Fusion and Privacy in Biometrics

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The i-PRoBe Lab

http://www.cse.msu.edu/~rossarun/i-probe/

- Integrated Pattern Recognition and Biometrics Lab
- Currently: 8 PhD Students + 1 PostDoc
- Graduated: 24 MS Students + 7 PhD Students

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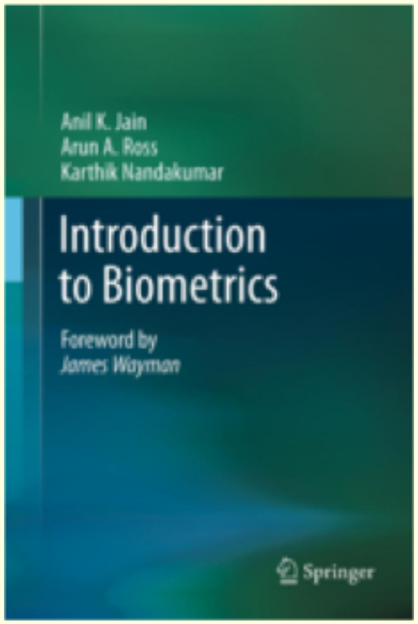
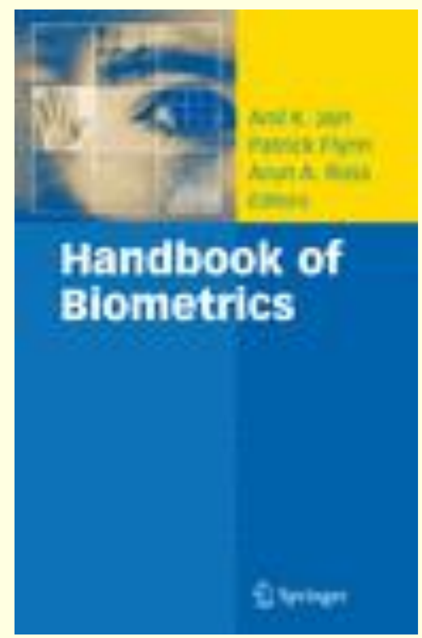
INTRODUCTION TO BIOMETRICS



HANDBOOK OF MULTIBIOMETRICS

HANDBOOK OF BIOMETRICS



Related Papers

- A. K. Jain, K. Nandakumar, A. Ross, "**50 Years of Biometric Research: Accomplishments, Challenges, and Opportunities**," Pattern Recognition Letters, Vol. 79, pp. 80 - 105, August 2016.
- A. Dantcheva, P. Elia, A. Ross, "**What Else Does Your Biometric Data Reveal? A Survey on Soft Biometrics**," IEEE Transactions on Information Forensics And Security (TIFS), Vol. 11, No. 3, pp. 441 - 467, March 2016.
- A. K. Jain and A. Ross, "**Bridging the Gap: From Biometrics to Forensics**," Philosophical Transactions of The Royal Society B, Vol. 370, Issue 1674, August 2015.
- A. K. Jain, B. Klare, A. Ross, "**Guidelines for Best Practices in Biometrics Research**," Proc. of 8th IAPR International Conference on Biometrics (ICB), (Phuket, Thailand), May 2015.

Biometric System

BIOMETRIC TRAIT

HUMAN MACHINE INTERFACE

PERSON

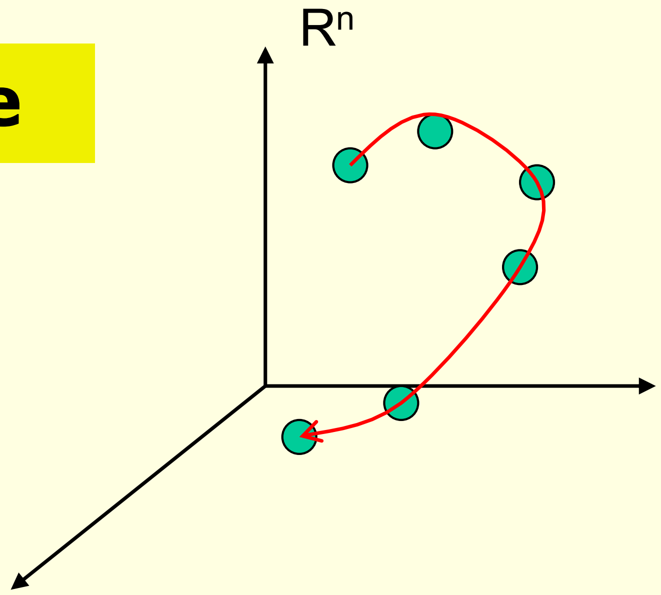
Ross/2018

Challenges in a Biometric System

- **Noise in sensed data**: e.g., defective sensors or unfavorable ambient/physiological conditions
- **Intra-user variations**: e.g., incorrect interaction with sensor, variations in user's biometric trait, sensor characteristics are modified
- **Distinctiveness**: e.g., capacity of biometric template is limited
- **Non-universality**: e.g., all users may not be able to successfully present the trait
- **Spoof attacks**: circumvent the system by imitation or using artificial traits

Intra-user variations

- **FNMR: False Non-Match Rate**



Inter-user similarity

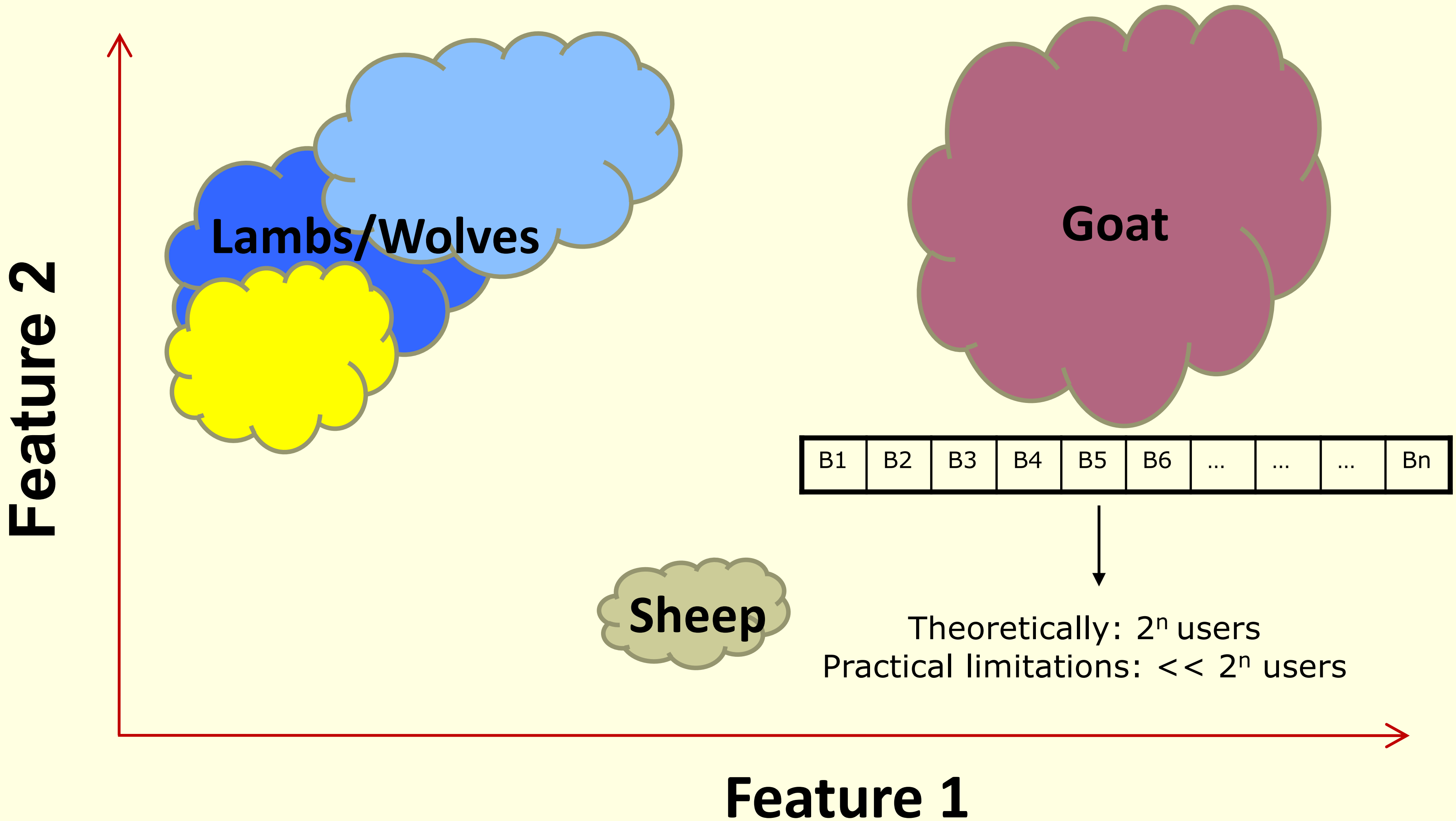
TWIN BROTHERS
© Martin Schoeller

MOTHER DAUGHTER
© PleasantonWeekly.Com

- **FMR: False Match Rate**

Capacity of a template

- Existence of a biometric "zoo": Different categories of users impact error rates in a different manner

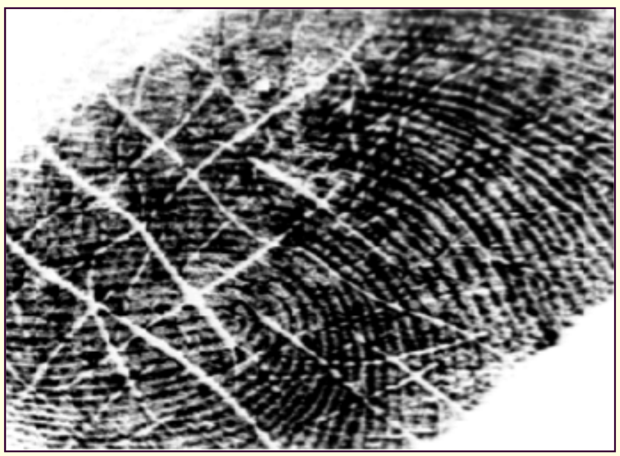


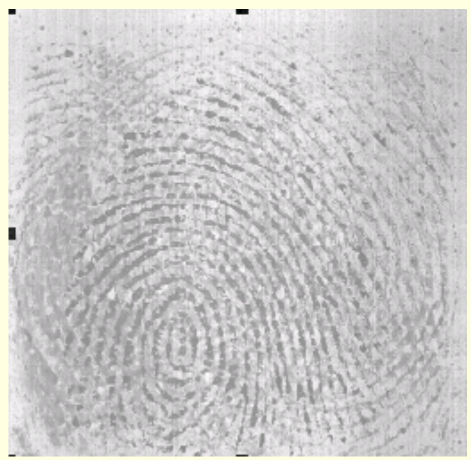
*Ross, Rattani, Tistarelli, "Exploiting the Doddington Zoo Effect in Biometric Fusion," BTAS 2009

Noisy Data

During enrolment

During recognition





Noise due to smearing, residual deposits, cuts and folds, etc

Can impact both FMR and FNMR

Non-universality

- Some people may consistently offer poor quality fingerprint images which means they have to be identified by some other means

Four impressions of a user's print exhibiting incomplete ridge information

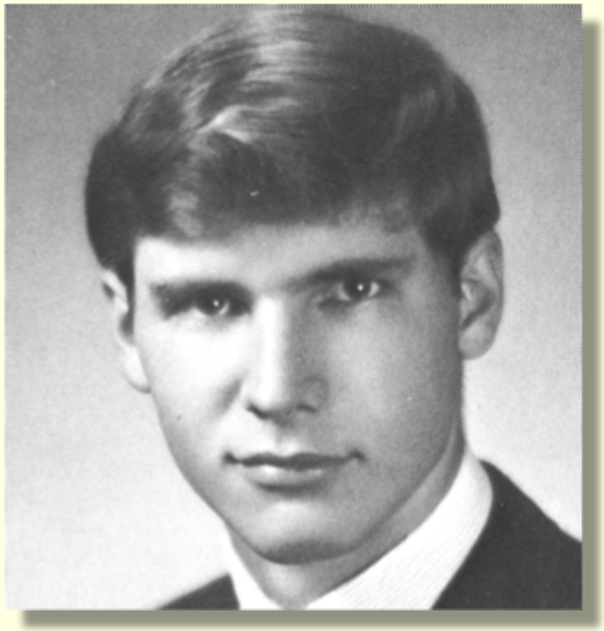
FTE: Failure-to-Enroll Problem

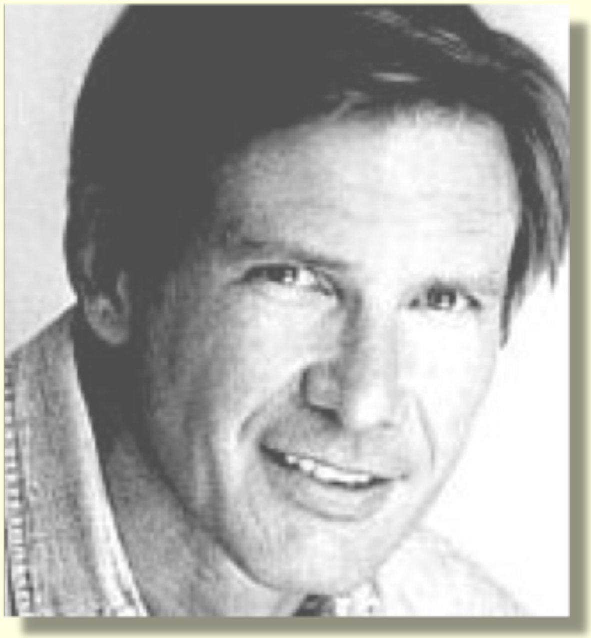
Jain, Prabhakar, Ross, "Fingerprint Matching: Data Acquisition and Performance Evaluation", MSU Technical Report TR99-14, 1999.

Changes Due to Illumination

nachoguzman.net

Biometric Ageing



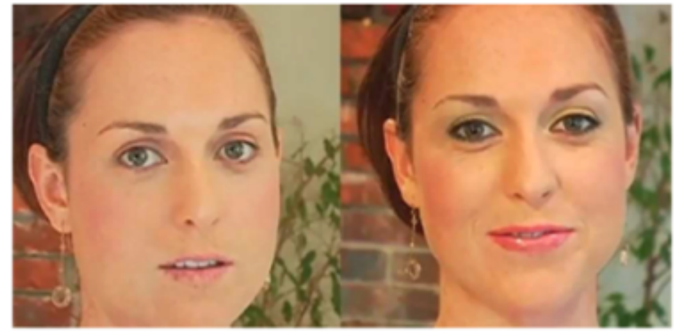


Heterogeneous Biometrics

Photo vs Sketch

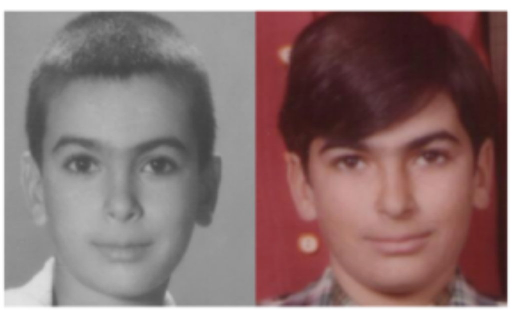
Fundamental Differences in Image Formation Characteristics

Before vs After Makeup



RGB vs NIR vs THM

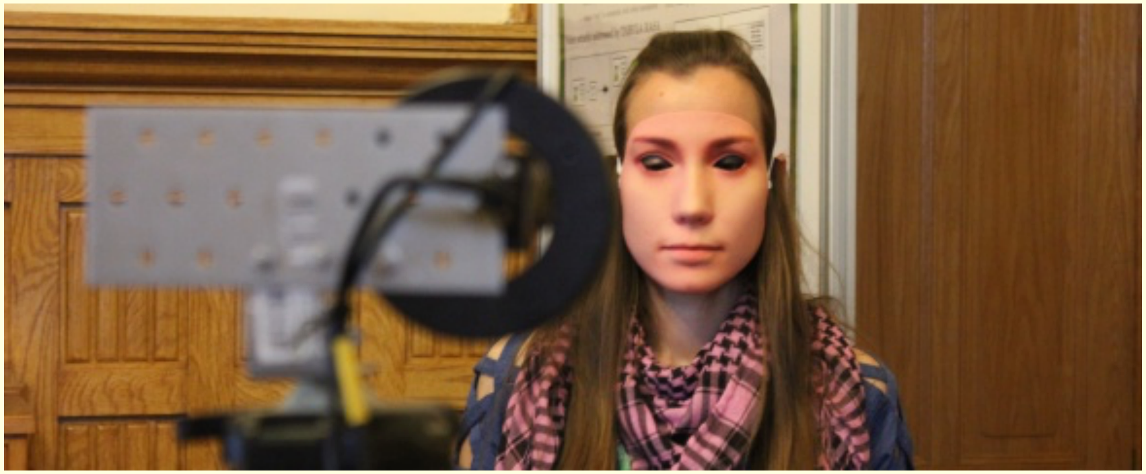
Young vs Old



2D vs 3D

Spoofing: Presentation Attack

- Spoofing: Altering one's trait or creating a physical artifact in order to "spoof" another person's trait

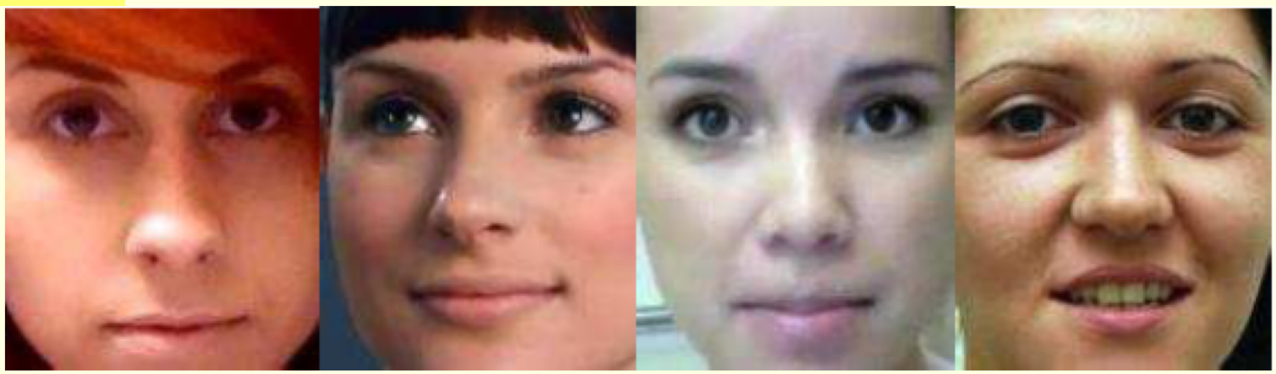


Images from https://www.idiap.ch/dataset/3dmad

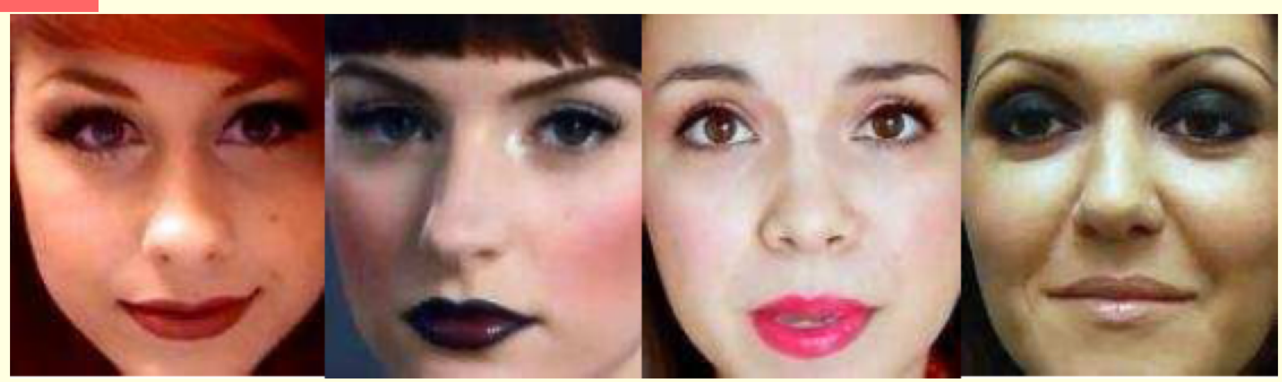
Obfuscation: Presentation Attack

- Obfuscation: Masking one’s own identity by altering the trait

BEFORE



AFTER



Dantcheva et al, “Can Facial Cosmetics Affect the Matching Accuracy of Face Recognition Systems?”, BTAS 2012

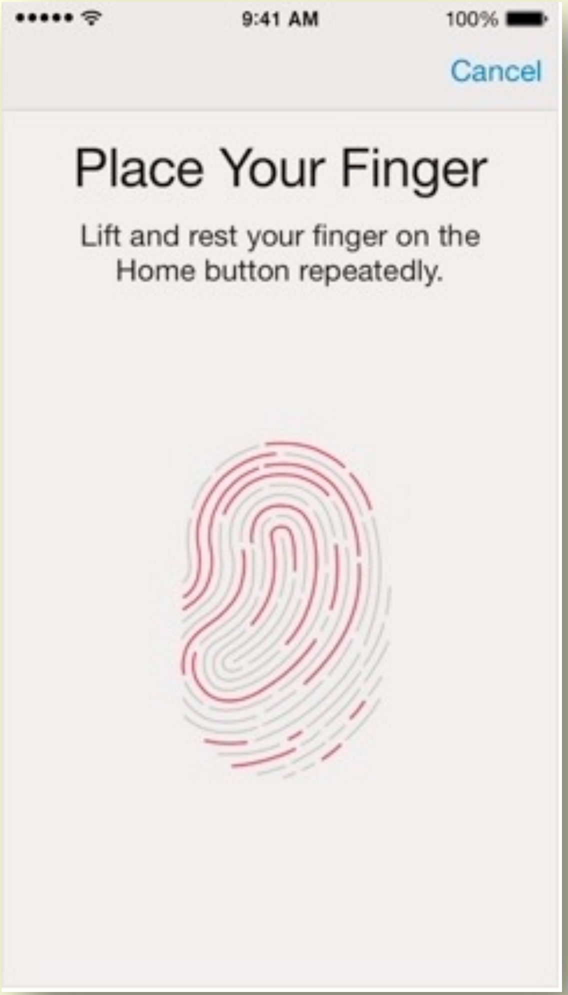
Fingerprint Alteration

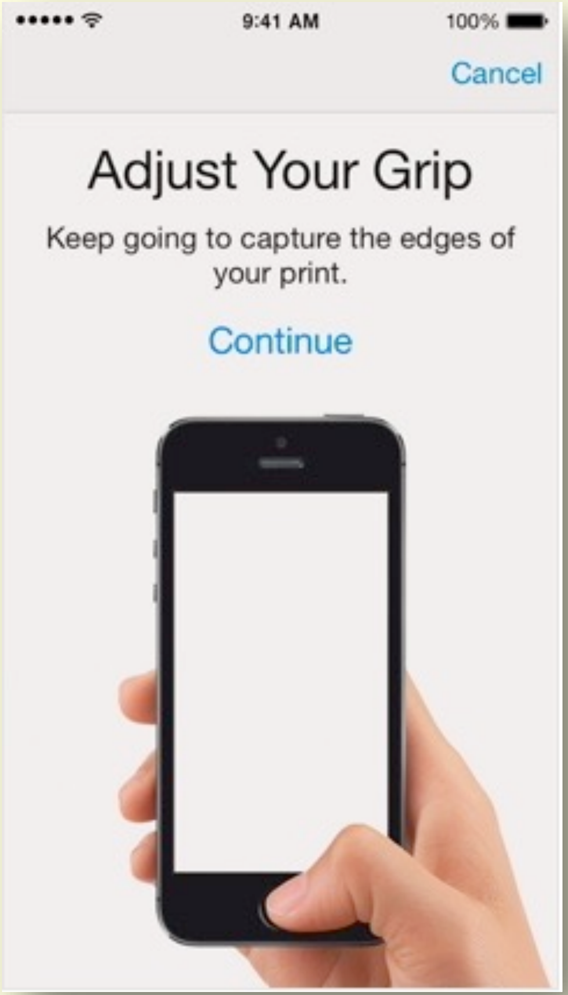
- 1995: Alexander Guzman was arrested by Florida officials for possessing a false passport
- He was found to have mutilated fingerprints
- After a two-week search based on manually reconstructing the damaged fingerprints and searching the FBI database, the reconstructed fingerprints were linked to the fingerprints of Jose Izquiredo who was an absconding drug criminal

The “Z”-cut

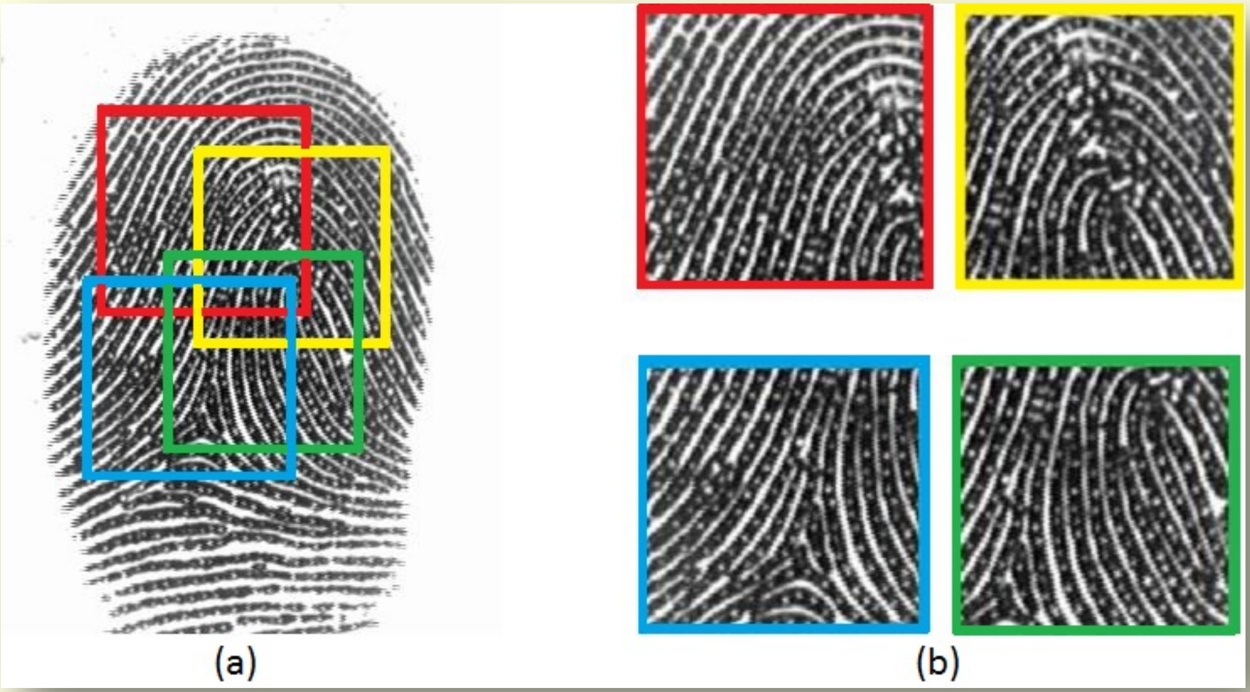
- His fingerprint mutilation process consisted of three steps: making a ‘Z’ shaped cut on the fingertip; lifting and switching two triangles; and stitching them back.

Small Fingerprint Sensors





Partial Fingerprints



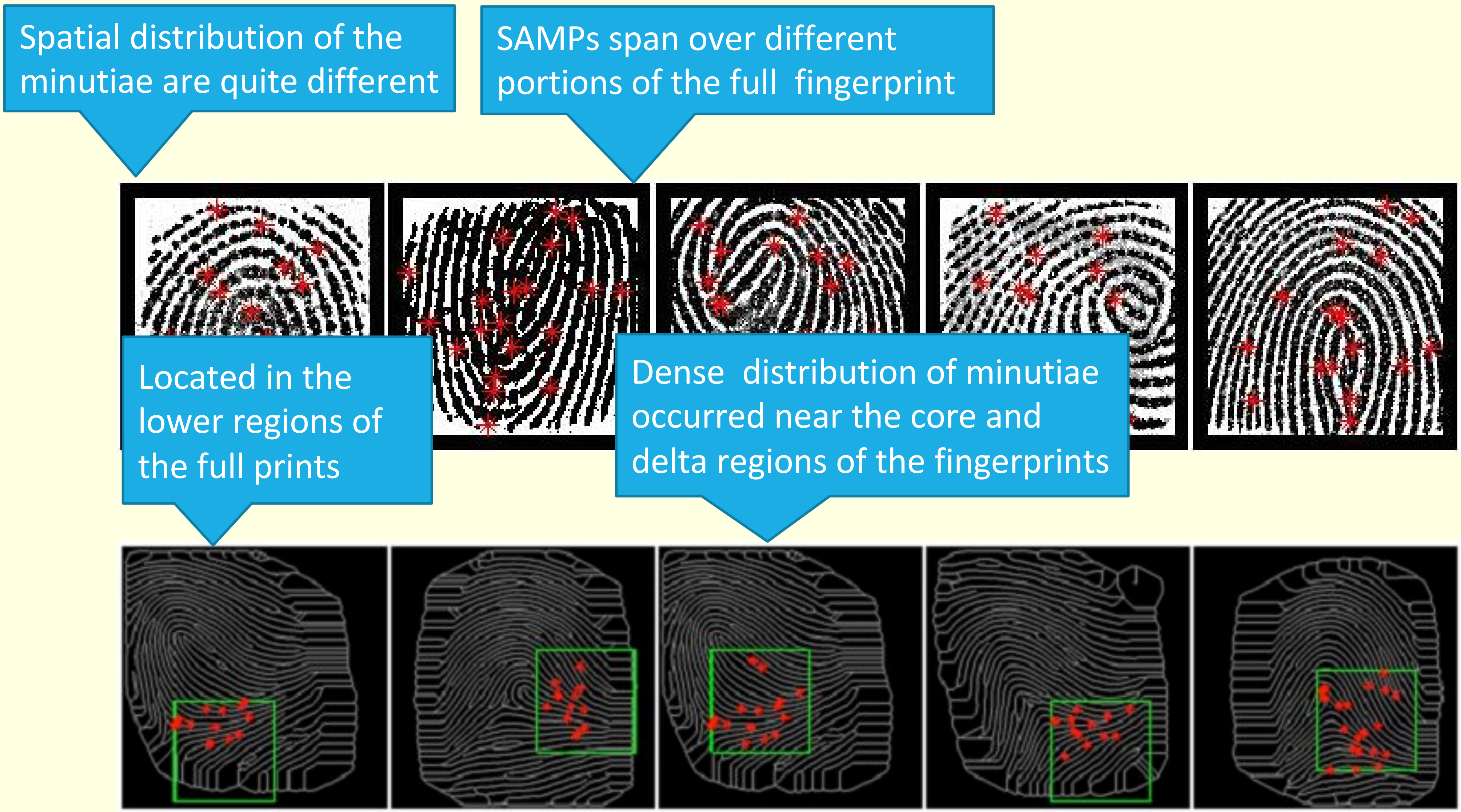
- Small sensors | Capture a limited portion of full finger
- Multiple partial fingerprints are captured | Enroll multiple fingers
- Access granted if the sensed partial fingerprint matches any one of the partial fingerprint of any enrolled finger

MasterPrints!

- Fingerprints that fortuitously match with a large proportion of the fingerprint population
- Could be either full prints or partial prints

Roy, Memon, Ross, "MasterPrint: Exploring the Vulnerability of Partial Fingerprint-based Authentication Systems," TIFS 2017

“MasterPrints”



Roy, Memon, Ross, “MasterPrint: Exploring the Vulnerability of Partial Fingerprint-based Authentication Systems,” TIFS 2017

Observations

- With a dictionary of 5 MasterPrints, and assuming a maximum of 5 attempts to be authenticated, it was possible to attack 26.46% users (each having 12 impressions per finger) in the FingerPass DB7 capacitive fingerprint dataset and 65.20% users (each having ≈ 80 partial impressions per finger) in the FVC optical fingerprint at an FMR of 0.1%.
- The attack accuracy varied greatly with the FMR value and the number of impressions per finger

Roy, Memon, Ross, "MasterPrint: Exploring the Vulnerability of Partial Fingerprint-based Authentication Systems," TIFS 2017

Attributes of a Biometric Trait

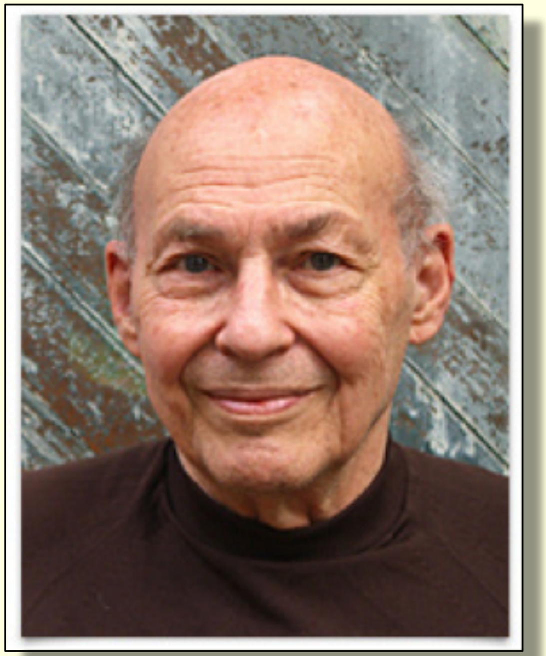
- **Uniqueness** (Is it distinctive across users?)
- **Permanence** (Does it change over time?)
- **Universality** (Does every user have it?)
- **Collectability** (Can it be measured quantitatively?)
- **Acceptability** (Is it acceptable to the users?)
- **Performance** (Does it meet error rate, throughput, etc.?)
- **Vulnerability** (Can it be easily spoofed or obfuscated?)
- **Integration** (Can it be embedded in the application?)

No biometric trait is "optimal", but many are "admissible"

Jain, Ross, Prabhakar. "An Introduction to Biometric Recognition," IEEE TCSVT, 2004

Evidence Accumulation and Information Fusion

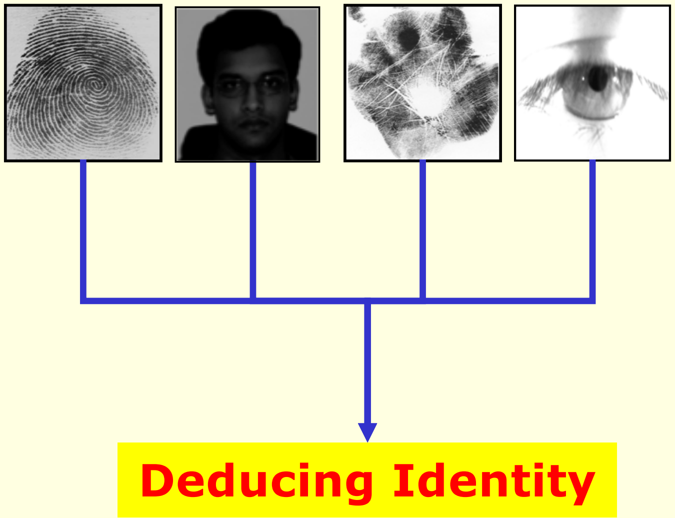
It is time to stop arguing over which type of pattern classification technique is best because that depends on our context and goal. Instead we should work at a higher level of organization and discover how to build managerial systems to exploit the different virtues and evade the different limitations of each of these ways of comparing things (Minsky 1991)



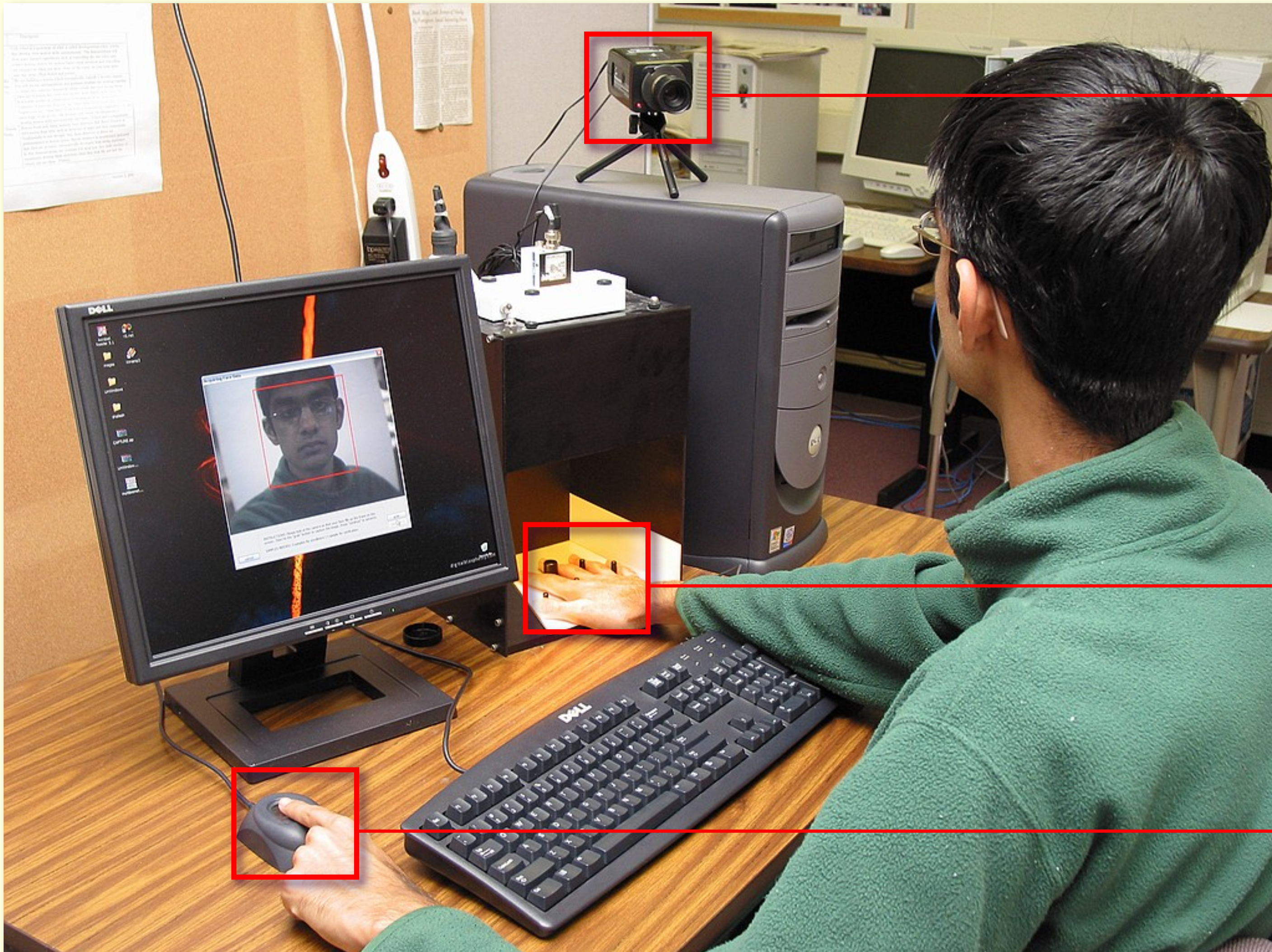
Marvin Lee Minsky
Born: August 9, 1927
Died: January 24, 2016

Biometric Fusion

- Combining multiple biometric evidence
- The identity of an individual is reinforced through multiple traits
- Especially significant in scenarios where partial biometric data is available



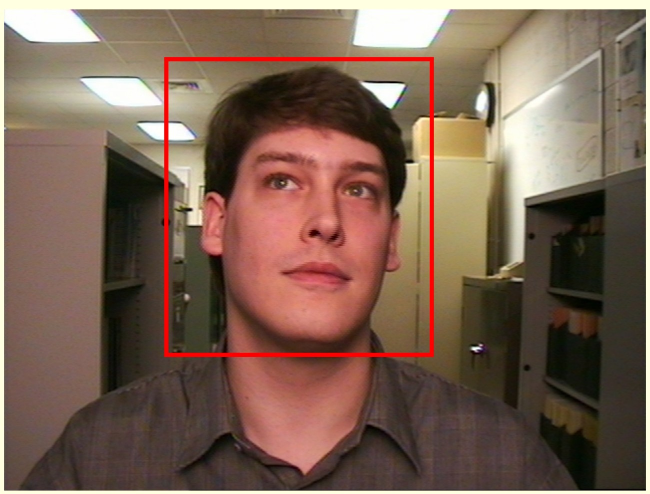
Information “Scavenging”

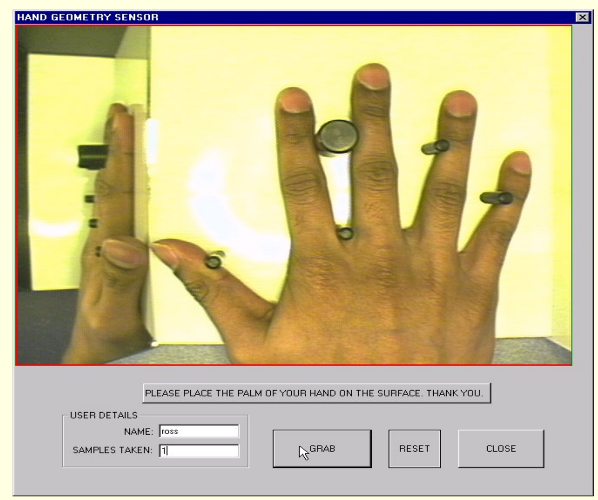


- Serial versus parallel mode of operation

Multibiometric Systems

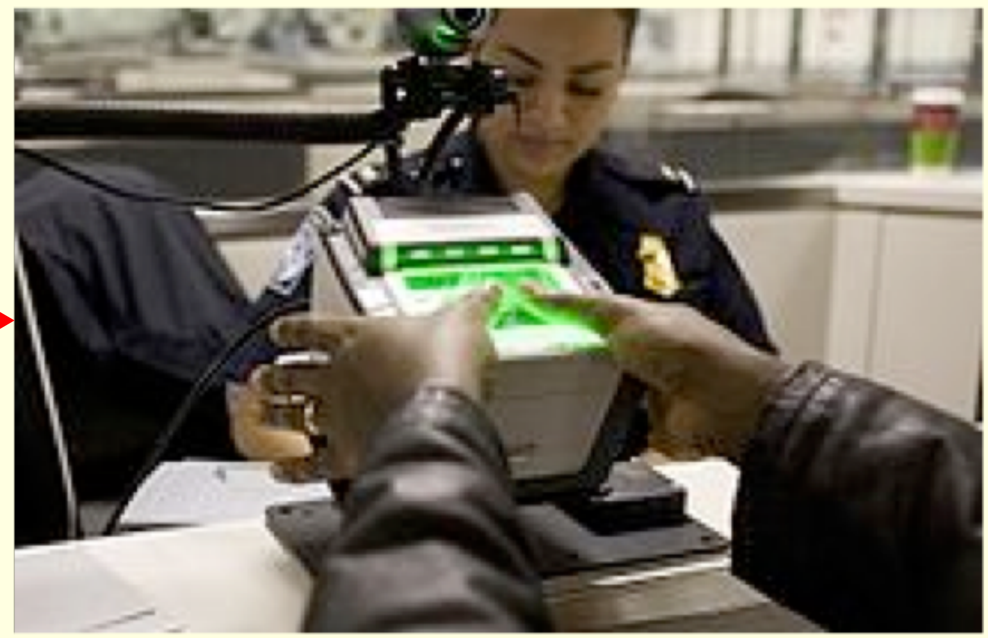
- Multiple sources of biometric information are integrated to enhance matching performance
- Increases population coverage by reducing failure to enroll rate
- Anti-spoofing; difficult to spoof multiple traits simultaneously





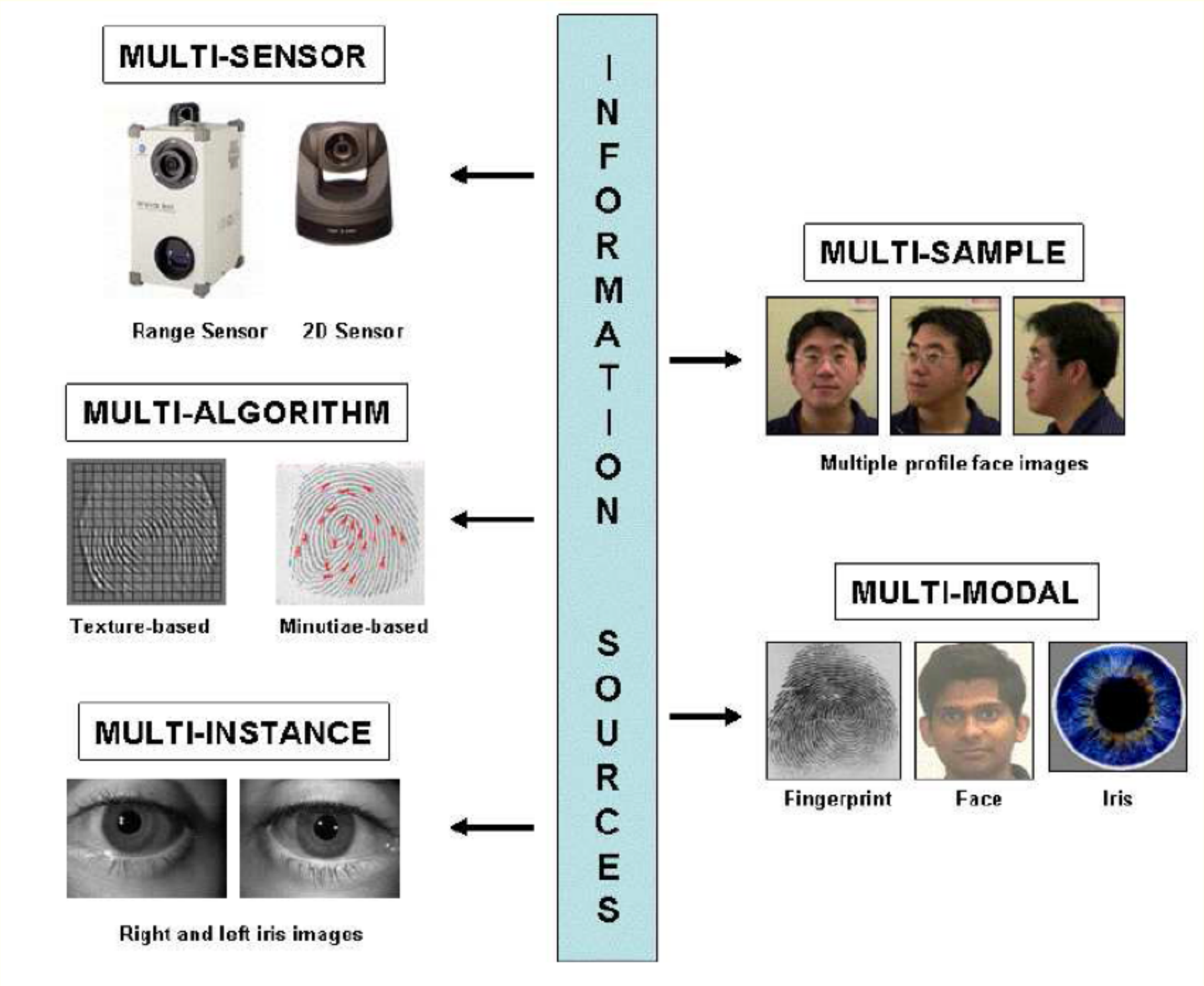
FBI and DHS

- The FBI fingerprint database has ten-print information of over 80 million individuals



- The US-VISIT (OBIM) database has information about the face and fingerprint of over 150 million individuals

Sources of Fusion



Levels of Fusion

Modality 1

Raw Data

Feature vector

X1	X2	X3	X4	X5	X6	…	Xn

Match Score

S1 = 50

Rank

Rank 1: Alice
Rank 2: Bob
Rank 3: Dan

Binary Decision

Genuine

Modality 2

Y1	Y2	Y3	Y4	Y5	Y6	…	Ym

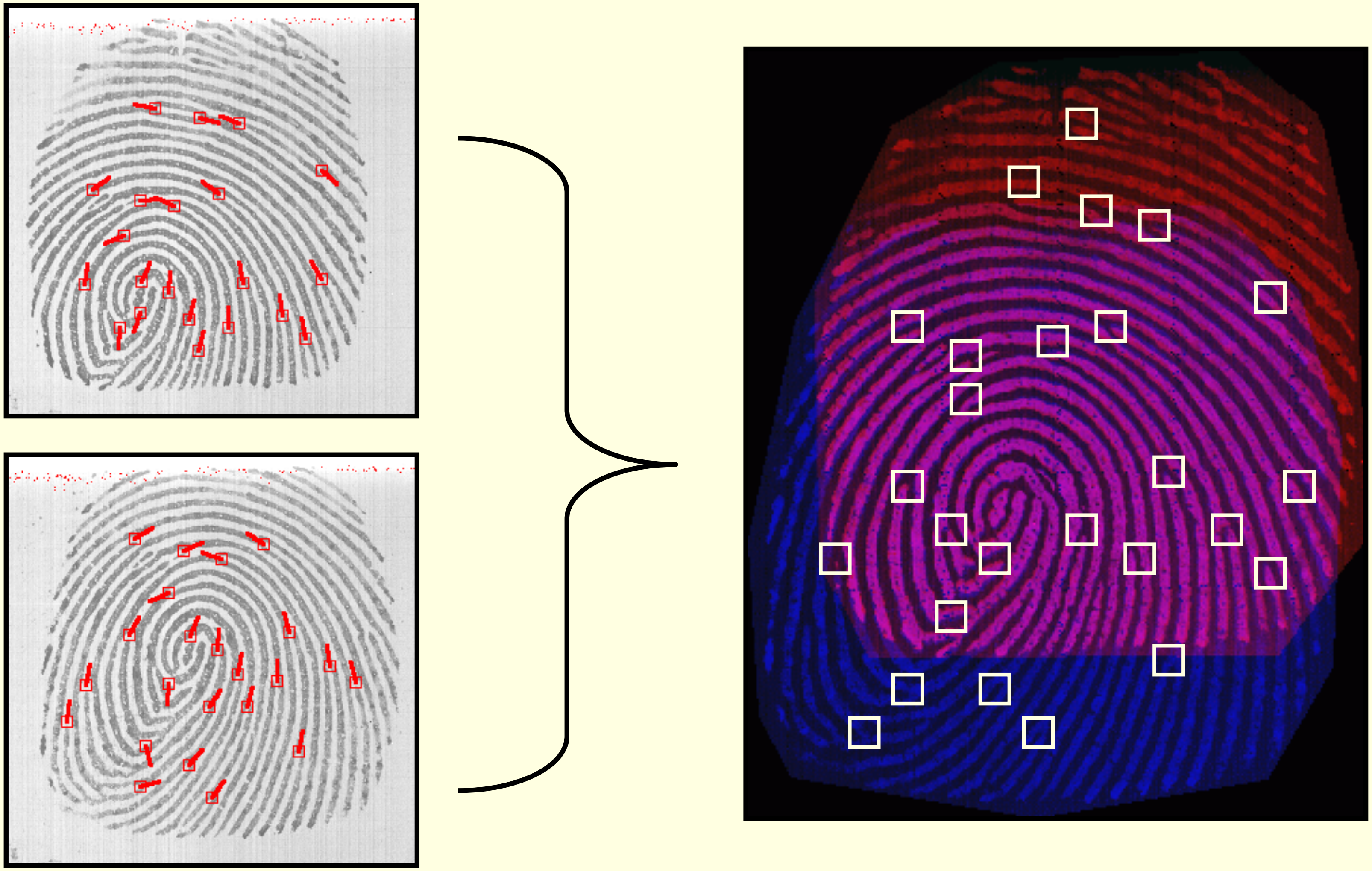
S2 = 75

Rank 1: Alice
Rank 2: Ed
Rank 3: Bob

Impostor

Data Level Fusion

- Mosaicing constructs a composite fingerprint image (or template) using multiple impressions of the same finger resulting in more information (e.g., minutiae points)

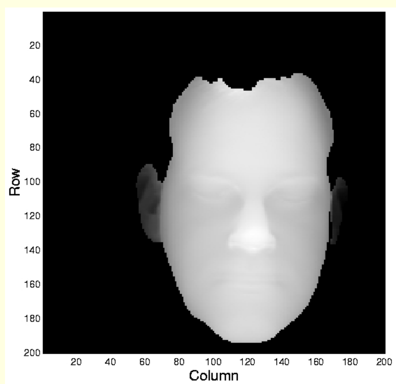


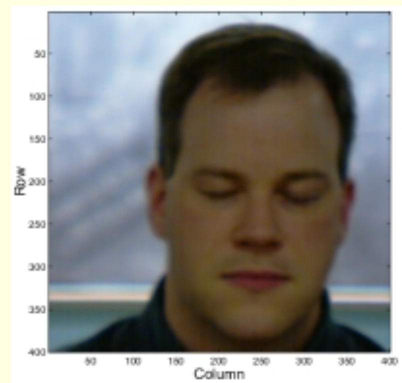
Ross et al , "Image Versus Feature Mosaicing: A Case Study in Fingerprints", SPIE, April 2006.

Data Level Fusion

- The raw data pertaining to multiple sensors are combined
  - e.g., the 2D face texture may be mapped to a 3D range image; matching performed in 3D space

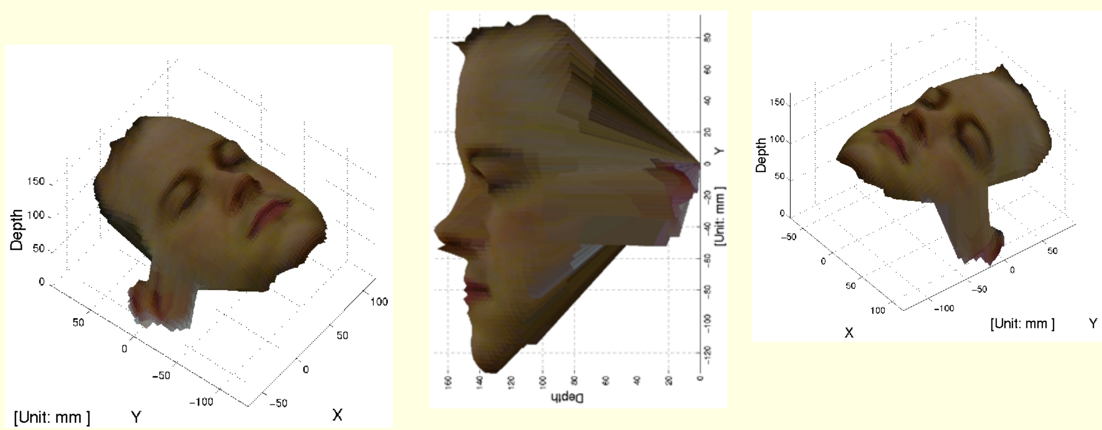
2.5D range data





2D color texture

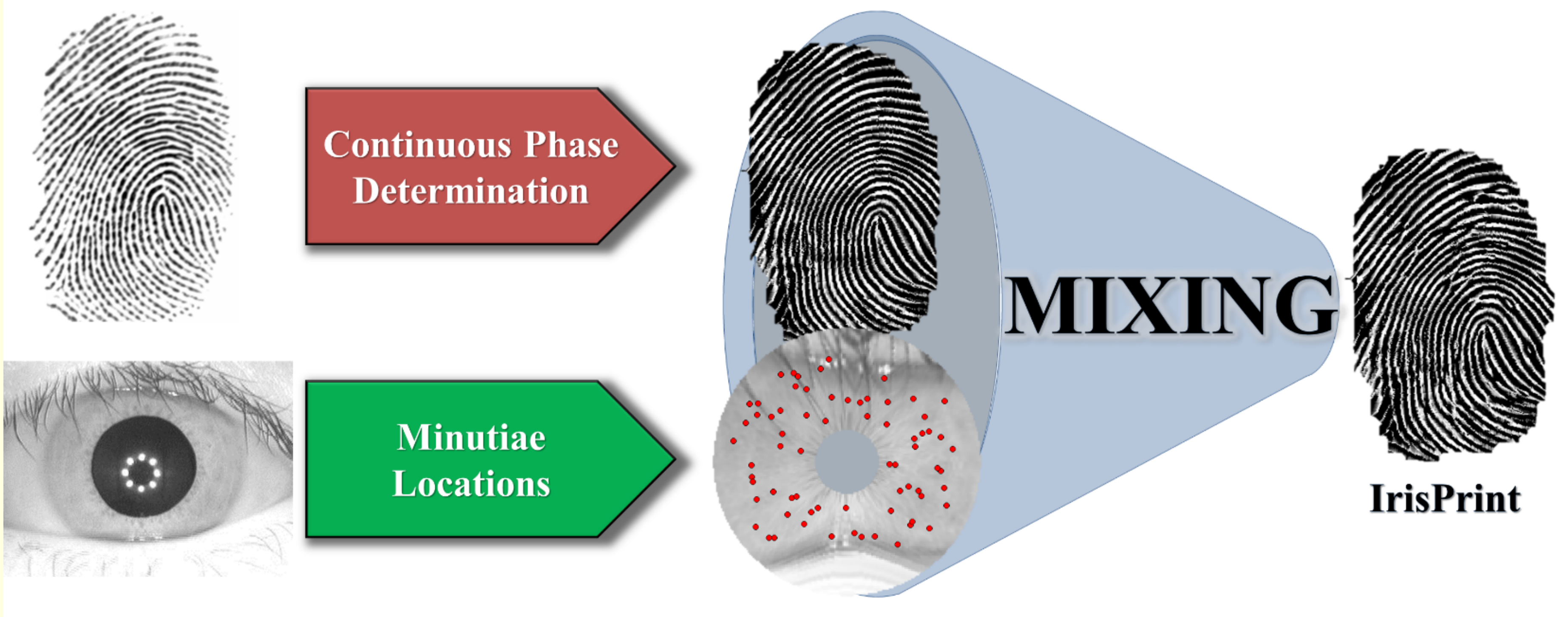
Texture-mapped appearance



R.-L. Hsu, ``Face Detection and Modeling for Recognition'', Ph.D. Thesis, 2002

Data Level Fusion

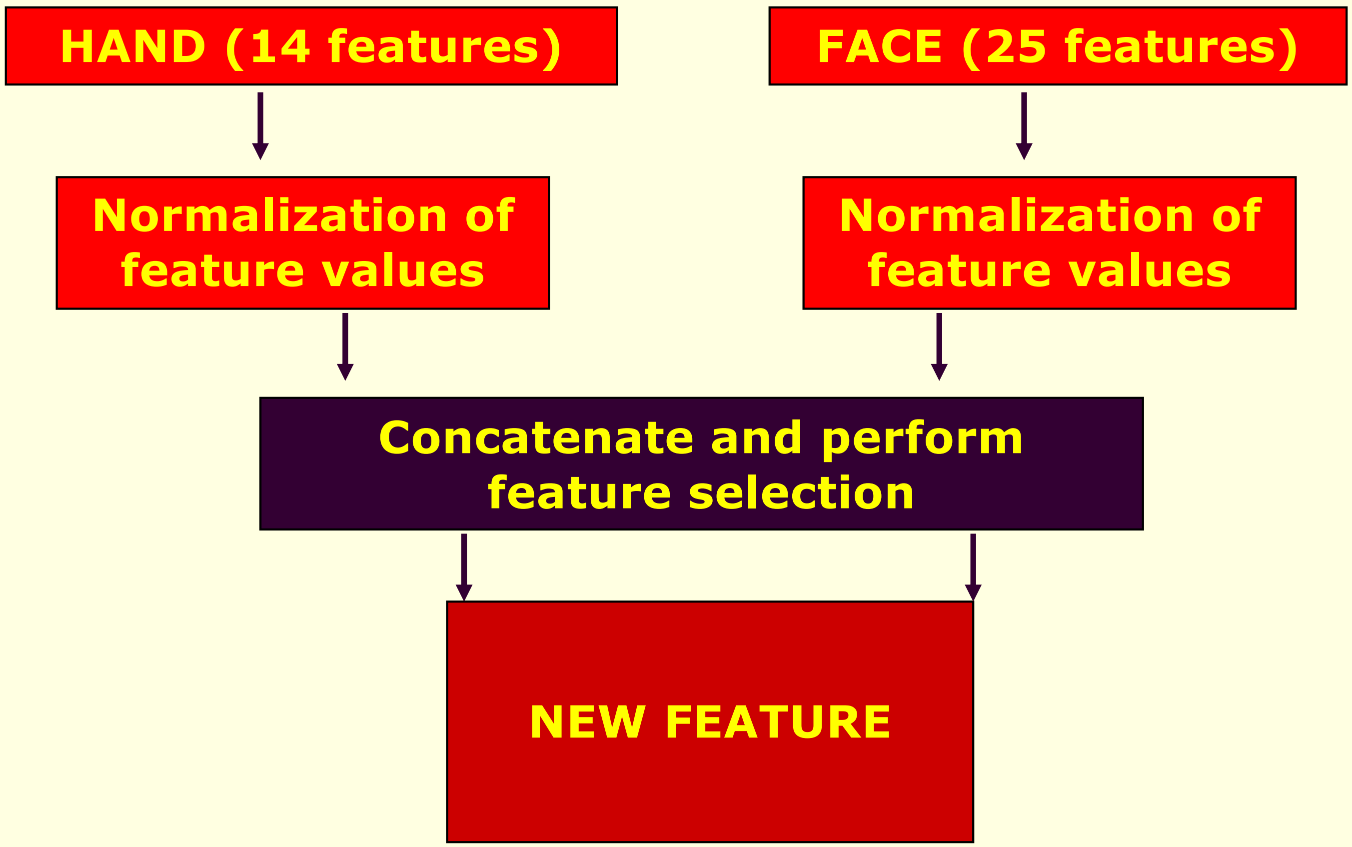
- Goal: To de-identify fingerprint and iris images by generating a new, possibly unique, and de-identified biometric
- IrisPrint can be used directly in the feature extraction and matching stages of an existing matcher without revealing the original images



Othman and Ross, "Fingerprint + Iris = IrisPrint," SPIE 2014

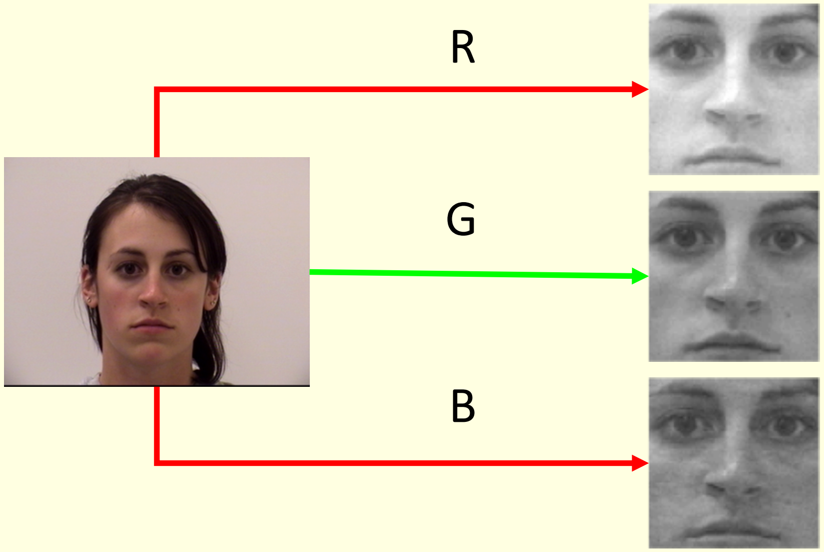
Feature Level Fusion

- The feature space of two modalities are combined
  - e.g., the feature vector of face combined with that of hand geometry



Ross, Govindarajan, "Feature Level Fusion of Hand and Face Biometrics", SPIE 2005.

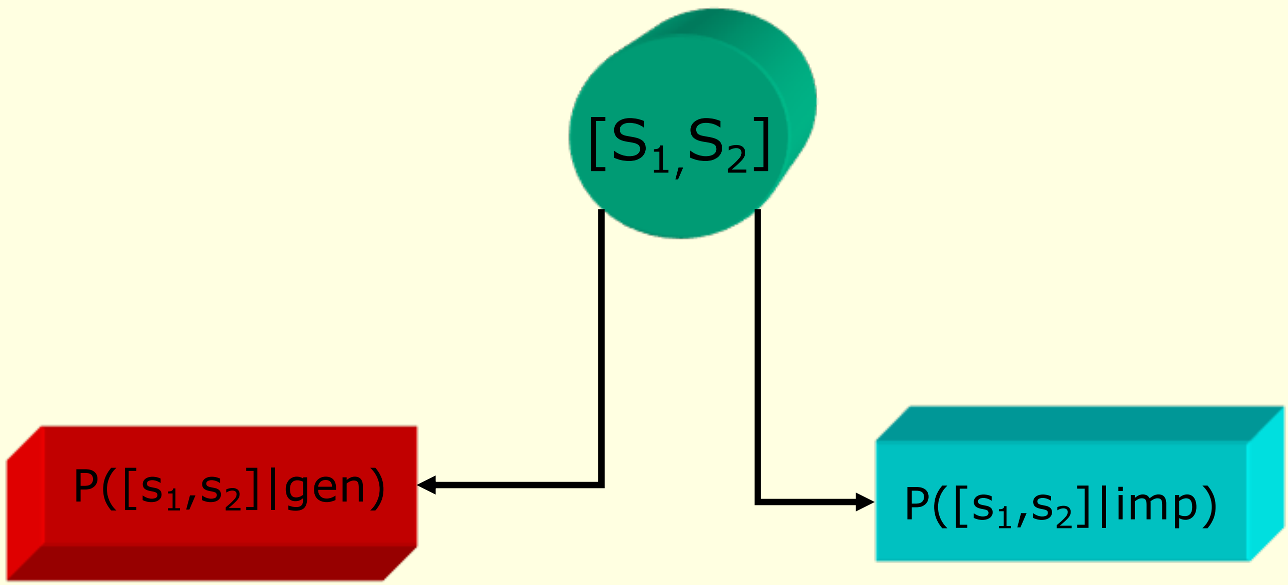
Feature Level Fusion



- Feature sets:
  - LDA-R : 18 features
  - LDA-G : 32 features
  - LDA-B : 40 features
- Feature-fused vector: 43 features

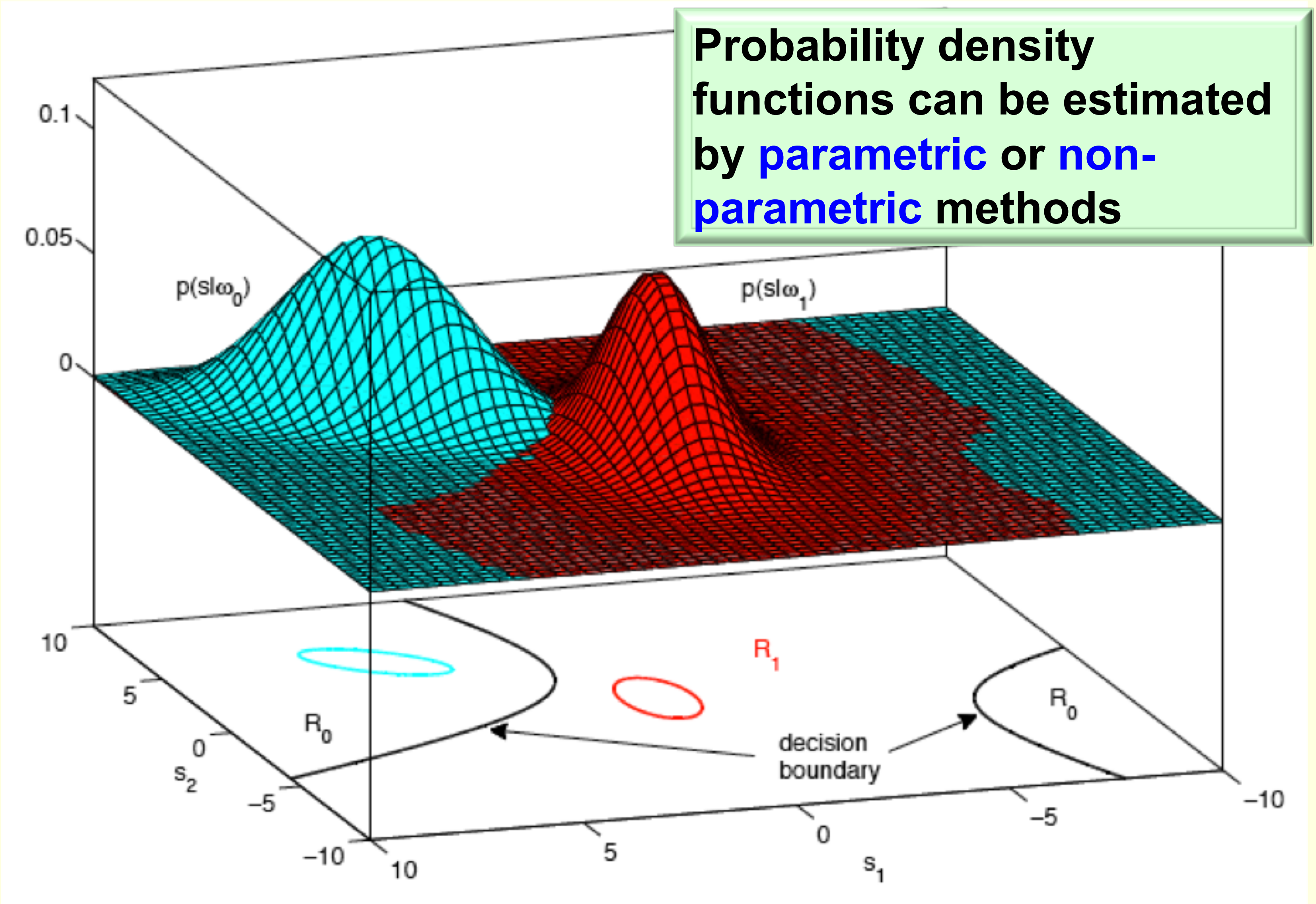
Ross, Govindarajan, "Feature Level Fusion of Hand and Face Biometrics", SPIE 2005.

Density-based Fusion



$$\frac{P([s1, s2] \mid gen)}{P([s1, s2] \mid imp)} > \text{Threshold}, \quad \text{then Genuine else Impostor}$$

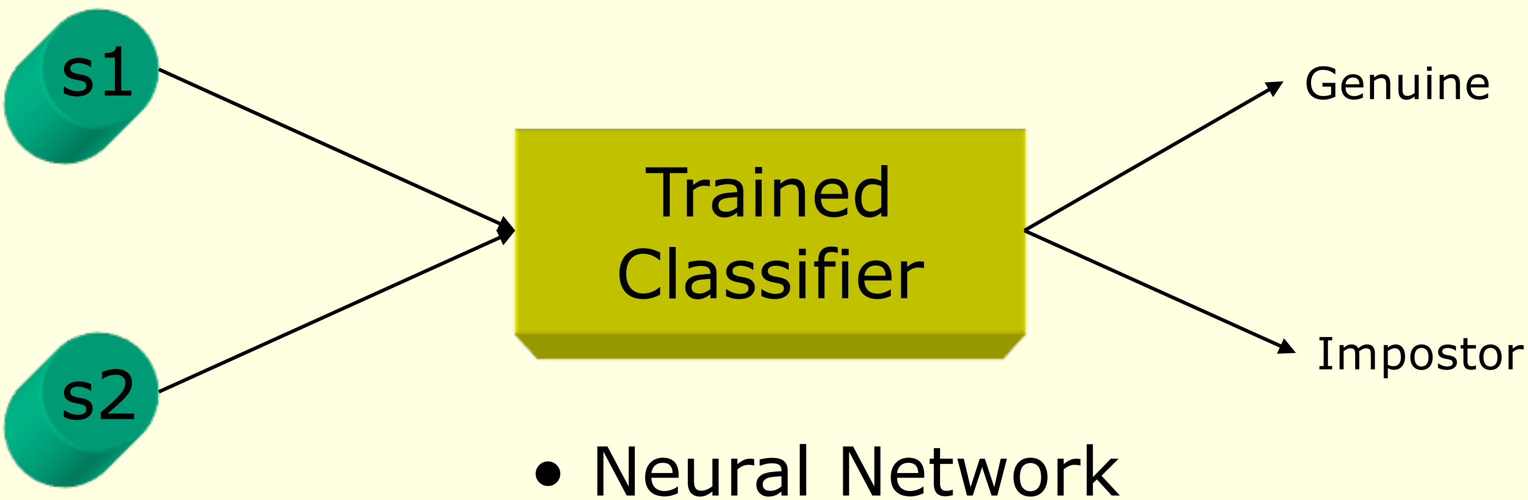
Density-based Fusion



Probability density functions can be estimated by parametric or non-parametric methods

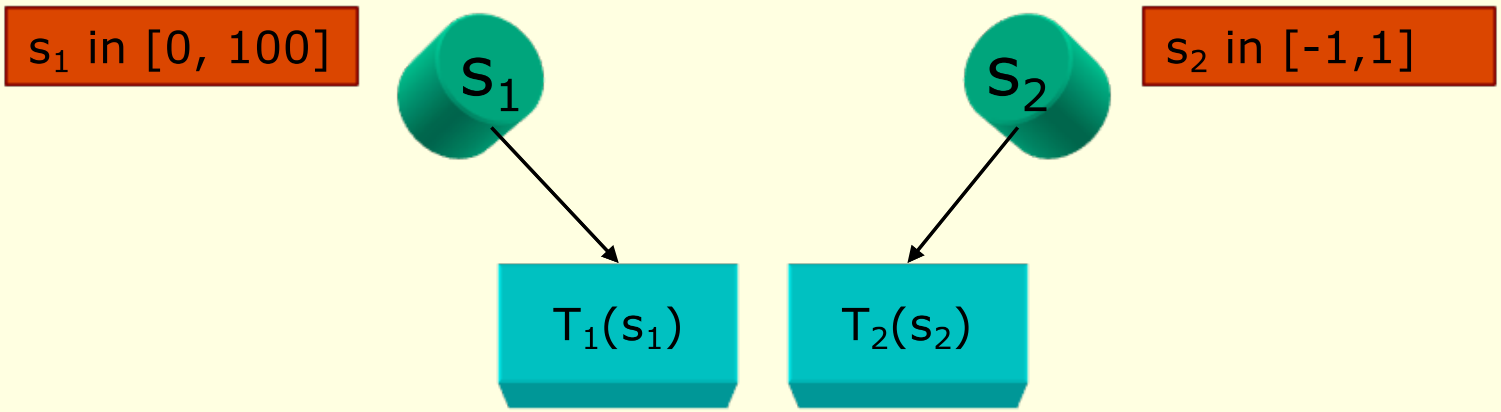
Classifier-based Fusion

- Match scores emitted by multiple sources are input to a trained classifier



- Neural Network
- SVM
- Decision Trees
- Nearest Neighbor
- Random Forest

Transformation-based Fusion



- The transformed scores can be combined using several different rules
  - $\min[T_1(s_1), T_2(s_2)]$
  - $\max[T_1(s_1), T_2(s_2)]$
  - $\mathrm{sum}[T_1(s_1), T_2(s_2)]$
  - $\mathrm{prod}[T_1(s_1), T_2(s_2)]$

T_i: Normalization Function

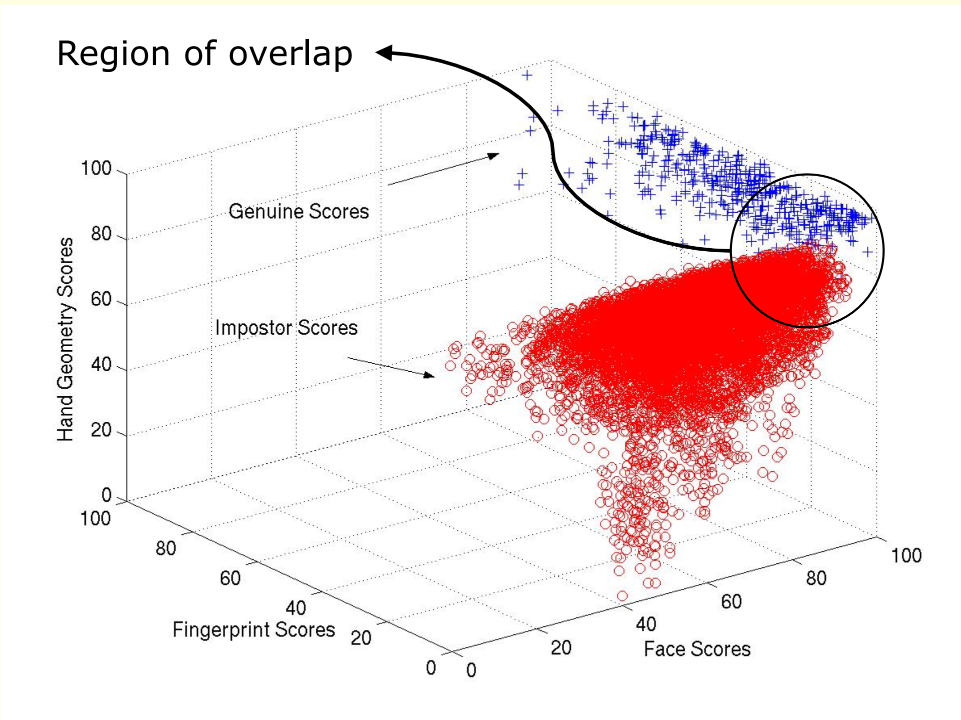
1. minmax
2. MAD
3. tanh

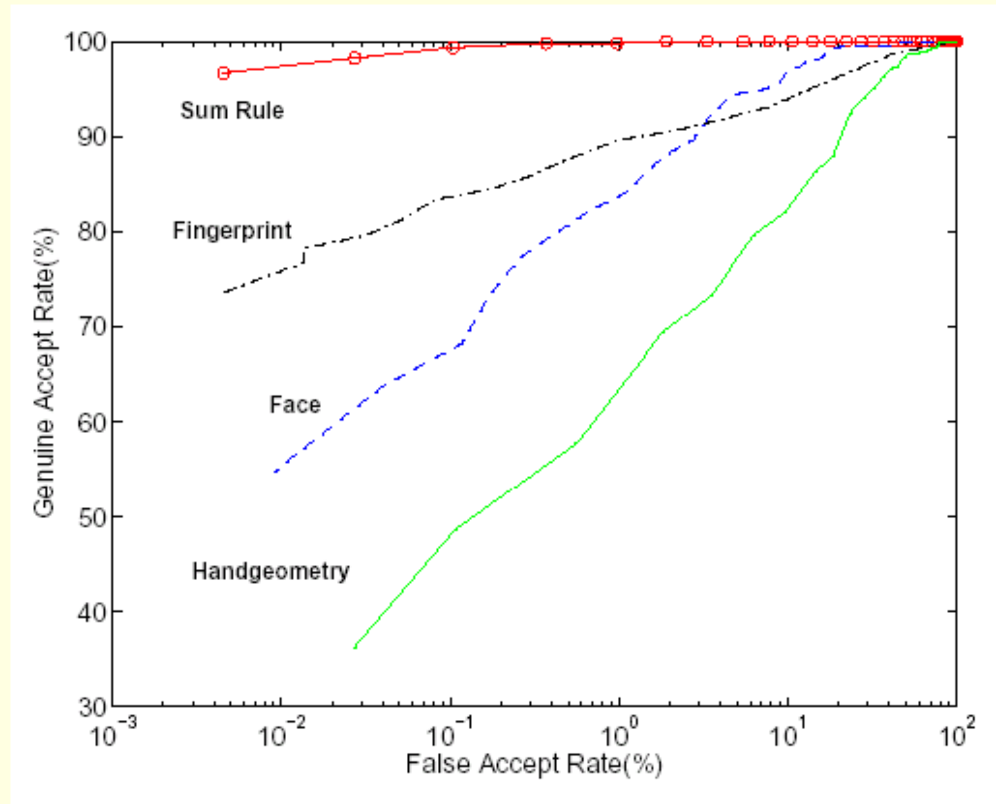
Jain, Ross, Nandakumar, "Score Normalization in Multimodal Biometric Systems," PR 2005

Simple Sum Rule

- Sum rule (weighted average of individual scores) has been shown to improve matching accuracy:

$$S = w_1 s_1 + w_2 s_2 + w_3 s_3$$





Ross and Jain, "Information Fusion in Biometrics", PRL 2003.

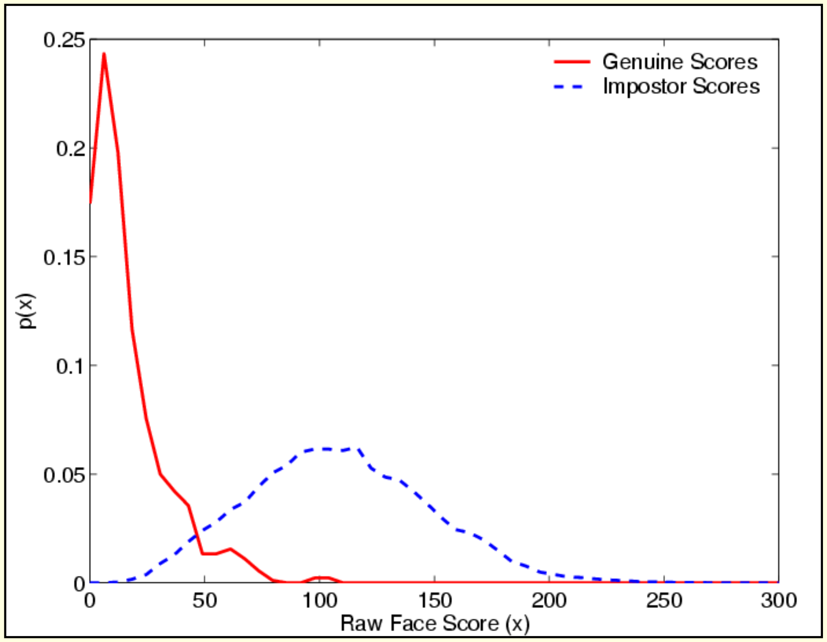
Score Normalization

- Scores output by individual matchers:
  - Non-homogeneous: distance or similarity
  - Ranges may be different; e.g., [0,100] or [0,1000]
  - Distributions may be different

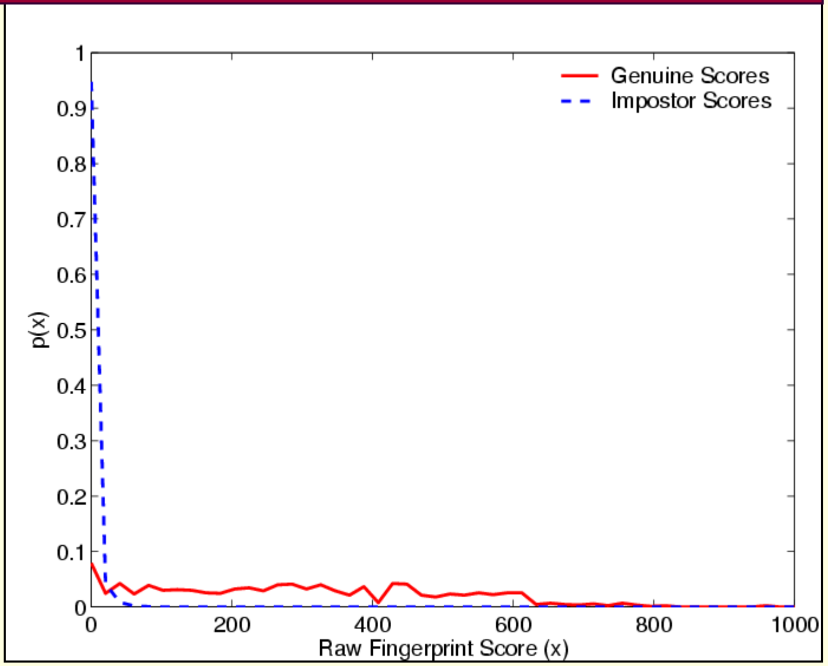
- To facilitate fusion:
  - Modify the location and scale parameters of score distributions of individual matchers
  - Apply transformation to scores present in the genuine-impostor overlap region

- Factors to consider:
  - Robustness: Should not be affected by the outliers
  - Efficiency: Estimated parameters of the score distribution should be close to the true values

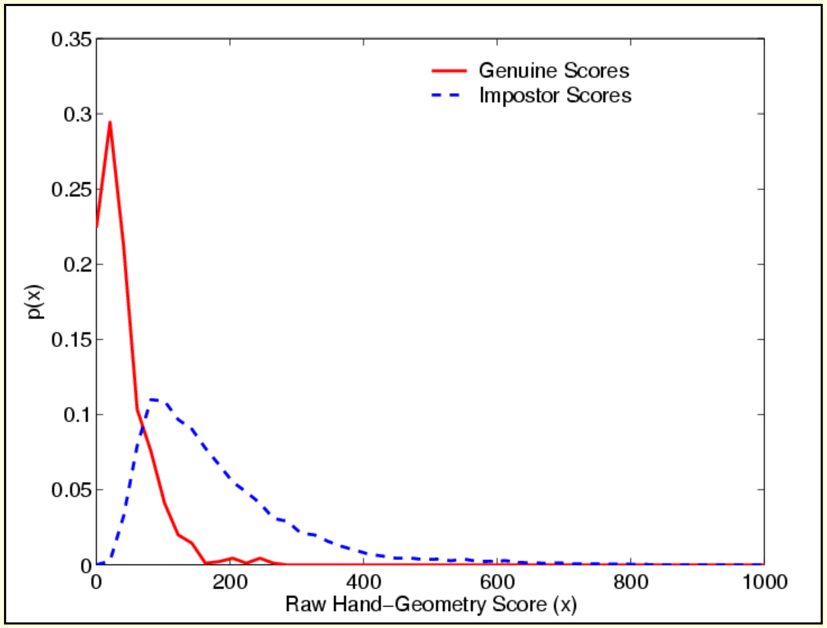
Match Score Distributions



Face



Fingerprint



Hand-geometry

Normalization Techniques

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

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

- Decimal scaling: Used when scores of different matchers differ by a logarithmic factor; e.g., one matcher has scores in the range [0,1] and the other matcher has scores in the range [0, 1000]

$$s' = \frac{s}{10^n},$$

$$n = \log_{10} \max\{s_k\}$$

Normalization Techniques

- Z-score:

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

- Median and Median Absolute Deviation (MAD):

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

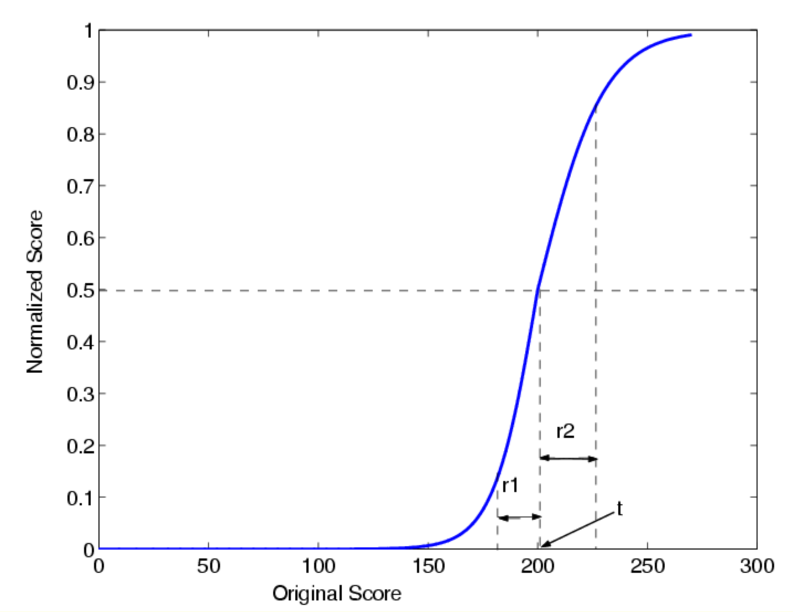
$$MAD = median(|\{s_k\} - median|)$$

- Double Sigmoid function:

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

r = r_1, if s < t

r = r_2, otherwise

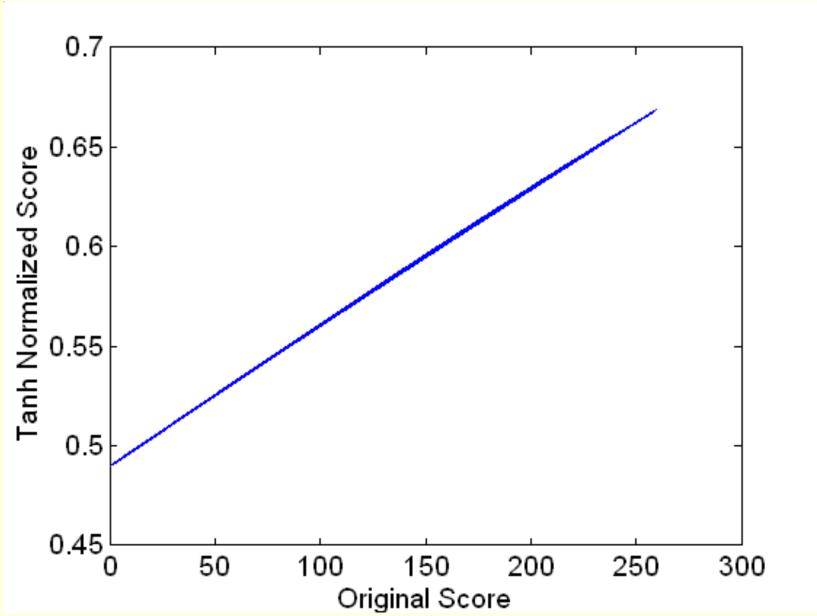


Normalization Techniques

- Tanh estimators:

$$s' = 0.5\left[\tanh\left(0.01\frac{(s-\mu_{GH})}{\sigma_{GH}}\right)+1\right],$$

where μ_{GH} and σ_{GH} are the mean and standard deviation estimates of the genuine score distribution as given by Hampel estimators*



- Min-max, Z-score, and Tanh normalization schemes are efficient
- Median, Double Sigmoid, and Tanh methods are robust

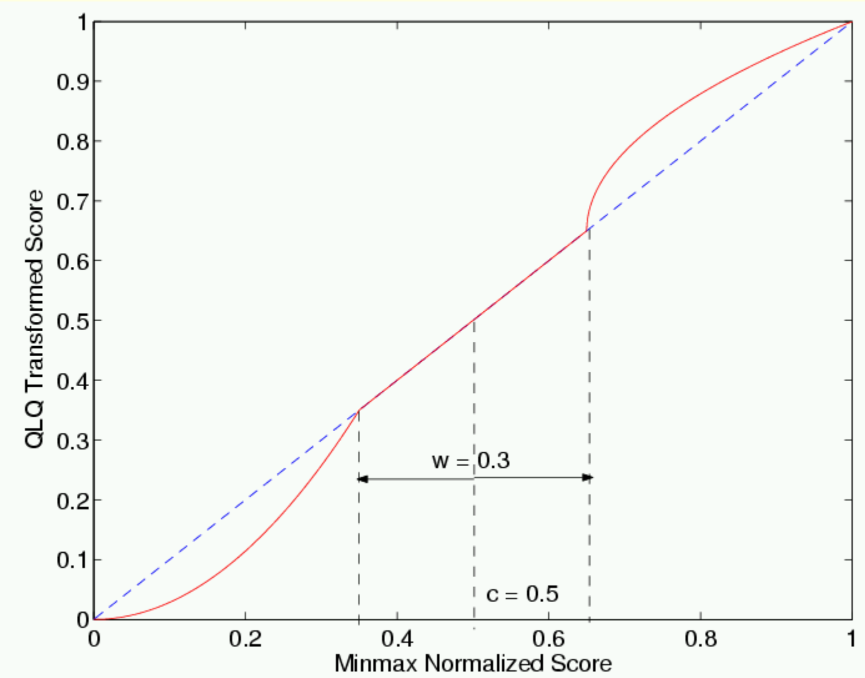
Hampel et al., Robust Statistics: The Approach Based on Influence Functions, 1986

Overlap Region

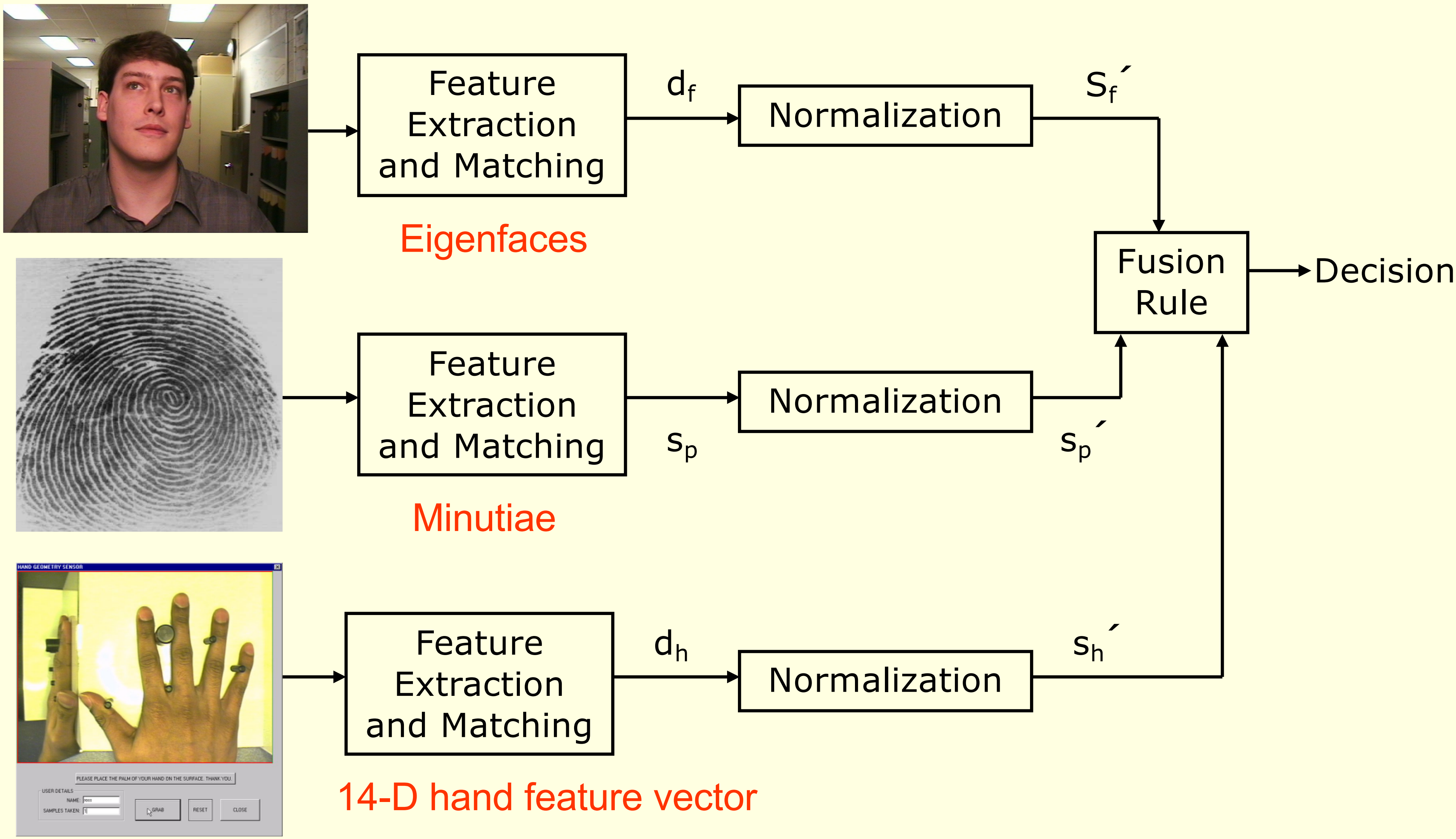
- QLQ transformation:

$$n_{QLQ} = \begin{cases} \frac{1}{(c-\frac{w}{2})} n_{MM}^2 & n_{MM} \leq (c - \frac{w}{2}) \\ n_{MM} & (c - \frac{w}{2}) \leq n_{MM} \leq (c + \frac{w}{2}) \\ (c + \frac{w}{2}) + \sqrt{(1 - c - \frac{w}{2})(n_{MM} - c - \frac{w}{2})} & \text{otherwise} \end{cases}$$

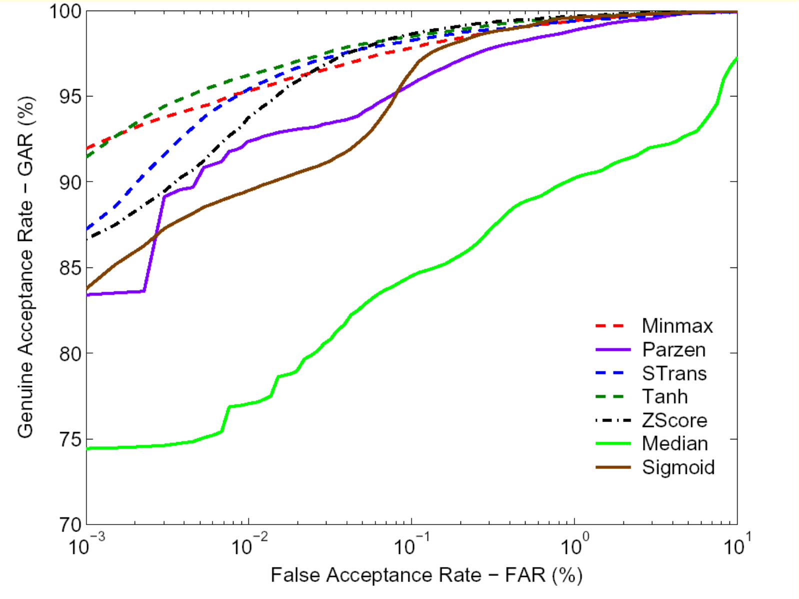
- n_{MM} is the min-max normalized score
- c is the center of the overlap regions
- w is the width of the overlap region



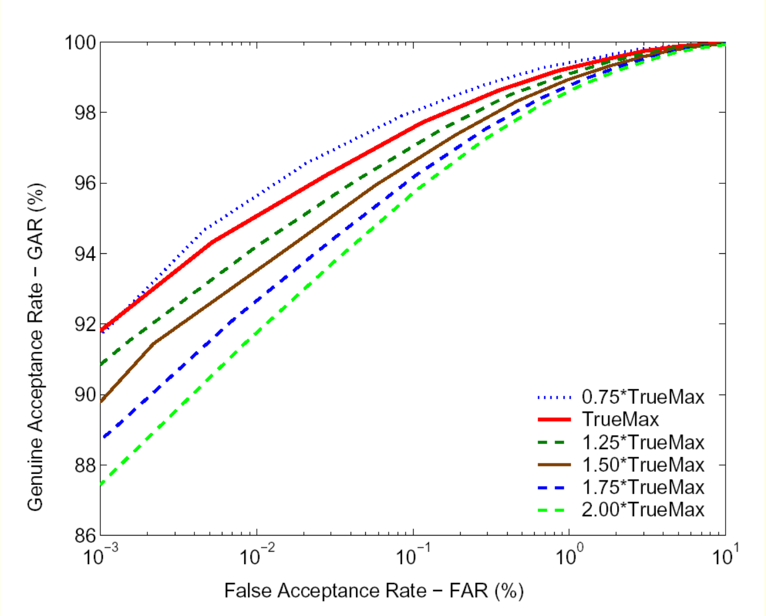
Score Level Fusion



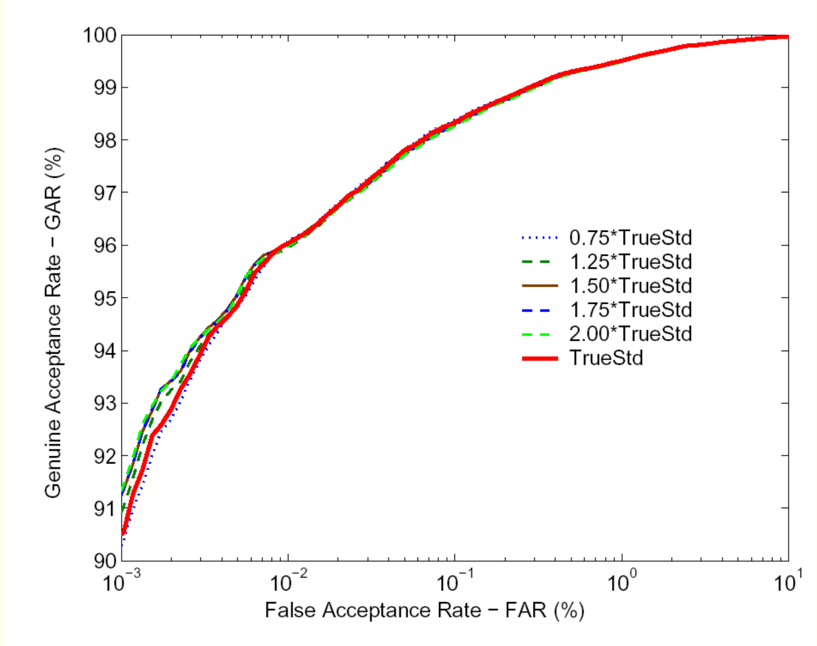
Effect of Normalization



(a) Results of various schemes



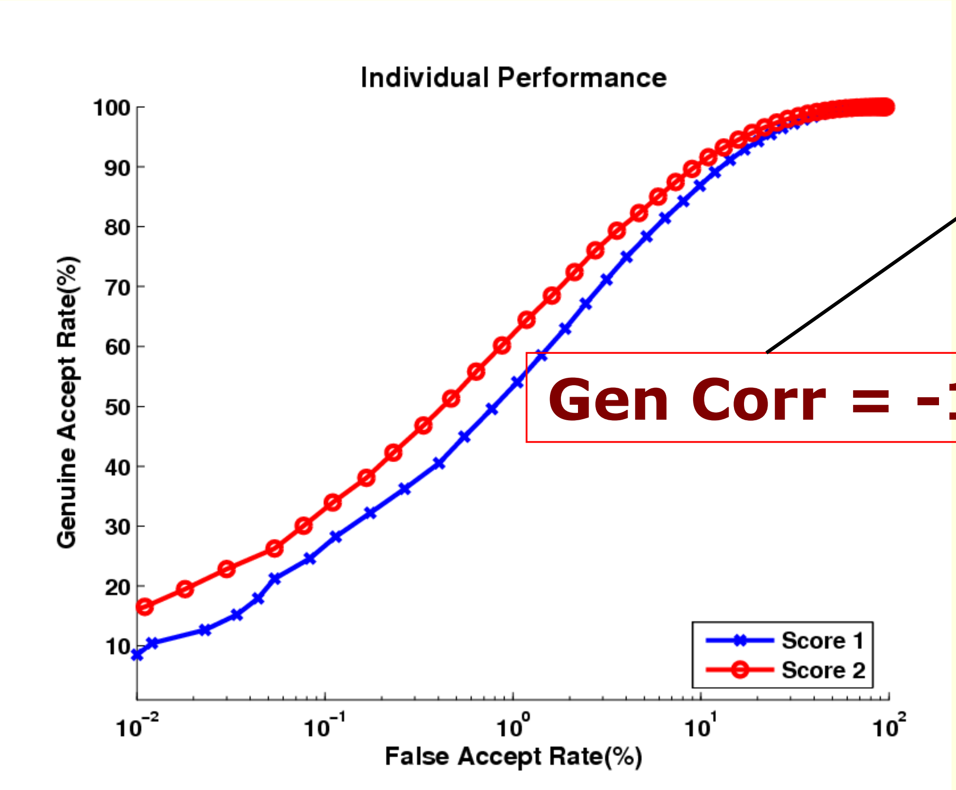
(b) Sensitivity to outliers - minmax

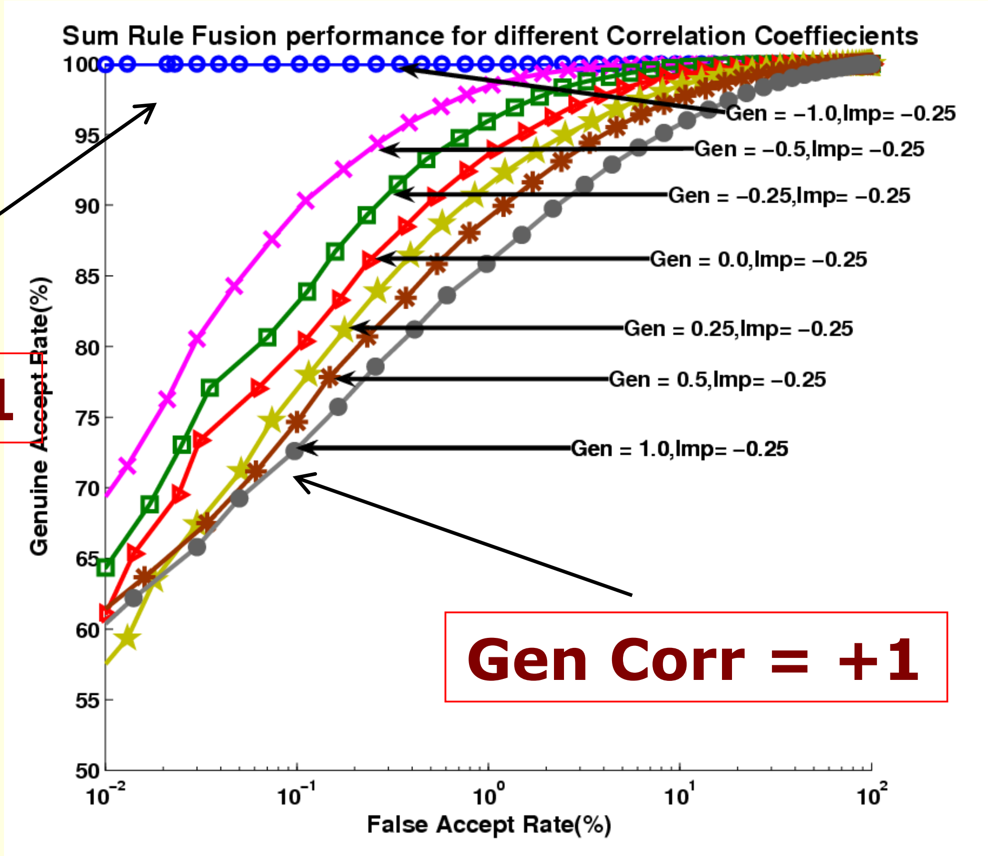


(c) Sensitivity to outliers - tanh

Jain et al, "Score Normalization in Multimodal Biometric Systems", Pattern Recognition 2005.

Is Fusion Always Beneficial?





SINGLE MODALITY

SUM RULE FUSION

- Negatively correlated or uncorrelated classifiers preferable

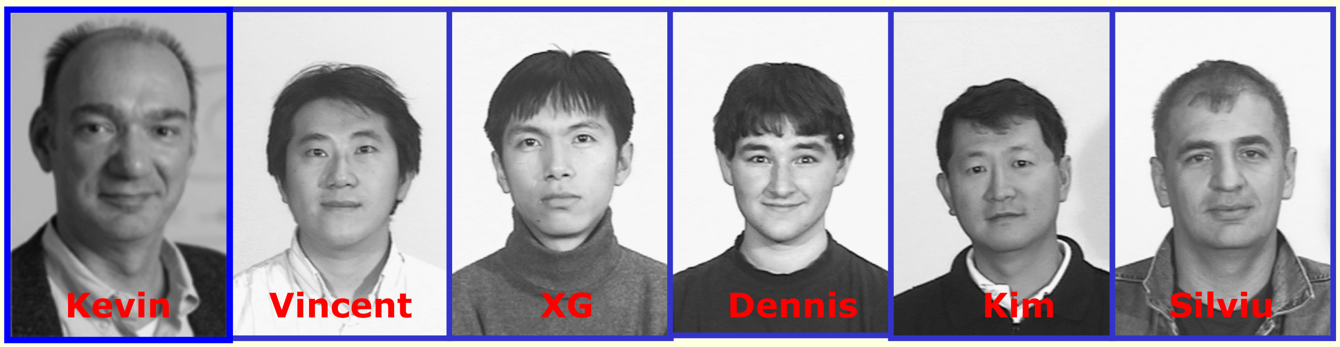
Identification Systems

- Given an input image:
  - Compare input against the enrolled identities using the matcher
  - Generate a ranking of the enrolled identities based on their match scores
- Ranks versus Scores
  - The score-normalization problem is avoided
  - The “absolute distance” between identities is lost

Rank-level Fusion

- Every biometric matcher ranks the identities in the databases
- Rank-level fusion consolidates the ranks associated with every subject

Database



Face Matcher	1	4	5	2	6	3
Finger Matcher	1	3	2	5	6	4
Iris Matcher	2	4	6	1	5	3

Notation Used

- N: number of users enrolled in the database
- C: number of matchers
- r_{ij}: the rank assigned to user j by the i^{th} matcher
- R_j: the rank for user j after applying rank level fusion

Fusion Schemes

- **Highest Rank Fusion**: The fused rank of a user is computed as the best rank generated by different matchers

$$R_j = \min_{i=1}^{C} \{r_{i,j}\}$$

- **Borda Count Fusion**: The fused rank of a user is computed as the sum of the ranks generated by different matchers

$$R_j = \sum_{i=1}^{C} r_{i,j}$$

T. Ho, J. Hull, and S. Srihari. Decision combination in multiple classifier systems. *IEEE Transaction on Pattern Analysis and Machine Intelligence (PAMI), 16(1):66–75, 1994.*

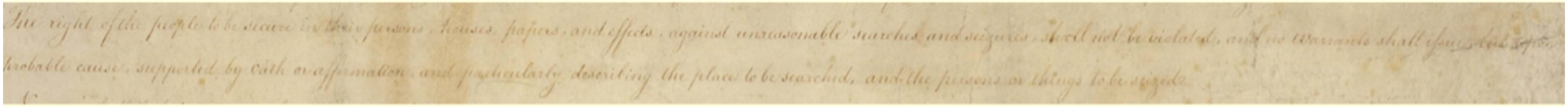
Decision-level Fusion

- Genuine or impostor?
  - 1 or 0?
- Fusion schemes
  - AND [Very strict]
  - OR [Very relaxed]
  - Majority Voting
  - Behavior Knowledge Space (BKS)

Ross et al, "Handbook of Multibiometrics," Springer 2006

Importance of Privacy

- "Privacy is the right to be let alone" [Samuel Warren and Louis Brandeis (1890)]
- "Privacy is the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others" [Alan Westin (1970)]
- "Privacy is the right of people to conceal information about themselves that others might use to their disadvantage" [Richard Posner (1983)]



PRIVACY IS DIFFERENT FROM SECURITY

Biometric Recognition

- Automated recognition of individuals based on their biological and behavioral characteristics

- Biological and behavioral characteristic of an individual from which distinguishing, repeatable biometric features can be extracted

H.T. F. Rhodes, Alphonse Bertillon: Father of Scientific Detection, Harrap, 1956

Identity vs Recognition

- We do not necessarily want to elicit identity
- We want to recognize a person

INPUT

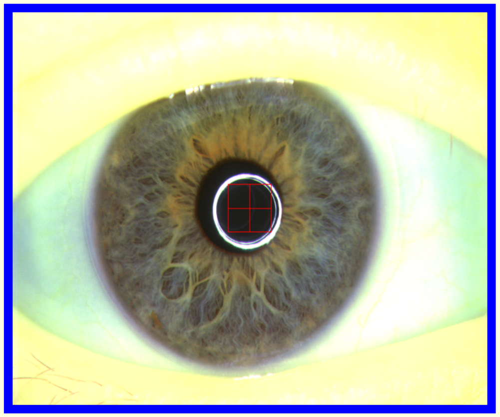
Based on a single fingerprint image, we cannot say this belongs to *Jane Doe*

REFERENCE

We need a reference fingerprint image that is known to belong to *Jane Doe* in order to make this assessment

Reference Biometric Images

- Some biometric systems may store the raw images of an individual as a reference image
  - e.g., face or fingerprint or iris image



- From a visual standpoint, face images are perceived to divulge more information about a person

Linking Across Databases

- Biometric data of an individual is sometimes stored in a central database with an identifier
- Cross-database matching may be done to track individuals
- Biometric data mining may be performed to glean information about identity
  - Large-scale processing of biometric data

Identifying People on the Web

- Faces of Facebook: Privacy in the Age of Augmented Reality (Alessandro Acquisti et al 2011)
- Convergence of three technologies:
  - face recognition, cloud computing, online social networks
- They investigated whether combination of publicly available Web 2.0 data and off-the-shelf face recognition software may allow large-scale, automated, end-user individual re-identification
- Started from an anonymous face in the street, and ended up with very sensitive information about that person, in a process of data "accretion”
- Combined face recognition with the algorithms they developed in 2009 to predict SSNs from public data

Information Leakage from Single Image

- Gender
- Age
- Ethnicity
- Medical ailment
- Familial relation
- Name/Address

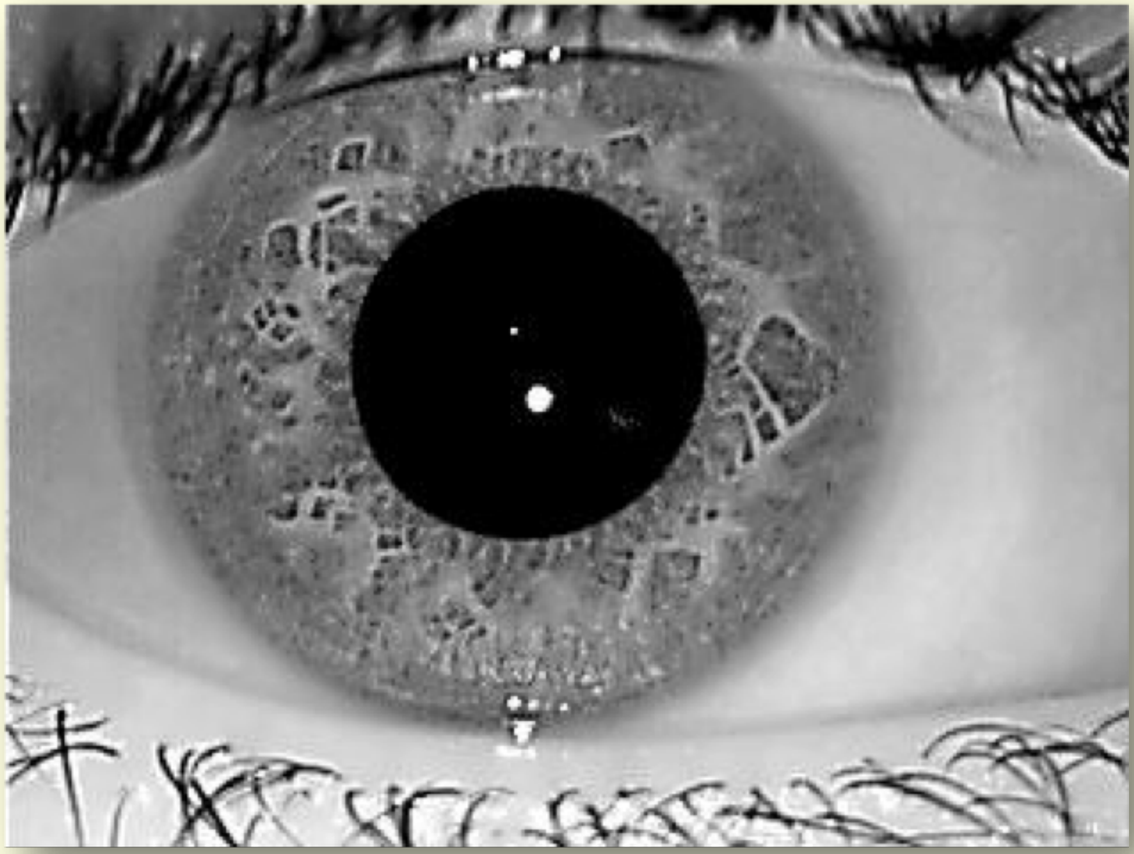
Automatic Extraction of Soft Biometric Information

- Age, Gender, Ethnicity, can be automatically derived from the face image
- That is, a trained classifier or a regressor may be used to automatically deduce certain soft biometric attributes

- Gender: Male
- Age: 25
- Health: Very good
- Eye Sight: Wears glasses
- Ethnicity: Asian Indian
- Name: Rohin

Also see, Dantcheva, Elias, Ross, “"What Else Does Your Biometric Data Reveal? A Survey on Soft Biometrics,” TIFS 2016

What *else* is revealed in an iris image?



- **Viewing the iris as a textural entity rather than just a binary code**

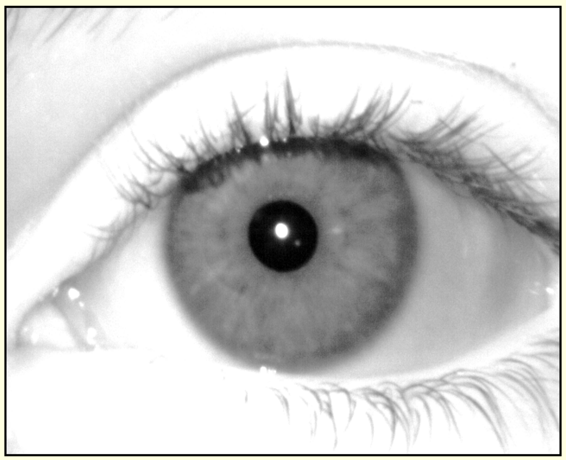
Iris: Levels of Information

- Biographical:
  Age, Gender, Race
- Anatomical:
  Distribution of crypts, Wolfflin nodules, pigmentation spots
- Environmental:
  Sensor, Illumination wavelength, Indoor/Outdoor
- Pathological:
  Stromal Atrophy
- Other:
  Pupil dilation level, Contact Lens

Not all information can be reliably extracted

But information can be aggregated

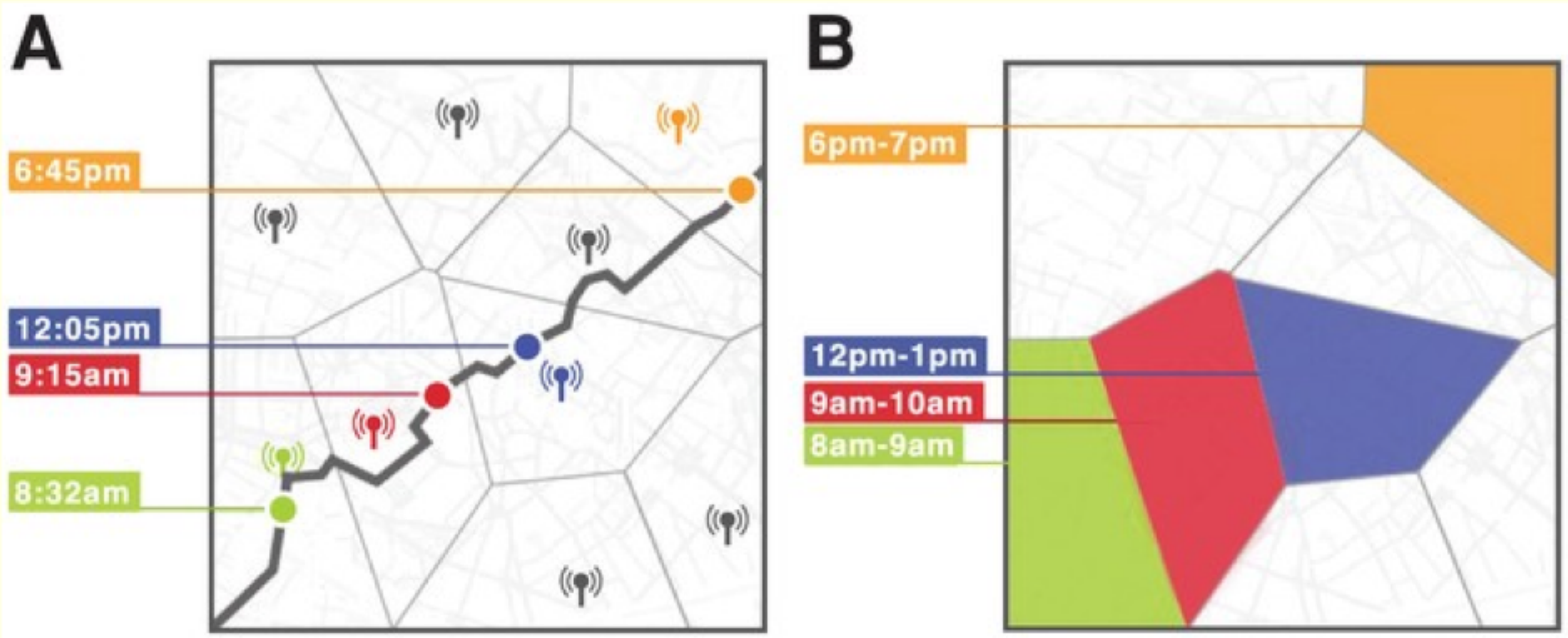
Semantic Description of Iris



- Subject is a Male (90%), White (85%)
- Image taken using an Aoptix camera
- Iris stroma is plain textured
- Highly constricted pupil suggests strong ambient illumination

Identification Without Biometric Data!

De Montjoye, Hidalgo, Verleysen & Blondel, "Unique in the Crowd: The Privacy Bounds of Human Mobility", Scientific Reports, vol. 3, 2013



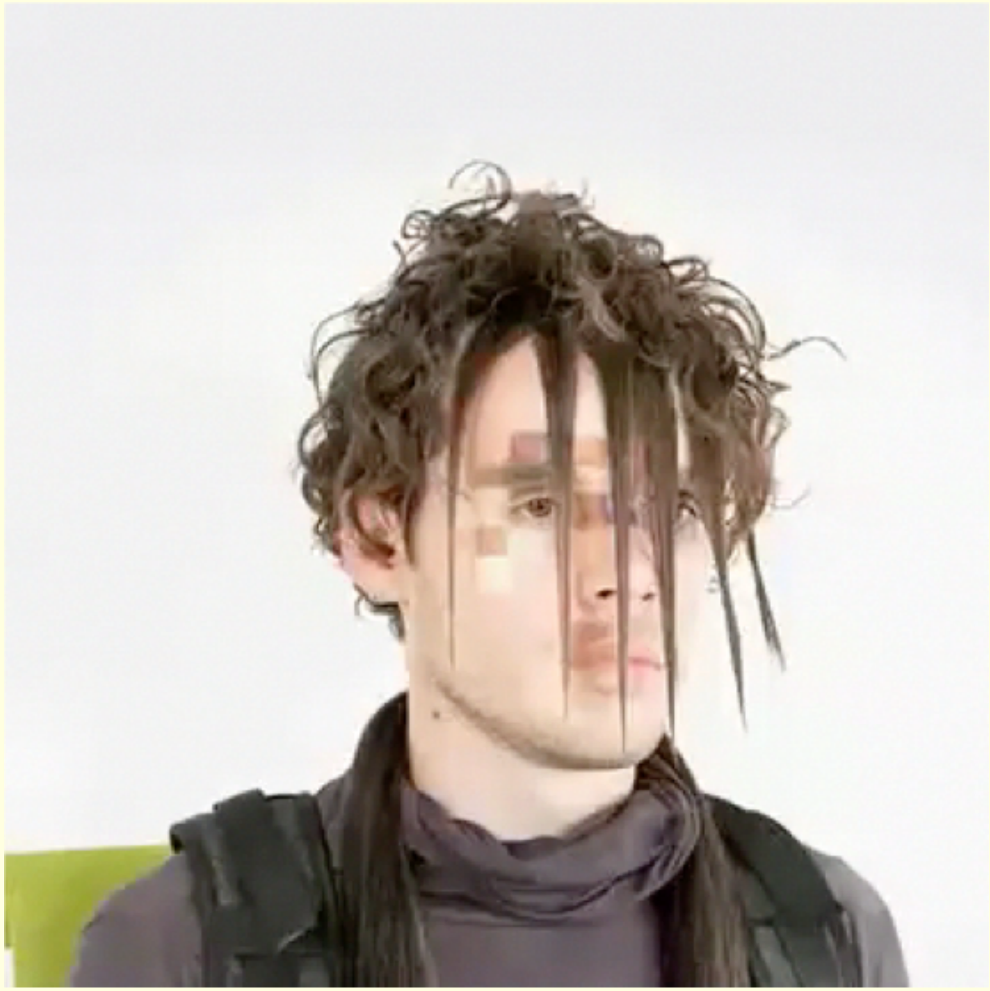
With just anonymous location data, it is possible to figure out "who you are" by tracking your smartphone

- 15 months of mobility data for 1.5 million individuals and found that human mobility traces are highly unique.
- 4 spatio-temporal points are enough to uniquely identify 95% of the individuals

Privacy Visor

https://www.youtube.com/watch?v=LRj8whKmN1M

Anti-Face!



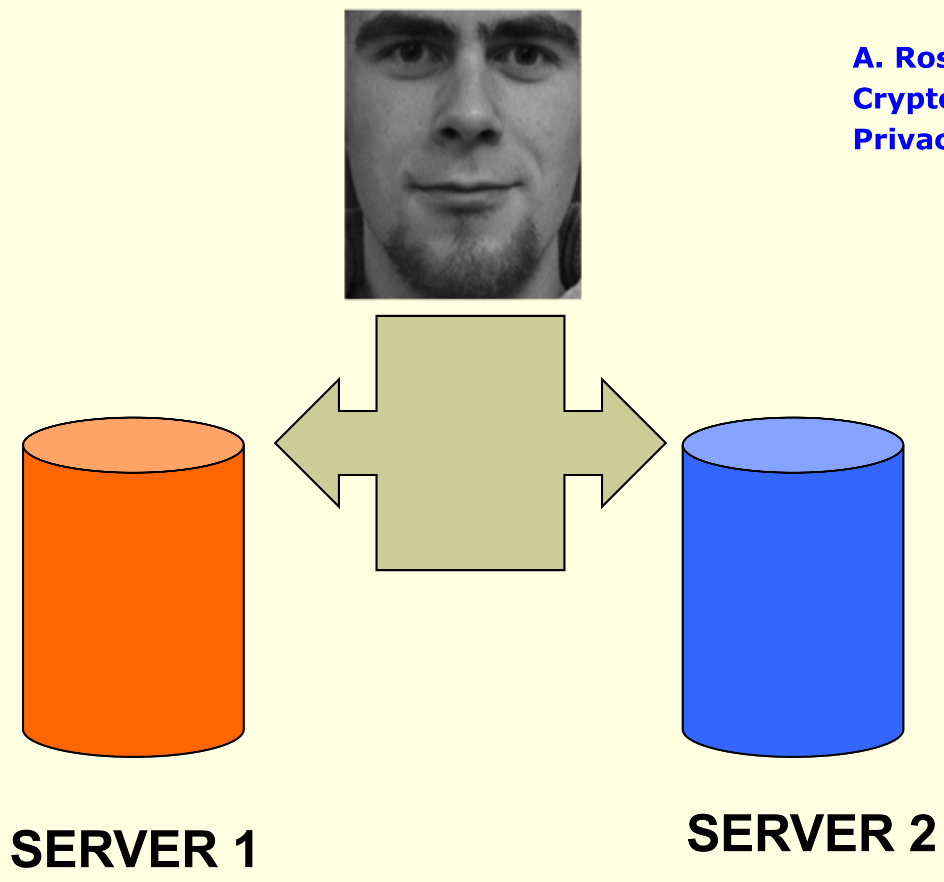
https://cvdazzle.com/

De-identification via Collaboration

Decomposing Face Images

- The input face image is decomposed and stored in two separate servers: either server will be unable to deduce original face image by themselves

A. Ross and A. Othman, "Visual Cryptography for Biometric Privacy," TIFS 2011



Visual Cryptography*

- Given an original binary image *T*, it is encrypted in *n* images, such that:

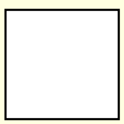
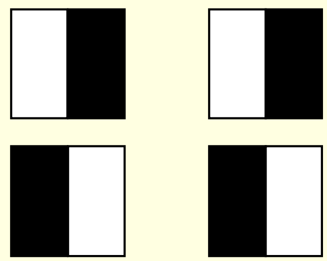
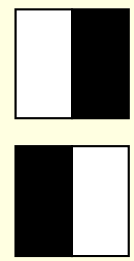
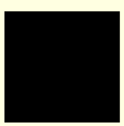
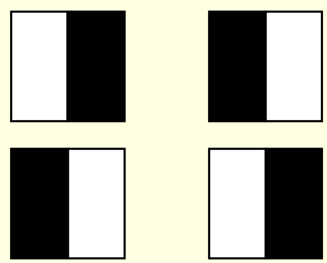
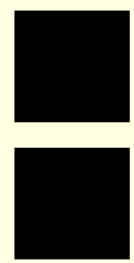
$$T = S_{h_1} \oplus S_{h_2} \oplus S_{h_3} \oplus \ldots \oplus S_{h_k}$$

where $\oplus$ is a Boolean operation , S_{hi} is an image which appears as noise, $k \leq n$, and *n* is the number of noisy images

- This is referred to as *k-out-of-n* VCS

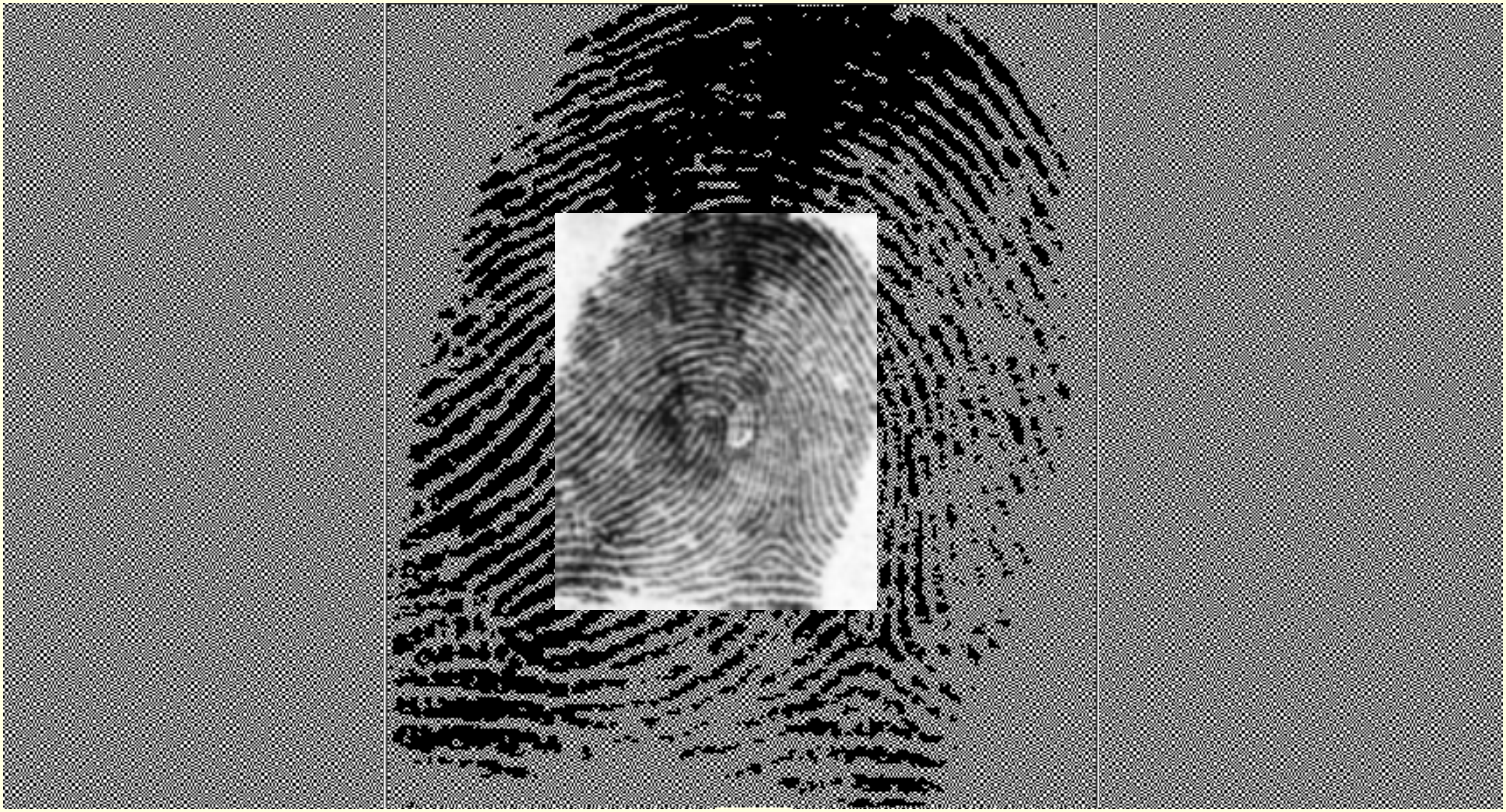
* M. Naor and A. Shamir, "Visual cryptography," in EUROCRYPT, pp. 1–12, 1994.

2-out-of-2 VCS

Pixel	Probability	Shares #1 #2	Superposition of the two shares	
	$p = 0.5$			White Pixels
	$p = 0.5$			
	$p = 0.5$			Black Pixels
	$p = 0.5$			

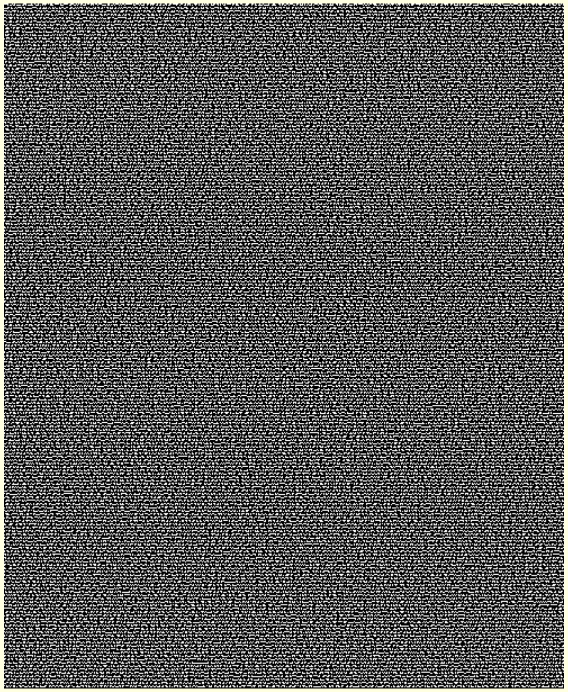
Decomposing a Binary Image

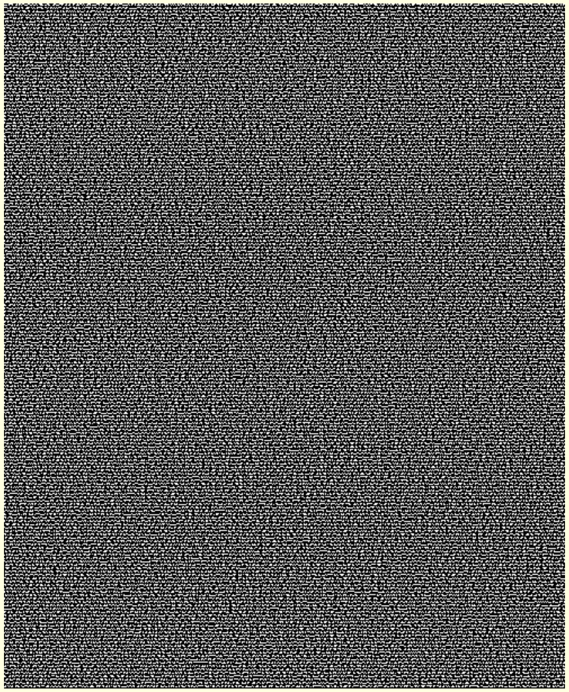
- Decomposing a fingerprint into two random images using Visual Cryptography



Decomposing a Face Image

- Decomposing a face into two random images?
  Problematic!





Gray-level Extended Visual Cryptography Scheme (GEVCS)

- VCS allows us to encode a secret image into n sheet images
- These sheets appear as a random set of pixels
- The sheets could be reformulated as natural images – known as host images

M. Nakajima and Y. Yamaguchi, “Extended visual cryptography for natural images,” Journal of WSCG 10(2), pp. 303–310, 2002.

Gray-level Extended Visual Cryptography Scheme (GEVCS)

PRIVATE IMAGE

HOSTS (PUBLIC IMAGES)

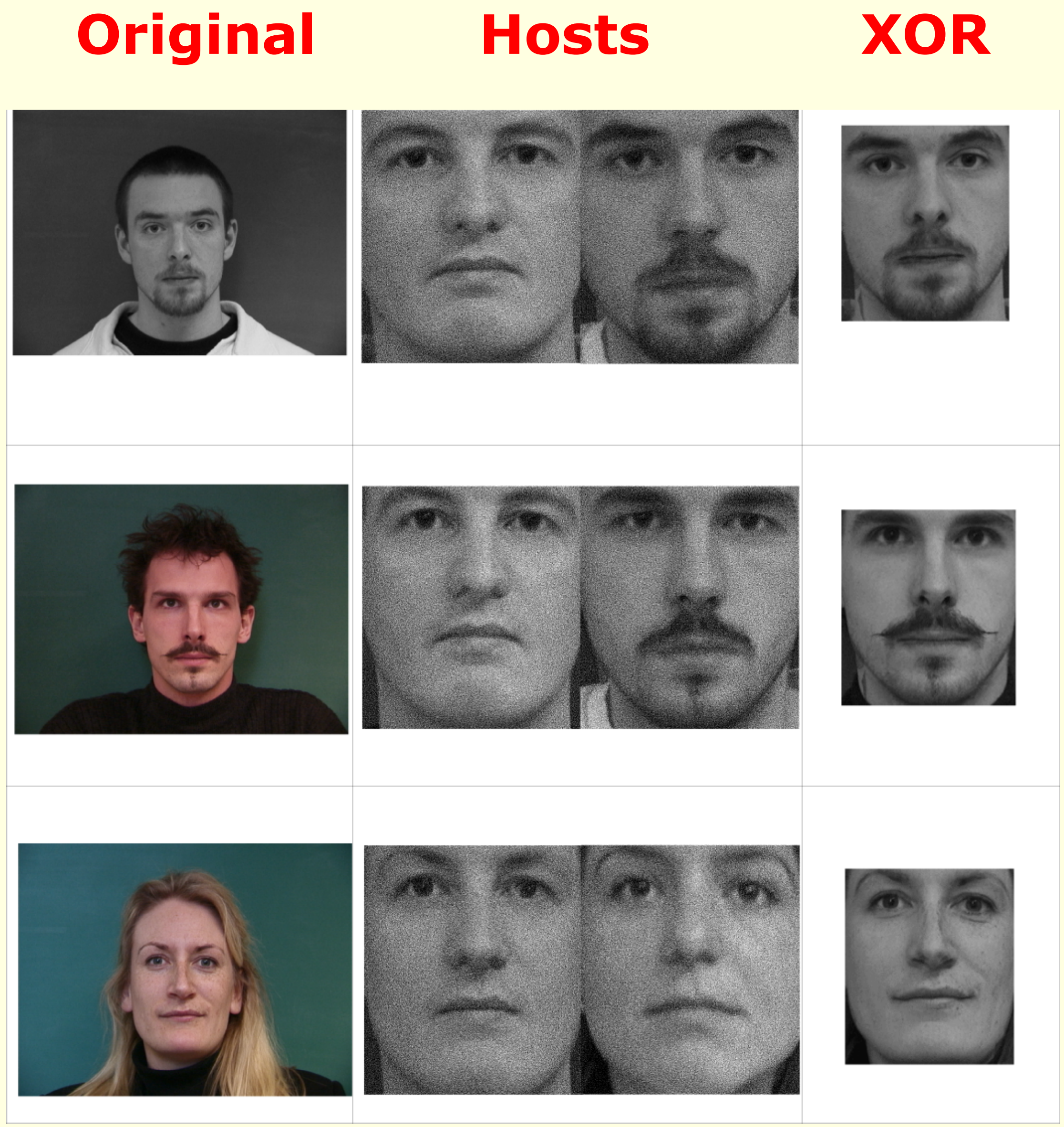
PRIVATE IMAGE AFTER DECRYPTION

HOSTS AFTER ENCRYPTION

Ross and Othman, "Visual Cryptography for Biometrics Privacy", TIFS 2011

Automated Host Image Selection

- The original image is encrypted into two dynamically selected host images



Face Visual Cryptography

Actual Face

HOST IMAGE IN SERVER 1

Simple XOR operator

HOST IMAGE IN SERVER 2

Ross and Othman, "Visual Cryptography for Biometrics Privacy", TIFS 2011

Face De-identification: Results

- Method to protect privacy of face images by decomposing it into two independent host (public) face images
- Original face image can be reconstructed only when both host images are available
- Either host image does not expose the identity of the original face image

Ross and Othman, "Visual Cryptography for Biometrics Privacy", TIFS 2011

De-identification via Mixing

Mixing Fingerprints

- An input fingerprint image is mixed with another fingerprint (e.g., from a different finger)
  - produces a new mixed fingerprint image that obscures the identity of the original fingerprint
- We consider the problem of mixing two fingerprint images in order to generate a new cancelable fingerprint image

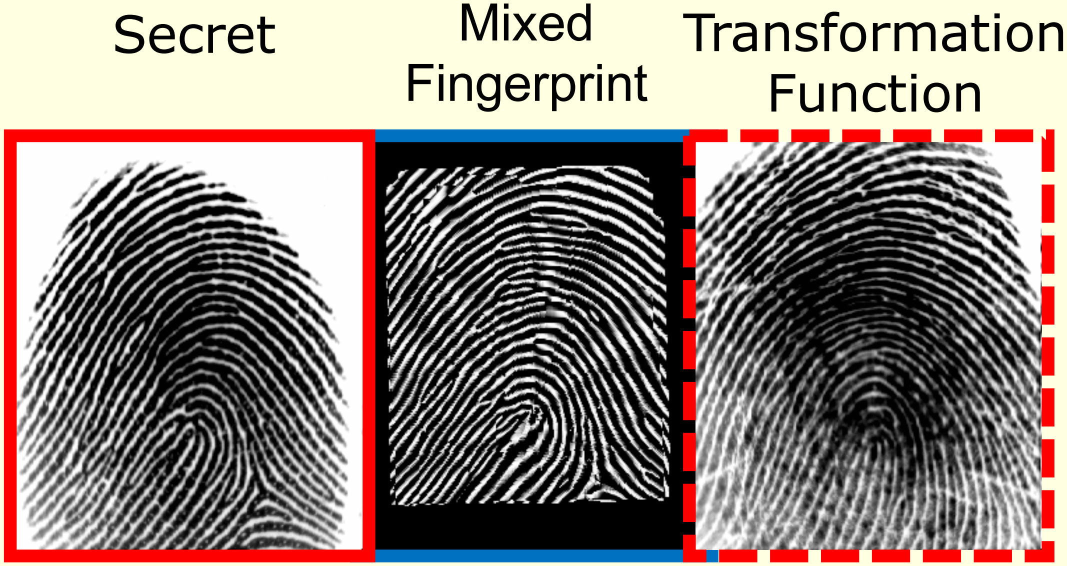
Othman and Ross, “On Mixing Fingerprints”, TIFS 2013

Applications

- To obscure the information present in an individual’s fingerprint image prior to storing it in a central database
- To generate a cancelable template, i.e., the template can be reset if the mixed fingerprint is compromised
- To generate virtual identities by mixing fingerprint images pertaining to an individual

Othman and Ross, “On Mixing Fingerprints”, TIFS 2013

Mixing Fingerprints



- Mixing fingerprints creates a new entity that looks like a plausible fingerprint:
  - It can be processed by conventional fingerprint algorithms
  - An eavesdropper may not be able to determine if a given fingerprint is mixed or not

Hologram Model

- The ridge flow of a fingerprint can be represented as a 2D Amplitude and Frequency Modulated (AM-FM) signal:

Realistic appearance

$$I(x, y) = a(x, y) + b(x, y) * \cos[\Psi(x, y)] + n(x, y)$$

Ridges and minutiae

K. G. Larkin and P. A. Fletcher. A coherent framework for fingerprint analysis: are fingerprints holograms? Opt. Express, 15(14):8667–8677, 2007.

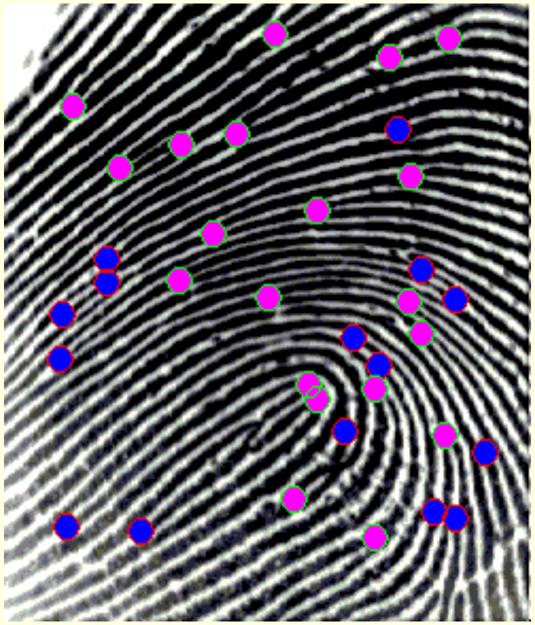
Helmholtz Decomposition

- Based on the Helmholtz Decomposition theorem, the phase **$\Psi(x, y)$** can be uniquely decomposed into two components:

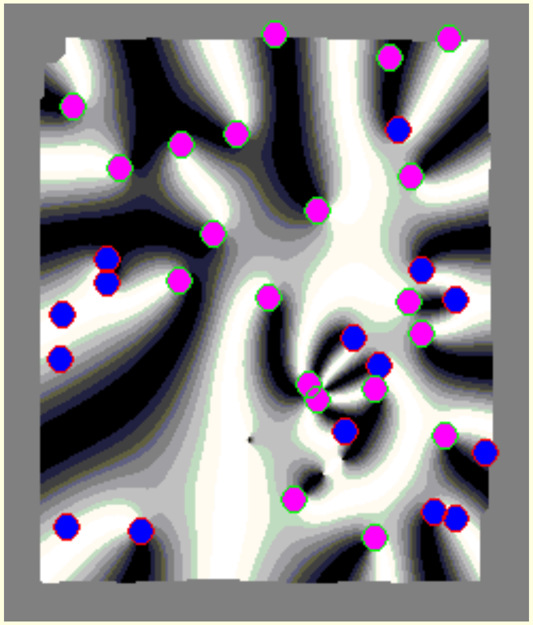
$$\Psi(x, y) = \Psi c(x, y) + \Psi s(x, y)$$

- The continuous component, **$\Psi c(x, y)$**, defines the local ridge orientation
- The spiral component, **$\Psi s(x, y)$**, characterizes the minutiae locations

Decomposition: Left Loop



Original



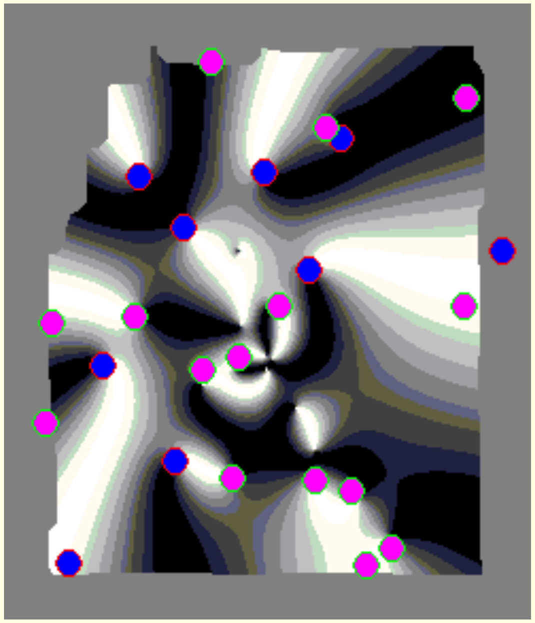
Spiral Phase

Continuous Phase

Othman and Ross, "On Mixing Fingerprints", TIFS 2013

Decomposition: Right Loop

Original

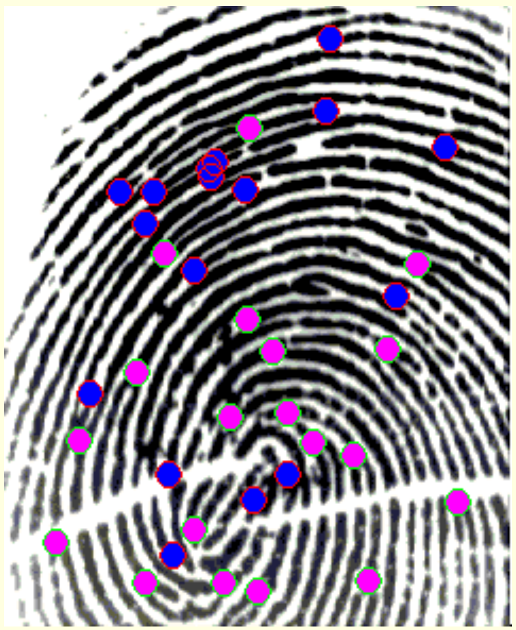


Spiral Phase

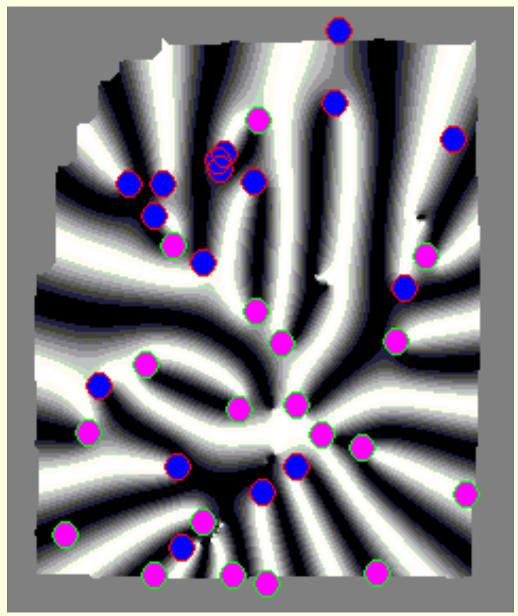
Continuous Phase

Othman and Ross, “On Mixing Fingerprints”, TIFS 2013

Decomposition: Whorl



Original



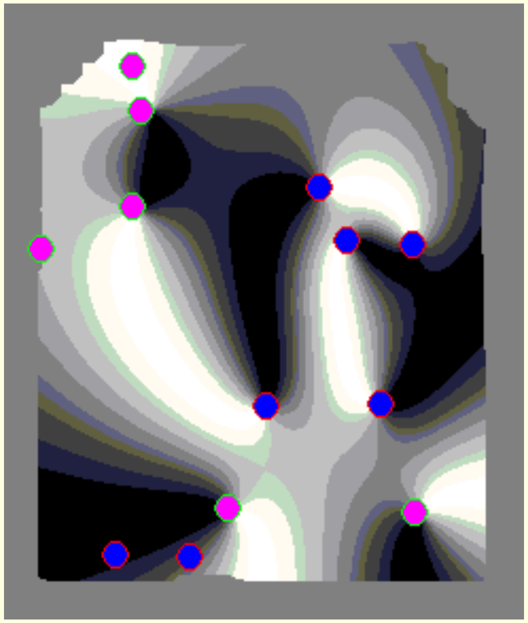
Spiral Phase

Continuous Phase

Othman and Ross, "On Mixing Fingerprints", TIFS 2013

Decomposition: Arch

Original



Spiral Phase

Continuous Phase

Othman and Ross, “On Mixing Fingerprints”, TIFS 2013

Mixing Fingerprints

- Let F_1 and F_2 be two different fingerprint images from different fingers, and let **$\Psi c_i(x, y)$** and **$\Psi s_i(x, y)$** be the pre-aligned continuous and spiral phases, $i = 1,2$.

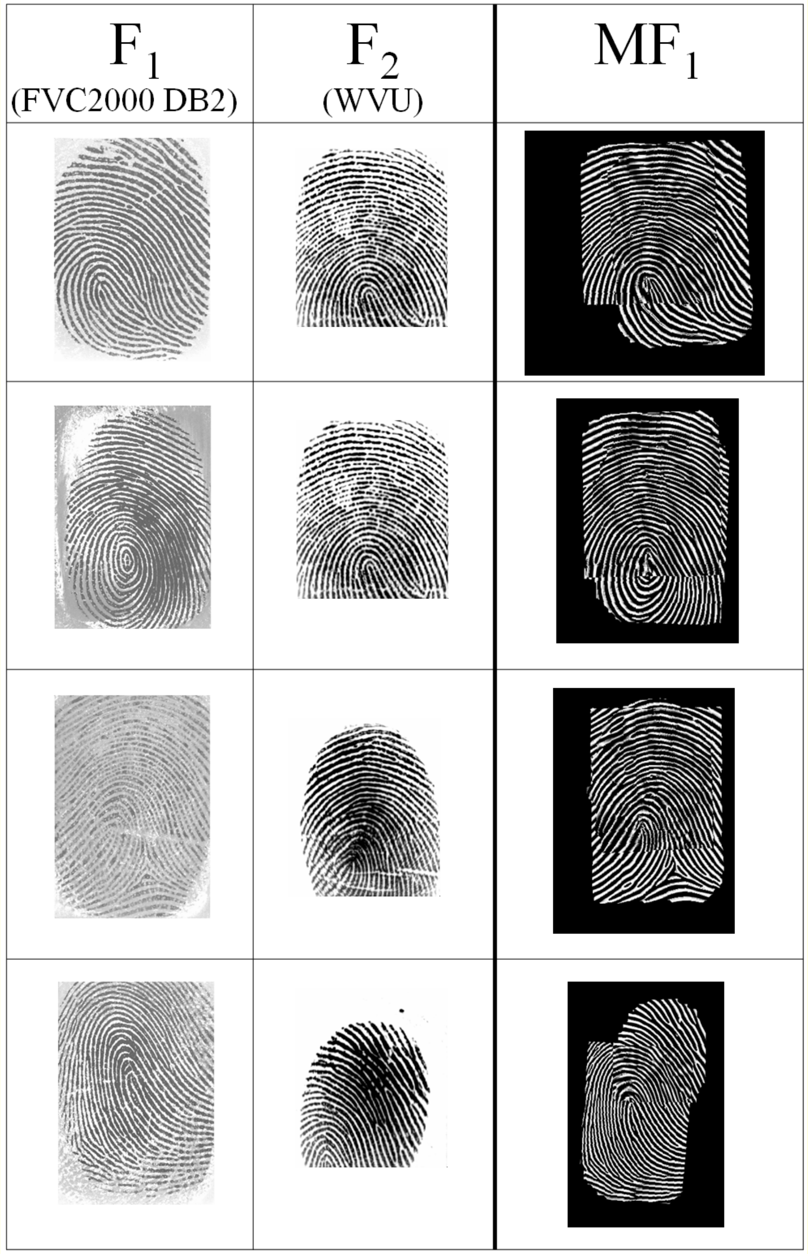
$$MF_1 = \cos[\Psi c_2(x, y) + \Psi s_1(x, y)]$$

$$MF_2 = \cos[\Psi c_1(x, y) + \Psi s_2(x, y)]$$

- The continuous phase of F_2 is combined with the spiral phase of F_1 which generates a new fused fingerprint image **MF_1**

Othman and Ross, "On Mixing Fingerprints", TIFS 2013

Mixed Fingerprint Images



Othman and Ross, "On Mixing Fingerprints", TIFS 2013

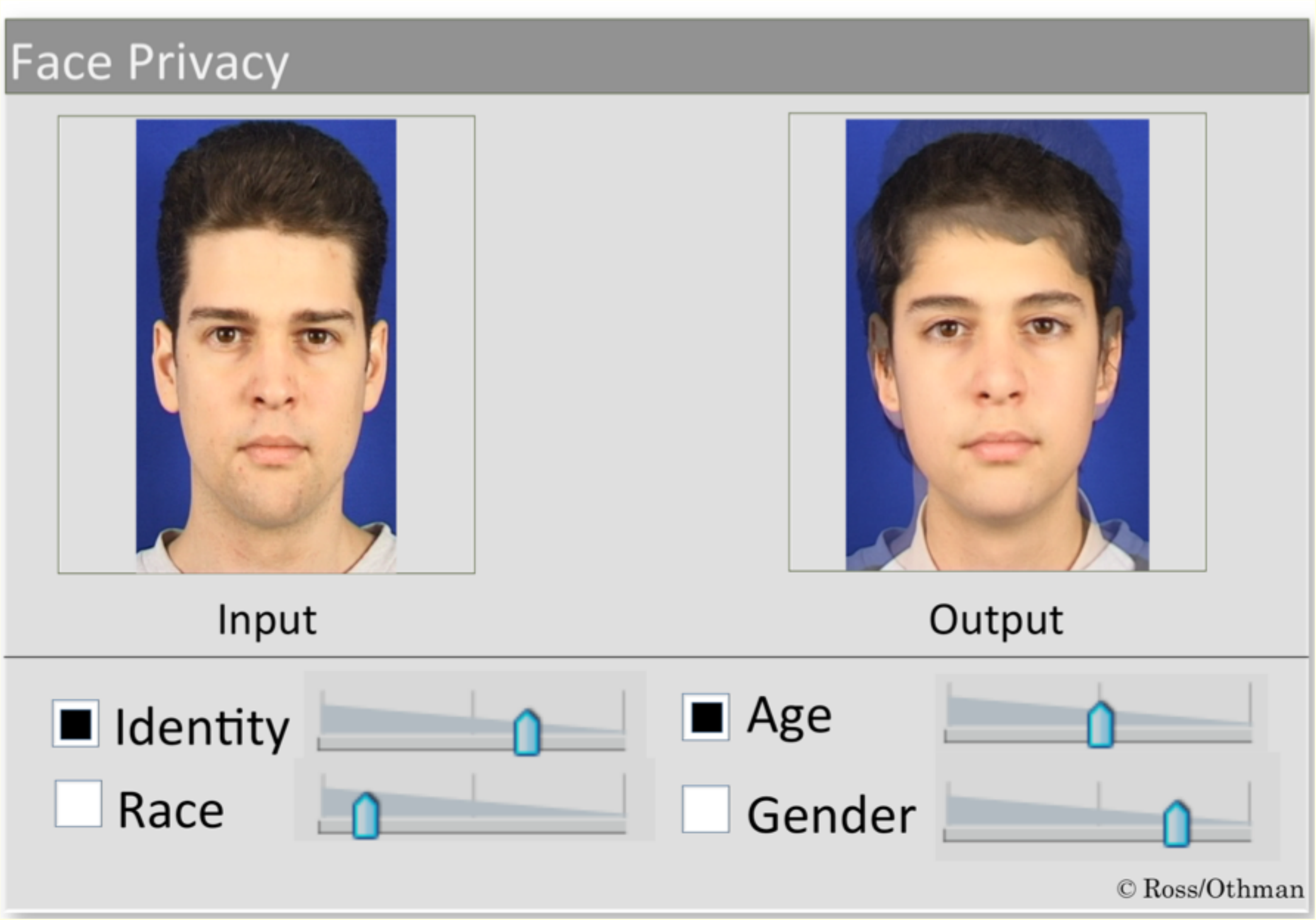
Mixing Fingerprints: Results

- Can the mixed fingerprint be used as a new biometric identity? (Yes)
- Are the original fingerprint and the mixed fingerprint correlated? (No)
- Does mixing result in cancelable templates? (Yes)
- If two different fingerprints are mixed with a common fingerprint, are the mixed fingerprints similar? (No)

Othman and Ross, "On Mixing Fingerprints", TIFS 2013

“Differential” Privacy

Soft Biometric Privacy



Othman and Ross, "Privacy of Facial Soft Biometrics," ECCVW 2014

Soft Biometric Privacy

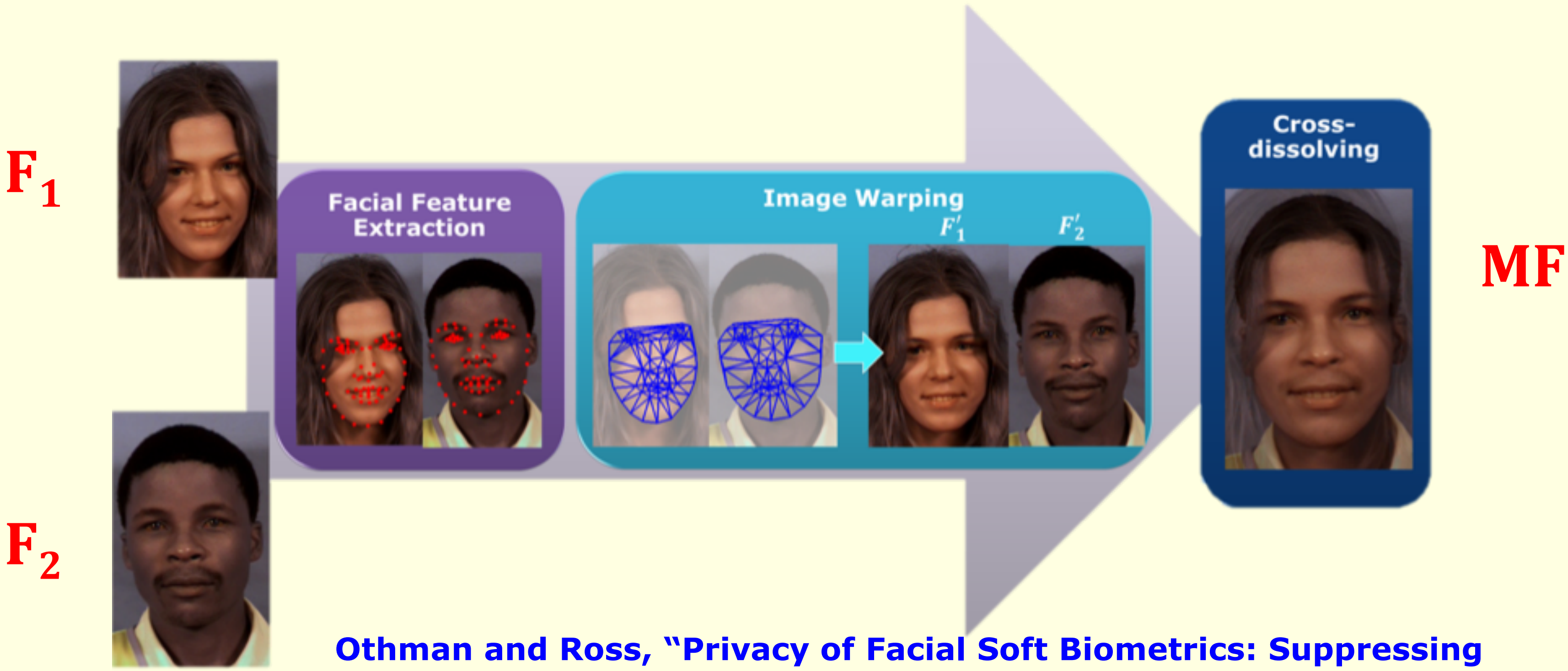
- Gender attribute of an input face image is progressively suppressed
- With respect to a face matcher the identity is preserved

Name	**Alice**	**Alice**	**Alice**	**Alice**
Gender	**Female** (confident)	**Female** (less confident)	**Male** (less confident)	**Male** (confident)

Othman and Ross, "Privacy of Facial Soft Biometrics: Suppressing Gender But Retaining Identity", ECCV Workshop, 2014

Face Morphing

- To generate a mixed face image, the principle of face morphing is used
- The mixed face image can be anywhere along a continuum from F_1 to F_2

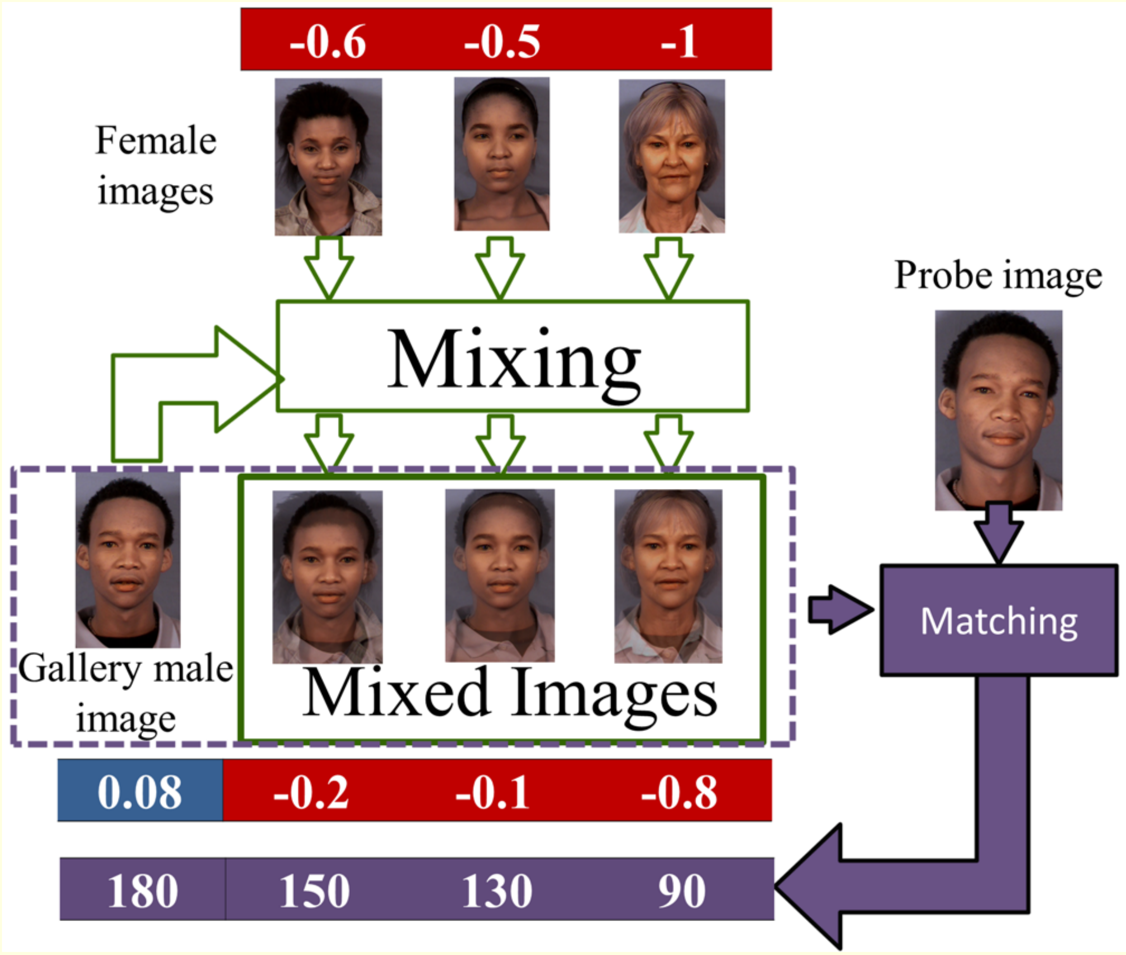


Othman and Ross, "Privacy of Facial Soft Biometrics: Suppressing Gender But Retaining Identity", ECCV Workshop, 2014

Similarity to the original images

- The resultant rank-1 accuracy is 95% and the EER is 5%

Othman and Ross, "Privacy of Facial Soft Biometrics: Suppressing Gender But Retaining Identity", ECCV Workshop, 2014



The identities of the originals have been preserved in the mixed faces

Gender Perturbation

ORIGINAL IMAGES

MODIFIED IMAGES

Othman and Ross, "Privacy of Facial Soft Biometrics: Suppressing Gender But Retaining Identity", ECCV Workshop, 2014

Recent Publications

- V. Mirjalili, S. Raschka, A. Namboodiri, A. Ross, "**Semi-Adversarial Networks: Convolutional Autoencoders for Imparting Privacy to Face Images**," Proc. of 11th IAPR International Conference on Biometrics (ICB 2018), (Gold Coast, Australia), February 2018
- V. Mirjalili and A. Ross, "**Soft Biometric Privacy: Retaining Biometric Utility of Face Images while Perturbing Gender**," Proc. of International Joint Conference on Biometrics (IJCB), (Denver, USA), October 2017.

Summary: Differential Privacy

- We explored the possibility of generating mixed face images that perturb the gender of a face image to different degrees

- Experiments on MUCT demonstrate that:
  - The new mixed face can potentially suppress the gender of an input face to different degrees (gender classifier)
  - The new mixed face image exhibits similarity with the original (face matcher)

Summary

- Visual Cryptography for decomposing a face image and storing it in two separate servers
  - Individual servers cannot identify the face
- Mixing fingerprints by combining the spiral and continuous phase components of two fingerprints
  - Cancellable fingerprints
  - Joint identity/Group Authentication
- Perturbing soft biometric information in face images by morphing face images