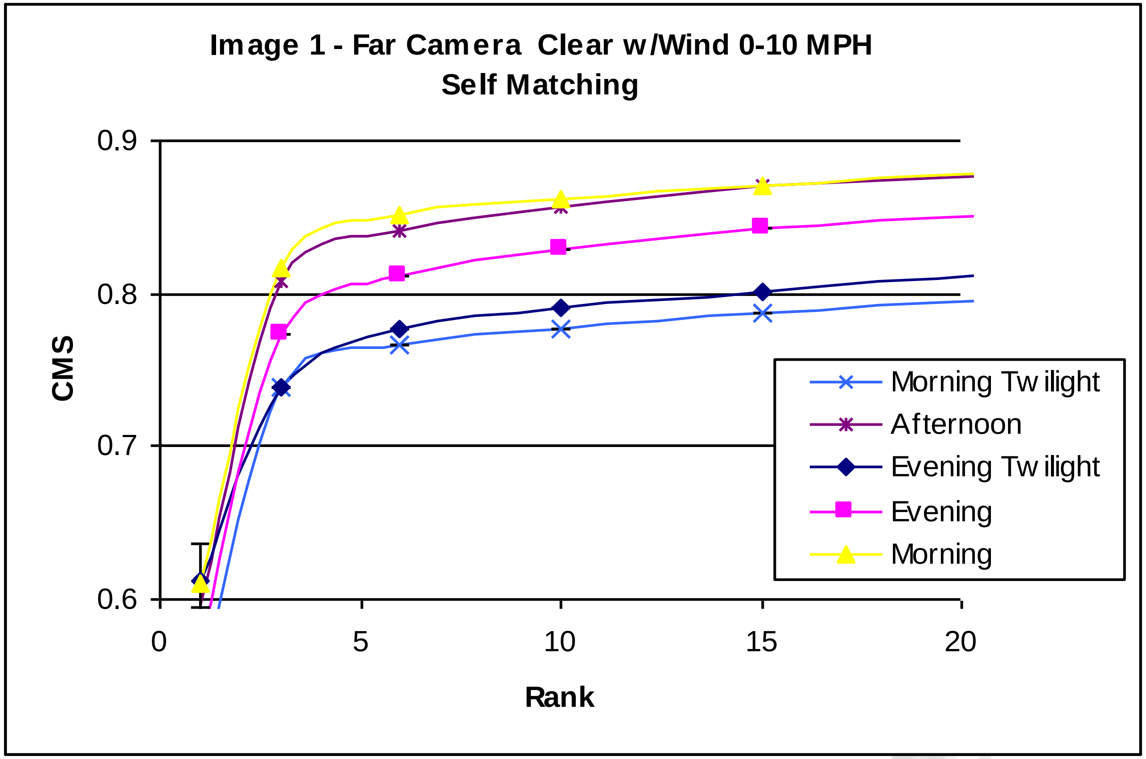




Afternoon



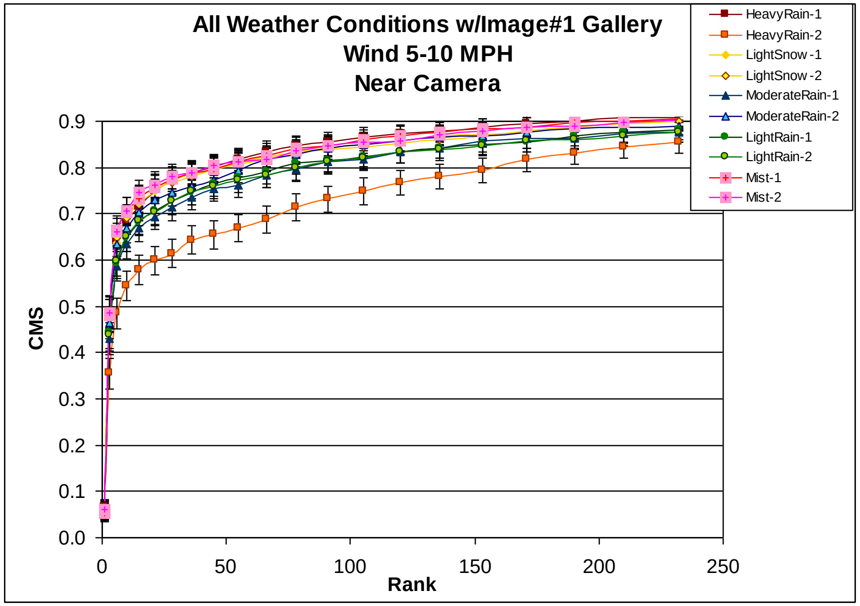
Evening Twilight

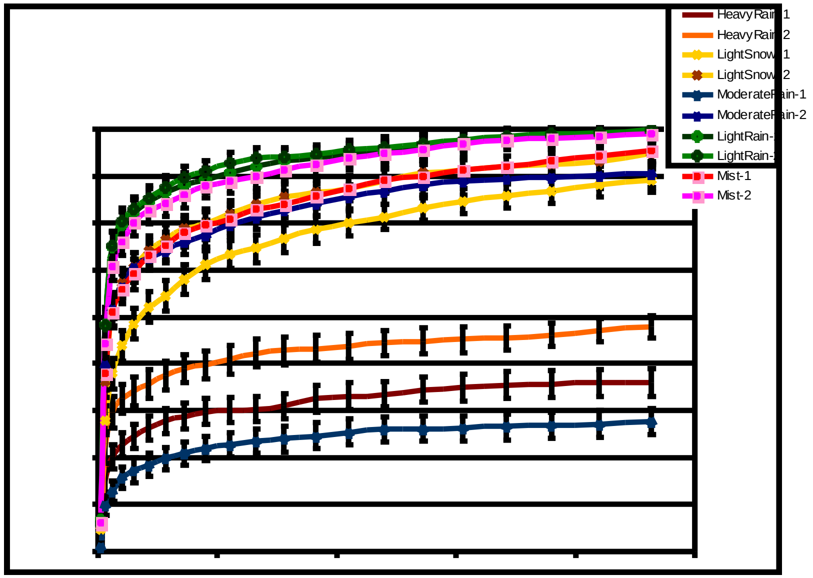


* leading commercial algorithm

Weather and Atmospheric Impacts

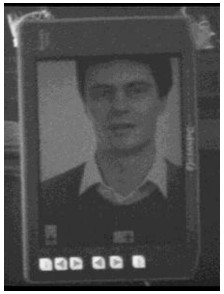
Weather





Rank 3 recognition about 50% (near) - much worse at 200ft

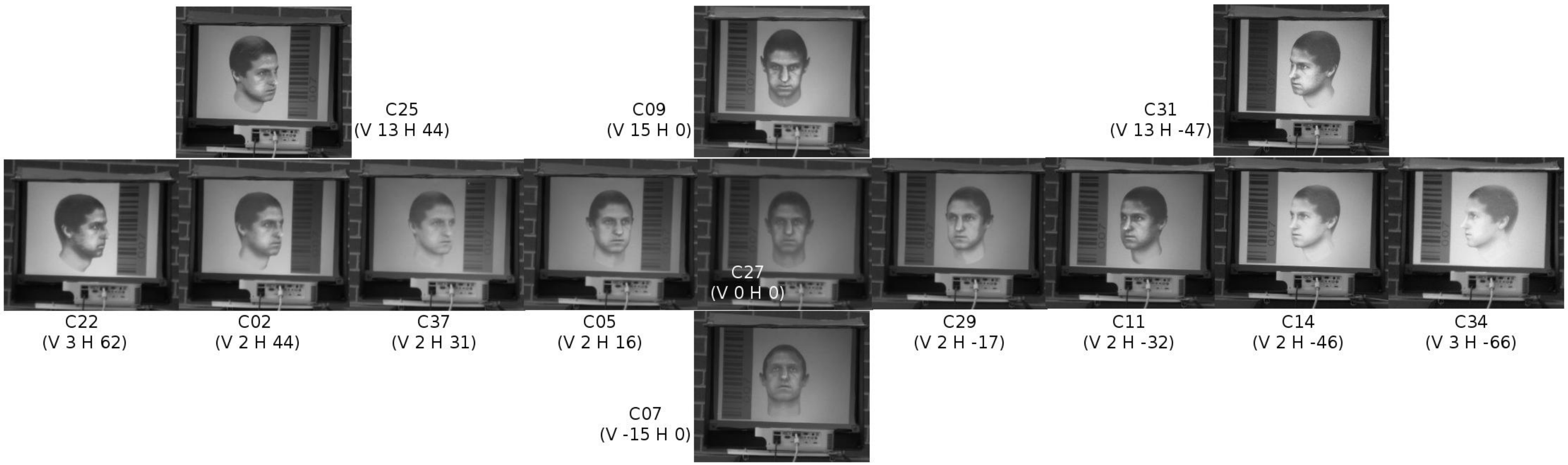
Clear



Snow

Rain

Full Evaluation Set: Re-Imaging CMU PIE



Complete PIE data set at 81M (indoors), 214M (outdoors), 214M with motion blur

(interested? See me for details)

Latest Photo-head Methodology

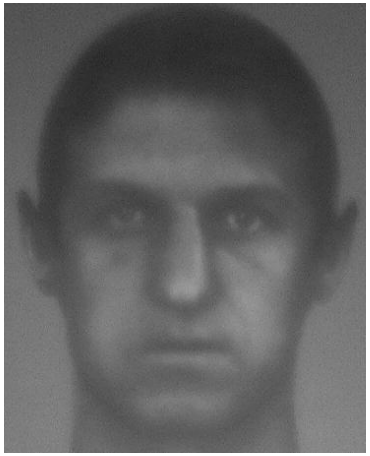
- Create 3D models from well known 2D Data
  - Consider a frontal and profile image
  - Establish key points on the face for alignment
- Models allow us to control for pose, and scene conditions
- Software: Forensica Profiler from Animetrics
  - http://www.animetrics.com/products/ForensicaProfiler.php

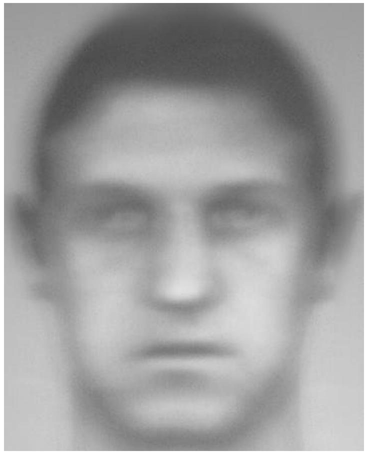
Full Evaluation Set: CMU PIE

Original Screen Shot

Re-imaged at 81M Indoors

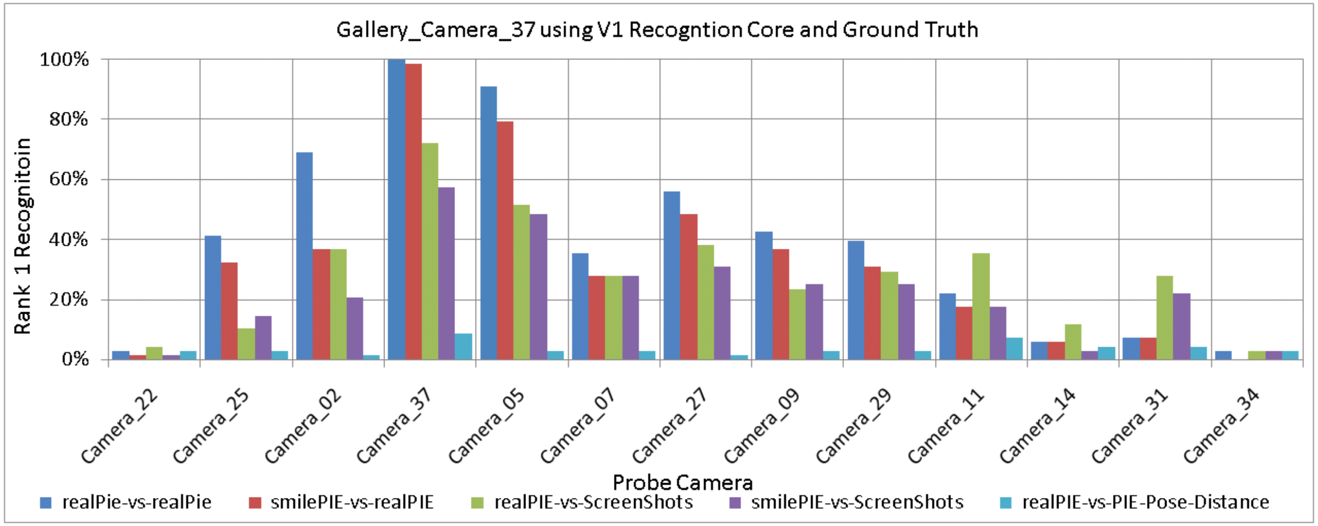
Re-Imaged at 214M

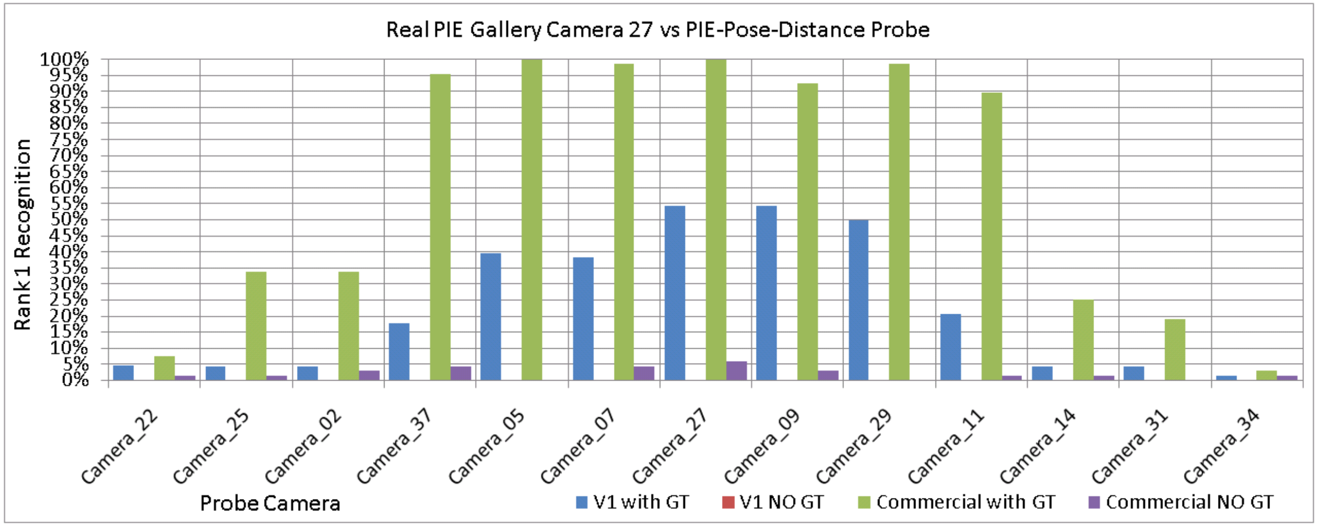




Re-Imaged at 214M with Motion Blur

Results for Re-imaged CMU PIE





Illumination Invariance

Illumination Invariance Methods

Passive Methods: Solve the problem by analysis of the images acquire.

- Illumination Variation Modeling
- Illumination Invariant Features
- Photometric Normalization
- 3D Morphable Models

Active Methods: Employ the active imaging techniques to overcome the illumination variance:

- 3D information acquisition
- Thermal Infrared Images
- Near-infrared Images

Xuan Zou; Kittler, J.; Messer, K.; , "Illumination Invariant Face Recognition: A Survey”, 2007

Illumination Invariance Methods

Illumination Variation Modeling:

- Linear subspaces, Illumination cone, Generalized photometric Stereo ….

Illumination Invariant Features:

- Direction of Gradient, shape from shading, Quotient Image, EigenPhase, Local Binary Pattern…..

Photometric Normalization:

- Histogram Normalization, Gamma Intensity correction, Local Normalization ….

Xuan Zou; Kittler, J.; Messer, K.; , "Illumination Invariant Face Recognition: A Survey", 2007

Comparison of Normalizations

Raw Normalized
From CVPR04 paper by
Socolinsky & Selinger

CSU
Normalized

Securics
Dual LUT
Normalized

Intensified Image Examples

Securics Dual LUT normalization

CSU Standard Normalization

Advanced Feature Detection

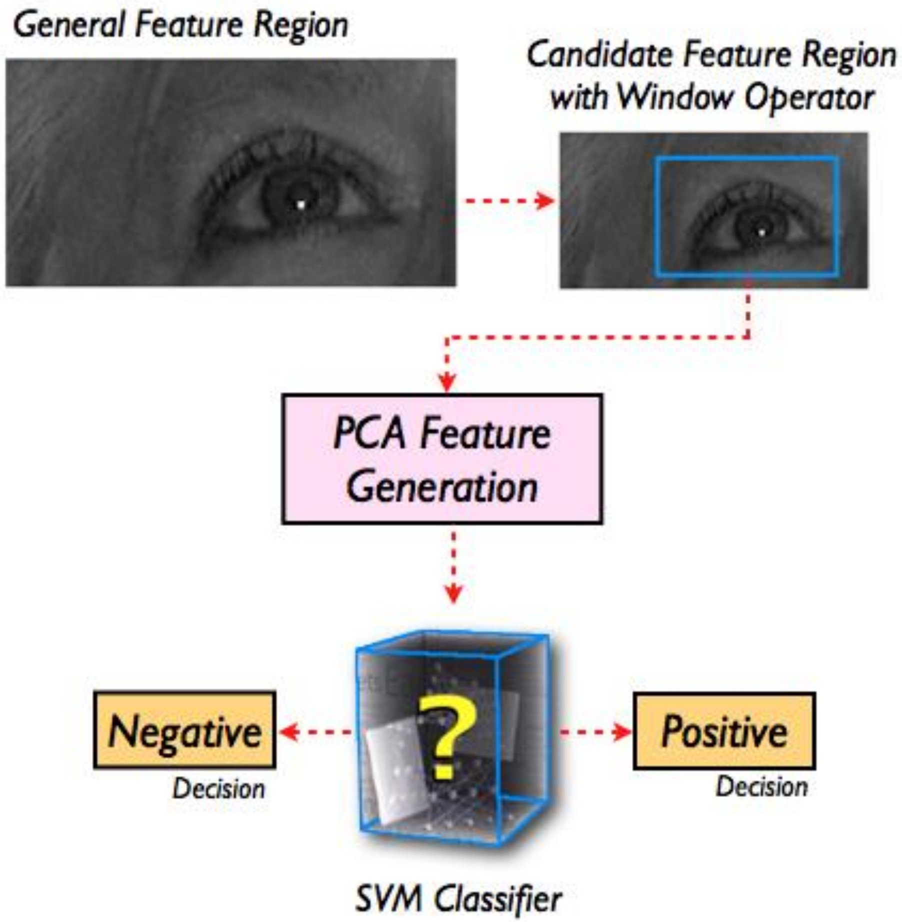
Advanced Feature Detection

- Once we've found a face (Viola-Jones works rather well, even in tough conditions), what do we do?
  - Pattern recognition often breaks down in unconstrained scenarios
    - Need features for geometric normalization, or for straight recognition
    - What if geometric or intensity requirements aren't fulfilled, because of distortion?
  - Proposed solution #1: *learn* over features gathered in the appropriate scenarios (Illumination, Pose, Distance, Weather)

Advanced Feature Detection

Build classifiers for different scenarios

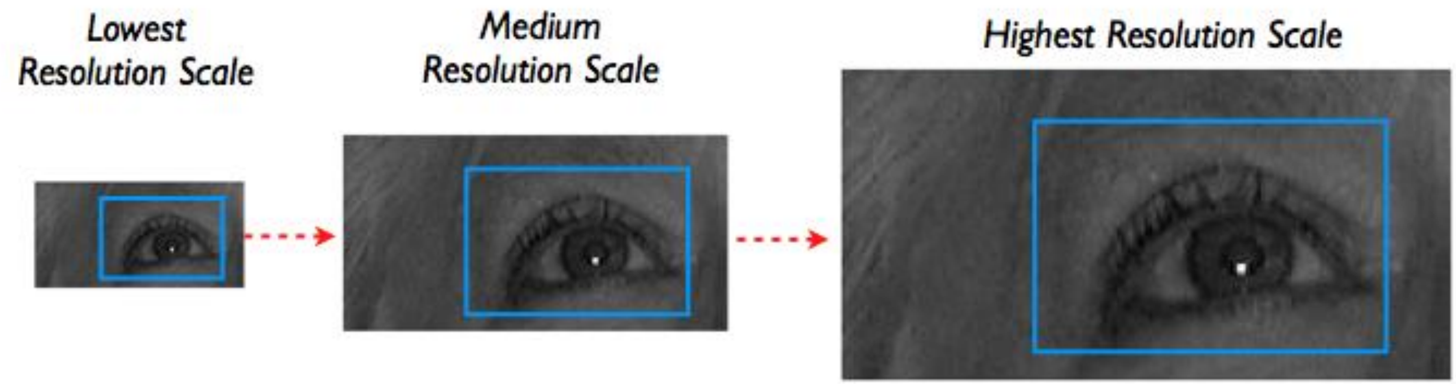
Advanced Feature Detection



PCA Feature Approach with Machine Learning

Addressing Performance

Multi-resolution approach: start small, and restrict the search space as the image is scaled up



Not without a space cost – total number of subspaces and classifiers:

$$(\textit{number of features} \times \textit{number of scales})$$

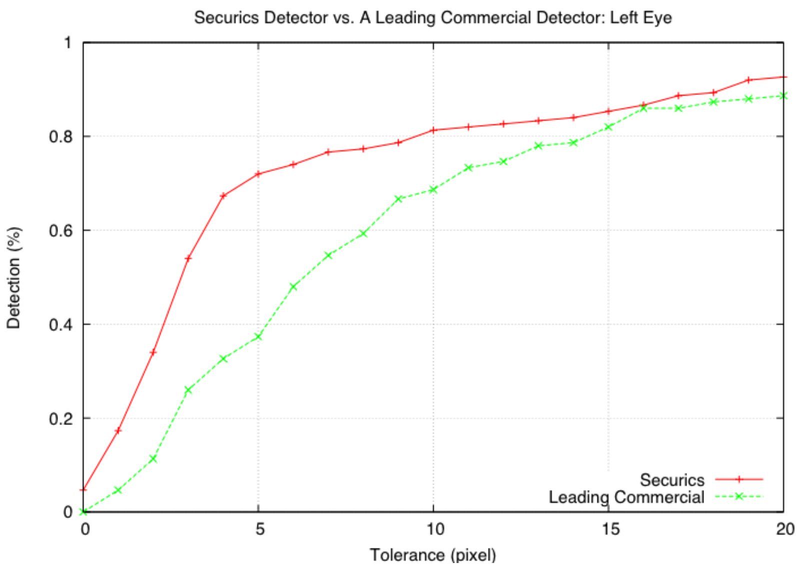
Advanced Feature Detection

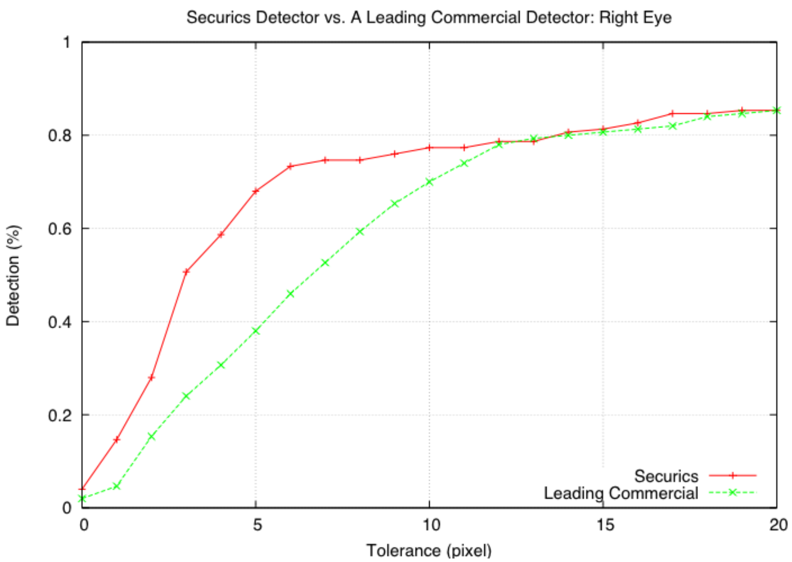
- Low-light evaluation: Subset of CMU PIE data set re-imaged in a controlled, dark, indoor "photo-head" setting

- Capture at 0.043 - 0.017 nits simulating a face at 100M
- Positive Training Set: 250 images x (8 1-pixel offsets from the ground-truth + ground-truth point)
- Negative Training Set: 250 images x 9 pre-defined negative regions around the ground-truth
- Testing Set: 150 images

Advanced Feature Detection

New detector vs. detector from a leading commercial vendor





Left eye: 1000 training example subspace, 4200 training example classifier

Right eye: 1200 training example subspace, 4200 training example classifier

Advanced Feature Detection

Left: Learning Based Detector

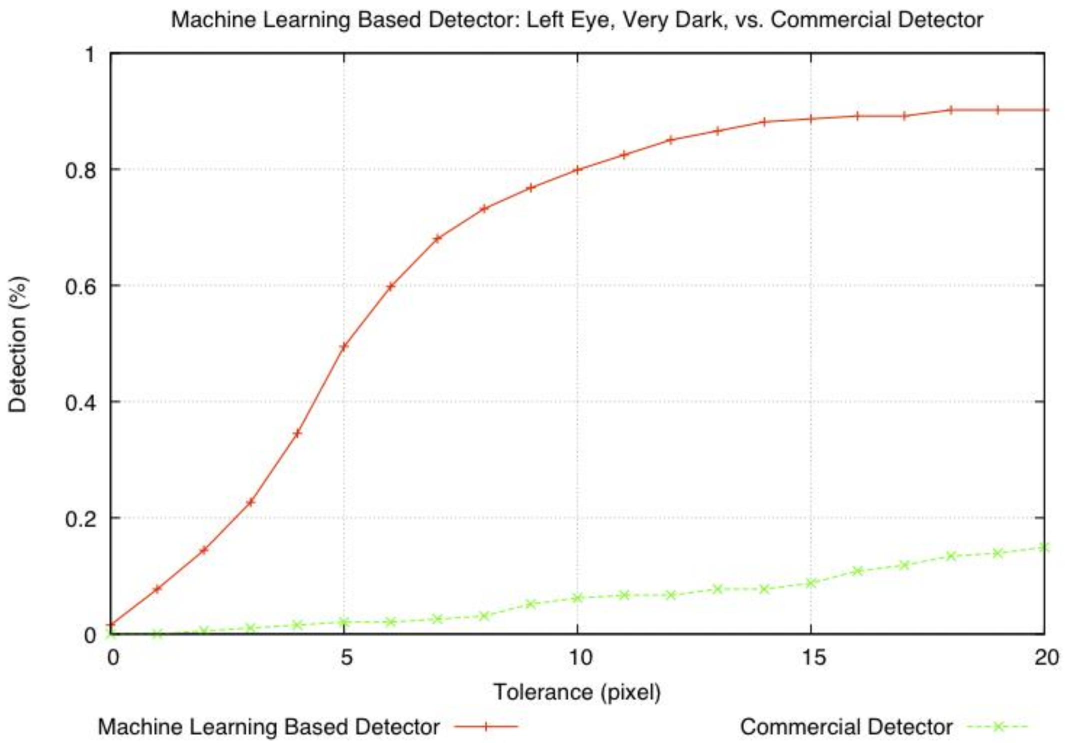
Right: A Leading Commercial Detector

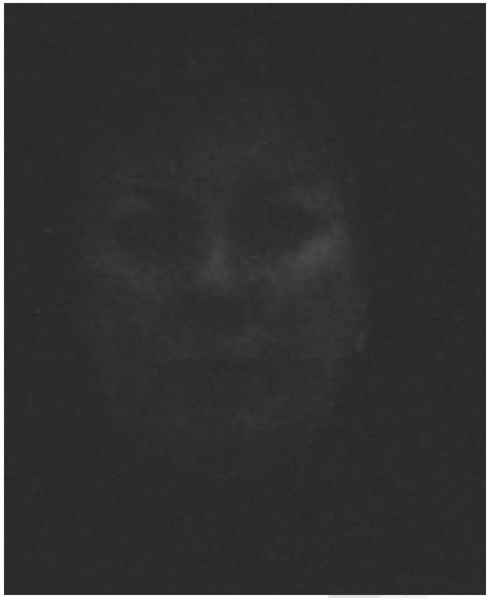
No Eyes Found

Qualitative Results

Advanced Feature Detection

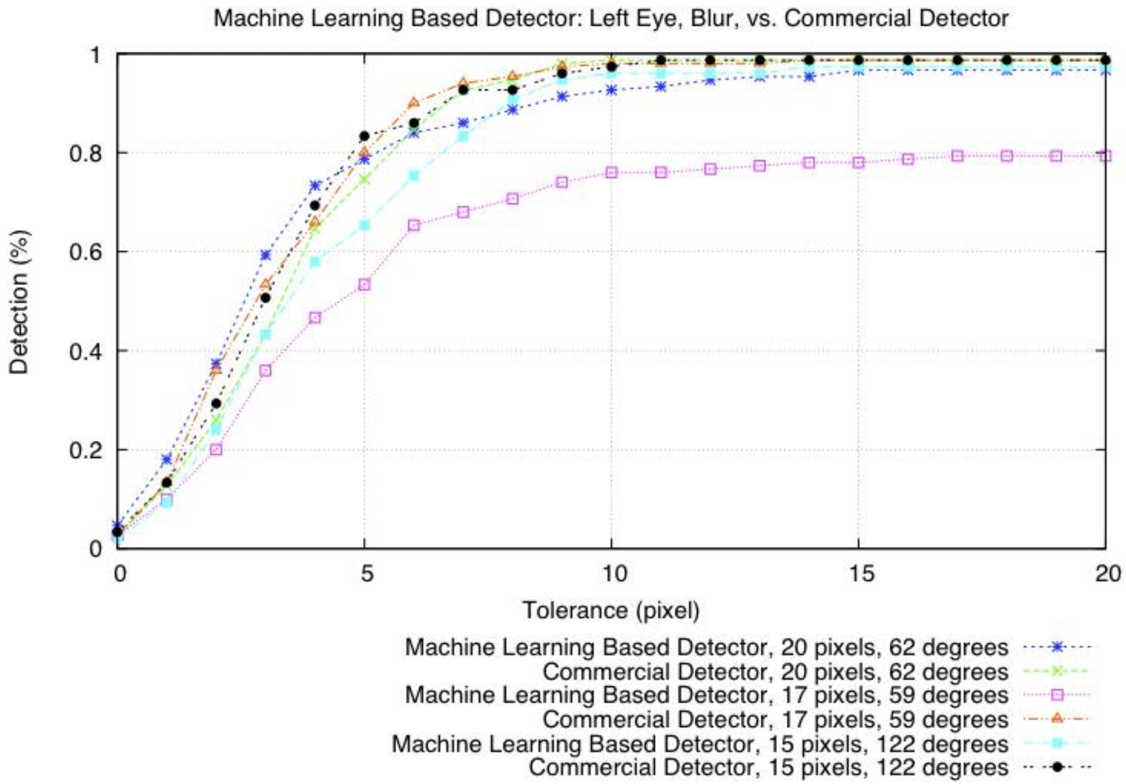
- Very Low-light Evaluation: FERET re-imaged at 0.0108 - 0.002 nits
- Gallery for training (1100 samples for subspace, 4200 for SVM)
- FAFC for testing





Advanced Feature Detection

- Blur Evaluation: FERET ba, bj, bk subsets
- 3 blur models for testing: 15 pixels - 122º, 17 pixels - 59º, 20 pixels - 62º



- SVM Trained on 2,000 base images using the 20 pixels, 52º model

- Subspace trained on 1,000 images from the same model

- Tested on 150 images with various levels of blur

Advanced Feature Detection

- Approach #2: Correlation Filters
  - After finding a face, what do we do?
    - Training and using classifiers for all types of unconstrained scenarios requires a considerable amount of storage and an accurate estimation of the degradations to be expected in the scenario which can be constantly changing.
    - Proposed solution: Incorporate estimates of the degradations such as noise and blur at run-time per frame into the eye detector.

Advanced Feature Detection

MACE Filter: $h = D^{-1}X(X'D^{-1}X)^{-1}u$

UMACE Filter: $h = D^{-1}m$

AACE Filter: $h = (D^{-1}m) \otimes BlurOTF$

Where: **D**: Average Power Spectrum from N training Images

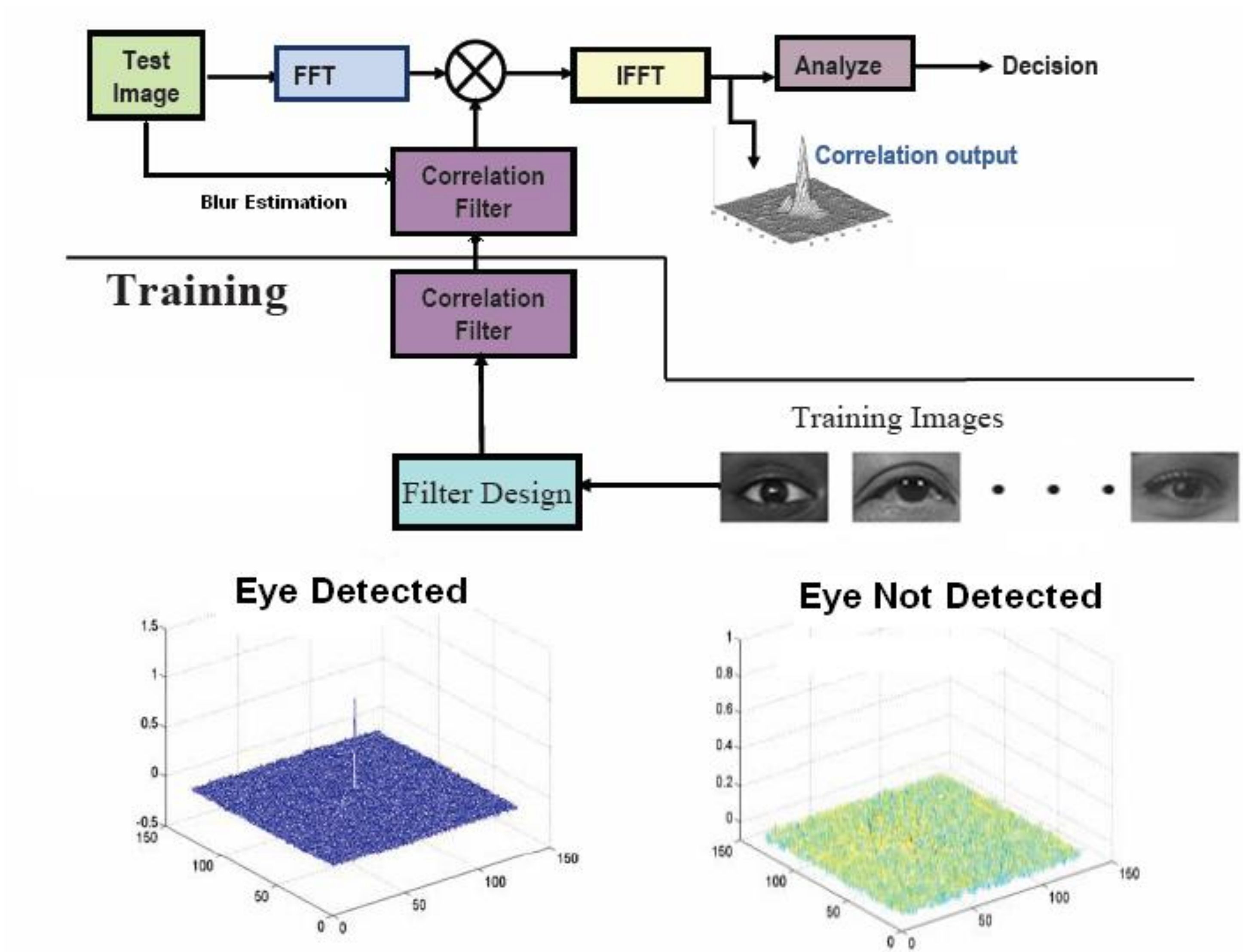
X: Matrix containing the 2D Fourier transform of the N training images

u: Desired filter output

m: 2D Fourier Transform of the average training image.

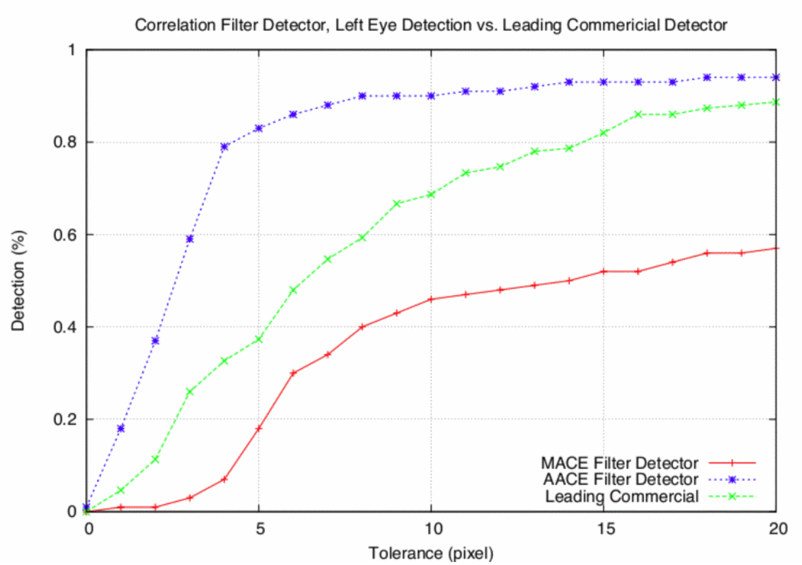
BlurOTF: blur optical transfer function

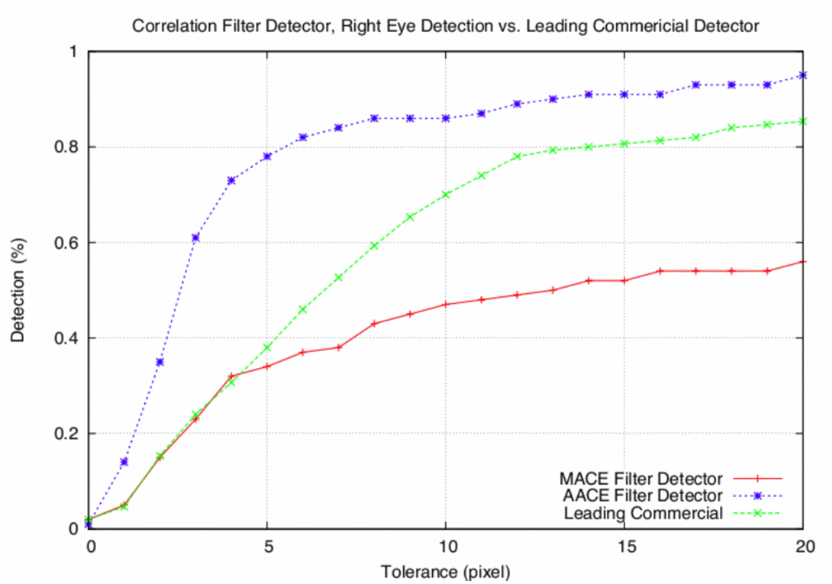
Advanced Feature Detection



Advanced Feature Detection

Correlation based detector vs. detector from a leading commercial vendor



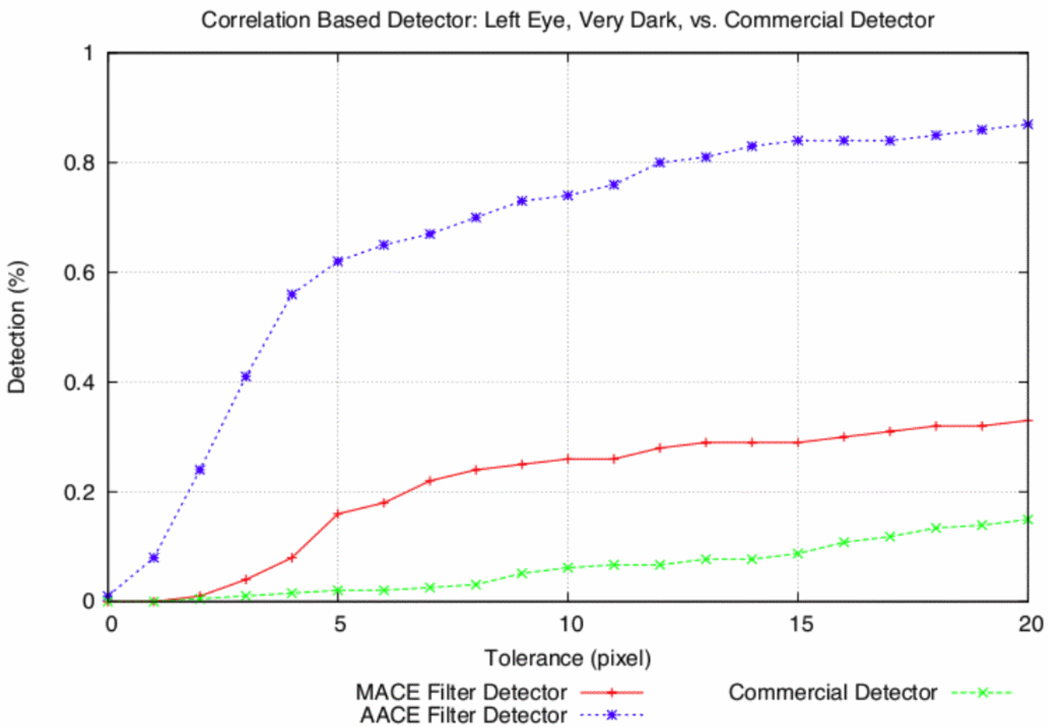


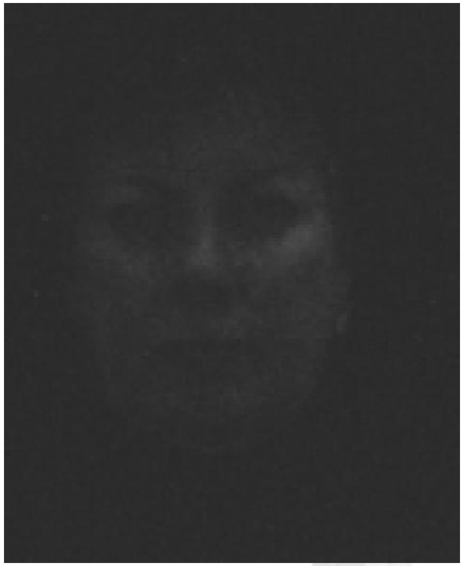
Left and Right eye

MACE filter: 6 training imgs. **AACE filter**: 266 training imgs.

Advanced Feature Detection

- Very Low-light Evaluation: FERET re-imaged at 0.0108 - 0.002 nits
- MACE Filter: 4 Training Images
- AACE Filter: 588 Training Images
- FAFC for testing

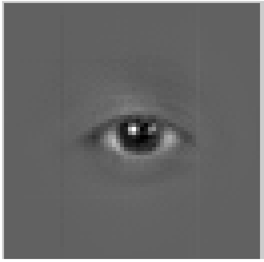




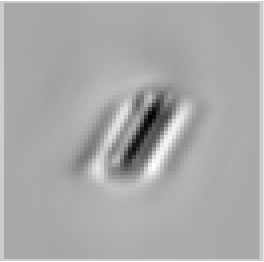
Advanced Feature Detection

- Blur Estimate Can Be Easily Convolved into AACE filter

Blur Model: 15 pixels - 122º



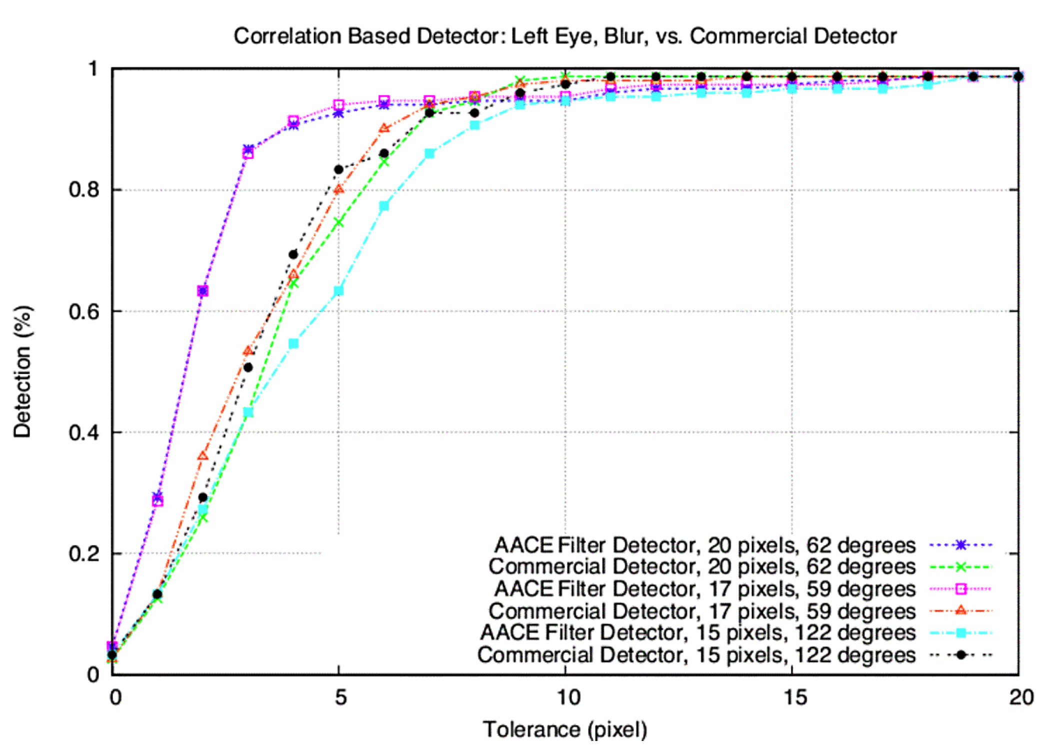
Original AACE Filter



AACE Filter Convolved with Blur Model: 15 pixels - 122º

Advanced Feature Detection

- Blur Evaluation: FERET ba, bj, bk subsets
- 3 blur models for testing: 15 pixels - 122º, 17 pixels - 59º, 20 pixels - 62º



- AACE filter trained on 1,500 original images then convolved with the 20 pixels, 52º model
- Tested on 150 images with various levels of blur

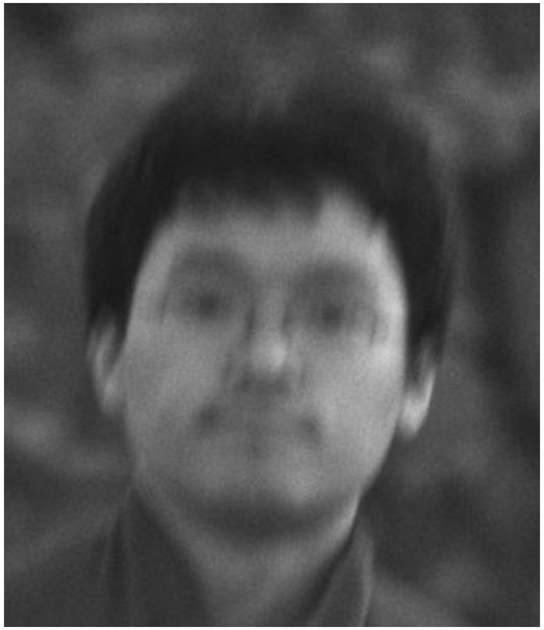
Mitigating the Effects of Blur

A nice sunny day…

TC-285 EMCCD, 1008x1002, 200M from camera, Daylight

Deblurring Algorithms and Analysis

Goal is to develop algorithms that can run in a real time system to estimate and compensate for the effects of motion blur and atmospheric blur from a single image

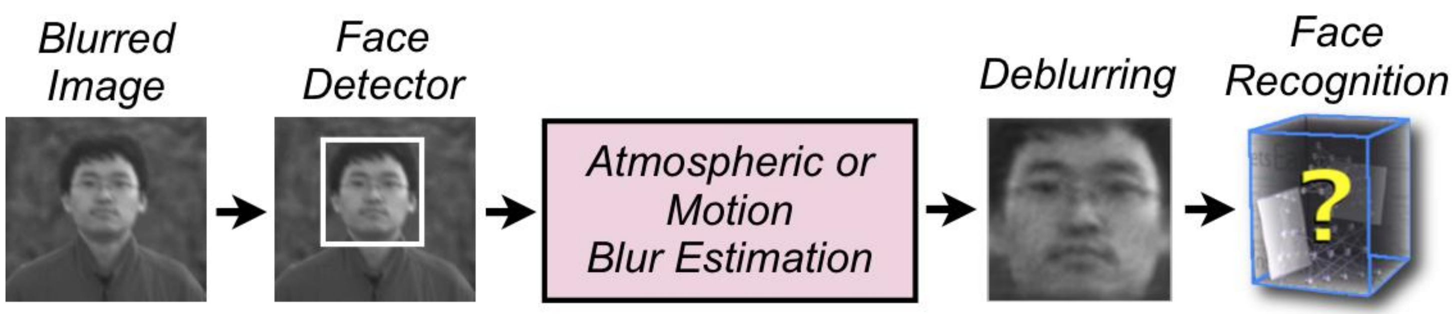


Motion Blurred Image

Atmospheric Blurred Image

Mitigating the Effect of Blur

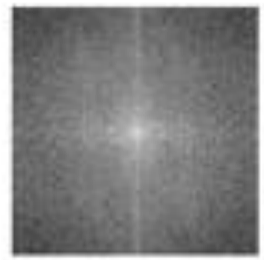
- Blur can have a severe impact on face recognition performance
  - Estimate motion and atmospheric blur and then apply deconvolution to mitigate blur before recognition: $g(x,y) = f(x,y) \otimes d(x,y) + n(x,y)$
  - Integrate process into recognition pipeline



Mitigating the Effect of Blur

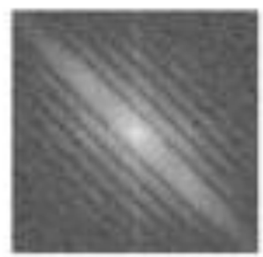
- Motion blur estimation
  - Use the Cepstrum of the image to identify blur angle and length

(a) Original image



(b) Cepstrum of original image

(c) Motion blur at 45˚



(d) Cepstrum of motion blurred image reflecting blur angle

Mitigating the Effect of Blur

- Image restoration for motion blur
  - CLS filter helps eliminate oscillations in output image

$$R_{CLS}(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \gamma |P(u,v)|^2}$$

γ controls low-pass filtering; $P(u,v)$ is the Fourier transform of the smoothness criterion function

Mitigating the Effect of Blur

- Atmospheric blur estimation
  - Deconvolve original image with Atmospheric Modulation Transfer Function:

$$F\{h\}(u,v) = e^{-\lambda(u^2+v^2)^\eta};\quad (u,v) \in \mathbb{R}^2,\quad \lambda > 0,\quad 0 < \eta \leq 1$$

u and v are frequency variables; λ controls the severity of the blur; η is an experimentally determined constant

Mitigating the Effect of Blur

- Image restoration for atmospheric blur
  - Straightforward application of Wiener filter

$$R_{Wiener}(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \frac{1}{SNR}}$$

Accurate Signal to Noise Ratio estimate is critical

Single Image Based Atmospheric Deblurring

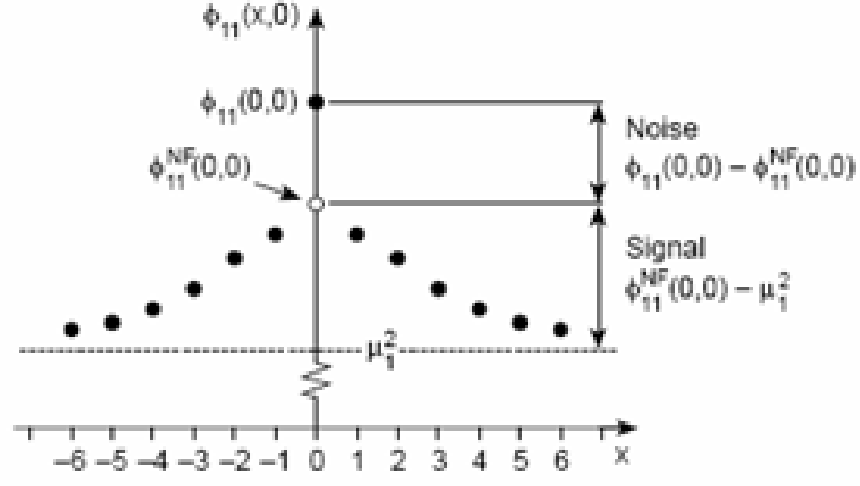
Atmospheric Blurred Image

Deblurred Image

Mirage-Mitigation™

Automated blur-parameter estimation

Single Image SNR Estimation



Representation of the Signal and Noise Components on a Plot of the Autocorrelation Function

$$\frac{\phi_{11}^{NF}(0,0) - \mu_1^2}{\phi_{11}(0,0) - \phi_{11}^{NF}(0,0)}$$

Where: $\phi_{11}^{NF}(0,0)$ is the value of the autocorrelation function (ACF) of the noise-free image at zero offset.

$\phi_{11}(0,0)$ is ACF value at the (0,0) x,y coordinate

μ_1^2 the mean value of the image squared

Single Image SNR Estimation

Motion Blurred Image

Deblurred SNR

Too Low

Deblurred SNR

Too High

Deblurred Correct

SNR

Mitigating the Effect of Blur

- Impact of image restoration applied to images with motion blur

Blur	None	10px	15px	20px
Baseline blurred	97.50	75.00	39.58	16.67
Deblurred	-	92.89	93.75	86.67

Rank 1 recognition results for a subset of FERET using a Gabor Jet + SVM recognition algorithm

10 pixel blur

Deblurred image

Mitigating the Effect of Blur

- Impact of image restoration applied to images with atmospheric blur

No Blur	Moderately Severe Blur	Deblurred
97.50	37.08	90.68

Rank 1 recognition results for a subset of FERET using a Gabor Jet + SVM recognition algorithm

Moderately Severe Blur

Deblurred image

Blind Deconvolution*

Known: Blurred Image

Unknown: Blur Kernel, Sharp Image, Noise ❺ Need to estimate

*A. Levin, Y. Weiss, F. Durand, and B. Freeman, “Understanding and Evaluating Blind Deconvolution Algorithms,” 2009.

Naïve $\text{MAP}_{x,k}$ estimation

Find a kernel k and latent image x minimizing:

Convolution constraint

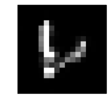
Sparse prior

Should favor sharper x explanations

A Better Intuition: Dimensionality Asymmetry

~10^5 measurements

Large, ~10^5 unknowns



kernel k

Small, ~10^2 unknowns

$MAP_{x,k}$ – Estimation unreliable.

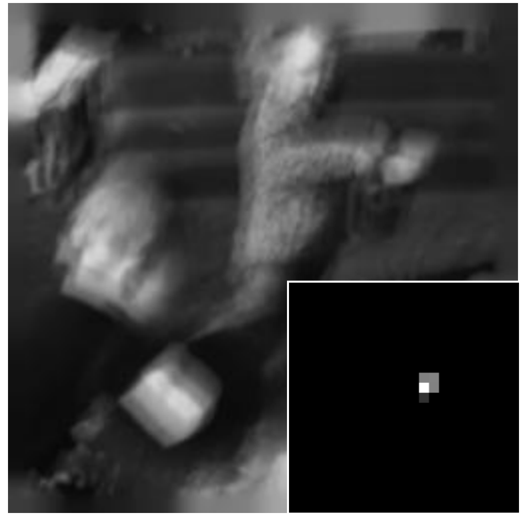
Number of measurements always lower than number of unknowns: #y<#x+#k

MAP_k – Estimation reliable.

Many measurements for large images: #y>>#k

Comparison of Techniques with Ground Truth

Ground truth

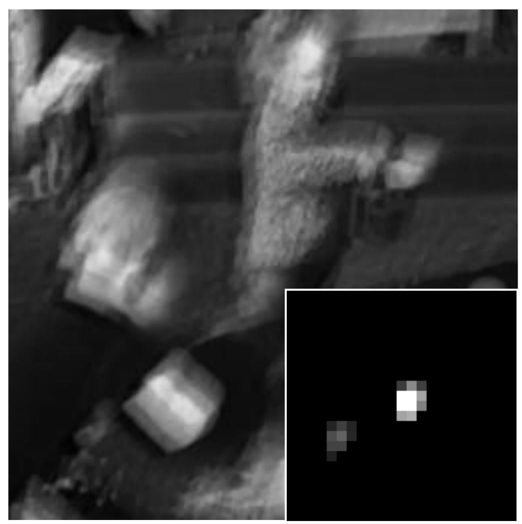


$\text{MAP}_{x,k}$

Fergus et al.[1] SIGGRAPH06
MAP_k, variational approx.

1. R. Fergus, B. Singh, A. Hertzmann, S.T. Roweis, and W.T. Freeman. “Removing camera shake from a single photograph,” *2006.*

1. Q. Shan, J. Jia, and A. Agarwala. “High-quality motion deblurring from a single image,” 2008.



Shan et al.[2] SIGGRAPH08
adjusted $\text{MAP}_{x,k}$

MAP_k, Gaussian prior

Applicability to Face Recognition

Fergus et al.[1] SIGGRAPH06
MAP$_k$, variational approx.

What is visually appealing may not work very well for recognition.

Evaluation for face recognition?

One use of Robust Features for Unconstrained Face Recognition

Non-Cooperative Face Recognition Methods

- Features Based Recognition
- 3D Approaches
- Video Based Face Recognition
- Pose and Occlusion Invariant Methods
- Biologically Inspired Methods

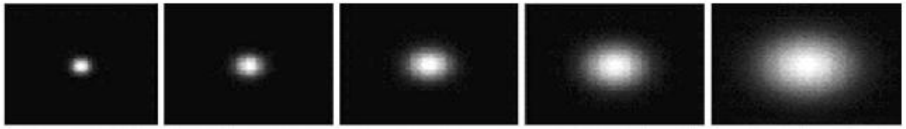
Features Used in Face Recognition

- PCA/LDA/ICA
- GABOR
- LBP
- SIFT
- Edges/Regions

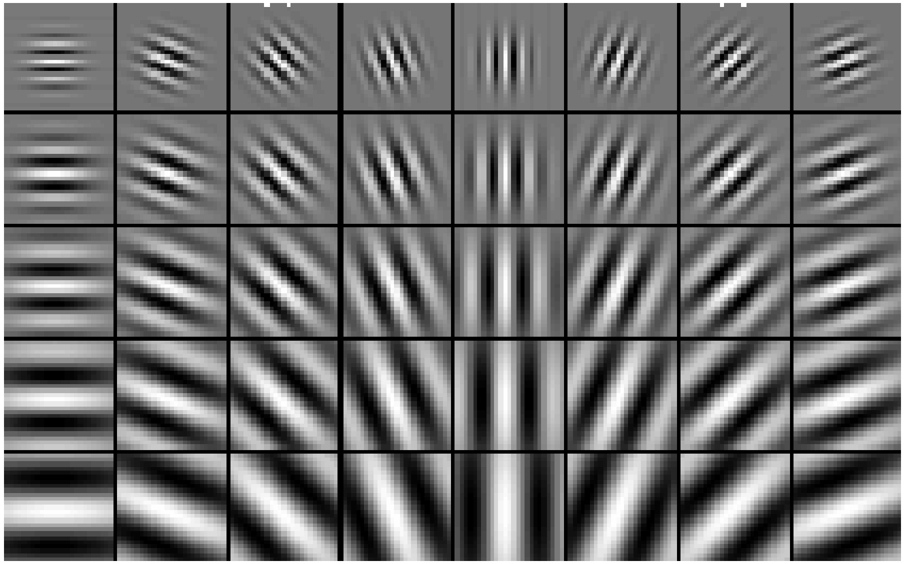
Gabor Wavelets

Gabor wavelets are hierarchically arranged, Gaussian-modulated sinusoids

40 Gabor wavelets of multiple scale and orientation



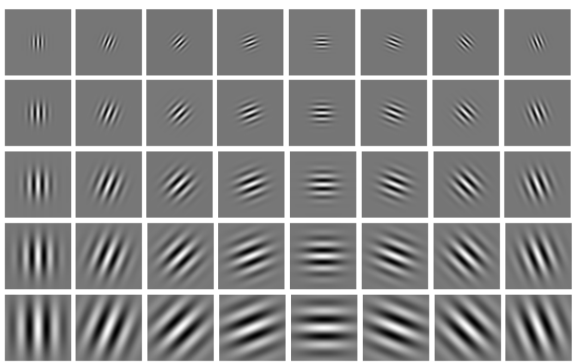
magnitude at 5 scales



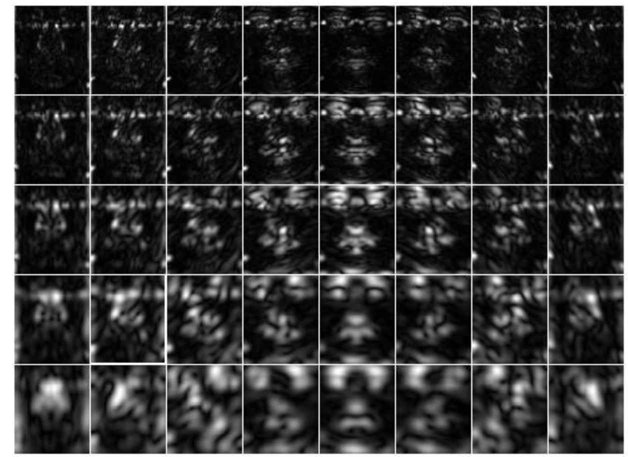
The real Parts at 5 scales and 8 orientations

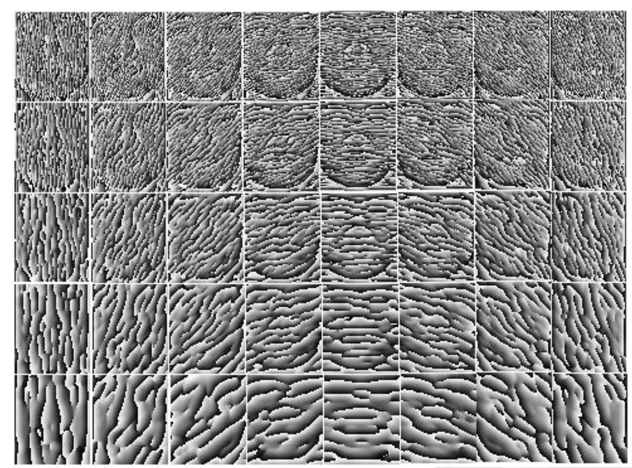
Gabor Face Description

- Provide a description of the local structure of the facial patterns



Convolution with the bank of frequency tuned filters





Gabor: Analytical Methods

- Graph Based methods:

- Elastic Bunch Graph Matching (EGBM)
- Face Bunch Graphs
- Dynamic Link Architecture (DLA)

- Non-Graph Based Methods:

- Manual Extraction of feature points
- Color based extraction
- Ridge/valley/Edge based feature points extraction
- Gaussian mixture model
- Non-Uniform sampling

*Angel Serrano, Isaac Martin de Diego, Cristina Conde, Enrique Cabello, Recent advances in face biometrics with Gabor wavelets: A review,2010)

Gabor:Holistic Method

Gabor convolution with the whole image, feature vector is extracted and downsampled and used for recognition.

- PCA/LDA, Kernel PCA/LDA
- Gabor 2D methods
- Local Binary Patterns
- No Downsampling

*Angel Serrano, Isaac Martin de Diego, Cristina Conde, Enrique Cabello, Recent advances in face biometrics with Gabor wavelets: A review,2010)

Motivation behind Gabor Wavelets in face recognition

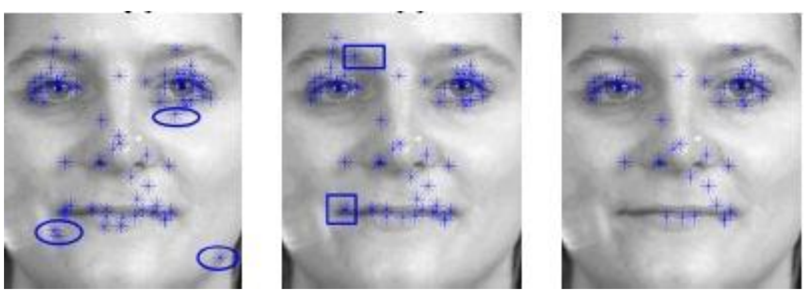
- **Biological Motivation:** Images in primary visual cortex (V1) are represented in terms of Gabor wavelets. The shapes of Gabor Wavelets are similar to the receptive fields of simple cells in the primary visual cortex.
- **Mathematical Motivation**: The Gabor wavelets are optimal for measuring local spatial frequencies.
- **Empirical Motivation:** They have been successfully used for distortion, scale and rotation invariant pattern recognition tasks such as handwritten, texture and fingerprint recognition.

*Linlin Shen, Li Bai, A review on Gabor wavelets for face recognition, 2006

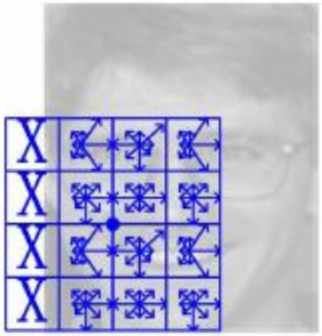
SIFT Features

SIFT (Scale Invariant Feature Transform)

- Popularly used in object recognition
- Key points descriptors defined at different locations of the image, with different scales and orientation.



Detected and retained keypoints



A Partial Descriptor

1. Bicego, M., Lagorio, A., Grosso, E., and Tistarelli, M. On the Use of SIFT Features for Face Authentication., 2006.
2. Cong Geng, Xudong Jiang, "SIFT features for face recognition", 2009

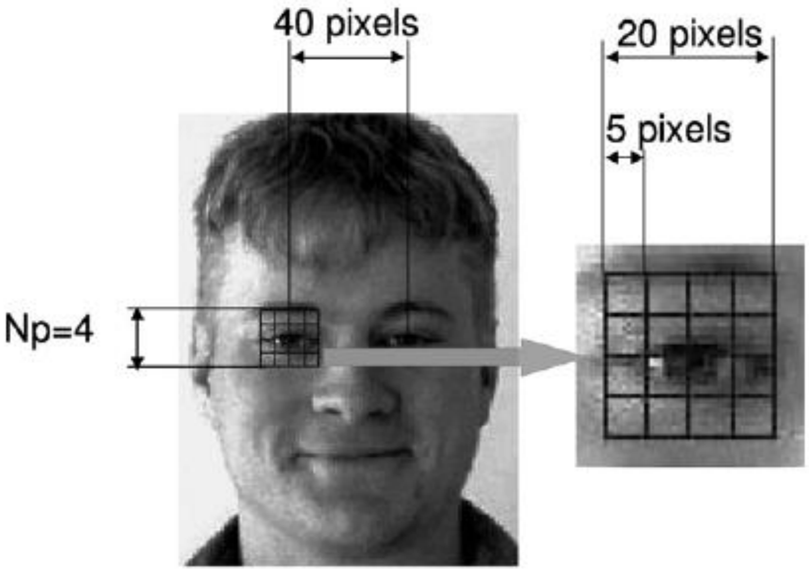
Findings from SIFT in Face Recognition

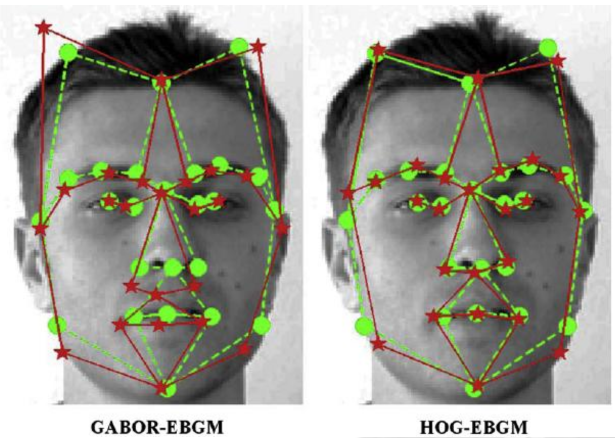
- Not very well suited for face recognition because of complexity, non-planarity and self-occlusion found in the face recognition problem.

- Some modifications in the original SIFT algorithms to be adopted in face recognition: Keypoint-Preserving-SIFT, Partial-Descriptor Keypoint, person-specific matching algorithms etc.

HOG Features

- Histograms of Oriented Gradient
- Facial Landmarks are detected using keypoint descriptor.
- The HOG descriptor is a local statistic of the orientations of the image gradients around a keypoint.
- HOG features are robust to changes in illumination, rotation and small displacements
- Results using HOG + EBGM shown better than Gabor + EBGM.





*Alberto Albiol, David Monzo, Antoine Martin, Jorge Sastre, Antonio Albiol, Face recognition using HOG-EBGM, July 2008

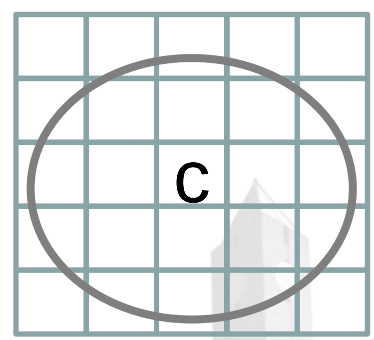
Local Binary Pattern

- Introduced as a texture descriptor
- Every image pixel is associated with the binary pattern obtained by comparing its intensity with the neighborhood
- Sensitive to Scale and Noise

81	5	10
54	52	0
99	90	77

1	0	0
1	c	0
1	1	1

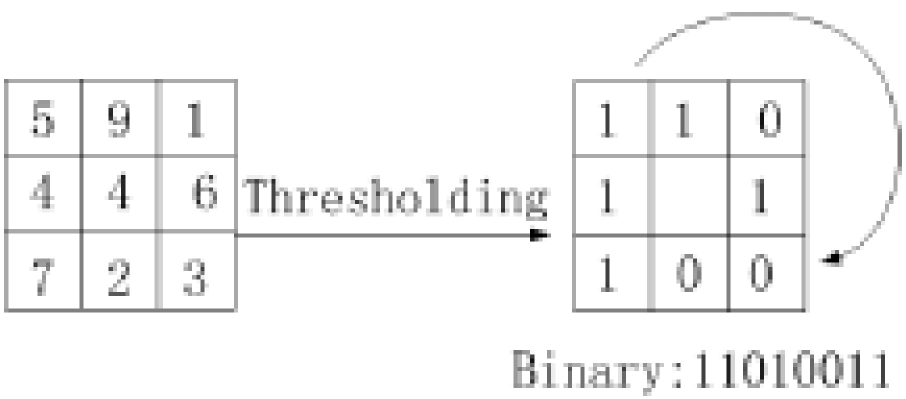
10001111

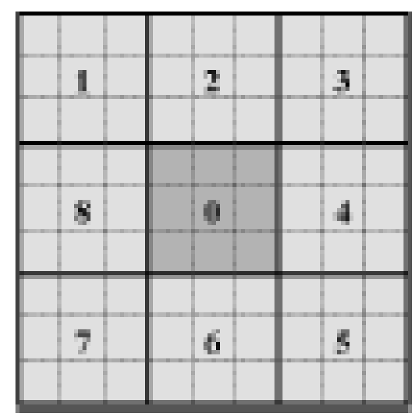


Variants of LBP

Multi-Scale Block LBP

- Average sum of intensity in each subregion is computed. These averages are thresholded by the central block.
- More robust than the basic LBP which is too local.

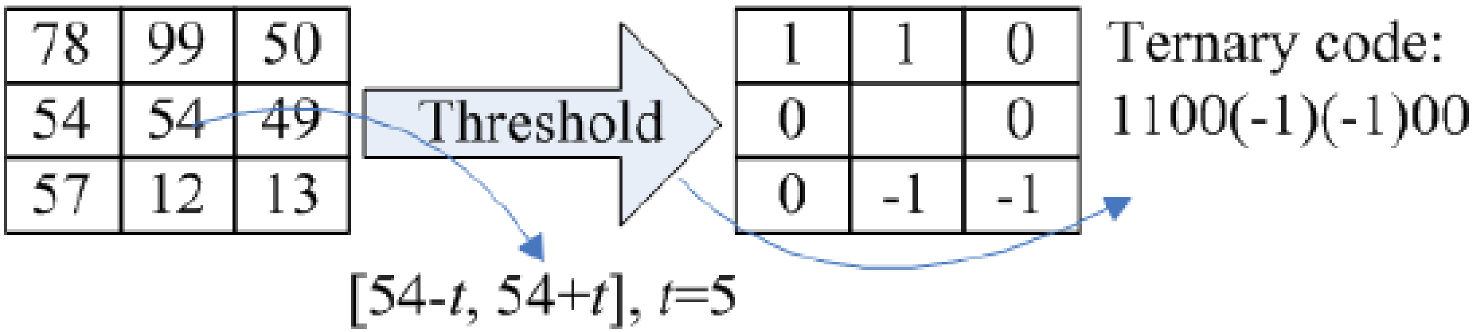




Shengcai Liao, Xiangxin Zhu, Zhen Lei, Lun Zhang, and Stan Z. Li, “Learning Multi-scale Block Local Binary Patterns for Face Recognition,” 2007.

Variants of LBP

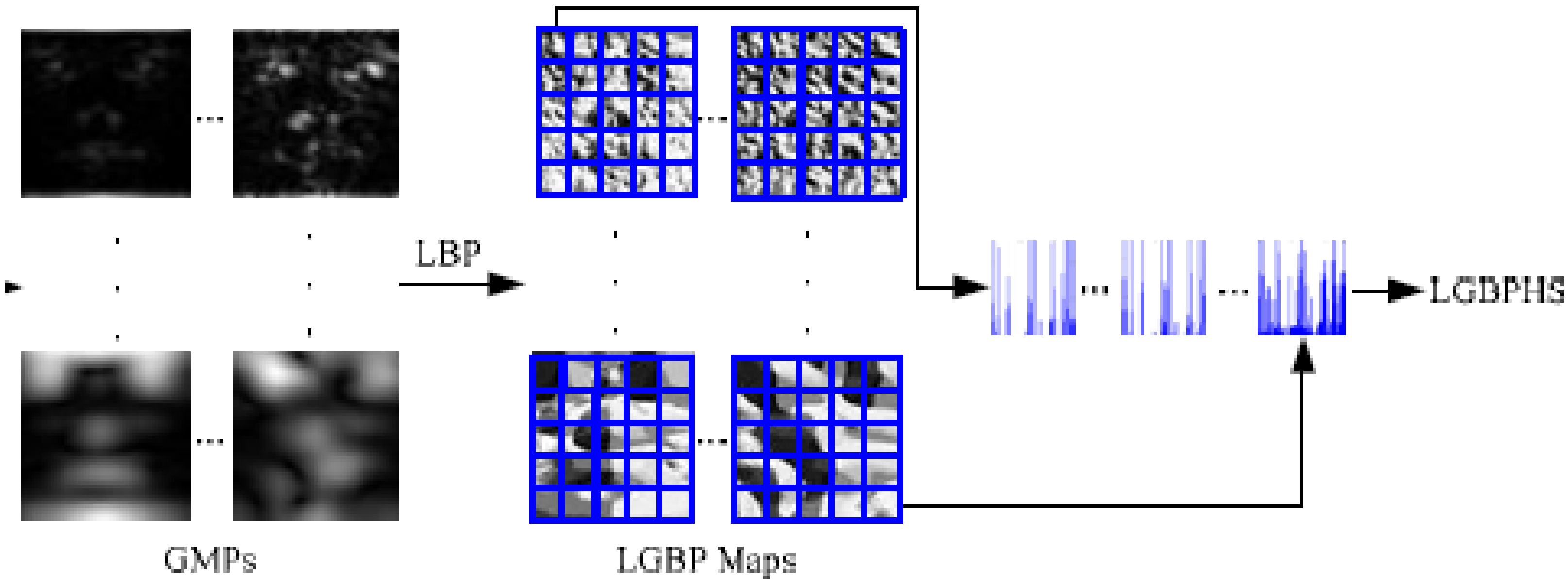
- **Local Ternary Pattern:** 3-valued coding that includes a threshold around zero for improved resistance to noise



*Xiaoyang Tan; Triggs, B.; , "Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions"

LBP on Gabor Magnitude map

- Each normalized images is converted into Gabor Magnitude map by convolving with Gabor filters.
- Local Binary Pattern Map of each GMP is generated and features are extracted and concatenated.



*Wenchao Zhang; Shiguang Shan; Wen Gao; Xilin Chen; Hongming Zhang; , "Local Gabor binary pattern histogram sequence (LGBPHS): a novel non-statistical model for face representation and recognition

GRAB Operator
General Region Assigned to Binary

A representation of GRAB-N

- Each NxN region computes the a measure (e.g. average intensity) in that region
- If the central measure is significantly different than measure for neighbor k, then set bit k to 1, else set to 0
- This model allows to incorporate changes in resolutions/scale, as well as camera noise.

Normalized Image

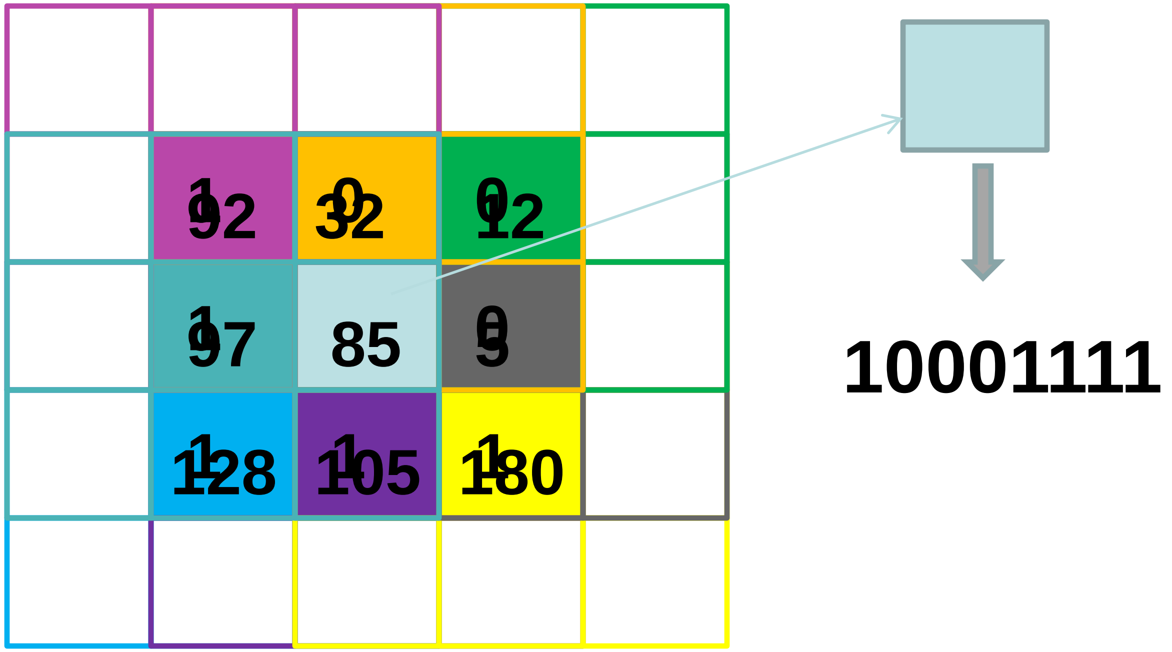
Smoothed Image computed using Integral image.

Grabbed Image

A. Sapkota, B. Parks, W. Scheirer, and T. Boult, “FACE-GRAB: Face Recognition with General Region Assigned to Binary Operator,” 2010

GRAB Operator

GRAB-3 Example



GRABBed Images

LBP and the lower windowed GRAB images are impacted by noise and low resolution artifacts. Higher GRAB windows have balance between texture information and noise.






Geo-Normalized Image

LB
P

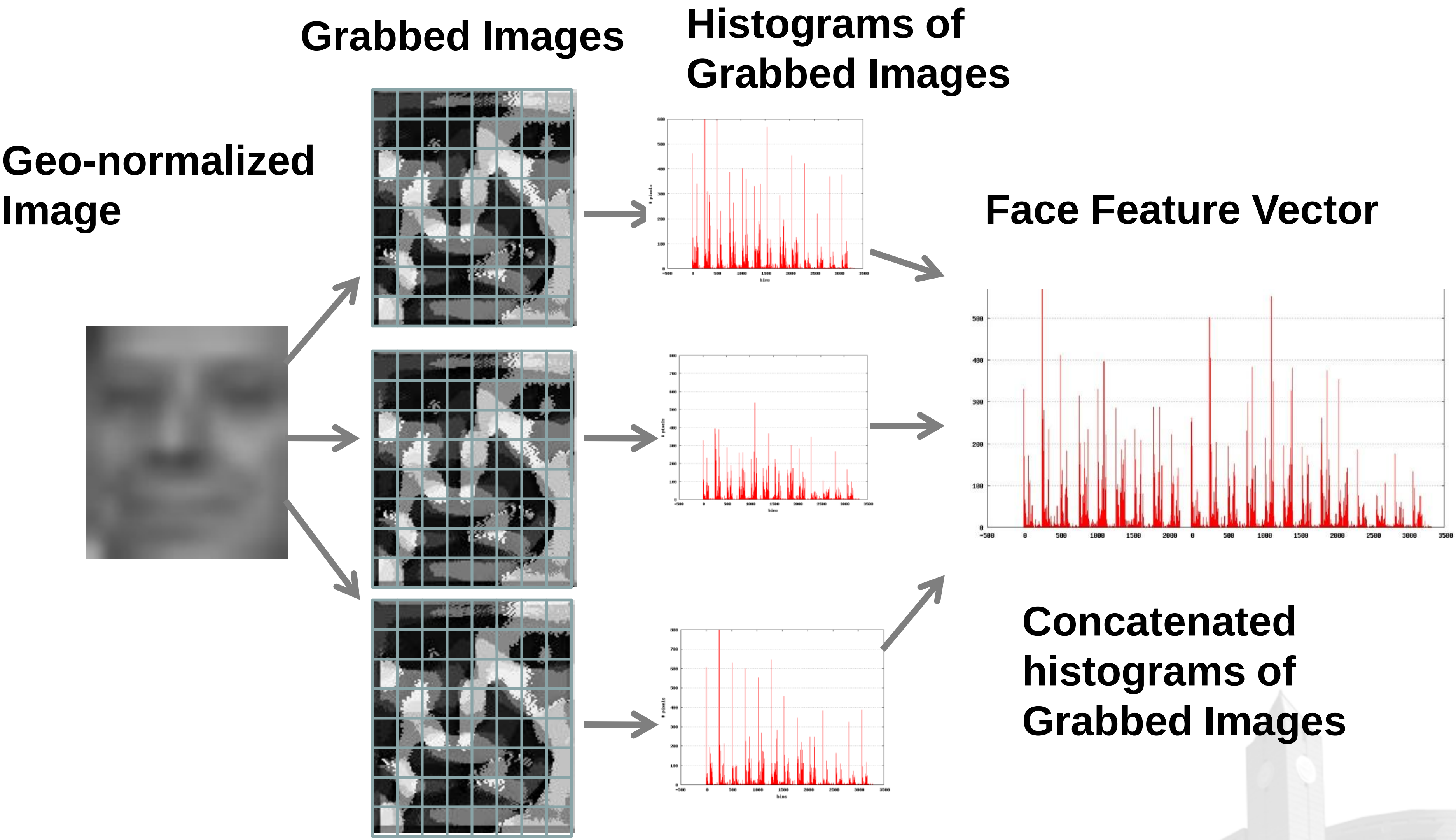
GRA
B-3

GRA
B-5

GRA
B-7

GRA
B-9

GRAB-FACE Description



Resolution Preprocessing

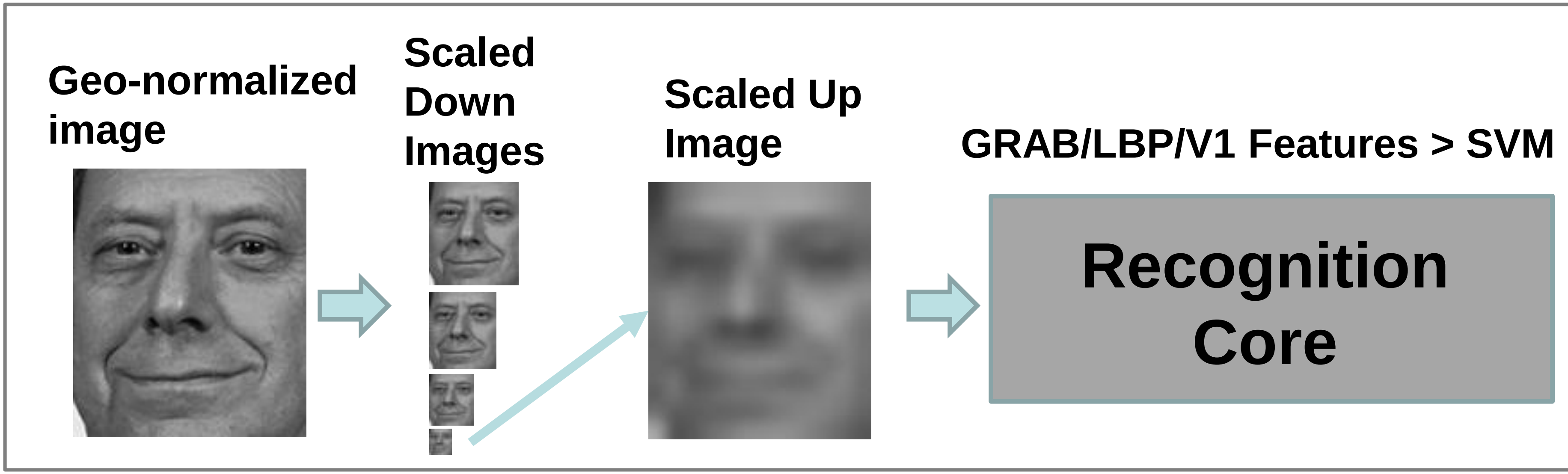


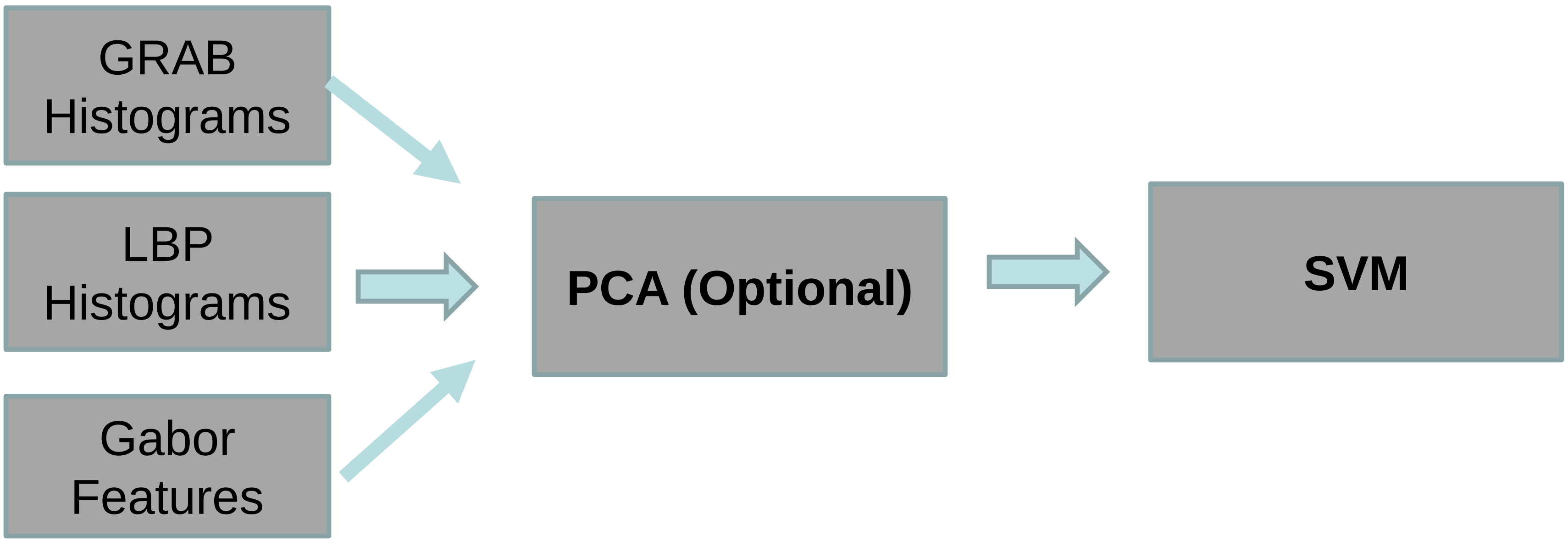
Image Sizes Used in the Experiments:

Gallery: 130 x 150

<u>**Probe:** 130 x 150</u>

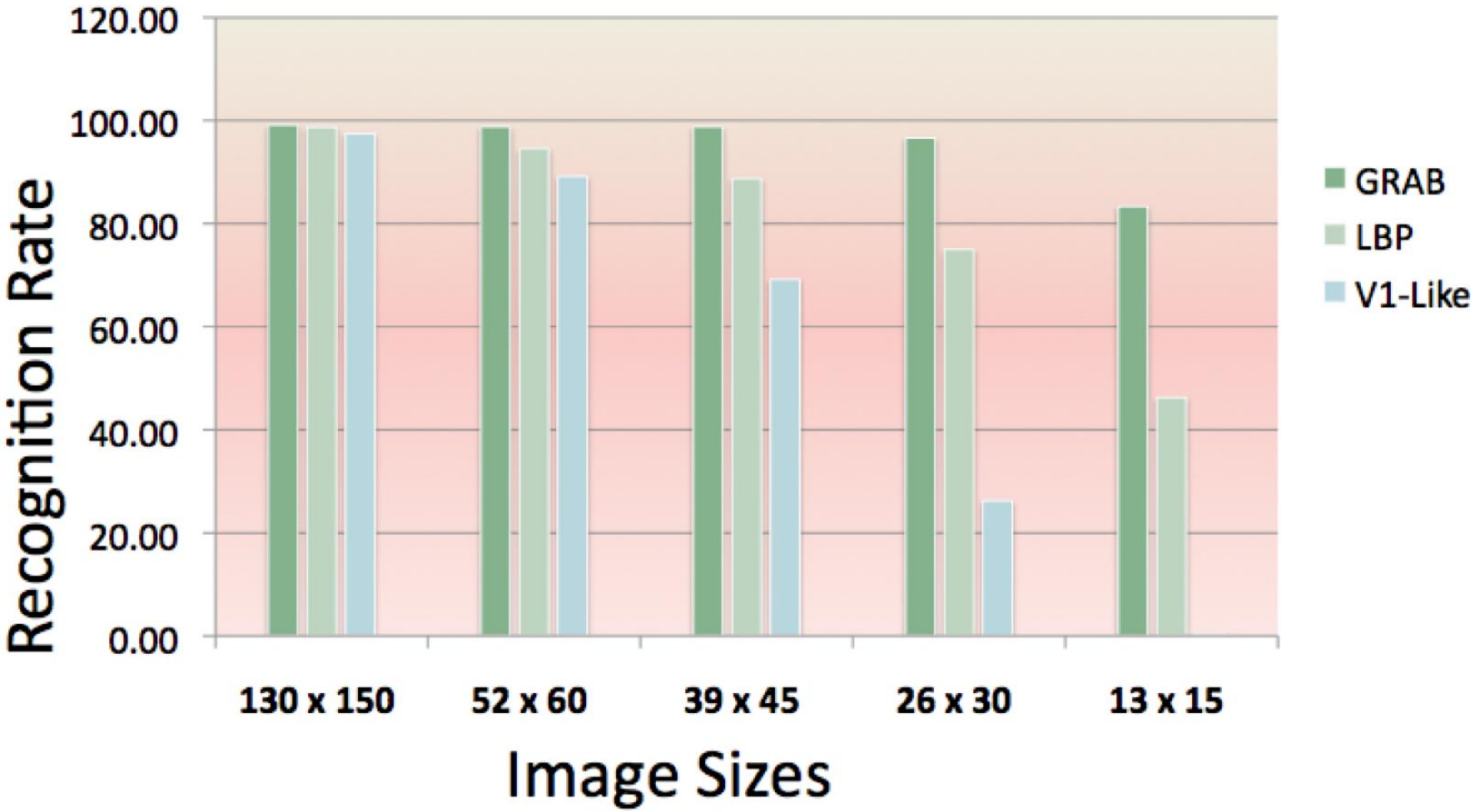
52x60 (60% Reduction of 130x150)
39x45 (70% Reduction)
26x30 (80% Reduction)
13x15 (90% Reduction)

Classification Method



- Support Vector Machine (SVM) was used
- Performance Gain using SVM compared to Nearest-Neighbor
- Results of LBP was verified using standard FERET protocol using Nearest Neighbor Classification
- PCA is important for Gabor features but did not help GRAB and LBP.

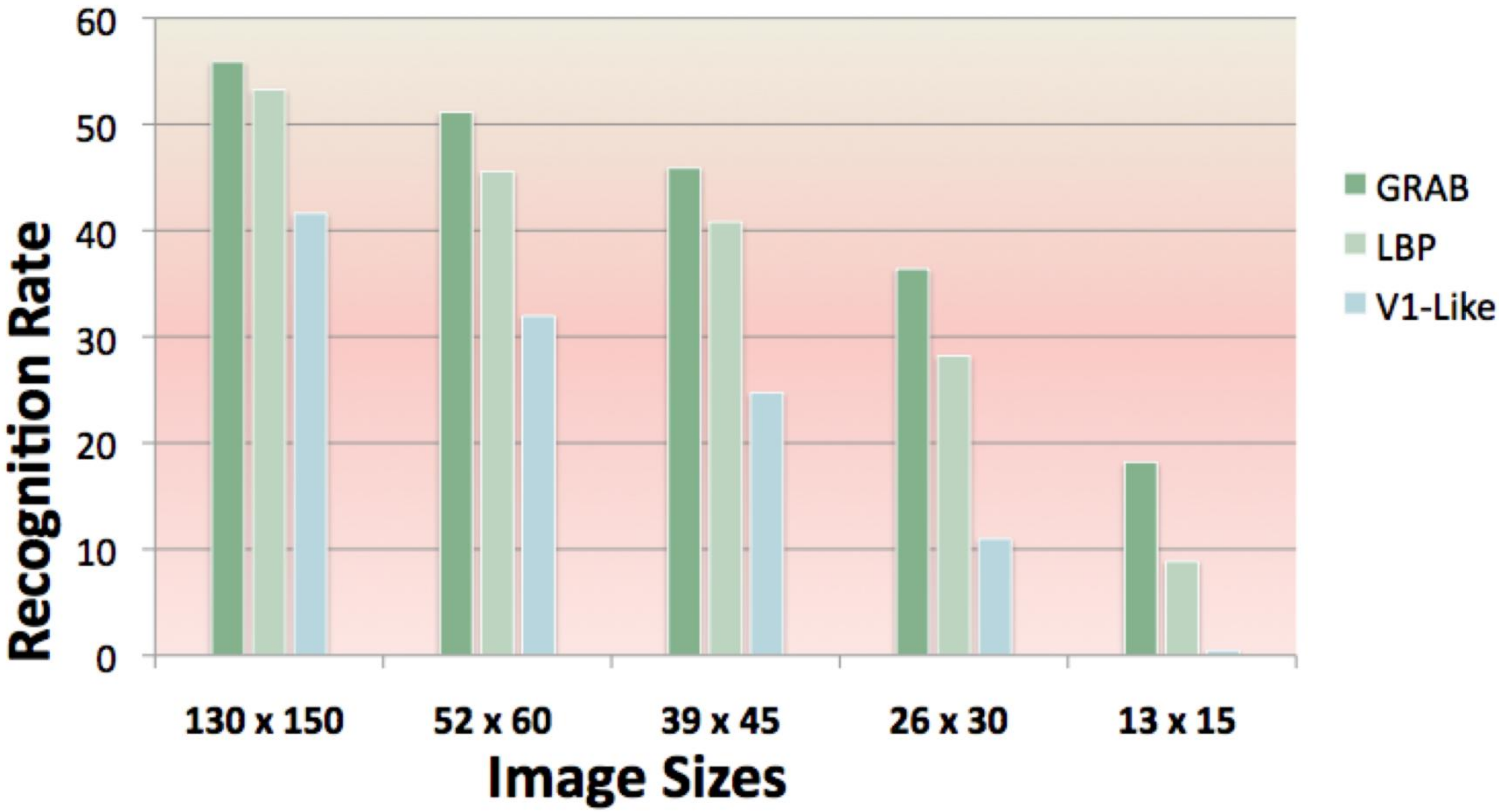
Results – FERET 240



GRAB vs. LBP vs. V1- Like – Rank 1 Recognition Rate

Gallery images → 130 x 150 ; Probe images → as shown

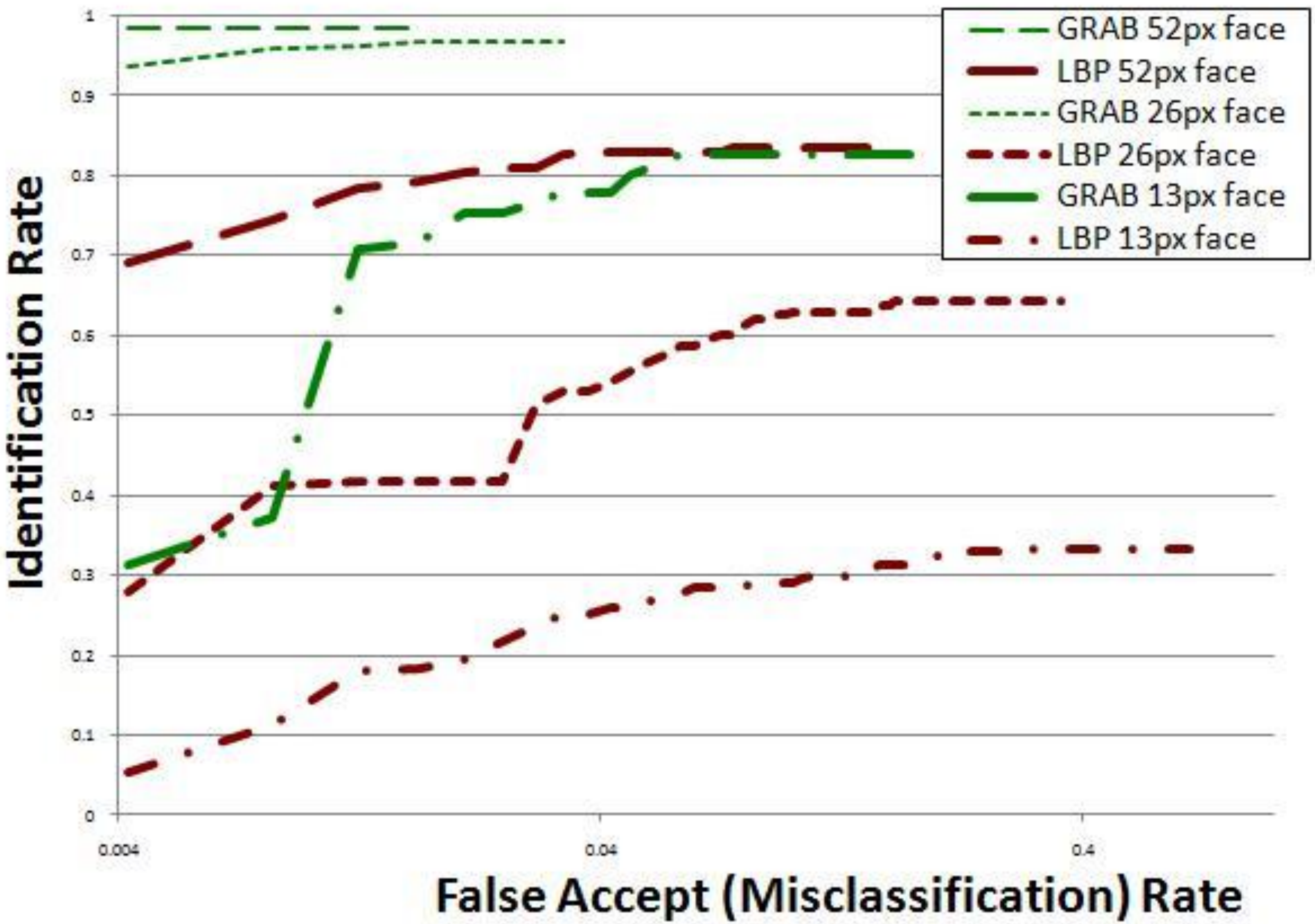
Results – LFW 610



GRAB vs. LBP vs. V1- Like – Rank 1 Recognition Rate

Gallery images → 130 x 150 Probe images → as shown

Results

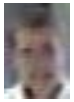


GRAB 52px face
LBP 52px face
GRAB 26px face
LBP 26px face
GRAB 13px face
LBP 13px face
Identification Rate
False Accept (Misclassification) Rate
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.004
0.04
0.4

How well can a face be represented using such features?

Issue with low resolution images and methods of solving.

Size: ~25x25

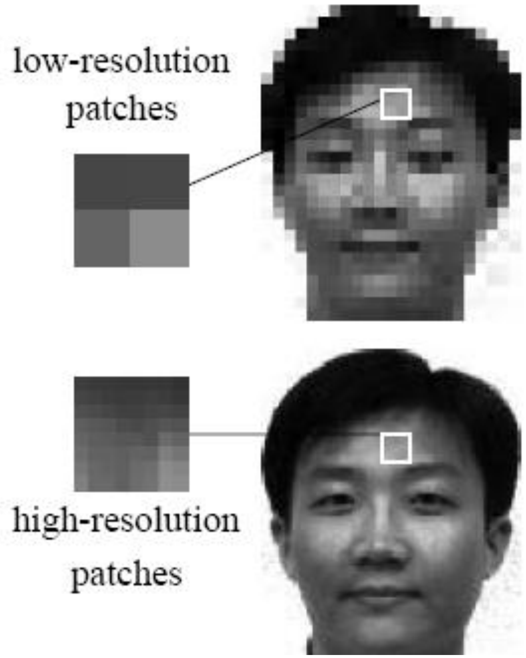


Methods used in face recognition

- Use super resolution/face hallucination or interpolation to reconstruct high resolution images from input images. Match the gallery and probe at high resolution.
- Downsample the gallery image and match low resolution probe with low resolution gallery.
- Other methods

Super Resolution/Hallucinating Faces

- Super-Resolution reconstruction produces one or a set of high-resolution images from one or a sequence of low-resolution frames.



- Depending upon the requirement the following techniques are available.

Input	output
Singe LR image	single HR image
Multiple LR frames	single HR image
Multiple LR frames	sequence of HR images

Super Resolution Observation Model

[illegible]

F_k geometric wrap : $[L^2 \times L^2]$

C_k blur matrix : $[L^2 \times L^2]$

D_k decimation operator: $[N_k^2 \times L^2]$

$\underline{Y}_k$ is a set of N observed images. 1<k<=N.

Each $\underline{Y}_k$ is of the size : $[N_k \times N_k]$

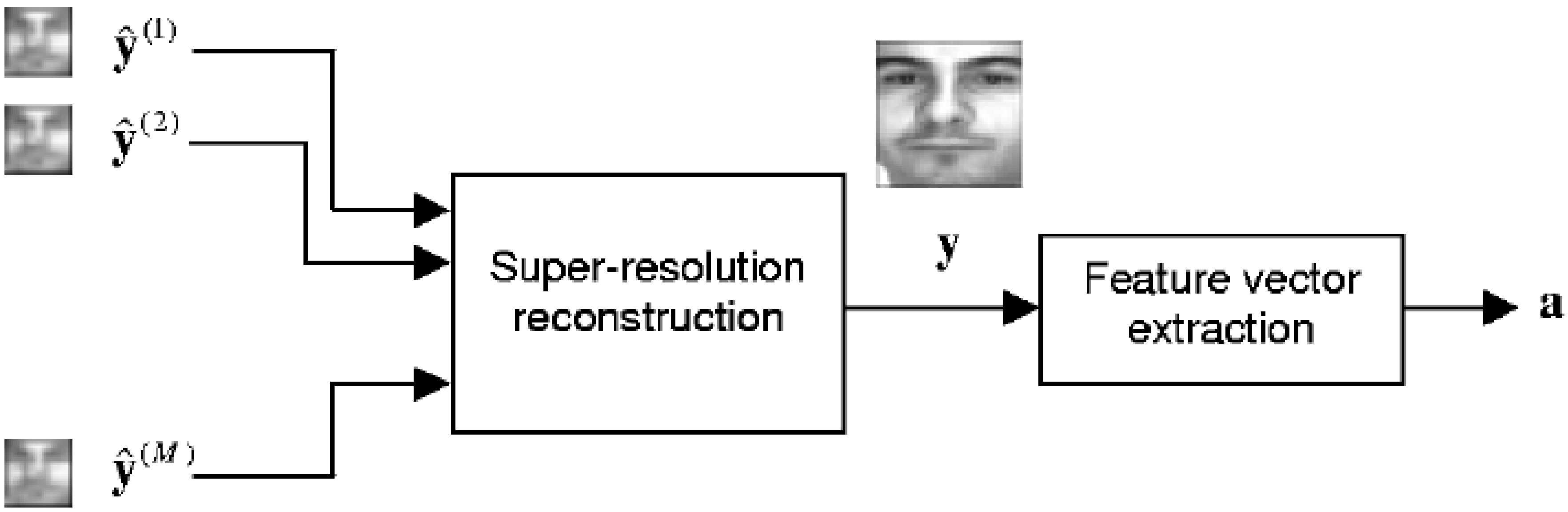
$\underline{X}$ is the single HR image of size : $[L \times L]$

solve the model equation to estimate the HR image

Reconstruction Based Super Resolution

At preprocessing stage (pixel level)

- Construct a high-resolution, visually improved face image that can later be passed to a face recognition system for improved performance.
- Complexity issue

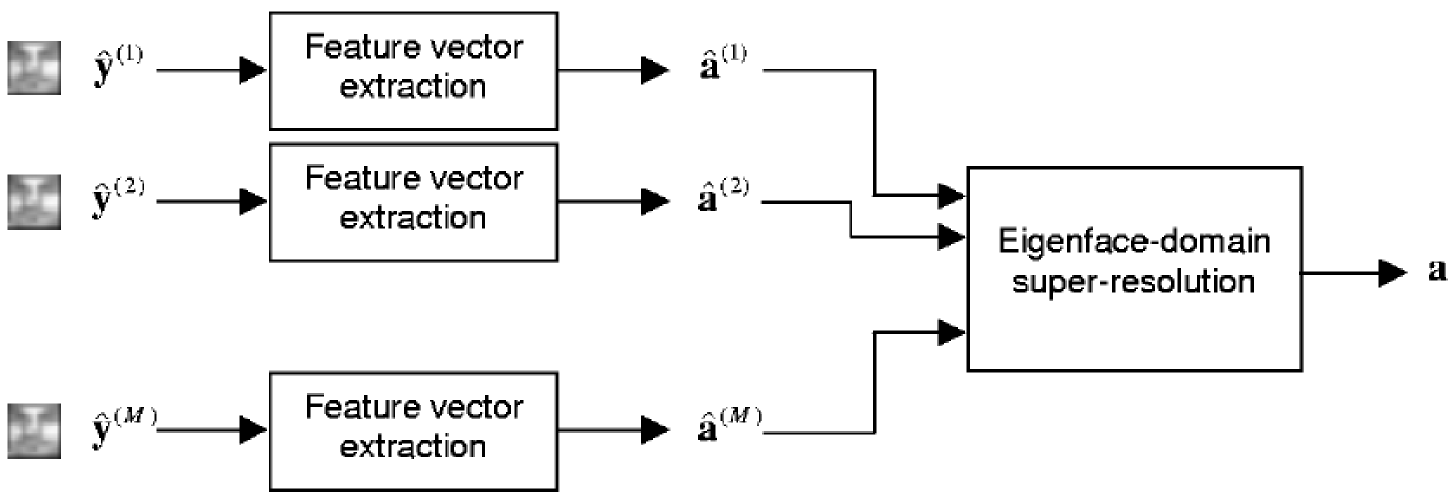


Hallucinating Faces Methods

At low dimensional face space(Face specific Recognition Based)

- Subspace based methods:
- Kernel Prior
- Reduces complexity, less prone to noise and, robust to registration errors.
- Baker at el. Face priors

One example:

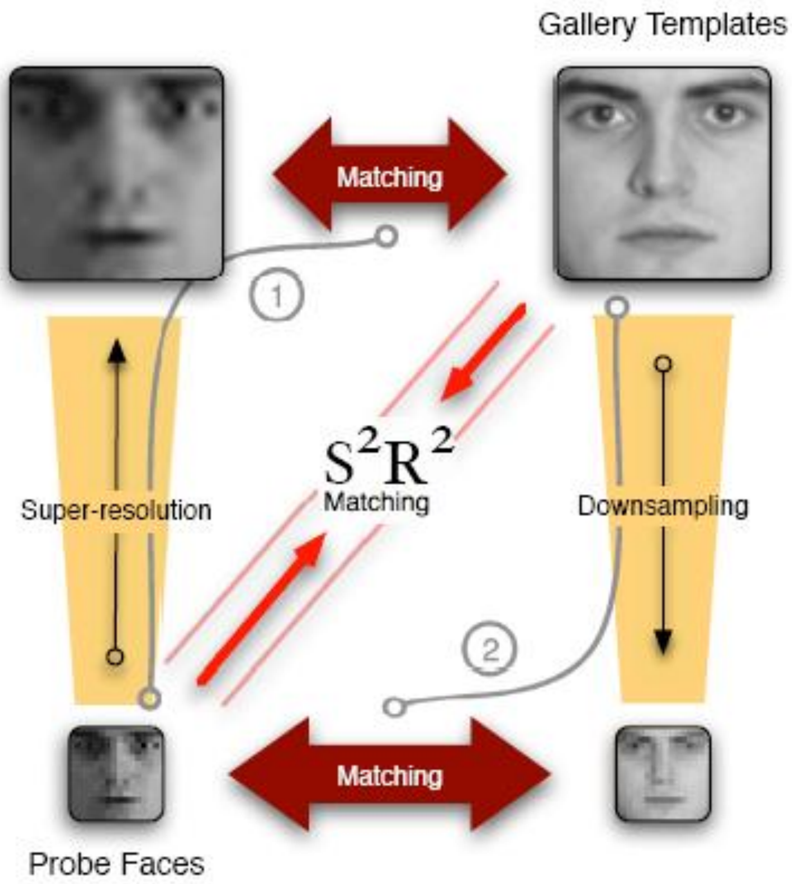


*Gunturk, B.K.; Batur, A.U.; Altunbasak, Y.; Hayes, M.H., III; Mersereau, R.M.; , "Eigenface-domain super-resolution for face recognition," 2003

Face Super Resolution Methods

Simultaneous super resolution and recognition:

- This approach simultaneously provides measures of fit of the super-resolution result, from both reconstruction and recognition perspectives.

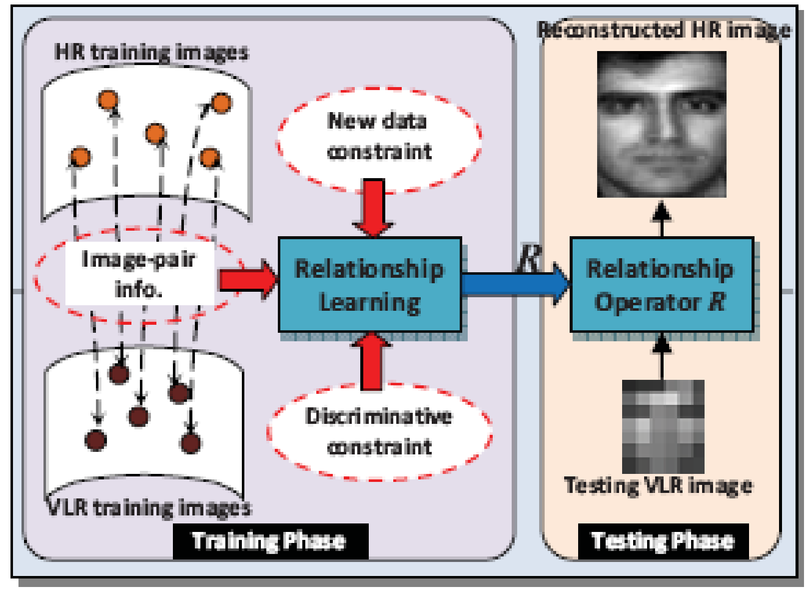


*Hennings-Yeomans, P.H.; Baker, S.; Kumar, B.V.K.V.; , "Simultaneous super-resolution and feature extraction for recognition of low-resolution faces, 2008

Face Super Resolution Methods

Relationship learning based super resolution

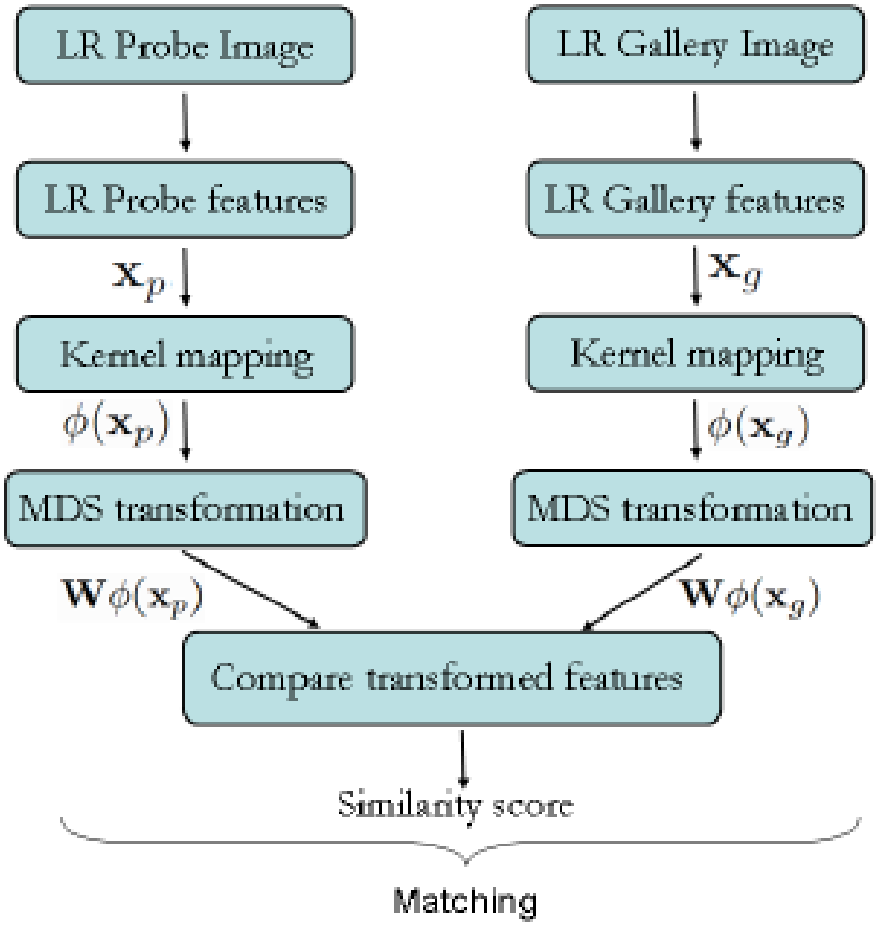
- Addresses the issue with resolution of face image lower than 16x16.
- Low-dimension of the VLR image space does not carry a good information for the super-resolution methods.
- Relationship R (in form of matrix) between HR image space and VLR image space is learnt. HR images can be reconstructed from the learnt R.



*Zou, W.W.W.; Yuen, P.C.; , "Very low resolution face recognition problem," 2010

Transformation of LR Images

- This method does not use super-resolution techniques.
- It rather goes through something called Multidimensional transformation, such that distance between LR images is close to the distance between HR images.
- Matching is done in transformed space on LR images.
- Training consists of LR and HR images and the transformation parameters are learnt based on the distance between multiple LR images and HR images separately.



*Biswas, S.; Bowyer, K.W.; Flynn, P.J.; , "Multidimensional scaling for matching low-resolution facial images",2010

Face Super Resolution Methods

- Reconstruction of SR face images using multiple occluded images of different resolutions which are commonly encountered in surveillance videos.
- Performs hierarchical patch-wise alignment and global Bayesian inference.
- Considers the spatial constraints and exploit the inter-frame constraints across multiple face images of different resolutions

*K. Jia, S. Gong, Face super-resolution using multiple occluded images of different resolutions, 2005

Low Resolution Images | Resulting Image | Ground Truth

SVDD and pre image method

- 1. Solve the SVDD problem: Model the data region for the normal faces as the ball resulting from the SVDD problem
- 2. Project the test images feature vector onto the spherical decision boundary in the feature space
- 3. Solve the pre-image and recognize using correlation method.

*Sang-Woong Lee, Jooyoung Park, Seong-Whan Lee, Low resolution face recognition based on support vector data description,2006

Some conclusions from S-R methods

- Fully automated rank 1 recognition rates are still likely to be poor despite the improvement provided by super-resolution. A fully automated recognition system is currently impractical.
- The surveillance system will need to operate in a semi-automated manner by generating a list of top machine matches for subsequent analysis by humans.

*Seong-Whan Lee, Stan Li, Frank Lin, Clinton Fookes, Vinod Chandran, Sridha Sridharan " Super-Resolved Faces for Improved Face Recognition from Surveillance Video",2007

Thoughts on Super Resolution and its Applicability

3D Face Recognition Methods

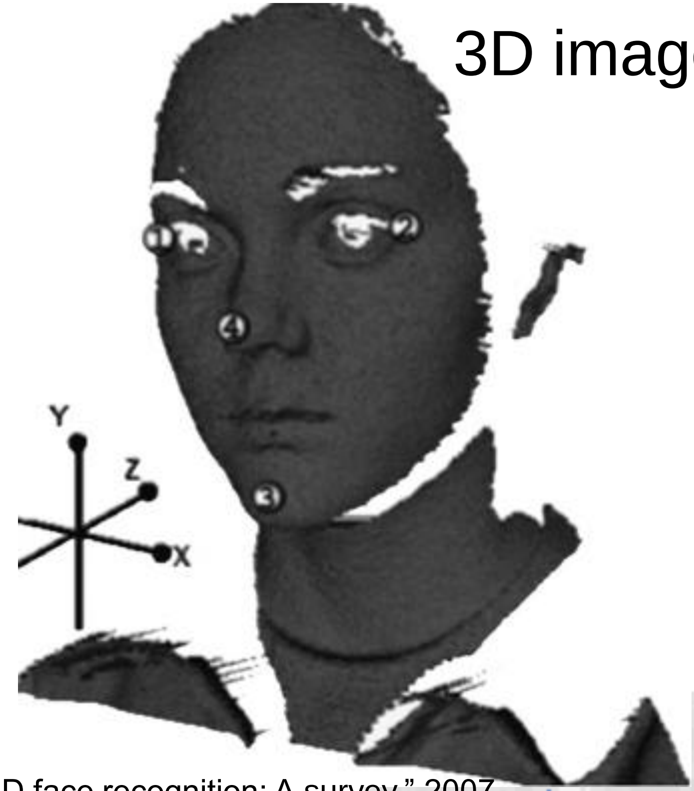
3D modeling

- Xu et al. (2004) : “Depth maps give a more robust face representation, because 3D intensity images are heavily affected by changes in illumination.”
- 3D models retain all the information about face geometry.
- Facial features like local and global curvatures in 3D models can have more discriminating power.

2D image

2.5D image

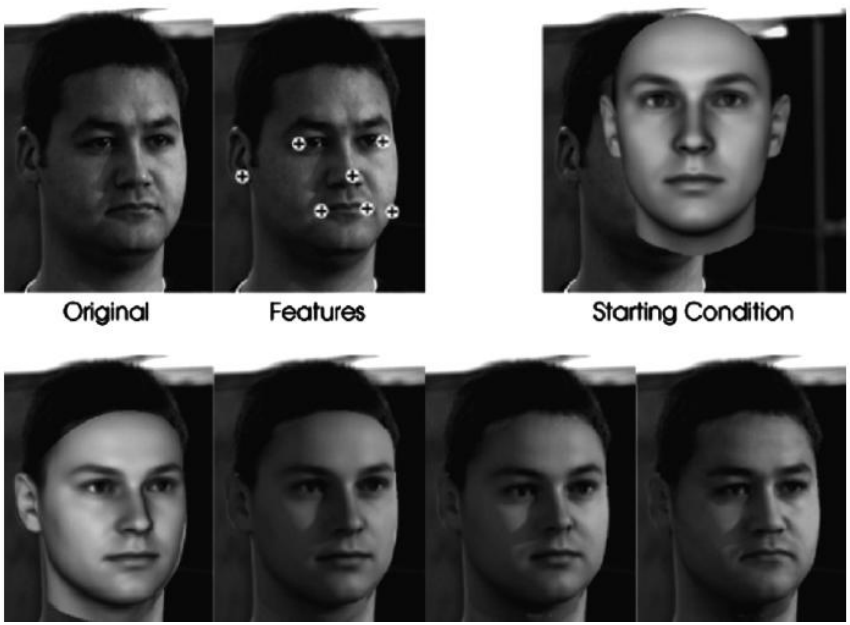
3D image

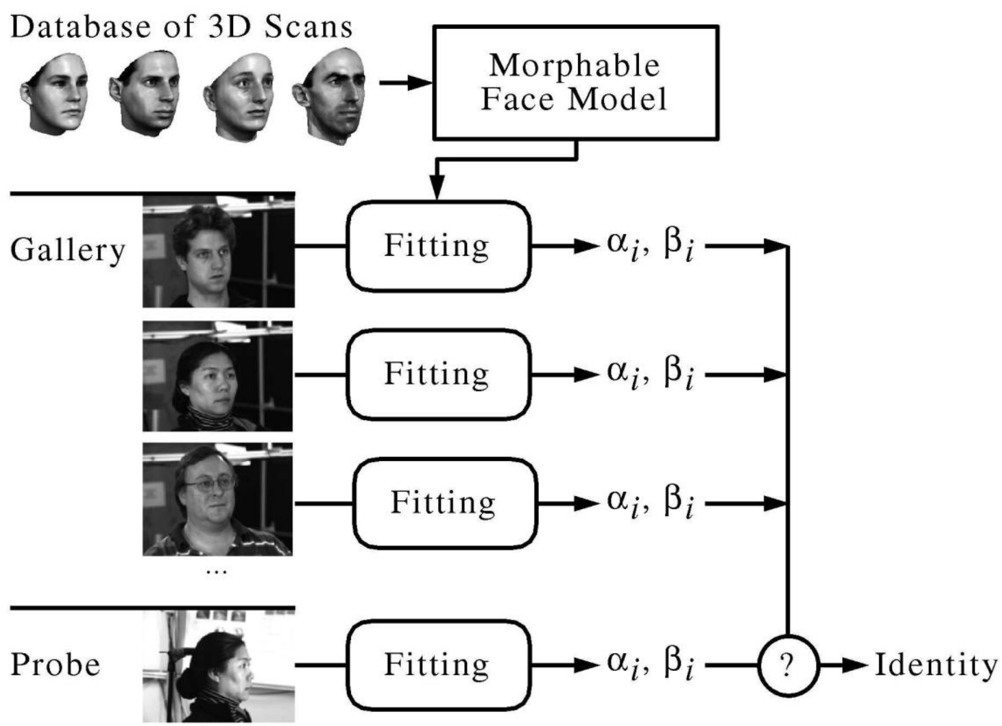


*Andrea F. Abate, Michele Nappi, Daniel Riccio, Gabriele Sabatino “2D and 3D face recognition: A survey,” 2007

3D face recognition methods

- **2D based methods**. 2D intensity images based algorithms but use 3D data.
- From one frontal 2D image, generate 3D morphable model.
- Recognition task is achieved measuring the Mahalanobis distance between the shape and texture parameters of the models in the gallery and the fitting model. Pic of 3D morphing techniques





*Blanz and Vetter Face Recognition Based on Fitting a 3D Morphable Model, 2003

3D face Recognition Methods

2D based methods: synthetic views

- Generate a 3D model.
- Synthesize many 2D views are synthesized to simulate new poses, illuminations and expressions.
- Use affine subspace matching techniques for recognition.

Concerns are:

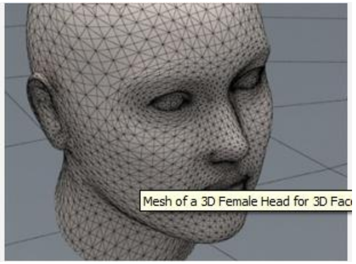
How realistic are the synthesized faces?

How precise is a 3D model reconstructed from one image?

*Lu et al. “Face Recognition with 3D Model-Based Synthesis” 2004

3D face recognition methods

- **Face recognition algorithms directly work with the 3D features or 3D features or surfaces.**
- Alignment is an issue:



- Acquisition of aligned images.
- Iterative Closest point

- 3D model generated from one frontal images and one profile image, global and local deformation applied and recognition based on matching features on 3D surface on mouth, nose and eyes. (Abdel-Mottaleb -2003)
- Iterative Closest Point Based methods (ICP)

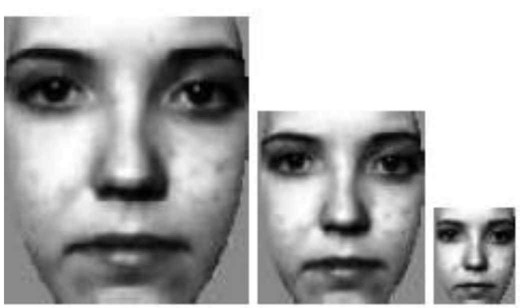
- ICP used to align faces and recognition performed using GMM. (Cook et al. - 2004)
- Point to point correspondence between landmark features and matching by comparing the surface volume. (Irfanoglu et al. 2004)
- 3D generation from several 2.5D images and recognition based on ICP. (Lu et al. - 2004)

*Andrea F. Abate, Michele Nappi , Daniel Riccio, Gabriele Sabatino “2D and 3D face recognition: A survey,” 2007

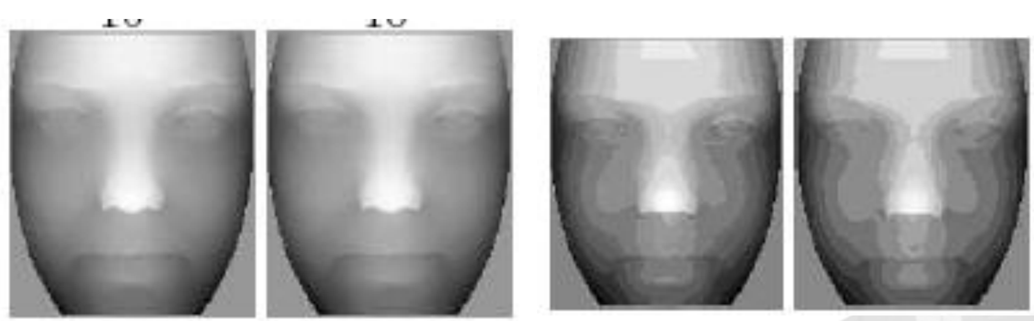
Multimodal Methods

Combine information from 2D images and 3D models.

- Chang et al. (2003) Chang et al. (2004):
- 2D and 3D have similar recognition performance when considered individually
- Combining 2D and 3D results using a simple weighting scheme outperforms either 2D or 3D alone
- Combining results from two or more 2D images using a similar weighting scheme also outperforms a single 2D image, and
- Combined 2D + 3D outperforms the multi-image 2D result
- Depth Data + Intensity + HMM (Tsalakanidou et al. 2003)
- 3D + texture information (Papatheodorou and Rueckert 2004)



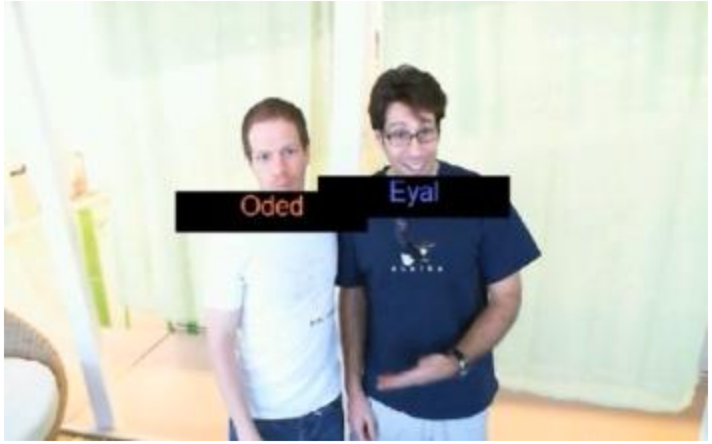
Intensity Resolutions



Depth Resolutions

Face Recognition from Video

Face Recognition From Video



Advantages from Video:

- More data available
- Temporal Integration
- Behavioral Cue
- Spatial and Temporal Sampling

- Video to video
- Still to video
- Video to still

http://blogs.technet.com/b/next/archive/2011/03/09/microsoft-demos-face-recognition-in-video.aspx

Face Recognition From Video

The curse of Dimensionality

Standard VGA (640x480)

1 frame: 300 KByte
30 frames: 1 MByte

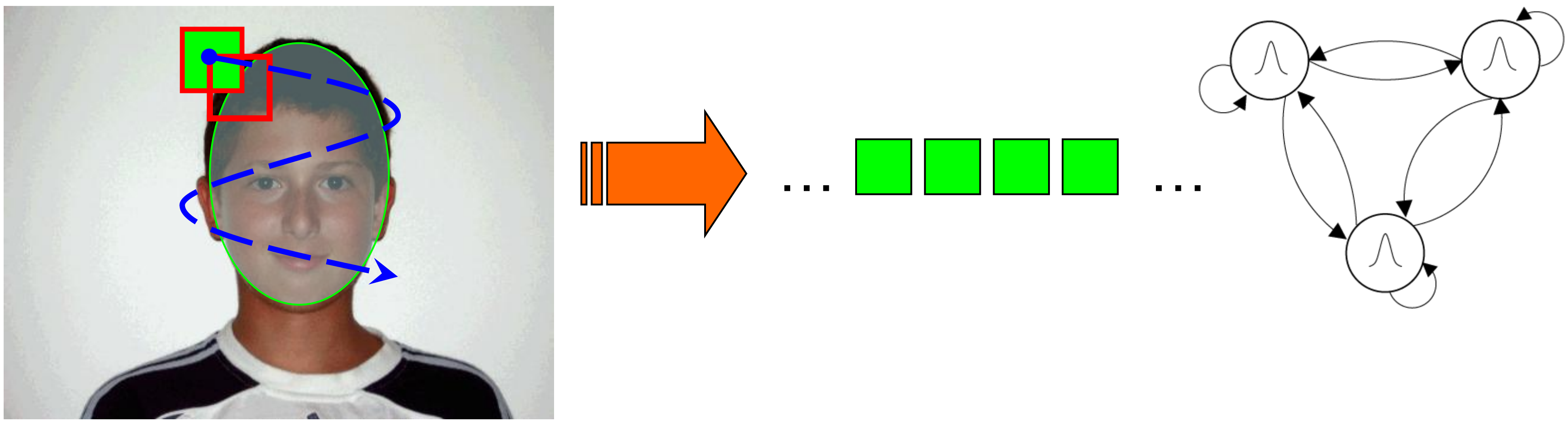
Standard video: ~1 MByte/Sec

The risk is to have too much data to be processed

How to exploit the added information in video?

Hidden Markov Models

- Statistical Analysis of sequence of patterns:



- This idea can be extended to multi-dimensional pattern and sequences.

Dynamic Hidden Markov Model

- Each image is modeled as a single HMM and the sequence of images as a sequence of HMMs

  (A. Hadid and M. Pietikainen. “An experimental investigation about the integration of facial dynamics in video-based face recognition”. *Electronic Letters on Computer Vision and Image Analysis*, 5(1):1-13, 2005.)

- The entire video is modeled as a single HMM

  (X. Liu and T. Chen. “Video-based face recognition using adaptive hidden Markov models”. In *Proc. Int. Conf. on Computer Vision and Pattern Recognition*, 2003.)

- The images and the sequence itself are modeled as a complex, hierarchical HMM-based structure

  (M. Bicego, E.Grosso, M. Tistarelli. “Person authentication from video of faces: a behavioural and physiological approach using Pseudo Hierarchical Hidden Markov Models”, Intl. Conference on Biometric Authentication 2006, Hong Kong, China, January 2006.)

Face Recognition from Video

Not just more data to be processes, the issues are:

- Data selection (pose, expression, illumination, noise…)
- Multi-data fusion (decision/score/feature level)
- 3D reconstruction/virtual views
- Resolution enhancement
- Expression and emotion analysis
- Behavioral analysis
- *Dynamic* video templates…?

Face Recognition in Video

- **Probabilistic recognition of human faces from video[1]**
- The joint posterior distribution of the motion vector and the identity variable is estimated using Sequential Importance Sampling at each time instant and then propagated to the next time instant.

- **Video based face recognition using probabilistic appearance manifolds[2]**
- Each registered person is represented by a low-dimensional appearance manifold in the ambient image space.
- *A maximum a posteriori formulation performed on test images by integrating the likelihood that the input image comes from a particular pose manifold and the transition probability to this pose manifold from the previous frame.*

1. R. Chellappa, V. Kruger, S. Zhou, “Probabilistic recognition of human faces from video,” 2002.
2. K. Lee, J. Ho, M. Yang and D. Kriegman, “Video based face recognition using probabilistic appearance manifolds,” 2003

Findings from Video based Analysis*

- Important findings:
- Short sequences do not have enough dynamic information to discriminate between individuals. So spatio-temporal algorithms may not do well when there is a short sequence.
- However, with a longer sequence good facial dynamics are achieved and spatio-temporal methods do well.
- Open question: How representative the face sequences should be in order to allow the system to learn the dynamics of each individual.
- Image quality affects both the representations, but image based methods are more affected. So for the face recognition with low quality images, spatio-temporal representations are more suitable.
- More than just rigid head motion, expressions or talking or laughing can add dynamics to face recognition.

*A. Hadid, M. Pietikinen, "From Still Image to Video-Based Face Recognition: An Experimental Analysis," 2004

Pose Invariant Methods

Pose Invariant Features

- Local approaches such as EBGM and LBP are more robust to pose variations than holistic approaches such as PCA and LDA. This is because local approaches are relatively less dependent on pixel-wise correspondence between gallery and probe images, which is adversely affected by pose variations
- The tolerance of local approaches to pose variations is limited to small in-depth rotations.
- These methods are not entirely robust to pose variations, because distortions exist in local image regions under pose variations.
- Under intermediate or large pose variations, pose compensation or specific pose-invariant feature extraction is necessary and beneficial.

Pose Invariant Features

- Four-point cross ratio and others.

  *Joseph L. Mundy, Andrew Zisserman, Geometric invariance in computer vision
- Affine transformation invariant features

  *Wide Baseline stereo matching based on locally affine invariant regions;
  An affine invariant interest point detector
- General transformation invariant features

  *Automatic acquisition of exemplar based representations for recognition from image sequences.

- Problems: Many features which are important for recognition are not selected as pose invariant and many selected features are not sufficient for recognition especially in a situation like face recognition.
- Affine invariant patches do not work for 45 degree or more rotation.

Pose Invariant Methods

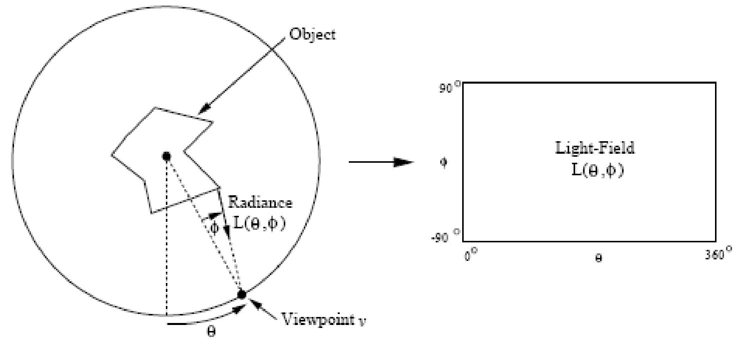
- **Real View Based Matching: Multiple gallery view of every subject to be matched.**
- D.J. Beymer, 1994
- R. Singh et al.(2007)

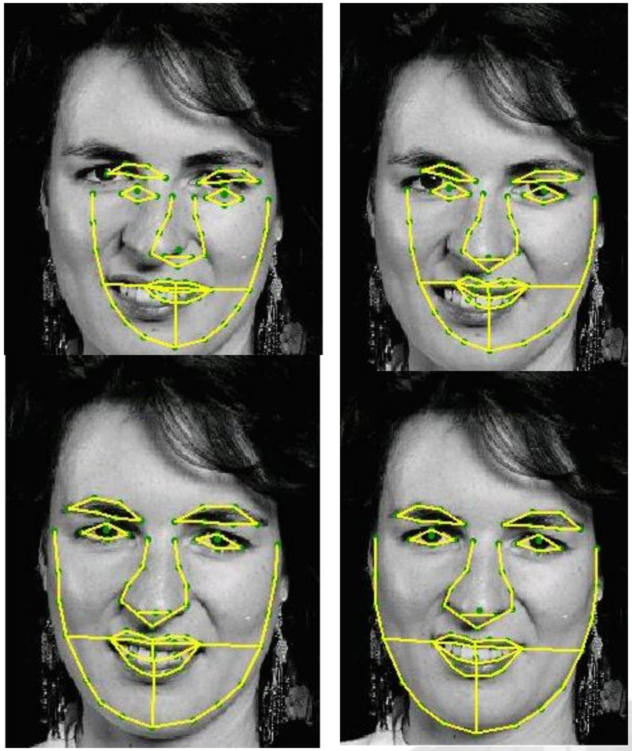
- Challenge: it is generally impractical to collect multiple images in different poses for real view-based matching

- **3D models based methods**
- 3D shape Models, feature based 3D reconstruction, image based 3D reconstruction

Pose Invariant Methods

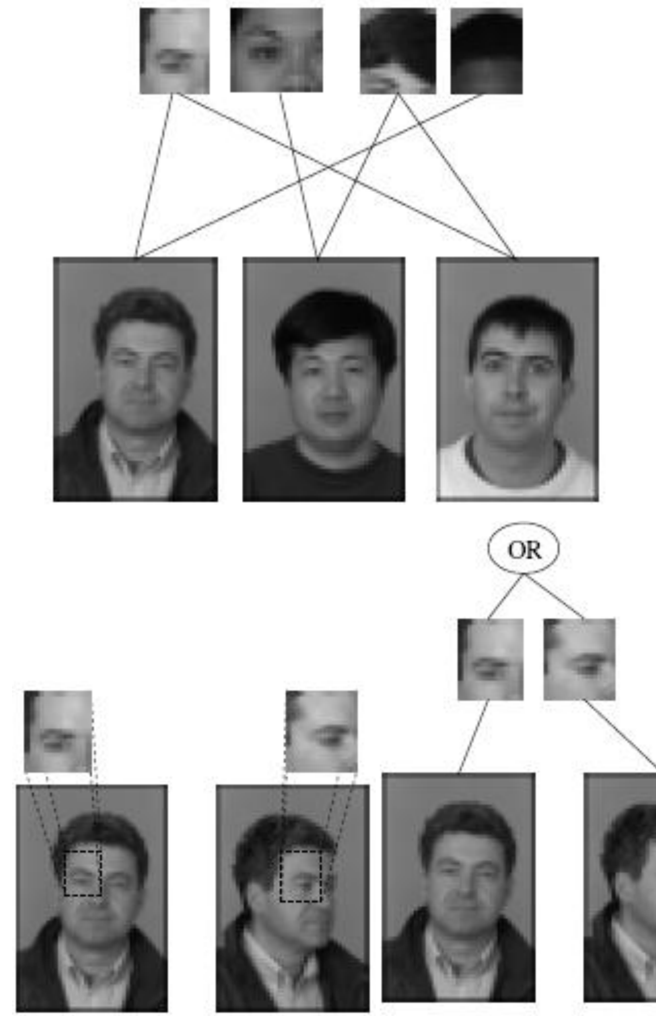
- **2D pose transformation: synthesize virtual views to substitute the demand of real views from a limited number of known views.**
- Active Shape Model, Active Appearance model, Pose Parameter Estimation, Eigen Light Field Methods, Linear Shape Model, Linear Regression estimation
- Learning patch correspondence.
- Limited by the larger variation in poses especially above 45 degree which results in discontinuity in 2D image Space.
- Suboptimal modeling of facial texture except AAM and Linear Shape model.





View Invariant Face Recognition

- **View Invariant Recognition using corresponding object fragments**
- Objects are represented using informative subimage or patches or fragments
- View invariance is obtained by introducing equivalence sets of fragments.
- Fragments depicting the same part viewed from different angles are grouped together to form an extended fragments.
- Recognition based on extended fragments.



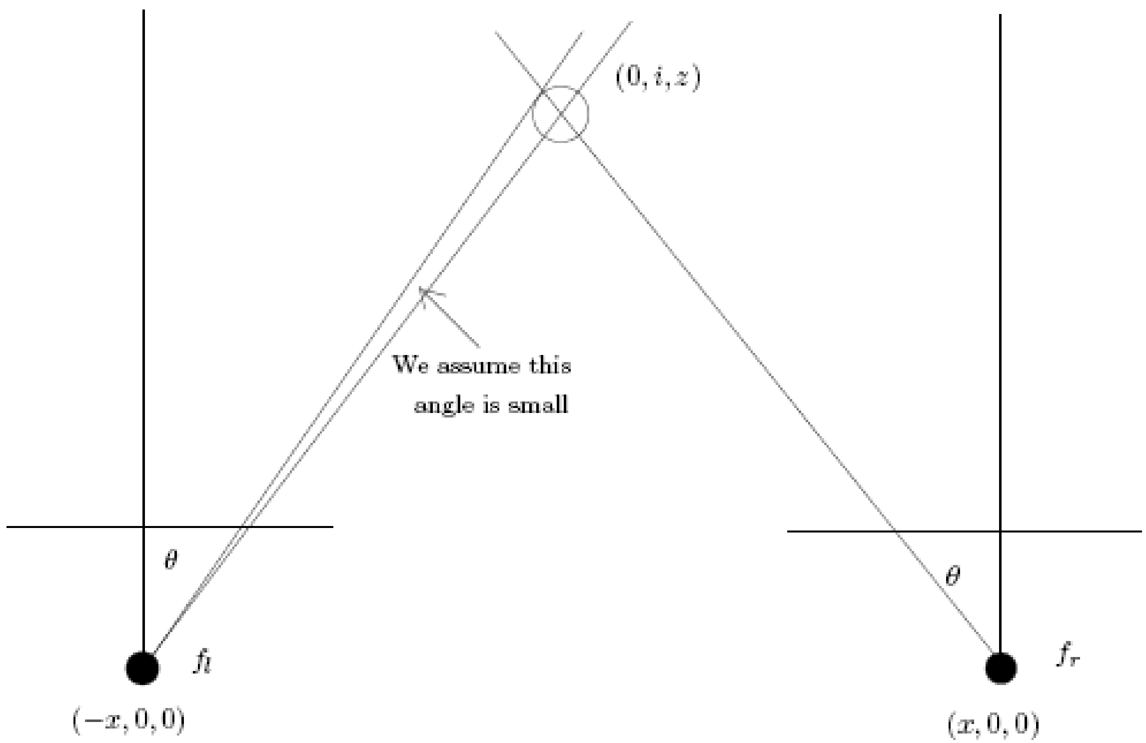
View variant fragments

Extended fragments

*Tomás Pajdla, Jirí Matas, Evgeniy Bart, Evgeny Byvatov, Shimon Ullman,"View-Invariant Recognition Using Corresponding Object Fragments" 2004

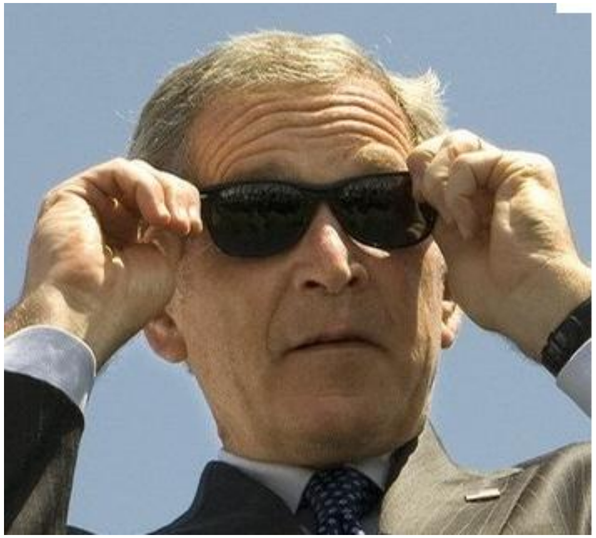
Pose Invariant Face Recognition

- Stereo Matching Method
- Stereo matching cost provides the measure for similarity between images, cost is robust to poses



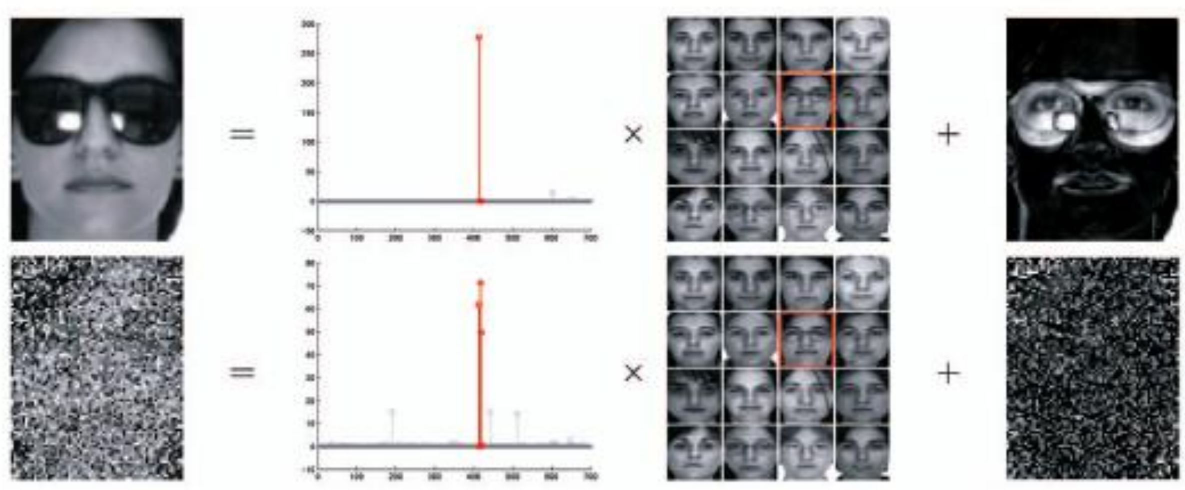
*Carlos D. Castillo, David W. Jacobs, "Using Stereo Matching with General Epipolar Geometry for 2D Face Recognition across Pose,“ 2009

Occlusion Invariant Methods



Occlusion Invariant Methods

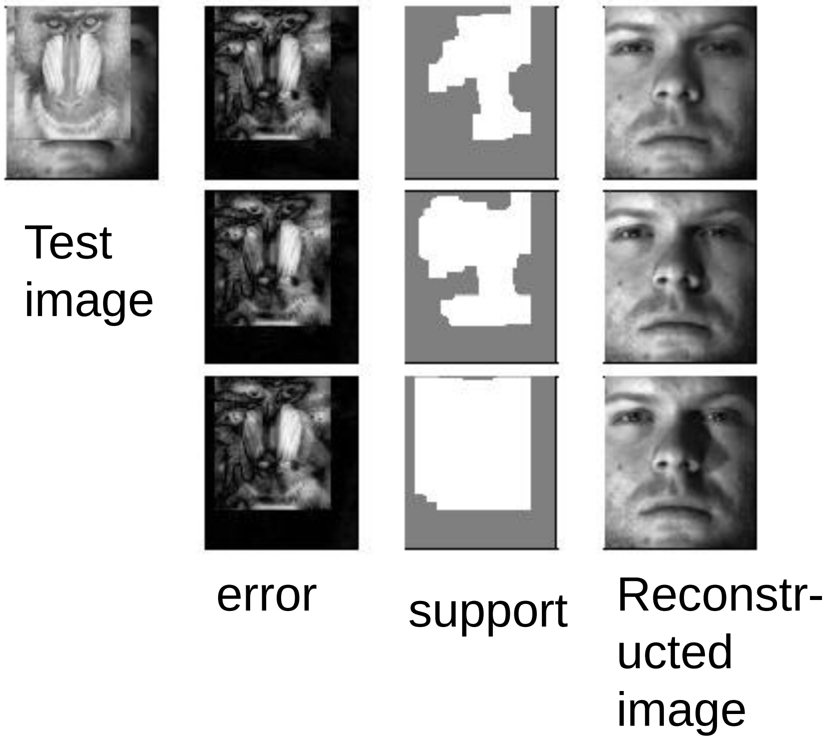
- Robust Face recognition via sparse Representation.
- If sparsity in the recognition problem is properly harnessed, the choice of features is no longer critical however the choice of the number of features is still critical.
- Test image can be represented as a linear combination of training samples and the identity can be found out by solving the linear representation (solving l1 norm minimization problem).



*John Wright, Allen Y. Yang, Arvind Ganesh, S. Shankar Sastry, Yi Ma, "Robust Face Recognition via Sparse Representation," 2007

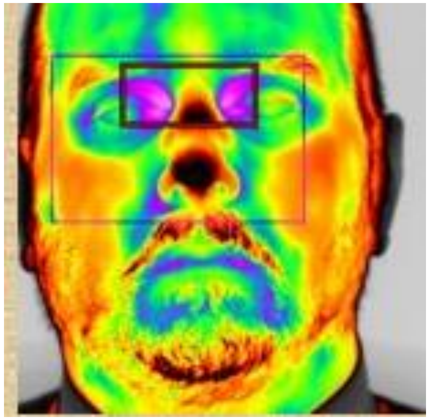
Occlusion Invariant Methods

- **Face Recognition With Contiguous Occlusion Using Markov Random Fields**
- Sparsity-based algorithms do well when pixels are corrupted randomly.
- For contiguous occlusion this method is better.
- Image models as a graph with pixels as nodes and edges joining the corresponding neighbors.
- Spatial continuity (of corrupted or non-corrupted pixels) is modeled by Markov Random Field
- Estimation of error support by using graph cuts.



*Zihan Zhou; Wagner, A.; Mobahi, H.; Wright, J.; Yi Ma; , "Face recognition with contiguous occlusion using markov random fields," 2009

Thermal Imaging



IR Imaging

- Infrared (IR) imagery for face recognition has shown to be less affected by illumination.
- Reflected IR (0.7- 2.4 μm) / near IR and thermal IR (2.4-μm - 14mm)
- Long–Range IR LWIR (Thermal IR):
- i) LWIR sensors collected the heat energy emitted by a body instead the light reflected
- ii) Has an invariant behavior under changes in illumination, being able to operate even in complete darkness
- iii) Human skin has a high emissivity in 8 – 12 μm presenting a thermal signature for each individual.

Thermal Imaging

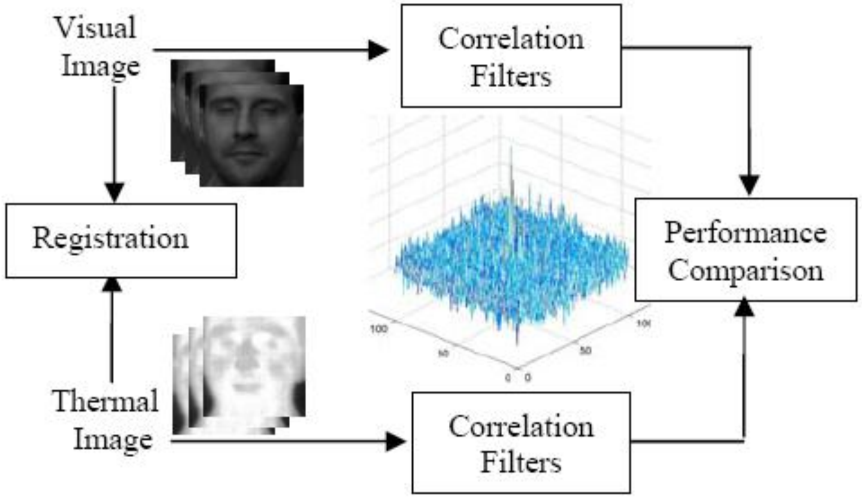
- **Challenges**
- Thermal signatures can be changed significantly according to different body temperatures caused by physical exercise or ambient temperatures.

- Thermal images of a subject wearing eyeglasses may lose information around the eyes since glass blocks a large portion of thermal energy.

- Thermal imaging has difficulty in recognizing people inside a moving vehicle.

Thermal Vs. Visual Face Recognition

- Comparison of visual and thermal imaging face recognition using correlation filters with both performing good on images of size as low at 3x32.
- Thermal face recognition showed higher performance than visual face recognition under various lighting conditions and facial expressions when no eyeglasses are present regardless of face recognition algorithms
- Eyeglasses affected the performance on thermal face recognition while the performance on Visual face it did not make much difference.
- Multi-Modality could be one direction.



*Jingu Heo, M. Savvides and V. K. Vijaya Kumar, “Performance Evaluation of Face Recognition using visual and thermal imagery with advanced correlation filters,” 2005.

LWIR Face Recognition

- “LWIR imagery of human faces is not only a valid biometric, but almost surely a superior one to comparable visible imagery.” The difficulty exists in the acquisition of thermal images.

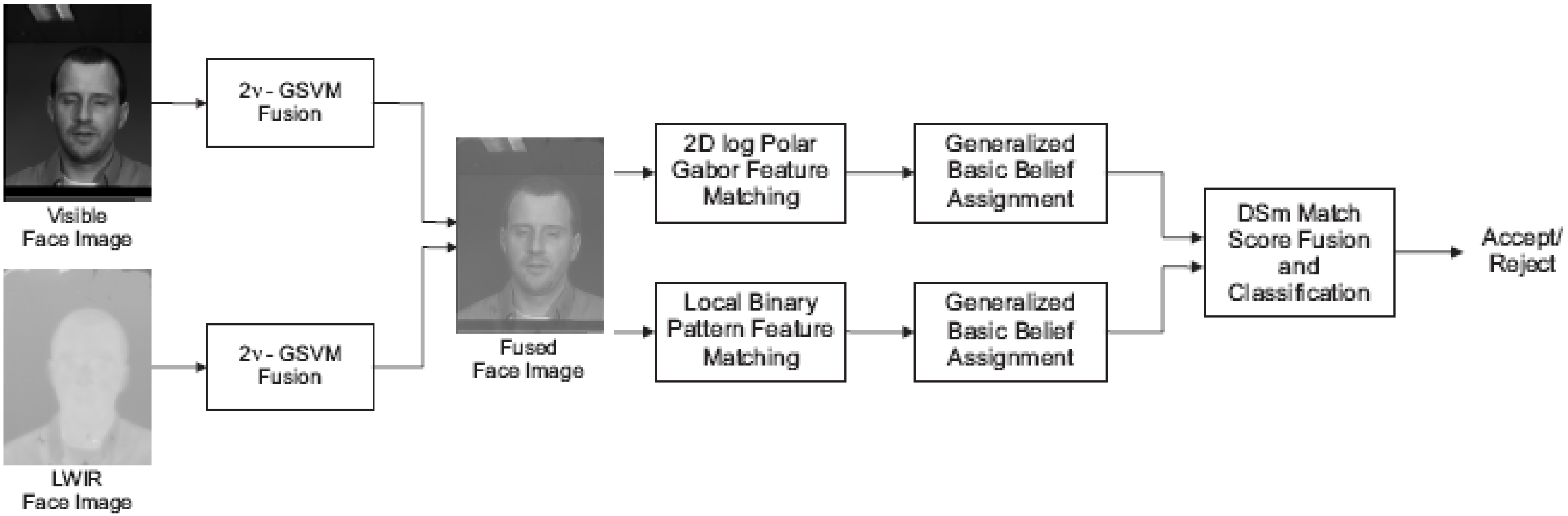
  *D. A. Socolinsky, and A. Selinger, “A Comparative Analysis of Face Recognition Performance with Visible and Thermal Infrared Imagery,” 2002.

- Local Binary Pattern on LWIR images.
- Performance comparable to state of the art methods even when subjects are wearing glasses.

  *Heydi Mendez, Cesar San Martin, Josef Kittler, Yenisel Plasencia, and Edel Garca, “Face Recognition with LWIR Imagery using Local Binary Patterns,” 2009.

LWIR Face Recognition

- Fusion of Visible Image and LWIR image. Match scores from multiple features and matching algorithms are fused for final recognition.

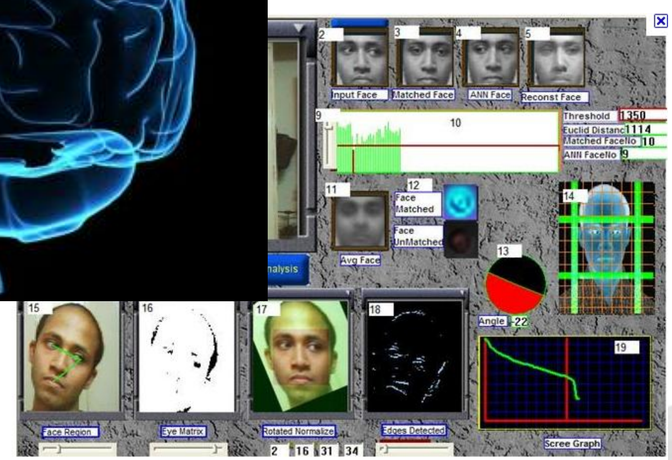


R. Singh, M. Vatsa, and A. Noore: Integrated multilevel image fusion and match score fusionof visible and infrared face images for robust face recognition

Biologically Inspired Methods

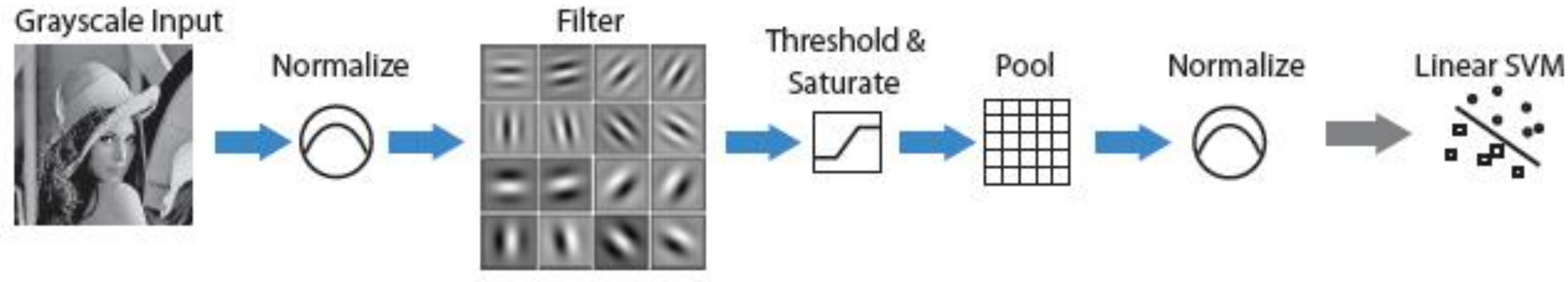
Biologically Inspired Methods

- Building the artificial visual systems or face recognition methods which capture the aspects of the computational architecture of the brain with the hope of achieving the computational ability like it.



V1-Like Method

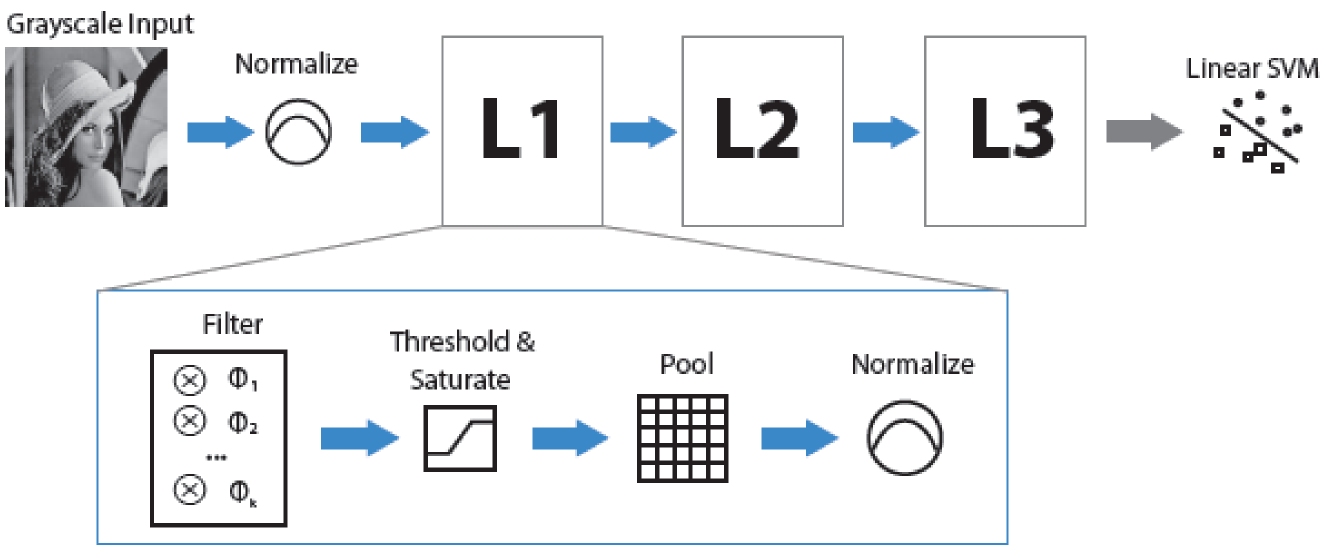
- Applying a set of 96 spatially local (43x43 pixels) Gabor wavelets to the image (with a one pixel stride)
- Normalize and threshold the output values.
- Experiments on LFW for pair matching.



*N. Pinto, J.J. DiCarlo, D.D. Cox, "How far can you get with a modern face recognition test set using only simple features?, 2009

High Throughput (HT) models

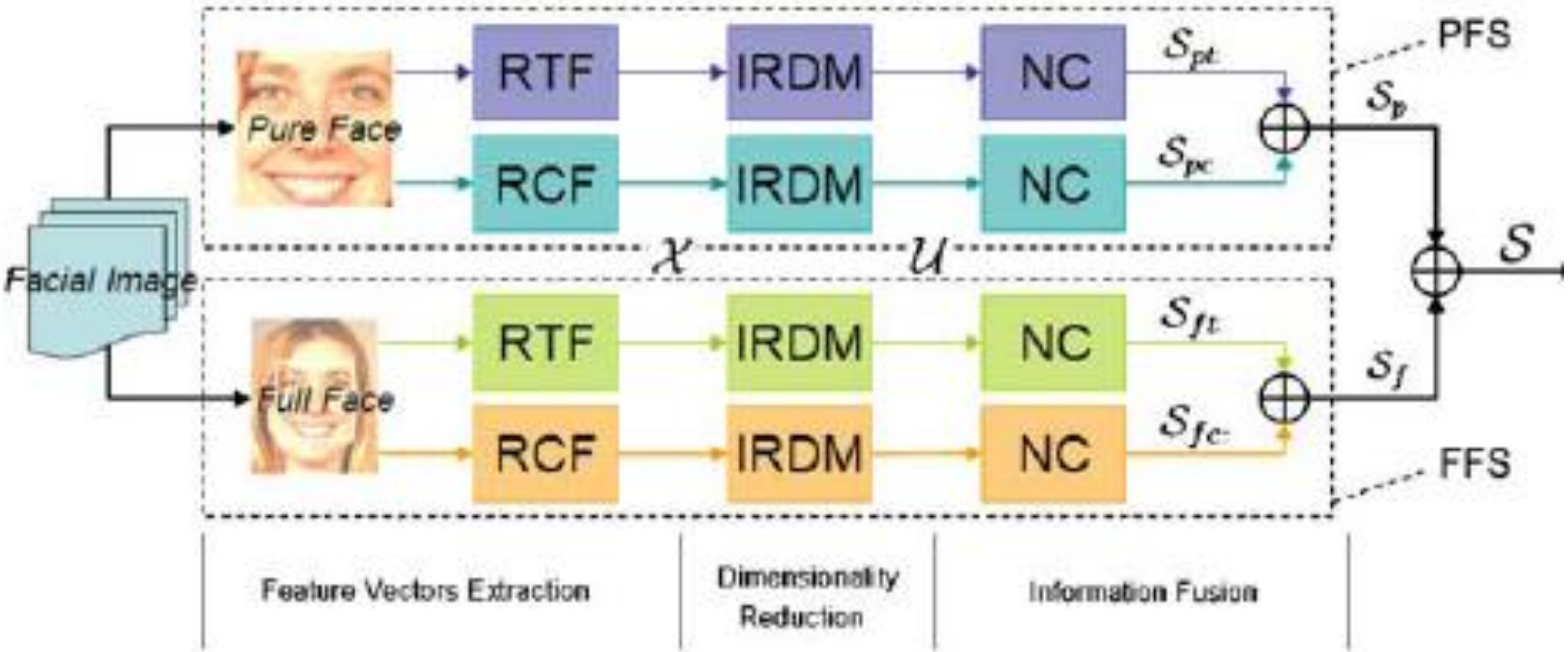
- Composed of a hierarchy of two or three layers.
- Each layer consists of cascade of liner and non-linear operations which produces the no-linear feature map of original image.



*N. Pinto, J.J. DiCarlo, D.D. Cox , Beyond Simple Features: A Large-Scale Feature Search Approach to Unconstrained Face Recognition, F&G 2011

Emulating biological strategies

- Integrates dual retinal texture and color features
- Incremental robust discriminant model for face coding

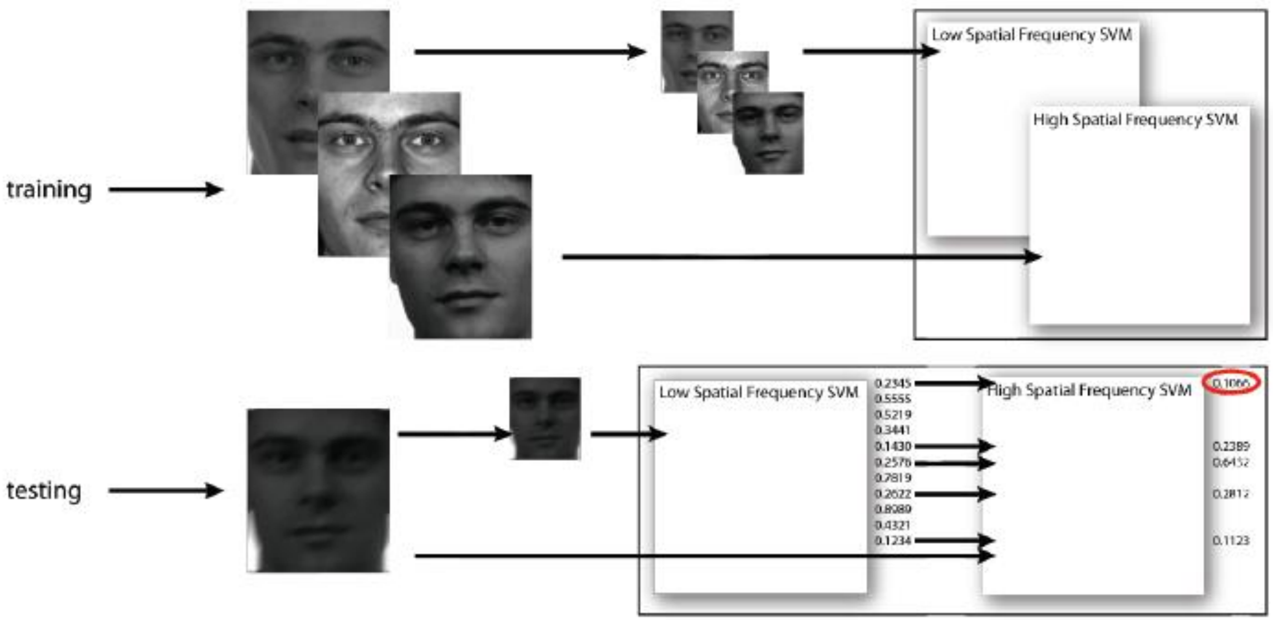


RTF—retinal texture feature, RCF—retinal color feature, IRDM—incremental robust discriminant model, NC—normalized cosine similarity measure, PFS—pure face system, FFS—full face system, $\mathcal{X}$— high-dimensional feature vector, $\mathcal{U}$— low-dimensional face code, $\mathcal{S}$— similarity score.

*Weihong Deng, Jiani Hu, Jun Guo, Weidong Cai, Dagan Feng, "Emulating biological strategies for uncontrolled face recognition," 2010

Top-Down Facilitation on multistage decisions

- Attempts to uses the decision making model of the human brain in face recognition.
- Use of low spatial frequency (LSF) imagery to facilitate recognition of high spatial frequency (HSF) representations of faces and objects.



*Parks, B.; Boult, T.; , "Top-down facilitation of multistage decisions for face recognition," 2010

Top-Down Facilitation on multistage decisions

- LSF classifier (SVM)
  - Train on 1/6 size gallery
  - Classify on 1/6 scaled probe
  - Use classification scores to “seed” HSF SVM
- HSF classifier (SVM)
  - Train on full-size gallery
  - Classify on full-size (but blurred) probe
  - Take into consideration scores from LSF SVM

Top-Down Facilitation on multistage decisions

- Results compared to Ideal Deblurring on Blurred FERET dataset.

	MSVM	Deblurred MSVM	1PS*
05px	95.42	95.42	97.50
10px	84.58	95.83	95.83
15px	62.08	95.42	94.58
20px	42.50	94.17	92.50

How can we leverage recent findings in other sciences?

Future Directions for Uncontrolled Face Recognition

- One system to solve all the problems?
- Multi-modality, features, methods, recognition score fusion
- More work on configurable information
- Consider ‘familiarity’
- Top Down expectations
- Long distance recognition: acquisition, preprocessing and recognition
- Face Recognition in camera network

*Rama Chellappa, Pawan Sinha, P. Jonathon Phillips, “Face Recognition by Computers and Humans”, 2010.

Popular Classification Methods

- Distance measures:

- Similarity or differences between the features using various distance functions. City block, cosine, etc.

- Statistical distances for the feature distributions: Bhattacharyya distance, Earth mover's distance, Mahalanobis distance etc.

- Normalized cross correlation.
- Bayesian Classifier

Support vector machines.

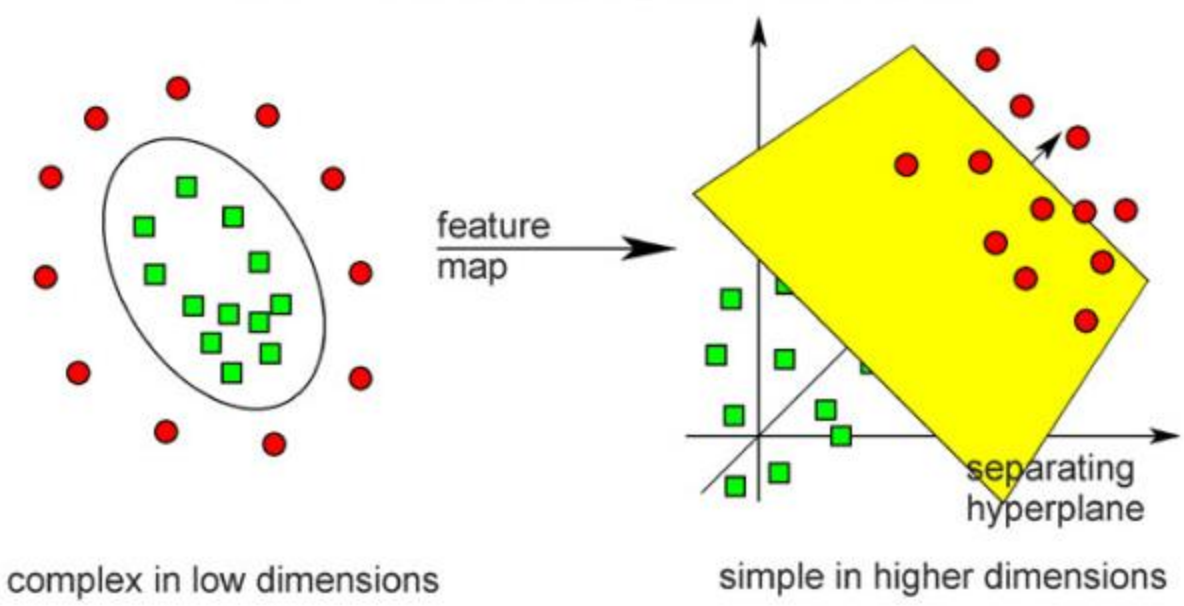
The separating hyperplane can be very complex

Problems may occur with outliers

The shape of the hyperplane depends on the population of the

Classes

Need for negative examples



Hidden Markov Models

Coding

- the image is scanned to obtain a sequence of *T* partially overlapped sub-images
- for each sub-image the DCT coefficients are computed
- only the most important *D* coefficients are retained
- the final sequence is composed by *DxT* symbols

Learning: train one HMM for each subject:

- the number of states is fixed *a priori*
- at the end we have one HMM for each subject

Recognition:

- Bayesian scheme: assuming a priori equally probable classes, an object is assigned to the class whose model shows the highest likelihood (Maximum Likelihood scheme)

Quality and Post Recognition Score Analysis

Findings from FRVT 2006

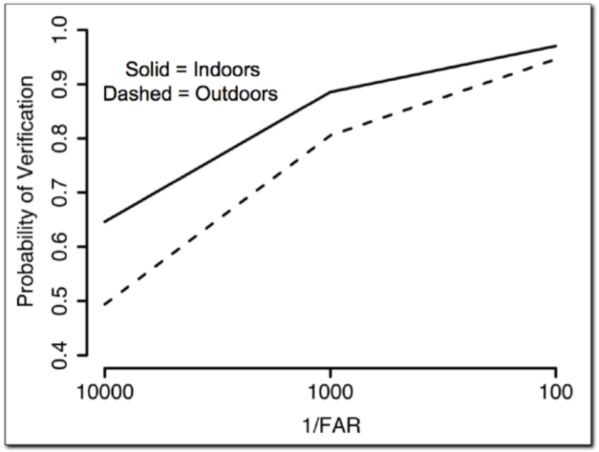
- Covariates: factors independent of an algorithm that may affect performance
  - Gender
  - Race
  - Size of the Face
  - Degree of Focus of Face
  - Wearing Glasses
  - Indoor our Outdoor Imagery
  - False Accept Rate

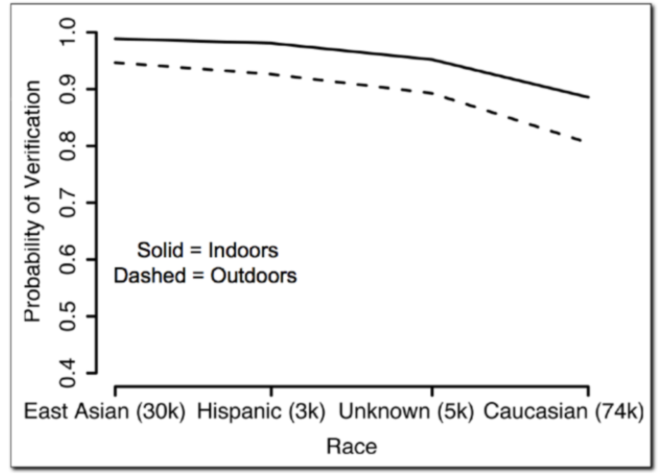
*J. Ross Beveridge, G. Givens, P.J. Philips, B. Draper and Y. Lui, "Focus on Quality, Predicting FRVT Performance," 2008.

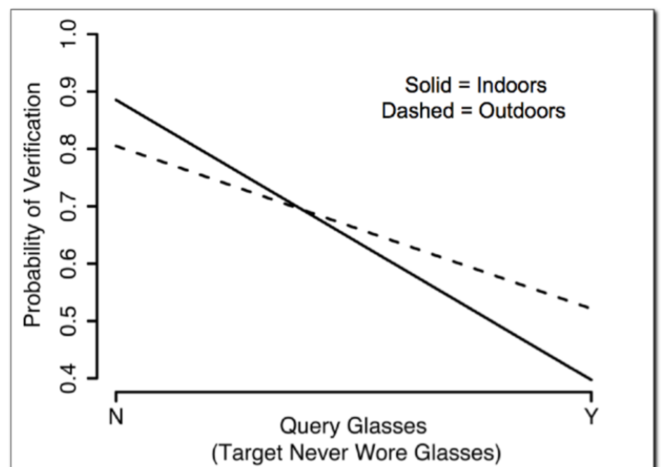
Face Region in Focus Measure (FRIFM)

- Face is transformed to a standard size
- Sobel edge mask is applied to the image to derive edges
- Average the Sobel edge magnitude within an oval defining the region of the face

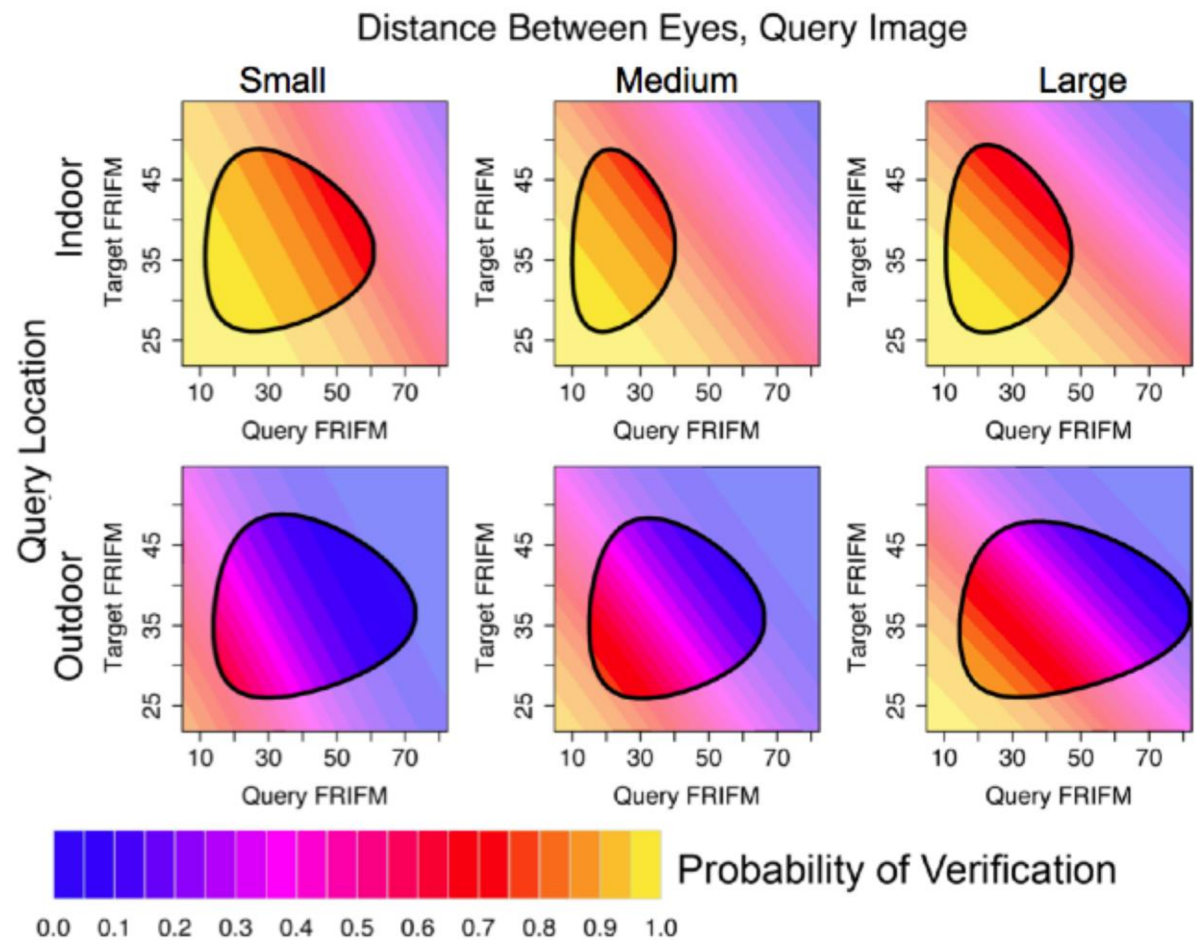
Covariate Findings







Multiple Factors & FRIFM



More Covariates*

- Older people are easier to recognize than younger people
- Recognition performance degrades as the time between probe and gallery images increases
- The effect gender decreases as subjects age
- Expression – is it better to be consistent or vary?
- Higher resolution imagery is always better
- Ethnicity – biased algorithms and data sets?

* Y. Lui, D. Bolme, B. Draper, J.R. Beveridge, G. Givens, P.J. Phillips, “A Meta-Analysis of Face Recognition Covariates”, 2009.

Image Quality

- A common approach: measure something about the image to "predict" its recognition performance

  - Sharpness
  - Contrast
  - Blur
  - Noise
  - Dynamic Range
  - Color
  - Distortion
  - Vignetting
  - Exposure
  - Software Artifacts

Blind Signal-to-Noise Ratio Estimator

- Specifically for Face Recognition
- Statistical properties of edge images change with quality
  - Have been shown to be correlated with underlying SNR*

Evaluate a fixed sized window around detected eyes

*Z. Zhang and R. Blum, "On Estimating the Quality of Noisy Images," 1998.

Blind Signal-to-Noise Ratio Estimator

- Statistical properties of edge image change with quality. Suppose the probability density function of an edge intensity image, $||\nabla I||$ is which is assumed to have mean μ.
- Choosing a window around eyes, define face image quality (FIQ) as:

$$Q' = \frac{\sum \text{edge above } 2\mu\text{'s pixels}}{\sum \text{edge pixels}} \simeq \int_{2\mu}^{\infty} f_{||\nabla I||}(r)dr$$

Image Quality vs. Recognition Rate

Obvious conclusion: correlation between quality and recognition rate over large amount of data

- In this plot, larger is better for quality
- Correlations for blind SNR-based face image quality to recognition rate are 0.922 and 0.930

Challenges for Image Quality Assessment

- Interesting recent studies from NIST
  - Iris[1]: three different quality assessment algorithms lacked correlation
  - Face[2]: out of focus imagery was shown to produce better match scores

1. P. Flynn, "ICE Mining: Quality and Demographic Investigations of ICE 2006 Performance Results," MBGC Kick-off workshop, 2008
2. R. Beveridge, "Face Recognition Vendor Test 2006 Experiment 4 Covariate Study," MBGC Kick-off workshop, 2008

Challenges for Image Quality Assessment

8

15

20

47

Apparent quality not always tied to rank.

80

138

191

Gallery

What’s the issue here?

- Quality is good as an “overall” predictor
  - Over a large series of data and time
- Quality does not work as a “per instance” predictor
  - One image analyzed at a time…

“Quality is not in the eye of the beholder; it is in the recognition performance figures!” - Ross Beveridge

Biometric Completeness*

- Theory of equivalence in matching and quality
  – A perfect quality measure for any algorithm would be equivalent to finding a perfect matching algorithm
  – Bounds are placed on the performance of quality as a predictor

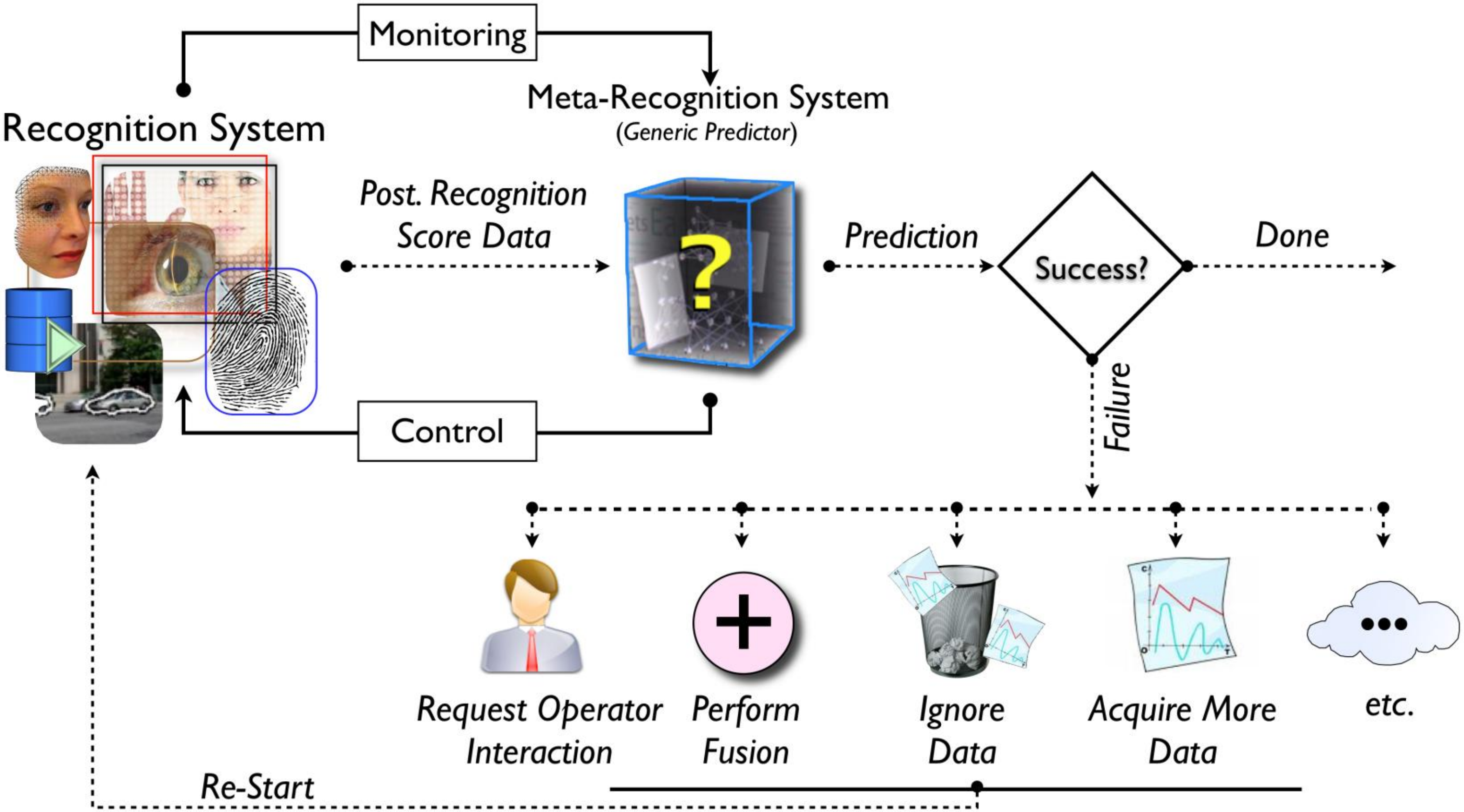
P.J Philips and J.R. Beveridge, "An Introduction to Biometric-Completeness: The Equivalence of Matching and Quality," IEEE BTAS, 2009.

Challenges for Image Quality Assessment

- Alternative to Image Quality Assessment: Post-Recognition Score Analysis
- Predict the performance of a recognition system based on its outputs for each match instance, rather than making decisions about the input imagery
- Meta-Recognition: Control the recognition system by knowing additional information about it

Only the recognition performance figures matter

Post-Recognition Score Analysis



Meta-Recognition Defined

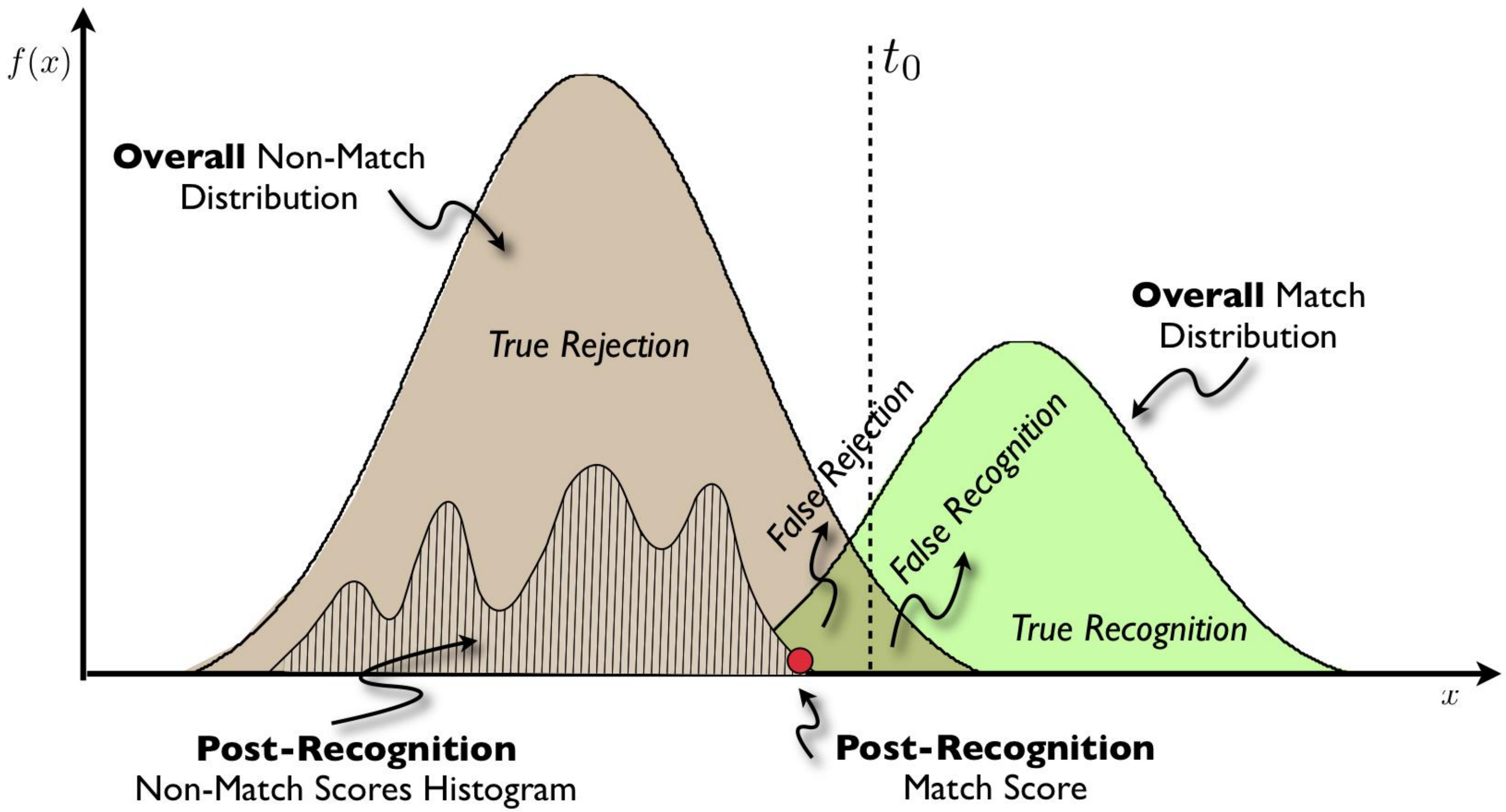
Inspired by meta-cognition study ("knowing about knowing")

Definition Let X be a recognition system. We define Y to be a meta-recognition system when recognition state information flows from X to Y , control information flows from Y to X, and Y analyzes the recognition performance of X, adjusting the control information based upon the observations.

Post Recognition Scores Analysis

- Lots of work out there for *verification*, but not much for recognition
- Cohort Analysis
- GPD Analysis
- Machine Learning Based Predictors
- Meta-Recognition

Post-Recognition Score Analysis



Types of Error

- False Recognition: Type I error
  - the probe does not have a corresponding entry in the gallery, but is incorrectly associated with a gallery entry
- False Rejection: Type II error
  - the probe has a corresponding entry in the gallery, but is rejected

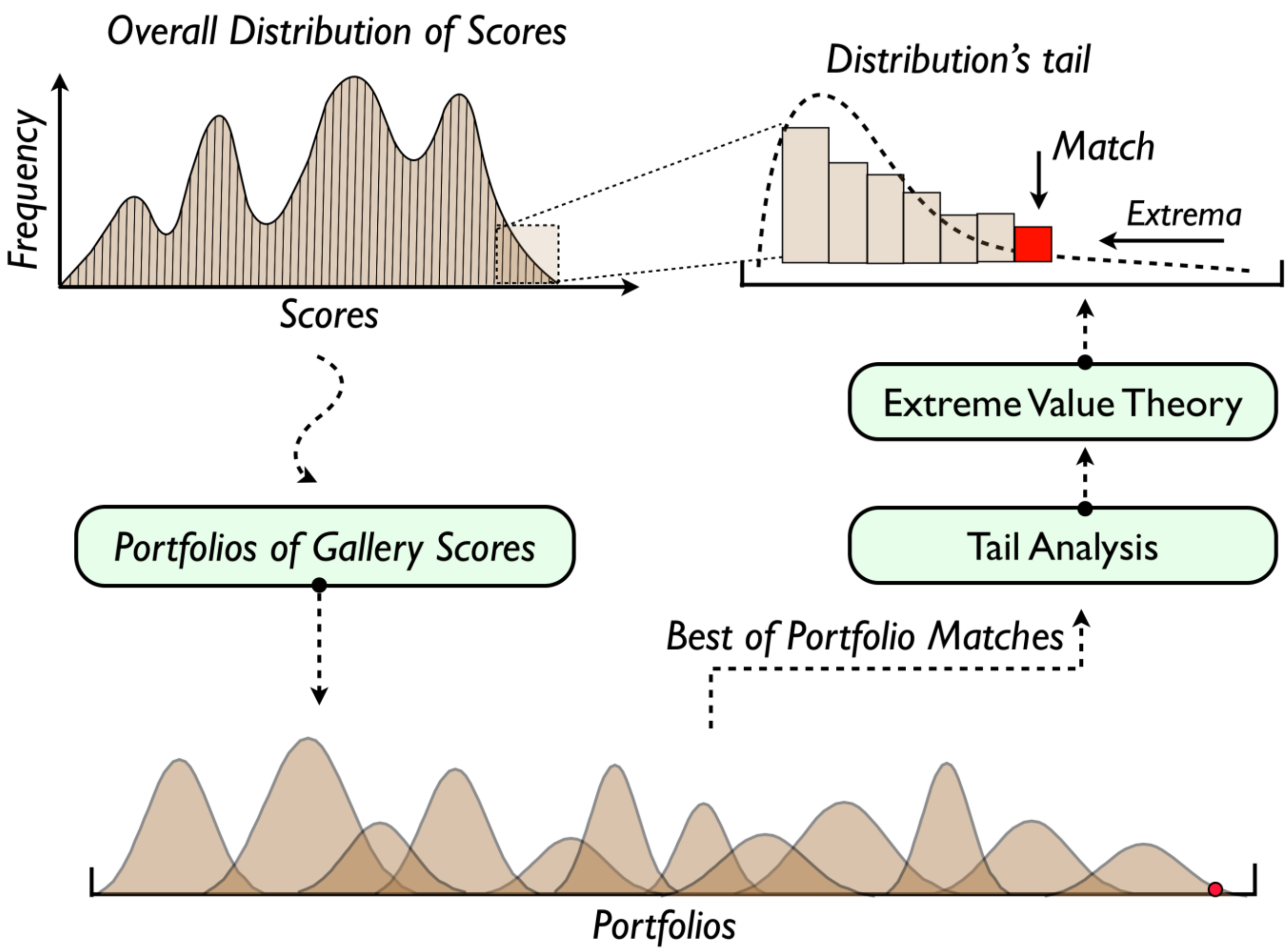
Wouldn't it be nice to detect such errors?

Formalization of Problem

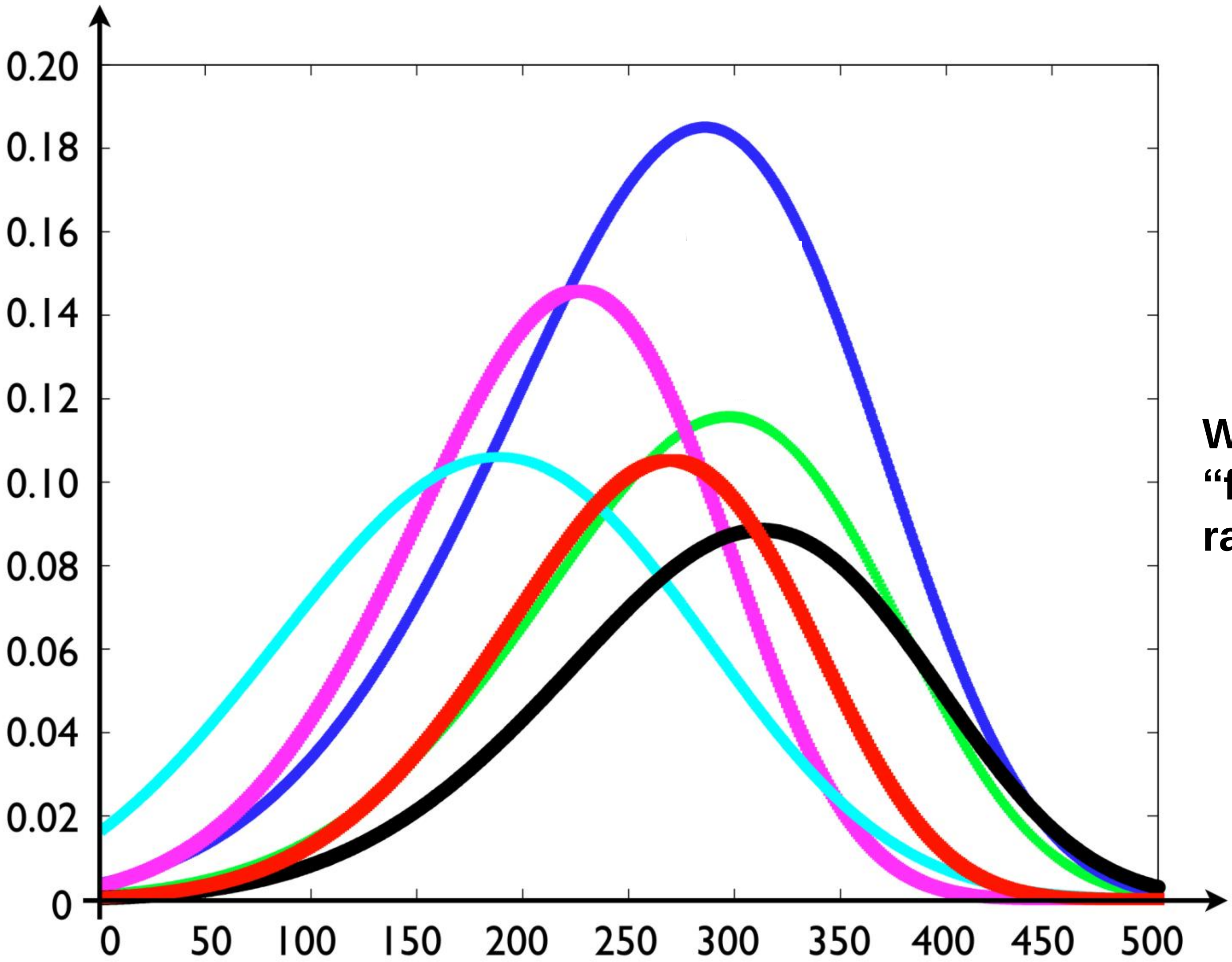
- Let $F(p)$ be the distribution of non-match scores that are generated by matching probe p
- Let $m(p)$ be the match score for that probe
- Let $S(K) = s_1, \ldots, s_k$ be the top K sorted scores
- Formalization of the null hypothesis H_0 for rank-k prediction is:

$$H_0(failure) : \forall x \in S(K),\ x \in F(p)$$

Meta-Recognition and Extreme Value Theory



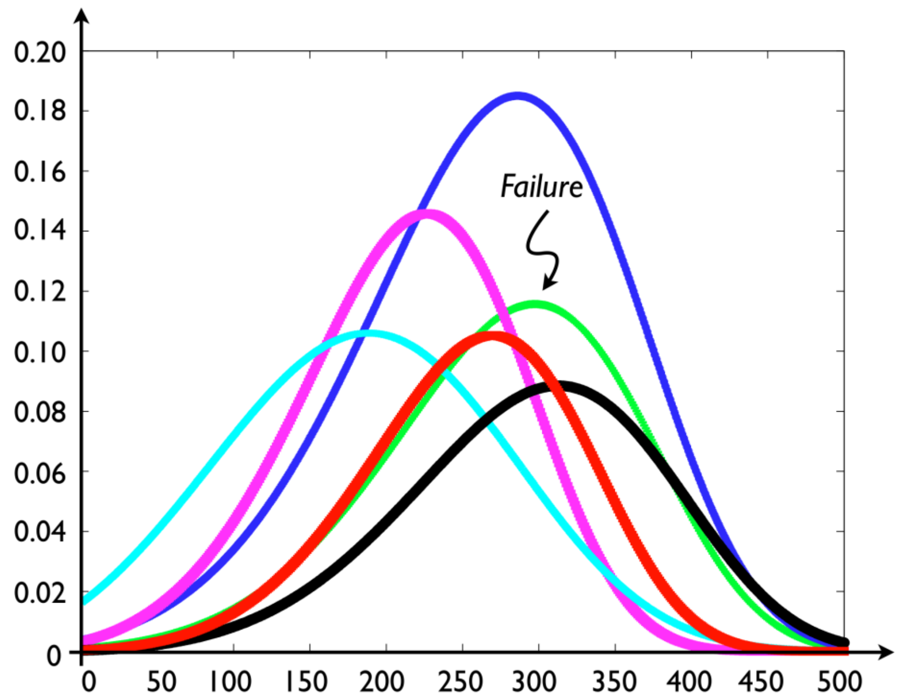
Weibull Distributions from Biometric Score Data



Which one is a "failure" (non-rank 1)?

Weibull Distributions from Biometric Score Data

- Visually, it is unclear which Weibull distributions are matches, and which are not
- The outlier test makes the distinction



Why does this work?

- The Extreme Value Theorem

Let $(s_1, s_2, \ldots)$ be a sequence of i.i.d. samples. Let $M_n = \max\{s_1, \ldots., s_n\}$. If a sequence of pairs of real numbers (a_n, b_n) exists such that each $a_n > 0$ and

$$\lim_{x \to \infty} P\left(\frac{M_n - b_n}{a_n} \le x \right) = F(x)$$

then if F is a non-degenerate distribution function, it belongs to one of three extreme value distributions.

Applying EVT to Biometric Data

- If we presume that match scores are bounded, then the distribution of the minimum (or maximum) reduces to a Weibull (or Reversed Weibull)
  - *The sampling of the top-n scores always results in a EVT distribution, and is Weibull if the data are bounded.*
- Generalize EVT to weaker assumption of exchangeable random variables (as opposed to i.i.d.)

Statistical Meta-Recognition

Require: A collection of similarity scores S

1. **Sort** and retain the n largest scores, $s_1, \ldots, s_n \in S$;
2. **Fit** a GEV or Weibull distribution W to $s_2, \ldots, s_n$, skipping the hypothesized outlier;
3. **if** $Inv(W(s_1)) > \delta$ **then**
4. $\quad s_1$ is an outlier and we reject the failure prediction (null) hypothesis H_0.
5. **end if**

Post-Recognition Score Analysis

	Conventional Explanation	**Prediction**	**Ground Truth**
Case 1	*False Accept*	Success	O
Case 2	*False Reject*	Failure	O
Case 3	*True Accept*	Success	P
Case 4	*True Reject*	Failure	P

- Meta-Recognition False Alarm Rate

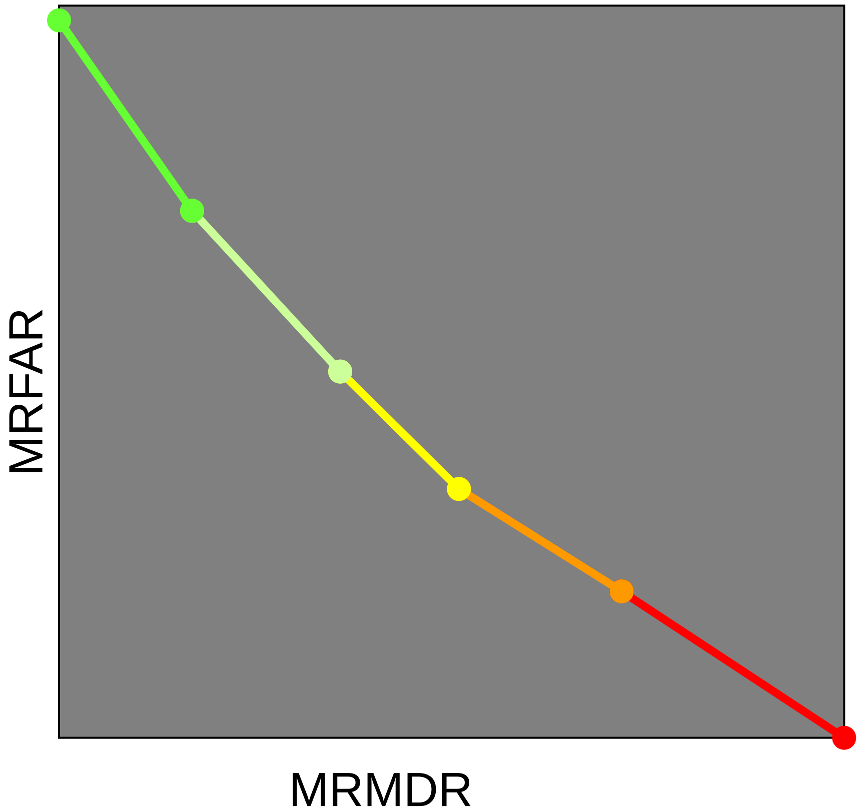
$$\text{MRFAR} = \frac{|\text{Case } 1|}{|\text{Case } 1| + |\text{Case } 4|}$$

- Meta-Recognition Miss Detection Rate

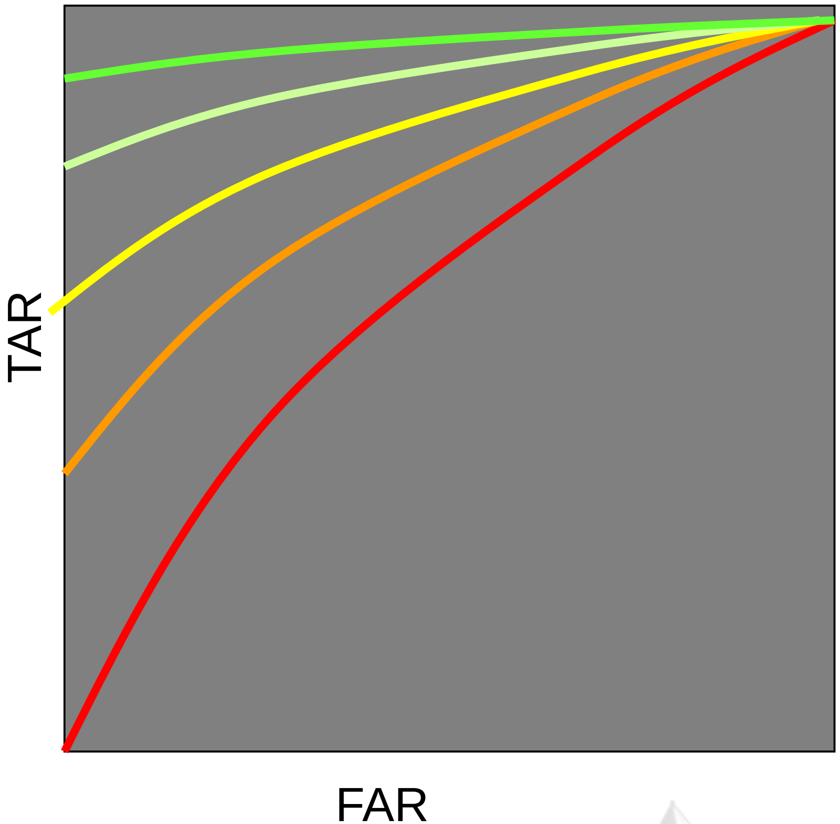
$$\text{MRMDR} = \frac{|\text{Case } 2|}{|\text{Case } 2| + |\text{Case } 3|}$$

Post-Recognition Score Analysis

Meta-Recognition
Error Tradeoff Curve



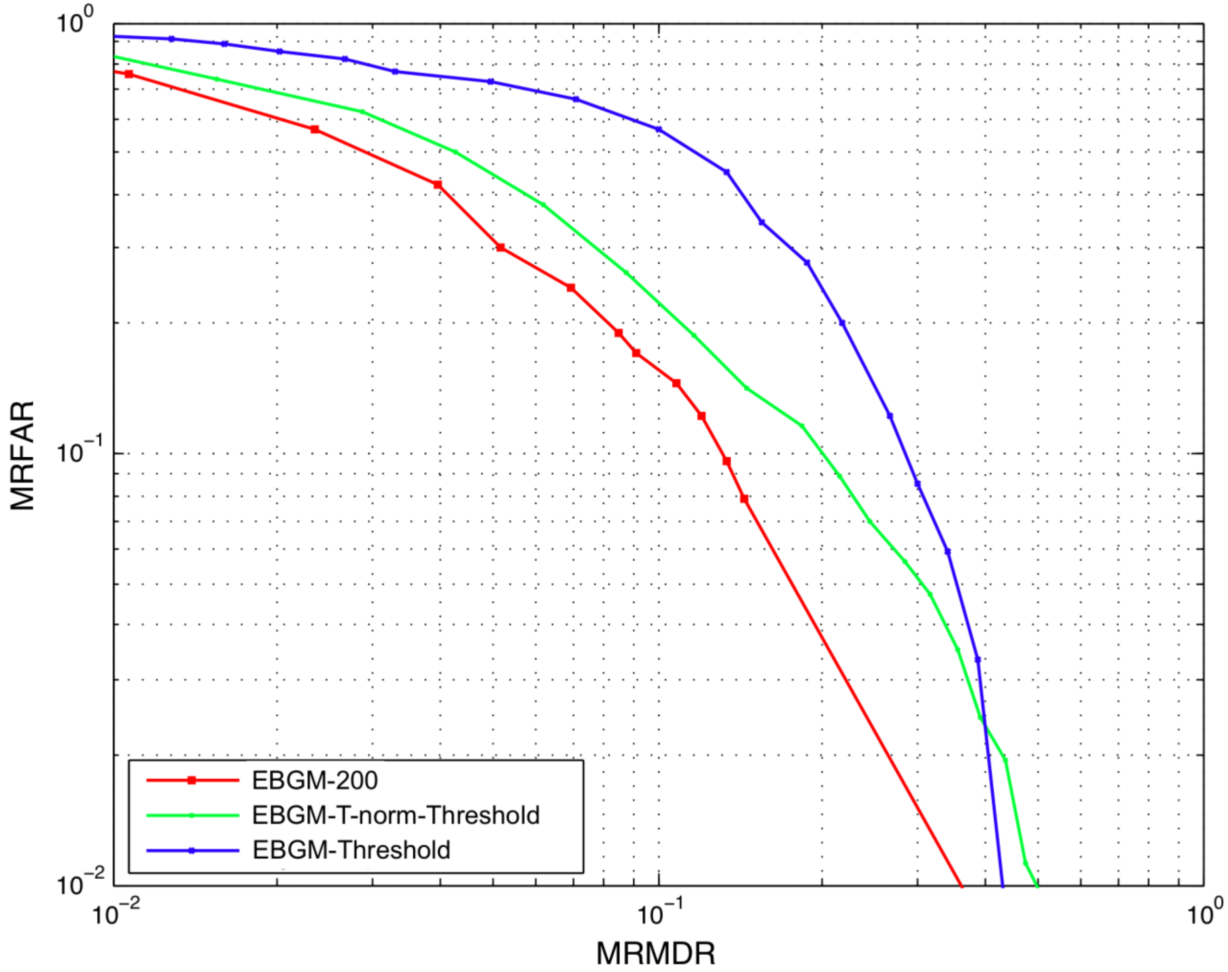
Quality-grouped ROC



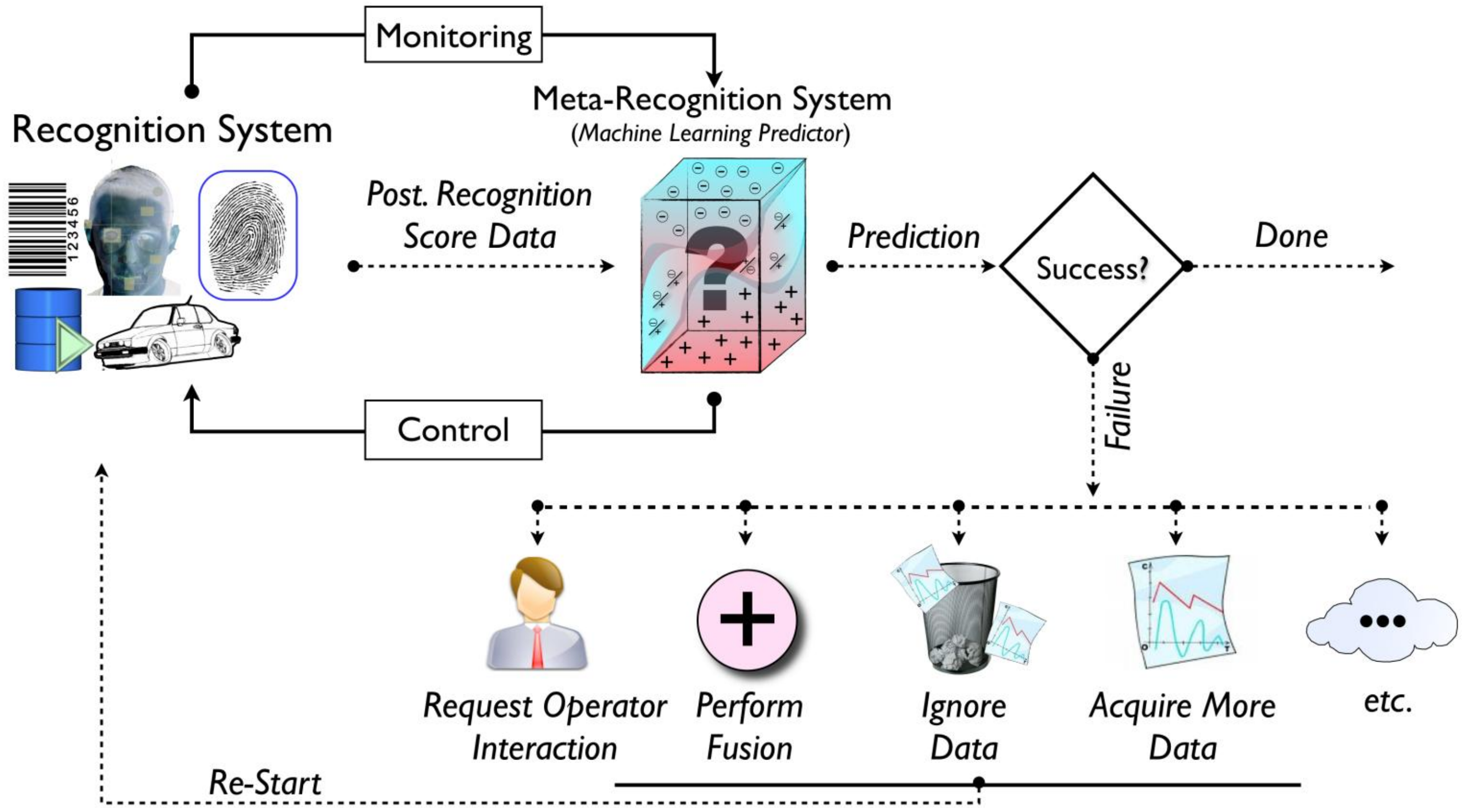
Uses Full Data Sets
Vary "quality" threshold

Segmenting gallery on quality
inflates the difference

Prediction Accuracy



There's more than one way to do it!



Meta-Recognition with Machine Learning

- Statistical meta-recognition provides a rigorous theoretical grounding, but is not the most accurate way to predict success or failure
- Machine Learning[1,2,3] can also be used to make predictions based on vectors of features computed from distance or similarity scores

1. W. Li, X. Gao, and T. Boult, “Predicting Biometric System Failure,” 2005.
2. T. Riopka and T. Boult, “Classification Enhancement via Biometric Pattern Perturbation,” 2005.
3. W. Scheirer and T. Boult, “A Fusion-Based Approach to Enhancing Multi-Modal Biometric Recognition System Failure Prediction and Overall Performance,” 2008.

M-R Features for Machine Learning

a) $\Delta_{1,2}$ defined as $(\textit{sorted-score}_1 - \textit{sorted-score}_2)$

b) $\Delta_{i,j,\ldots,k}$ defined as $((\textit{sorted-score}_i - \textit{sorted-score}_j), (\textit{sorted-score}_i - \textit{sorted-score}_{j+1}), (\textit{sorted-score}_i - \textit{sorted-score}_k))$, where $j = i + 1$

c) Discrete Cosine Transform (DCT) coefficients of the top-n scores

Rank-1 Machine Learning Training

Require: A collection of similarity score sets $S_1^+, \ldots, S_n^+$. For each S_i^+, the best score is a correct match

Require: A collection of similarity score sets $S_1^-, \ldots, S_n^-$. For each S_i^-, the best score is an incorrect match

1. **while** $I \leq n$ **do**
2. **Sort** the scores, $s_1, \ldots, s_n \in S_i^{+}$
3. **Compute** feature f using $s_1, \ldots, s_n$; tag '+1'
4. **Sort** the scores, $s_1, \ldots, s_n \in S_i^{-}$
5. **Compute** feature f using $s_1, \ldots, s_n$; tag '-1'
6. $i \leftarrow i + 1$
7. **end while**
8. **Train** an SVM classifier using all $2n$ tagged feature vectors generating the classification model M_{SVM}

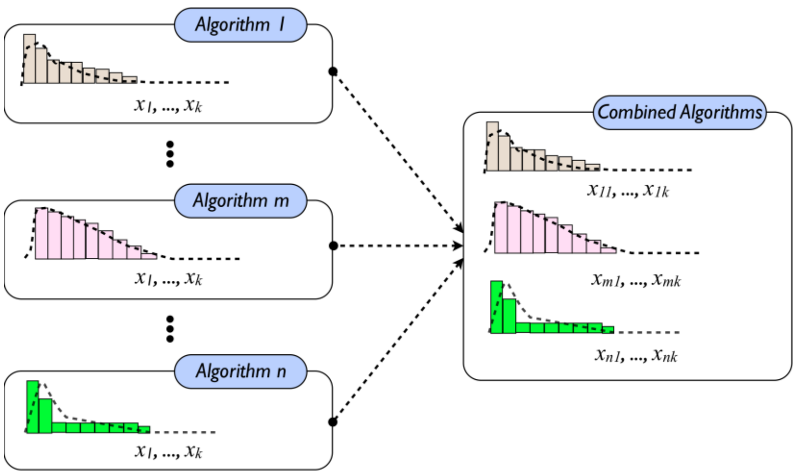
Rank-1 Machine Learning Meta-Recognition

Require: A collection of similarity scores S

1. **Sort** the scores, $s_1, \ldots, s_n \in S$
2. **Compute** feature f using $s_1, \ldots, s_n$
3. **Classify** using the classification model M_{SVM}
4. **if** *class-label* $c^* \geq 0$ **then**
5. **Predict** Success
6. **else**
7. **Predict** Failure
8. **end if**

Feature- and Decision-Level Fusion for ML-MR

Combine data from one or more algorithms:



Consider a combination of different score features:

$$\mathcal{V}_{\Phi_1}(x_1, x_2, ..., x_n) \quad \mathcal{V}_{\Phi_2}(x_1, x_2, ..., x_n) \quad \cdots \quad \mathcal{V}_{\Phi_k}(x_1, x_2, ..., x_n)$$

$$\mathcal{V}\begin{pmatrix} x_{\Phi_{1,1}}, x_{\Phi_{1,2}}, \ldots, x_{\Phi_{1,n}}, \\ x_{\Phi_{2,1}}, x_{\Phi_{2,2}}, \ldots, x_{\Phi_{2,n}}, \\ \ldots \\ x_{\Phi_{k,1}}, x_{\Phi_{k,2}}, \ldots, x_{\Phi_{k,n}} \end{pmatrix}$$

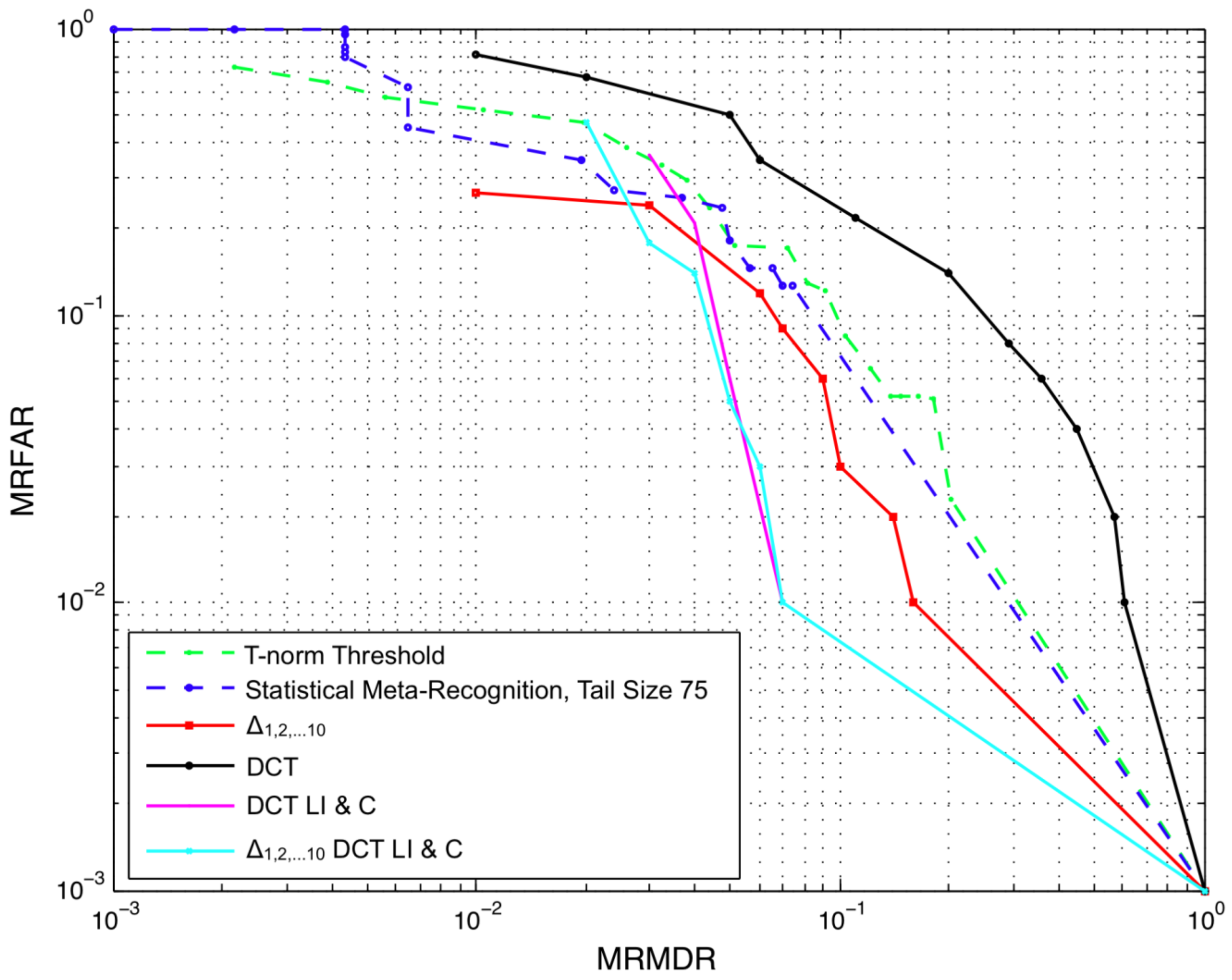
Group Threshold:

$$\mathcal{T}\begin{pmatrix} D(\Phi_1) \\ D(\Phi_2) \\ \vdots \\ D(\Phi_n) \end{pmatrix}$$

Individual Threshold:

$$\begin{matrix} \mathcal{T}_1(D(\Phi_1)) \\ \mathcal{T}_2(D(\Phi_2)) \\ \vdots \\ \mathcal{T}_n(D(\Phi_n)) \end{matrix}$$

Prediction Accuracy



Fusion and Security

WHY Fuse across multiple algorithms or sensors? To Reduce (some or all of):

- False acceptance rate
- False rejection rate
- Failure to enroll rate
- Failure to acquire rate
- Susceptibility to spoofing

For unconstrained face recognition, the more data input we have, the better…

Biometric Fusion

- Combine multiple sources of data, multiple modalities and/or algorithms.
- Often presented as intuitive that it will improve, but must be careful not to let weak algorithms/modalities pull down good ones.

Approaches to Multi-biometric Fusion

Mult-imodal, Multi-algorithmic, Multi-instance
Multi-sensorial, Hybrid

“Levels” of Fusion:

1. Signal (Feature or Sample)
2. Score
3. Decision

Fusion and Security

- Fusion at the matching score level (distance or similarity scores) offers the best tradeoff in terms of information content and application of fusion
- Empirical evaluation has indicated that a combination approach is better than a classification approach

Fusion and Security

• Normalization required to bring <u>dissimilarly scaled</u> matching scores into a common basis

• Many techniques – some require significant *a priori* data

• Techniques listed in ISO Technical Report "Multimodal and other Multibiometric Fusion" (TR 24722)

Min-max	Adaptive
Z-score	a) Two-quadrics (QQ)
Median absolute deviation (MAD)	b) Logistic
Hyperbolic tangent (Tanh)	c) Quadric-line-quadric (QLQ)
BioAPI	Biometric Gain against Impostors (BGI)
	Borda count

Classes of Normalization*

- Fixed Score Normalization
  - Parameters used for normalization are determined *a priori* using a fixed training set
  - Must have accurate training data!
- Adaptive Score Normalization
  - Estimates parameters based on the scores at hand for a particular recognition instance
- Robust Normalization
  - Insensitivity to outliers

A. Jain, K. Nandakumar, A. Ross, “Score Normalization in Multimodal Biometric Systems. Pattern Recognition,” 2005.

Fusion and Security

- Min-max normalization: Given matching scores $\{s_k\}$, $k = 1, 2, \ldots, n$ the normalized scores are given by:

$$s' = \frac{s - \min\{s_k\}}{\max\{s_k\} - \min\{s_k\}}$$

- Z-score:

$$s' = \frac{s - \mu}{\sigma}$$

- Median and Median Absolute Deviation (MAD):

$$s' = \frac{(s - median)}{MAD}$$

$$MAD = median(|\{s_k\} - median|)$$

- Double Sigmoid Function:

$$s' = \frac{1}{1 + \exp\left(-2\left(\frac{s-t}{r}\right)\right)}$$

$$r = r_1, \text{if } s < t$$
$$r = r_2, \text{otherwise}$$

More Sophisticated Fusion Approaches

- Tanh[1] Estimators – fixed score normalization that is robust to noise
  - Compute "genuine score distribution" from Hampel estimators
  - Estimate mean and standard deviation from "Genuine score distribution"
  - Take the hyperbolic tangent of a z-score like calculation
  - Hampel estimators rely on *ad hoc* parameter selection

*F. Hampel, P. Rousseeuw, E. Ronchetti, W. Stahel: Robust Statistics: The Approach Based on Influence Functions. Wiley, New York (1986)

Fusion and Security

- Problem: Classify input pattern Z into one of m possible classes ($c_1, \ldots, c_m$) based on evidence provided by R classifiers
- Let x_i be the feature vector for the i^{th} classifier derived from Z; x_i's are independent
- Assign $Z \to c_j, \text{if } g(c_j) \geq g(c_k), 1 \leq k \leq m, k \neq j$

Product Rule: $$g(c_r) = \prod_{i=1}^{R} P(c_r|x_i)$$

Sum Rule: $$g(c_r) = \sum_{i=1}^{R} P(c_r|x_i)$$

Max Rule: $$g(c_r) = \max_i \ P(c_r|x_i)$$

Min Rule: $$g(c_r) = \min_i \ P(c_r|x_i)$$

Fusion Problems for Security Watchlists

- Formal theories for existing fusion algorithms presume consistent data and work to address noise. What happens when user intentionally attempts to thwart system by changing/destroying their data.
- We need an approach to predict when a particular modality/algorithm is failing and then ignore it.

The Strange Case of Juan Carlos Ramirez Abadia

- Cali Cartel Trafficker
- Aware of surveillance tools deployed by law enforcement, including automated face recognition
- Underwent extensive facial surgery to evade face recognition
- Apprehended after the DEA matched a voice sample

Juan Carlos Ramirez Abadia

Abadia also made use of steganography…

Why is it better to predict what modality failed?

- Per instance failure prediction is critical for sensitive installations, screening areas, and surveillance posts

Face Recognition Algorithm

Rejected (not in DB)

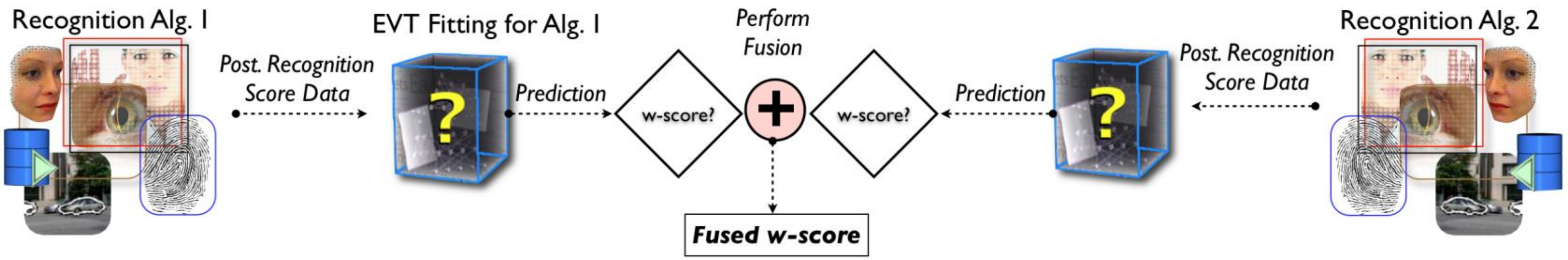
Ramirez Abadia

Prediction can choose the appropriate modality

Voice Recognition Algorithm

Recognized (as Ramirez Abadia)

Robust Fusion: Extreme Value Theory for Recognition Score Normalization*



- w-score normalization changes raw scores to probability scores based on the theory of meta-recognition
- Generalizes to all recognition algorithms producing a distance or similarity score

*W. Scheirer, A. Rocha, R. Micheals and T. Boult, “Robust Fusion: Extreme Value Theory for Recognition Score Normalization,” 2010.

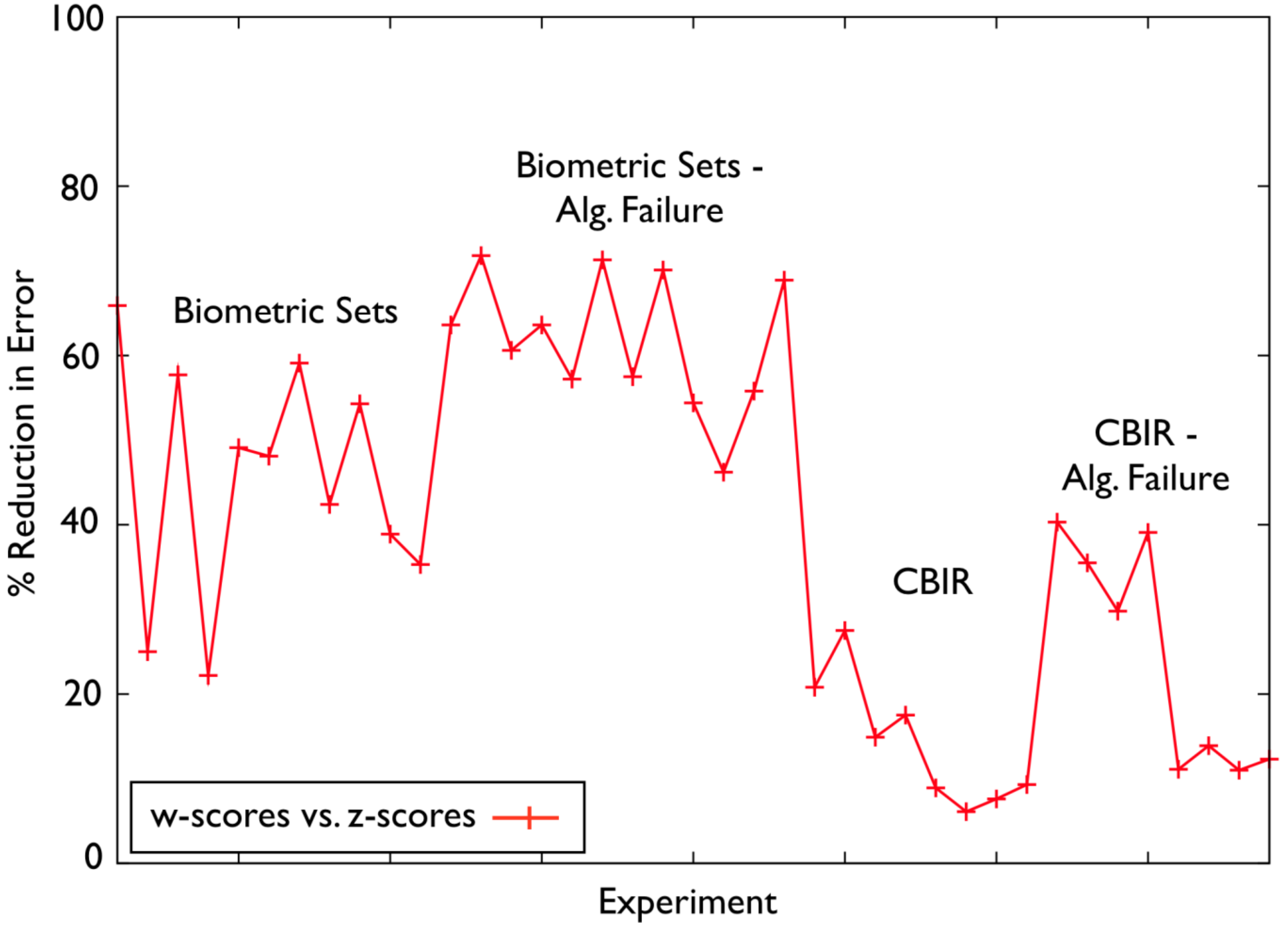
w-score Normalization

Require: A collection of similarity scores S, of vector length m, from a single recognition algorithm j

1. **Sort** and retain the n largest scores, $s_1, \ldots, s_n \in S$;
2. **Fit** a GEV or Weibull distribution W to $s_2, \ldots, s_n$, skipping the hypothesized outlier;
3. **while** $k < m$ do
4. $\quad s_k' = \mathrm{CDF}(s_k, W_k)$
5. $\quad k \leftarrow k + 1$
6. **end while**

To fuse across algorithms/sensors: apply sum rule

w-score fusion vs. z-score sum with failures or active imposters

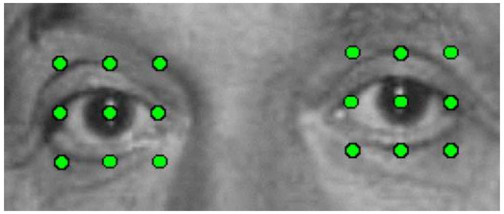


Broad Applicability: here we show biometrics *and* Content-based Image Retrieval

Eye Perturbations

Predict when failure likely, and if so perturb location of features and choose best alternative.

Use a Neural Net* to predict probable failure from top similarity scores.

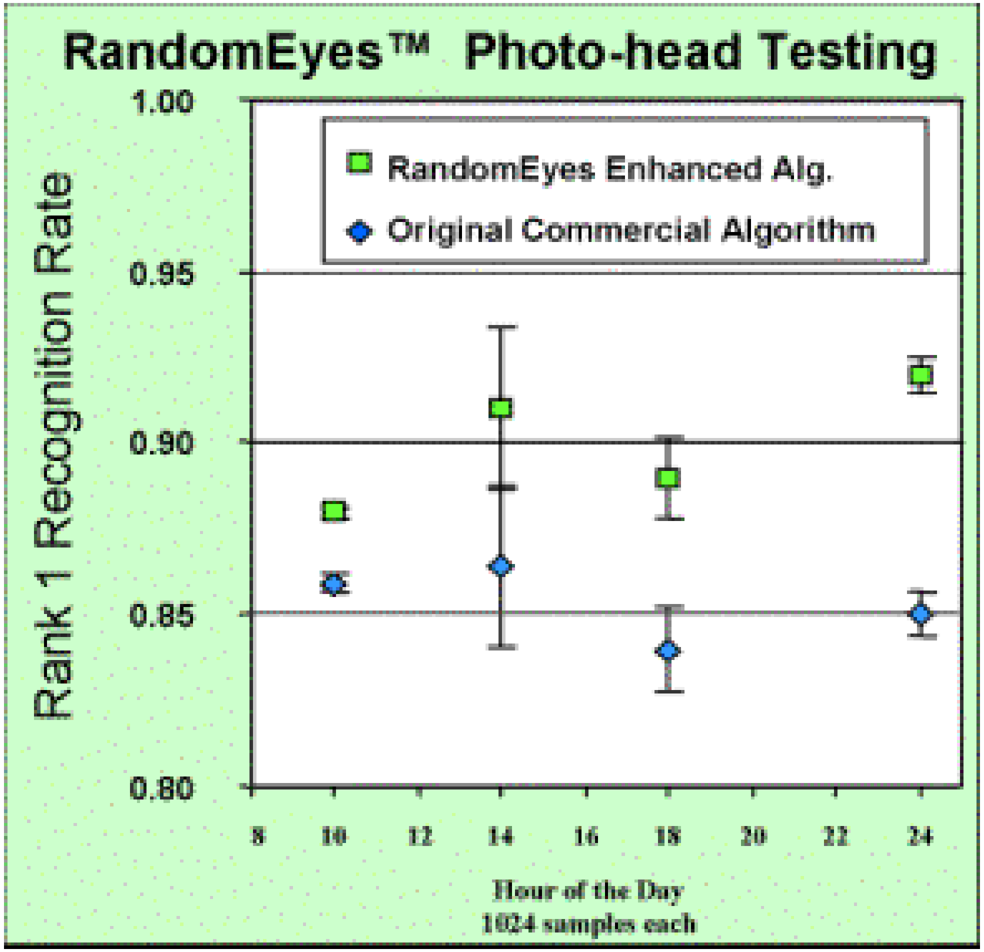


Features for prediction:

- Eight Wavelet coefficients from a 4 point discrete Daubechies wavelet transform applied to top 8 sorted similarity scores.
- Each probe had 4 gallery images so we added two other features, number of matching IDs in top 8 and next highest rank of top ranked ID (=9 if none).

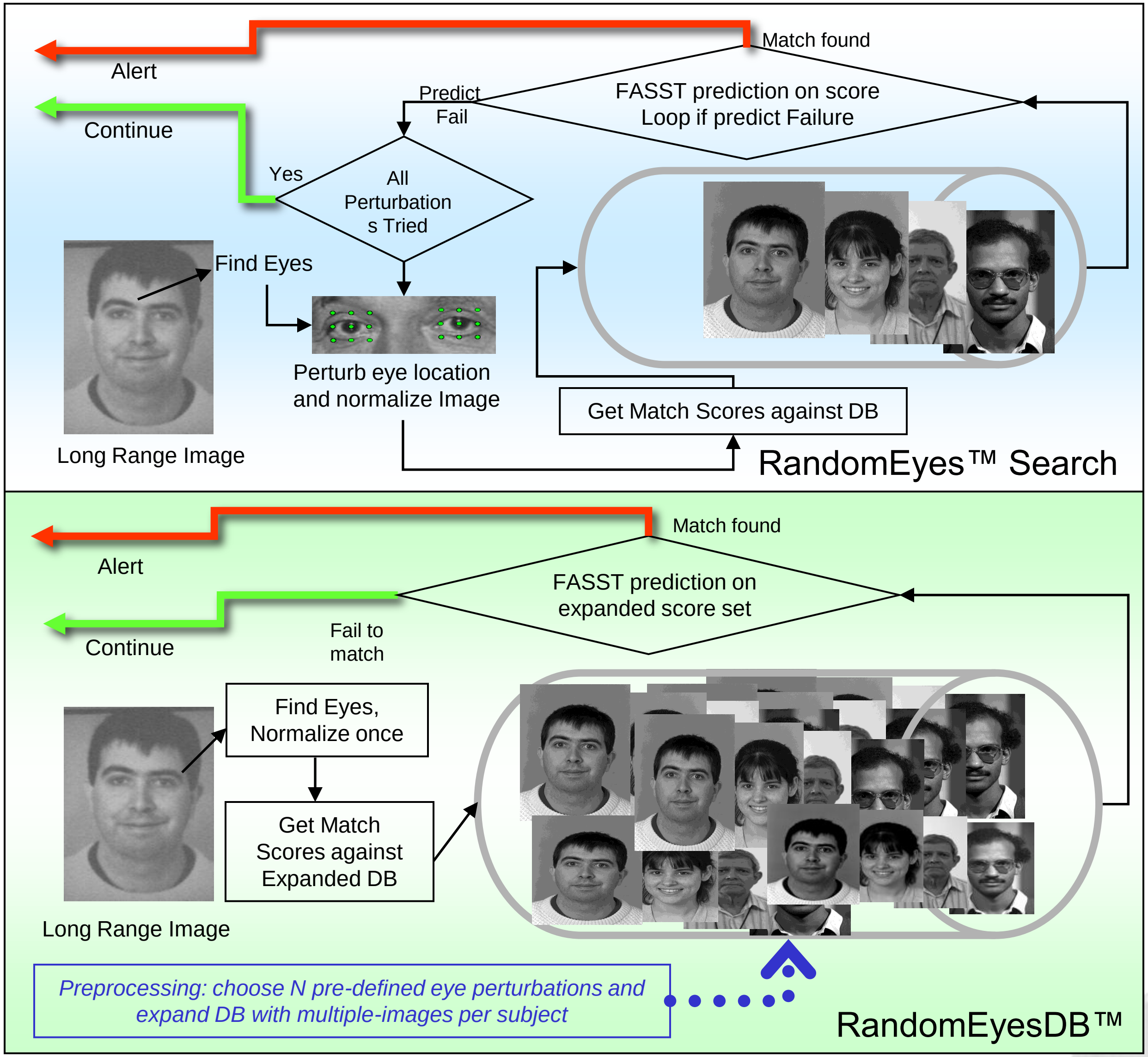
*T. Riopka and T. Boult, “Classification Enhancement via Biometric Pattern Perturbation,” 2005.

Eye Perturbations on Weather Data



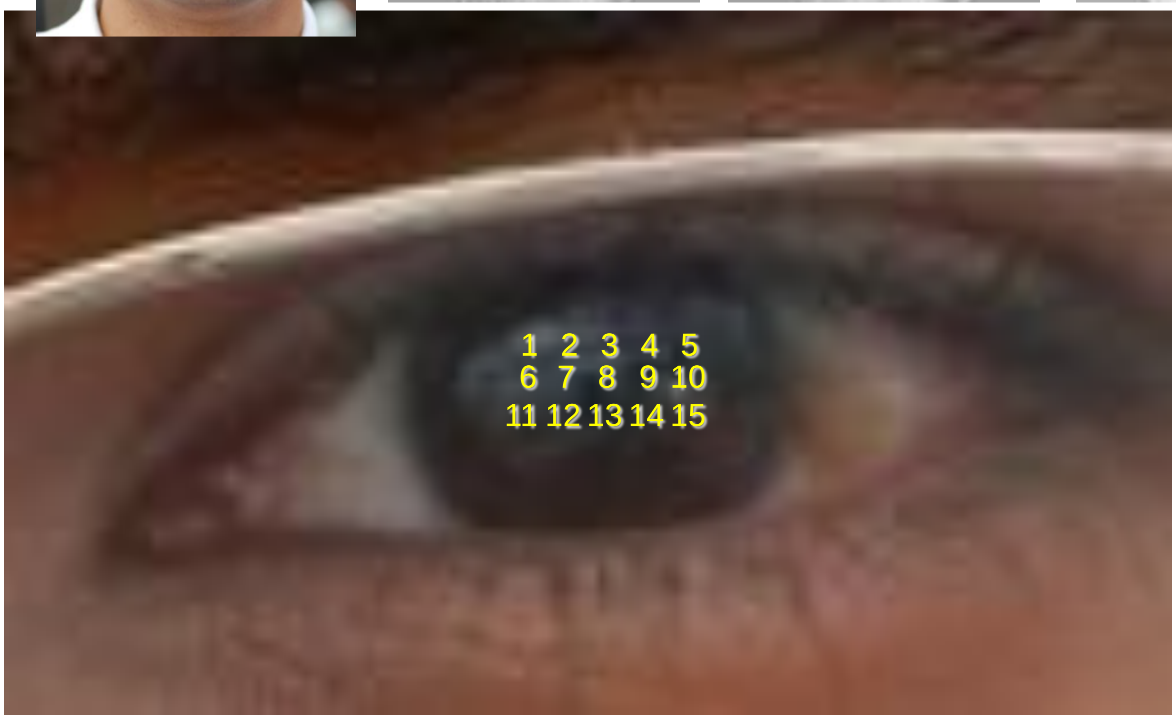
Enhancements show significant improvement!
Commercial Algorithm Enhanced with Eye Perturbations
Versus a Leading Commercial Algorithm (2003)

New Matching Paradigm Designed to reduce latency/processing



RandomEyesDB™ Perturbations

5x3 perturbations per eye for gallery image (225 perturbations total)



Summary

- We are far from solving the unconstrained face recognition problem
  - Strong impact on what we can deploy today
- Good solutions must consider all parts of the system
  - Image Acquisition, Image Enhancement, Feature Localization, Recognition Approach, Post-Recognition Score Analysis

Summary

- Areas that deserve more research attention
    - Pose Invariance
    - Occlusion Invariance
    - Robust Features
    - Biologically Inspired Vision
    - Post-Recognition Score Analysis

Thank You!

(Any final questions???)