Forensic Pattern Recognition

Anil K. Jain
Michigan State University
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http://biometrics.cse.msu.edu/

Examples of Forensic Patterns

Fingerprint

Face

Scars, Marks, and Tattoos (SMT)

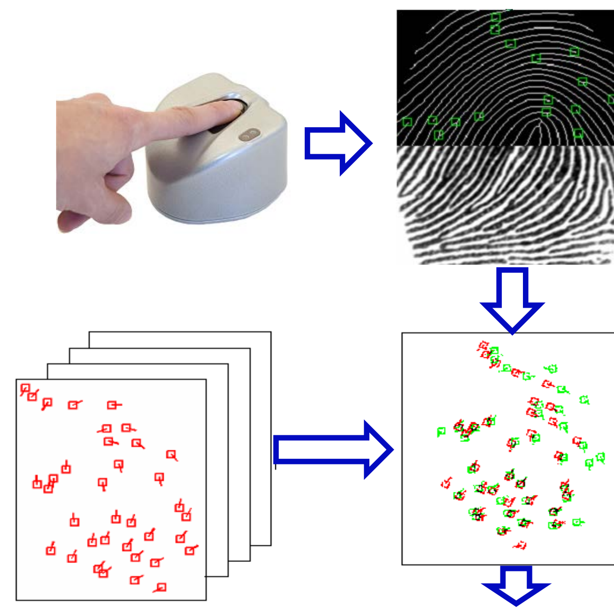
Ballistic image
(breech face impression)

Forensic Pattern Recognition Systems

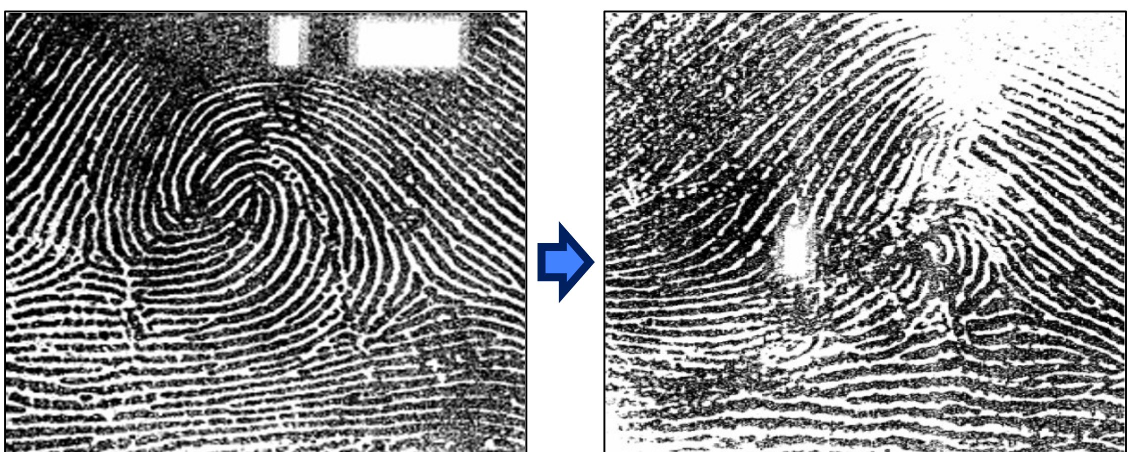
Morpho (2012)

Morpho (2014)

IBM (1998)



Morpho (2013)



Double-loop changed to left loop

Composite to Photo Matching

(Gallery of *one million* mug shots)

Race: White
Gender: Male
Age: 20 to 30

1a

1b

*1c**

1x

1y

1z

Tamerlan Tsarnaev

(*b*) WITH DEMOGRAPHIC FILTERING (WHITE MALE, 20-30)

	1a	*1b*	*1c*	mean
1x	5,432	27,617	**112**	353
1y	518	25,780	1,409	686
1z	3,958	14,670	1,142	1,416
mean	424	5,790	**71**	**82**

S. Klum, H. Han, B. Klare and A. K. Jain, "The FaceSketchID System: Matching Facial Composites to Mugshots", *IEEE Transactions on Information Forensics and Security*, December 2014.

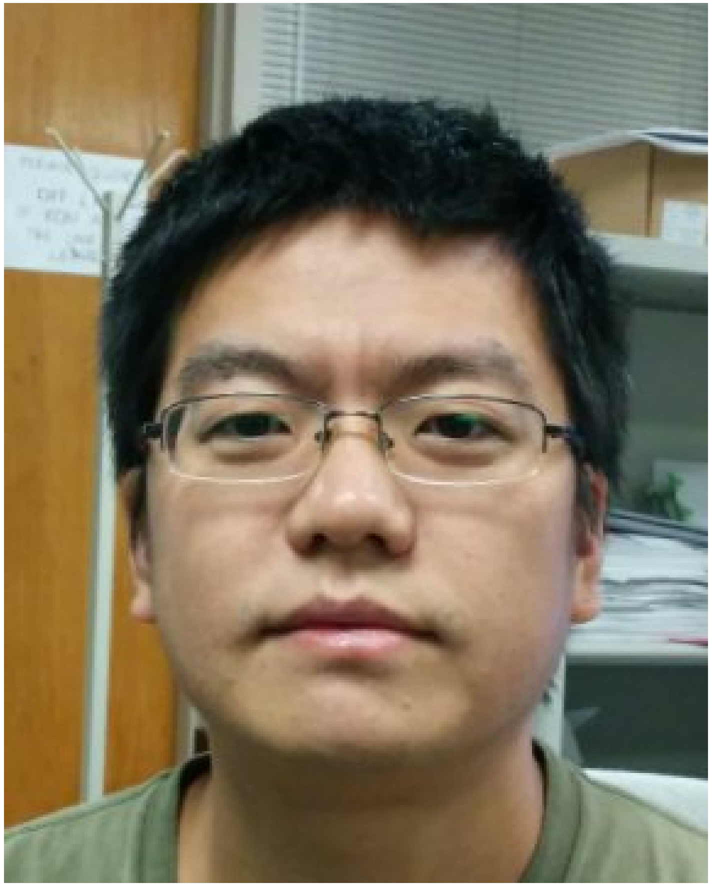
Outline

- Design of pattern recognition system
- Fingerprint matching
- Face recognition
- Ballistic image matching
- Summary

Pattern Recognition

- Given an input pattern, make a decision about the pattern
  - Fully automatic (“lights out” mode)
  - Semi-automatic (human in the loop)
- Types of decisions
  - Verification (1:1 comparison; same source)
  - Search (1: N comparisons; watch list)
  - Classification (e.g., fingerprint type)
- Why?
  - Throughput, cost, consistency, ease examiner workload,…

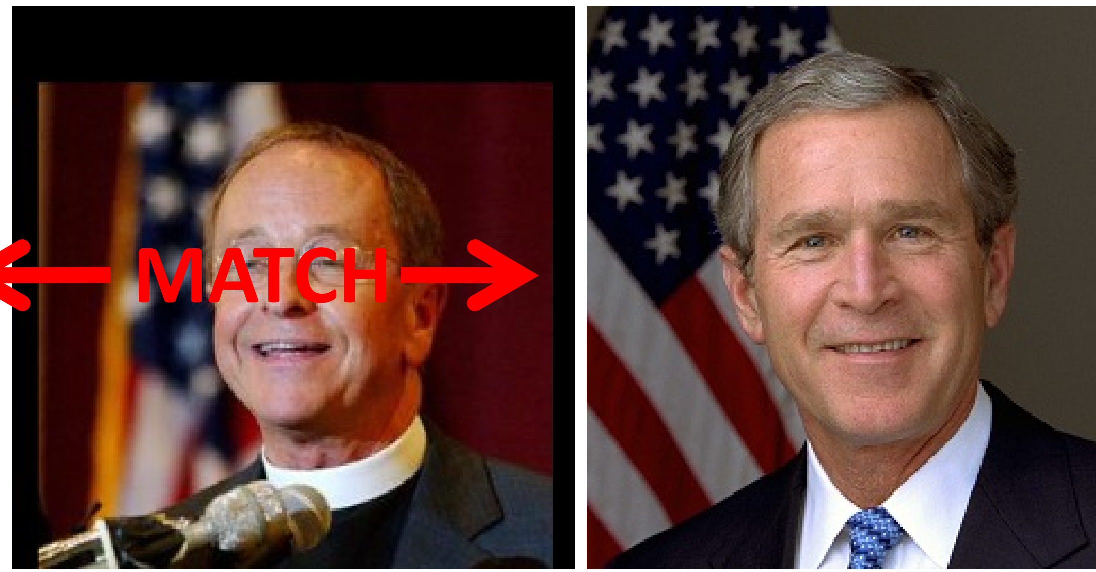
Verification



Same person?

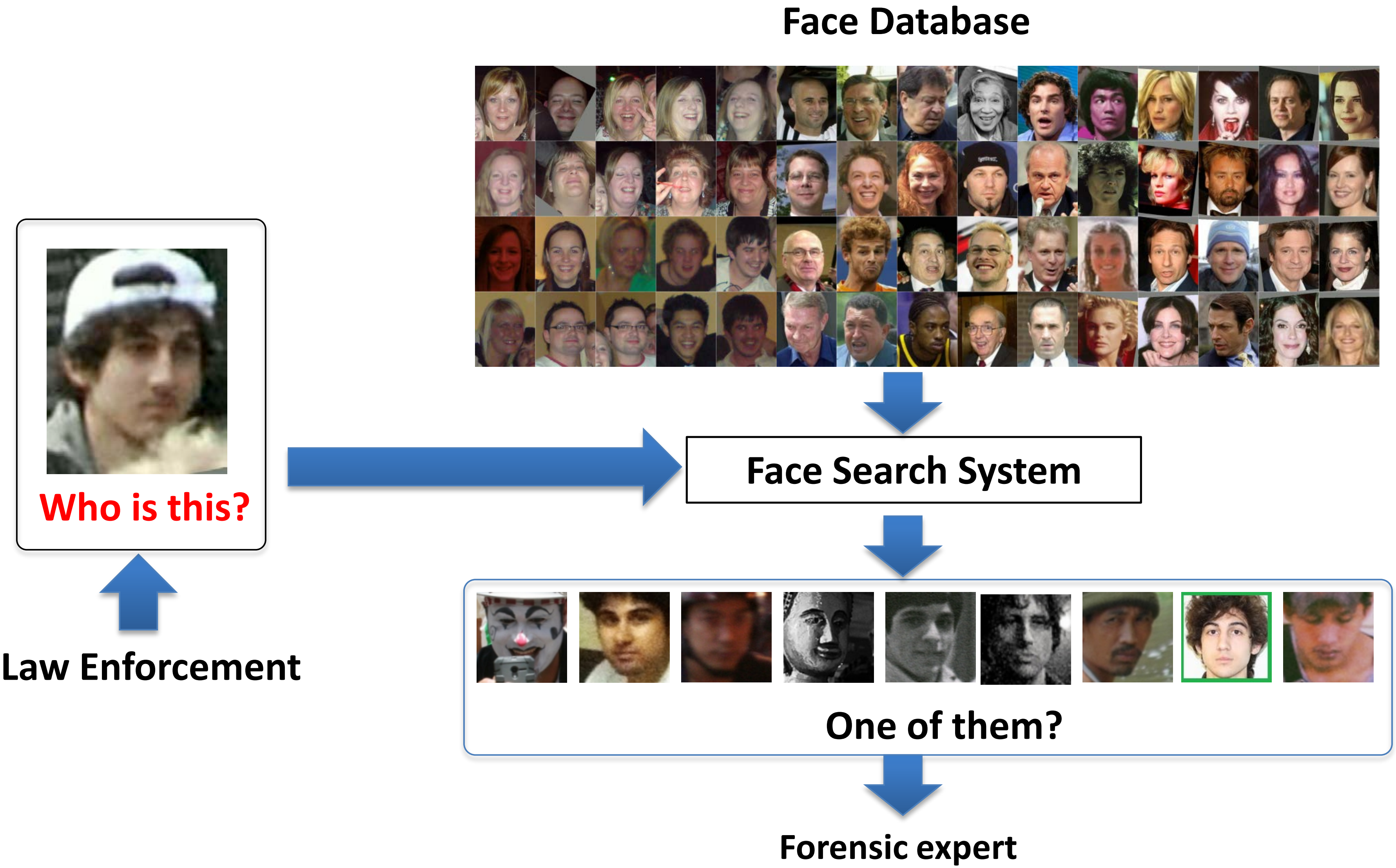
Search

Probe *Gallery*

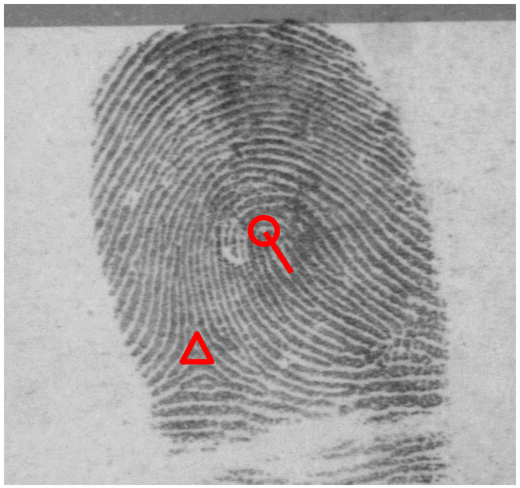


What if the suspect is not in the database (Open set search)?

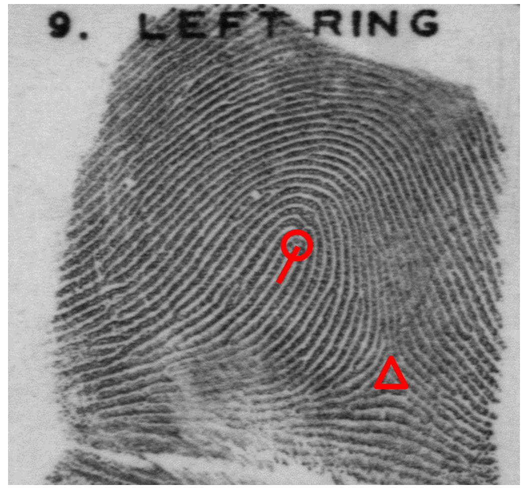
Semi-automated Search



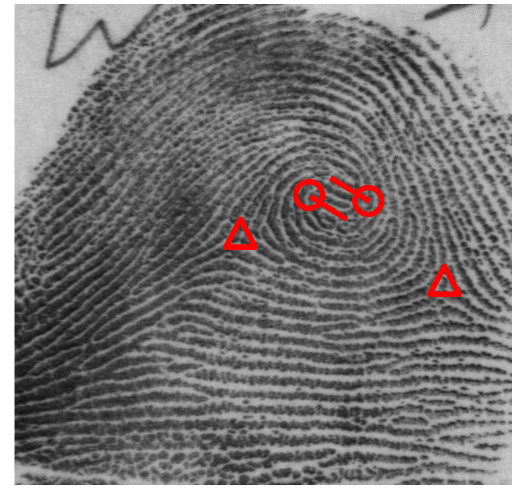
Fingerprint Classification



Right loop



Left loop

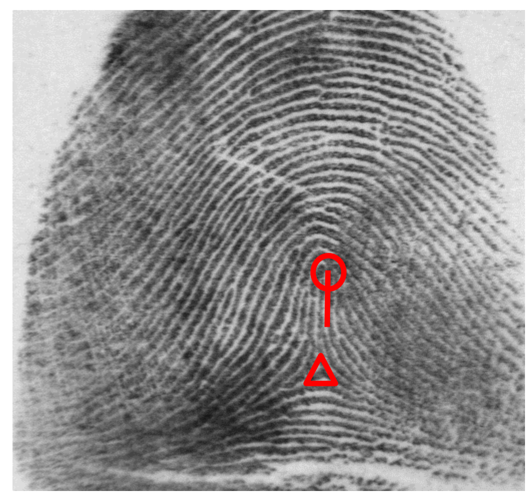


Whorl

○ : Core

△ : Delta

Arch



Tented arch

Why is Pattern Recognition Difficult?

Jan 1995

Gallery seed

Jul 1998

Score=0.99

Nov 1999

Score=0.62

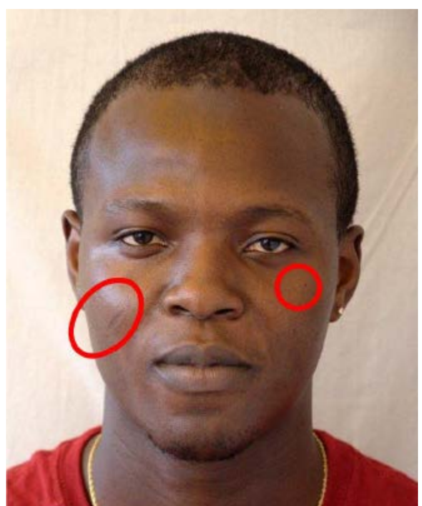
Nov 2003

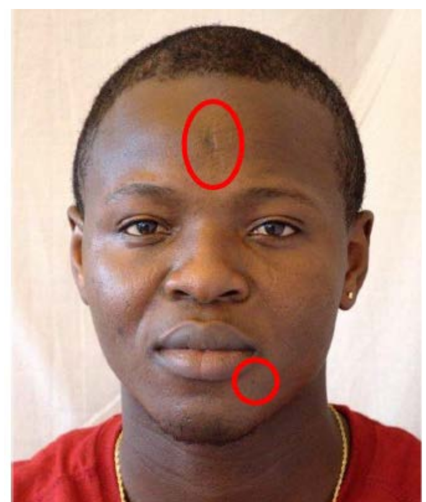
Score=0.41

Feb 2005

Score=0.26

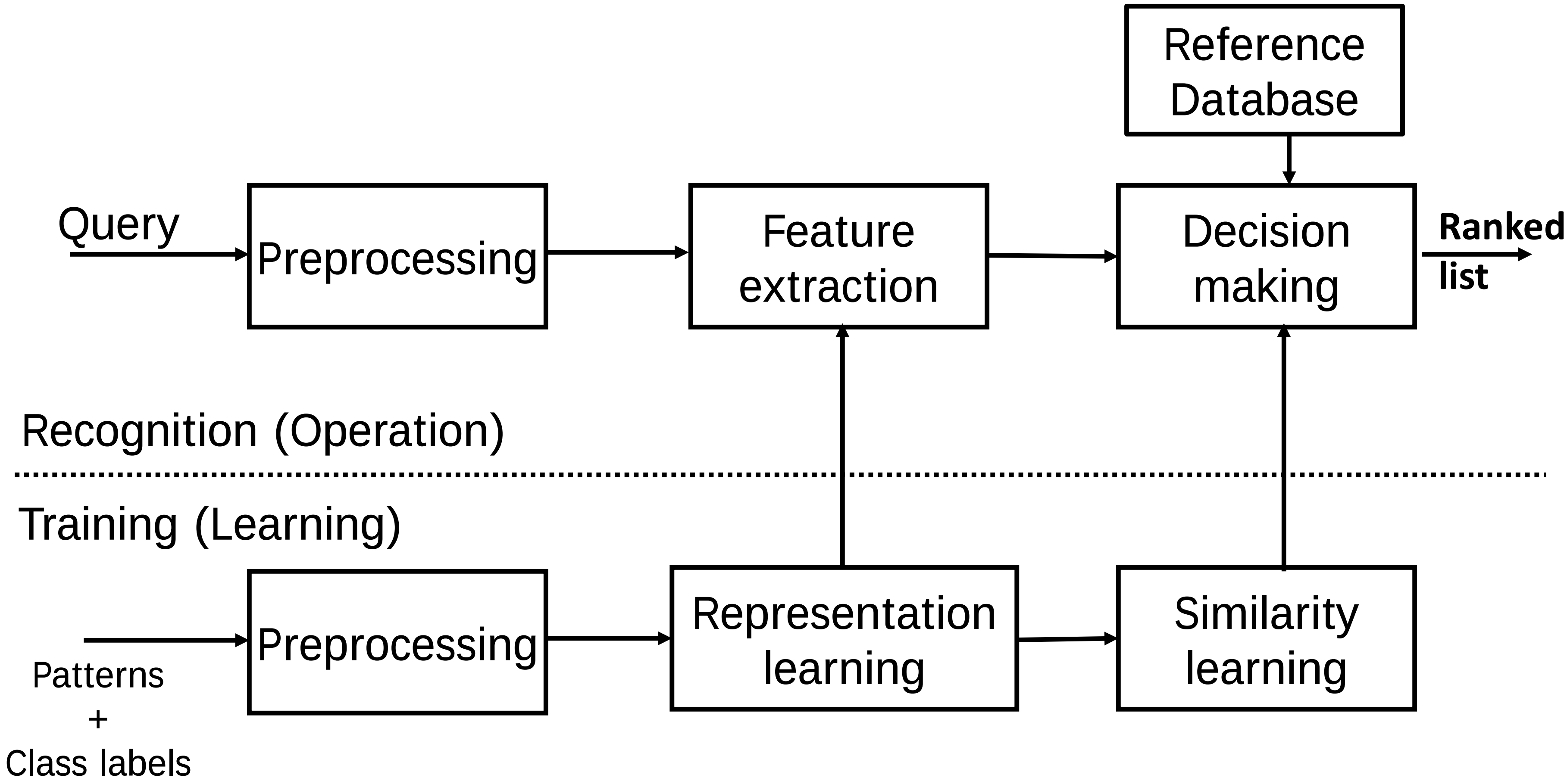
Intra-class variability





Inter-class similarity

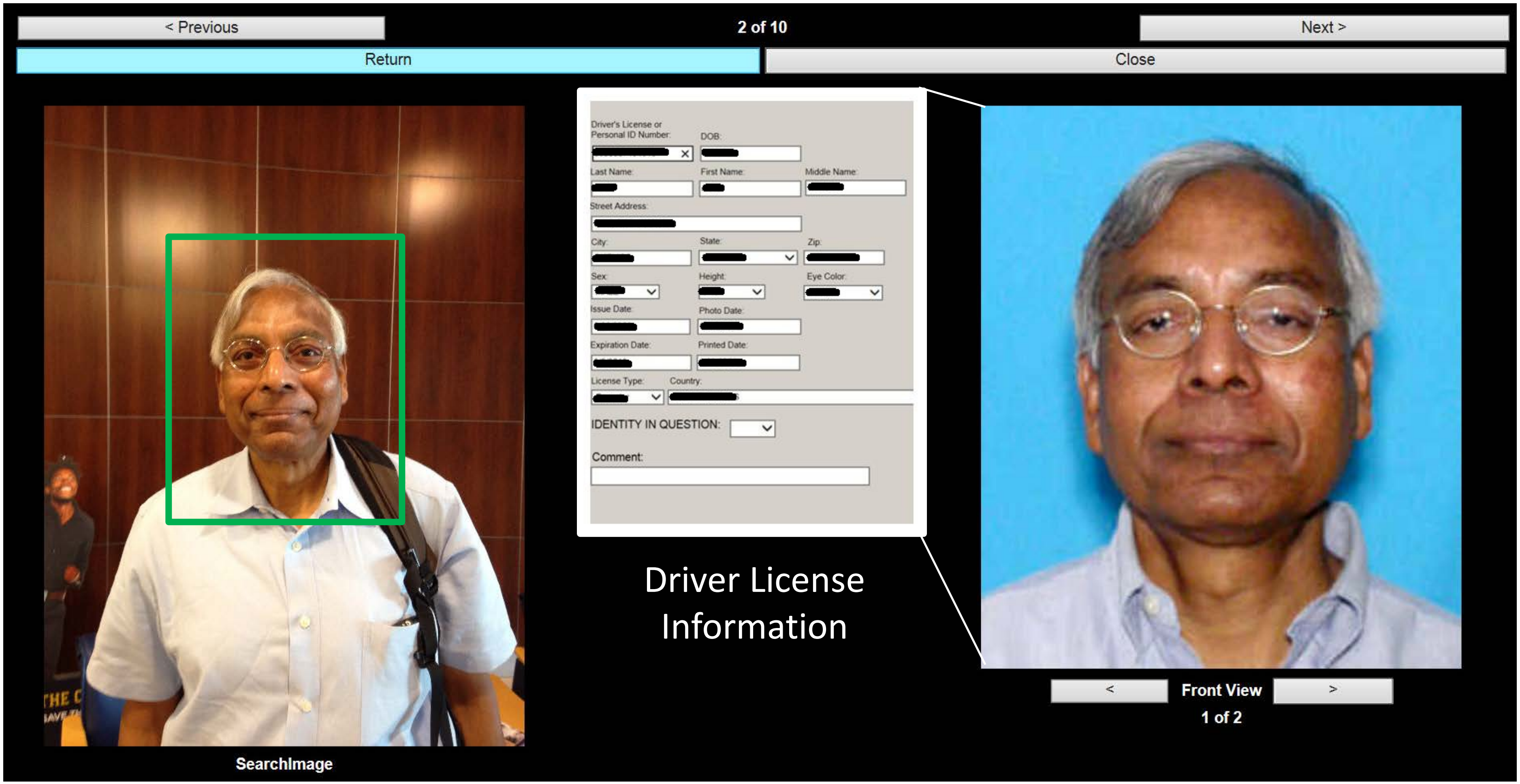
Forensic Pattern Recognition System



Challenges: domain knowledge, requirements, training & test data, "invariant" features, "robust" matcher

SNAP
Statewide Network of Agency Photos

Courtesy: Pete Langenfeld, MSP



Gallery: 30M DMV photos + 4M mugshot photos

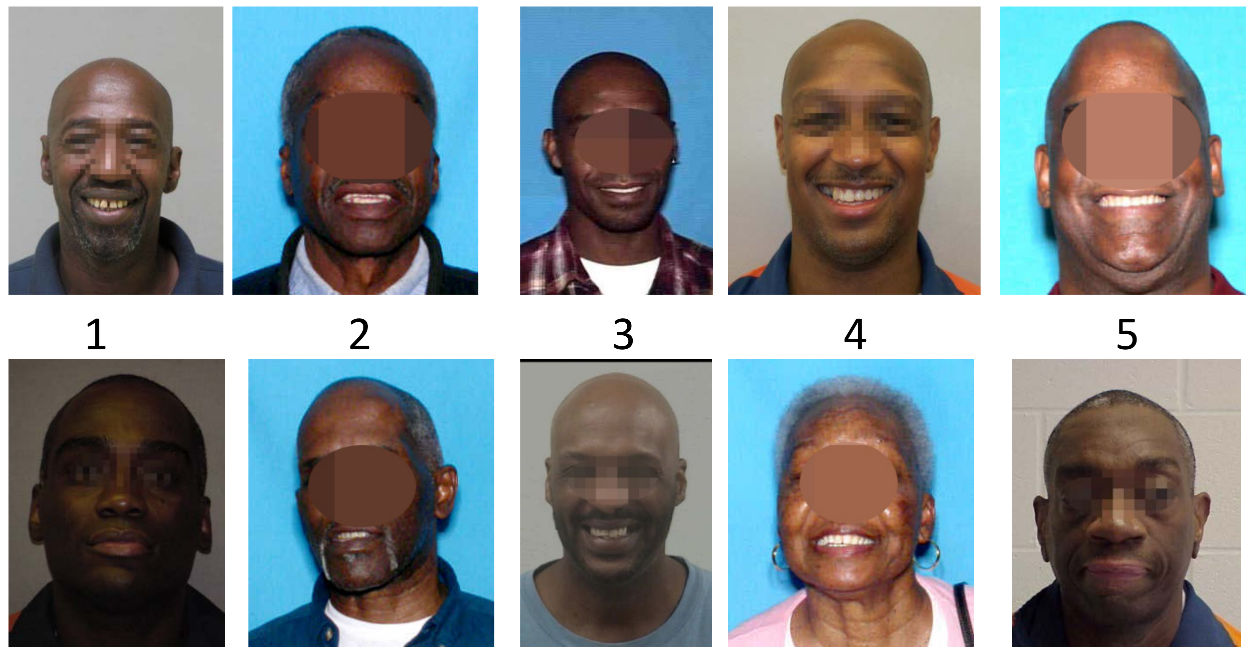
2009 driver license photo

SNAP

Statewide Network of Agency Photos

Probe Image

Top-10 retrievals

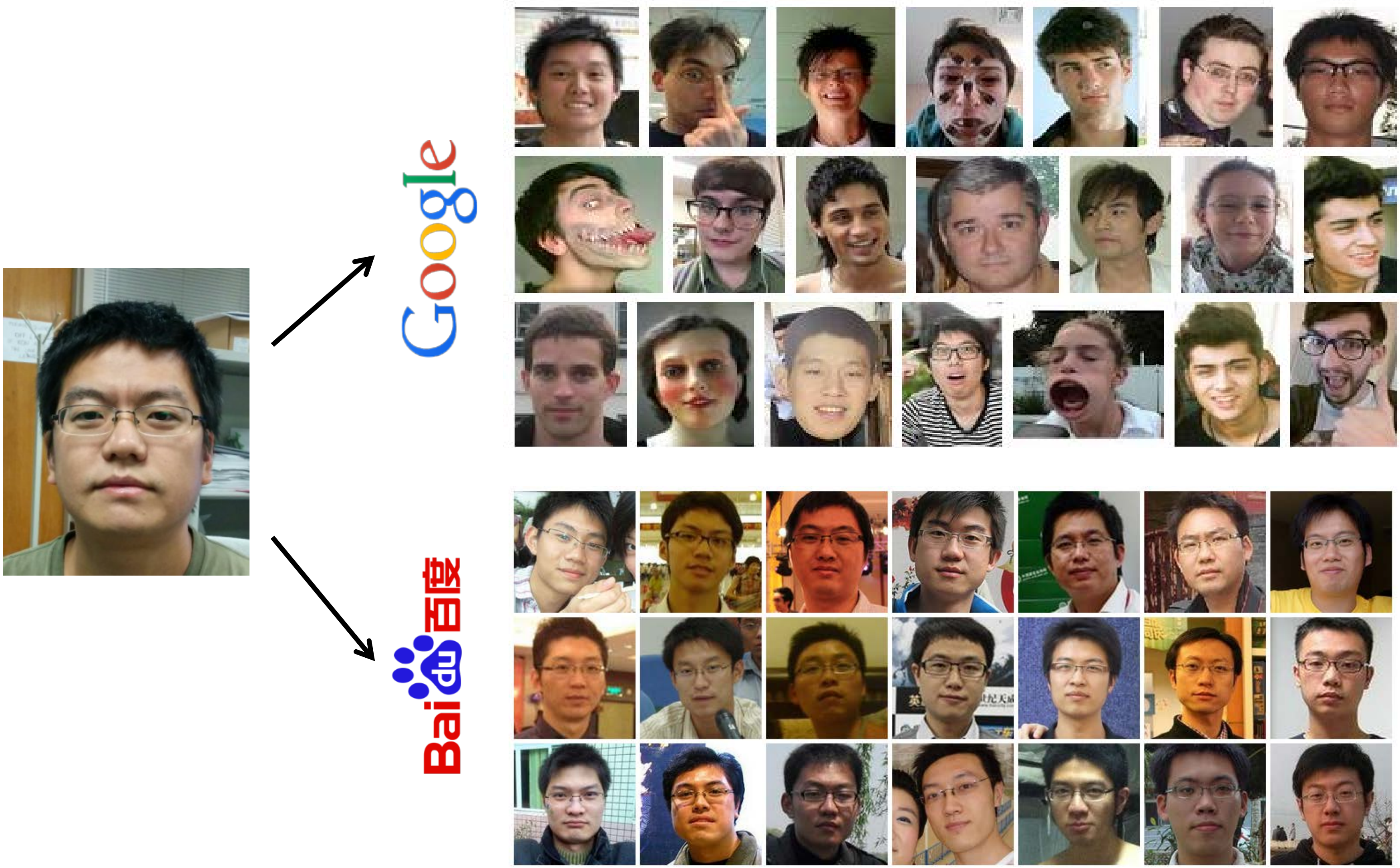


Gallery: 30M DMV photos + 4M mugshot photos

Smile makes a difference!

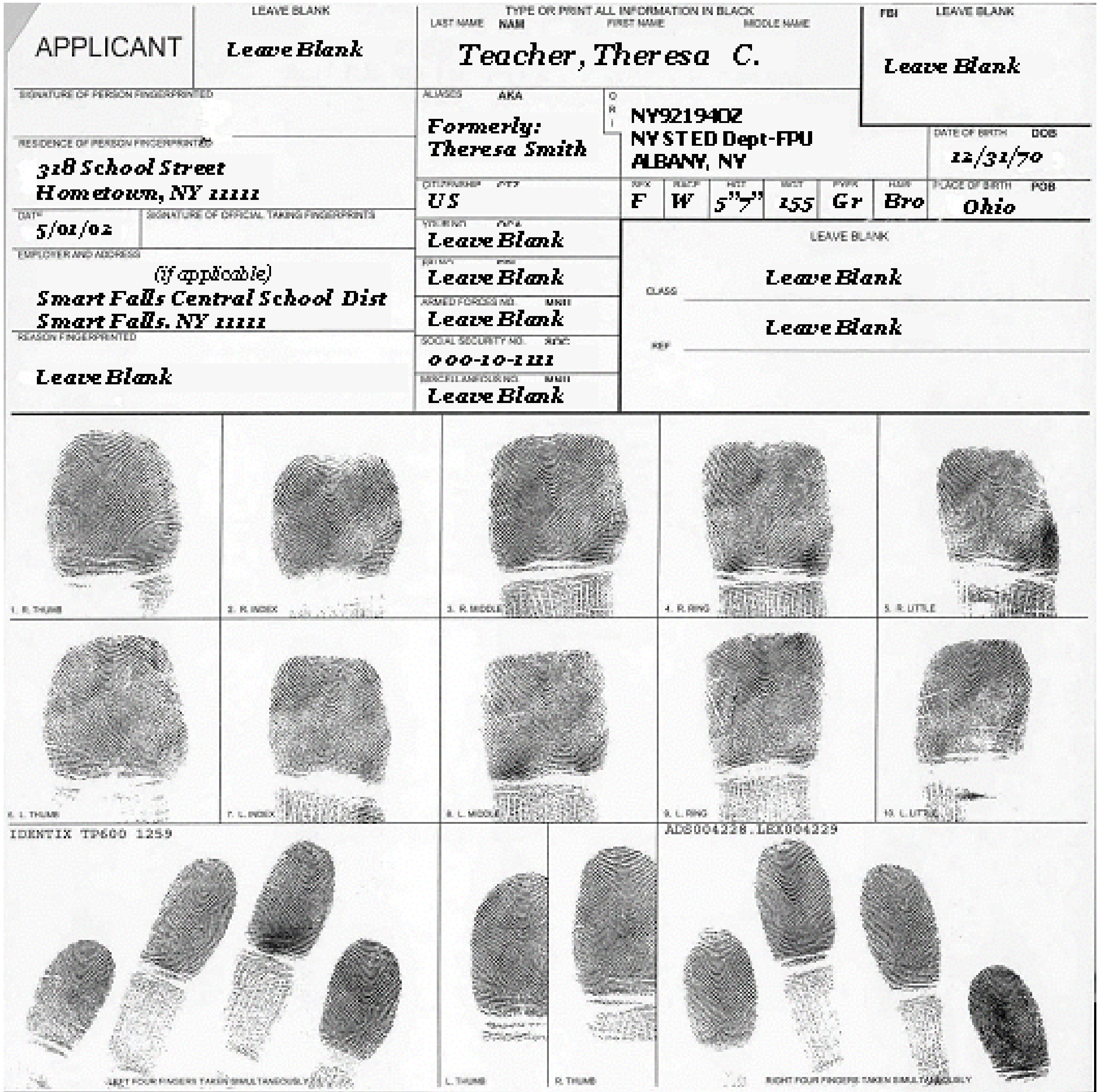
Courtesy: Pete Langenfeld, MSP

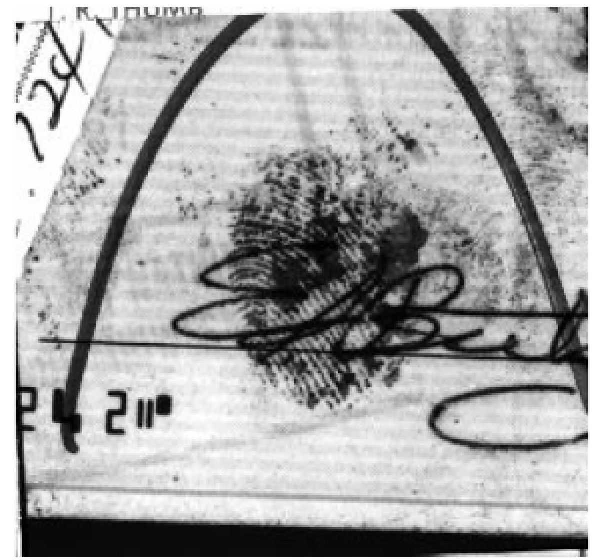
Bias in Automatic Face Search



Fingerprint Matching

Rolled, Plain (Slap) and Latent Fingerprints





Drivers of Fingerprint Technology

- Progress in processor, storage & sensing technology
- Applications beyond forensics
  - National registries (Aadhaar program in India has enrolled 900 million residents; tenprints, 2 irides, face), mobile unlock and payment

Processor & Storage Technology

Michigan AFIS (1989)

Enrollment of 724K subjects; average of 400 tenprint search/day @15K comparisons/sec.

Michigan AFIS (2015)

Enrollment of 4M; 2K tenprint search/day, 35 latent search/day, 5 latent palm search/day @25M comparisons/sec.

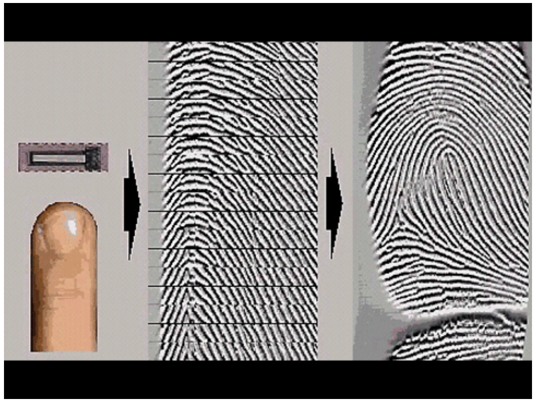
Courtesy, Scott Blanchard, MSP

Fingerprint Readers

Identix
12.5cm x 18cm x 6cm; 1 lb.
Cost: ~$1,500 (1995)

Digital Persona
(Optical)

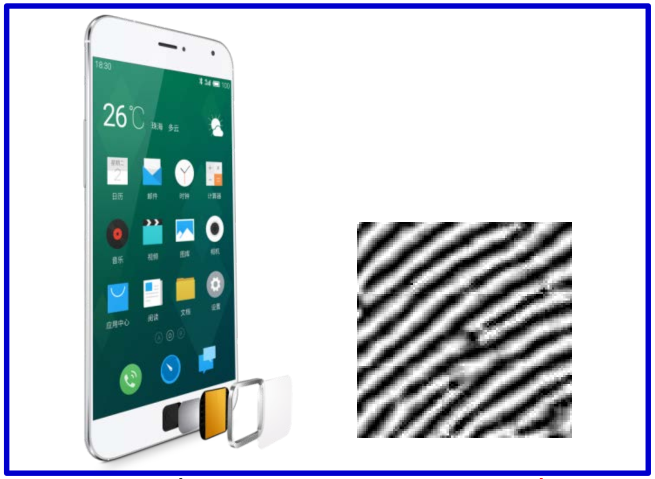
Lumidigm
(Multispectral)



Authentec, Swipe sensor
(Capacitive)

Crossmatch
(Optical)

Morpho “Finger on the Fly”
(Contactless)



Goodix
(Capacitive)

96x96 pixels
(500PPI)

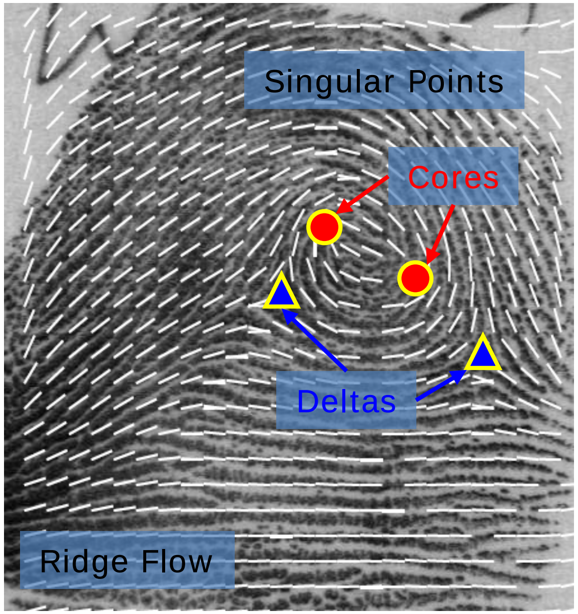
NIST Evaluations

Test	Database & Evaluation	Performance
FpVTE 2003	10K plain fingerprints; 1:1 comparison (Medium scale)	FRR = 0.6% @FAR=0.01%
FpVTE 2012	30K subjects (plain fingerprints) against 100K subjects (plain fingerprints); 1:N comparison (open set)	FNIR=1.9% @FPIR=0.1% (right index finger)
ELFT-EFS 2011	1,114 latent prints against 100K subjects (Rolled + Plain)	Rank-1: 62.2%
ELFT-EFS 2012	1,066 latent prints against 100K subjects (Rolled + Plain)	Rank-1: 67.2%

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

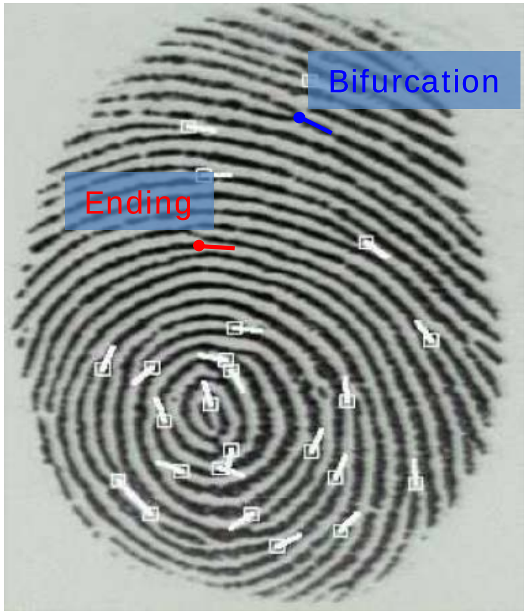
Fingerprint Features

Ridge flow and pattern type



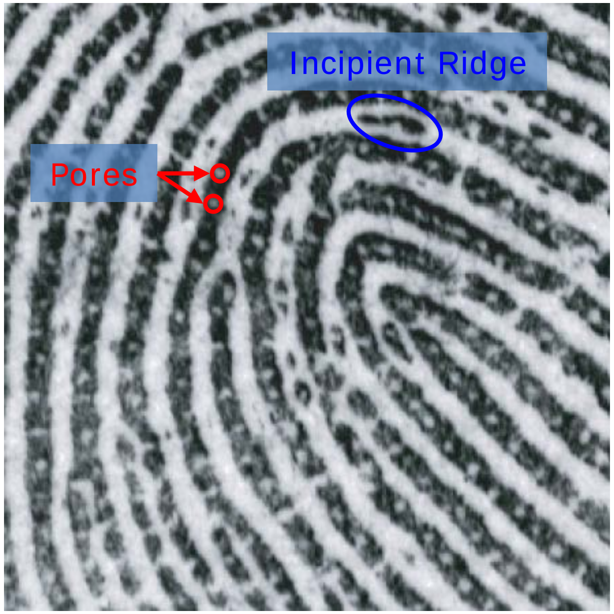
Level-1 Features

Minutiae



Level-2 Features

Pores and incipient ridges

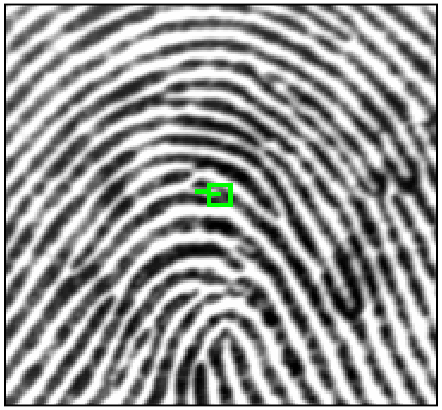


Level-3 Features

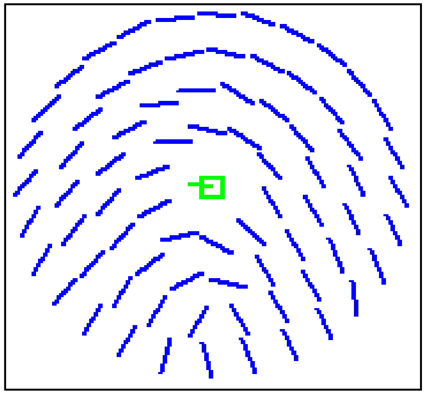
All AFIS use Level-1 and Level-2 features + some proprietary features

Minutiae Descriptor

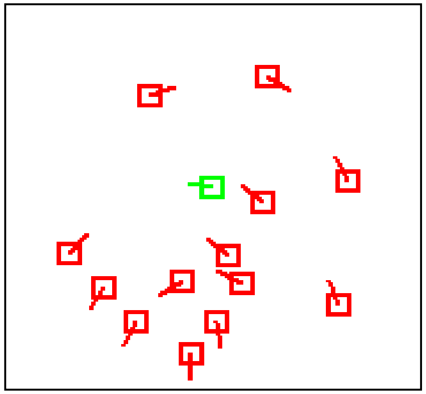
- More than just (x, y, theta)
- Ridge flow-based Descriptor
  - Ridge flow values in the minutiae neighborhood
- Neighboring minutiae-based descriptor
  - Set of minutiae in the neighborhood



Minutia neighborhood

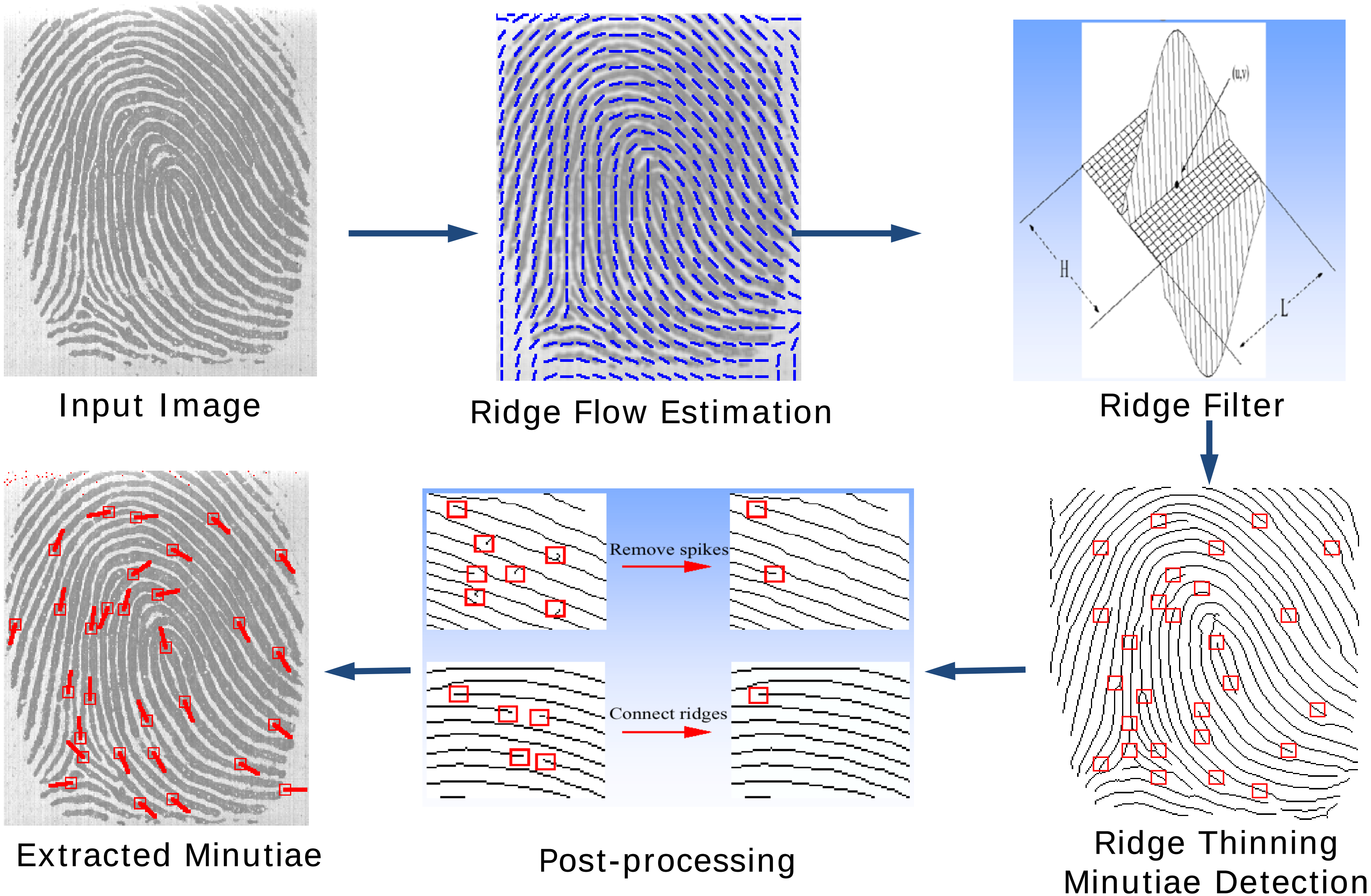


Ridge flow-based descriptor



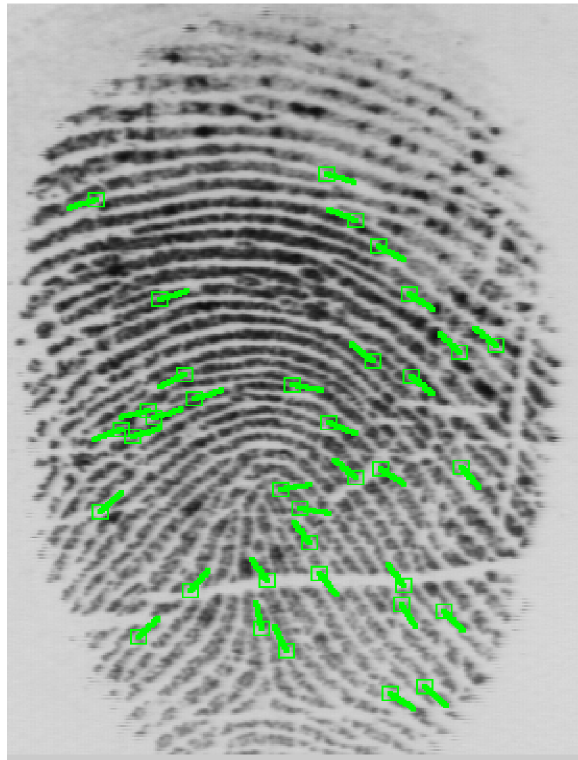
Neighboring minutiae-based descriptor

Automatic Minutiae Extraction

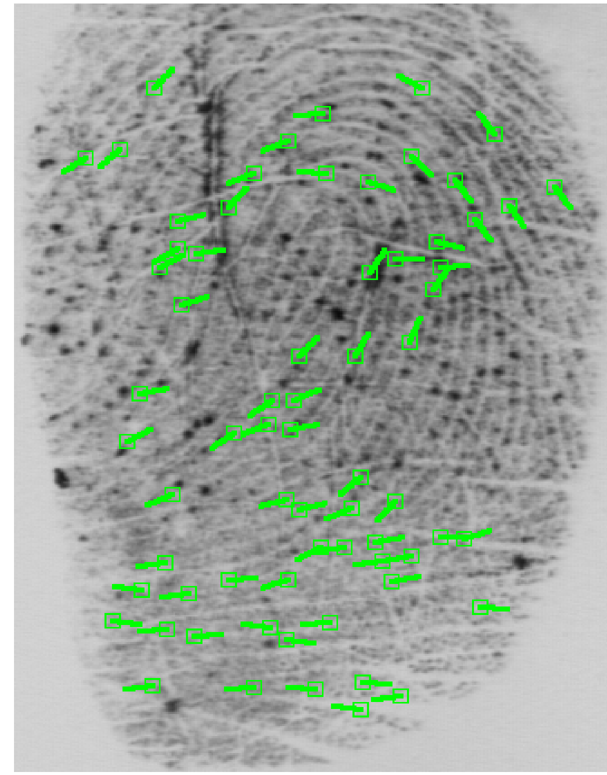


Fingerprint Image Quality

#False Minutiae = 0

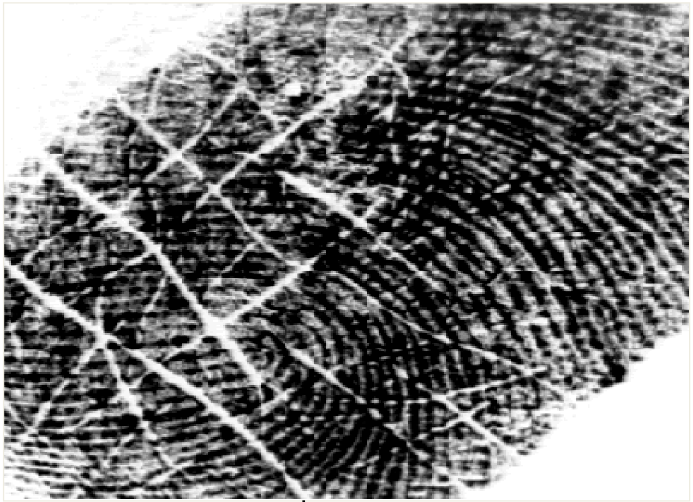


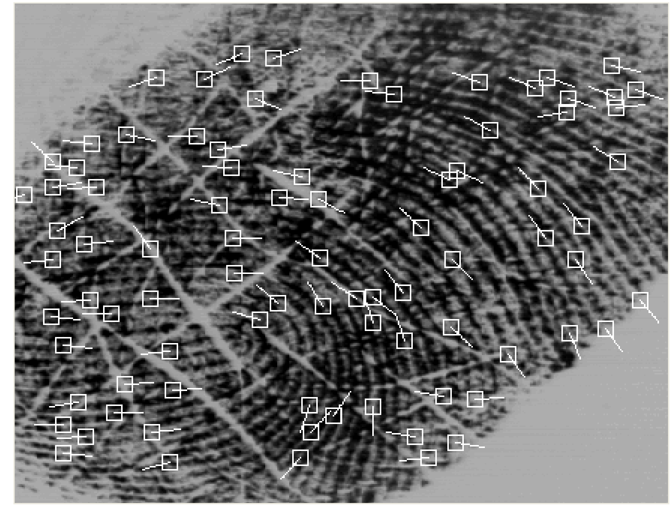
#False Minutiae = 7



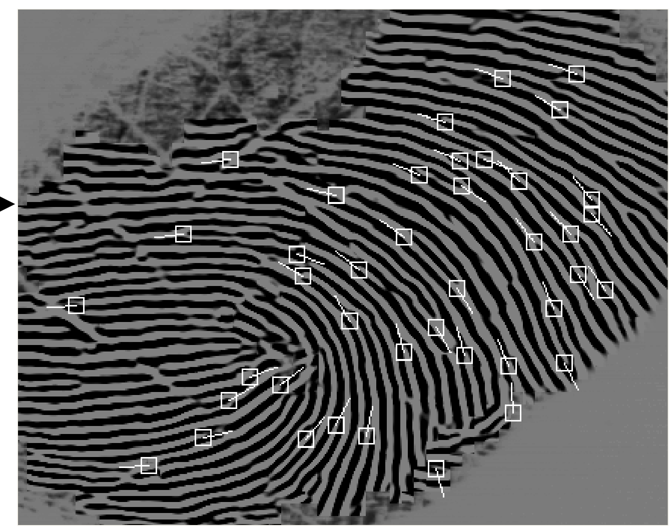
#False Minutiae = 27

Image Enhancement





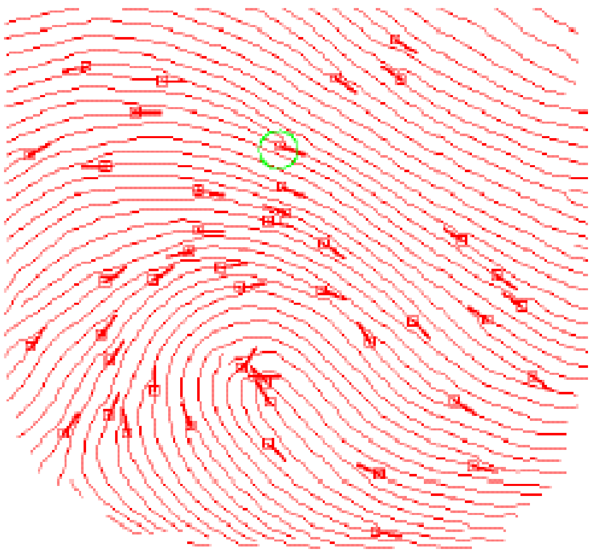
Minutiae extraction before enhancement



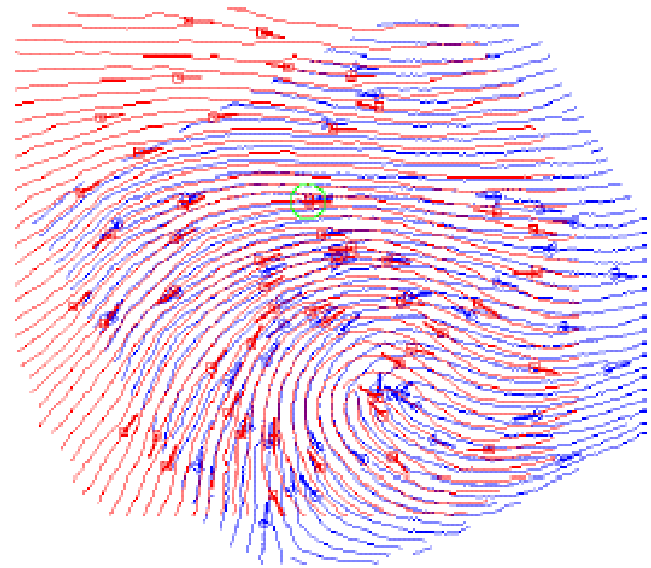
Minutiae extraction after enhancement

L. Hong, A.K. Jain, S. Pankanti and R. Bolle, "Fingerprint Enhancement", *Proc. IEEE Workshop on Applications of Computer Vision*, Dec. 1996

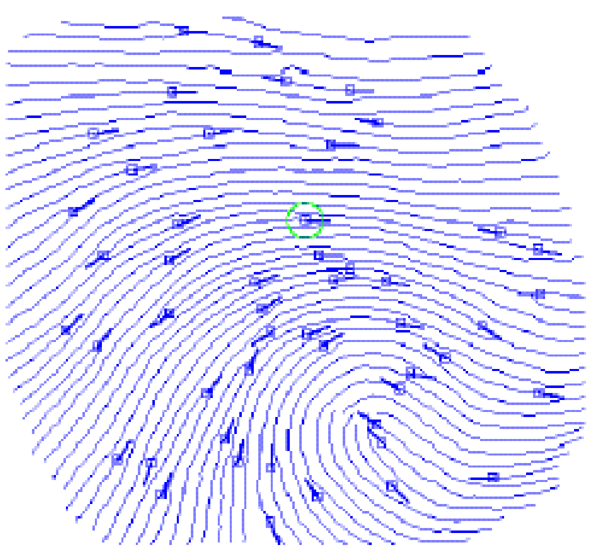
Fingerprint Matching



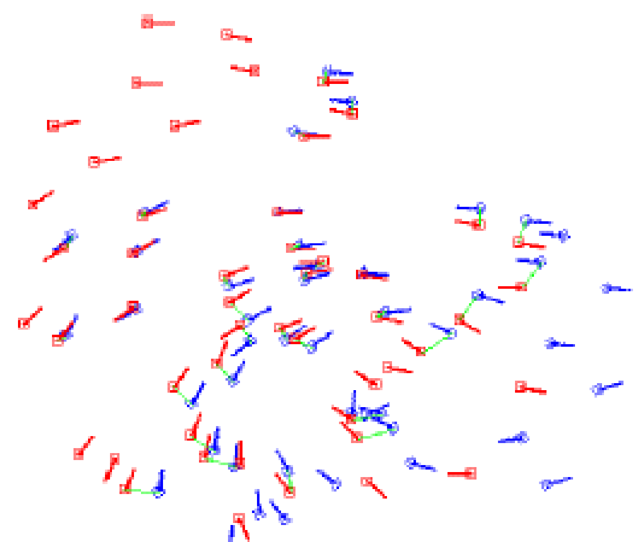
Query



Alignment

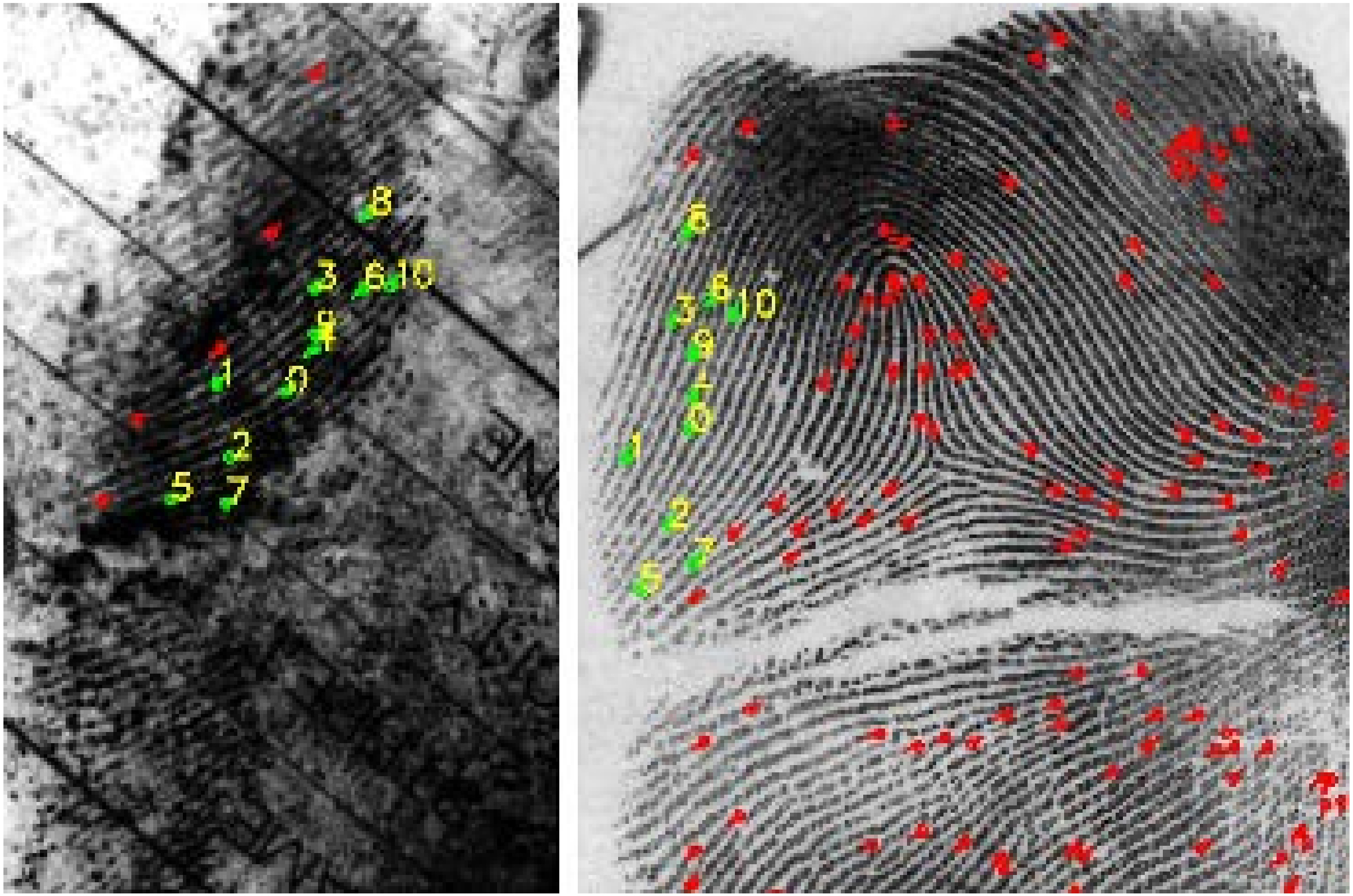


Template



Minutiae correspondence

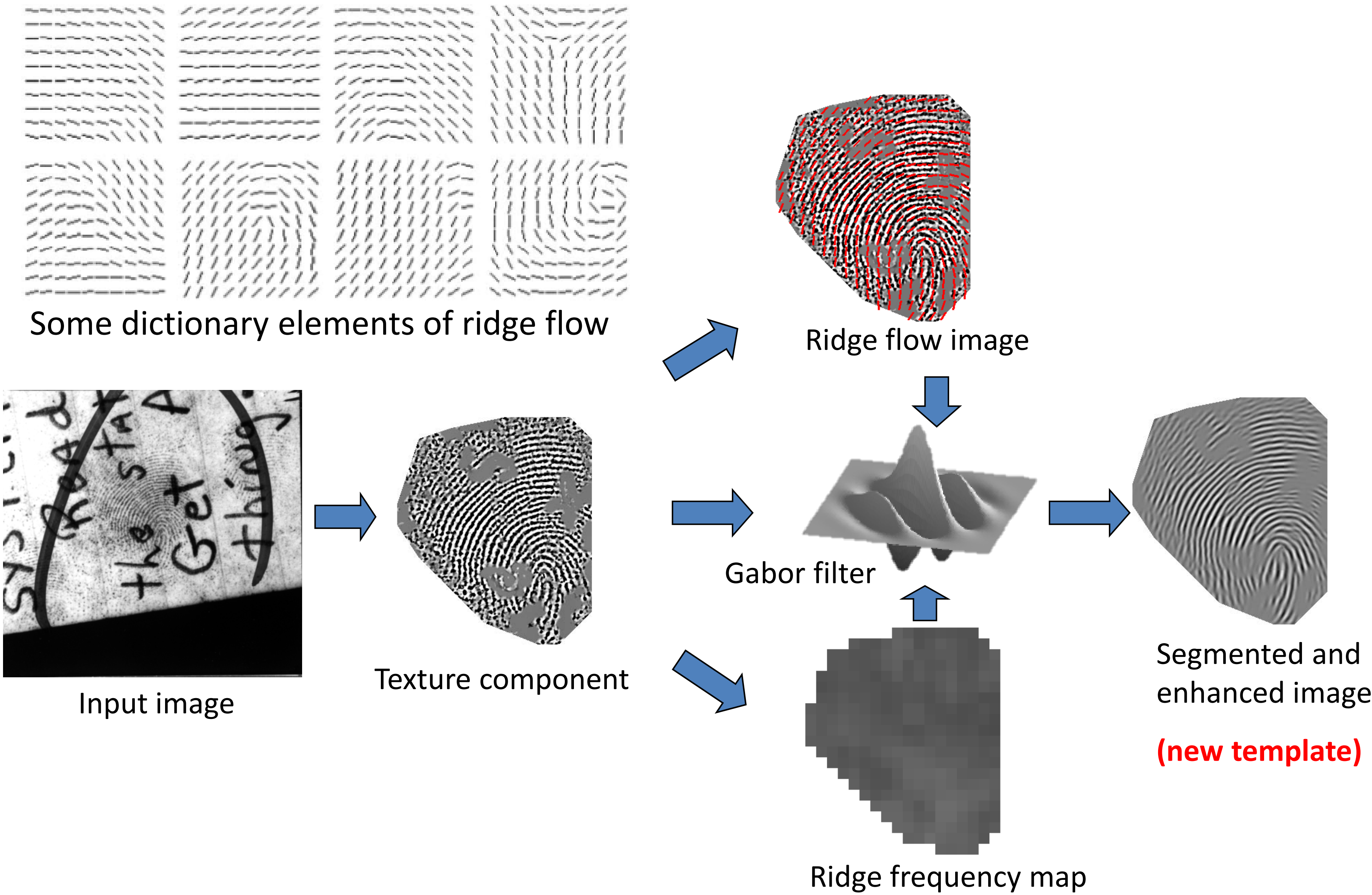
Latent Fingerprint Matching



Same source?

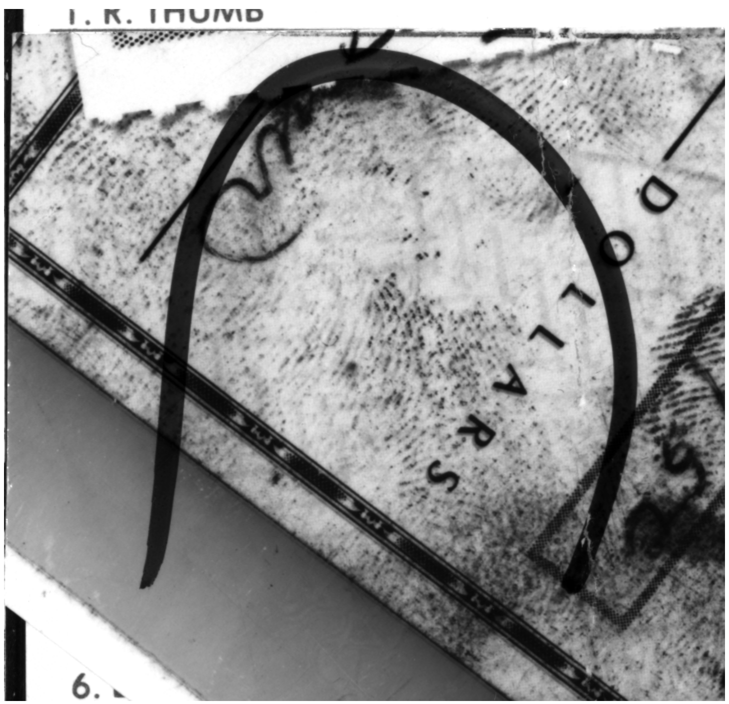
Challenges: Complex background, low ridge/valley contrast, small print area, distortion

Latent Segmentation & Enhancement

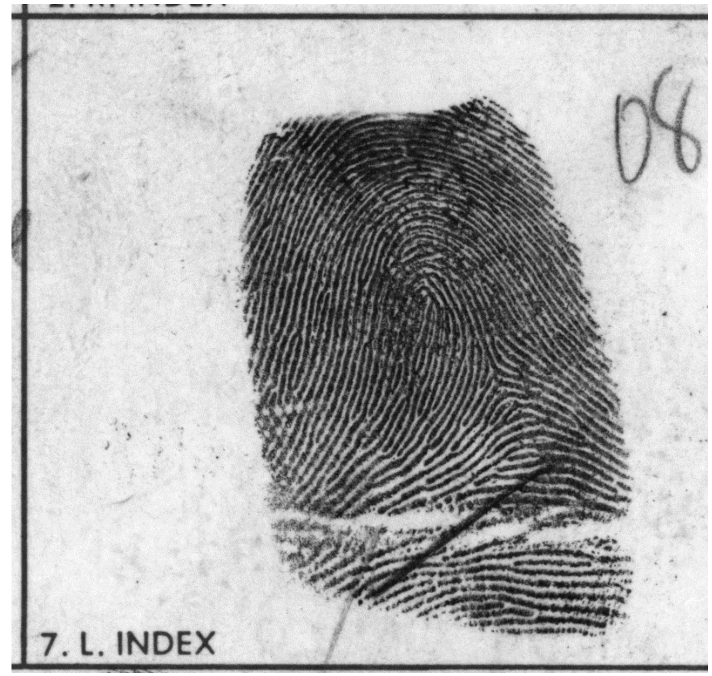


Cao, Liu and Jain, Segmentation and Enhancement of Latent Fingerprints: A Coarse to Fine Ridge Structure Dictionary, IEEE Trans. PAMI, 2014

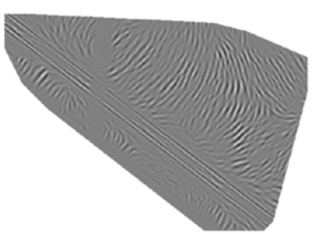
Evaluation on NIST SD 27



Latent (retrieval rank 180)



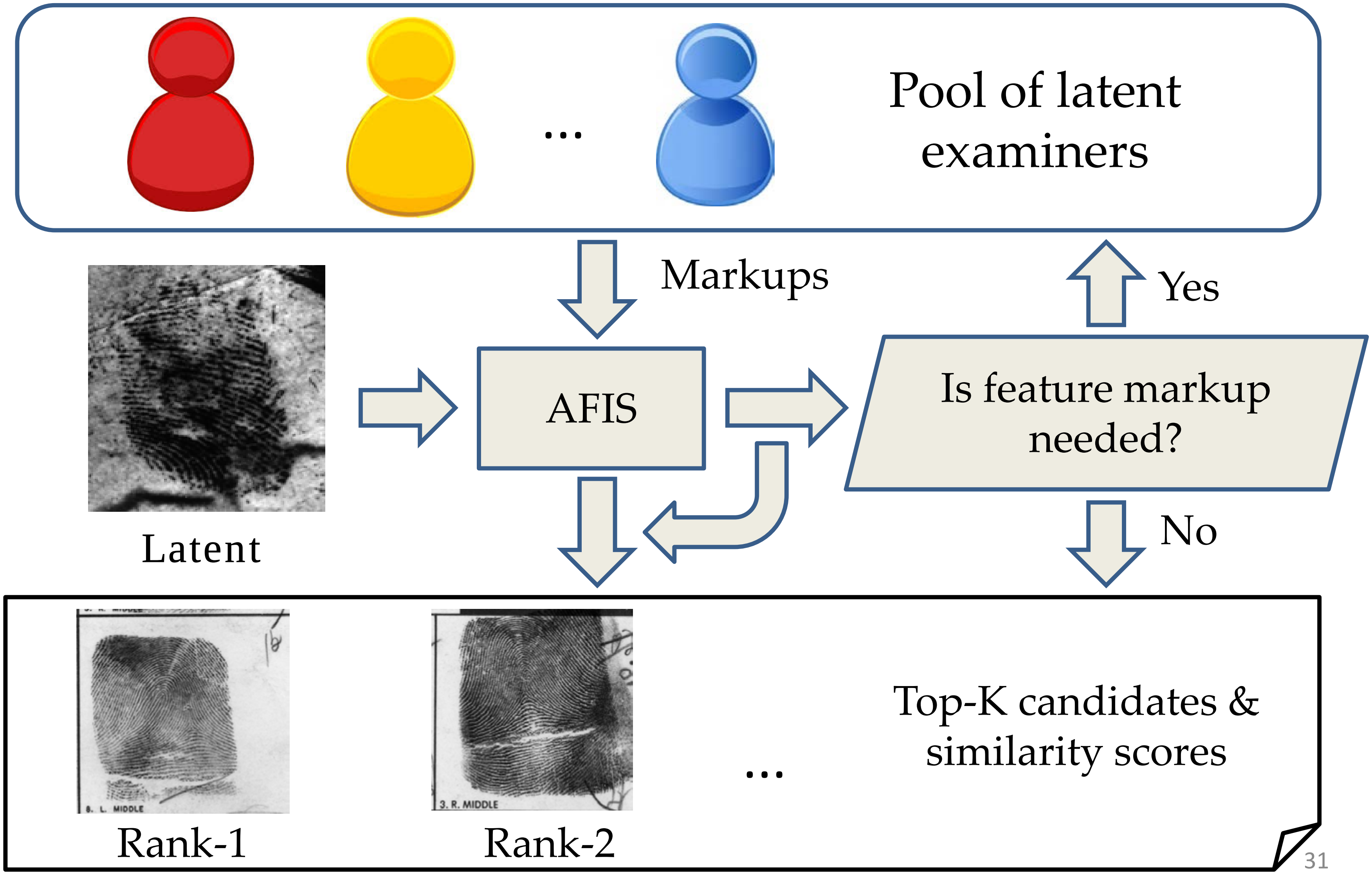
Mate



Preprocessed latent

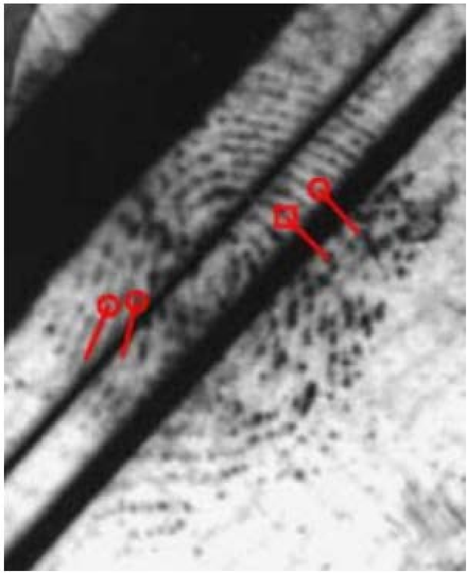
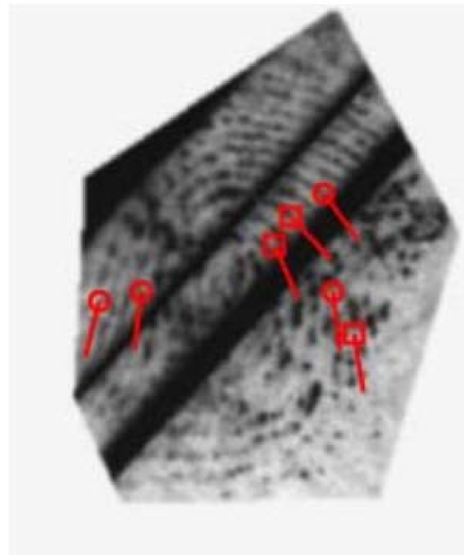
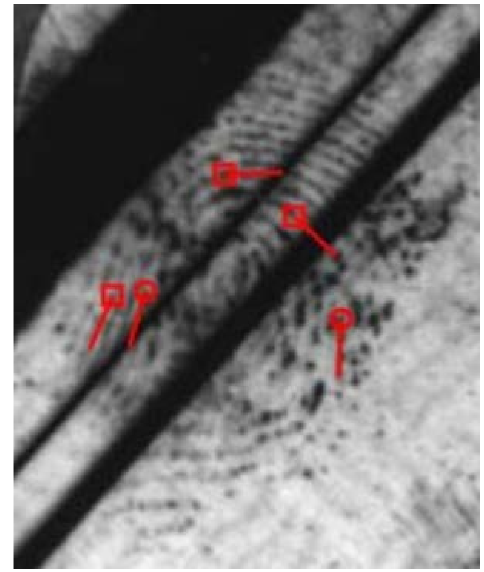
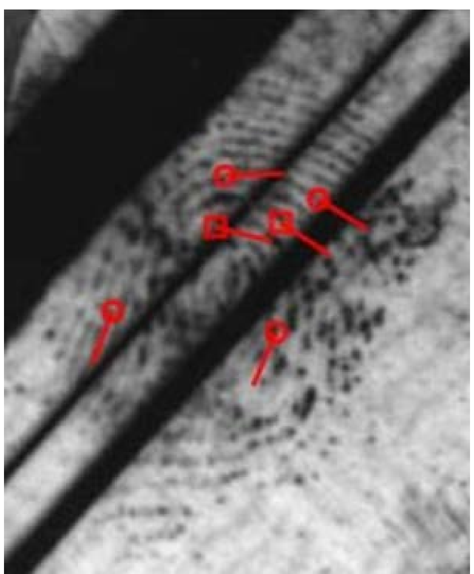
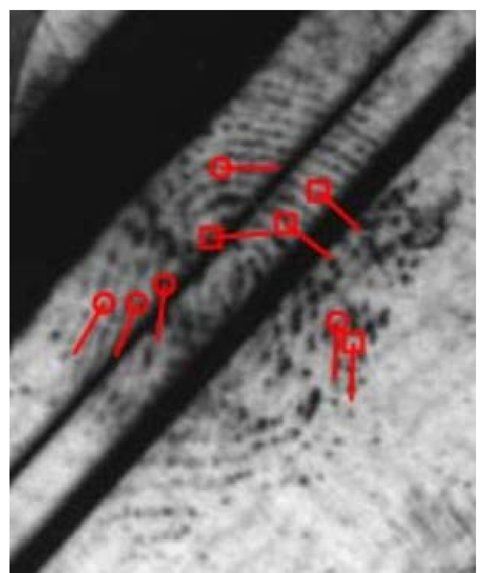
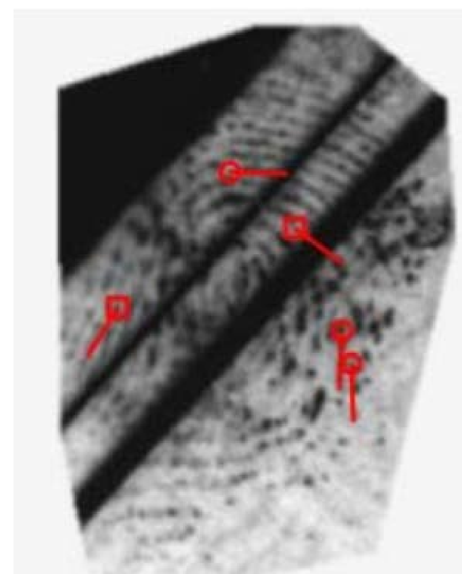
Image + preprocessed latent retrieved the mate at rank 4

Expert Crowdsourcing Framework

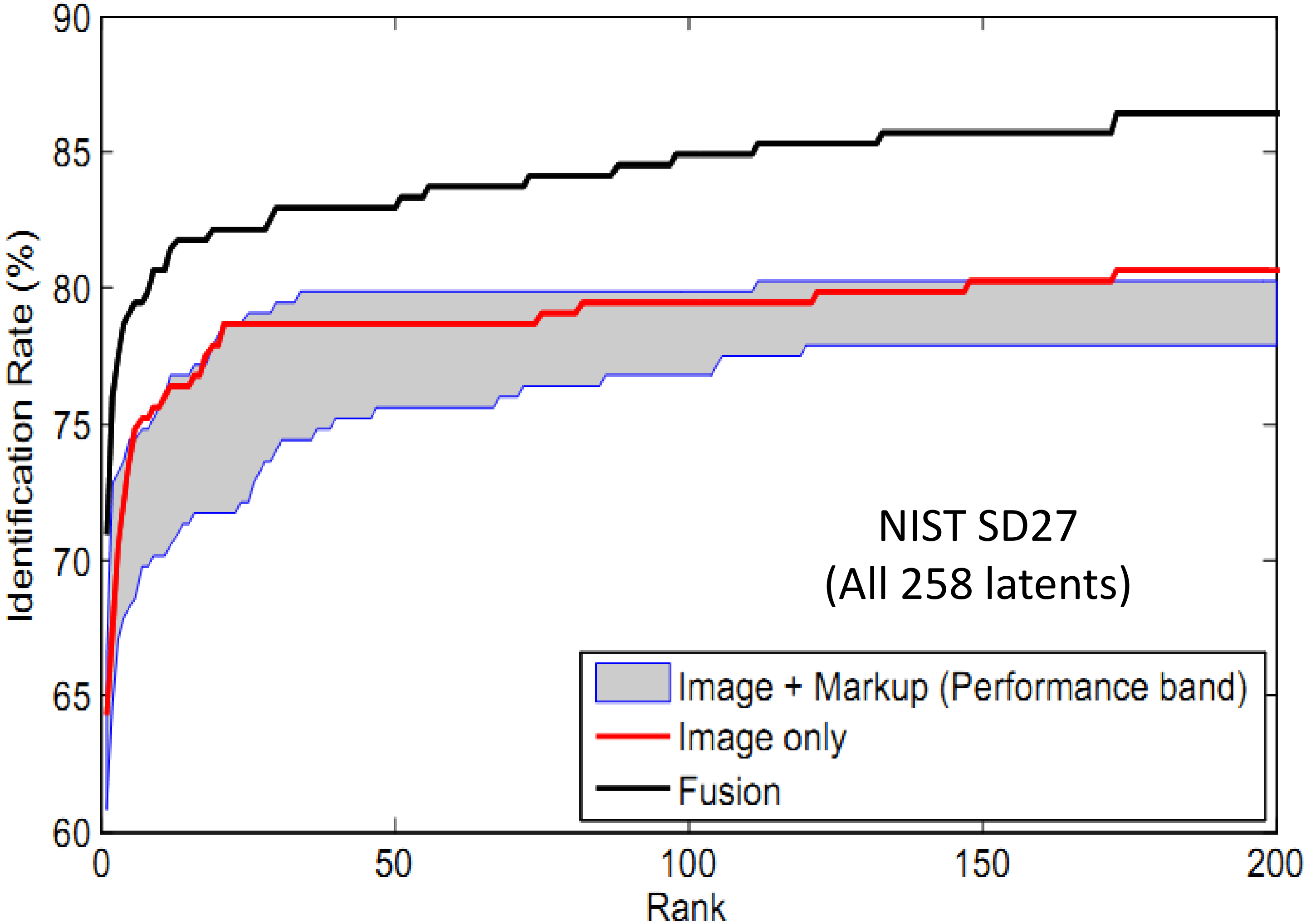


S. S. Arora, K. Cao, A. K. Jain and G. Michaud, "Crowd Powered Latent Fingerprint Identification: Fusing AFIS with Examiner Markups", *ICB*, 2015

Sample Markups by Six Examiners

Crowdsourcing Improves Performance



Improvements in Rank-1 hit rate: 8% (all latents), 2% (good), 8% (bad), 12% (ugly)

Automatic Face Recognition

Drivers of Face Recognition Technology

Cameras everywhere (surveillance to mobile phones), de-duplication

Information in a Face

Identity: ABC

Age: ~ 40

Gender: Male

Ethnicity: White

Hair: Short, Brown

Moustache: Yes

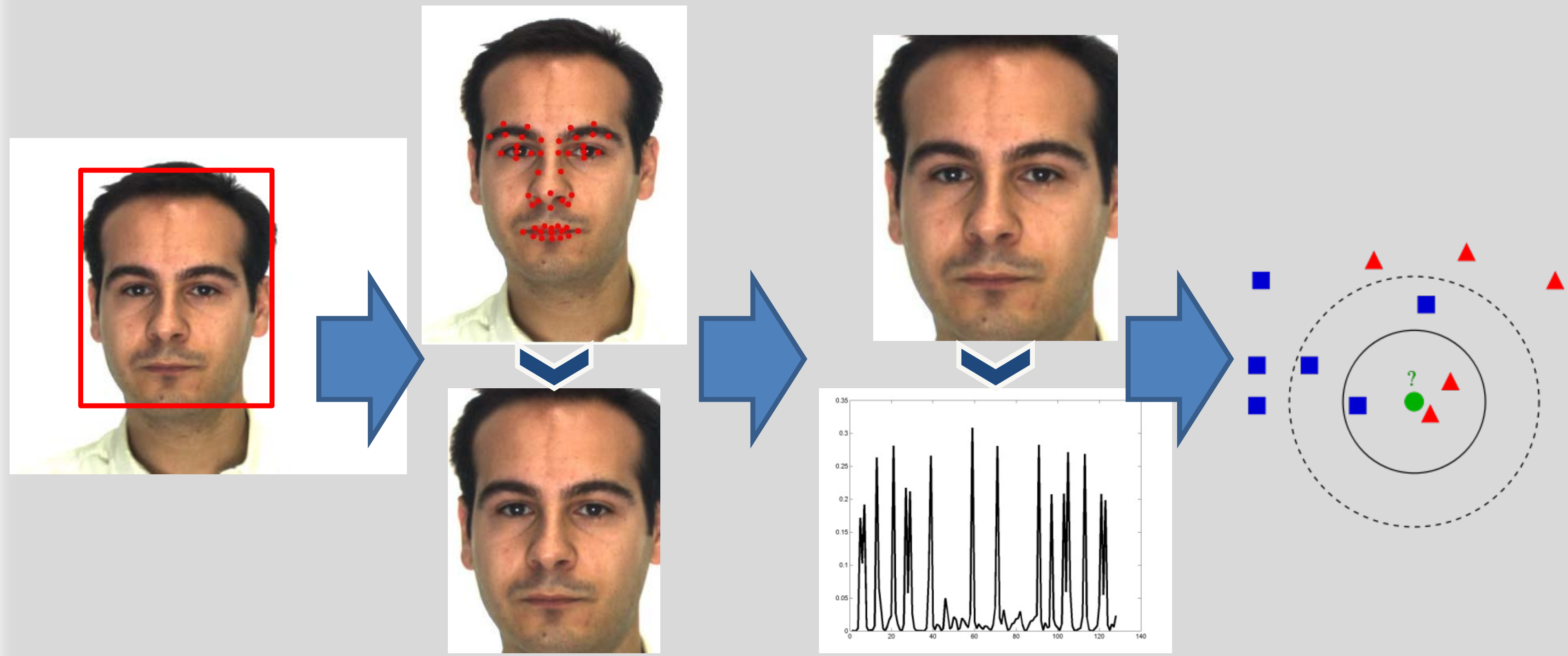
Beard: Yes

Mole: Yes

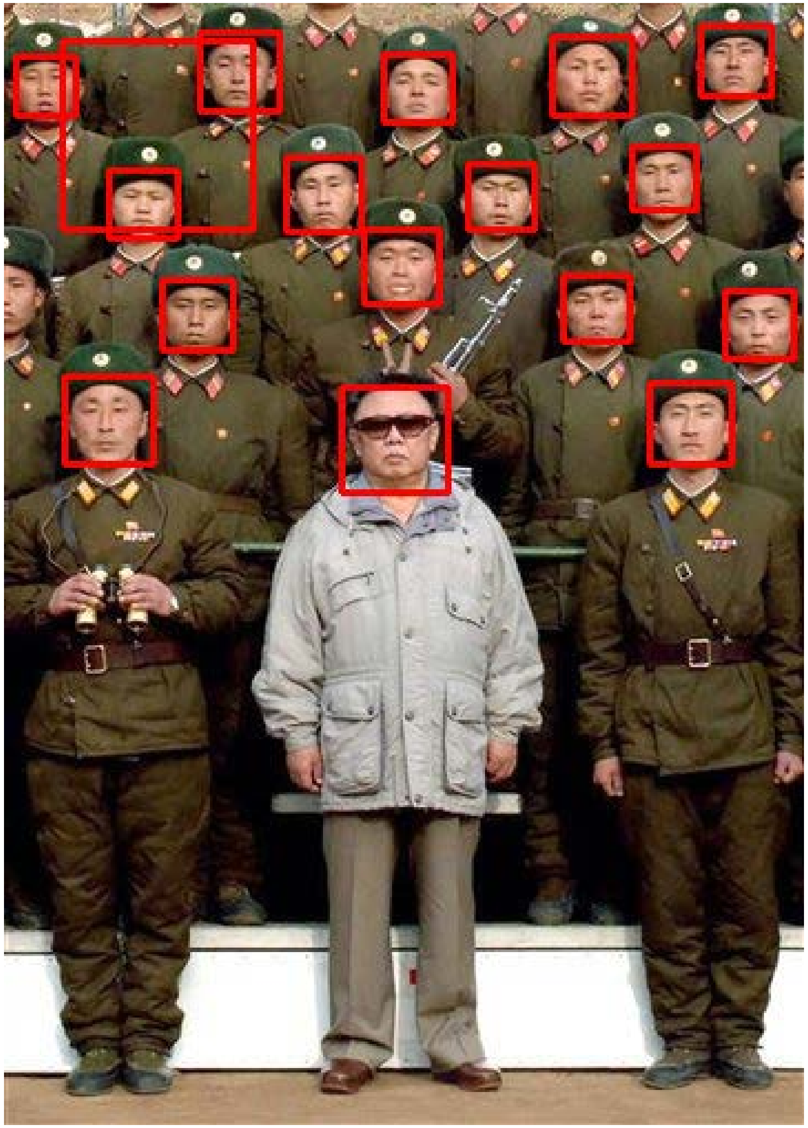
Scar: Yes

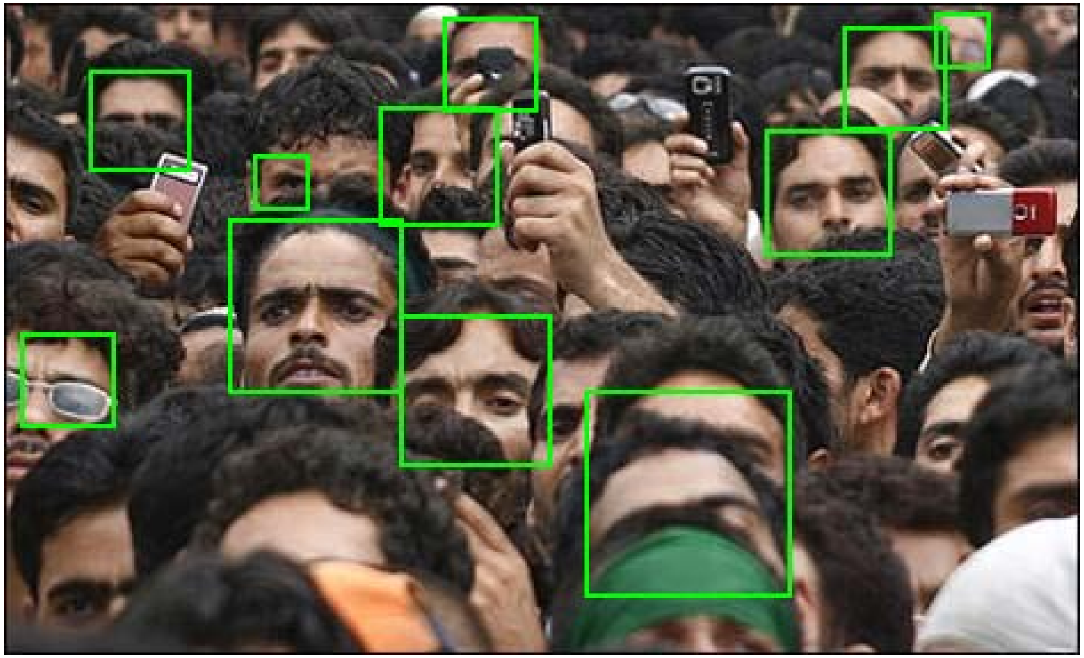
Other attributes: expression, emotion

Automated Face Recognition



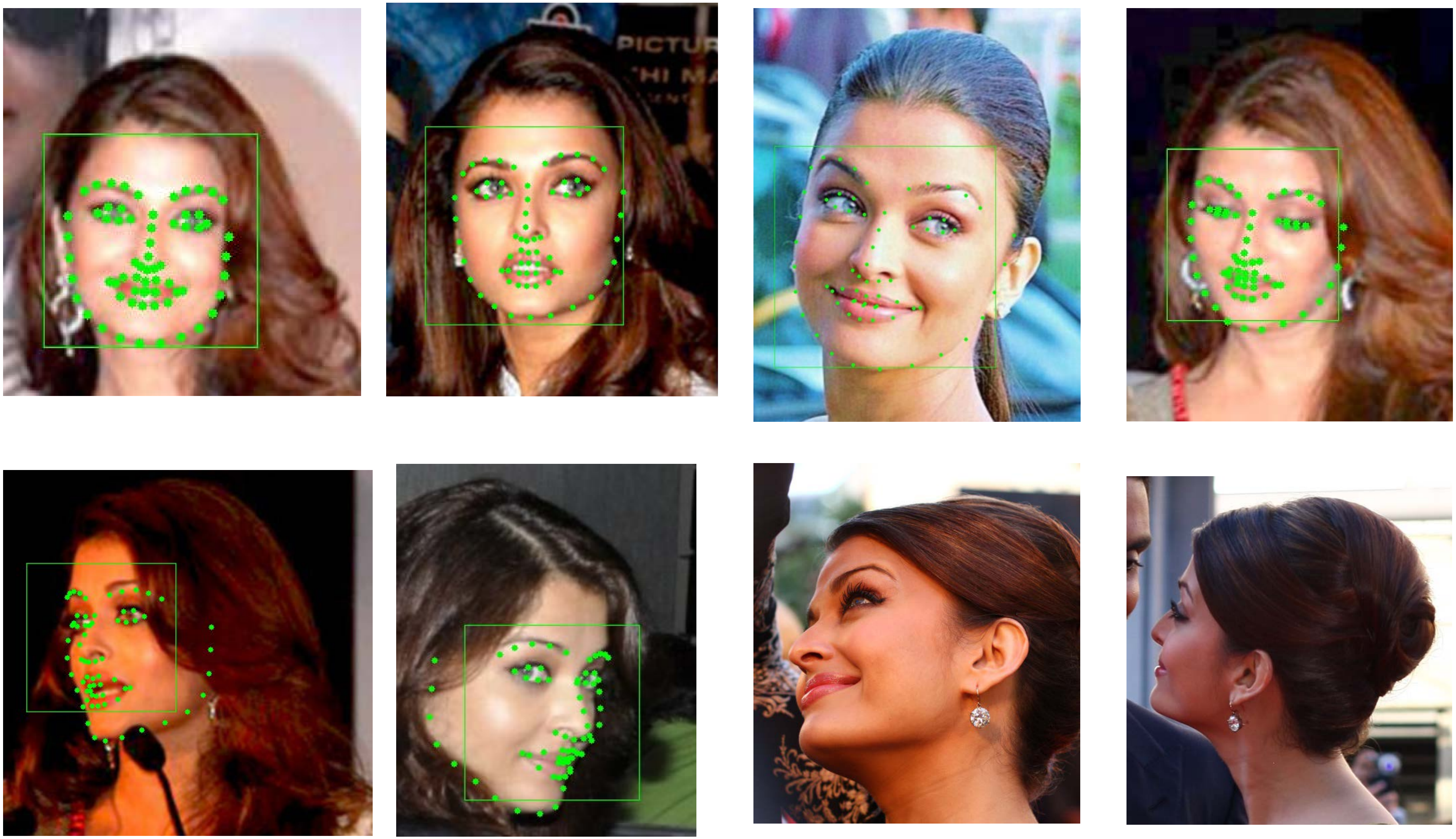
Face Detection





Two-class classification: face v. non-face

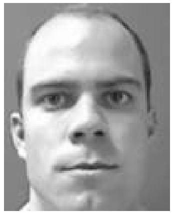
Facial Landmark Extraction



Images of one subject in NIST IJB-A data, overlaid with V-J detector & dlib landmarks

Face Representation: Holistic

Input face



EigenFaces
(PCA)

...

56.4 38.6 -19.7 9.8 -45.9 19.6 -21.4 14.2

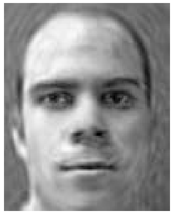
Fisherfaces
(LDA)

...

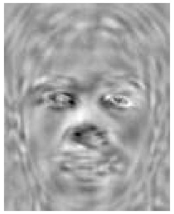
18.3 35.6 -17.5 -27.6 60.6 -20.8 41.9 -9.6

Reconstructed face

PCA



LDA

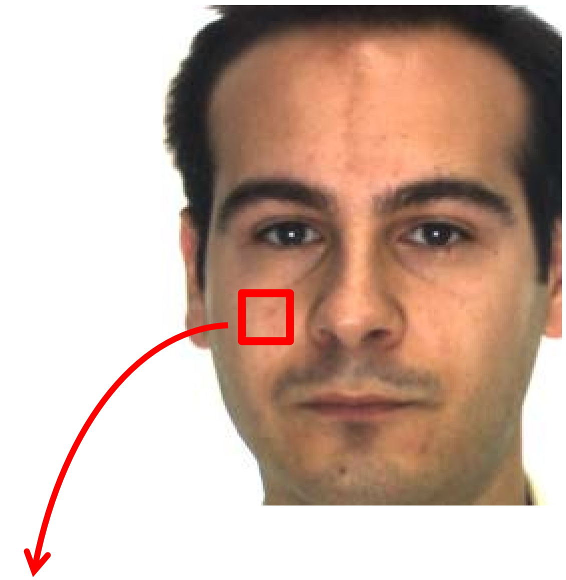


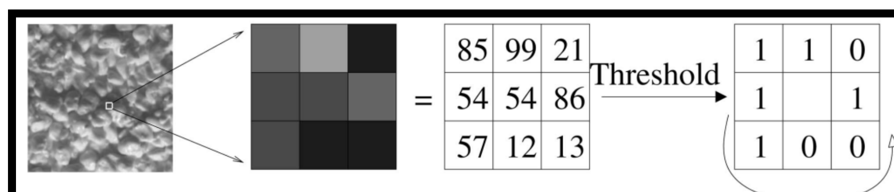
Minimize reconstruction error

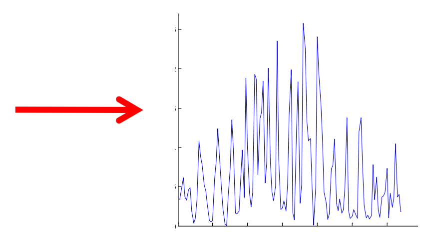
Maximize between-class to within-class scatter

Face Representation: Local

- Local Binary Patterns (LBP)
  - Represent a local region as distribution of LBP features
    - normalized histogram
  - Improved accuracy over appearance-based methods
- Multi-resolution LBP (MLBP)

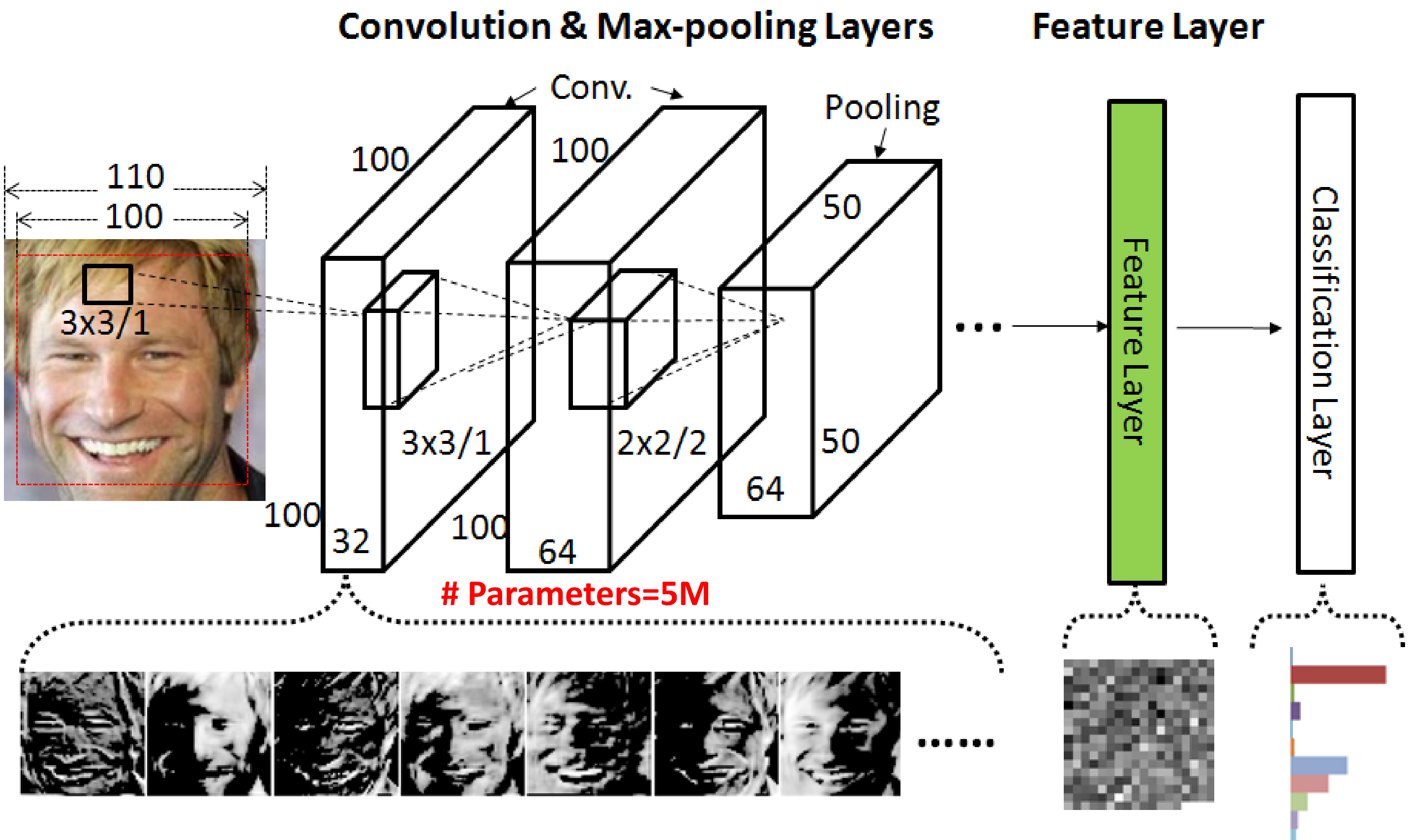






Histogram of LBP feature values

Convolutional Neural (Deep) Network



Input Image

Preprocess input faces

Convolutional Layers and Pooling layers

Training deep network

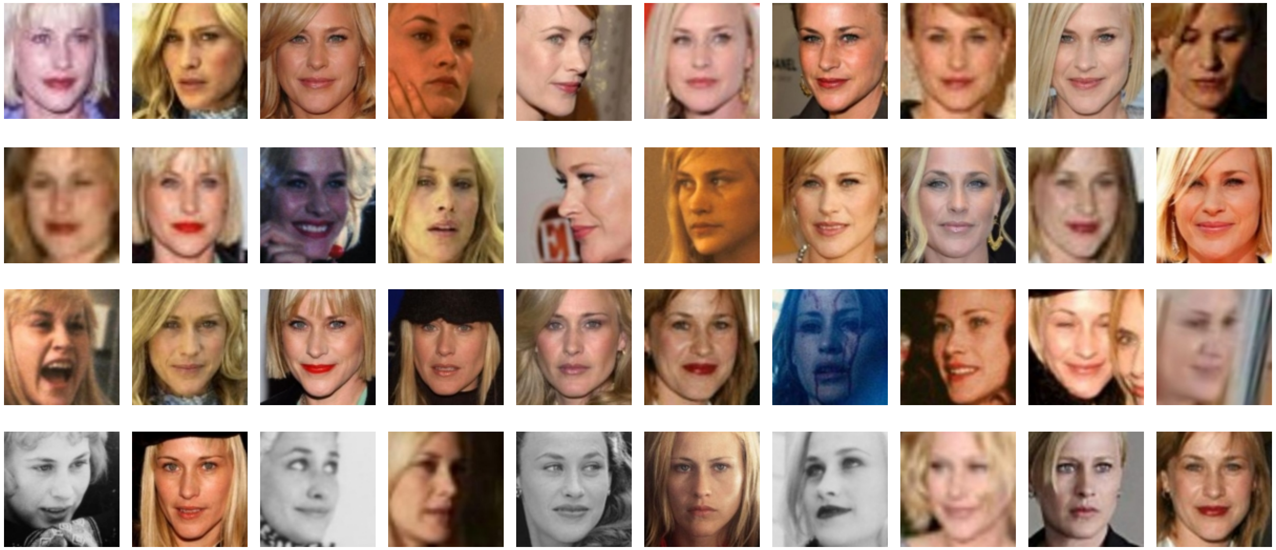
Feature representation

Learned deep features

Deep Network Training

- Deep ConvNet is trained with CASIA-Webface dataset
  - Original 494, 414 images of 10,575 subjects; landmarks could be detected in only 435,689 images of 10,575 subjects (88% of images)
  - Average: 38 images/subject
- Preprocessing: face and landmark detection
  - Align face images using the centers of eyes and mouth

Different subjects (#subjects = 10,575)



Multiple images of the same subject, # image = 247

State of the Art: Verification

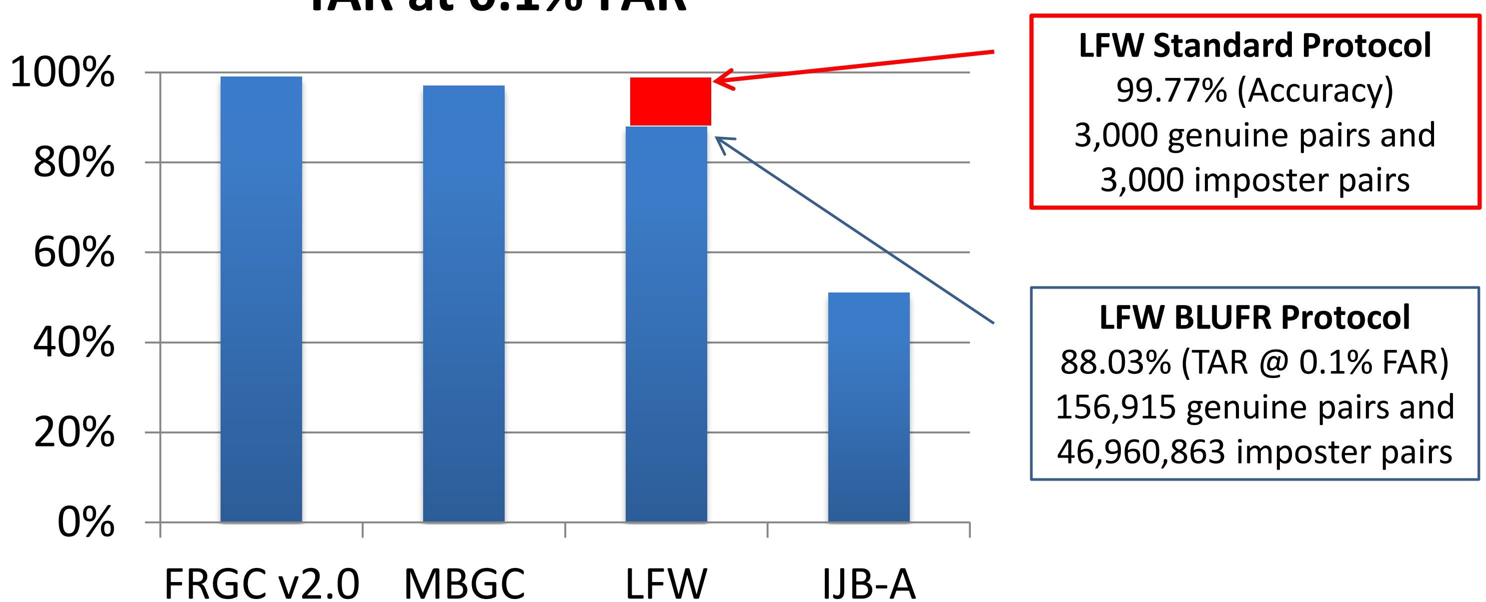
FRGC v2.0 (2006)

MBGC (2010)

LFW (2007)

IJB-A (2015)

TAR at 0.1% FAR

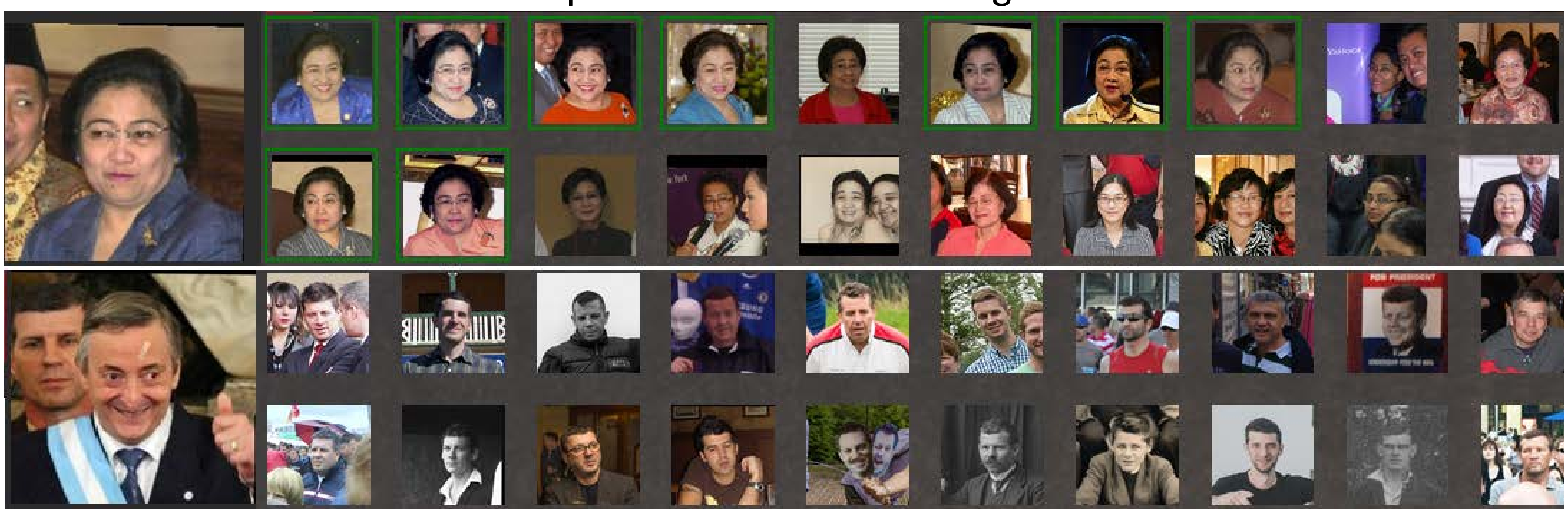


D. Wang, C. Otto and A. K. Jain, "Face Search at Scale: 80 Million Gallery", arXiv, July 28, 2015

Close/Open Set Face Identification

	PCSO (mugshots)			LFW (web)			IJB-A (web)		
Closed set (CMC @ Rank 1)	0.864			0.602			0.676		
Closed set (CMC @ Rank 10)	0.989			0.786			0.764		
Open set (FNIR @ 0.1 FPIR)	0.211			0.412			0.278		
Open set (FNIR @ 0.01 FPIR)	0.333			0.645			0.414		
Experimental Setting: Gallery size, # genuine queries, # imposter queries	1M	3K	7K	80M	3.3K	4K	80M	11K	4K

Two examples of face retrieval using LFW Dataset



Ballistic Image Matching

Firearm Crime Statistics

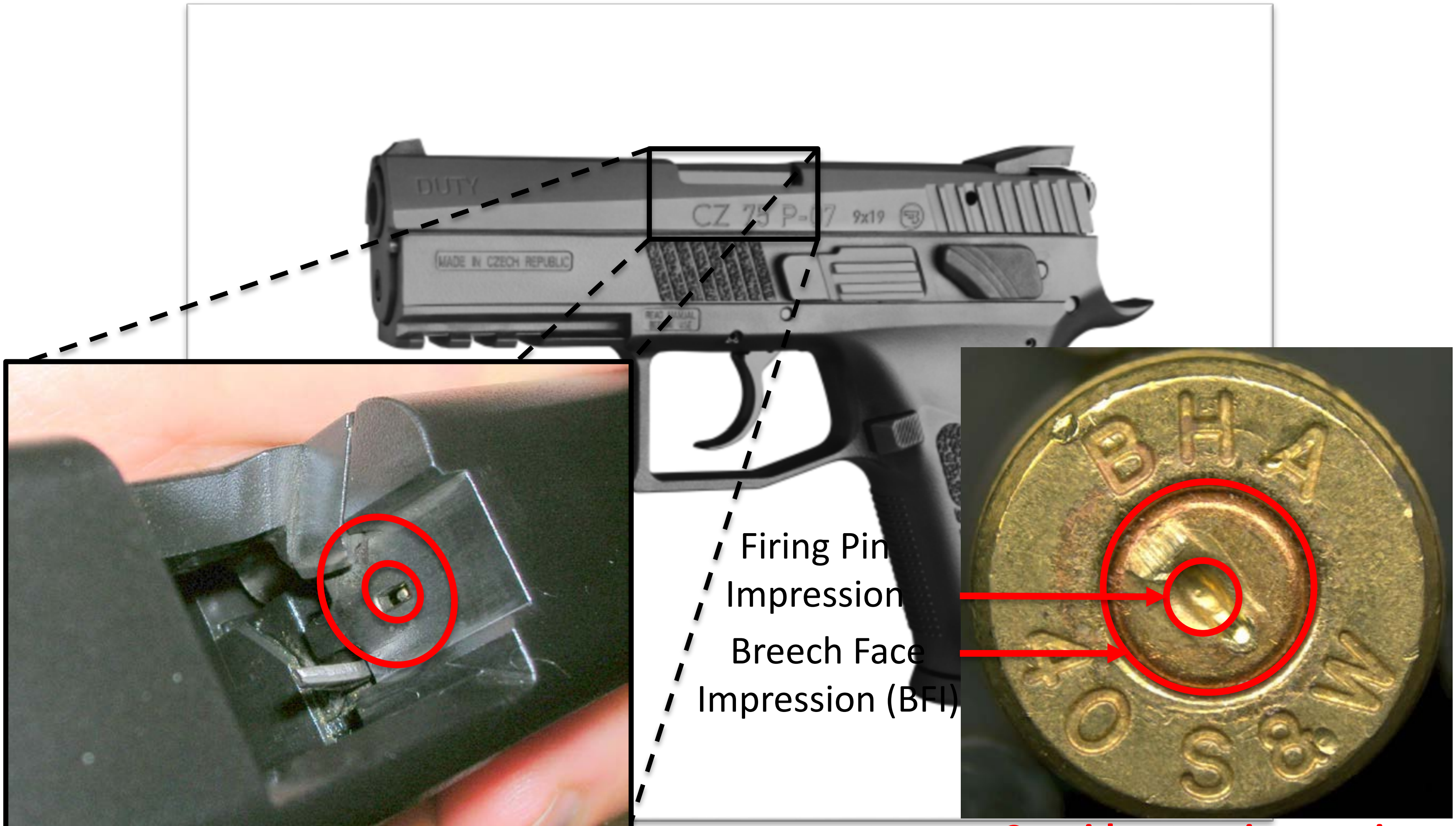
- 500,000 firearms related crimes/year
- 1,000+ examination cases per month at Michigan State Forensics Lab
- Firearms in court:
  - Colorado theater shooting http://news.yahoo.com/judge-colorado-theater-massacre-case-allows-ballistics-evidence-220343397.html
  - Missouri conviction overturned http://www.stltoday.com/news/local/crime-and-courts/missouri-judge-throws-out-ballistic-evidence-in-murder-case/article_b7cdf420-a792-515d-9a02-3deeb6a6881d.html
- Manual comparison is tedious, subjective and time-consuming (~2 hours)

M. Planty and J. Truman. Firearm violence, 1993-2011. Technical Report NCF 241730, U.S Department of Justice, May 2013

Firearm Overview

Striations on the bullet

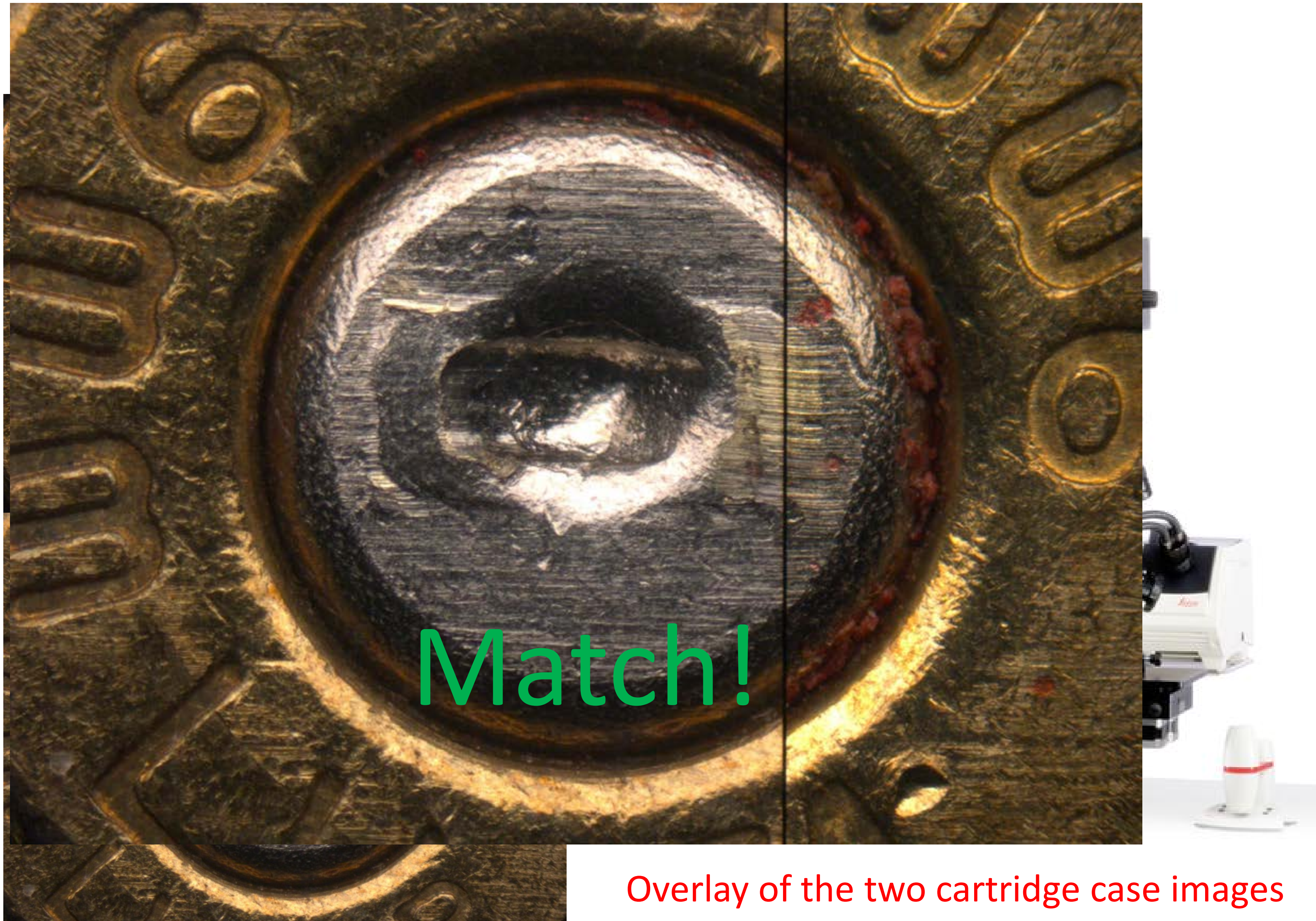
Firearm Overview



Cartridge case impressions

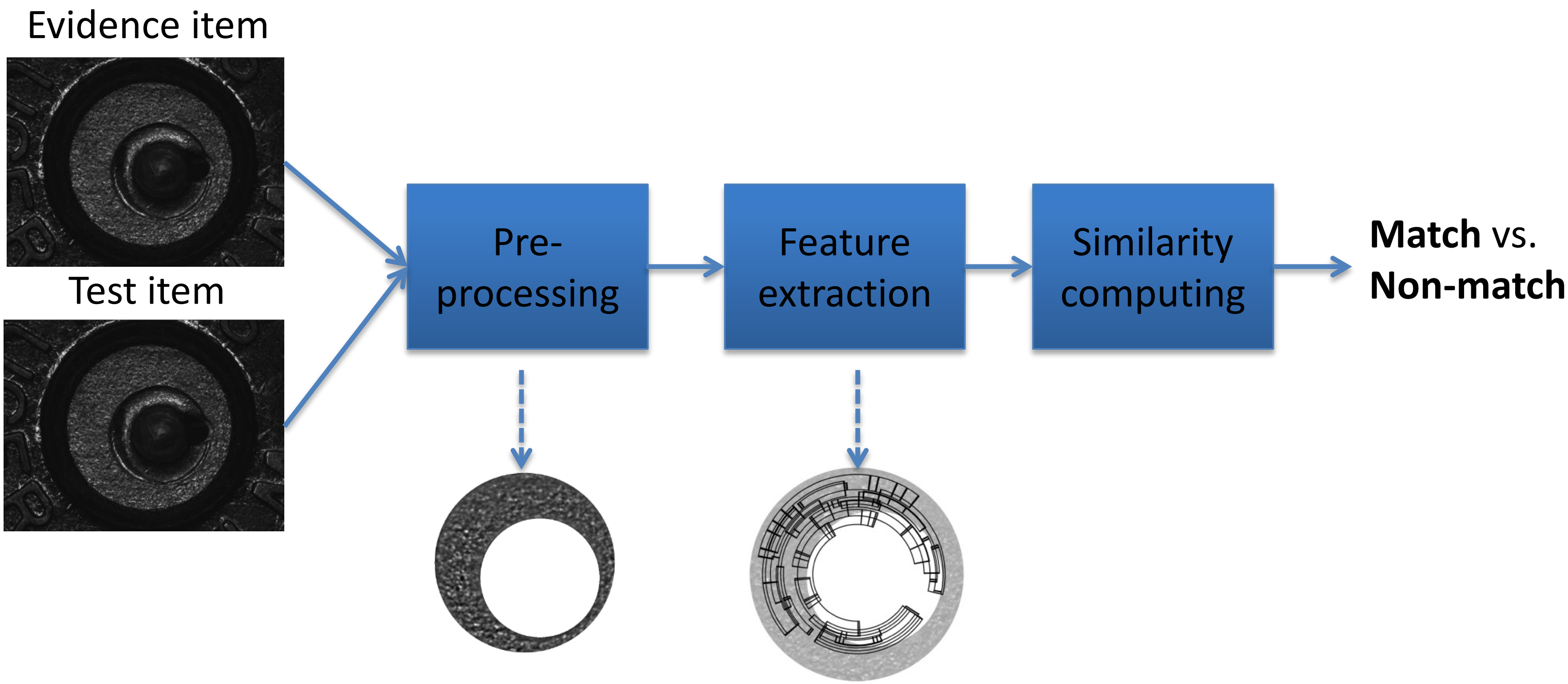
Current Practice: Manual Comparison

Compare evidence cartridge case with a test cartridge case



Overlay of the two cartridge case images

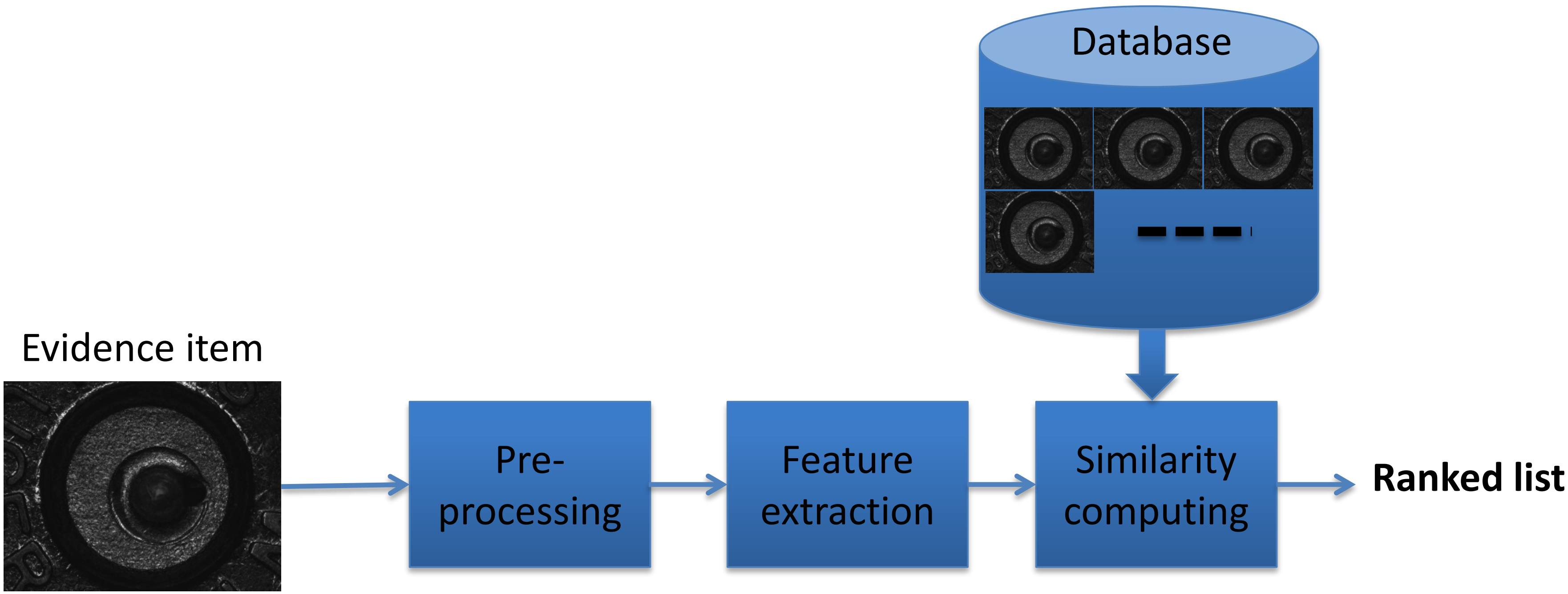
Automated System for Breach Face Impression Comparison



Learning: Which features (appearance, texture) and what similarity measure?

J. Roth, A. Carriveau, X. Liu and A. K. Jain, "Learning-based Ballistic Breech Face Impression Image Matching", IEEE *BTAS*, Arlington, Virginia, September 8-11, 2015

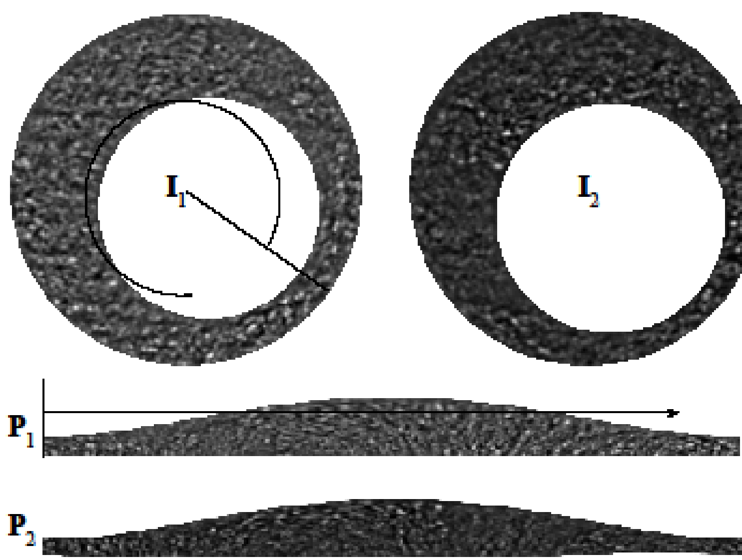
Automated System for Breach Face Impression Search

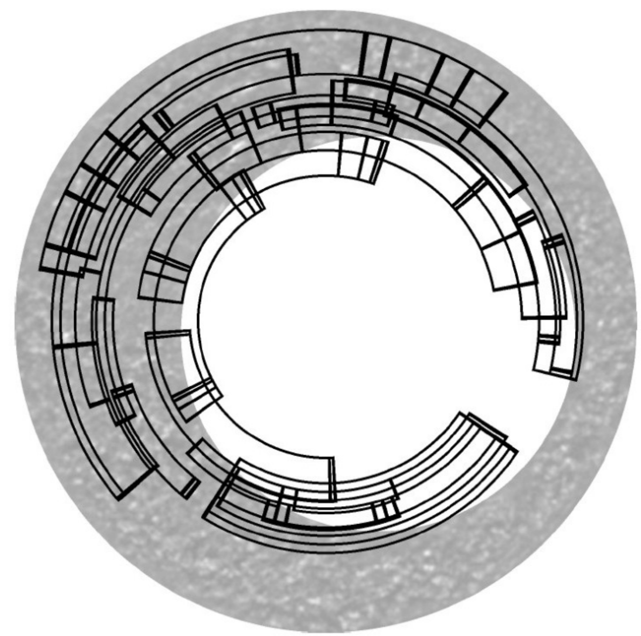


Learning: which features to select and what similarity measure?

Ballistics Pattern Matching

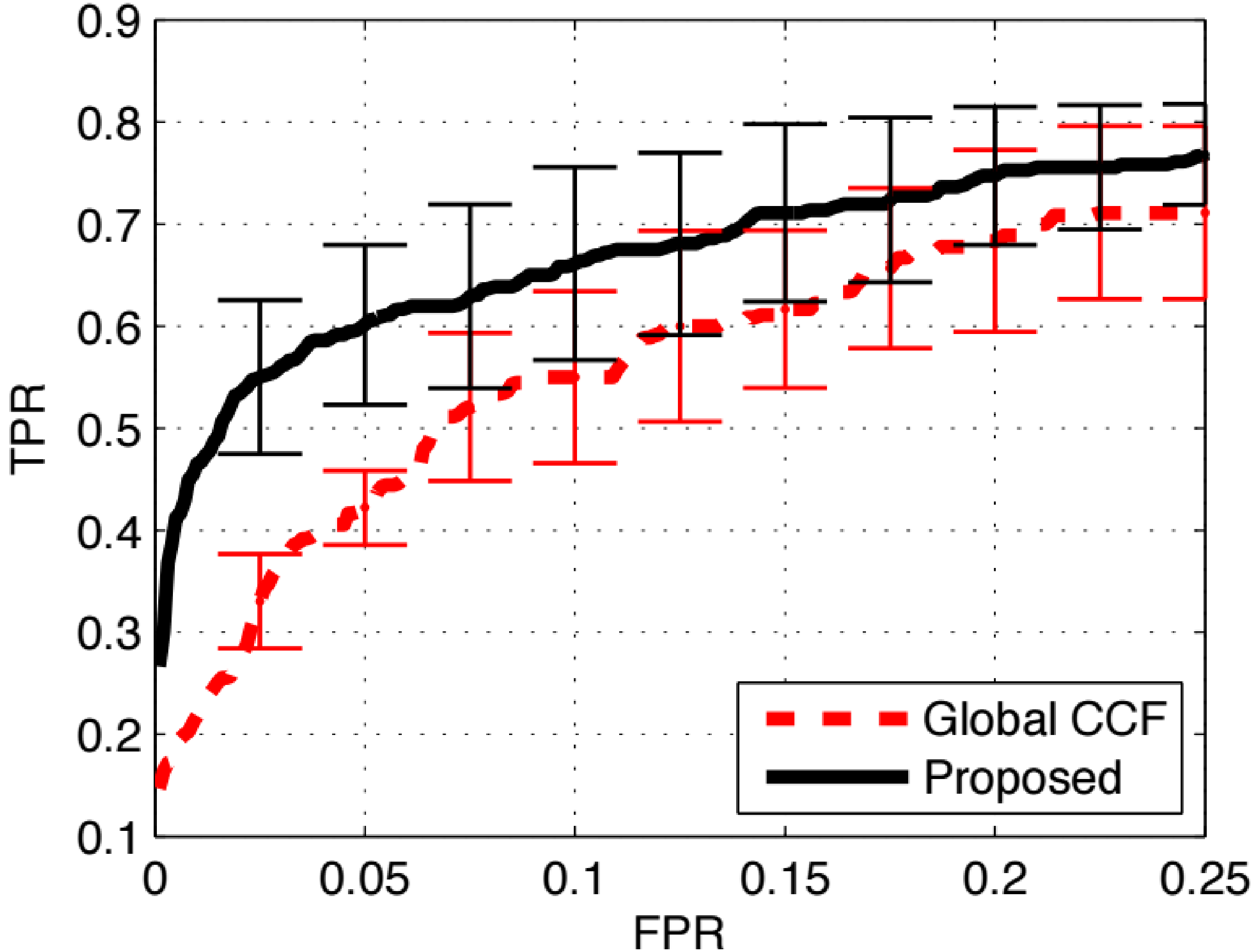
- Focus on breech face impression
- Operational forensic laboratory (OFL) data via 73 Glocks (2/glock), courtesy of Michigan Forensics Division
- Features are extracted in the “unrolled” image space and learned via “boosting”





RoC Curve for Operational Forensic Ballistic Data

Perfect recognition on the NIST dataset collected in controlled lab setting



5-fold cross validation

Summary & Challenges

- Designing recognition systems is challenging
  - Intra-class variability
  - Noise and distortion
- Domain knowledge & system requirements needed
- Lack of operational forensic databases for
  - Designing robust recognition systems
  - Developing probabilistic models
  - Studying discriminative capacity & persistence
- Google trained its FR system on ~200M images of 8M identities (we trained on 460K faces of 10K identities)
- How to involve CS/EE community in forensics?

Identical Quadruplets

Haircuts help to avoid confusion among the four six-year-old twins

http://www.cbsnews.com/8301-503543_162-57508537-503543/chinese-mom-shaves-numbers-on-quadruplets-heads/