Latent Fingerprint Matching
A Survey

Presented by

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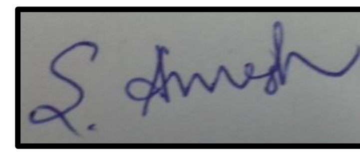
Biometrics

- Use of distinctive anatomical and behavioral characteristics for automatically recognizing individuals.

Bertillonage, 1879

Fingerprint, 1893

Signature

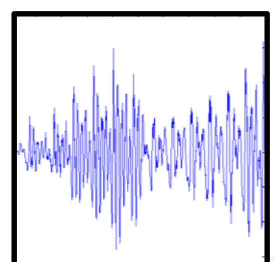


Gait

Face

Iris

Voice



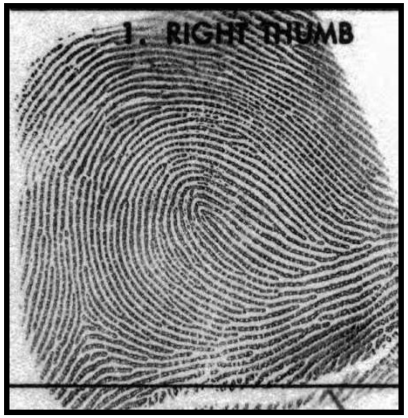
Images from various sources in internet

Fingerprints

- The pattern of interleaved ridges and valleys on the tip of the finger

"Perhaps the most beautiful and characteristic of all superficial marks are the small furrows with the intervening ridges and their pores that are disposed in a singularly complex yet even order on the under surfaces on the hands and the feet."

Francis Galton, *Nature*, June 28, 1888




Images from various sources in internet

Fingerprints - types

Inked

Live-scan

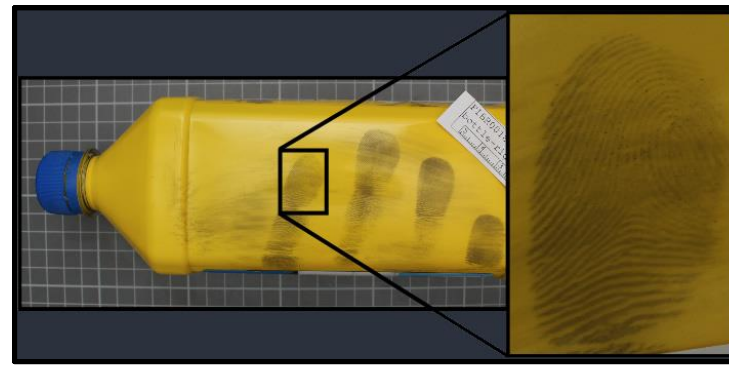
Latent

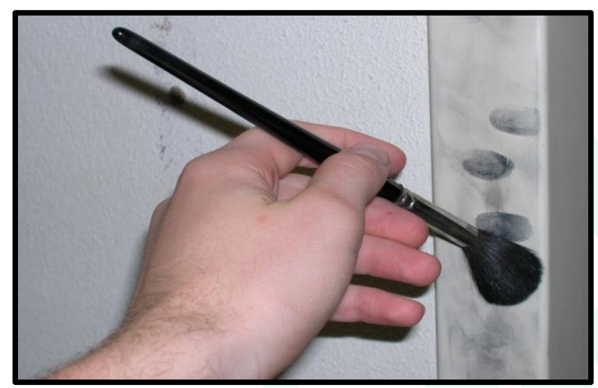
Images from various sources in internet

Latent fingerprints

- Not immediately visible to human eyes
- Forensic applications – crime scene investigation





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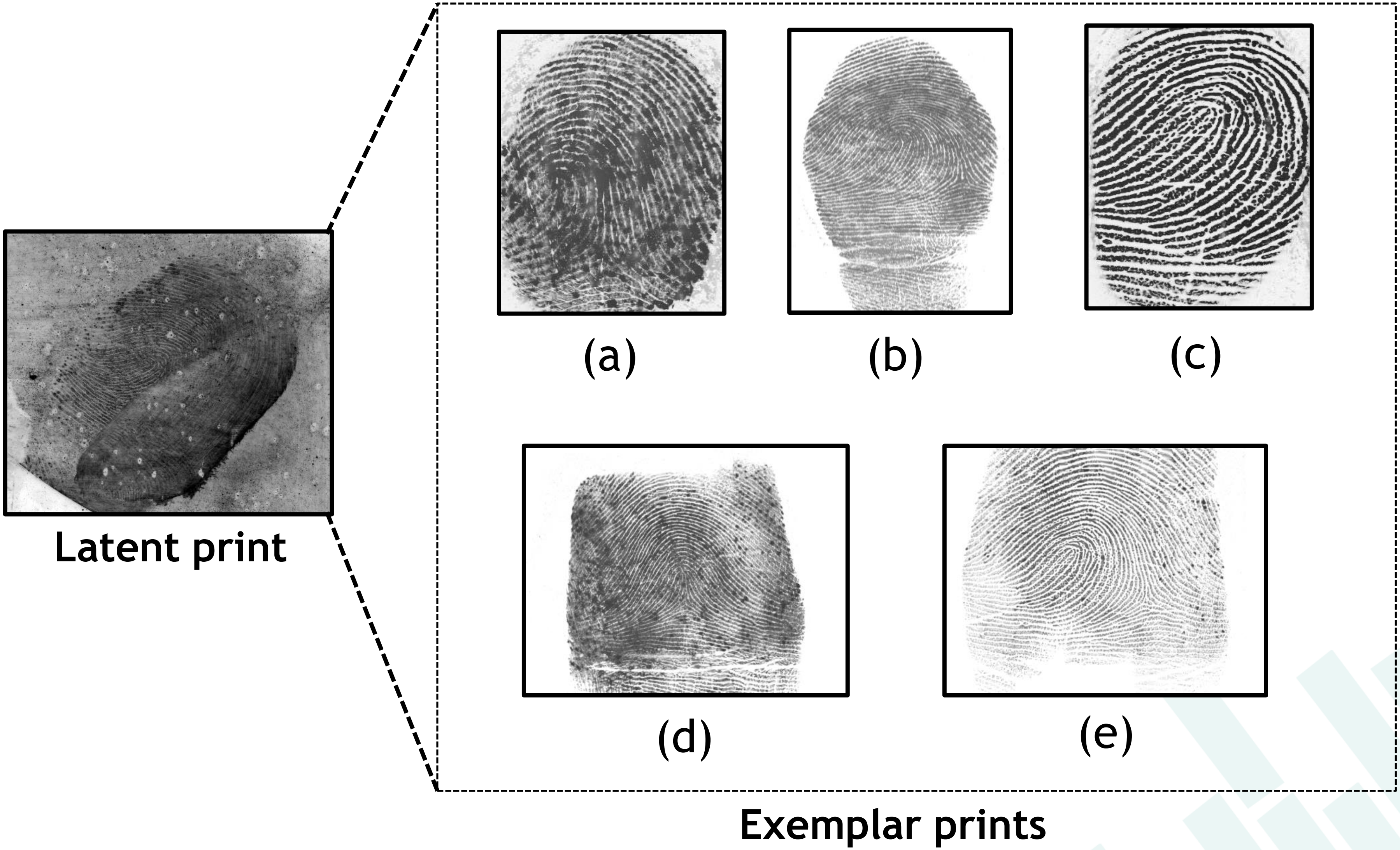
The big problem

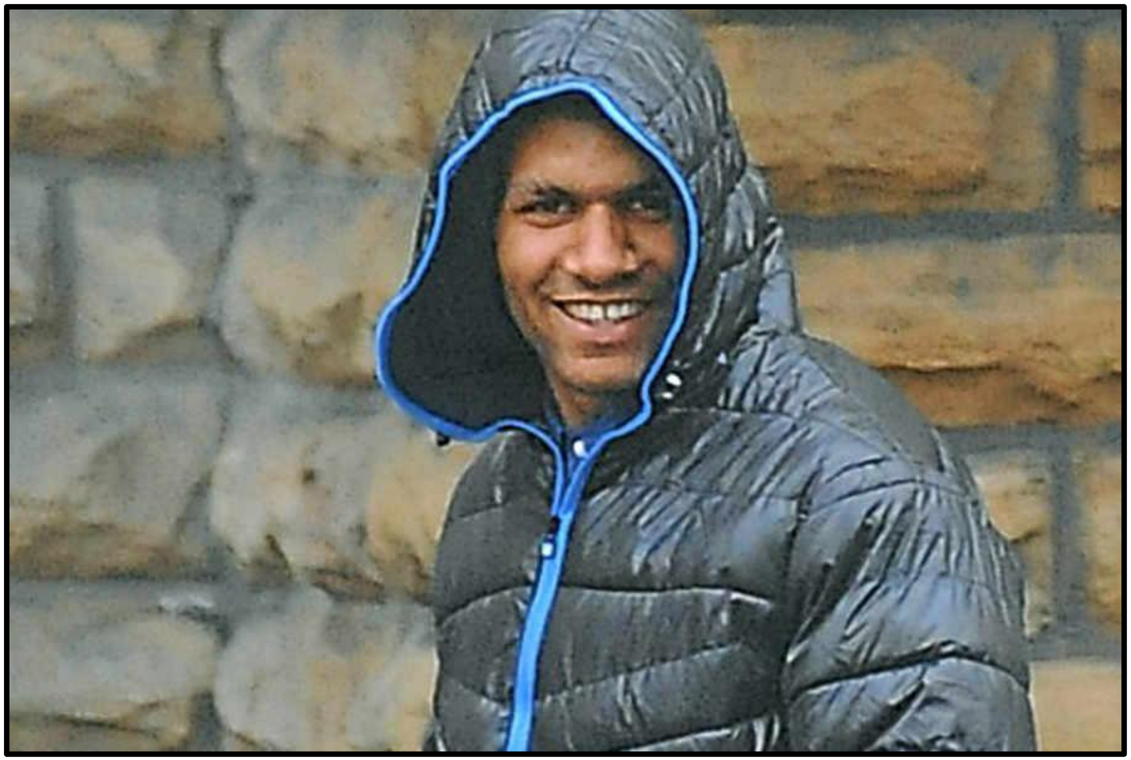


Common mis-understanding ...

Movie: Jack Reacher, 2012

News article – Aug 9, 2013

- A burglary remained unsolved for seven years – because fingerprints of the defendant weren't of a good enough quality to link him to the case.



Tyrone Spence

http://www.expressandstar.com/news/crime/2013/08/09/burglar-finally-fingered-for-wolverhampton-theft-seven-years-ago/

Challenges

Availability of partial fingerprints

Poor ridge quality

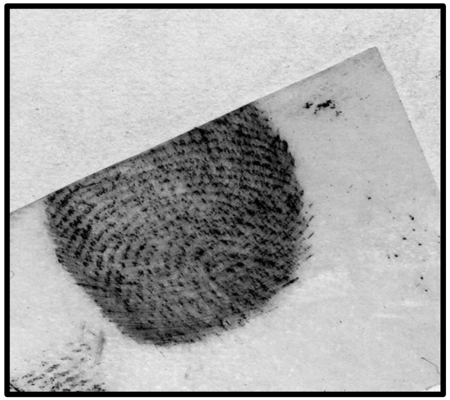
Presence of background noise

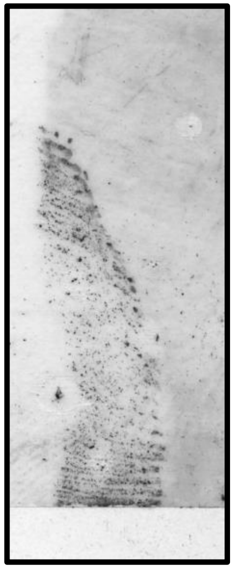
Non-linear ridge distortion

Lack of databases

Lack of experts

Lack of scientific procedure





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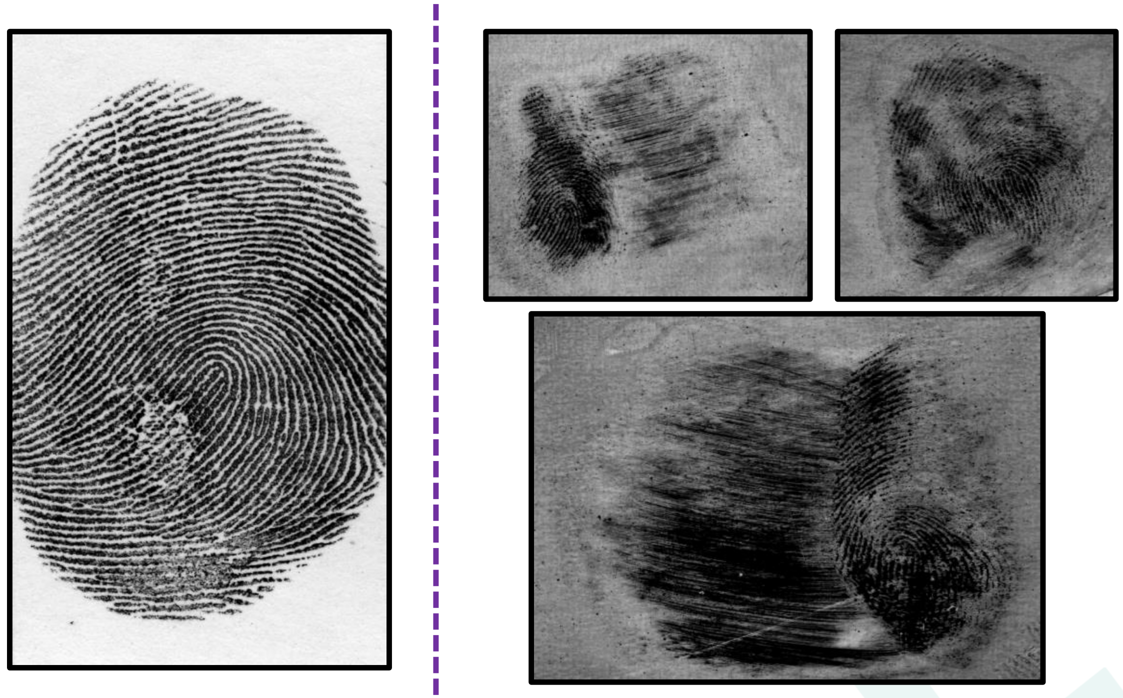

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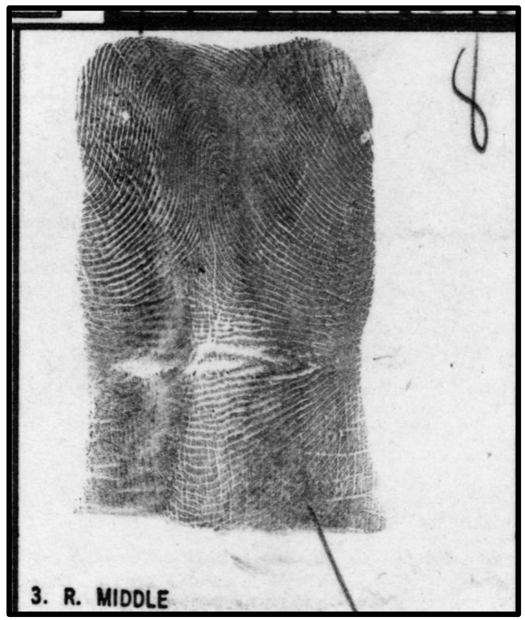

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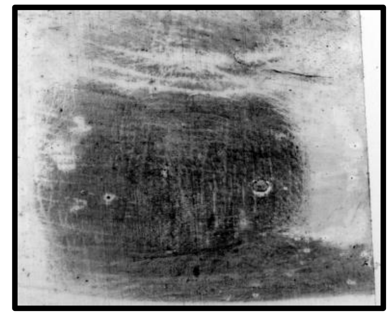

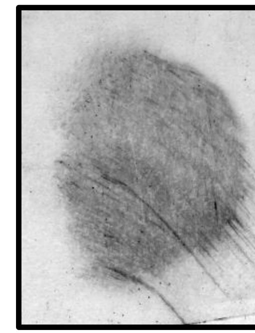

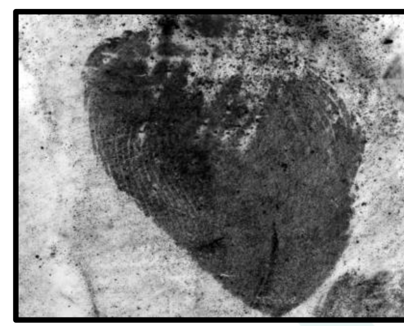

Challenges

Availability of partial fingerprints

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Lack of databases

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Lack of scientific procedure

NIST SD-27 : 258 images

IIITD Latent : 1046 images

Challenges

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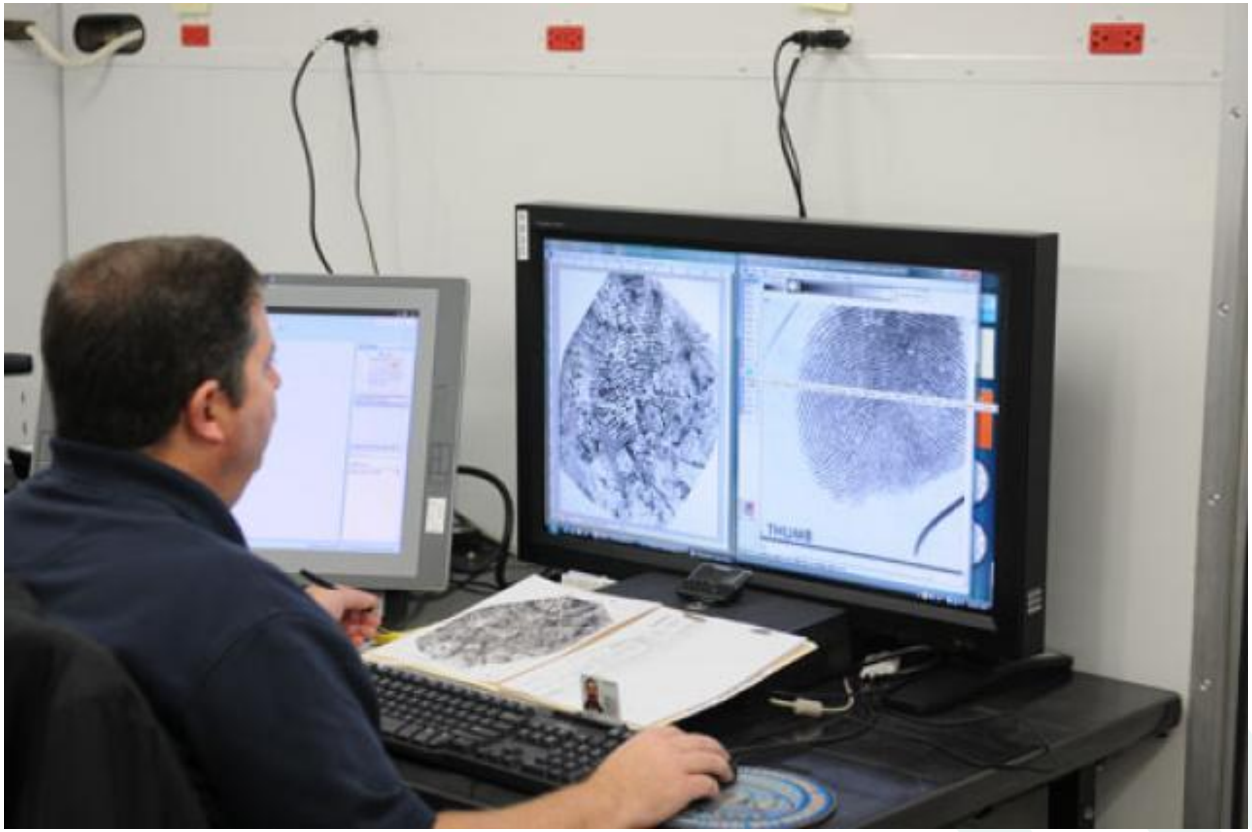

Image source: http://www.army.mil/article/39956/

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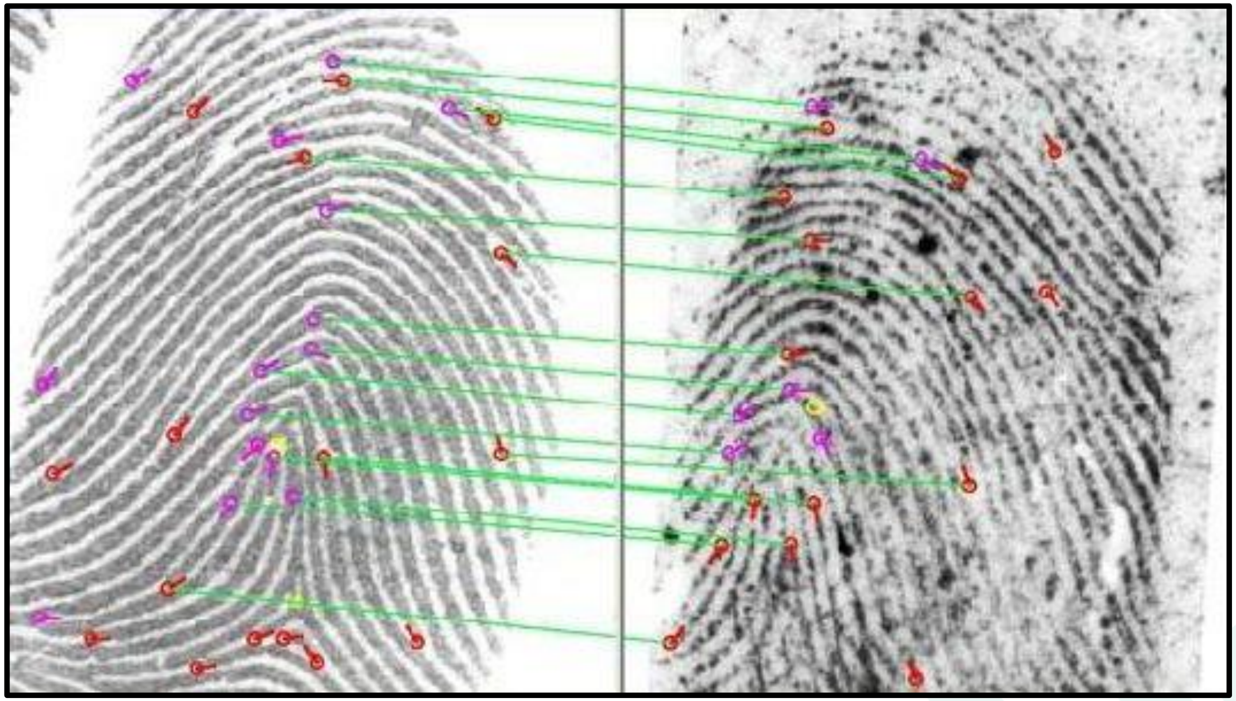
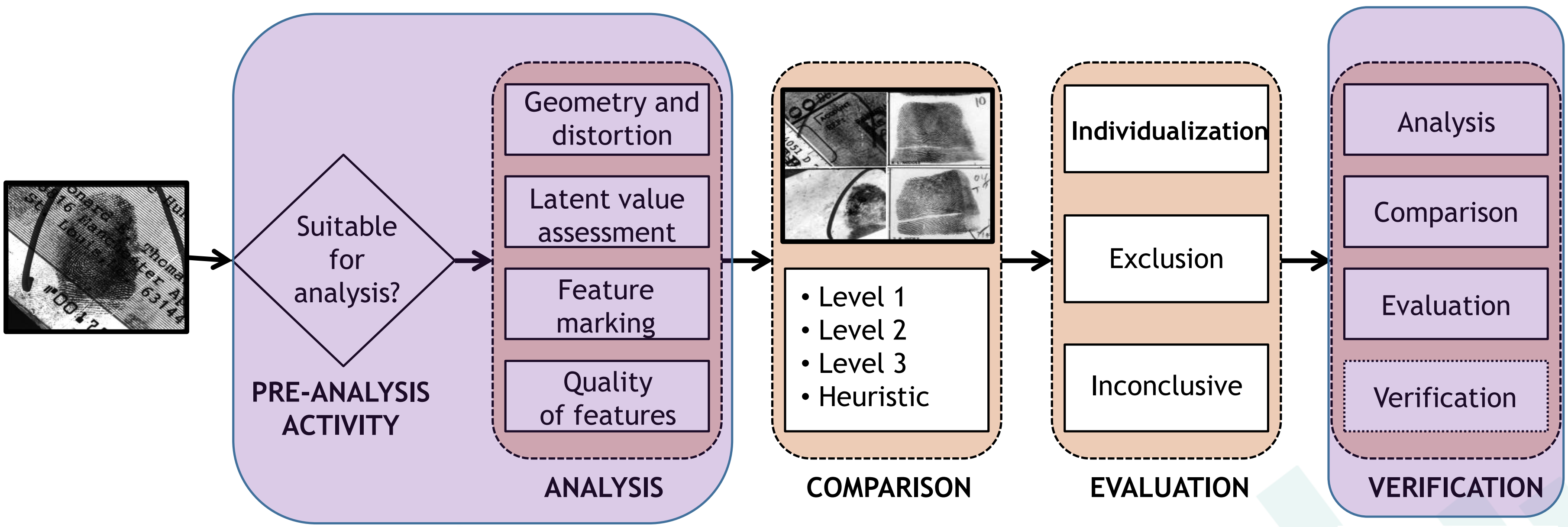


Image source: Internet

ACE-V Methodology

- ACE-V: Analysis, Comparison, Evaluation, Verification
- Structured guide for friction ridge prints



ID: Value for Identification
EO: Value for exclusion
V: No value

Human analysis of ACE-V

Effect of verification stage

Research	Aim	#participants	#comparisons	Results
Wertheim et al., 2006	Effect of verification in ACE-V	16	160	1. None of the expert were able to verify even one error.
Langenberg, 2009	Comparison of ACE and ACE-V	6	271	1. All 9 false positives detected during verification. 2. Number of erroneous exclusions doubled during verification.

Human analysis of ACE-V

Effect of additional information

Research	Aim	#participant	#comparisons	Results
Dror et al., 2005	Analyzing the bias of the examiner	27	2484	1. Manipulated with emotional stories and explicit photos. 2. Increased likelihood matching for ambiguous fingerprints.
Dror and Charlton, 2006	Consistency when provided additional information	6	48	1. Only 33.3% of the trials were consistent. 2. Reason – active and dynamic nature of human's processing of information.
Hall and Player, 2008	Consistency with emotional context	70	-	1. Context did not have any effect on the final judgment of the experts.

Human analysis of ACE-V

Effect of context

Research	Aim	#participant	#comparisons	Results
Dror et al., 2006	Influence in decision by a context	5	-	1. Additional context saying “no-match”. 2. 80% of the examiners provided contradictory decisions.
Dror et al., 2011	Influence under the context of target full prints	20	200	1. During analysis, a variation of about *(2.6 ± 3.5)* minutiae was observed. 2. Feedback used to attune the examiner’s analysis strategies.

Take away …

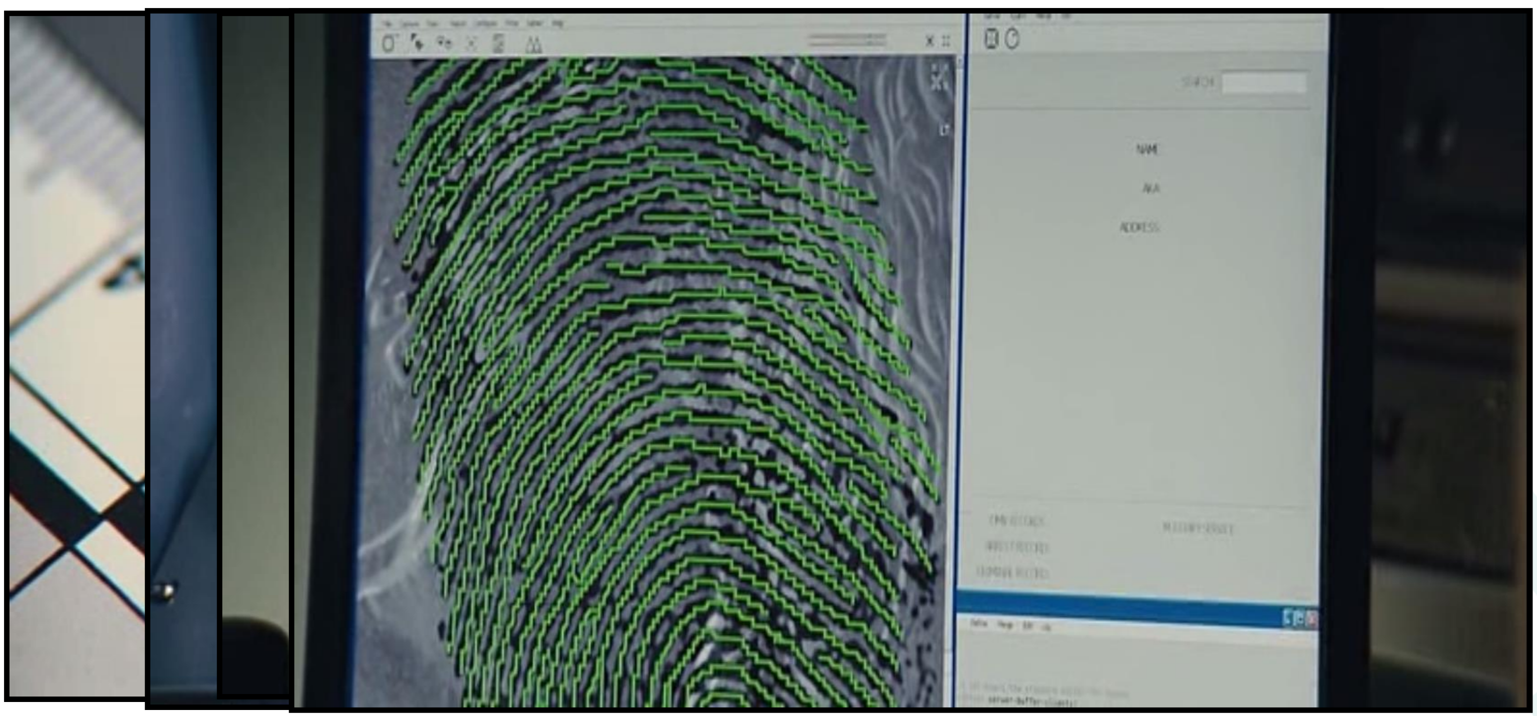
- Human examiners set very high threshold and are very cautious.
- Subjective and prone to inconsistencies.
- Studies show contradictory results.
- Not scalable for large scale latent fingerprint matching.

Need for an automated system ?

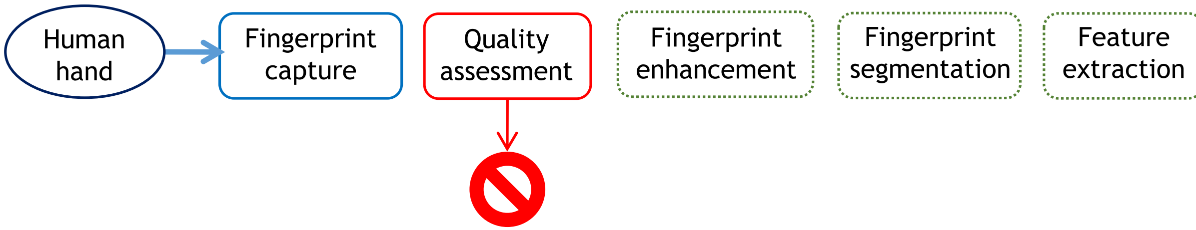
- Quick and avoid inconsistencies.
- Ex: FBI's Integrated Automated Fingerprint Identification System (IAFIS).
- Semi automated system – 74 million subject criminal gallery.
- Unsolved latent files till Feb, 2013 - 436,099

http://www.fbi.gov/about-us/cjis/fingerprints_biometrics/iafis/iafis_facts

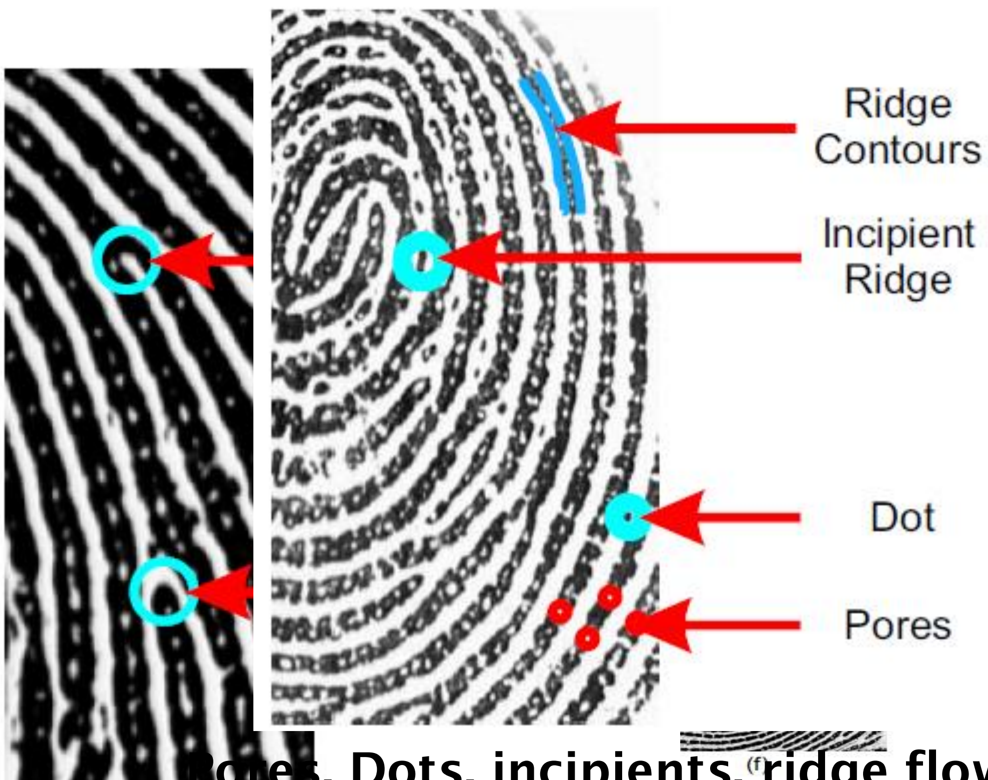
Latent fingerprint matching system



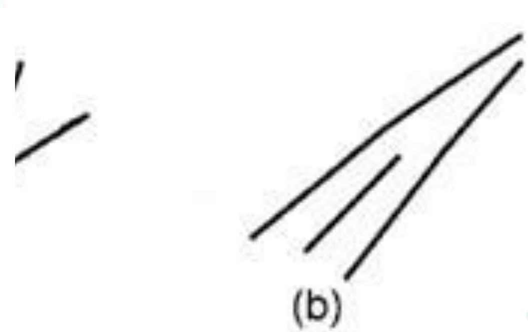
Latent fingerprint matching system



Level 3 :



urcation (b) Ridge

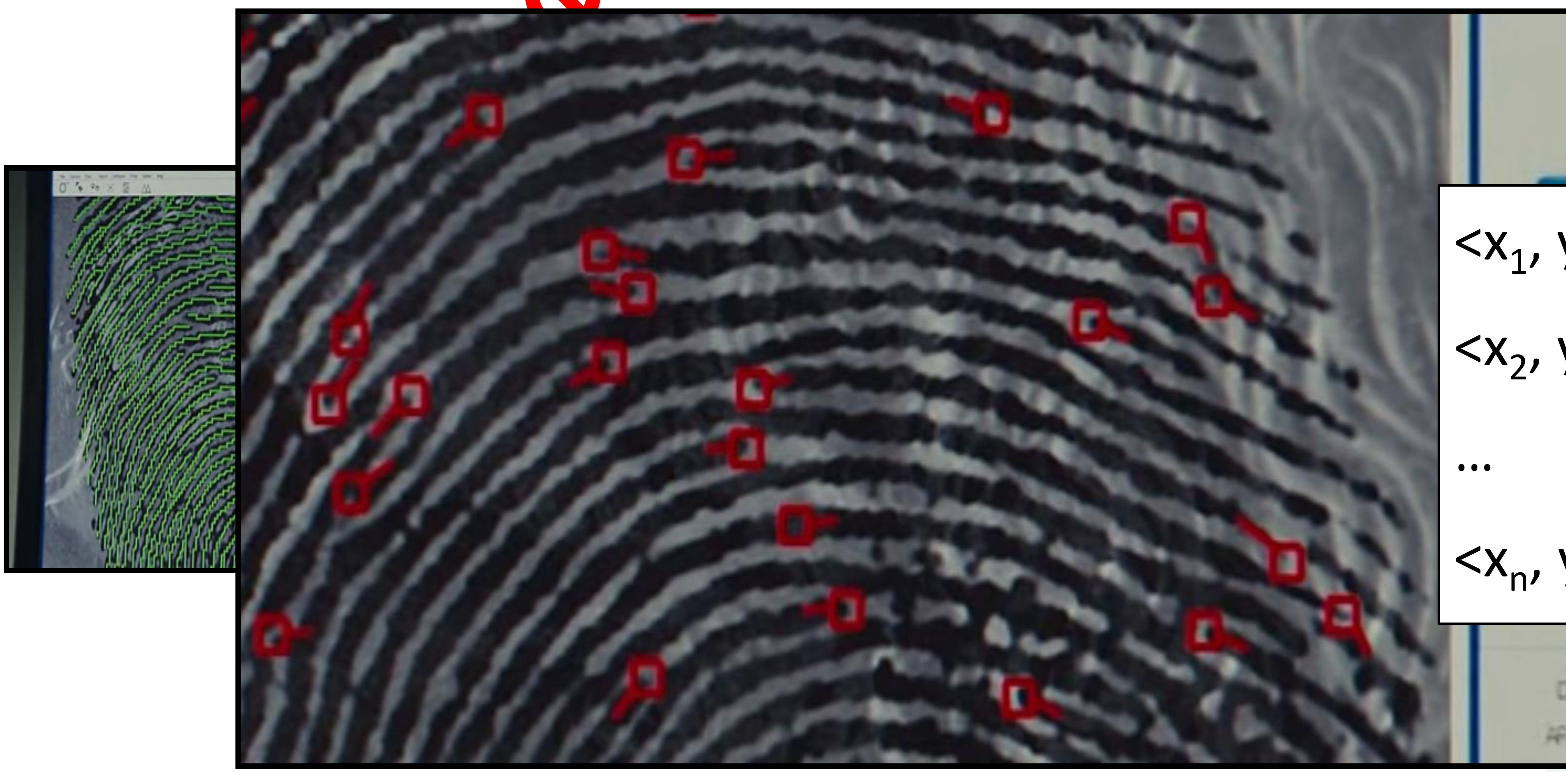


(f) whorl

Pores, Dots, incipients, ridge flow map

Latent fingerprint matching system

Human hand → Fingerprint capture → Quality assessment → Fingerprint enhancement → Fingerprint segmentation → Feature extraction



$<x_1, y_1, \theta_1>$

$<x_2, y_2, \theta_2>$

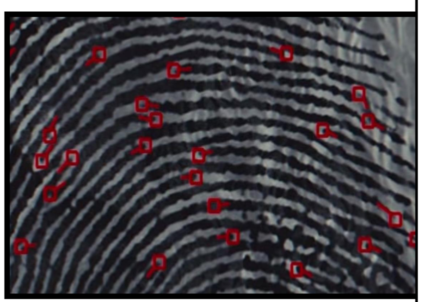
…

$<x_n, y_n, \theta_n>$

Latent fingerprint matching system

Human hand → Fingerprint capture → Quality assessment → Fingerprint enhancement → Fingerprint segmentation → Feature extraction → Feature matching → Match Scores → Individualization Decision

Enrolled database → Feature matching



$<x_1, y_1, \theta_1>$

$<x_2, y_2, \theta_2>$

…

$<x_n, y_n, \theta_n>$

$<x_1, y_1, \theta_1>$
$<x_2, y_2, \theta_2>$
…
$<x_n, y_n, \theta_n>$

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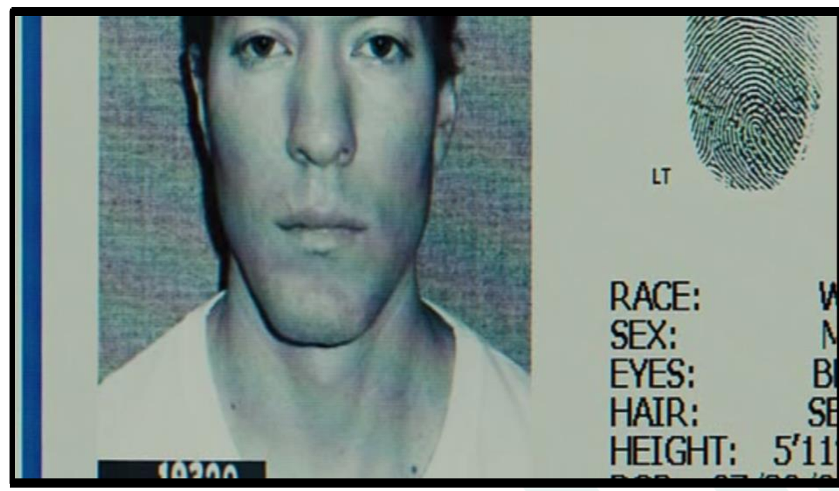

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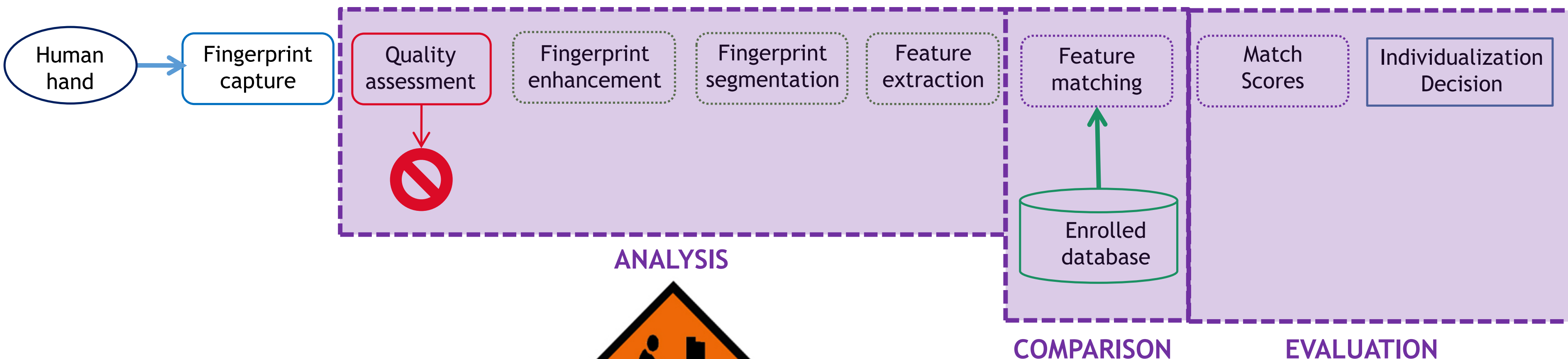


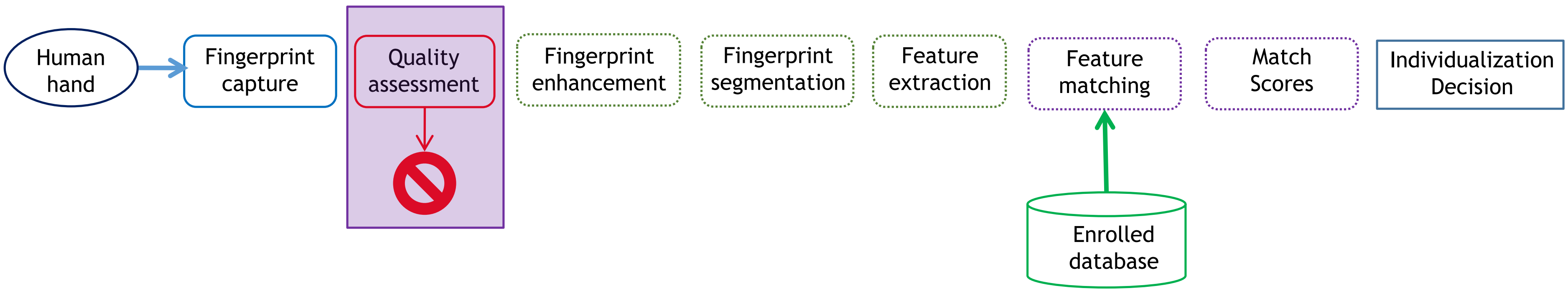
Common mis-understanding …

Movie: Jack Reacher, 2012

Databases

Database	#Classes	#Images	Characteristics
NIST SD-27 (A)	258	258	1. Latent to rolled fingerprint matching 2. Manually annotated features available 3. 500ppi and 1000ppi exemplars
IIITD Latent fingerprint	150	1046	1. Latent, mated 500ppi and 1000ppi exemplar 2. Lifted using black powder dusting process 3. Captured directly using a camera
IIITD SLF	300	1080	1. Simultaneous latent with mated slap 500ppi 2. 2 sessions of simultaneous latent fingerprint 3. Latent fingerprint images have to be cropped
WVU latent fingerprint	449	449	1. Latent to rolled fingerprint matching 2. Manually annotated features available 3. 500ppi and 1000ppi exemplars
ELFT-EFS public challenge	1100	1100	1. 500ppi and 1000ppi images in WSQ format 2. Database not publicly available 3. Manually annotated features available

Latent fingerprint matching system

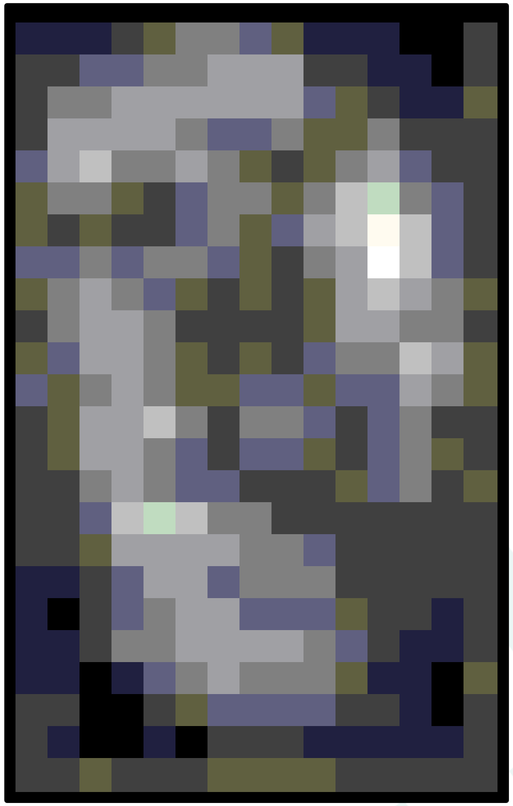


Latent quality assessment

- Direct predictor of matching performance

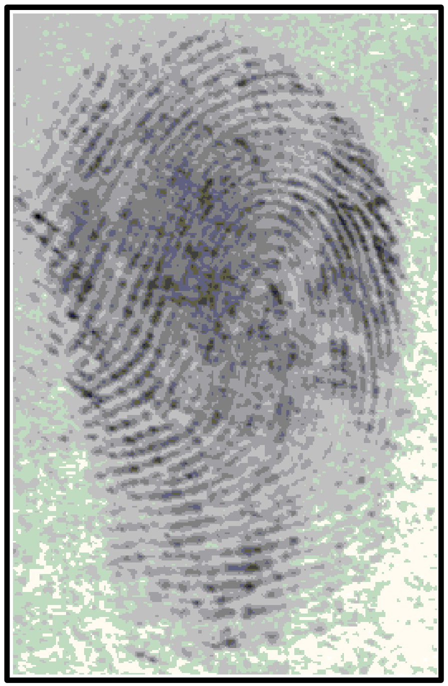
Global quality = 45

Local quality map

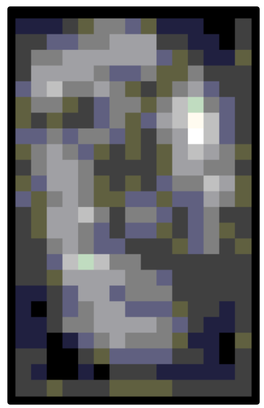


Latent fingerprint quality

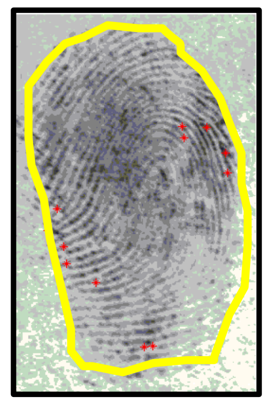
- Quality is the measure of amount of matching information



Ridge continuity map



Minutiae and convex hull



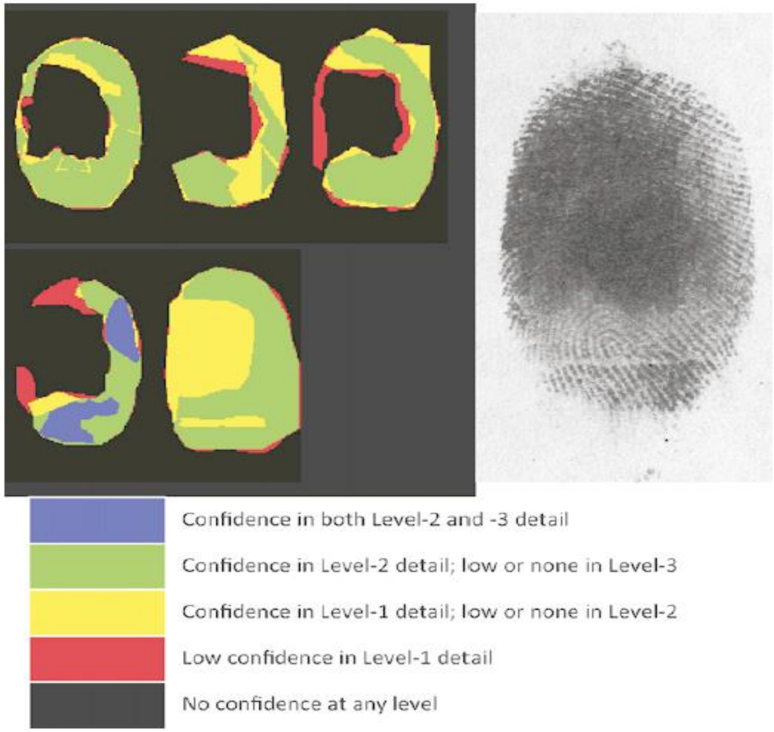
Quality value

Latent quality assessment

Research	Approach	Database	Results
Yoon et al., 2012	Ridge continuity maps, number of minutiae	NIST-SD 27 + WVU	1. 2 class – {VID, not-VID} 2. 60% classification accuracy for automatically extracted features.
NFIQ 2.0, 2013	Set of all features for quality	Proprietary	1. A score value of 1-100 2. Improved recognition error rate
Hicklin et al., 2013	Manual analysis of clarity and quality	Proprietary	1. Color coded clarity 2. Labeling inconsistent

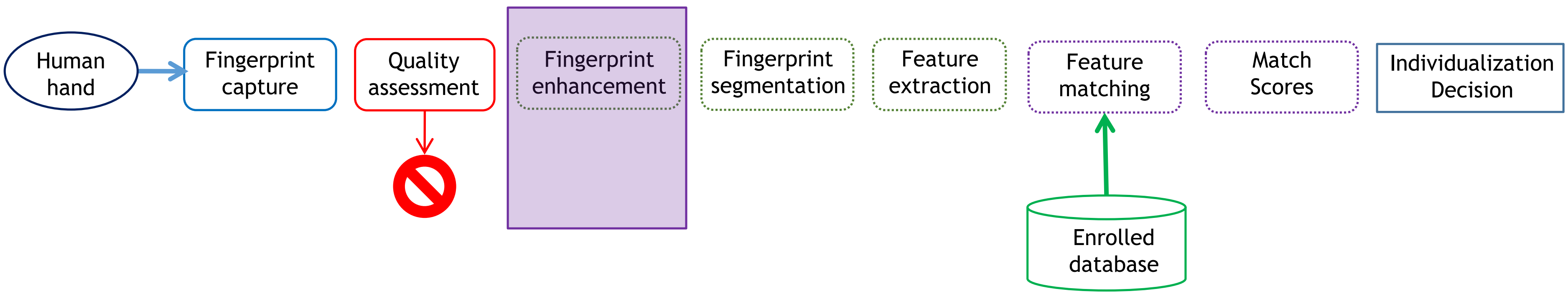
Research challenges

- Automated quality and clarity assessment
- Local quality maps

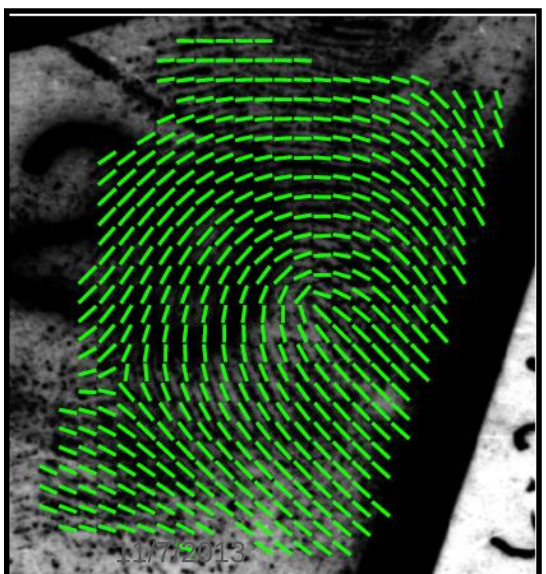


- Quality is more than number of minutiae

Latent fingerprint matching system



Latent fingerprint enhancement

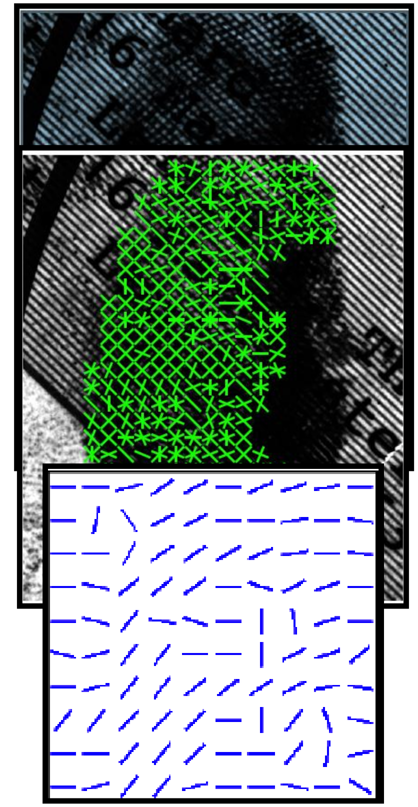


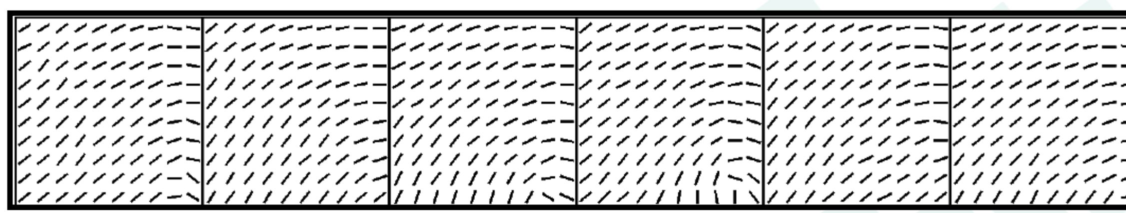
Latent fingerprint

Coarse orientation field

Reference dictionary

Regularized orientation field





Latent fingerprint enhancement

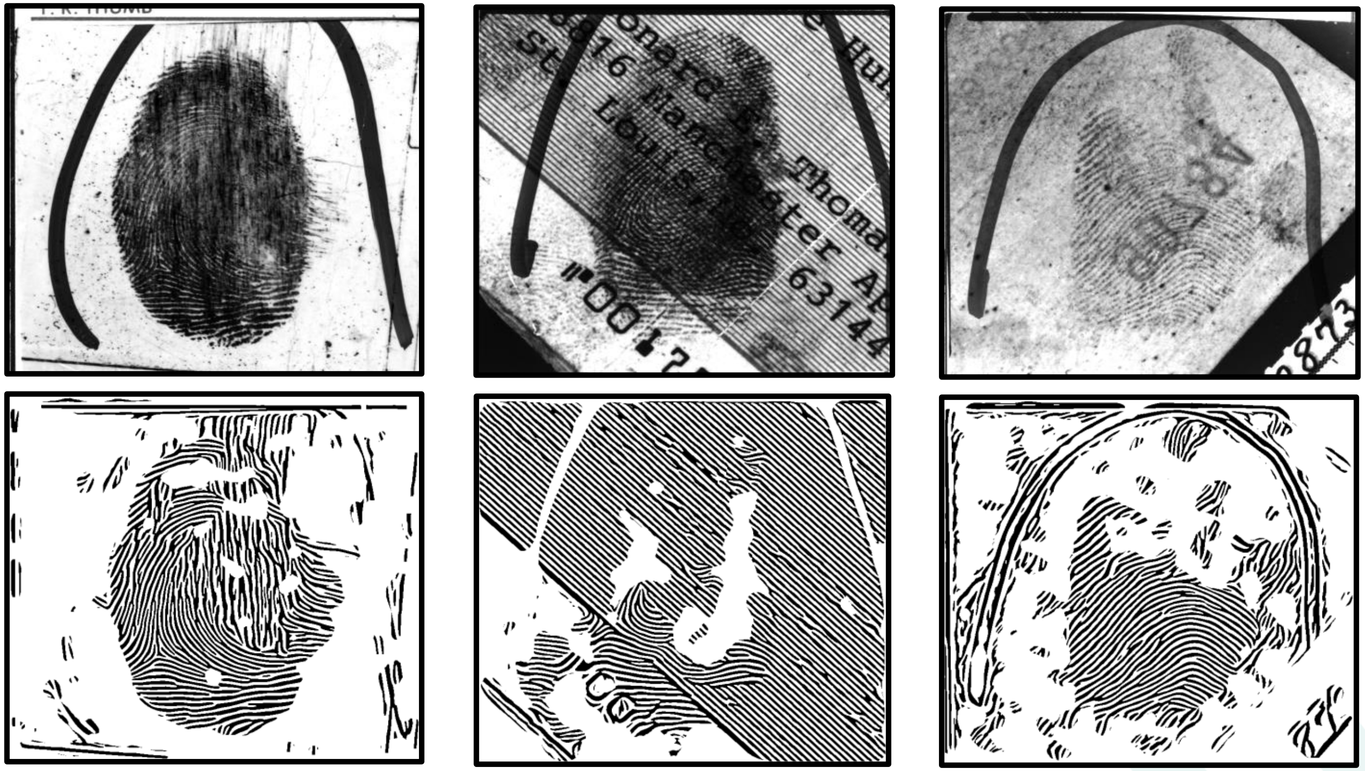
Research	Approach	Database	Results
Yoon et al., 2010	Orientation field regularization using “zero pole”	NIST-SD 27	1. Enhancement improves rank-1 accuracy from 20% to 35%
Yoon et al., 2011	Coarse orientation fitting using RANSAC	NIST-SD 27	1. Rank-1 matching accuracy from 12% to 26%
Feng et al., 2012	Dictionary of reference orientation patch	NIST-SD 27	1. Average estimation error in orientation is 18.44°

Research challenges

1. Noisy data

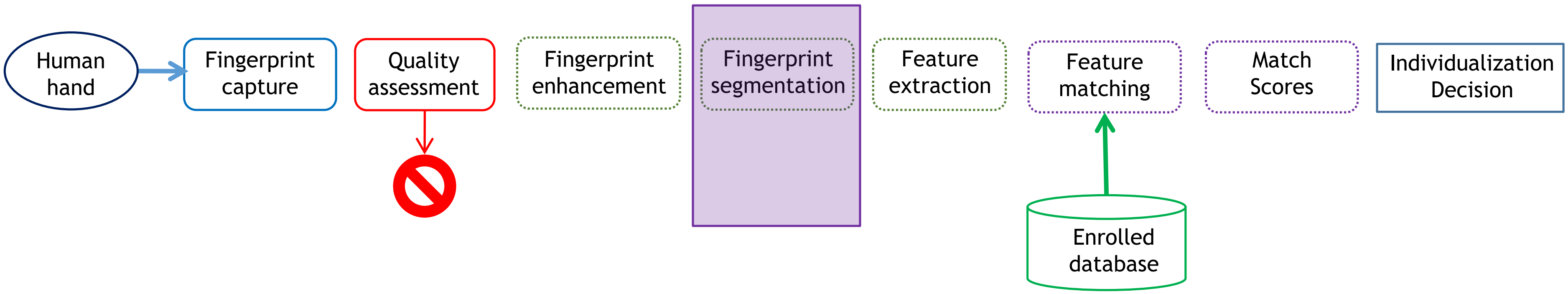
Latent fingerprints

After enhancement

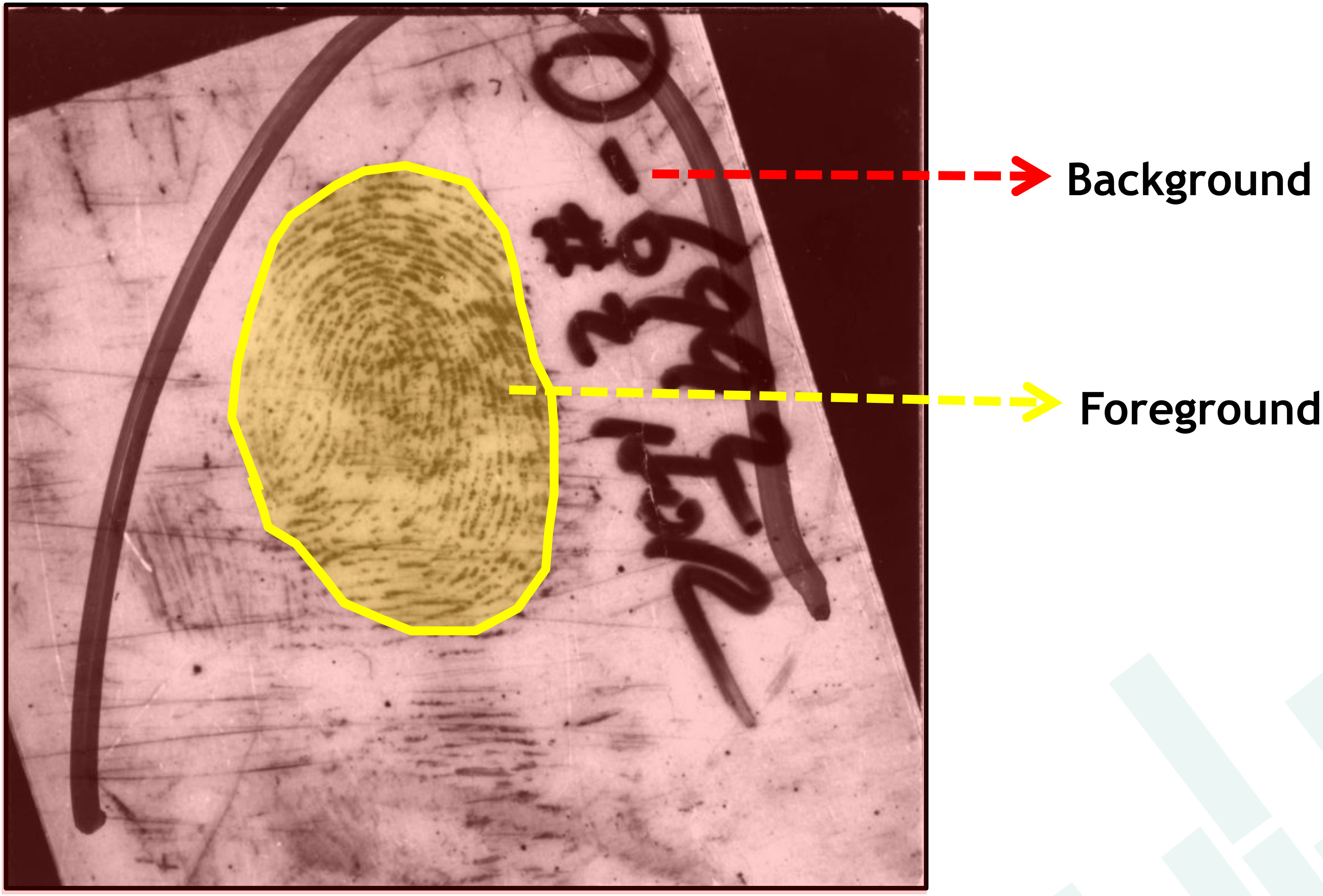


2. Need for a metric to evaluate enhancement

Latent fingerprint matching system

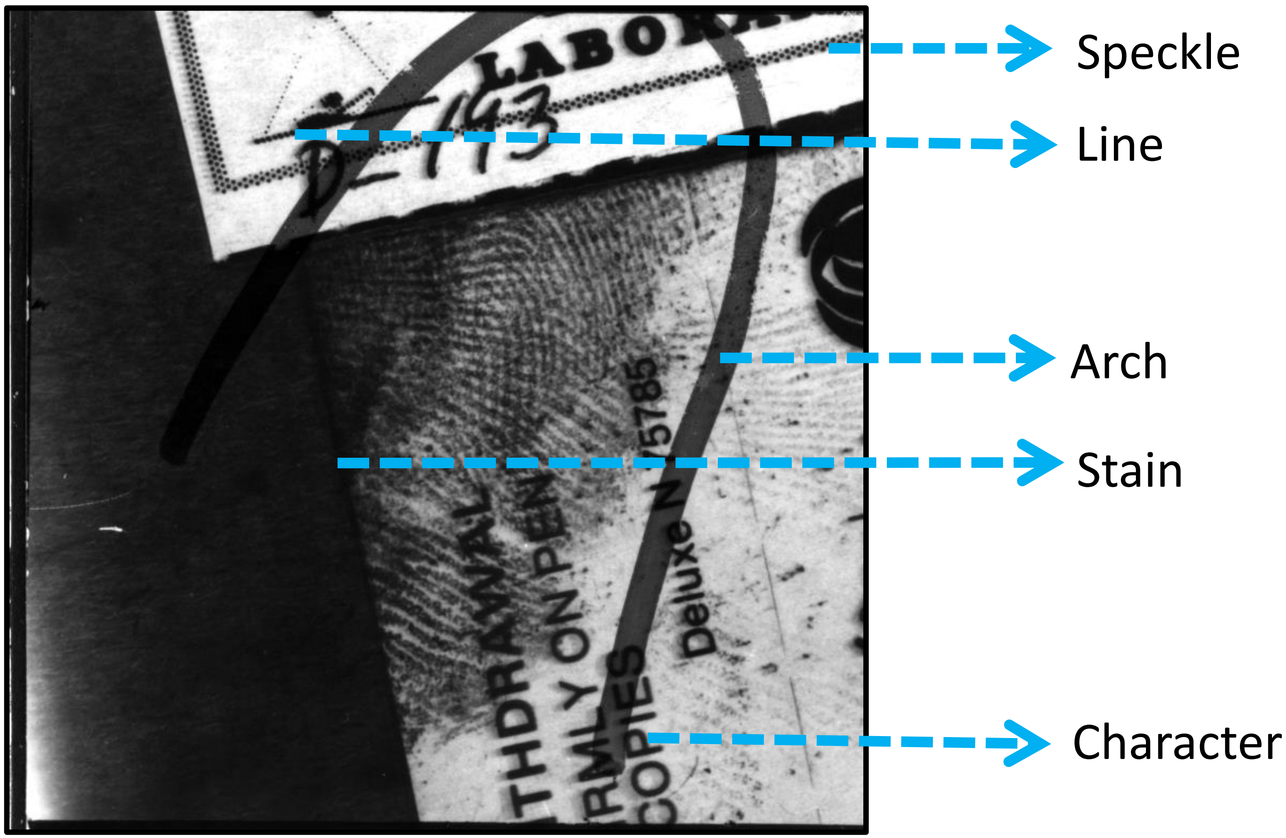


Latent fingerprint segmentation

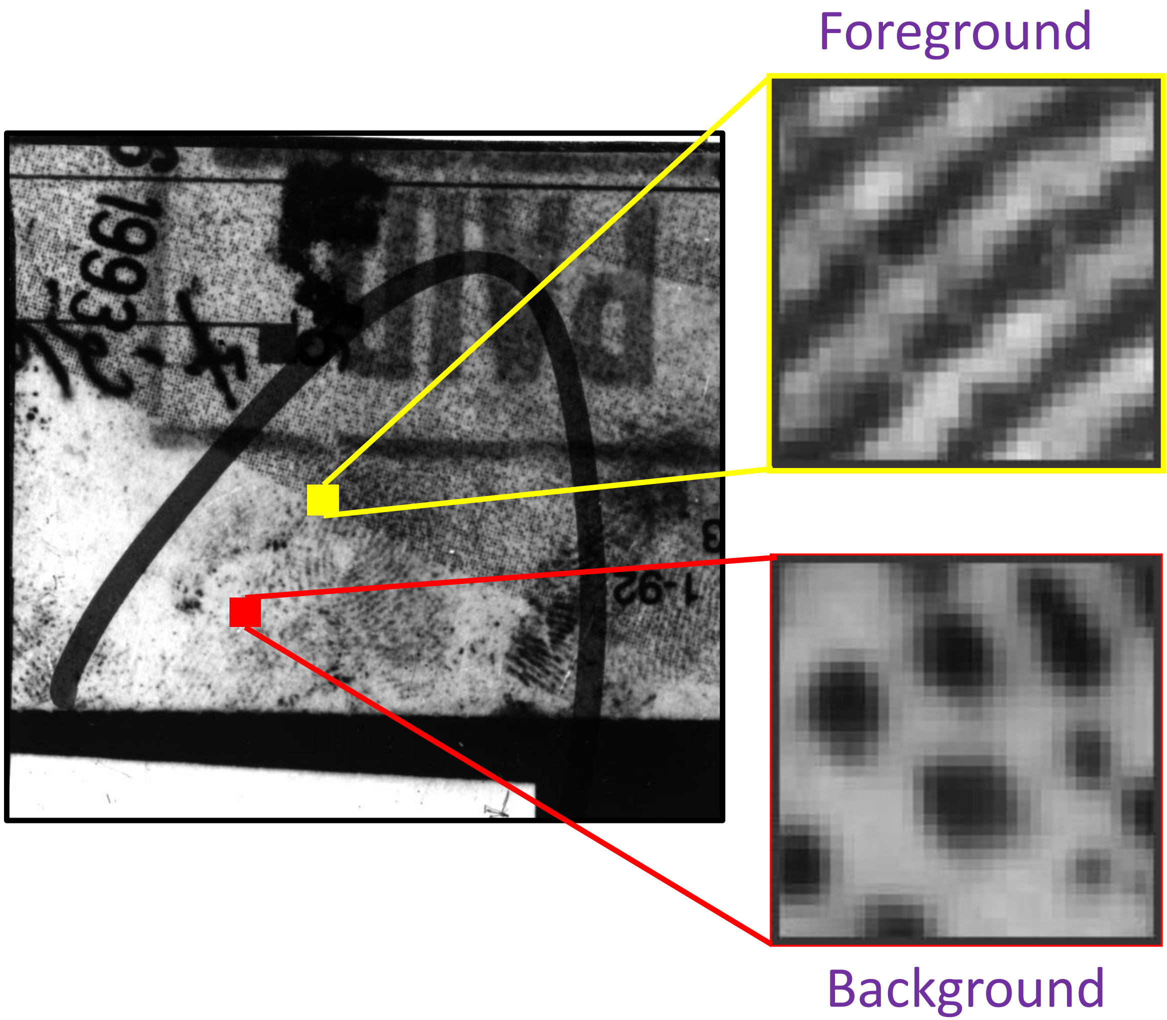


Latent fingerprint segmentation

Challenges



Latent fingerprint segmentation



Features used:

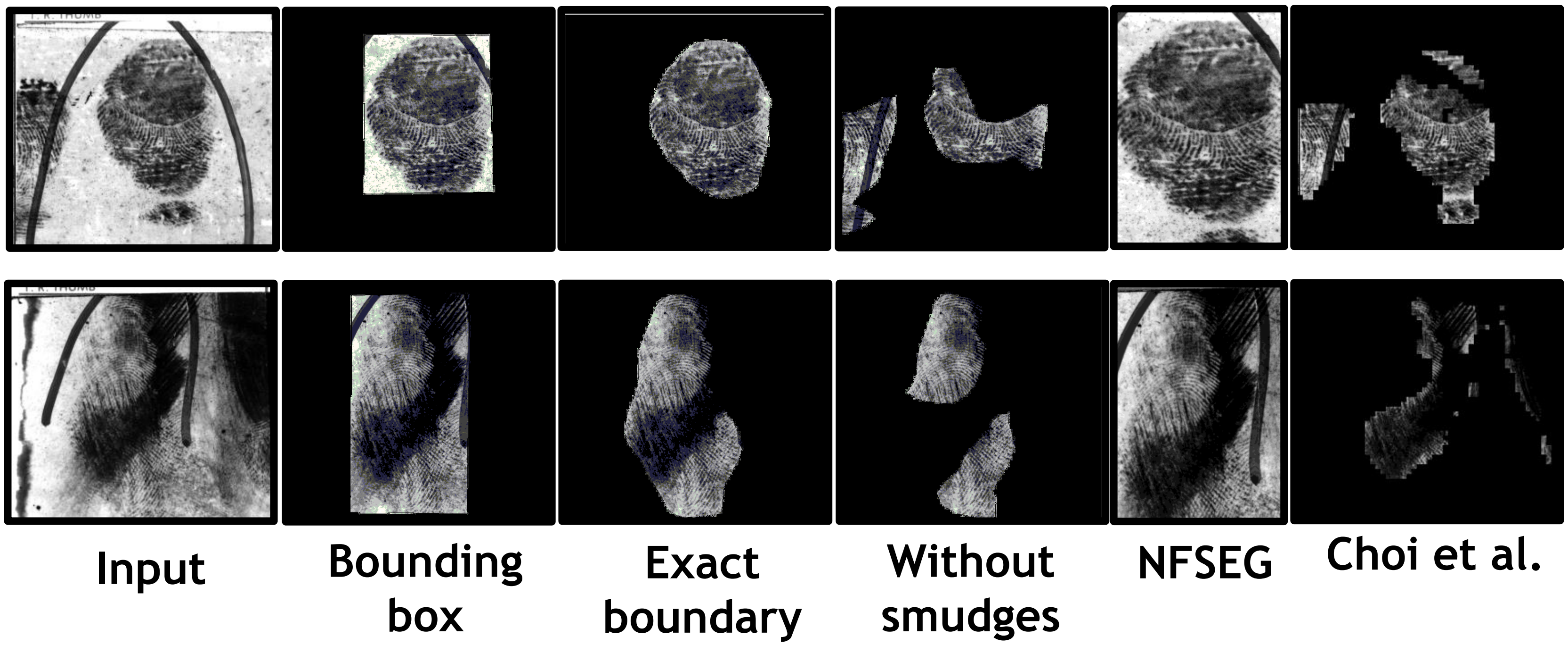
1. Ridge orientation
2. Ridge frequency
3. Ridge correlation
4. Ridge texture

Latent fingerprint segmentation

Research	Approach	Database	Results
Karimi and Kuo, 2008	Ridge frequency estimation	2 images from NIST-SD 27	1. No quantitative results
Short et al., 2011	Cross-correlation strength	NIST-SD 27	1. Verification – EER of 33.8%
Zhang et al., 2012	Adaptive Total Variational (TV-L1) model	3 images from NIST-SD 27	1. No quantitative results
Zhang et al., 2012	Directional Total Variational (DTV) model	3 images from NIST-SD 27	1. No quantitative results
Choi et al., 2012	Orientation + frequency tensor	NIST-SD 27 and WVU DB	1. Rank-1 matching accuracy for NIST SD-27 : 16.28% WVU DB : 35.19%

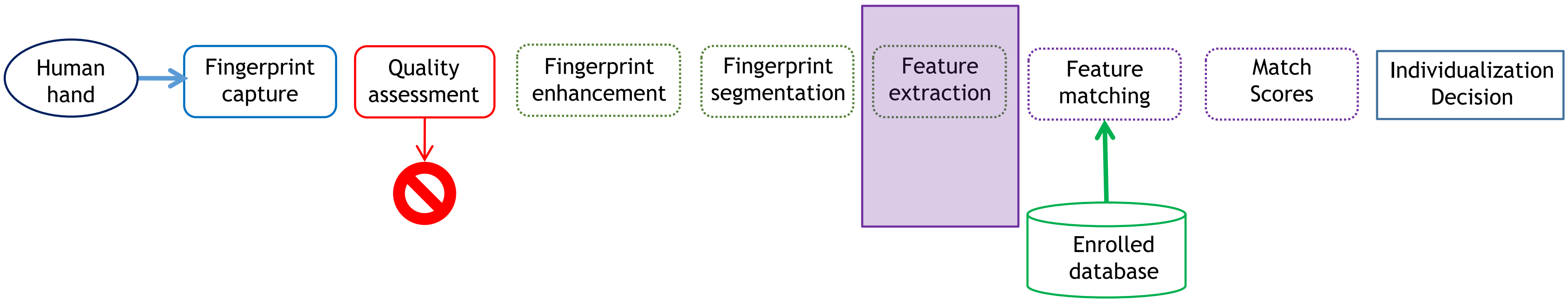
Research challenges

1. Standard definition



2. Metric to determine segmentation accuracy

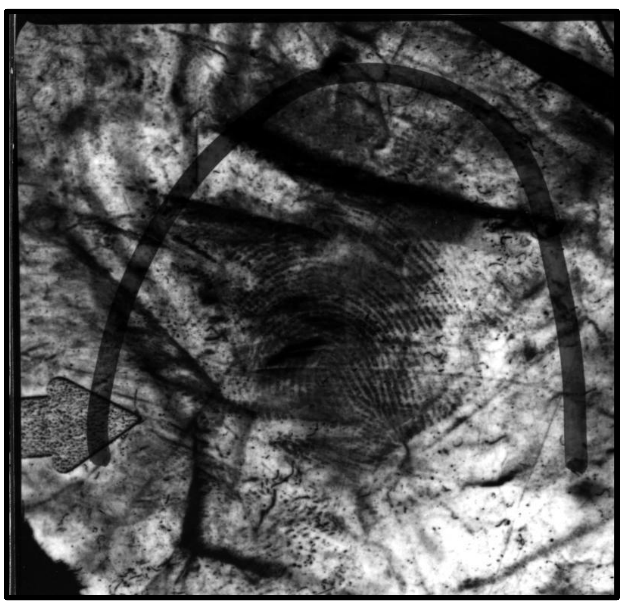
Latent fingerprint matching system

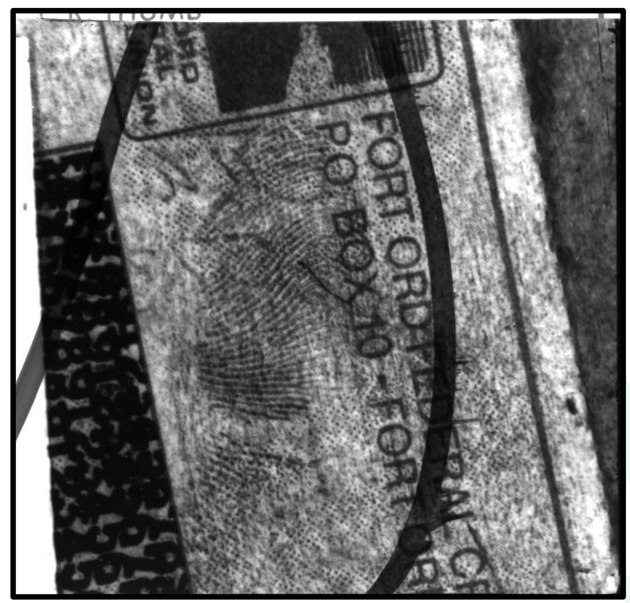


Latent fingerprint feature extraction

- Automatic level-2 feature extractor for latent fingerprint is still an open research problem

- Challenges: Very poor quality and noisy data





Latent fingerprint feature extraction

Level-1 features

Research	Approach	Database	Results
Feng and Jain, 2008	DB filtering using pattern type, singular point, orientation field	NIST-SD 27	1. Penetration rate of 39% 2. Rank-1 matching performance from 70.9% to 73.3%
Su and Srihari, 2010	Core point detection using Gaussian process	NIST-SD 27	1. Core point prediction accuracy of 84.5%

Latent fingerprint feature extraction

Level-2 and level-3 features

Research	Approach	Database	Results
Puertas et al., 2010	Manual extraction with automatic extraction	Proprietary	1. 6 (avg.) spurious minutiae per print 2. Latent quality is an open problem
Paulino et al., 2010	Fuse automatic and manually marked minutiae	NIST-SD 27	1. Boosted max score fusion gave max accuracy
Jain and Feng, 2011	Singular points, ridge flow map, ridge wavelength map, ridge quality map, fingerprint skeleton, minutiae points, ridge correspondence, level-3 features	NIST-SD 27 (A)	1. Rank-1 accuracy from 34.9% (only minutiae) to 74% (all features) 2. Use level-3 only when level-2 fails

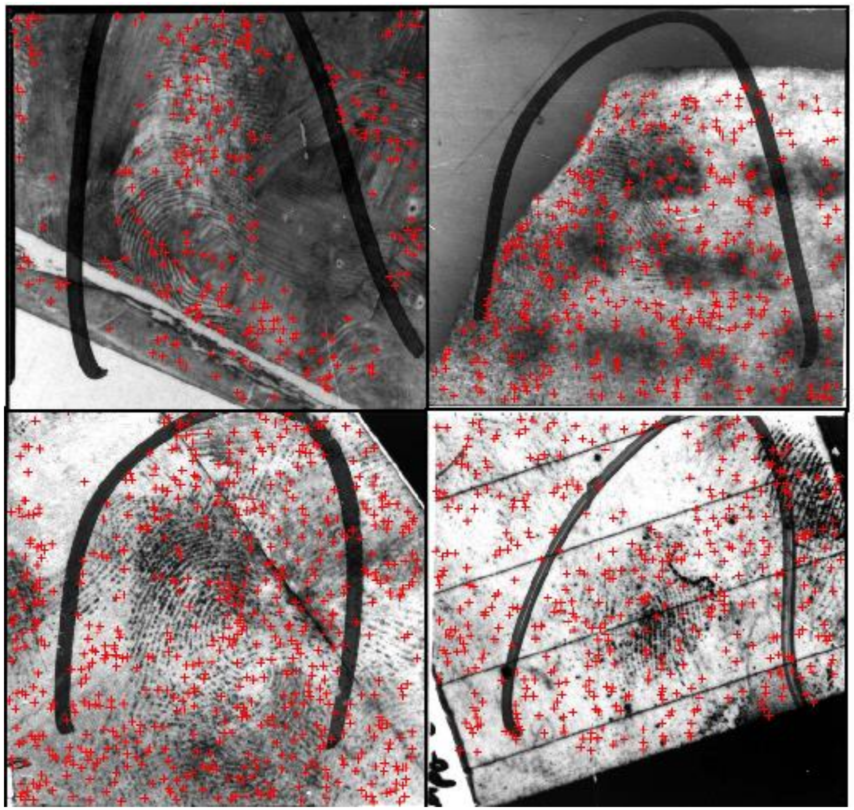
Latent fingerprint feature extraction

Other descriptors

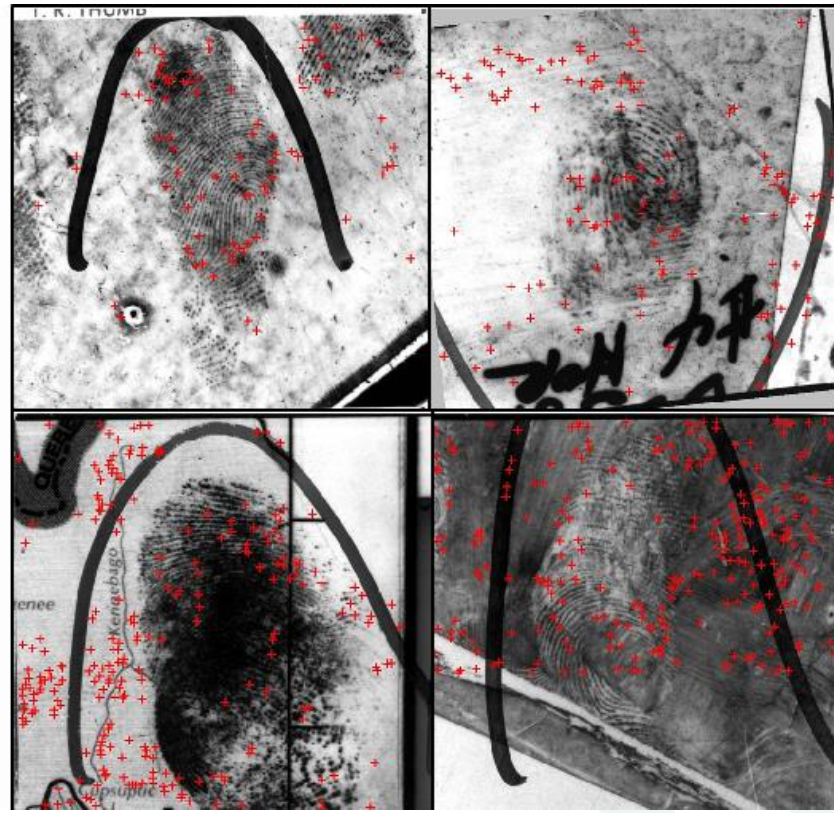
Research	Approach	Database	Results
Vatsa et al., 2008	1. Pore and ridge with minutiae 2. RDWT based quality	Proprietary	1. Rank-1 identification accuracy of 87.5%
Paulino et al., 2013	1. Local descriptor based Hough transform 2. MCC code for minutiae	NIST SD-27	1. Rank-1 identification accuracy is 57.4%

Research challenges

1. Spurious minutiae



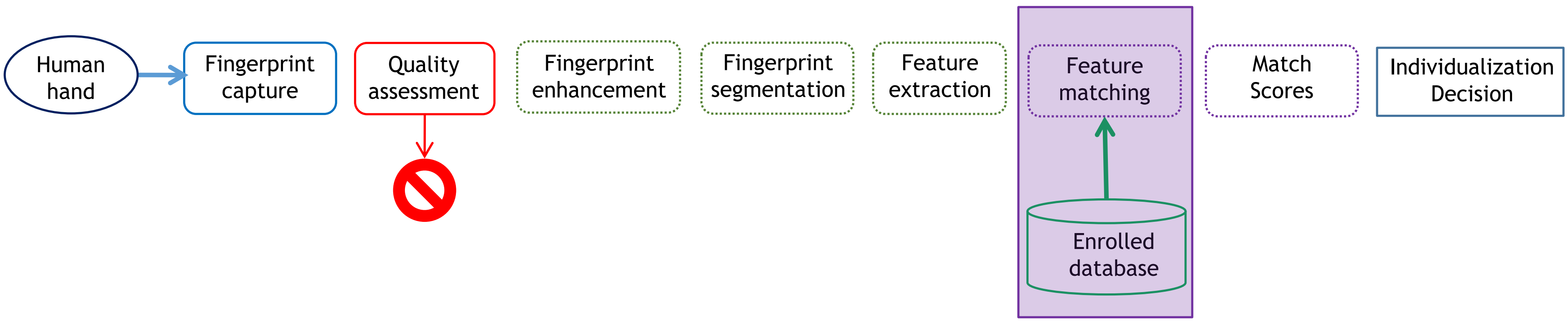
VeriFinger



NBIS

2. Explore additional latent specific features

Latent fingerprint matching system



Latent fingerprint matching

- Increase inter-class variation and
  Decrease intra-class variation

Latent fingerprint matching

Effect of fusion

Research	Approach	Database	Results
Jain et al., 2008	1. Local minutiae matching 2. Global minutiae matching	NIST-SD 27	1. An rank-1 matching accuracy of 79.5% with weighted match score fusion
Feng et al., 2009	1. Rank level, match score level, feature level fusion	ELFT-EFS	1. Rank-1 identification accuracy of 83% from 57.8% for boosted-max fusion
Dvornychenko, 2012	1. Fusion of classifiers 2. Fusion of features	Proprietary	1. Rank-1 matching performance boost of 6-15% for feature fusion

Latent fingerprint matching

Performance of tenprint matchers

Research	Approach	Database	Results
Mikaelyan and Bigun, 2012	1. Establish ground truth in NIST SD-27 2. K-plet and Bozorth3 (NBIS)	NIST-SD 27	1. EER of Bozorth3: 36% K-plet: 40%
Kargel et al., 2012	1. Five matchers: Source –AFIS, FVS, NBIS, Biometrics SDK, Innovatrics IDKit	Proprietary	1. Very poor performance

Research challenges

- Extraction of reliable valid features

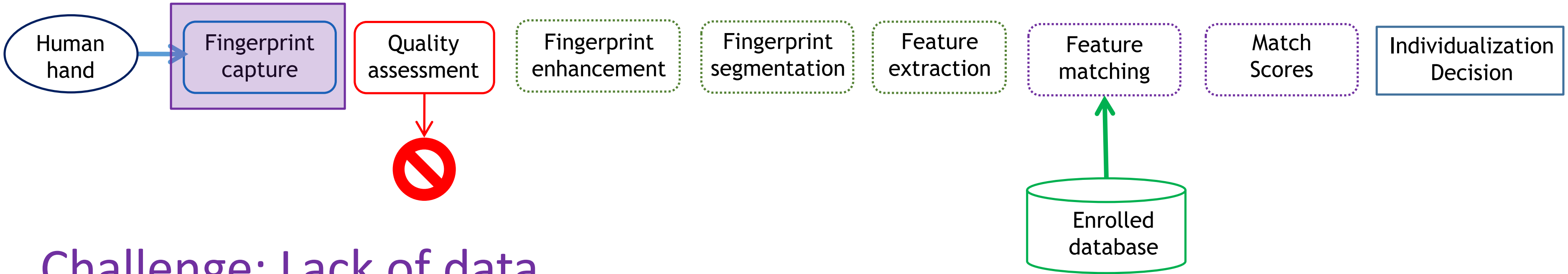
- Research in feature extraction would drive research in feature matching

- Use of machine learning algorithms for matching

Summary – state of the art

Process	State of art	Technique	Accuracy
Quality assessment	Yoon et al., 2012	Ridge clarity maps	Rank-100 improvement of 69% to 86% in combined NIST SD-27 and WVU database
Enhancement	Yoon et al., 2011	STFT + RANSAC	Rank-20 improvement from 10% to 51% in NIST SD-27
	Feng et al., 2012	Dictionary of orientation patches	Rank-20 matching accuracy of 35% in NIST SD-27
Segmentation	Choi et al, 2012	Orientation and frequency tensor	Rank-1 identification accuracy 1. NIST SD-27: 16.28% 2. WVU DB: 35.19%
Feature extraction	Paulino et al., 2013	Hough transform + MCC	Rank-1 accuracy of 57.4% in combined NIST SD-27 and WVU database
Feature matching	Jain and Feng, 2011	Local and global matching	Rank-1 accuracy of 74% on NIST SD-27 (A)

My research directions



Challenge: Lack of data

IIITD Latent

- Latent with 500 and 1000ppi flat
- Captured directly using camera
- 1046 images, 150 classes

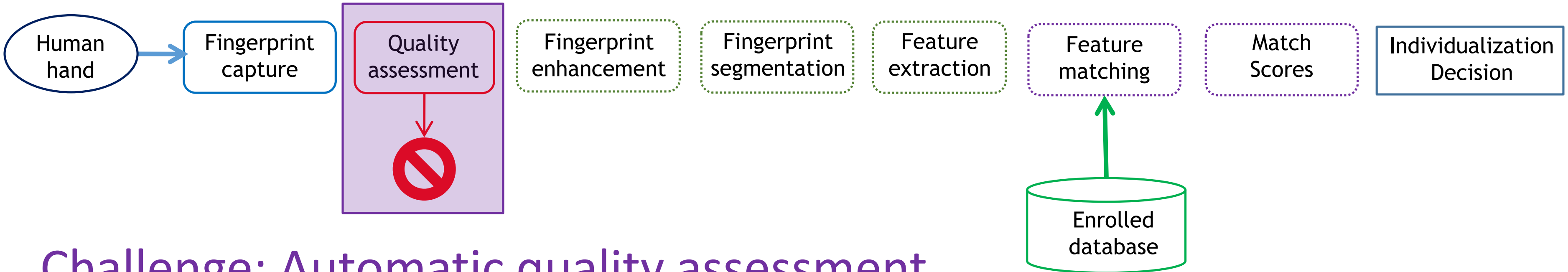
IIITD SLF

- Simultaneous latent fingerprint
- Latent images can be cropped
- 1080 images, 300 classes

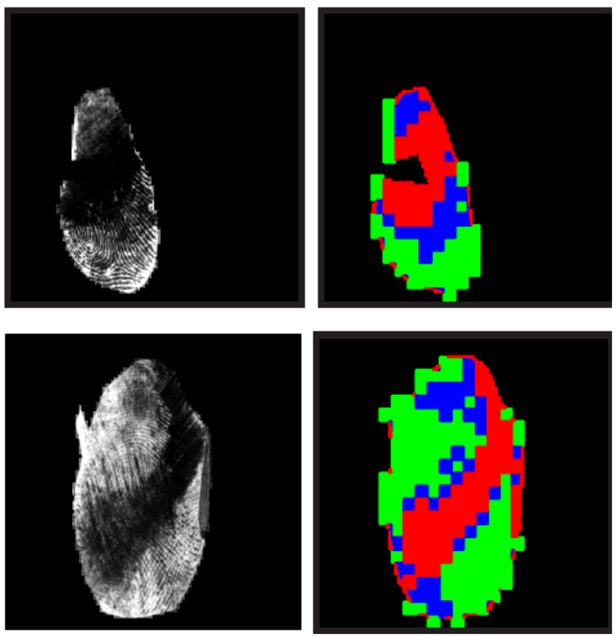
IIIT MOLF

- Three sensors, latent and multiple latent
- 1000 classes and more than 20000 images

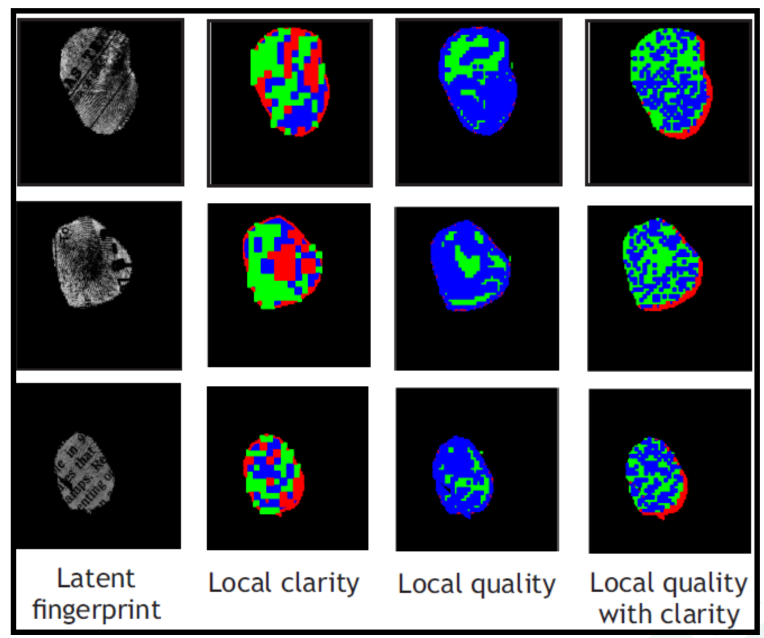
My research directions



Challenge: Automatic quality assessment

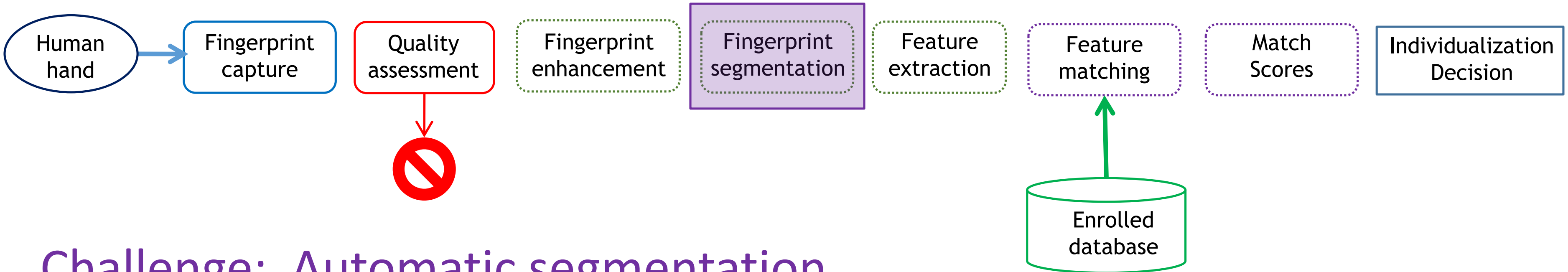


Local clarity assessment



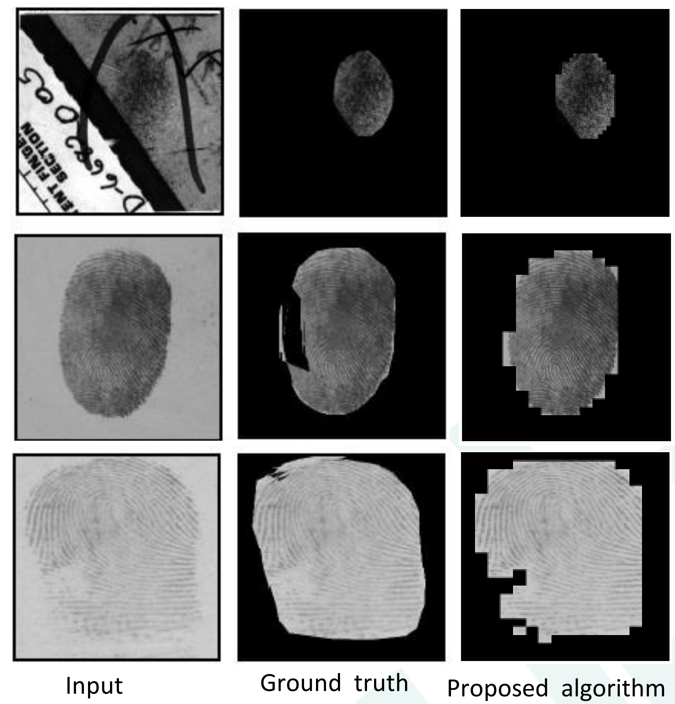
Local quality assessment

My research directions

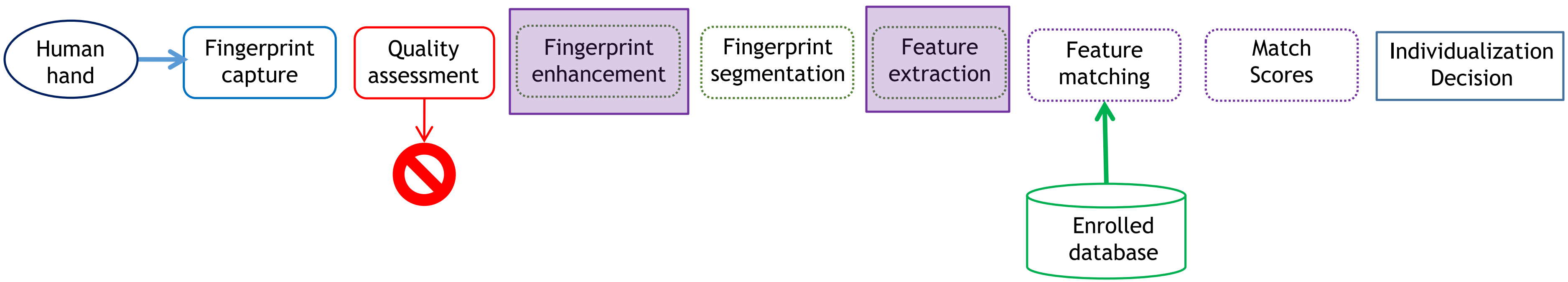


Challenge: Automatic segmentation

1. Binary classification problem
2. Foreground ridge pattern representation
3. RDF based classification



My research directions



Courses – CGPA: 9.5/10

- Probability and statistics
- Image analysis
- Introduction to biometrics
- Pattern recognition
- Machine learning
- Computer vision
- Technical communication (audit)
- Information retrieval
- Probabilistic graphical model (independent study)

Teaching assistant:

- Probability and statistics
- Data structures and algorithms
- Machine learning
- Pattern recognition

Awards and recognition

- TCS Research Scholarship (2010-2014)
- Selected for BTAS – 2013 and BTAS – 2012 doctoral consortium
- Reviewer of
  - Information Fusion (Elsevier)
  - ICB – 2013
  - BTAS - 2013

Publications

- **A. Sankaran**, A. Jain, T. Vashisth, M. Vatsa, R. Singh, "Latent Fingerprint Segmentation using Randomized Decision Forests", *IEEE Transactions on Information Forensics and Security*, 2013 **(under review).**
- **A. Sankaran**, M. Vatsa, R. Singh, "Latent Fingerprint Matching: A Survey", *Forensic Science International, Elsevier,* 2013 **(under review).**
- **A. Sankaran**, M. Vatsa, R. Singh, "Automated Clarity and Quality Assessment for Latent Fingerprints", *In Proceedings of International Conference on Biometrics: Theory, Applications and Systems*, 2013 **(accepted).**

- **A. Sankaran**, M. Vatsa, and R. Singh, "Hierarchical Fusion for Matching Simultaneous Latent Fingerprint," *In Proceedings of International Conference on Biometrics: Theory, Applications and Systems*, 2012.

- **A. Sankaran**, T.I. Dhamecha, M. Vatsa, and R. Singh, "On Matching Latent to Latent Fingerprints", *In Proceedings of International Joint Conference on Biometrics*, 2011.
- T.I. Dhamecha, **A. Sankaran**, R. Singh, and M. Vatsa, "Is Gender Classification Across Ethnicity Feasible using Discriminant Functions?", *In Proceedings of International Joint Conference on Biometrics*, 2011.

Thank you

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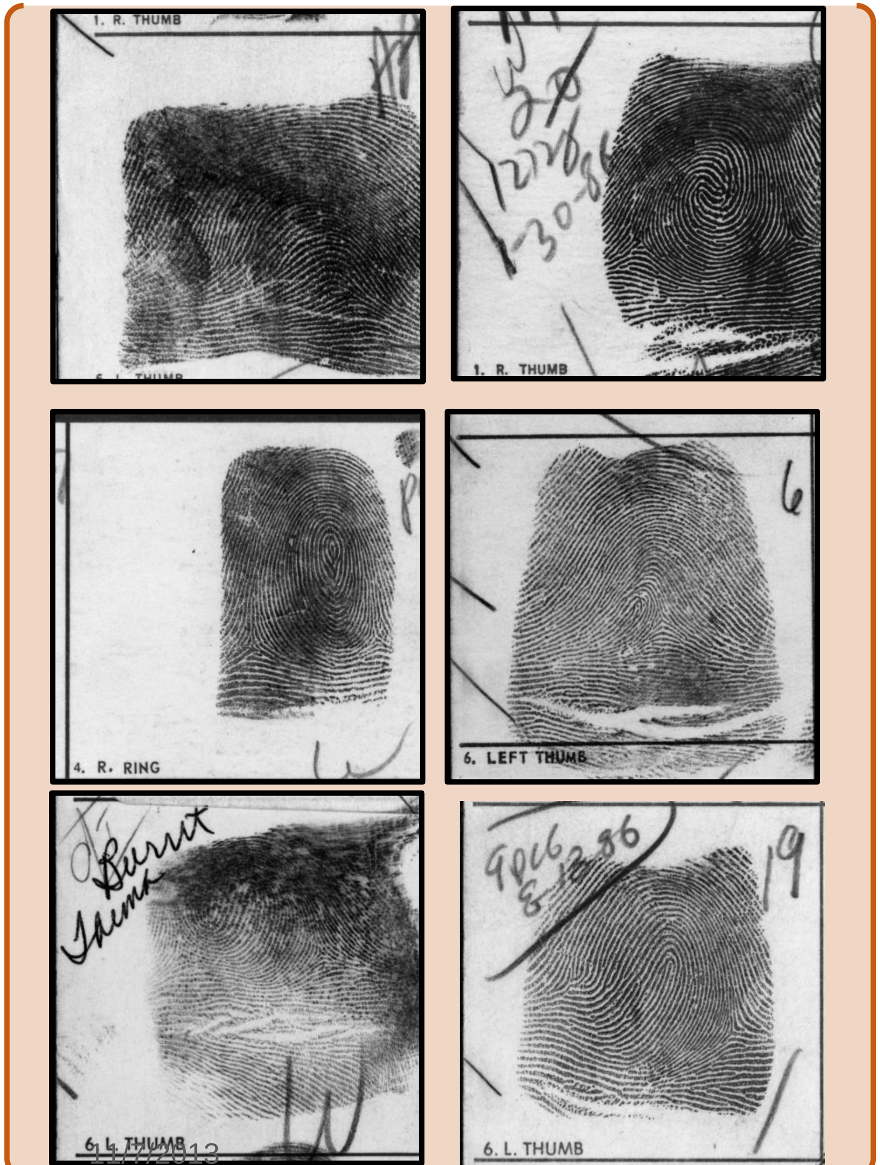
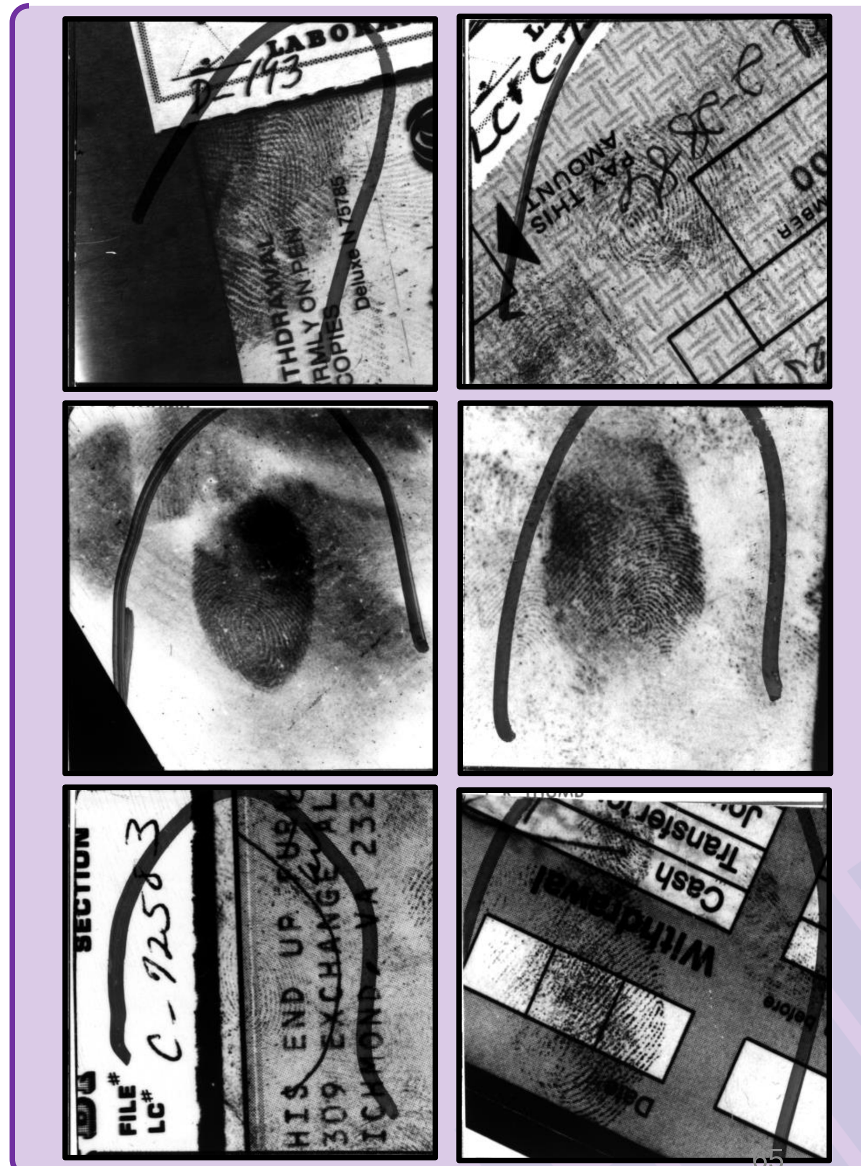
INFORMATION TECHNOLOGY
DELHI

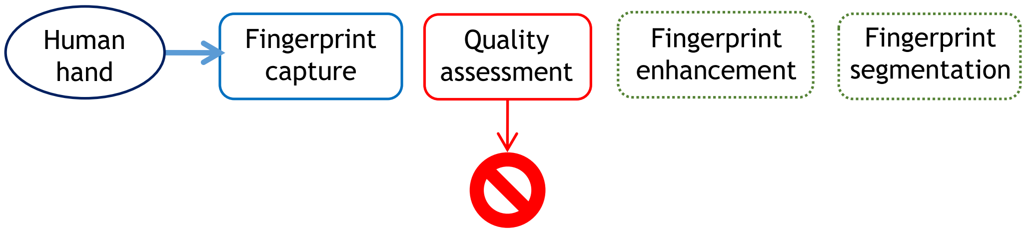
Backup slides

Latent fingerprint matching





Latent fingerprint matching system



Yoon, Soweon, Jianjiang Feng, and Anil K. Jain. "Latent fingerprint enhancement via robust orientation field estimation." *Biometrics (IJCB), 2011 International Joint Conference on*. IEEE, 2011.

Latent fingerprint matching system

Human hand → Fingerprint capture → Quality assessment → Fingerprint enhancement → Fingerprint segmentation → Feature extraction

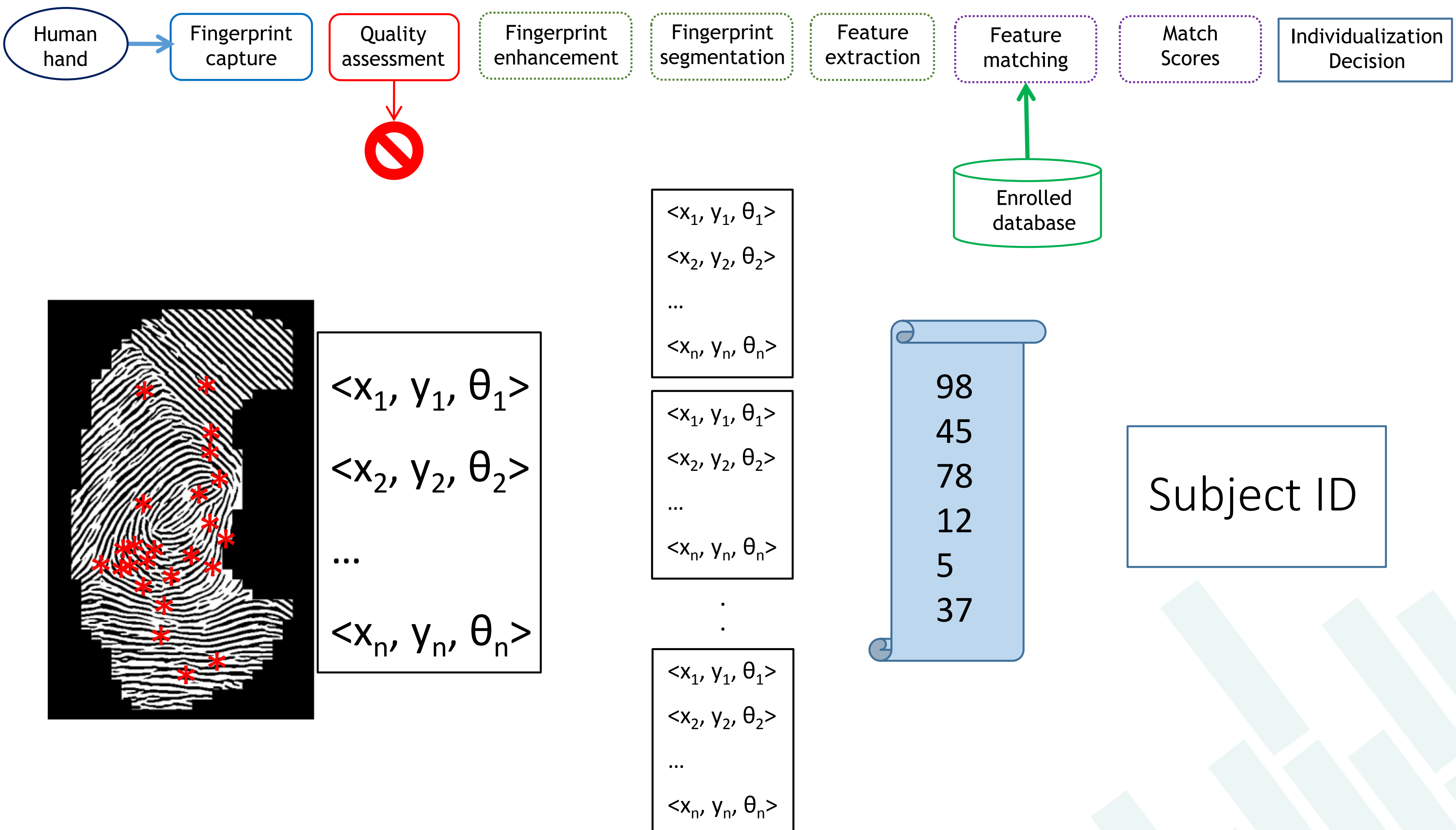
$<x_1, y_1, \theta_1>$

$<x_2, y_2, \theta_2>$

…

$<x_n, y_n, \theta_n>$

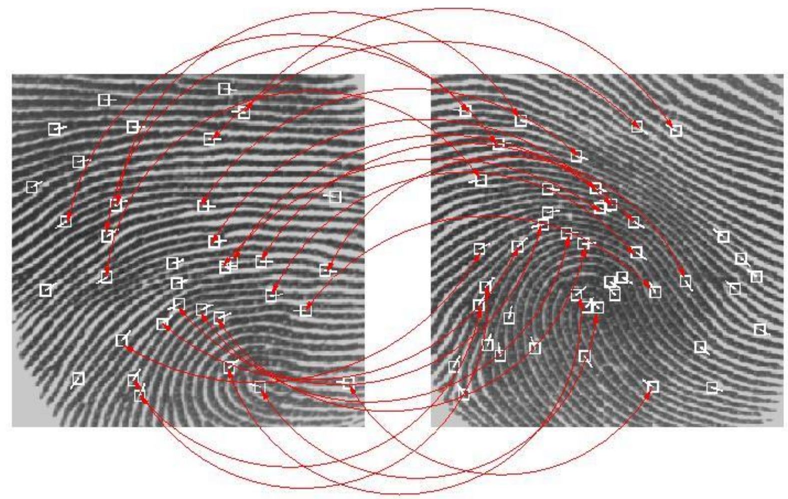
Latent fingerprint matching system



Concluding remark #1

Forensic experts

AFIS



Human cognition

Computational and technology aided techniques

Images from various sources in internet

Concluding remark #2

Process	Features used in literature	Evaluation metrics
Segmentation	1. Orientation tensor, frequency tensor [47] 2. Correlation strength [44] 3. Adaptive total variation (TV-LI) [45] 4. Directional total variation (TV-L2) [46]	1. Missed Detection Rate 2. False Detection Rate 3. Rank-K matching
Quality Assessment	1. NFIQ1.0 features, frequency domain analysis, local clarity analysis, orientation flow, radial power spectrum, ridge valley uniformity, Gabor filters, and minutiae count [54] 2. Gabor filters [55] 3. Ridge clarity map, number of minutiae [56]	1. VID and non-VID classification 2. Rank-K matching of different quality bins
Quality Enhancement	1. Dictionary of orientation patches [60] 2. Candidate orientation map, singular points[59, 58]	1. Average estimation error of orientation (in degrees) 2. Rank-K matching of different quality bins
Matching	1. Singular points, ridge flow map, ridge wavelength map, ridge quality map, fingerprint skeleton, minutiae points, ridge correspondence, level-3 features [69] 2. Orientation field, ridge flow, quality map, manual minutiae [72] 3. MCC descriptor for minutiae [48] 4. Manually and automated extracted minutiae [68, 67]	1. Rank-K matching