

Fusion Aspects of Non-Cooperative Biometrics

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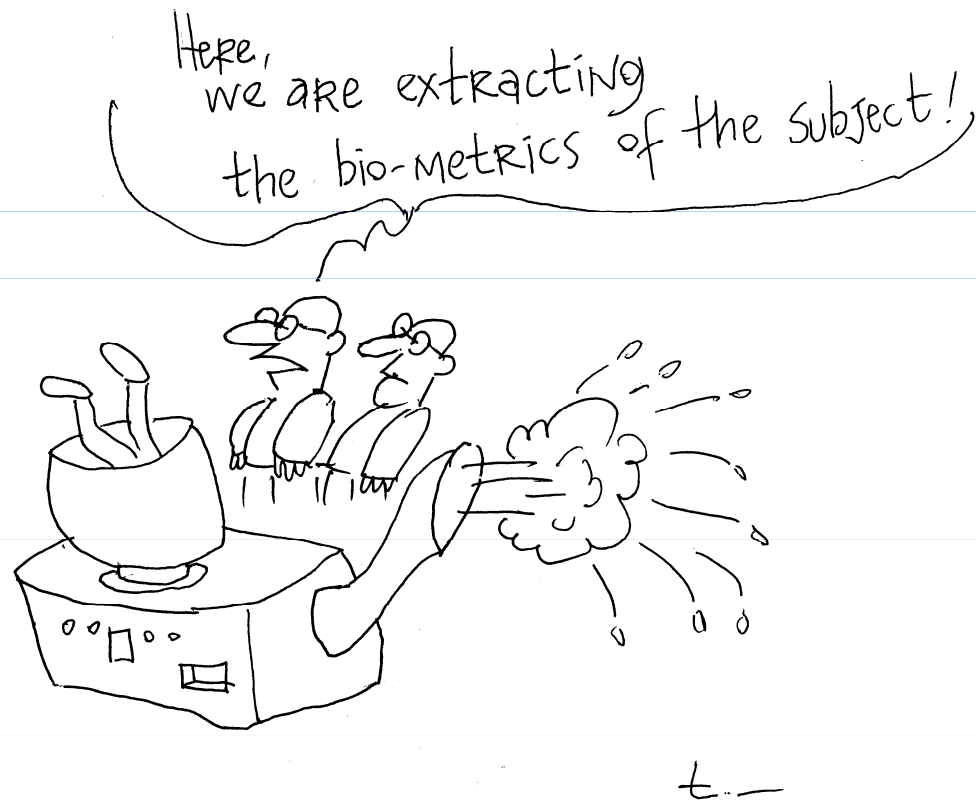
<http://biometrics.cse.msu.edu>

March 28, 2011

Outline

- Biometrics
- Fusion methods
- Design Issues
 - What & how to fuse
 - Image quality
 - Missing data
 - Sequential processing
- India's Unique ID (UID) project
- Non-cooperative subjects
 - Fingerprints
 - Face
 - Soft biometrics
- Army Science Board Questions

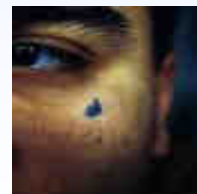
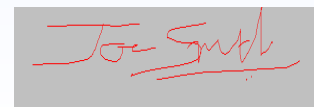
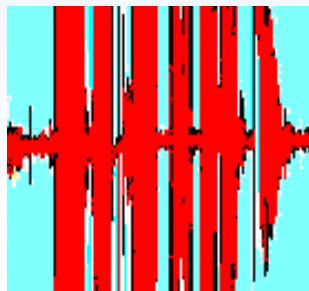
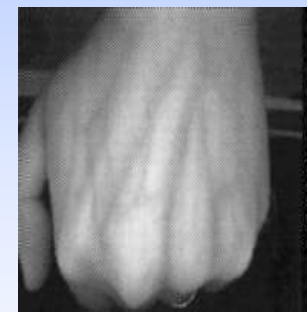
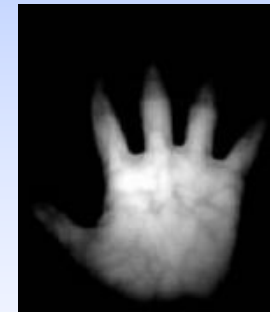
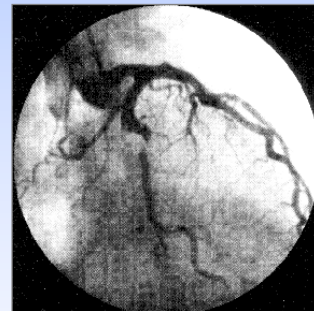
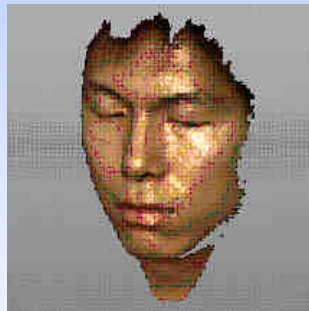
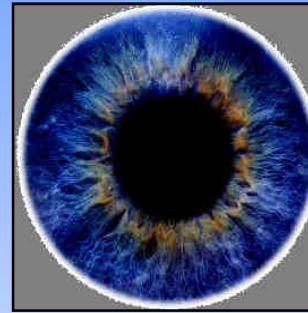
Biometrics



Prof. Tyfun Agkul, Istanbul Technical University

Biometric Recognition

Automatic method for recognizing humans based on one or more intrinsic **anatomical or behavioral traits**



New Biometric Traits



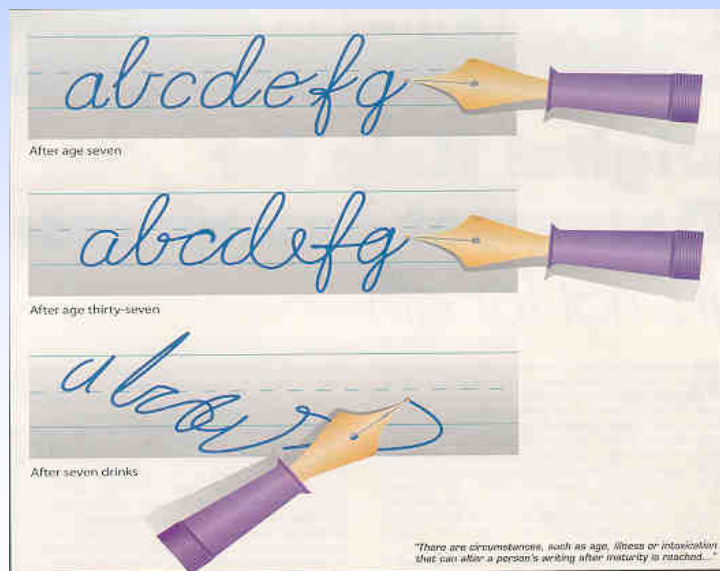
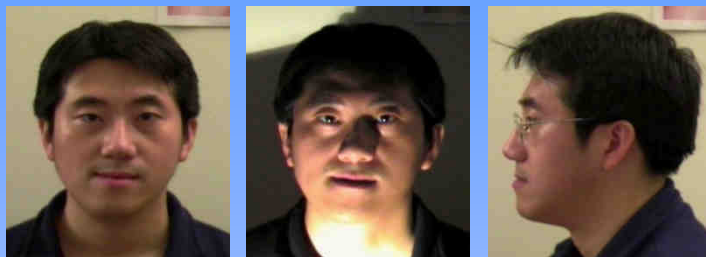
Fundamental Premise

Biometric traits are **unique & permanent**

- Intra-class variability is small
- Inter-class separation is large

All biometric systems exhibit non-zero error rates

Intra-Class & Inter-Class Variations



Large intra-class variability

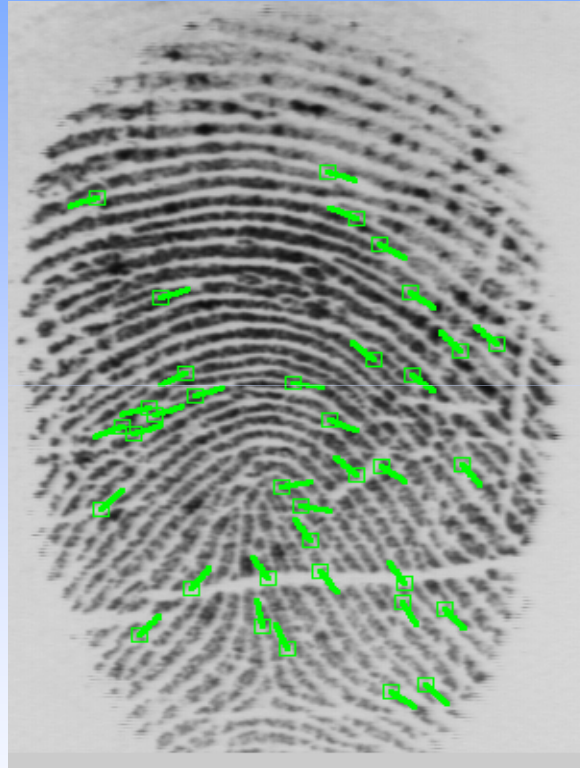


Large inter-class similarity

Image Quality



False Minutiae = 0

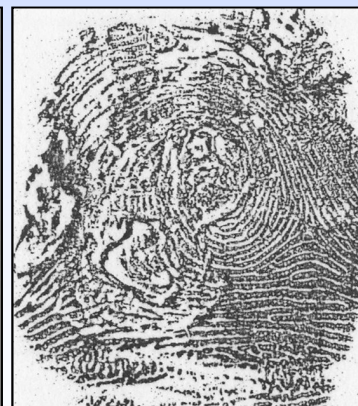


False Minutiae = 7



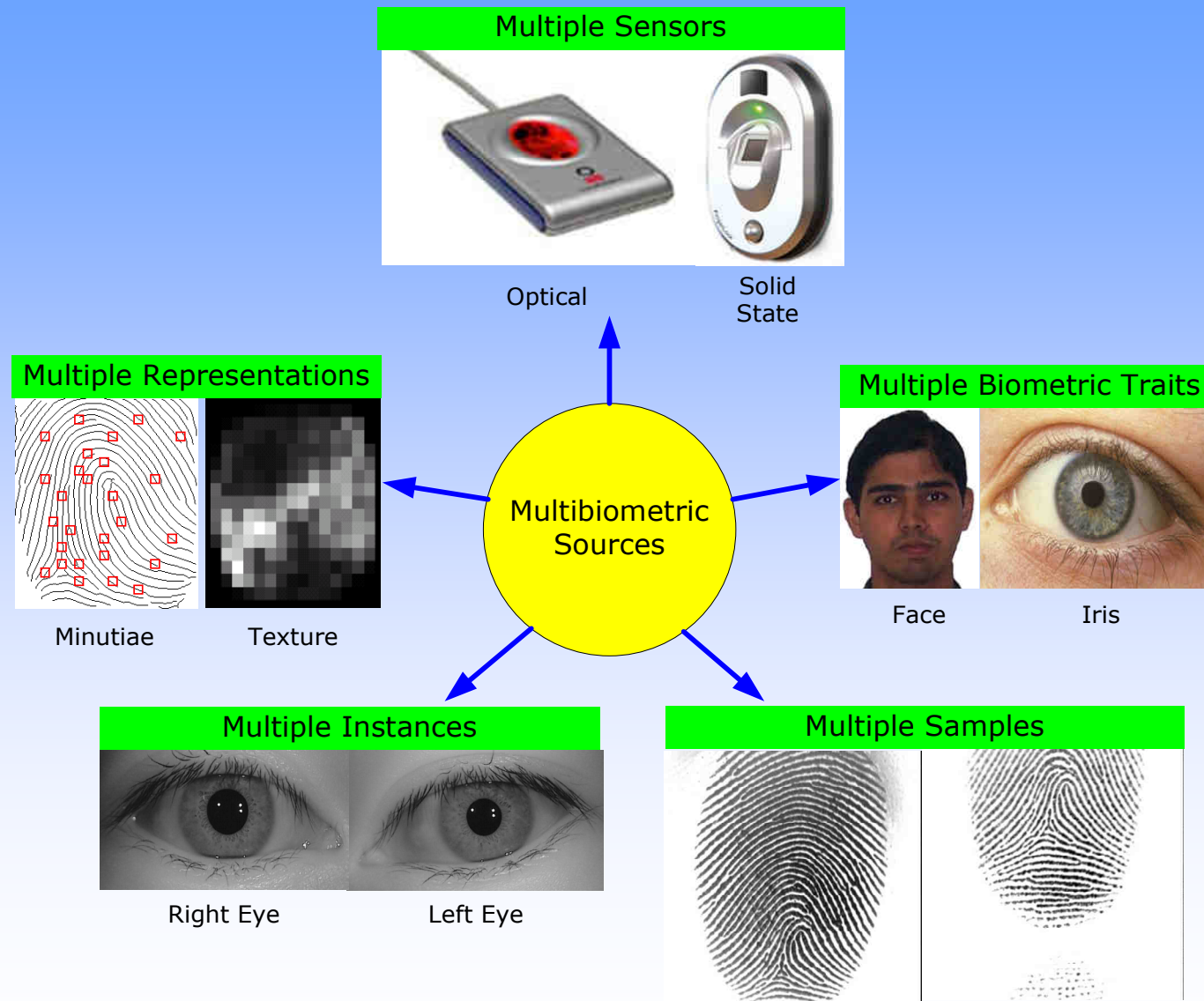
False Minutiae = 27

Spoofing & Obfuscation



<http://www.dailymail.co.uk/news/worldnews/article-1201126/Calais-migrants-mutilate-fingertips-hide-true-identity.html#>
<http://news.bbc.co.uk/2/hi/europe/3593895.stm>

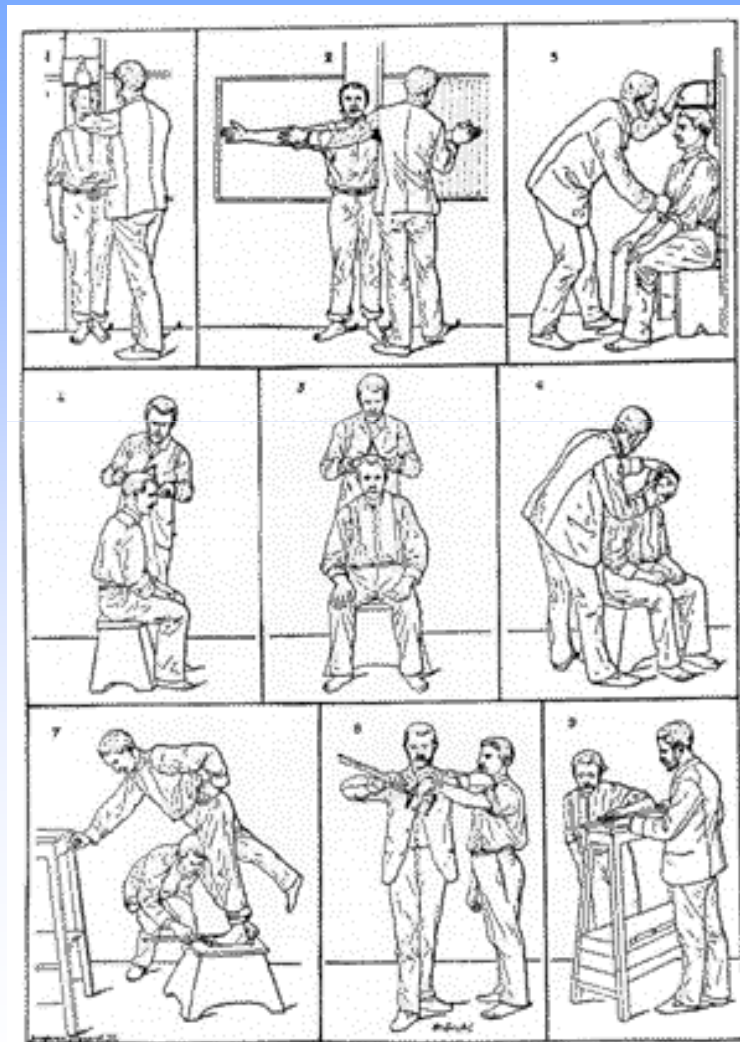
Biometric Fusion



Boost recognition accuracy, increase availability & enhance security

Bertillon System

Invented in 1882; **earliest multibiometric system**



(Ch. Brown)

Height	79.6	Head Length	19.8	L. Foot	27.1	Circle-Head	Age 22	Born in	
Eng. Height	5-10 3/4	Head width	16.3	L. Mid. F.	11.2	Periph. Z	Apparent Age		
Out. A.	75.5	Chin width	14.4	L. L.M. F.	8.7	Ch. Mel	Nativity	Louisville, Ky.	
Trunk	94.9	R. Ear	6.8	L. Fore A.	46.6	Post	Occupation	Johnson	

Remarks Incident to Measurements:




1663

DESCRIPTIVE

Incl. Body	Ridge Box	Beard	Shaved
Height M	Base (Ear) floor shoe	Hair	Black
Width Brn	DIMENSIONS		Complexion
Feet	Length	Projection	Weight
	6r	6r	165
	Feet	Chin	Build
		M. Prom	M. Slim

BUREAU OF IDENTIFICATION
Department of Police,
Tulane Ave. and Saratoga St.
New Orleans, La.

Measured Feb 1 1912
By Jno. J. Jones

Fingerprint Card

APPLICANT		LEAVE BLANK <i>Leave Blank</i>		TYPE OR PRINT ALL INFORMATION IN BLACK LAST NAME Teacher, Theresa C.		FBI LEAVE BLANK <i>Leave Blank</i>	
SIGNATURE OF PERSON FINGERPRINTED		AKA Formerly: Theresa Smith		O R I NY9219402 NYSTED Dept-FPU ALBANY, NY		DATE OF BIRTH DOB 12/31/70	
RESIDENCE OF PERSON FINGERPRINTED 318 School Street Hometown, NY 11111		CITIZENSHIP FTY US		SEX RACE HT WT AGE EYES HAIR F W 5'7" 155 Gr Bro		PLACE OF BIRTH POB Ohio	
DATE 5/01/02		SIGNATURE OF OFFICIAL TAKING FINGERPRINTS		LEAVE BLANK			
EMPLOYER AND ADDRESS <i>(if applicable)</i> Smart Falls Central School Dist Smart Falls, NY 11111		IDENTITY FTY Leave Blank		CLASS Leave Blank			
REASON FINGERPRINTED Leave Blank		ARMED FORCES NO. MNI Leave Blank		REF Leave Blank			
		SOCIAL SECURITY NO. SSC 000-10-1111					
		MILITARY SERVICE NO. MNI Leave Blank					
1. R. THUMB		2. R. INDEX		3. R. MIDDLE		4. R. RING	
5. R. LITTLE		6. L. THUMB		7. L. INDEX		8. L. MIDDLE	
9. L. RING		10. L. LITTLE		IDENTIX TP600 1259			
LEFT FOUR FINGERS TAKEN SIMULTANEOUSLY		L. THUMB		R. THUMB		RIGHT FOUR FINGERS TAKEN SIMULTANEOUSLY	

Mobile Multi-biometric Devices



Cogent Fusion

*Fingerprint
Face
Iris*



Morpho RapID

*Fingerprint
Face*



Datastrip DSVII

*Fingerprint
Face
Iris*



L-1 HIIDE

*Fingerprint
Face
Iris*

Current ARL funding to Cogent Systems (with MSU, USC, WVU) is prototyping a system with face, finger, iris, voice and periocular traits

Field Data Acquisition



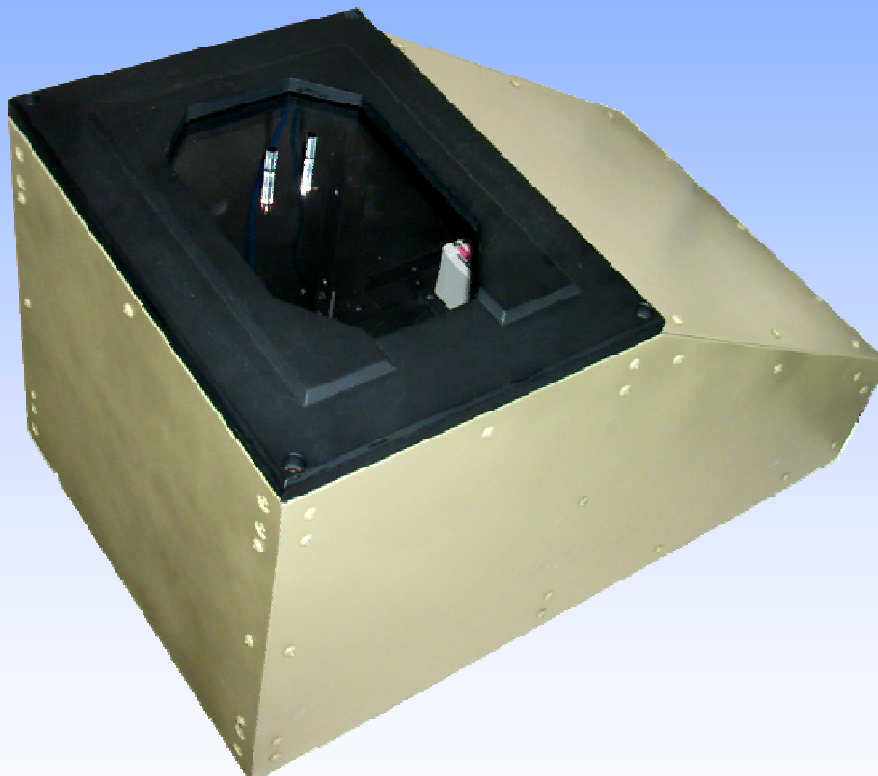
U.S. forces use HIDE (**Handheld Interagency Identity Detection Equipment**) during neighborhood patrols to capture fingerprints, irises and face in an effort to find insurgents (<http://online.wsj.com/article/SB125910374196463061.html>)

Multi-biometrics: Design Issues

- What to fuse?
- Fusion level?
- How to fuse?
- How to handle missing data?
- How to utilize sample/user specific characteristics?

What to Fuse?

Choice of traits for fusion should be based on:
accuracy, availability, cost & acquisition time



Multispectral, whole-hand scanner (Lumidigm & MSU, Army SBIR); single placement of hand allows fusion of fingerprint, palmprint & hand shape.

Rowe, Uludag, Demirkus, Parthasaradhi and Jain, " A Multispectral Whole-hand Biometric Authentication System, *Proc. Biometric Symposium, Biometric Consortium Conference*, Baltimore, September 2007

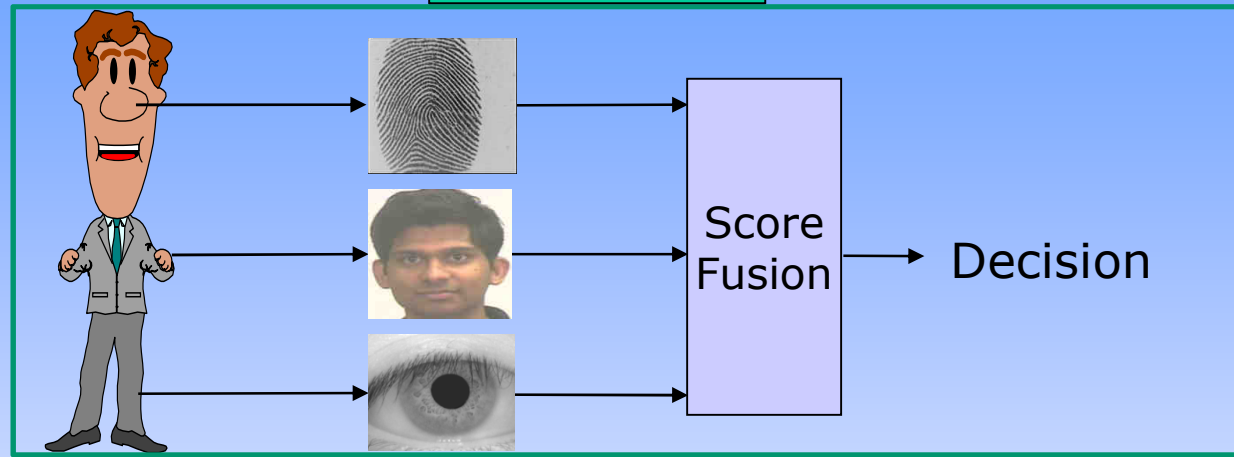
Fusion Level

- Score level
 - Sum score fusion with **normalization**
 - Weighted sum score
 - Likelihood ratio (**LR**) fusion
- Rank level
 - Highest rank
 - Borda count
- Decision level
 - Majority voting

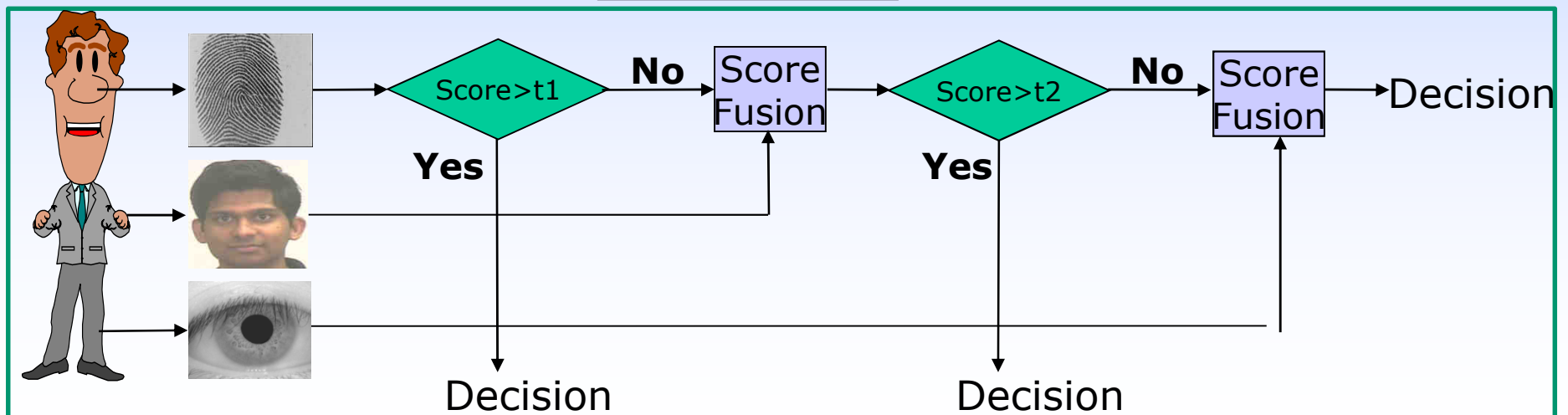
Feature level fusion is difficult since COTS vendors are not likely to provide the proprietary features

Parallel vs. Cascade Fusion

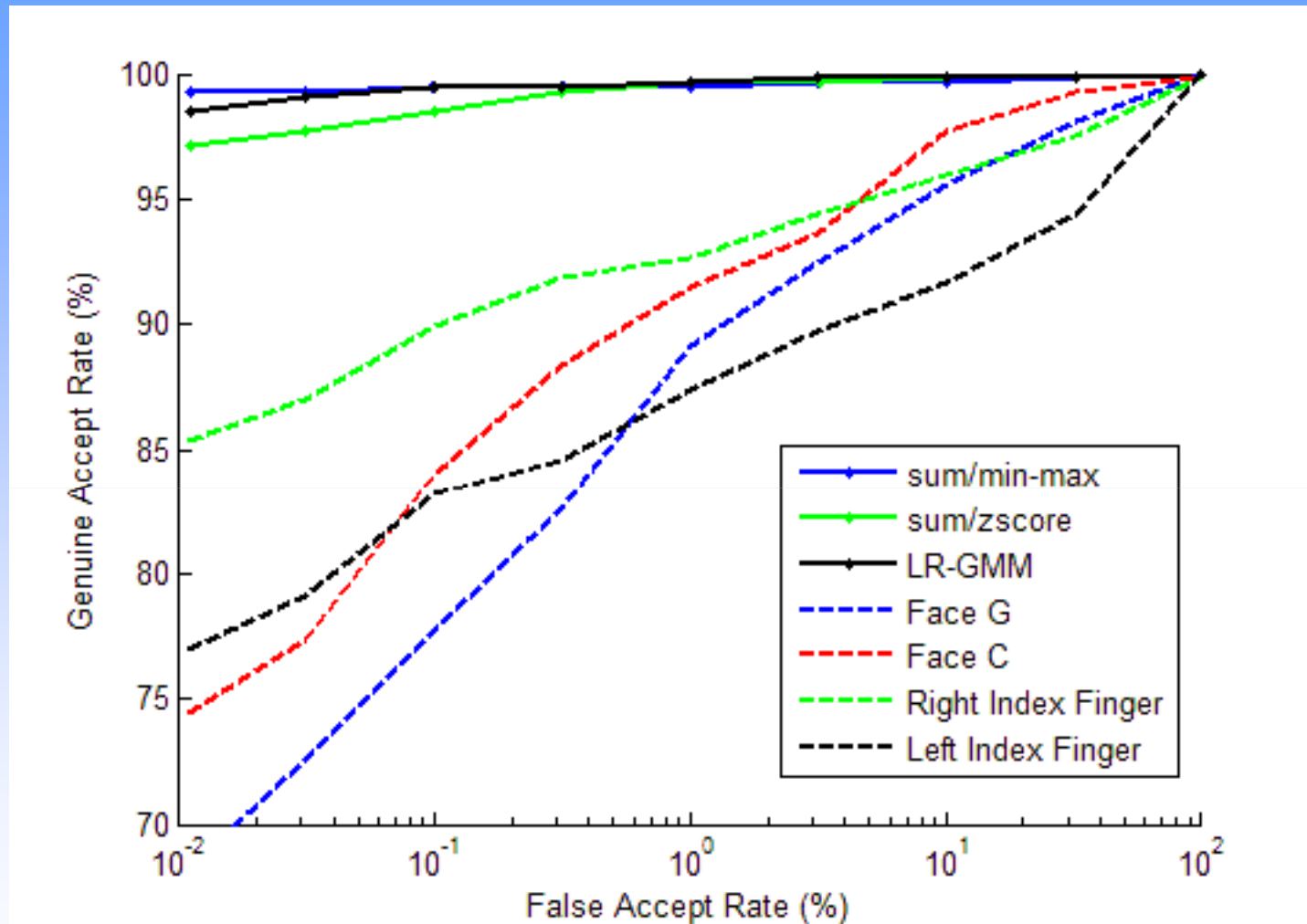
Parallel Fusion



Cascade Fusion



Score-Level Fusion

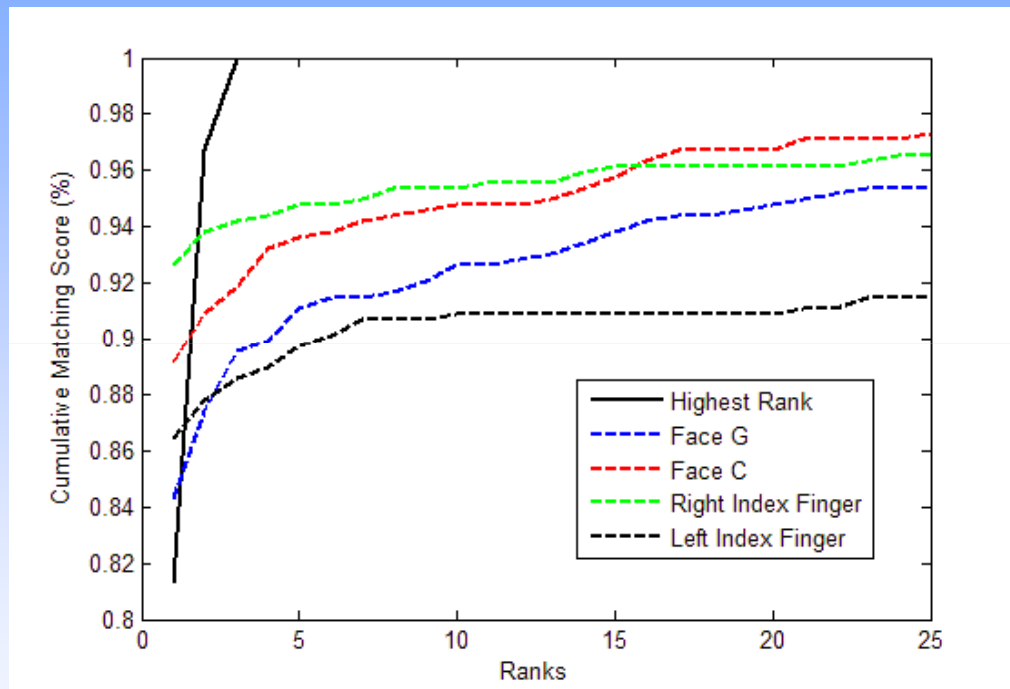


Dataset: NIST BSSR1 (517 subjects, scores of 2 face matchers, left index finger match score and right index finger match score).

Nandakumar, Chen, Dass and Jain, "Likelihood Ratio Based Biometric Score Fusion", *IEEE Trans. PAMI*, Vol. 30, No. 2, pp. 342-347, February 2008.

Rank/Decision Level Fusion

Highest Rank Fusion



Majority Decision Fusion

Modality	Rank-1 Accuracy
Face G	84.33%
Face C	89.17%
Right Finger	92.65%
Left Finger	86.46%
Majority Voting	99.03%

Dataset: NIST BSSR1 (517 subjects, scores of 2 face matchers, left index finger match score and right index finger match score)

LR Fusion With Quality

- Estimate **joint density of match score and image quality** to assign weights to individual matchers; K matchers are assumed to be independent

$$QPFS(\mathbf{S}, \mathbf{Q}) = \prod_{k=1}^K \frac{P(S_k, Q_k \mid \text{genuine})}{P(S_k, Q_k \mid \text{impostor})} \geq \eta$$

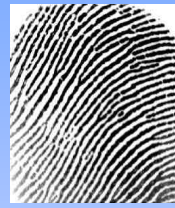
Biometric Sample Quality

Quality indicates **reliability** of the respective match score

Fingerprint
(NFIQ)



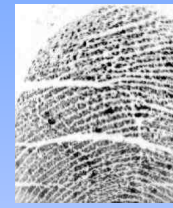
Q=1



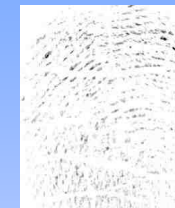
Q=2



Q=3



Q=4



Q=5

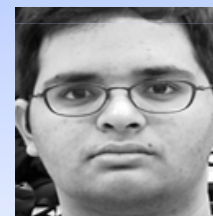
Face
(Symmetry (Q^m),
Sharpness (Q^p))



$Q^m=0.7$



$Q^m=0.01$



$Q^p=0.95$



$Q^p=0.02$

Pair-wise Iris
(CWT)



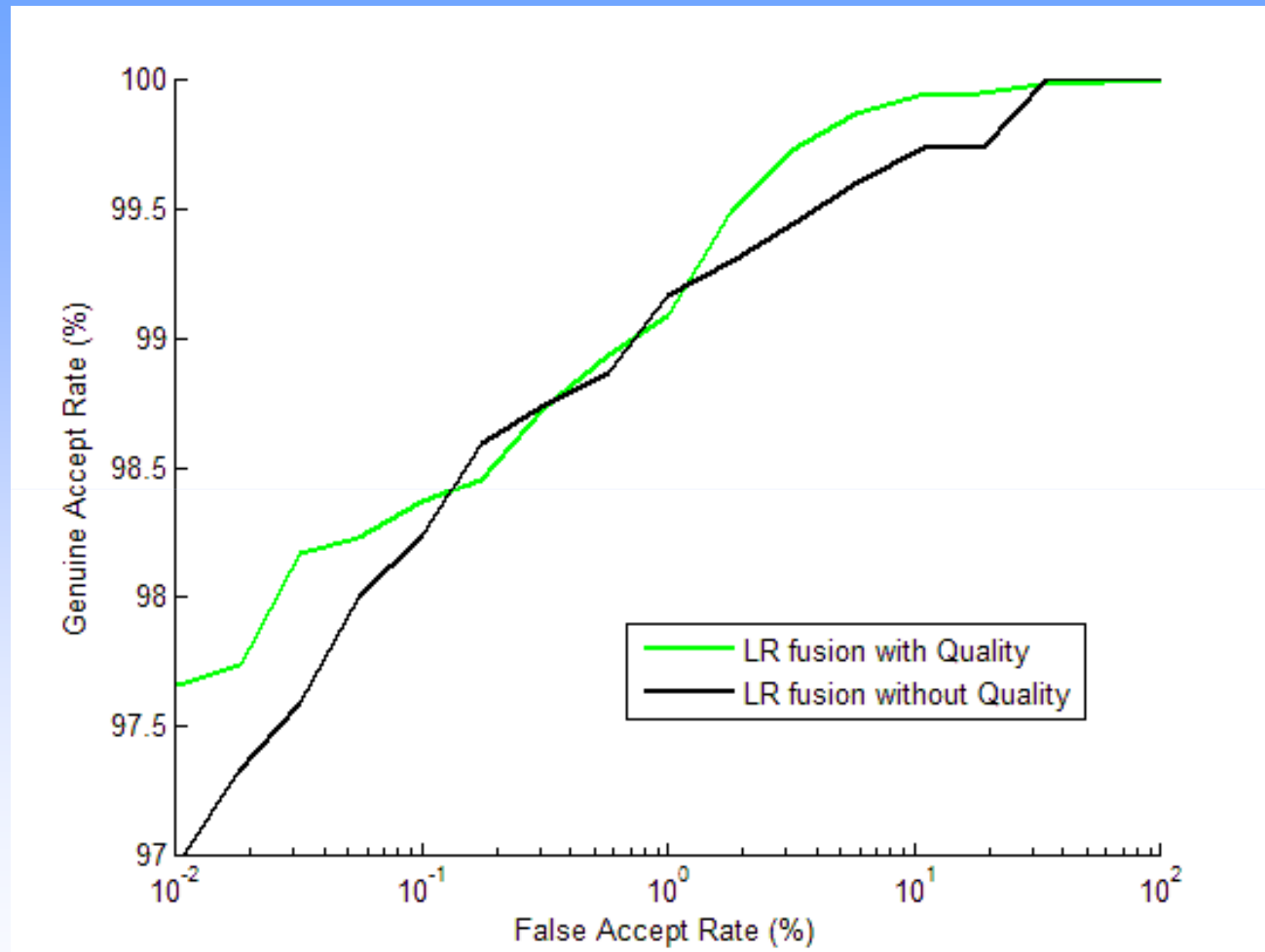
$Q_{\text{iris}}=0.80$



$Q_{\text{iris}}=0.42$

Quality of a match is product of individual sample qualities i.e. $Q_{ij} = Q_i Q_j$

Quality Based Fusion



ROC curves for LR fusion with and without quality for a subset of WVU data (face and finger images for 261 subjects)

Quality Based Fusion

	Face	Left thumb	Left index	Right thumb	Right index
Probe images					
Gallery images					
Genuine scores	0.45	0.04	0.02	0.01	0.07
Maxi. Imp. scores	0.55	0.05	0.08	0.03	0.04
Genuine quality	0.04, 0.22	0.56	0.56	0.56	0.56

This probe (face and 4 fingerprints) was successfully matched using quality-based sum fusion, but was rejected without quality-based fusion

Quality weighs the evidence appropriately!

Missing Data in Fusion

- Missing data is frequently encountered in **identification scenarios**
 - Missing templates
 - Incomplete queries
- Two approaches
 - **Likelihood ratio**: LR of missing scores is set to 1
 - **Highest rank**: subjects with missing modalities given the lowest rank

Nandakumar, Jain and Ross, "Fusion in Multibiometric Identification Systems: What about the Missing Data?", *Proc. 3rd Int'l Conf. on Biometrics*, Alghero, June, 2009.

Sequential Fusion

- Process good quality traits first
 - Poor quality samples may not be required if sufficient evidence is accumulated
- Order biometric traits using **quality specific accuracy**

$$g^k(q) = 1 - EER^k(q)$$

- Modify match score based on quality

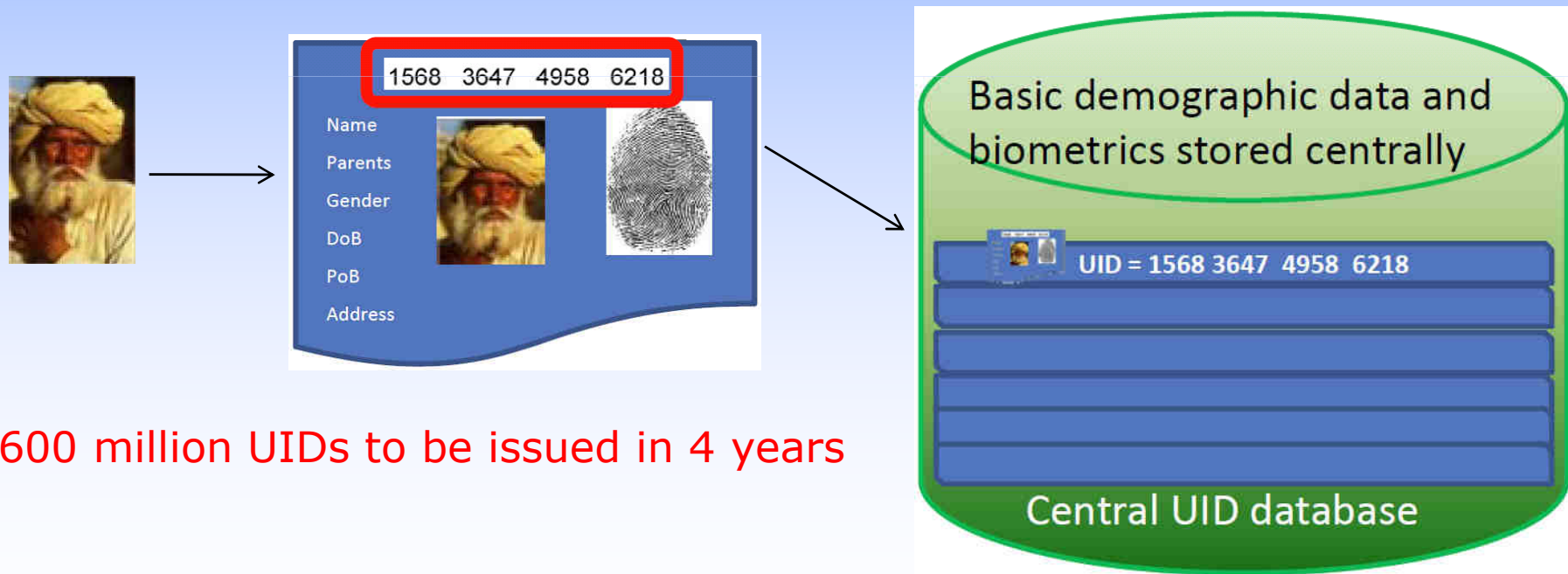
$$s_m(s, q) = \sum_{k=1}^m g^k(q_k) s_k$$

In fusion of fingerprint, face & hand geometry, 28% of genuine users required only fingerprint, 13% required both fingerprint and face, & 59% required all three modalities; impostors had to submit all three modalities

India's UID Project

“Issue a unique identification number (UID) to Indian residents that can be verified and authenticated in an online, cost-effective manner, and that is robust enough to eliminate duplicate and fake identities.”

UID ⇔ Unique number ⇔ Random number



600 million UIDs to be issued in 4 years

<http://uidai.gov.in/>

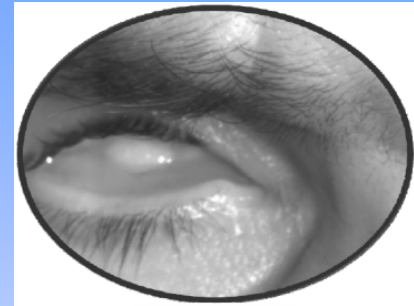
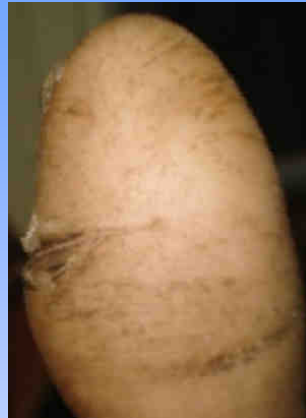
Error Rate Requirements

- India's Unique ID project: ~ 1 billion enrollments
- Identification system performance
 - False Negative Identification Rate (FNIR)
user is enrolled, but his identity is not returned
 - False Positive Identification Rate (FPIR)
user is not enrolled, but an identity is returned
- Suppose for $N = 10^9$ users, we require
 - FNIR = 1 in a million = 0.0001%
 - FPIR = 1 in 100,000 = 0.001%
- To meet this criteria, we need a matcher with
 - FMR $\approx 10^{-12}$ % and FNMR = 0.0001%
- Best matcher: FMR = 0.01% at FNMR = 0.6%

Data Collection Environment (UID)



Biometric Trait



Missing thumb



Missing ring & pinky

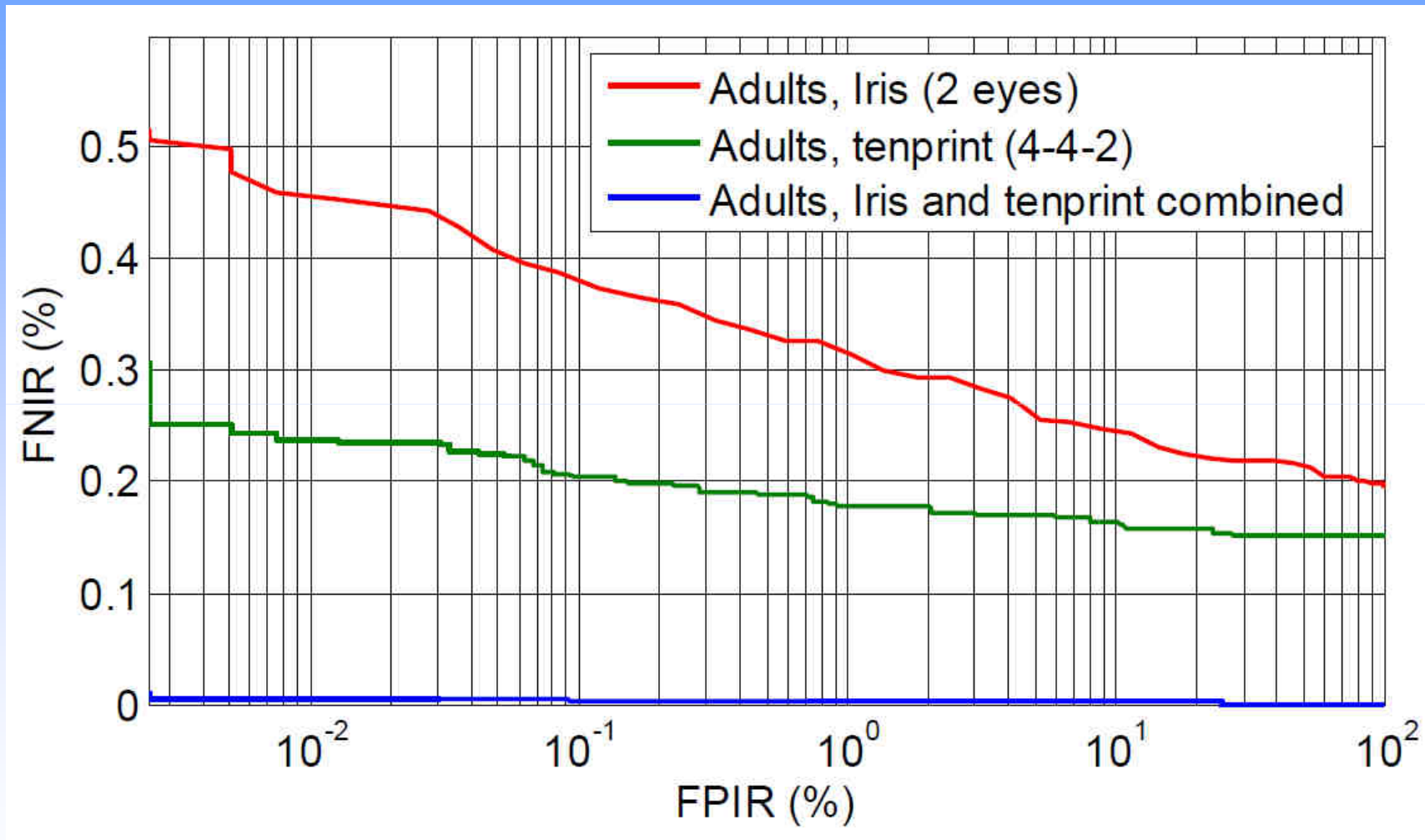


Eye disease

UID Missing Data

	Percentage of enrollees
One or more fingers missing or otherwise not capturable	1.2%
Either or both eyes missing or otherwise not capturable	0.5%
Missing all 10 finger and both eyes	0.01%

UID: Identification Rates (20K)

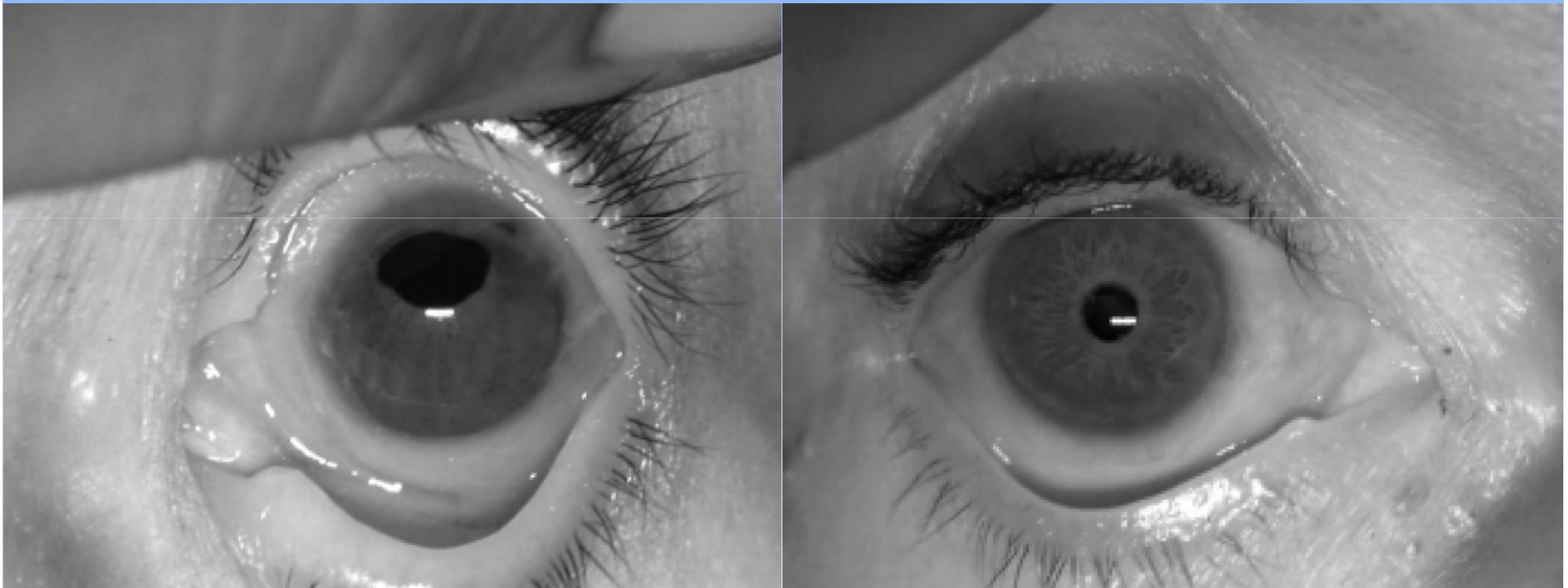


FPIR: Likelihood that a person's biometrics is seen as a duplicate

FNIR: Likelihood that system is unable to identify a duplicate enrollment

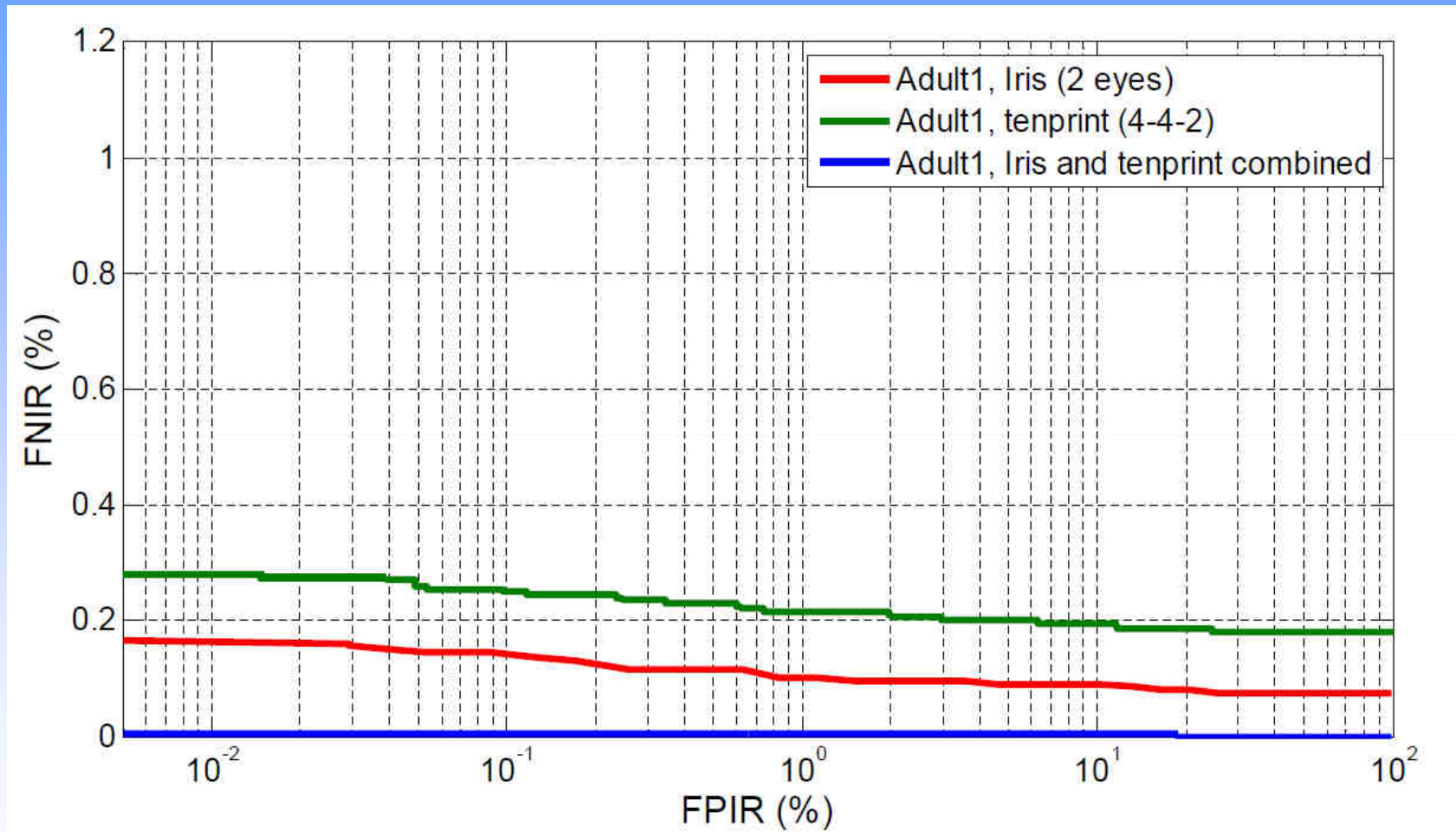
UID: Special Acquisition Process

Subjects are asked to open their eyes with fingers during iris capture



UID: Identification Rates (20K)

(Special iris acquisition)

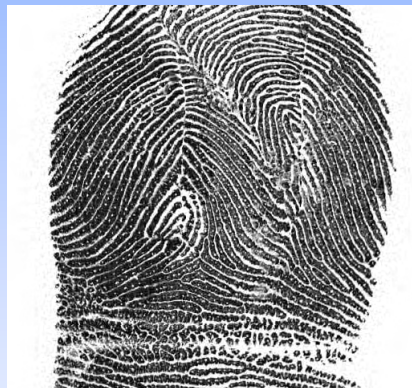


FPIR: Likelihood that a person's biometrics is seen as a duplicate

FNIR: Likelihood that system is unable to identify a duplicate enrollment

Non-Cooperative Subjects: Fingerprints

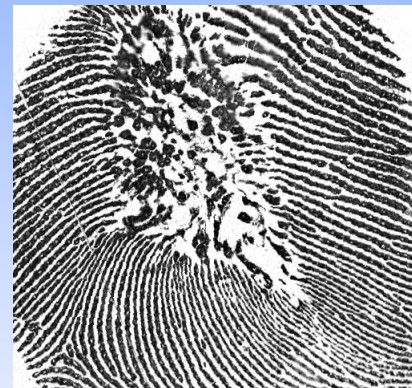
- To evade identification, subjects may
 - alter some friction ridge pattern
 - change the impression order of the fingers
 - Introduce deformation during image capture
- Automatic detection of altered prints (FPR=1%)



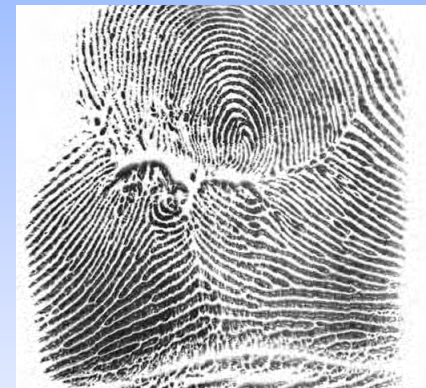
NFIQ=2



NFIQ=4



NFIQ=2



NFIQ=2

- Altered impressions identified in NIST14 DB



NFIQ of 1 indicates the highest quality and 5 indicates the worst quality

Fingerprint Deformation

(NIST SD 24)

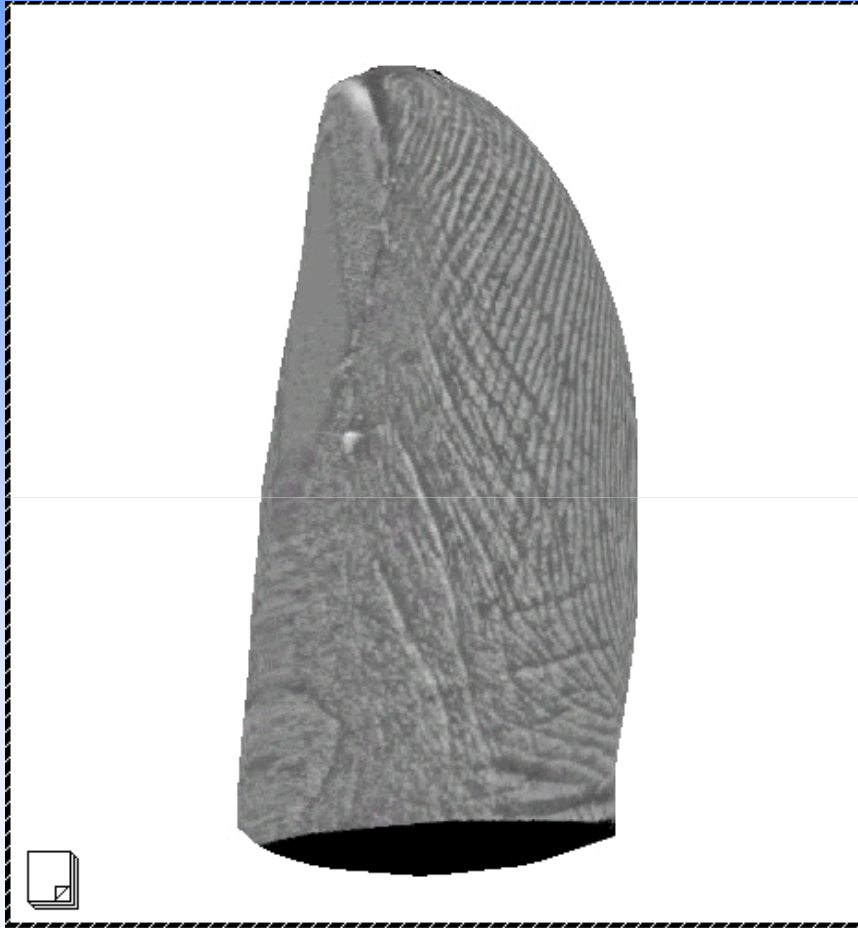


Rotation

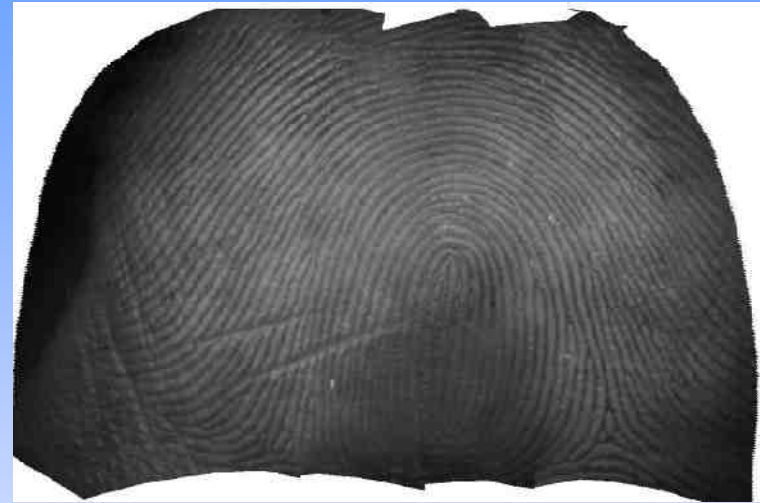


Shifting

Touchless 3D Fingerprint Acquisition



TBS Touchless 3D image



Virtual "rolled" image

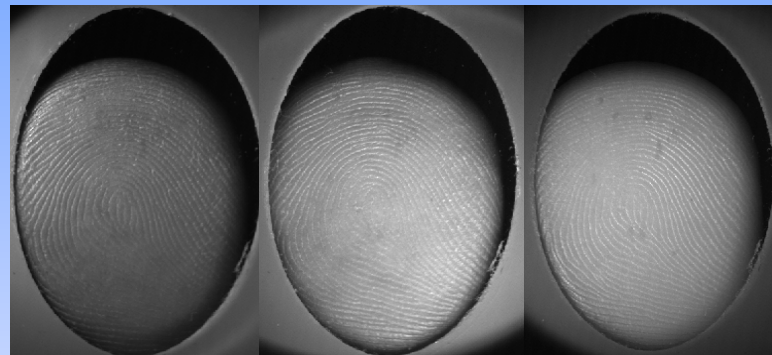


Ink on paper

TBS & MSU effort funded by NIJ

Multispectral Imaging

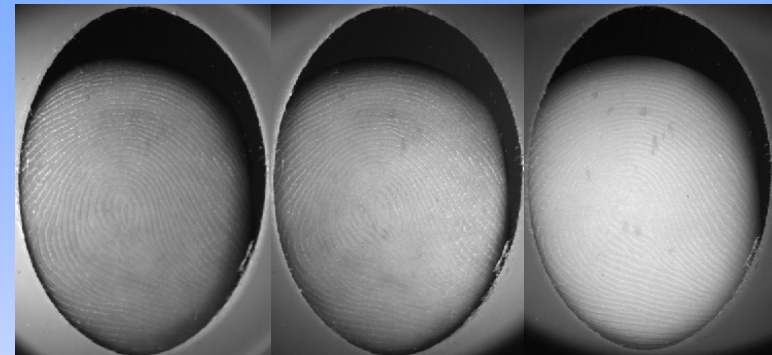
Multiple wavelengths capture fingerprint features at different depths (**surface and subsurface**) of derma



430 Non-polarized (Blue)

530 Non-polarized (Green)

630 Non-polarized (Red)

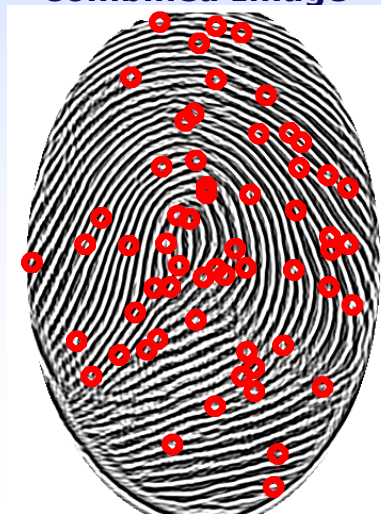


430 Polarized (Blue)

530 Polarized (Green)

630 Polarized (Red)

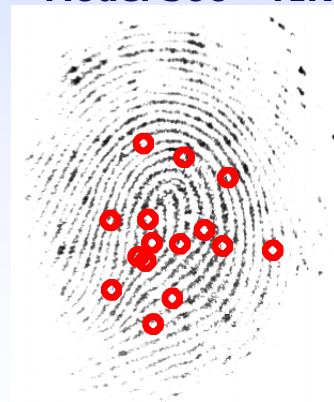
**Jupiter 1.10
Combined Image -**



Better image
quality & **spoof
detection**

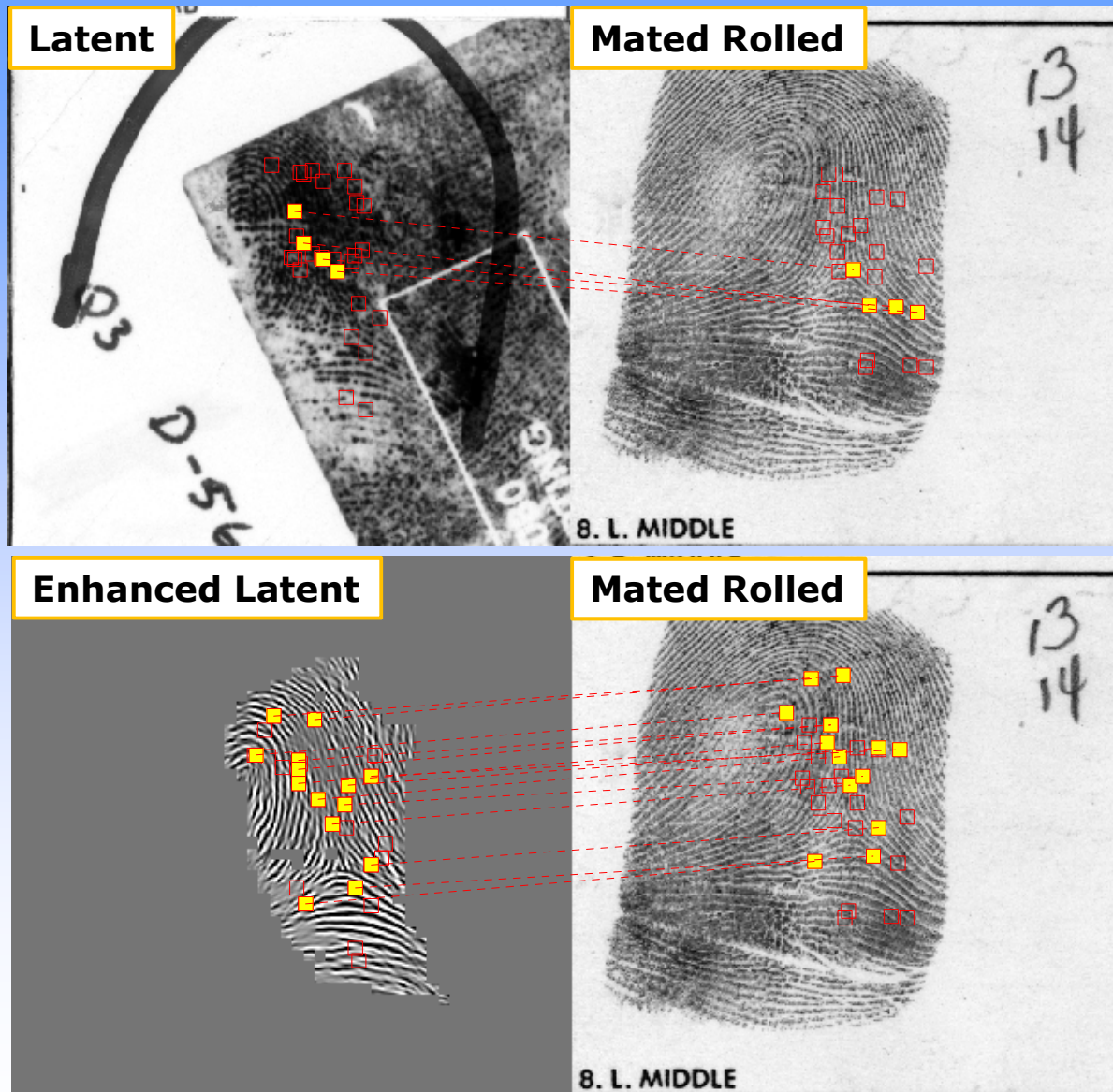
vs.

**Cross Match Verifier
Model 300 - TIR**



Lumidigm

Latent Enhancement



Matched Minutiae: 4
Matching Score: 6
Rank: 93



Matched Minutiae: **14**
Matching Score: **45**
Rank: **1**

* Latent DB: 258 from NIST SD 27
* Background DB: 15,758 from NIST SD 27, 4, and 14
* Minutiae matcher: VeriFinger SDK 4.2

* Soweon Yoon, Jianjiang Feng, and Anil K. Jain, *On Latent Fingerprint Enhancement*, SPIE, April 2010.

Non-Cooperative Subjects: Face

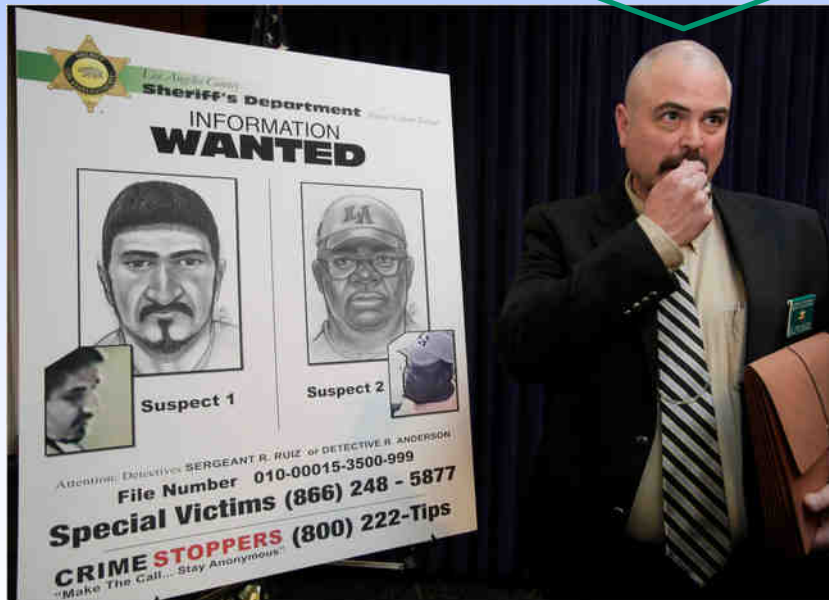
- Introducing intrinsic variations (plastic surgery, disguise, facial accessories,..)
- Difficult imaging environment (night time, at a distance, partial face,..)
- Only verbal description of face (including soft biometrics and demographic information) available instead of face image

Sketch From Video

The New York Times

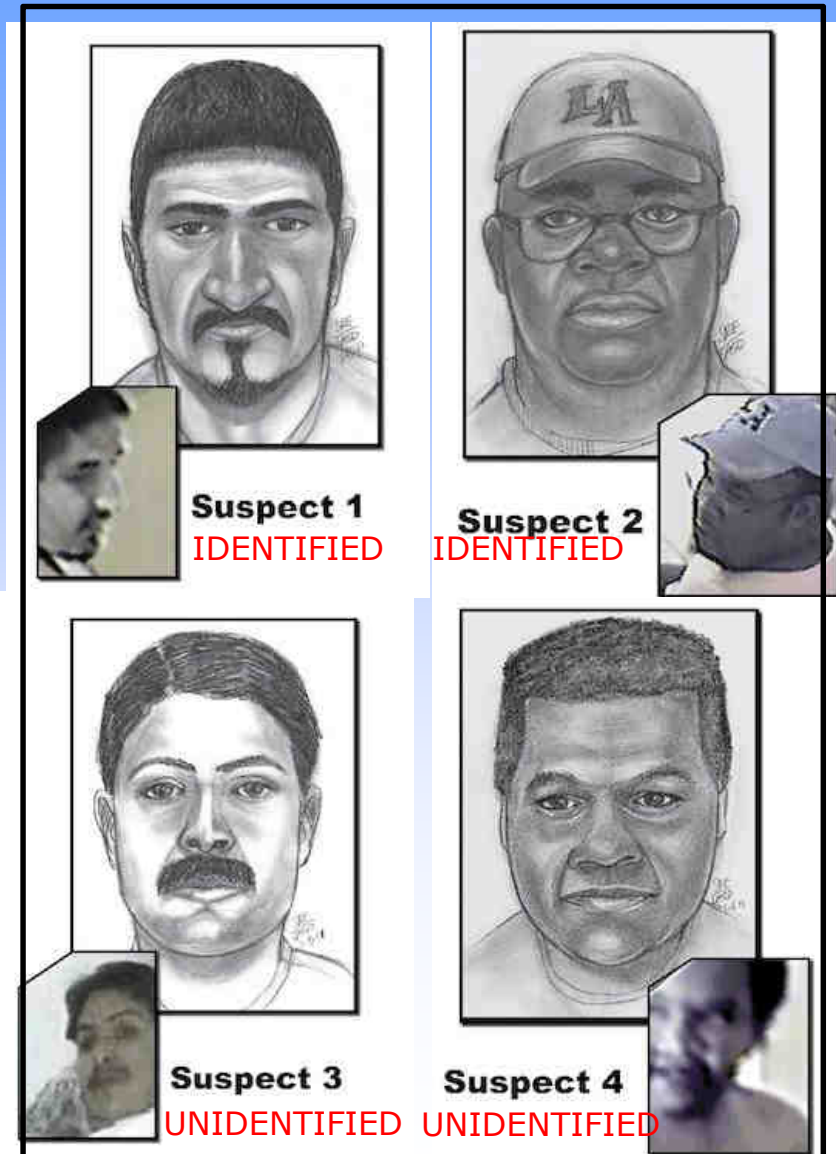
Los Angeles Officials Identify Video Assault Suspects

"Composite drawings of four of the suspects have been made based upon video images"

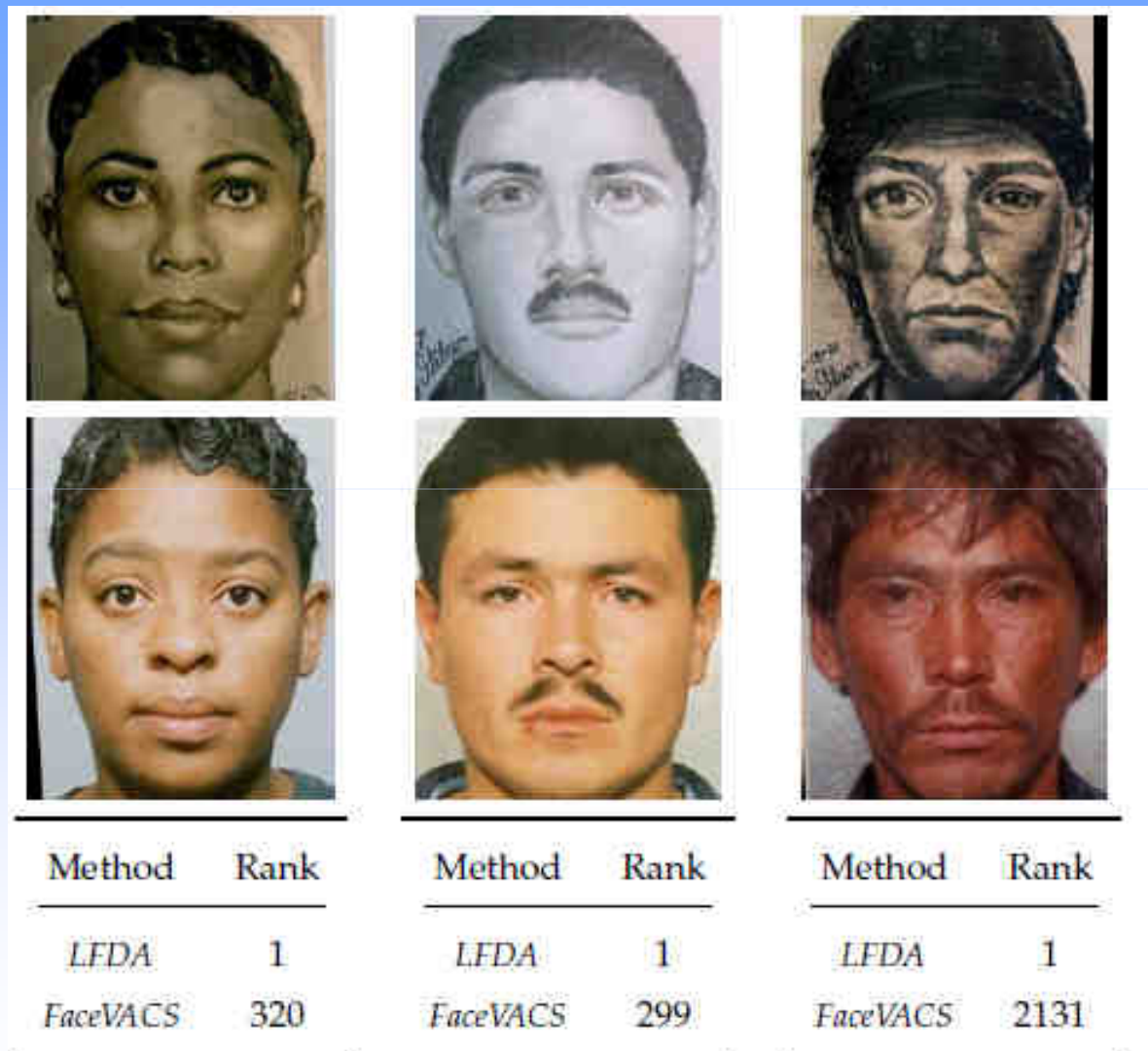


<http://www.nytimes.com/2011/01/08/us/08disabled.ht>

<http://www.lacrimestoppers.org/wanted.aspx>



Sketch to Photo Matching



B. Klare, Z. Li, and A. K. Jain, "Matching Forensic Sketches to Mug shot Photos", TPAMI, March 2011

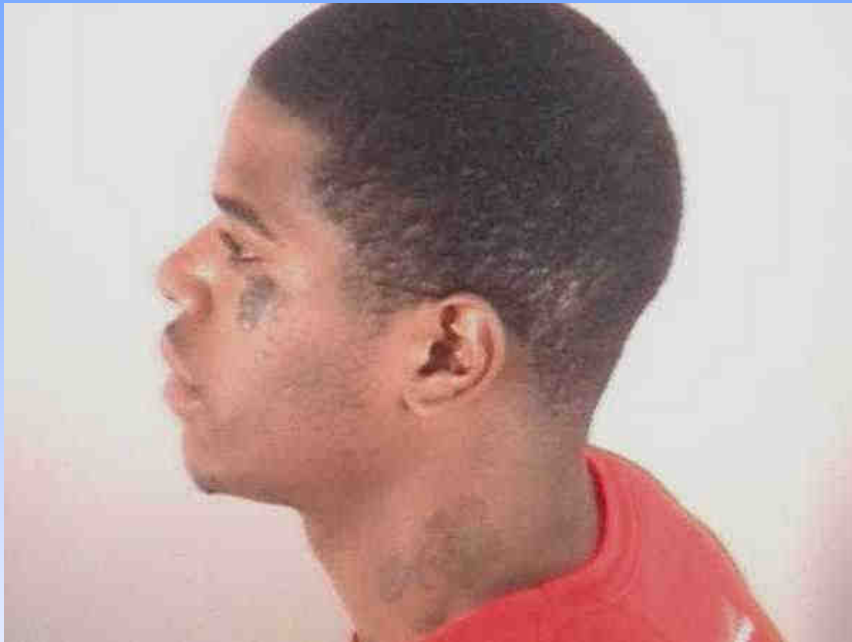
Partial Face Recognition

- Recognize an unaligned arbitrary piece of face; need robust & invariant representation



Correctly classified partial faces;
gallery consists of 10K faces

Facial Tattoo Caught in Surveillance Camera



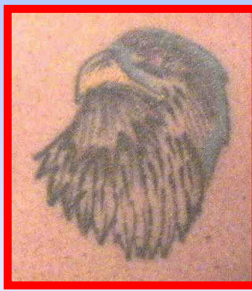
Detroit police say they have linked at least six armed robberies at an ATM on the city's west side after matching up a tipster's description of the suspect's distinctive tattoos.

www.DetroitisScrap.com/2009/09/567/

TattooID System



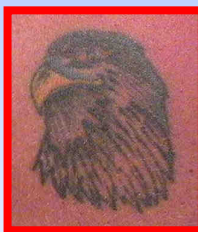
Query1



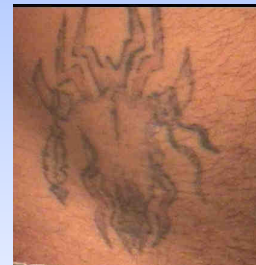
163



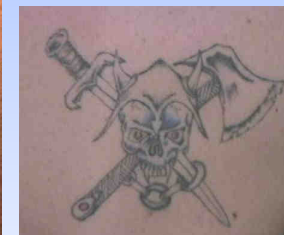
157



111



27



26



26



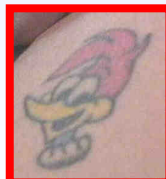
26



Query2



168



92



69



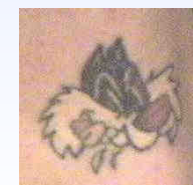
64



63



62

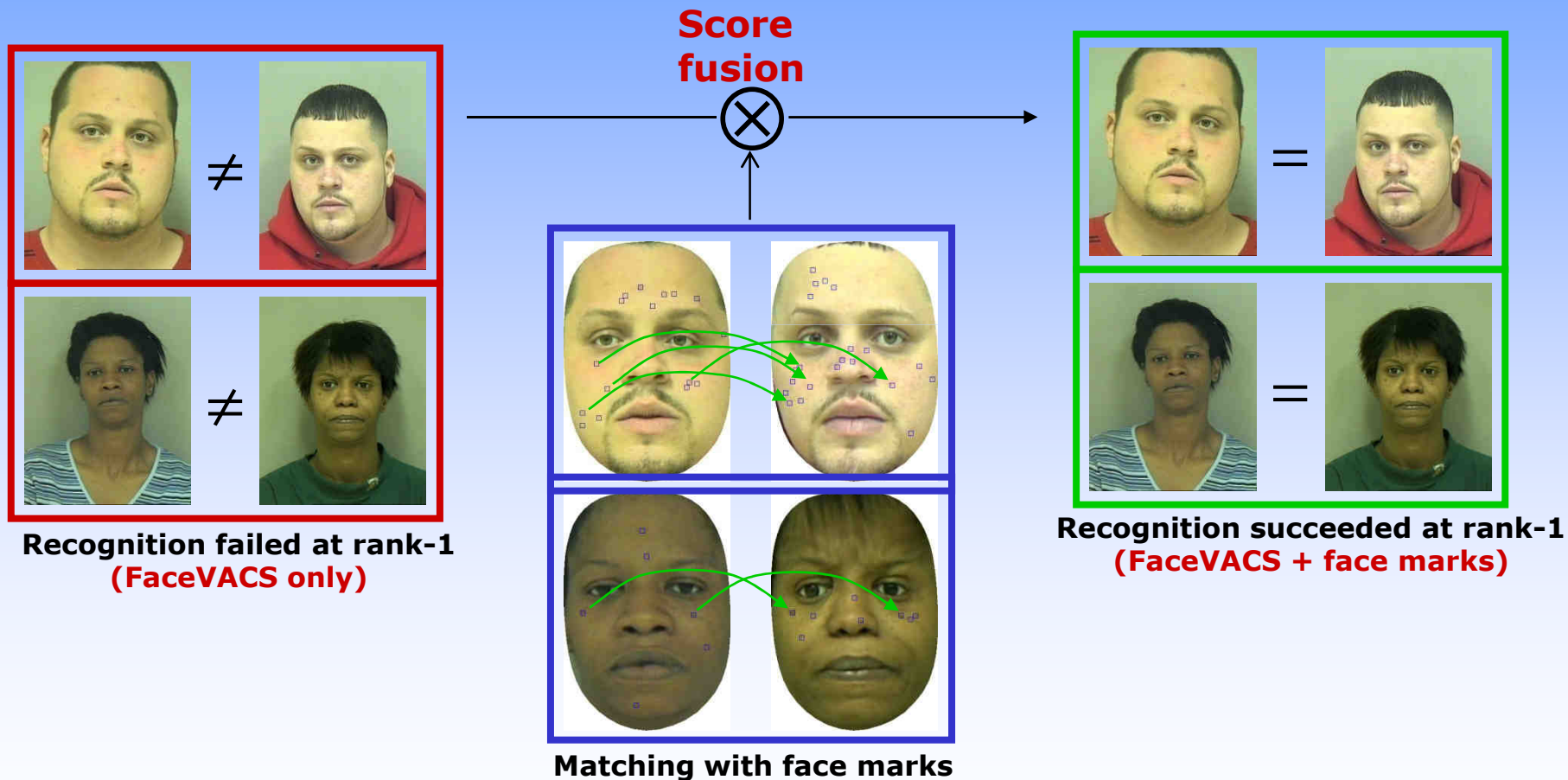


61

Research supported by ARO and FBI Biometric Center of Excellence

Fusion with Facial Marks

Rank-1 accuracy improves from 89.3% to 90.7%



U. Park and A. K. Jain, "Face Matching and Retrieval Using Soft Biometrics," *IEEE Trans. Information Forensics and Security (TIFS)*, Vol. 5, No. 3, pp. 406-415, 2010.

Age Invariant Matching

Probe Images



Age 51



Age 40



Age 42



Age 62

Gallery Images



Age 41



Age 34



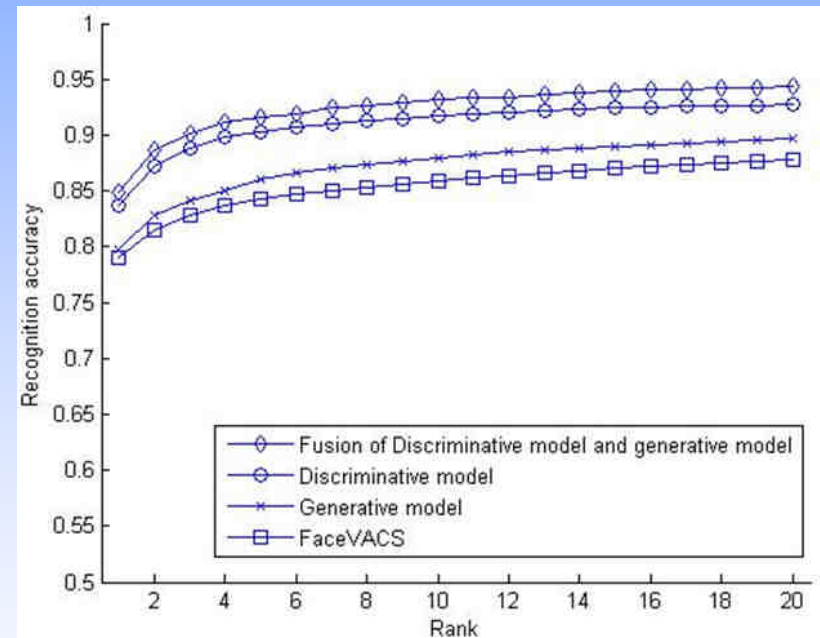
Age 41



Age 62

FaceVACS and generative method fail;
discriminant method succeeds

Discriminant method fails;
FaceVACS and generative methods succeed



Face Recognition At A Distance

- Telescope + NIR illuminator (up to 300 m)
- Telescope provides high res. face image with large standoff
- NIR illuminator enables face acquisition at night; NIR light is not visible to human eye (covert applications)

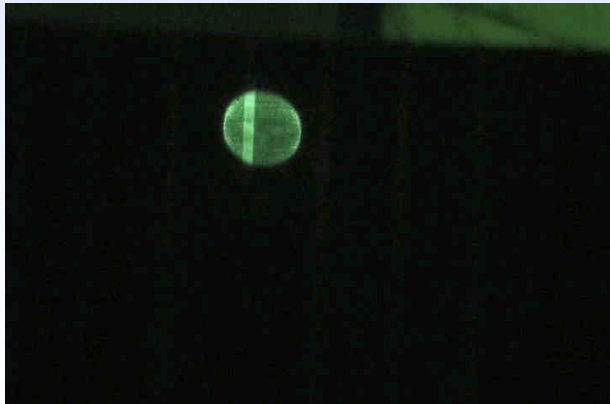


Telescope, Sky-Watcher

Aperture diameter: 180 mm, Focal length: 2700mm



NIR-illuminator, KM-1000M
Lanics



Using regular video camera with NIR illuminator (30 m)



Using telescope + NIR illuminator (30 m)

Army Science Board Questions

1.1 How well these algorithms perform with low/poor quality samples? What are the algorithm design features that limit their usefulness for low/poor quality samples?

All systems exhibit a significant degradation in accuracy in processing low quality samples. In NIST FpVTE, GAR of the best system at 0.01% FAR dropped from ~100% for best quality fingerprints to ~75% for poor quality prints. Similar results were observed for face (FRVT 2006) and iris (ICE 2006). State-of-the-art algorithms can support decision-quality matches with *only* moderate to low level of confidence for poor quality data.

Key obstacles: (i) estimating type and degree of noise (distortion, non-uniform illumination, etc.), (ii) design of noise-specific image enhancement, (iii) extracting discriminative features

Army Science Board Questions

1.2 Are you aware of any new algorithms or algorithms under development that address the limitations of current algorithms and that offer better performance for low/poor quality samples?

Multi-spectral & touch-less 3D sensors provide better quality fingerprint images from non-cooperative users; multispectral face/iris sensors are being explored.

Methods for improving recognition performance for low quality samples: (i) super-resolution, (ii) 3D morphable models, (iii) fusion of multiple video frames, (iv) new face representation schemes (which, for example, do not require eye locations for alignment)

Army Science Board Questions

1.3 Can any conclusions be drawn on the utility of multi-mode fusion in which the underlying feature data are poor and/or the match scores from each mode are low? Are there any approaches other than match score fusion (e.g., sequential application of each mode to narrow populations scoring above a particular threshold) that might operate better with low/poor quality biometric samples?

UID results show that multimodal fusion improves the performance for low quality samples. FpVTE 2003 showed that (i) image quality and no. of fingers had the greatest effect on matching accuracy, (ii) fusion of two top fp matchers improved the performance.

Sequential fusion, on an average, reduces the no. of biometric traits to be used. Use of demographic data can filter the database thereby improving the accuracy.

Quality-based score level fusion can take care of quality issues in some of the modalities.

Army Science Board Questions

1.4 There may be utility in employing algorithms in which “confidence” thresholds can dynamically be adjusted in response to the tactical situation; i.e., from high confidence in one scenario to lower confidence in another scenario. How easily can thresholds be adjusted with current algorithms? Are the adjustments automated or do they require operator intervention?

Adjusting the matching thresholds is easy if done manually. One can provide a menu that allows the operator to choose the level of confidence required, which can be easily converted to an appropriate threshold based on the ROC curve. All quality-based fusion schemes are in effect ways of manipulating the threshold automatically. In fact, even for a single modality it is possible to estimate the conditional probability of a match based on the quality. This is an indirect way of changing the threshold automatically depending on the quality of the acquired sample. However, it may not be possible to improve the overall accuracy of a unibiometric system just by adjusting the matching threshold.

Army Science Board Questions

1.5 If a subject whose biometric is captured non-cooperatively is among the enrollees in a data base, how confident can we be that the feature extractions and therefore the templates of the data in the data base and the newly captured data are interoperable so that matching algorithms can be exercised? In other words, the data captured non-cooperatively are very likely of different, probably degraded, quality to compare against what is available in the data base. For instance, a finger print from one finger will have a very different template than that from a rolled print of all five fingers. Similarly, iris or facial data captured at a great distance will have different templates than those from a close distance. Do we have any experience in this regard? We can imagine a new set of templates can be applied so they can be interoperable. How practical will that be to a FOB operator, who may have to act quickly, and also with regard to the bandwidth allocation?

For fingerprints, distortion of templates has been attempted (e.g., Ross & Jain's work based on TPS, Cappelli et al.'s work on modeling plastic distortion). For face, 3D models can be used to generate new gallery images that match the viewpoint and illumination conditions of the probe image. I am not aware of any such work for the iris modality. I don't see how the FOB operator can change the template in order to make them compatible with the query. The operator could possibly specify the type of distortion in the query manually, which may allow the system to modify the template or query accordingly.

Army Science Board Questions

1.6 More than likely, the subject whose biometric is captured non-cooperatively is not among the enrollees in a data base. In such a case, how do we exercise matching process? Do we have any experience in this?

It is not clear, what is meant by “the subject is not among the enrollees in a database”. If there is a way to know this information beforehand, then there is no need to perform biometric matching.

The only case that I can think of is open set vs. closed set identification. If we have reason to believe that the subject is definitely among the enrollees, then we have to assign the subject to the best matching identity, irrespective of the match score. On the other hand, for open set identification it is possible to have a reject option.