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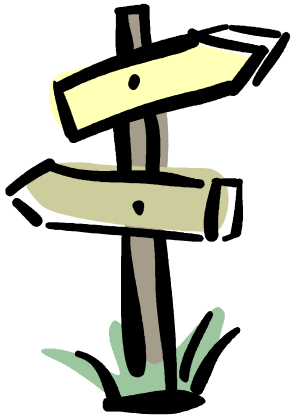
Fingerprint recognition

State-of-the-art
and new directions

Outline

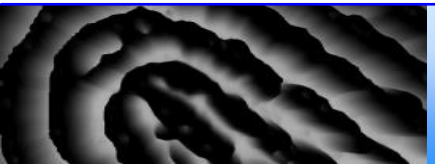
State-of-the-art

- Fingerprint anatomy
- Fingerprint acquisition
- Feature extraction
- Fingerprint comparison
- Performance evaluation
- Synthetic fingerprints



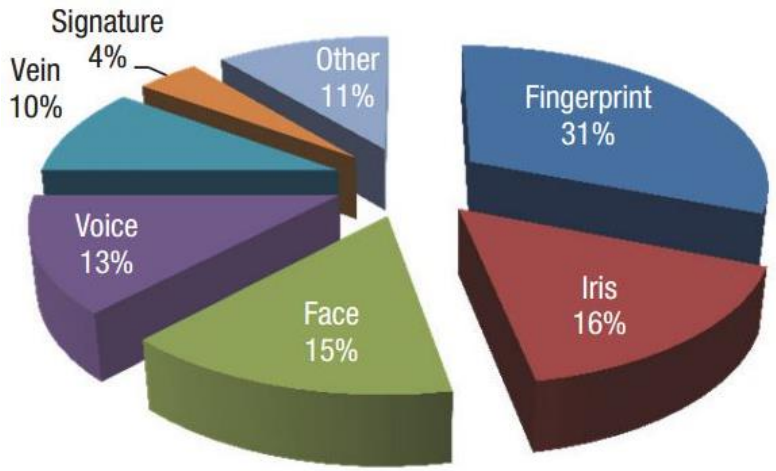
Main challenges

- Fake fingerprints
- Double-identity fingerprints
- Altered fingerprints
- Latent fingerprints



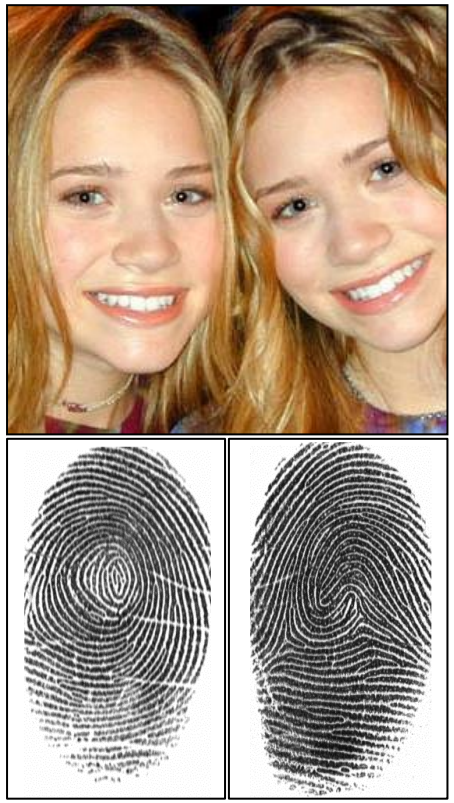
Why fingerprints?

Biometrics market share (2016)

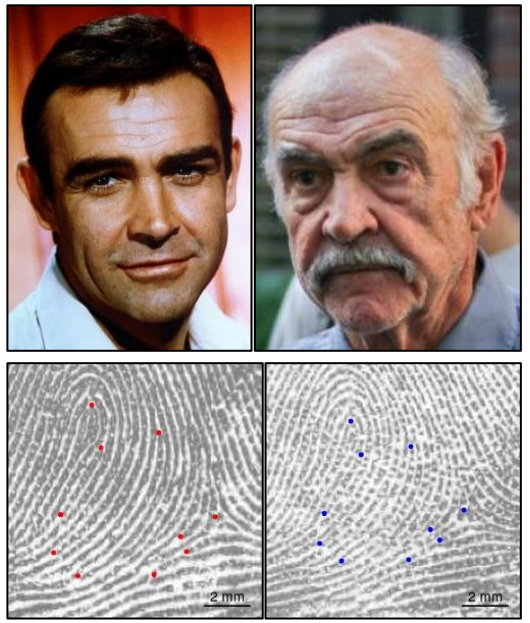


- Highly distinctive and unique
- Persistent
- Publicly accepted as reliable (evidence in a court of law)

Identical twins have different fingerprints

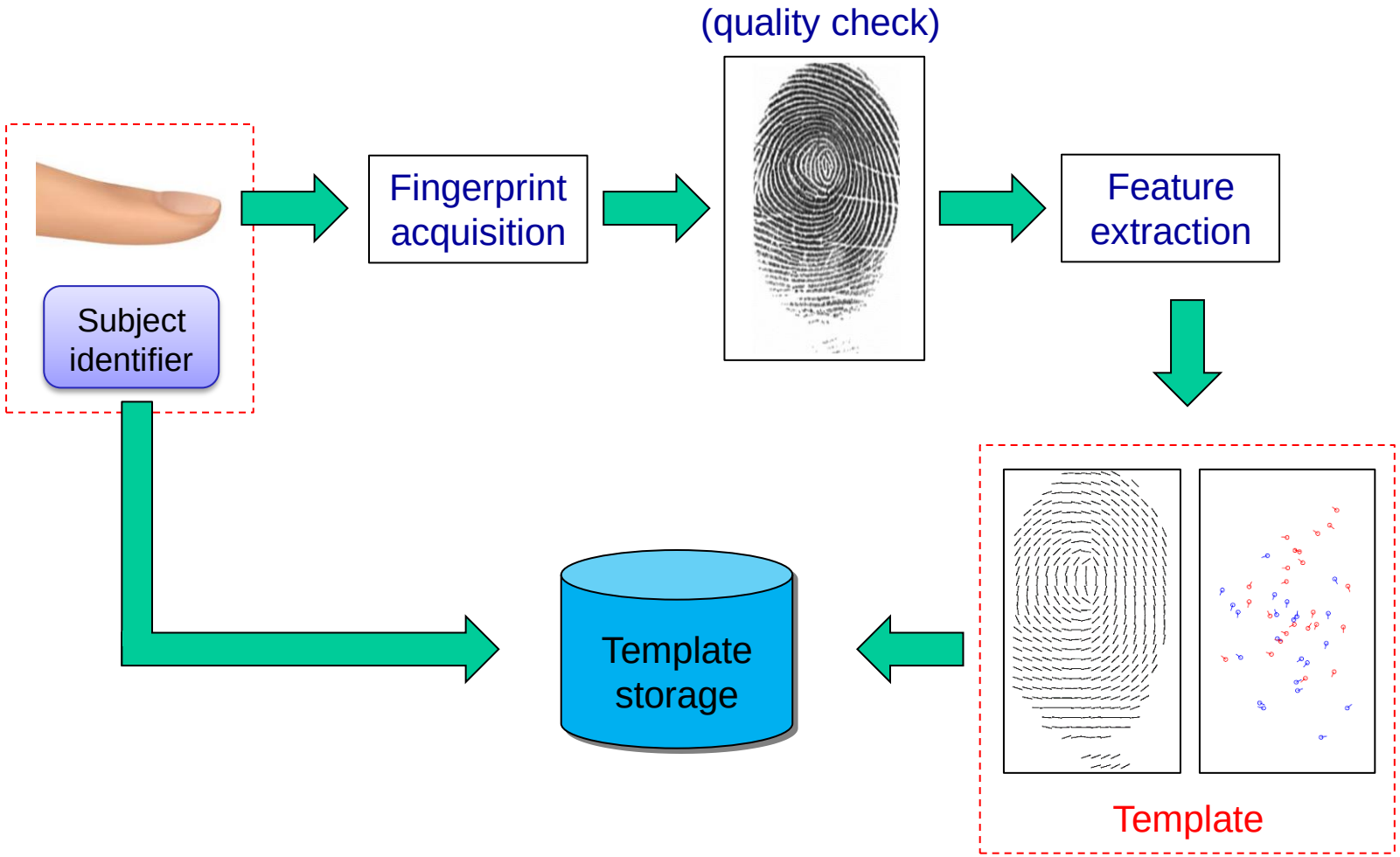


Do not change during the lifetime of a person



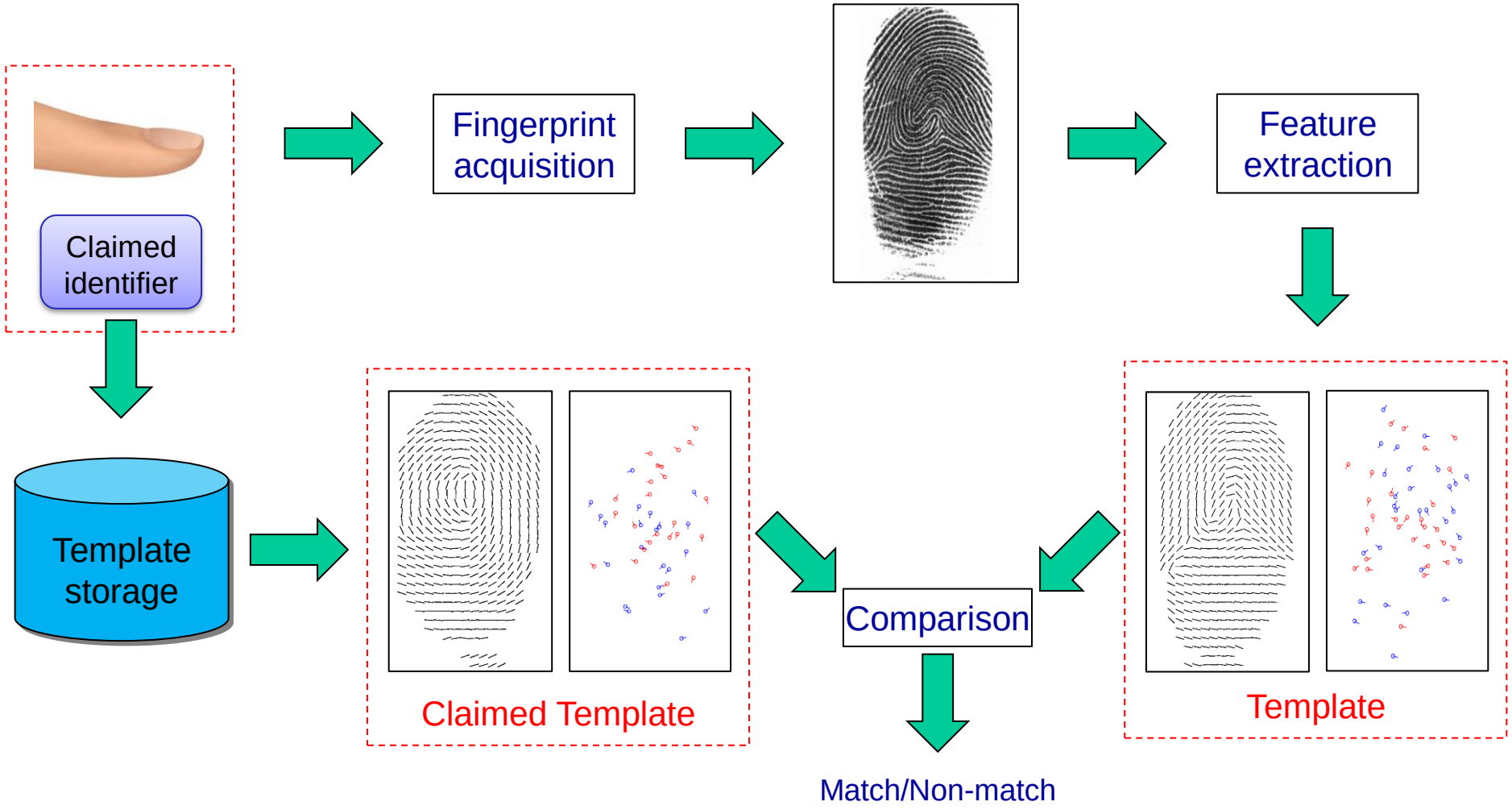
How does a biometric system work? (1)

Enrolment



How does a biometric system work? (2)

Verification

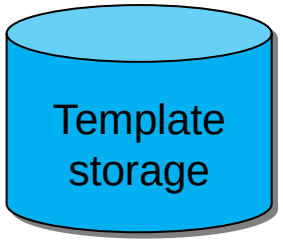


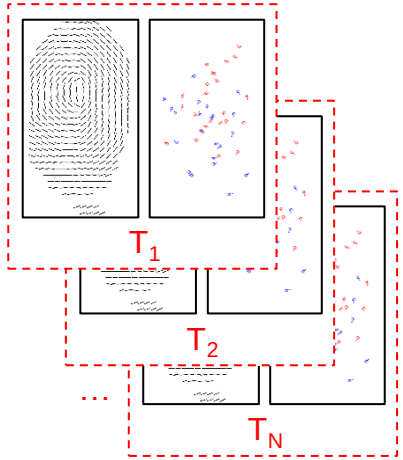
How does a biometric system work? (3)

Identification

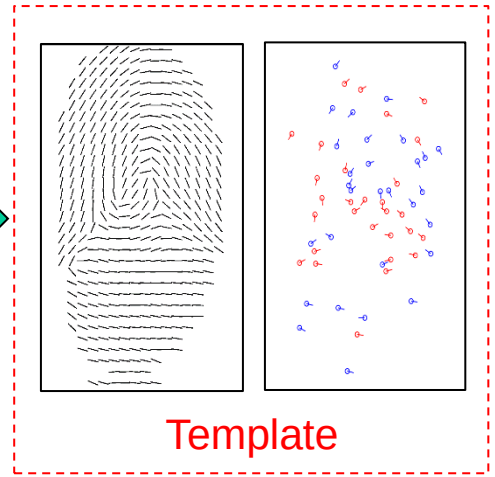
Fingerprint acquisition

Feature extraction

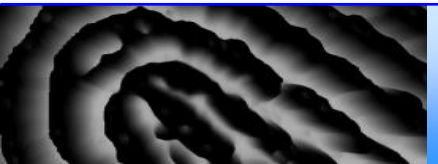




Pre-selection and comparison

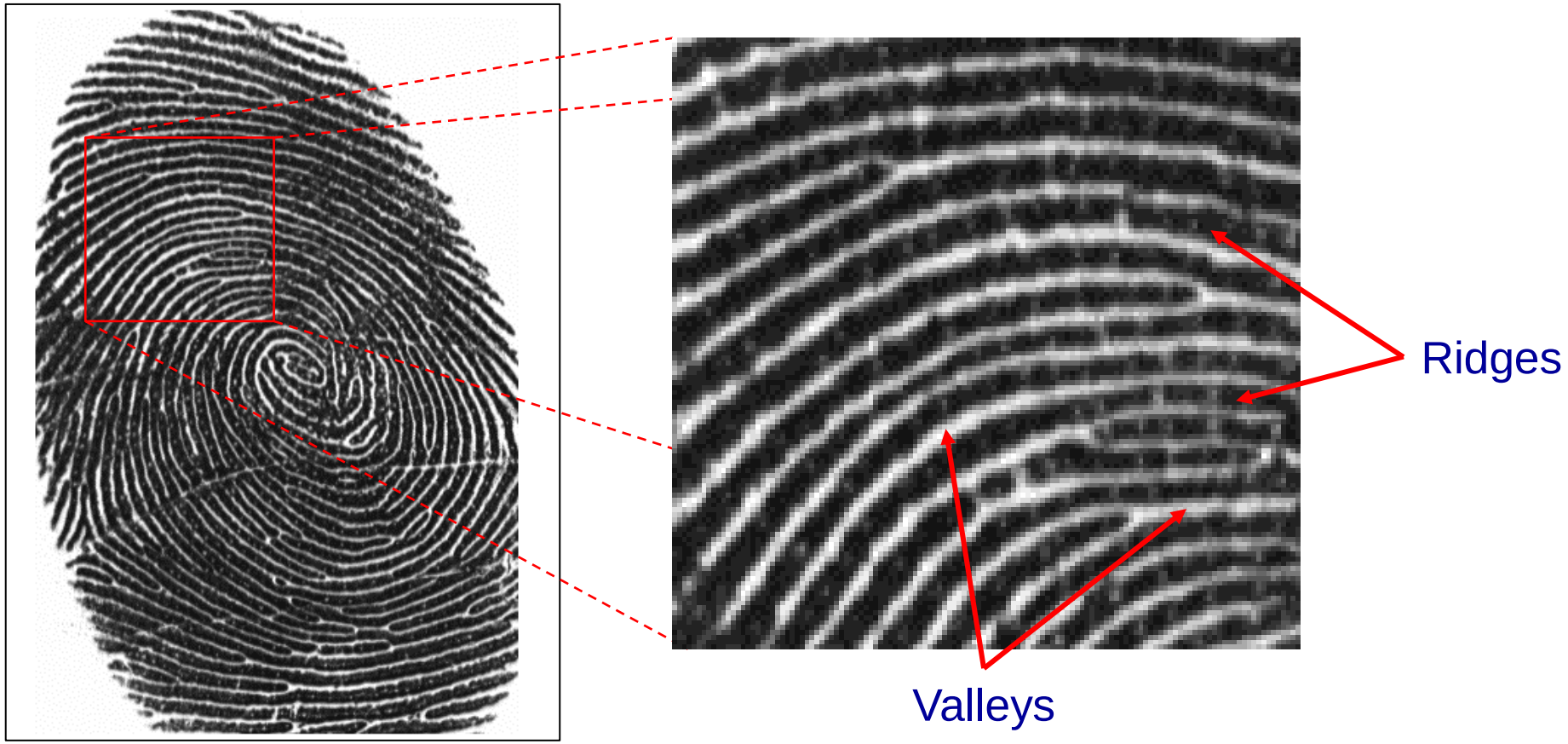


Candidate list or "not identified"



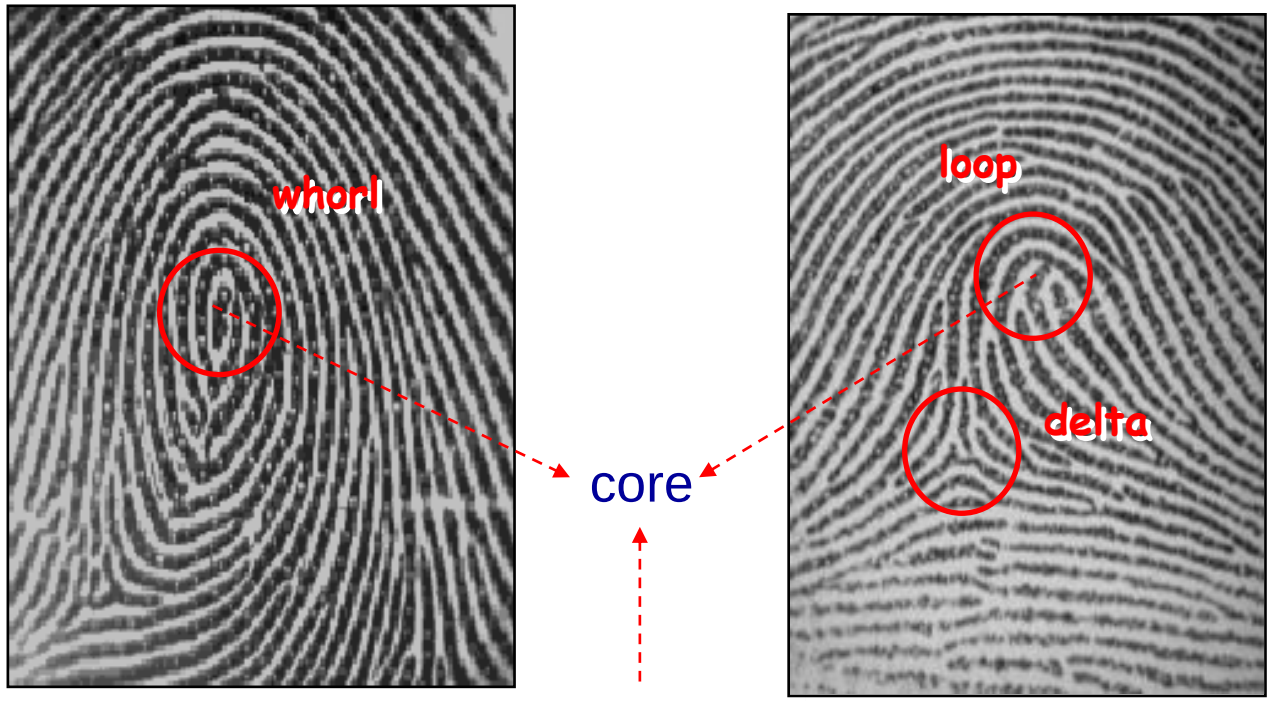
Fingerprint anatomy

A fingerprint is composed of a set of lines (ridge lines), which mainly flow parallel, making a pattern (ridge pattern).

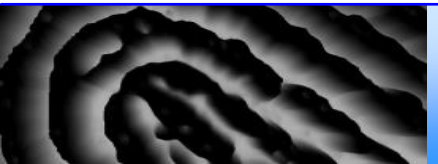


Singularities

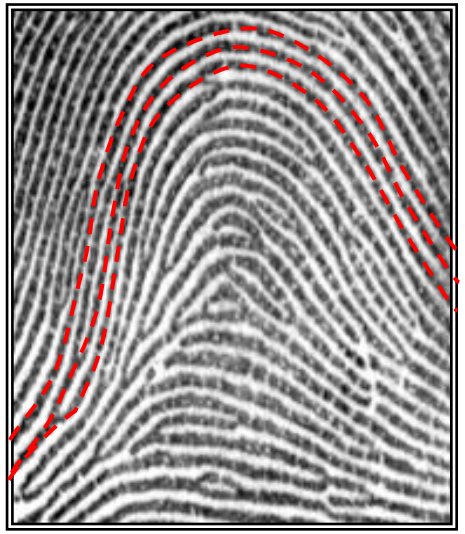
Sometimes the ridge lines produce local macro-singularities, called whorl (O), loop (U) and delta (Δ).



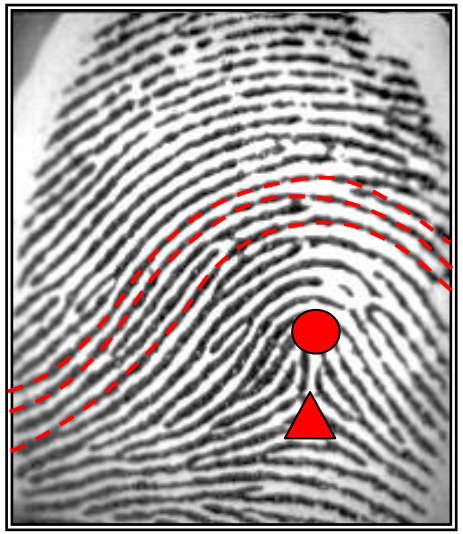
The center of the northernmost loop/whorl type singularity



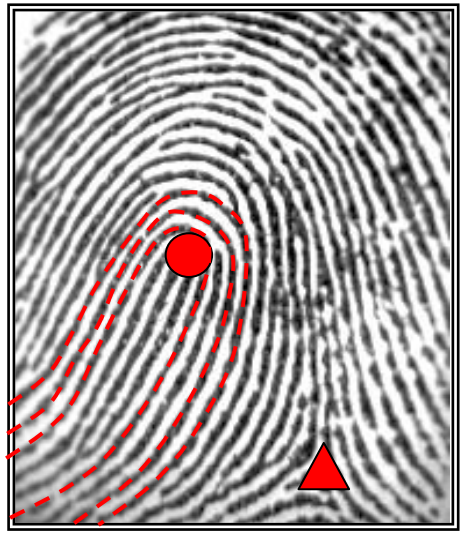
Classes



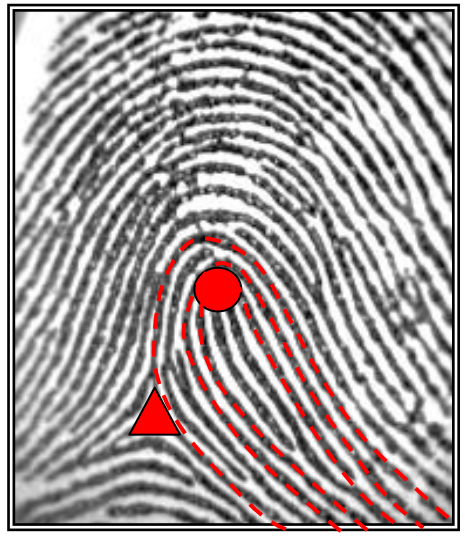
arch (plain)



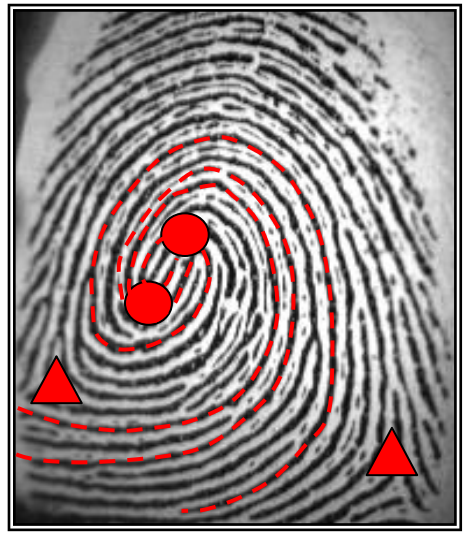
tented arch



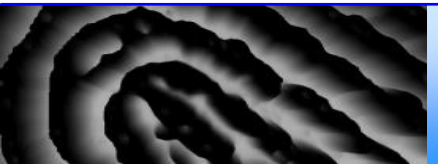
left loop



right loop

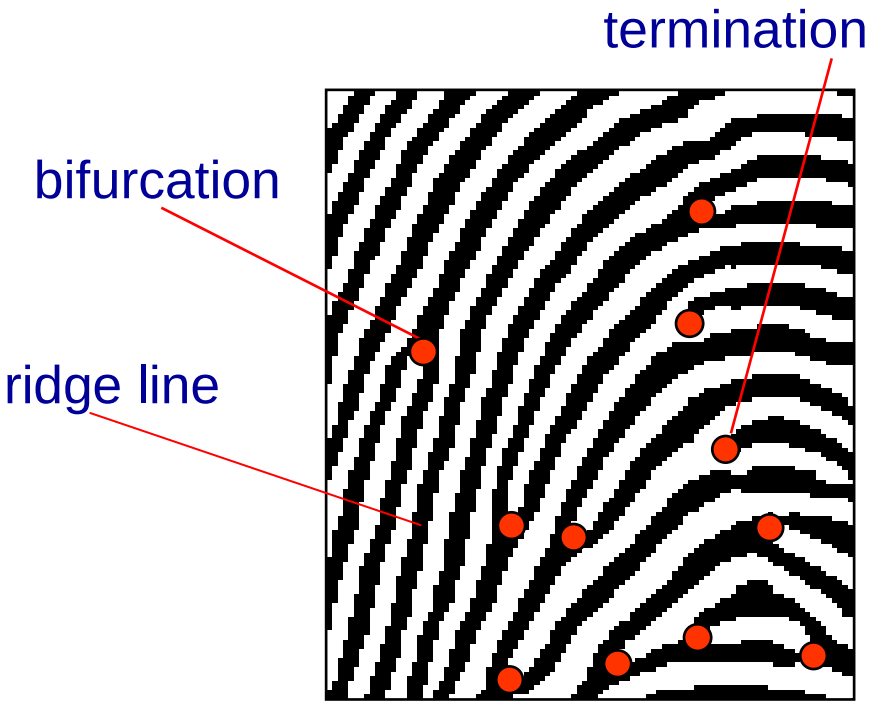


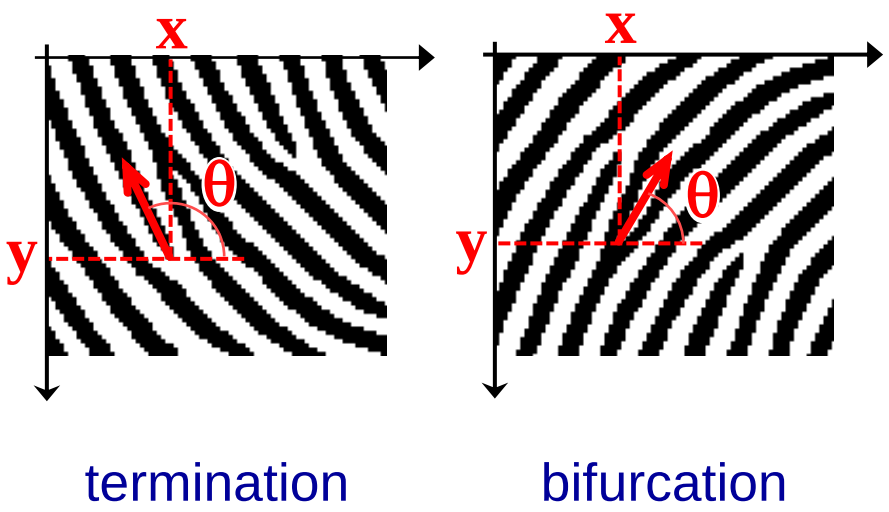
whorl



Minutiae

Minutiae are determined by the termination or the bifurcation of the ridge lines; they are usually represented by the coordinates (x, y), the angle θ between the minutia tangent and the horizontal axis, and the type (termination/bifurcation).





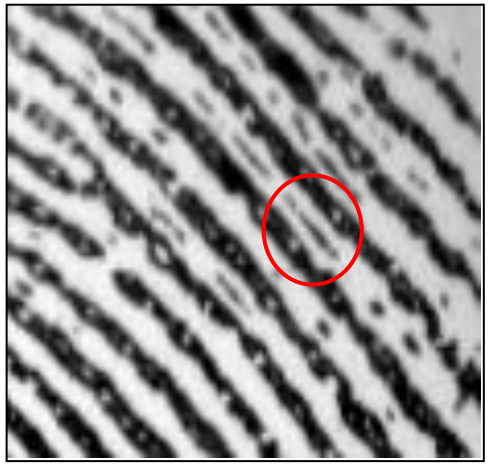
termination bifurcation

Sweat pores

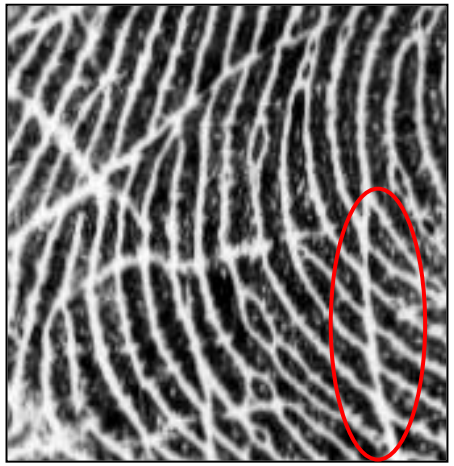
At the very-fine level (e.g., acquisition at 1000 dpi) it is possible to identify sweat pores (from 60 to 250 μm), incipient ridges, creases, etc.

sweat pores

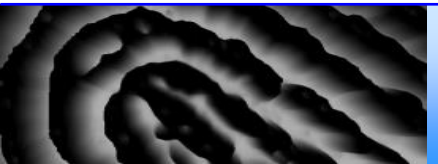
incipient ridges



creases



A fingerprint in 3D



Fingerprint scanners

1990

Bulky
Optical (FTIR)
Scanners

2000

Desktop
fingerprint
scanners
(mainly optical)

Access Control
and T&A stations

2010

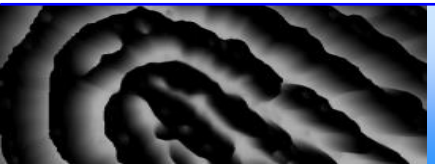
Small touch and
swipe sensors
(mainly capacitive)
integrated in laptops

2013

Small capacitive
sensors in the
«home button»
of mobile phones

2019

In-display Sensor
(CMOS →TFT)



Online fingerprint acquisition: examples

Optical

HiScan

Verifier 300 LC 2.0

MSO350

UareU 4000

Capacitive

TouchChip TCS1

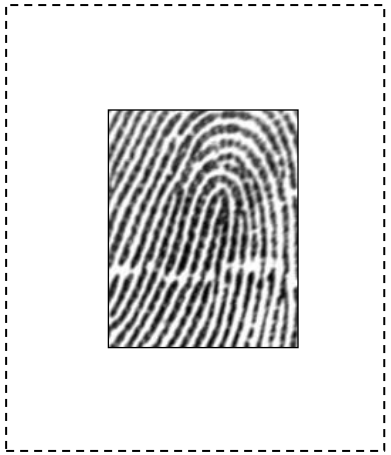
AES 4000

Thermal

FingerChip AT77C101B

Main device parameters

Resolution

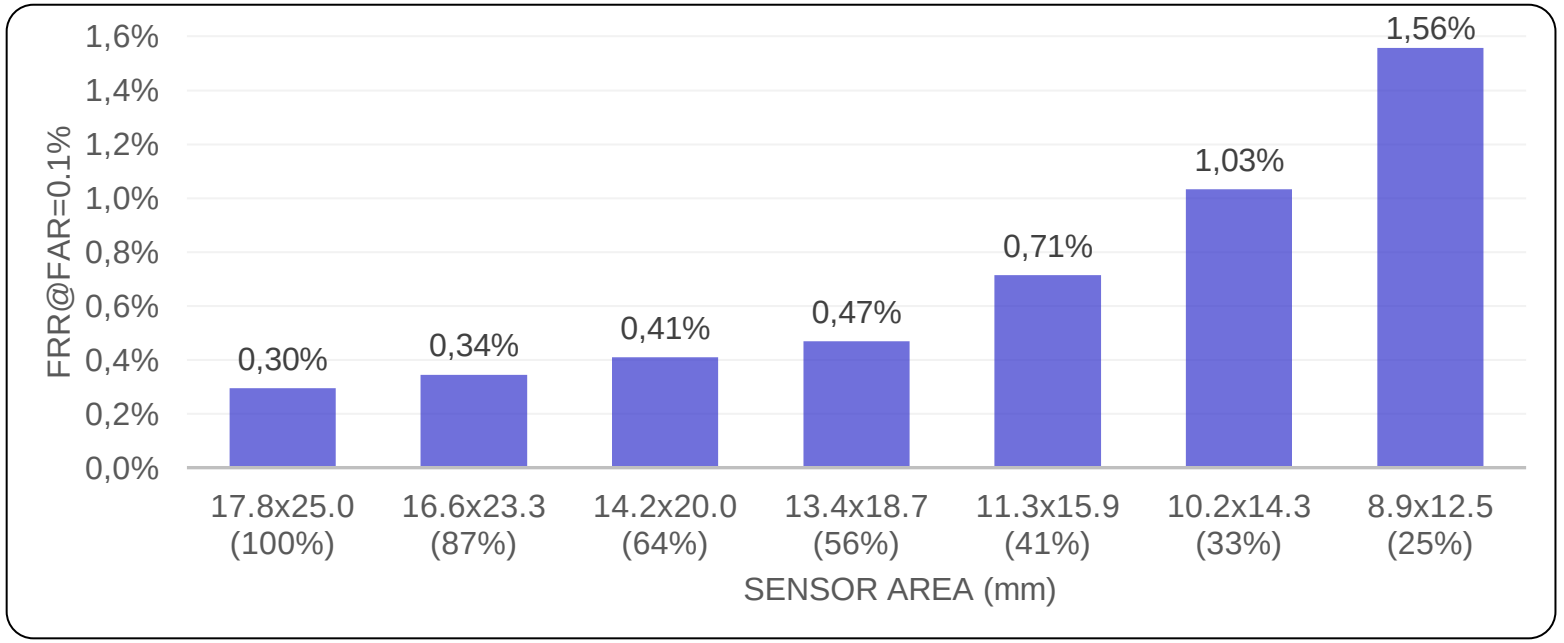


Acquisition area

Dynamic range

Geometric accuracy

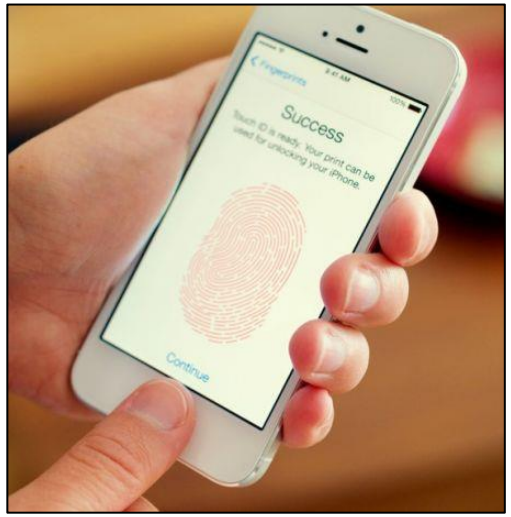
Problems with small area sensors (1)



Smartphone sensors: we can expect an accuracy drop ranging from 10× to 100× when using very small area sensors (5×5 mm^2) instead of large area ones (20×25 mm^2)

Problems with small area sensors (2)

Comparing small patches increases the risk of false matches



Roy, Memon & Ross

MasterPrint: Exploring the Vulnerability of Partial Fingerprint-based Authentication Systems

IEEE Transactions on Information Forensics & Security, 2017

Bontrager et al.

DeepMasterPrints: Generating MasterPrints for Dictionary Attacks

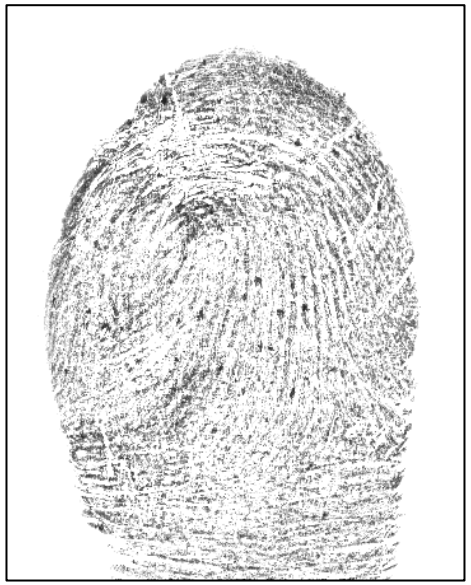
BTAS, 2018

Optical Coherence Tomography (OCT) sensor

In particular scenarios, imaging below fingertip surface might be a useful alternative to traditional fingerprint sensing:

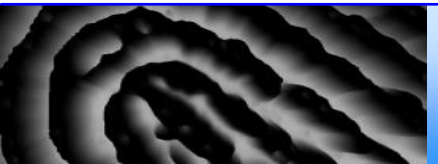
- altered fingerprints (intentional/unintentional)
- fake fingerprints

Optical scanner
(fingertip surface)



Optical Coherence Tomography
(below fingertip surface)

After one hour of sandpaper!



Smartphone camera

Fingerprint acquisition using a high-resolution smartphone camera could be a suitable solution in specific scenarios such as:

- border control
- eDocument verification
- smartphone login

Main problems:

- low contrast
- complex background
- natural lighting
- finger distance and rotation with respect to the camera

Optical scanner

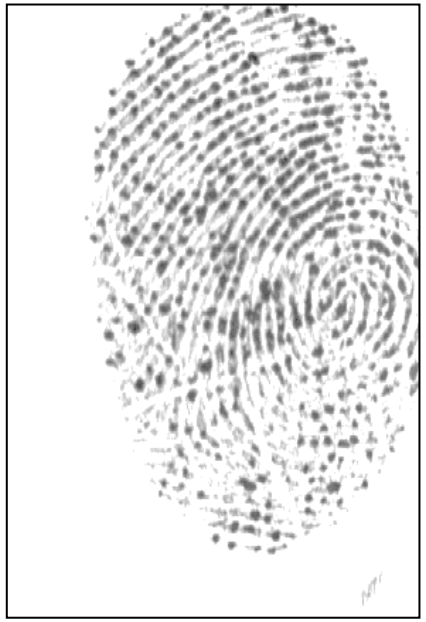
Smartphone camera

Image quality

Low quality fingerprints:

- scarcely prominent ridge lines (manual workers, elderly people)
- too dry or too wet fingerprints

Good quality



Dry fingerprint

Wet fingerprint

Intrinsically low quality image

NFIQ

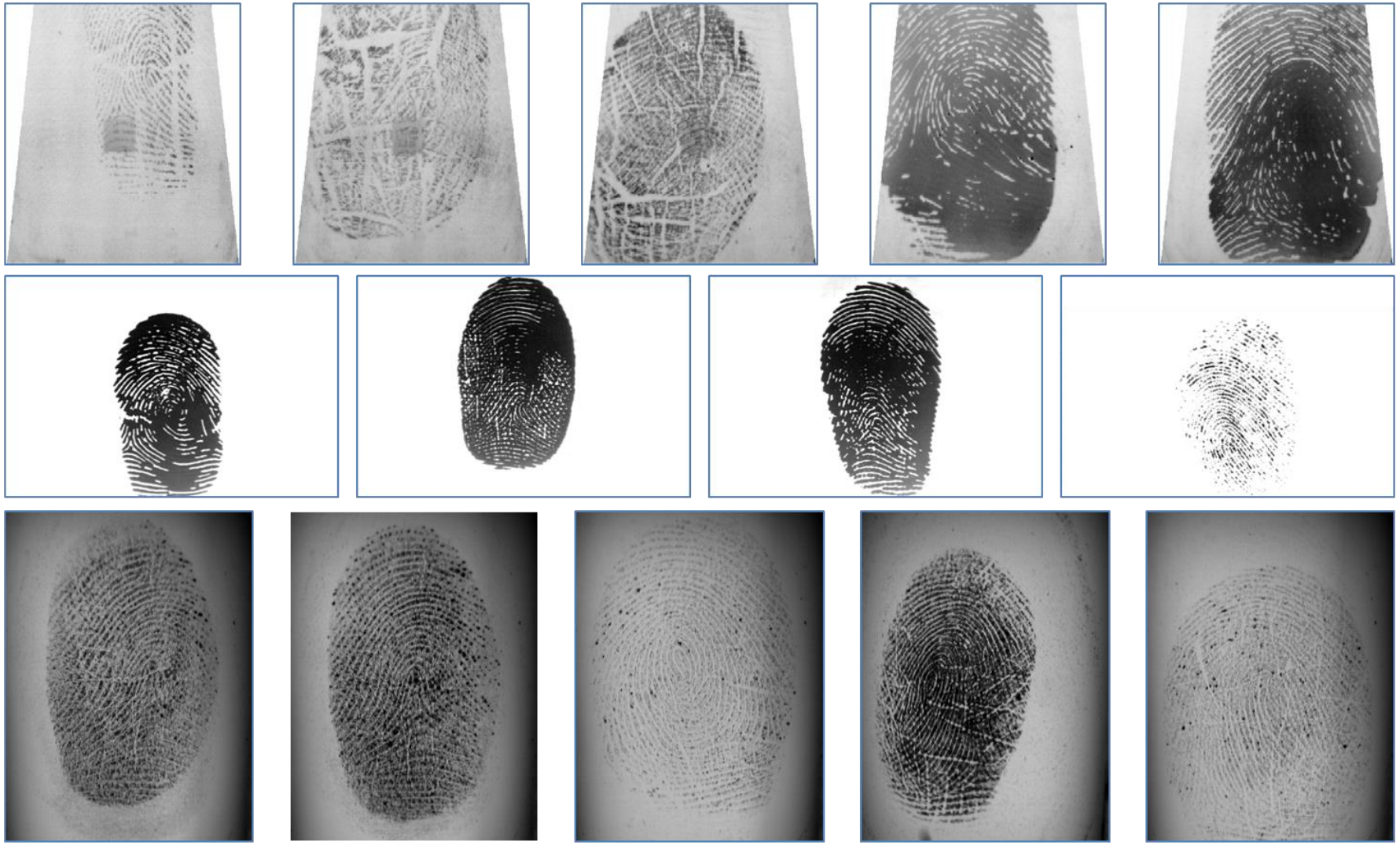
NIST Fingerprint Image Quality (NFIQ) is the *de facto standard* to quantify fingerprint quality (open source).

NFIQ (1.0) assigns to a fingerprint a value in {1,2,3,4,5} which is in inverse proportion with its quality.

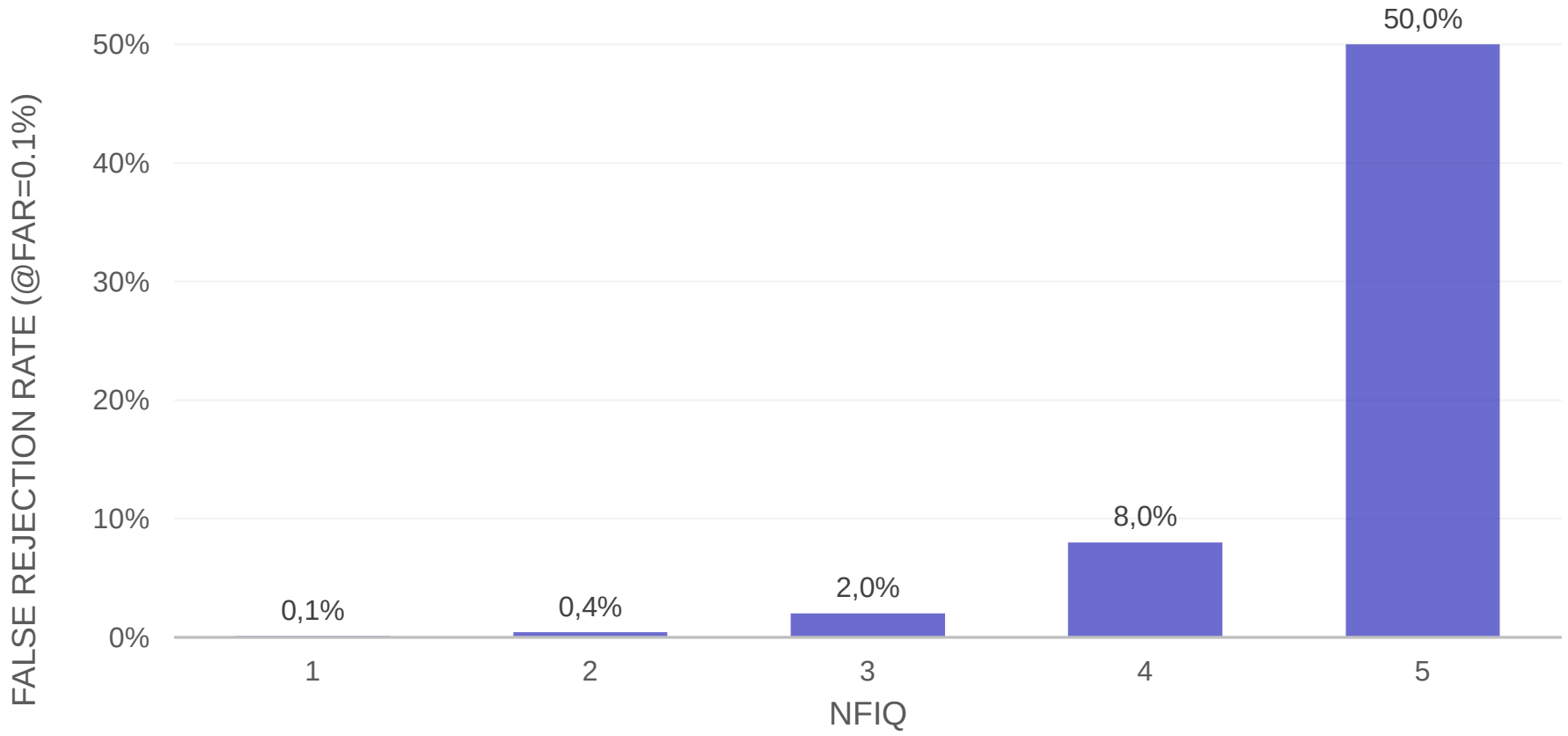
NFIQ is an operational quality measure aimed at predicting automatic fingerprint recognition performance:

- 1 → excellent quality → small errors → high accuracy
- 5 → poor quality → high errors → low accuracy

NFIQ=5 examples



Quality/accuracy tradeoff



Source: Tabassi E., “The Last 1% - Biometric Quality Assessment for Error Suppression”, Biometric Consortium Conference, 2007.

NFIQ 2.0

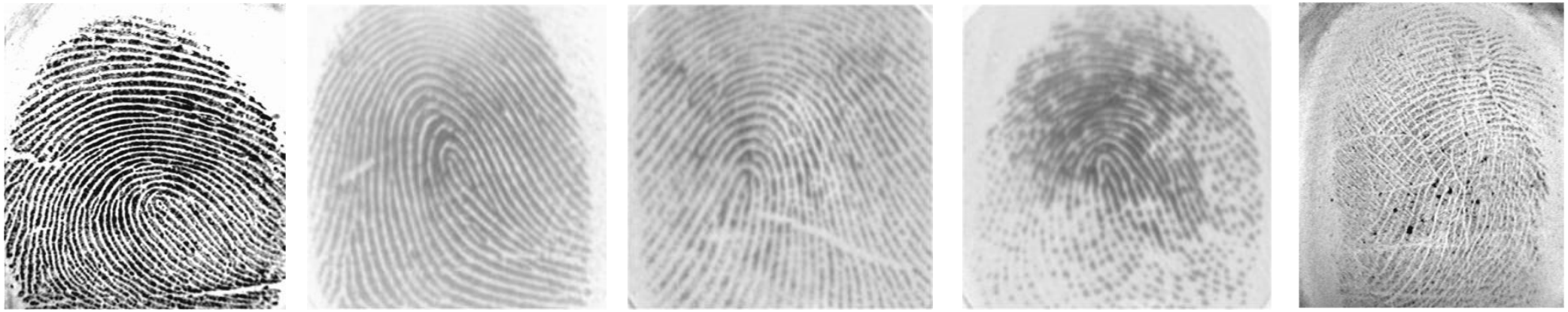
Released April 2016 (open source)

NFIQ 2.0 quality value is in [0..100]

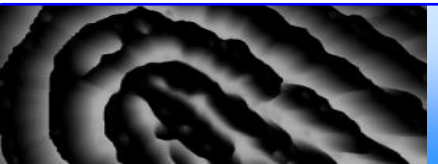
- 0 lowest quality value
- 100 highest quality value

Quality features

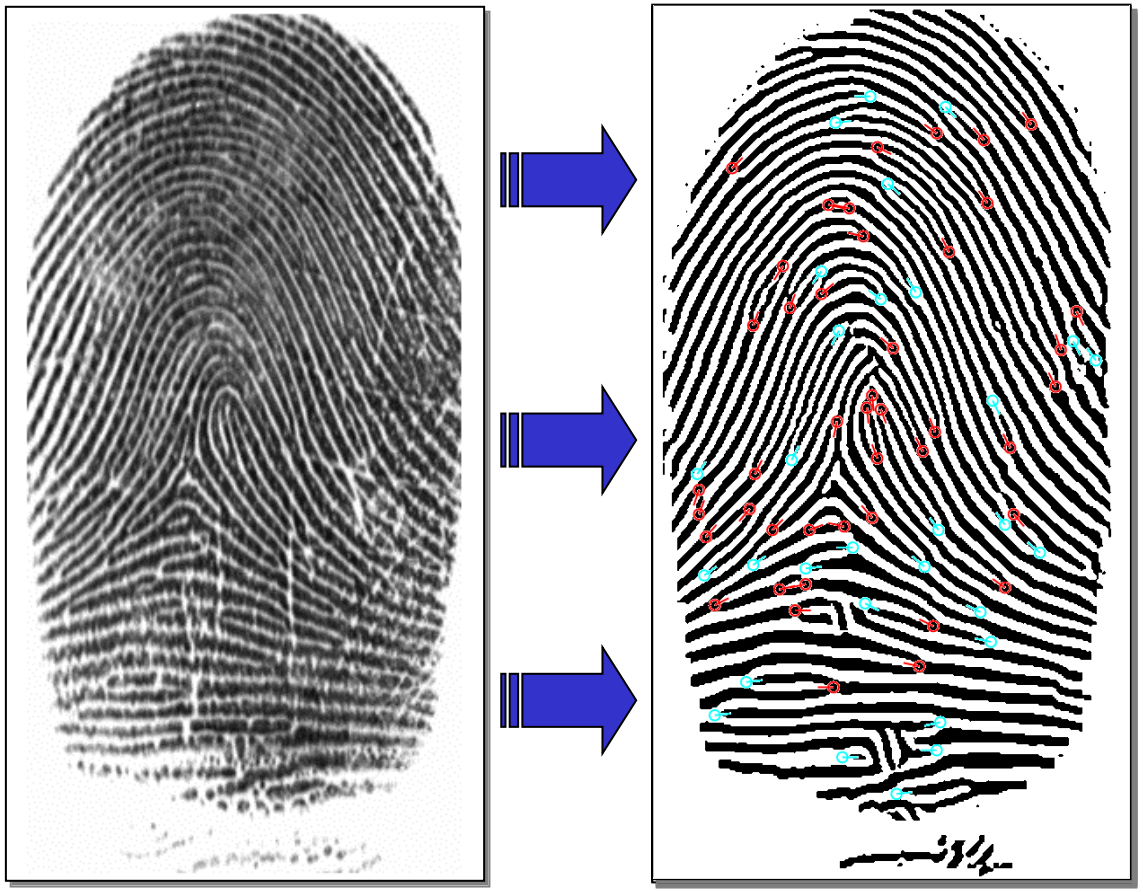
- 155 evaluated
- 14 selected (e.g., orientation certainty, ridge valley uniformity, …)

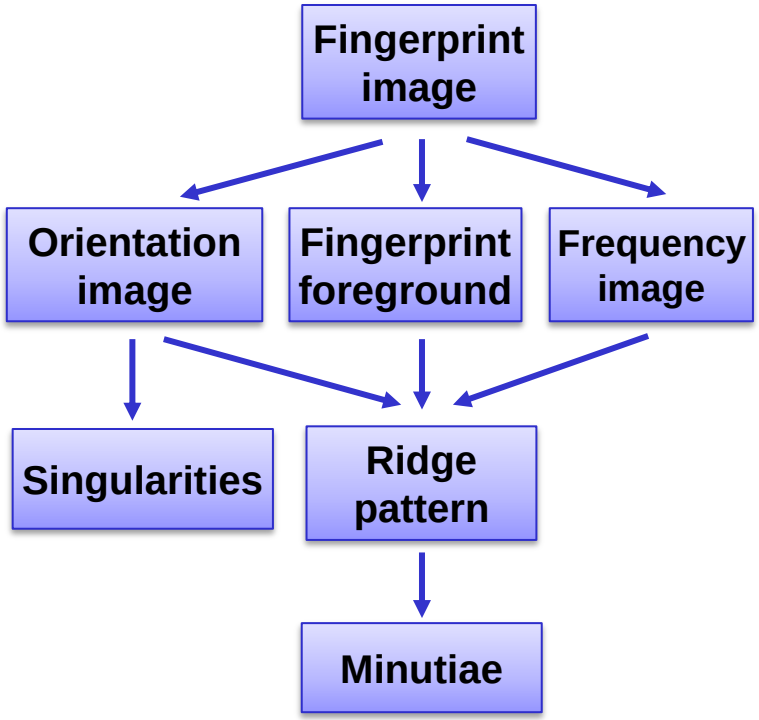


91 61 41 21 1



Feature extraction: main steps

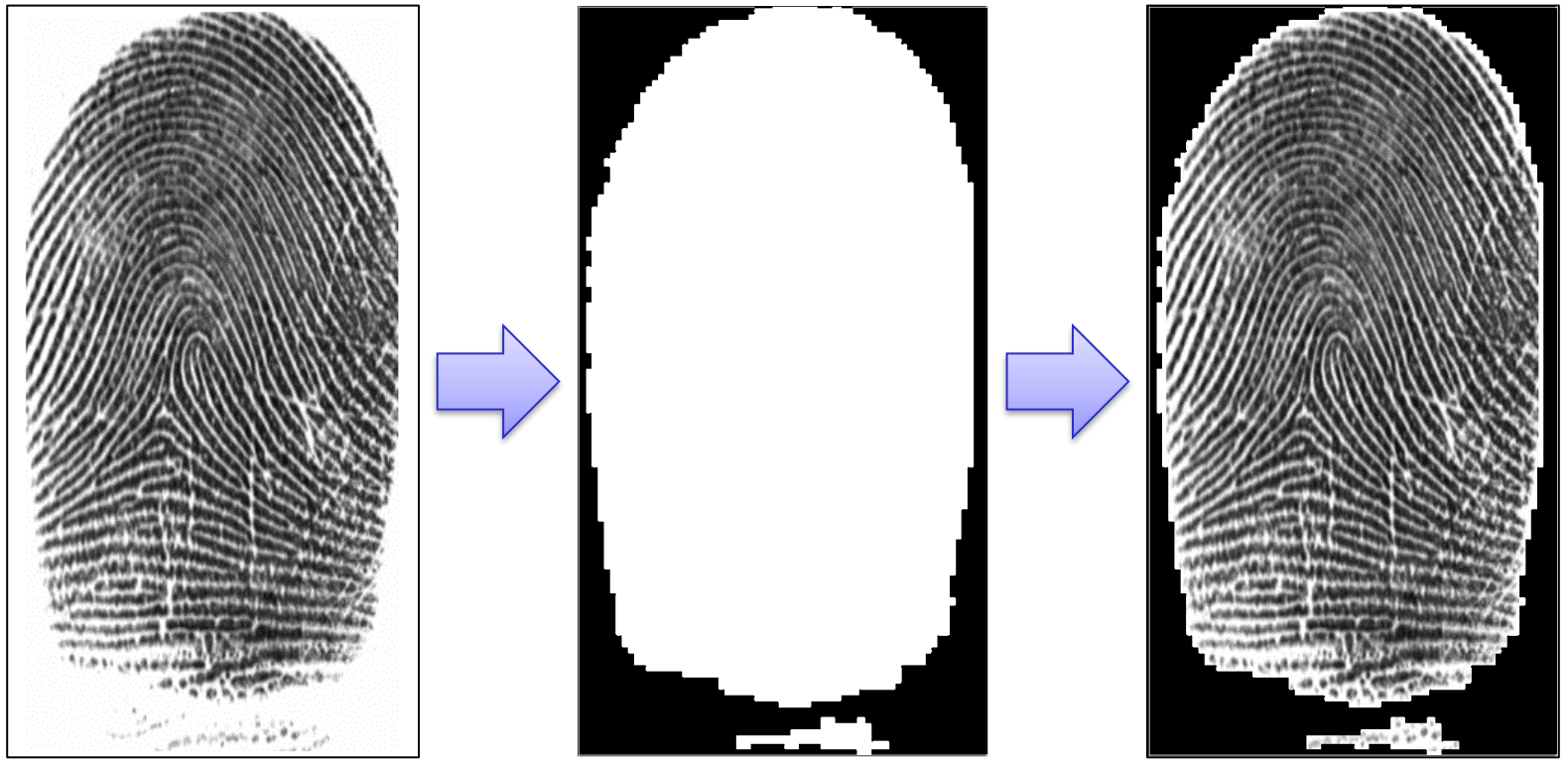




Segmentation

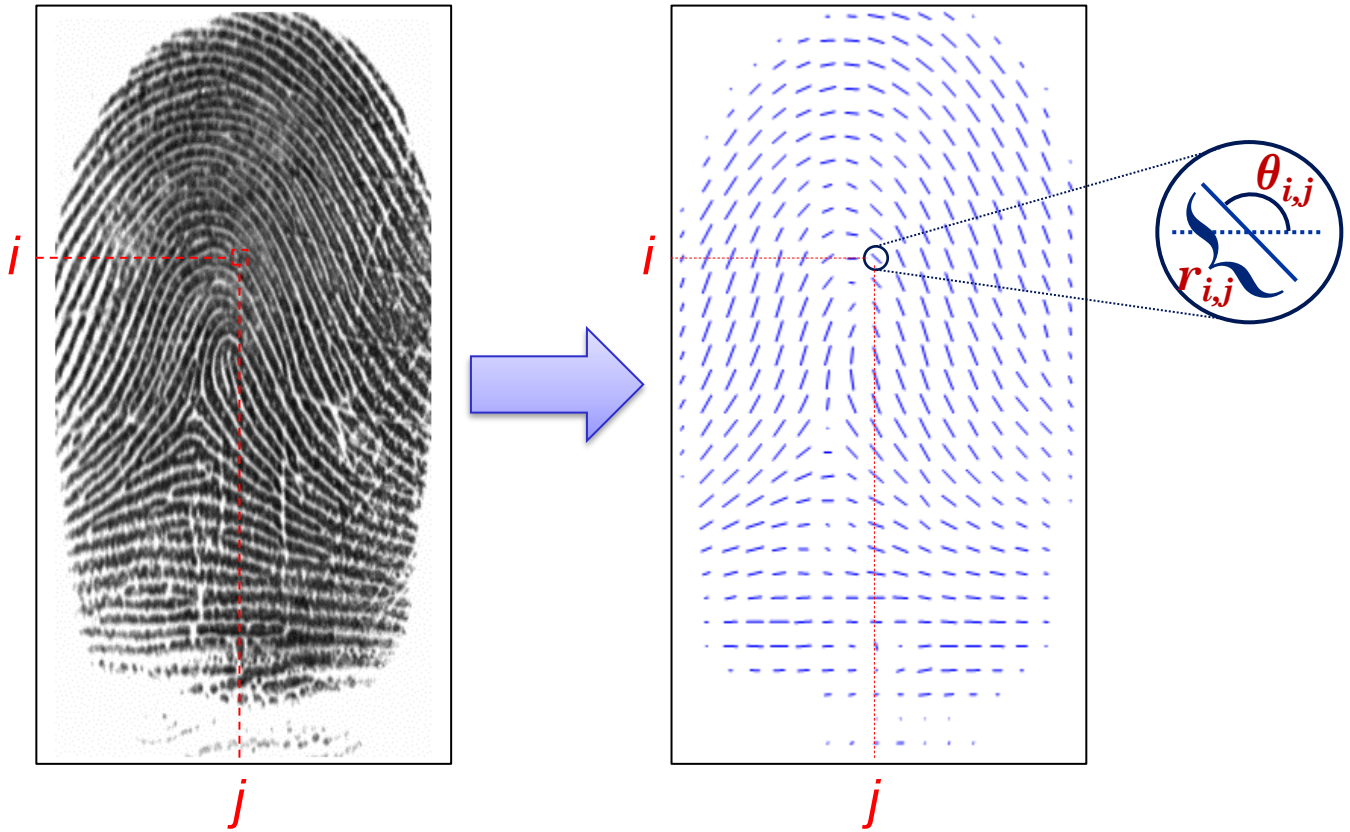
The segmentation stage is aimed at separating the fingerprint area (foreground) from the background.

The foreground is characterized by the presence of a striped and oriented pattern; background presents a uniform pattern.

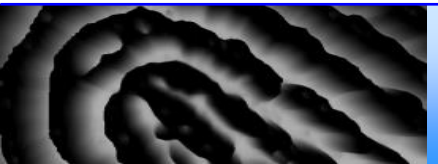


Local ridge orientation

The local ridge orientation at $[i, j]$ is the angle $\theta_{ij} \in [0,180°[$ that the fingerprint ridges form with the horizontal axis in an arbitrary small neighborhood centered at $[i, j]$.



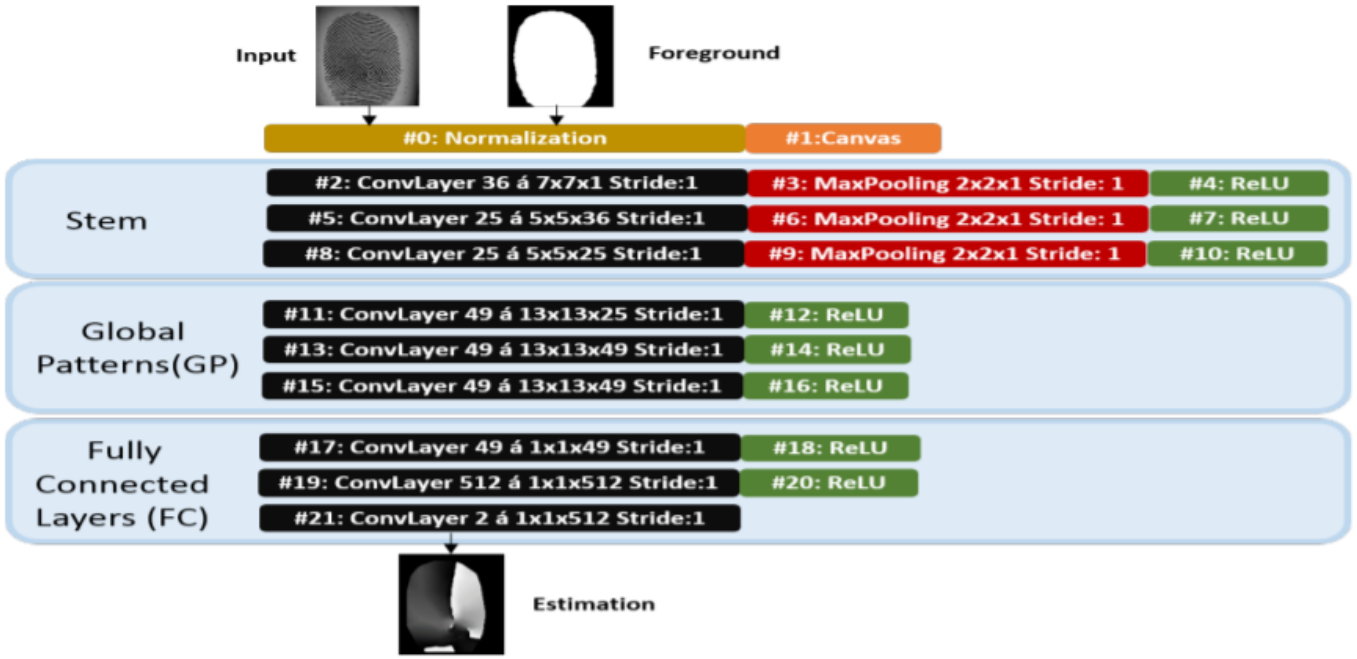
The simplest approach to extract local ridge orientations is based on computation of gradient phase angles.



Orientation extraction with CNN

P. Schuch, S. D. Schulz and C. Busch, "Deep expectation for estimation of fingerprint orientation fields," IJCB, Denver, CO, 2017.

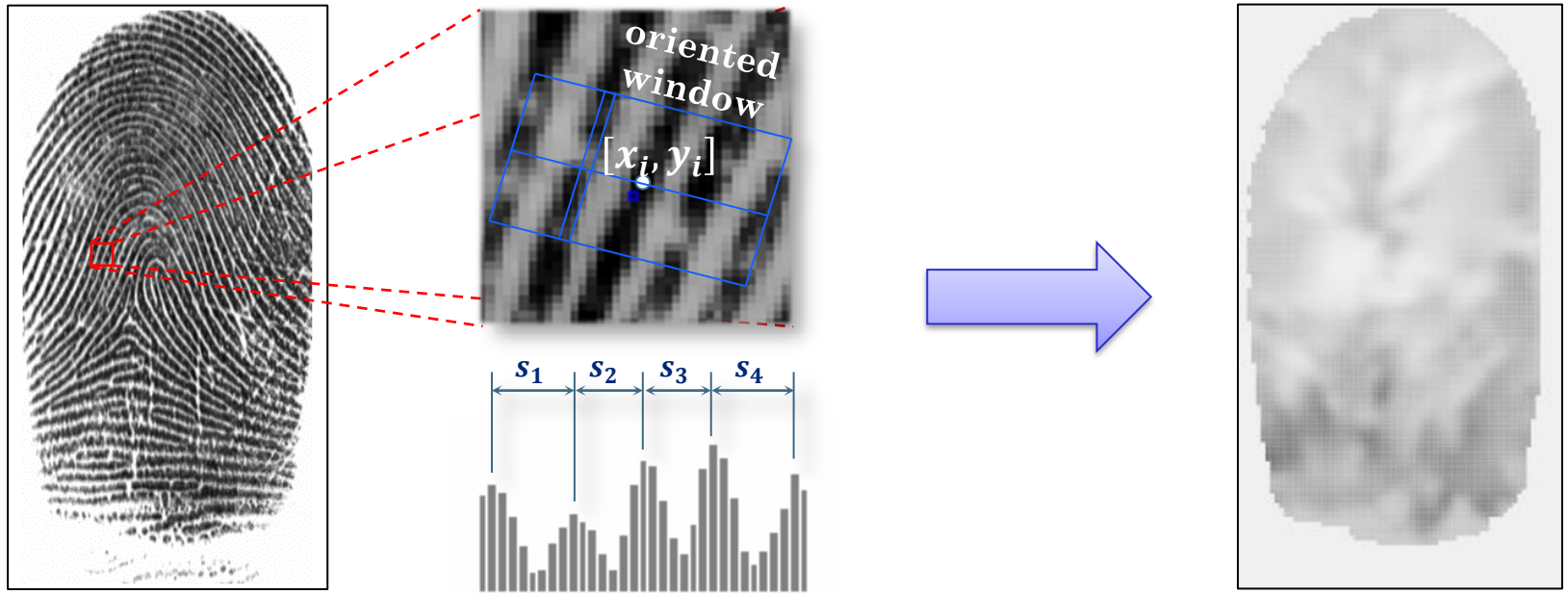
- Best Performing Approach (May 2018) on FVC-onGoing FOE
- In principle orientation estimation is a regression problem, but classification often proved to be better.
- Deep Expectation: weighted mean instead of winner take all



Local ridge frequency

The local ridge frequency f_{xy} at $[x, y]$ is the number of ridges per unit length along a hypothetical segment centered at $[x, y]$ and orthogonal to the local ridge orientation θ_{xy}.

A possible approach is to count the average number of pixels between two consecutive peaks of gray-levels along the direction normal to the local ridge orientation.



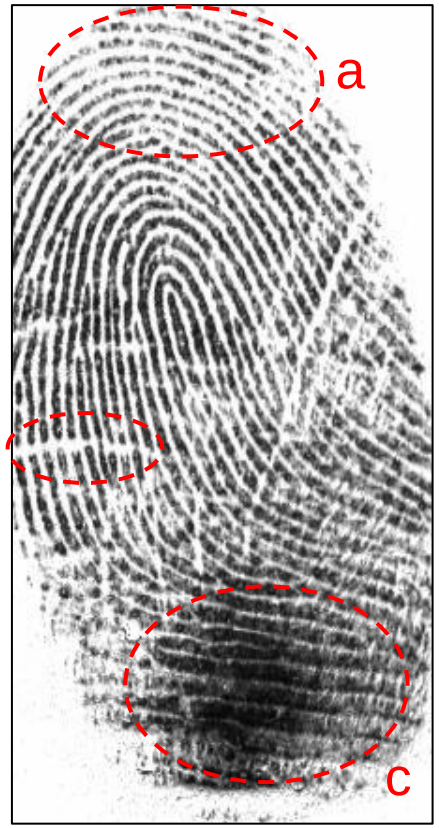
Enhancement (1)

The performance of feature extraction and comparison algorithms are strictly related to the image quality.

The objective of enhancement techniques is to improve the fingerprint image quality.

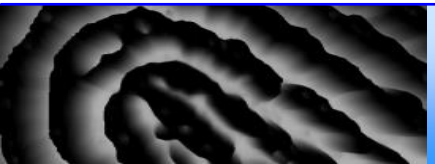
Typical degradations:

a. ridge lines are not continuous;
b. cuts, creases and bruises on the finger;
c. parallel ridges are not well separated.



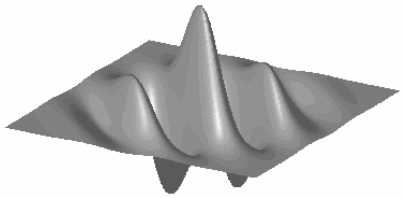
The most widely used technique for fingerprint enhancement is based on contextual filters.

In contextual filtering, the characteristics of the filter used change according to the local context.

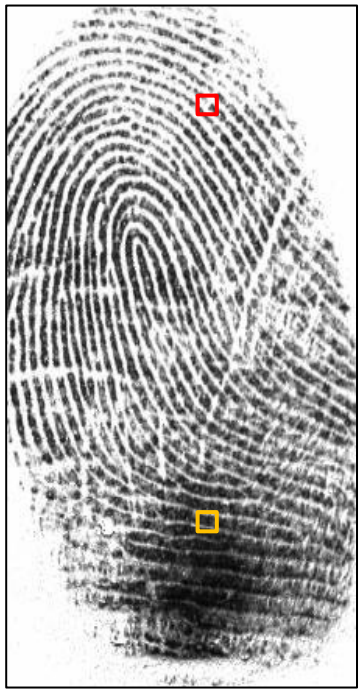


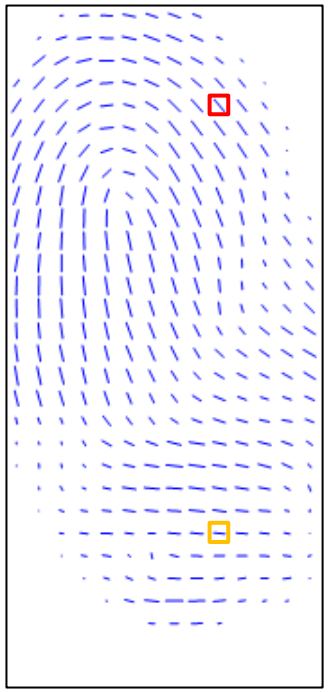
Enhancement (2)

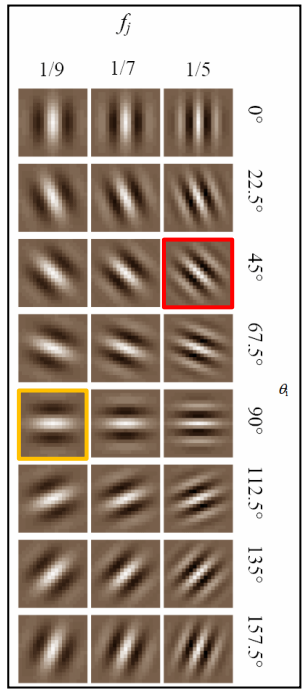
The local context of a fingerprint is represented by the ridge orientation and frequency.

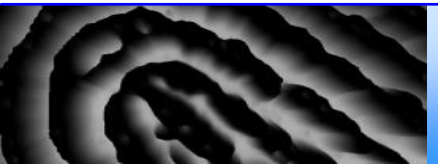


Gabor filter: sinusoidal plane wave tapered by a Gaussian.

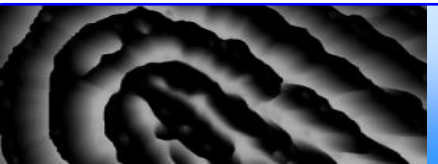








Enhancement (3)



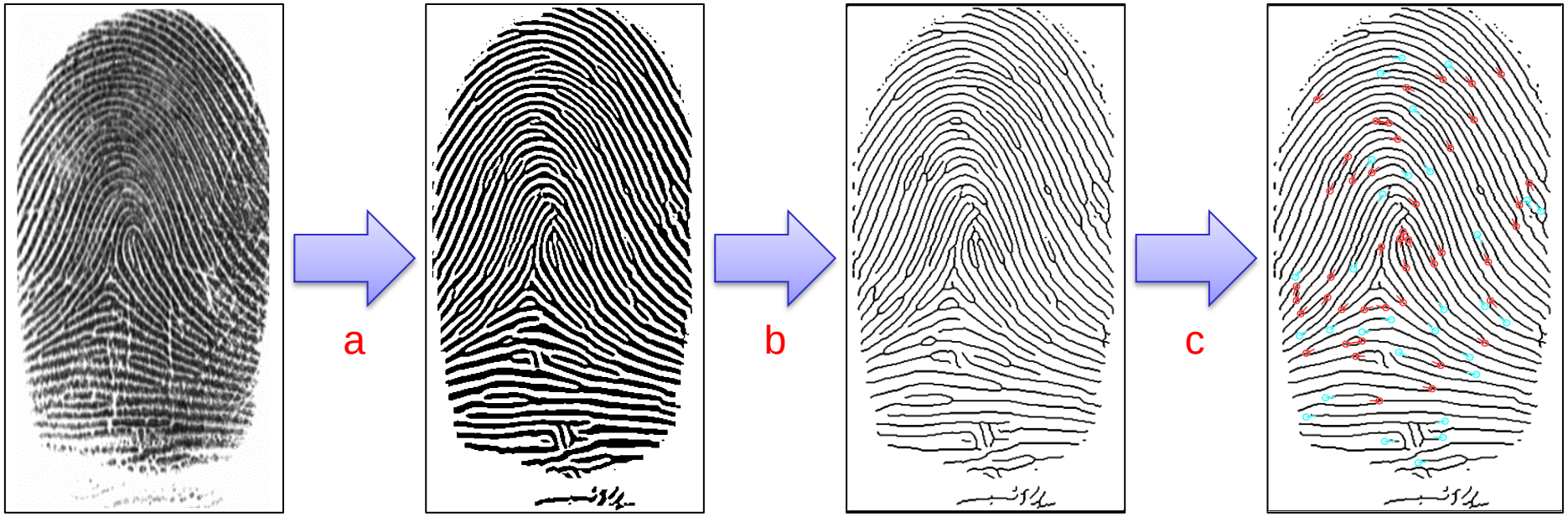
Minutiae detection (1)

Traditional approach:

a. Enhancement/Binarization: conversion into a binary image;

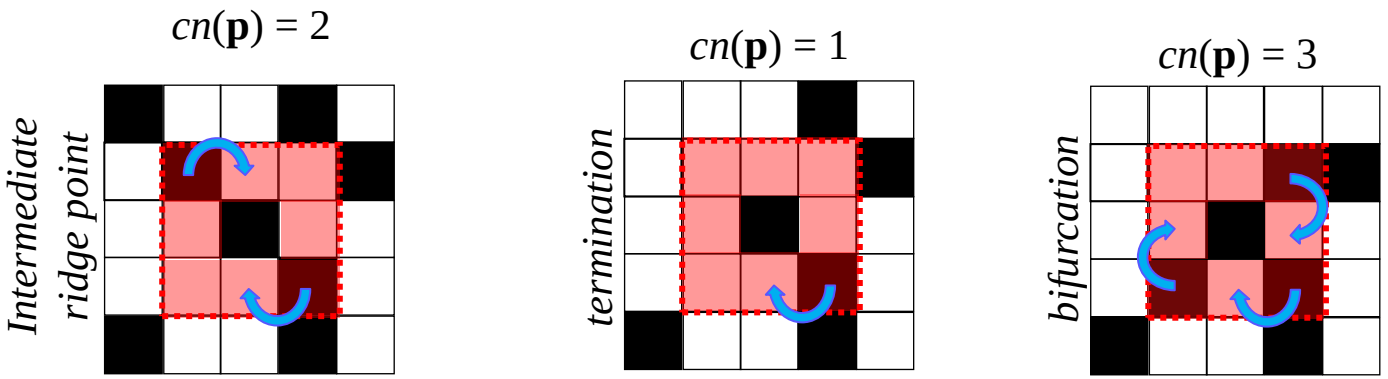
b. Thinning: the binary image is thinned to reduce the ridge thickness to one pixel;

c. Detection: an image scan then allows to detect minutiae.



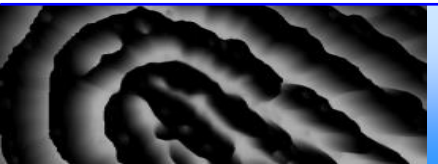
Minutiae detection (2)

Minutiae detection is based on the computation of the crossing number (*cn*):



It is simple to note that a pixel **p** is:

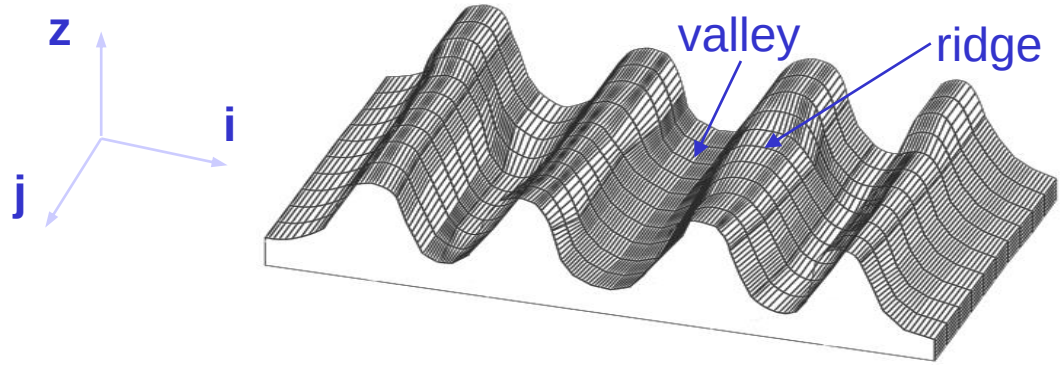
- an intermediate ridge point if *cn*(**p**)=2;
- a termination if *cn*(**p**)=1;
- a bifurcation if *cn*(**p**)=3;
- part of a more complex minutia if *cn*(**p**)> 3.



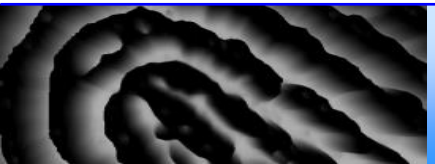
Direct Gray-Scale Minutiae Detection (1997)

- Problems of the binarization-based approaches:
  - **information** may be **lost** during the binarization process
  - thinning may introduce a large number of **spurious minutiae**
  - binarization and thinning were **time-consuming** (especially 25 years ago!)

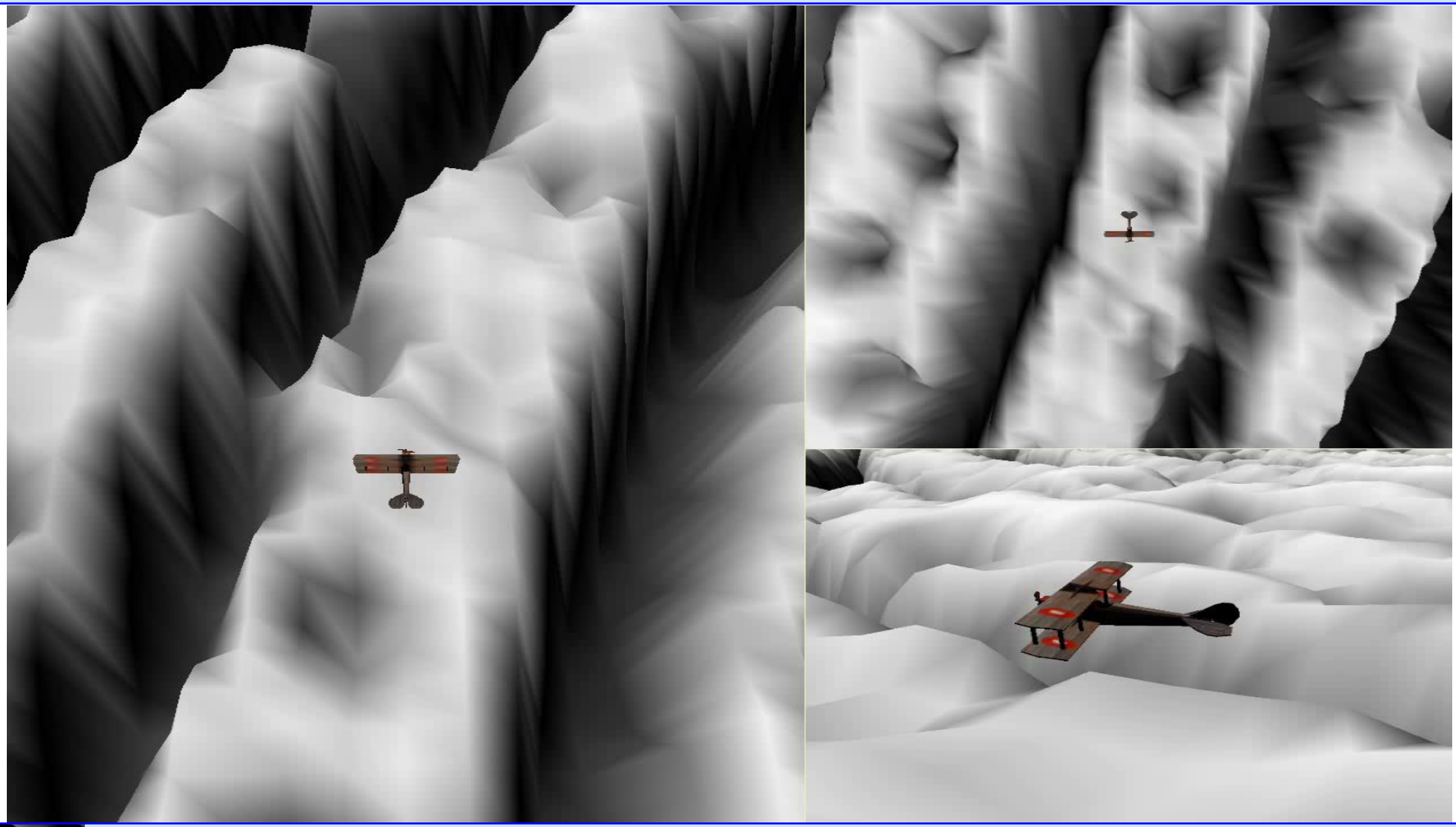
Follow the ridge lines on the gray-scale image, by “sailing” according to the local orientation of the ridge pattern

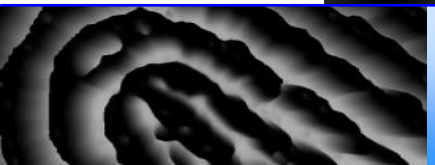


D. Maio, D. Maltoni, “Direct Gray-Scale Minutiae Detection in Fingerprints”, *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 19, no. 1, 1997.



Direct Gray-Scale Minutiae Detection - Demo

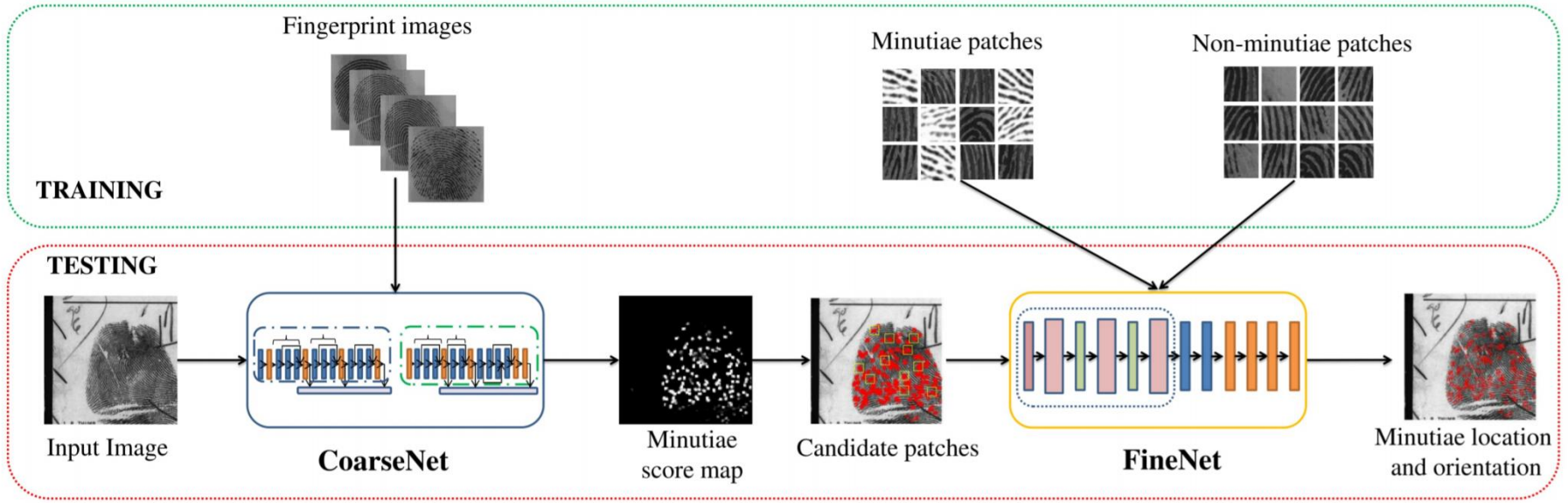




Minutiae detection with CNN

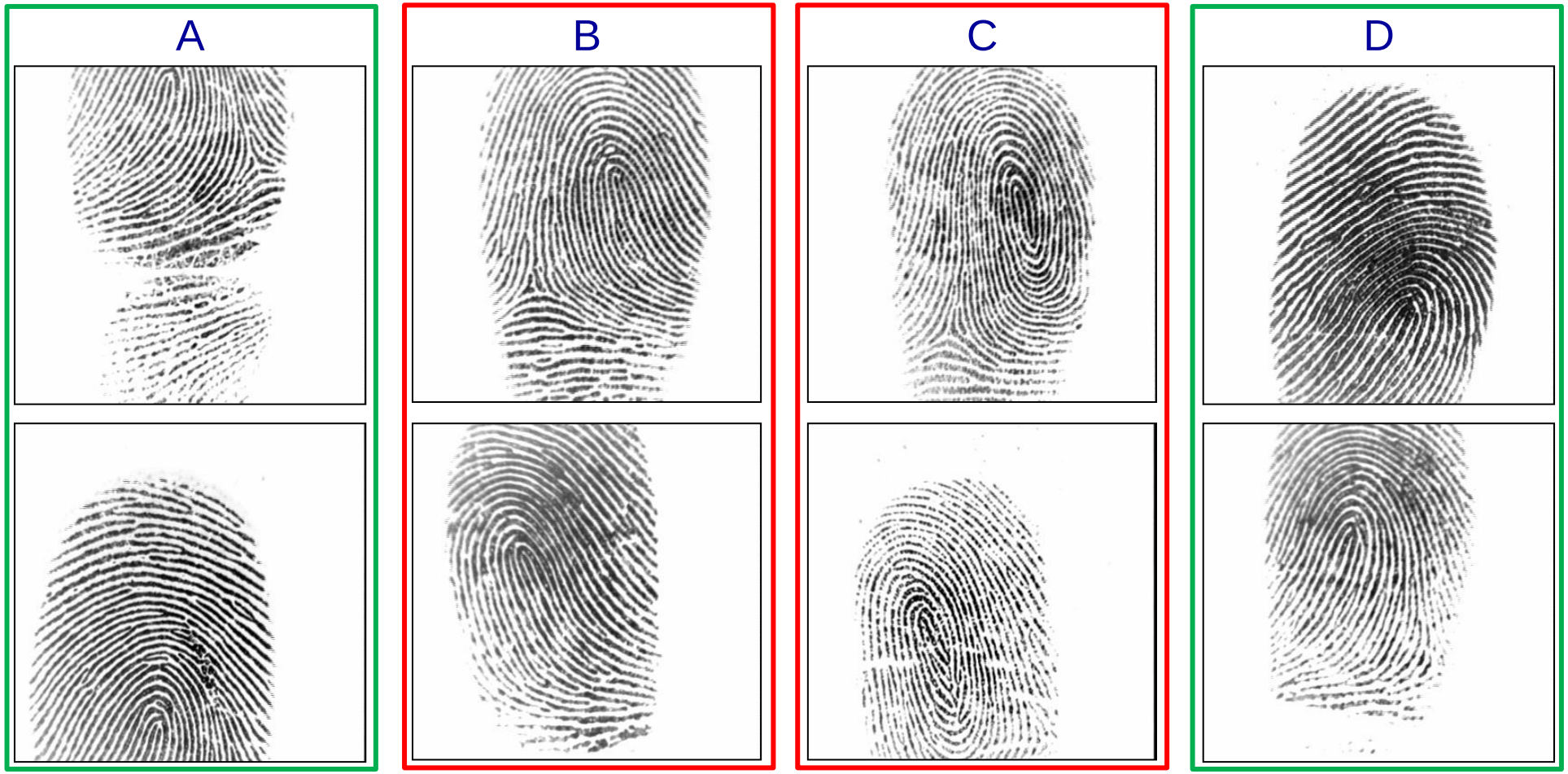
Dinh-Luan Nguyen, Kai Cao, Anil K. Jain, “Robust Minutiae Extractor: Integrating Deep Networks and Fingerprint Domain Knowledge”, ICB 2018.

- Classification of many patches is slow
- Object detection is not appropriate for minutiae patches
- Segmentation + Fine Classification is a smart approach

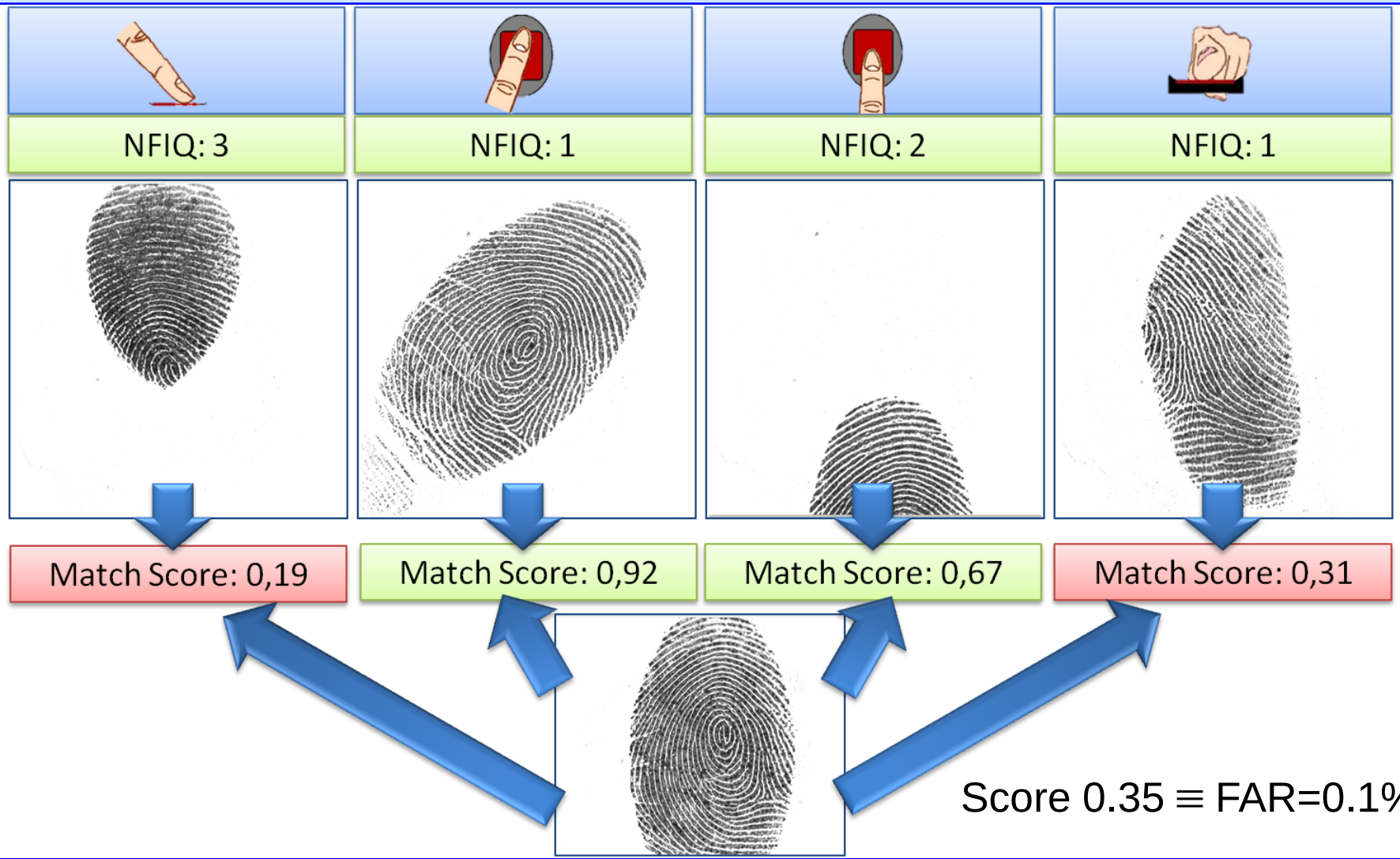


Fingerprint comparison

During comparison, the degree of similarity between two fingerprints is evaluated.

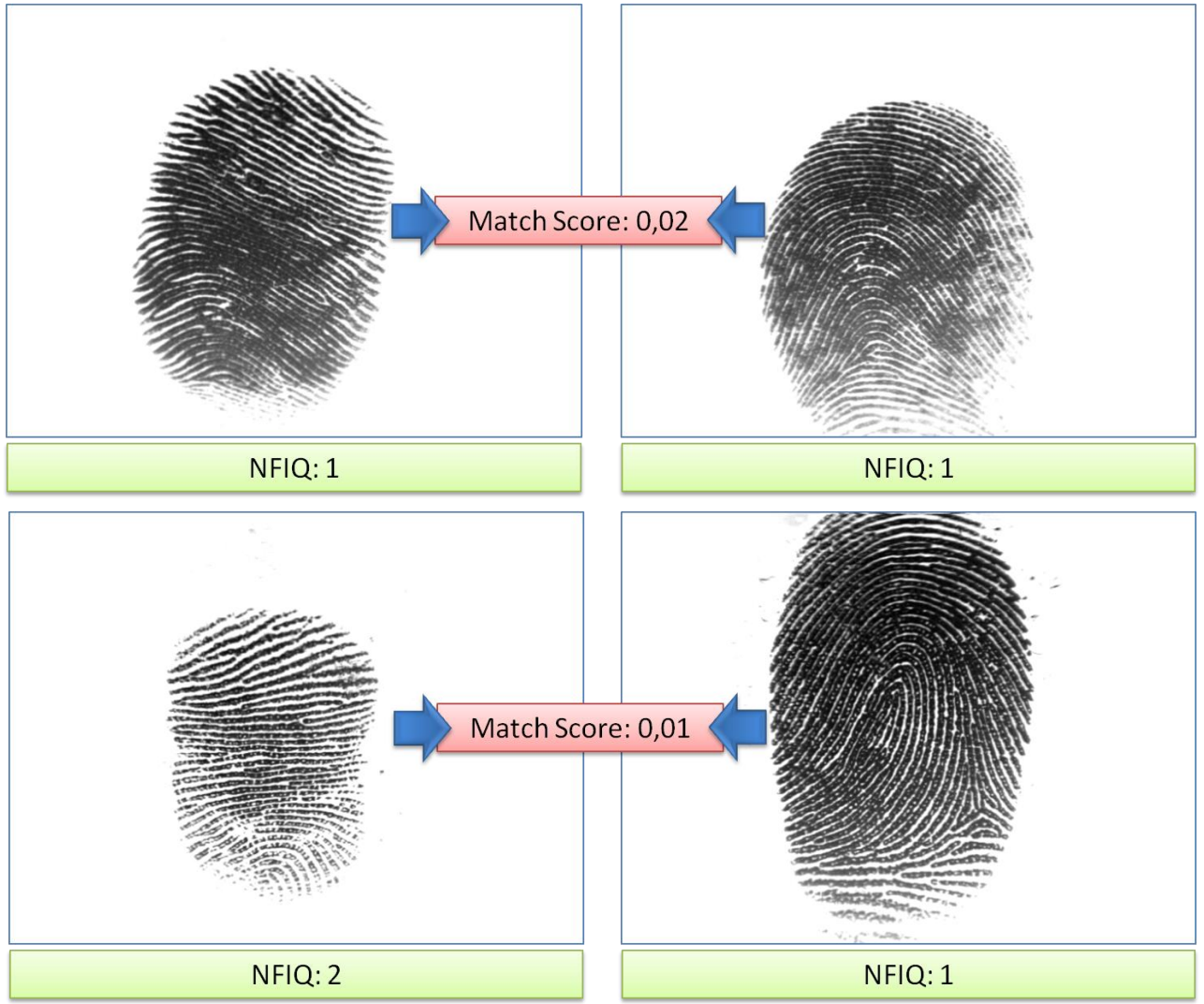


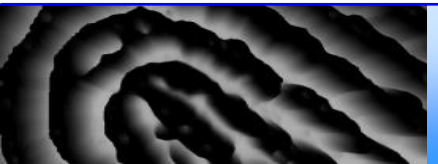
Bad positioning



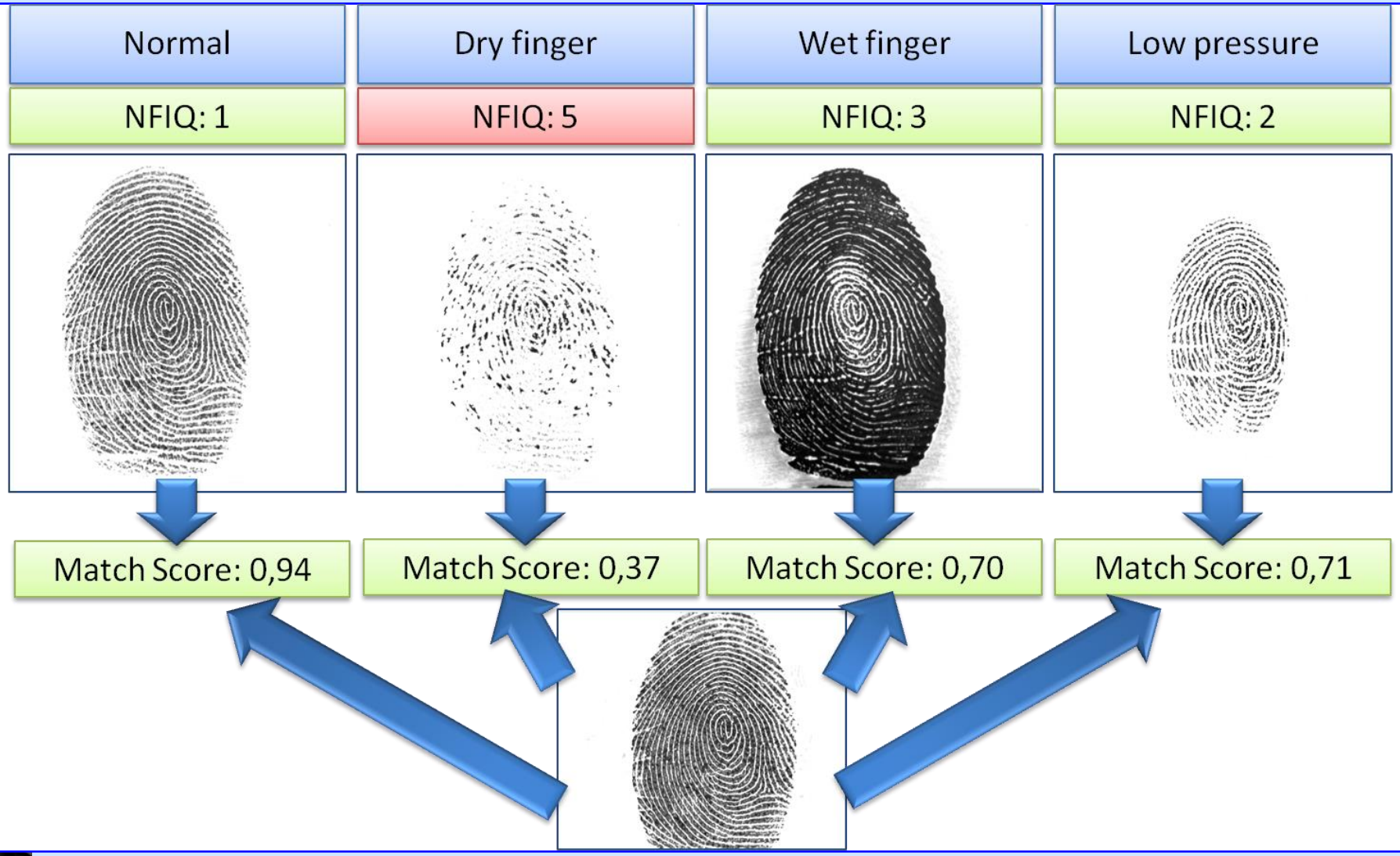
Score 0.35 ≡ FAR=0.1%

Non-linear distortions





Bad skin conditions and wrong pressure



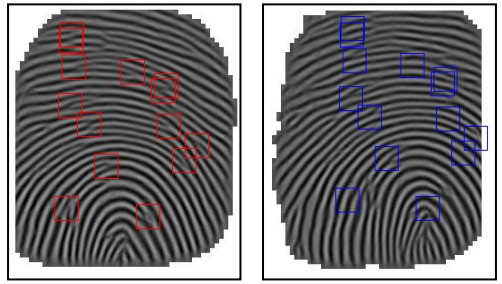
Approaches (1)

Minutiae-based

It consists in finding the maximum number of minutiae pairs between two minutiae templates. Introduced more than 50 years ago, it is still the most popular approach.

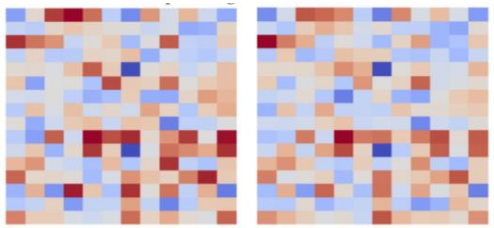
Correlation-based

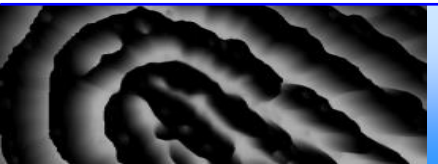
Fingerprint patches are superimposed and the correlation between corresponding pixels is computed for different alignments. Used with small-area & low-resolution scanners.



DNN features (2019)

Fixed length descriptions extracted by Deep Neural Networks recently proved to be effective for rolled fingerprints.



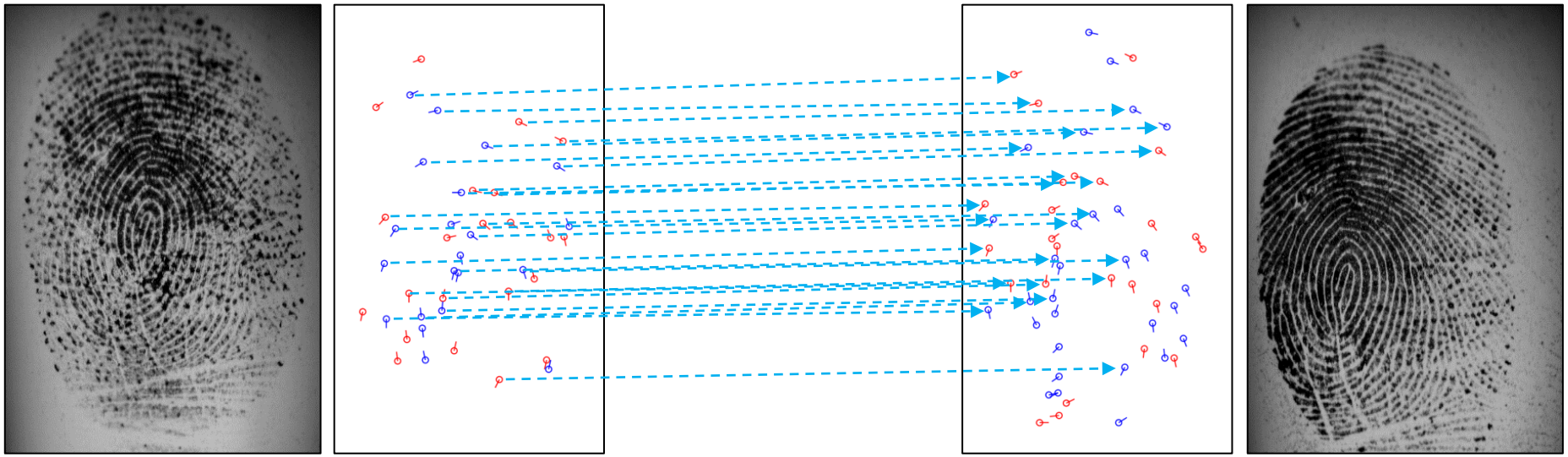


Minutiae-based (1)

In minutiae-based comparison, the fingerprint is represented by a feature vector of variable length whose elements are the fingerprint minutiae.

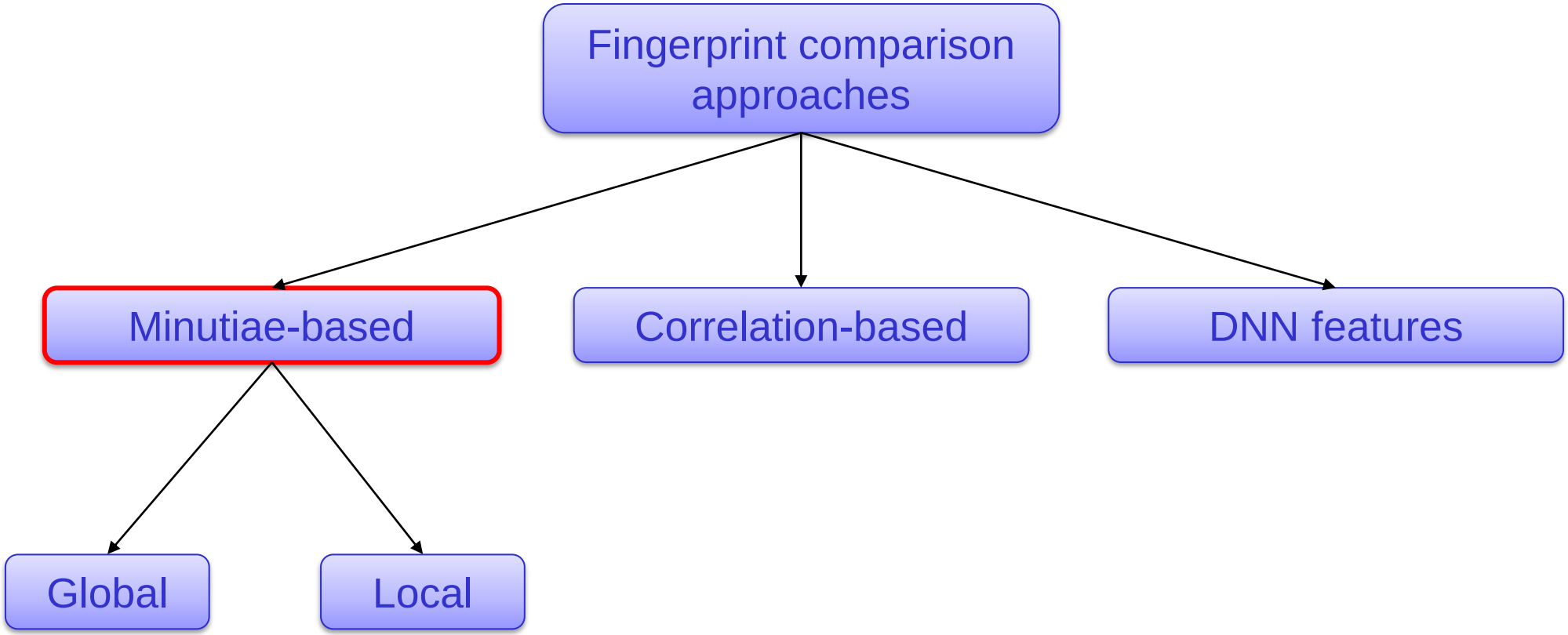
A minutia is represented by the tuple $m = \{x, y, \theta, t\}$ containing the minutia coordinates, its orientation and type.

$T_1 = \{m_1, m_2, \ldots, m_u\}$ $T_2 = \{m'_1, m'_2, \ldots, m'_v\}$



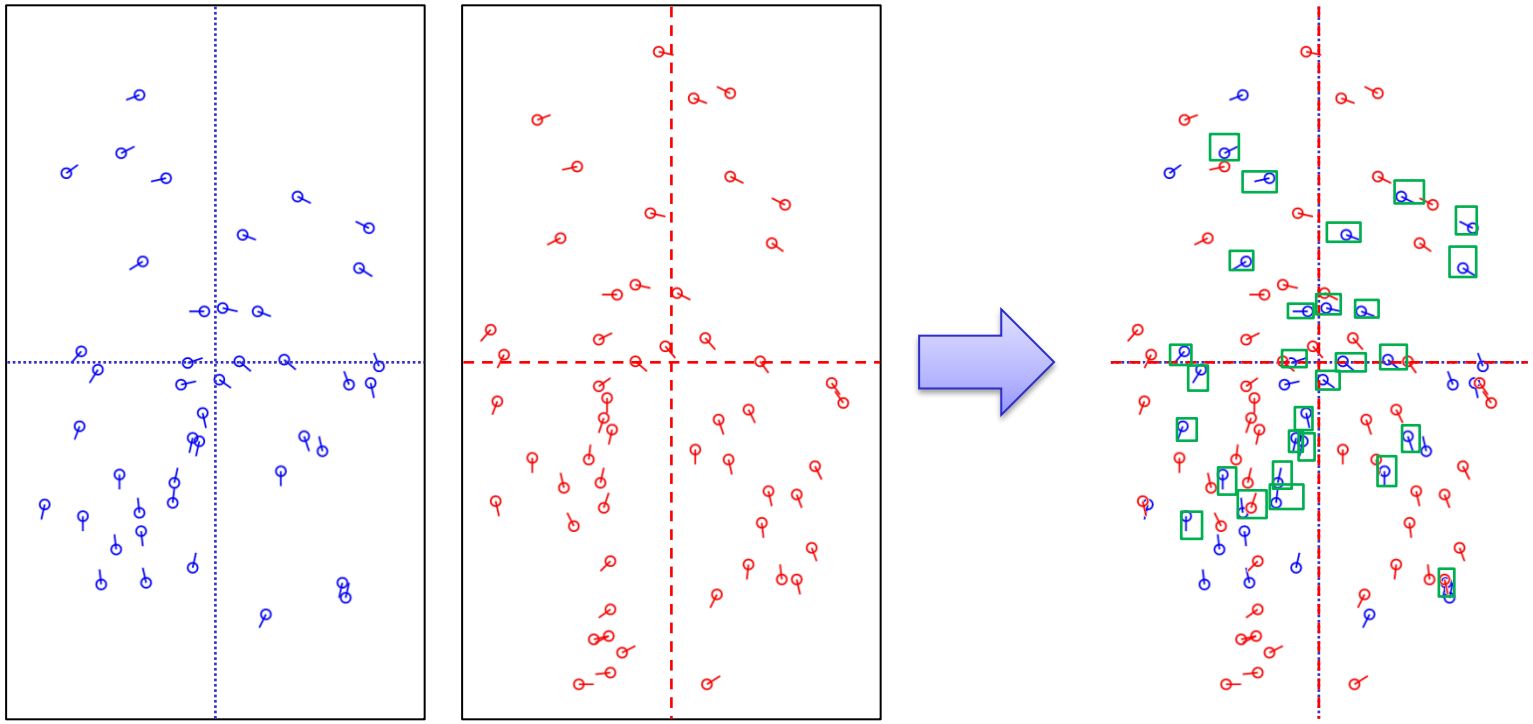
$$score = \frac{\#pairs}{(u+v)/2}$$

Minutiae-based (2)

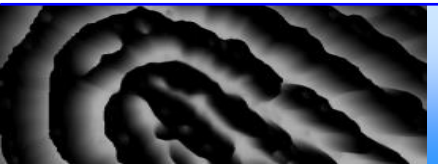


Global minutiae-based approaches

The objective of global minutiae-based approaches is to apply a global transformation that allows to maximize the number of resulting paired minutiae.



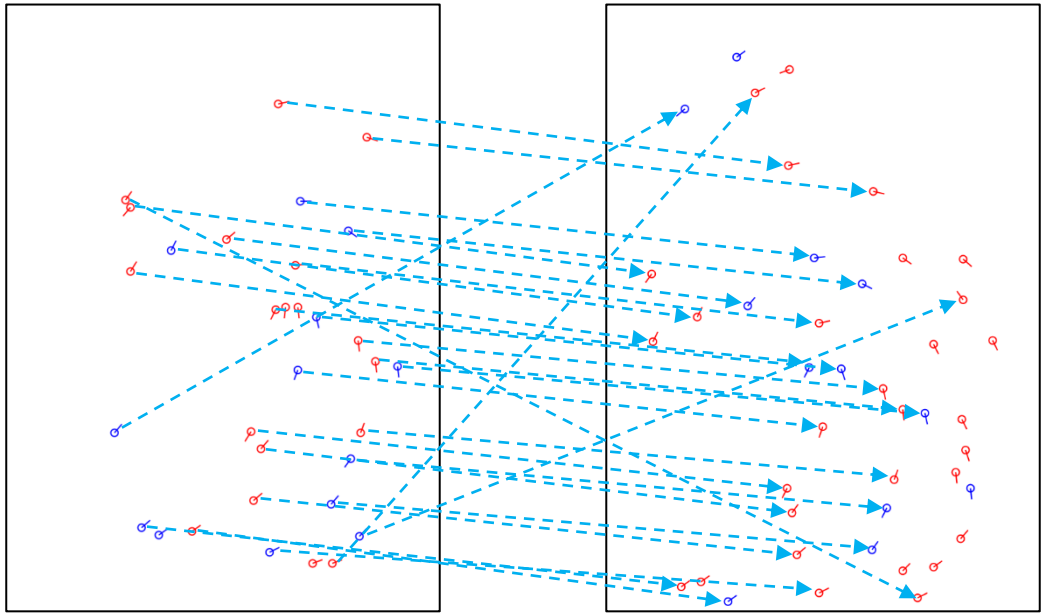
Typically use Hough transform or Ransac implementations to find the best rigid transformation to align two minutiae sets.



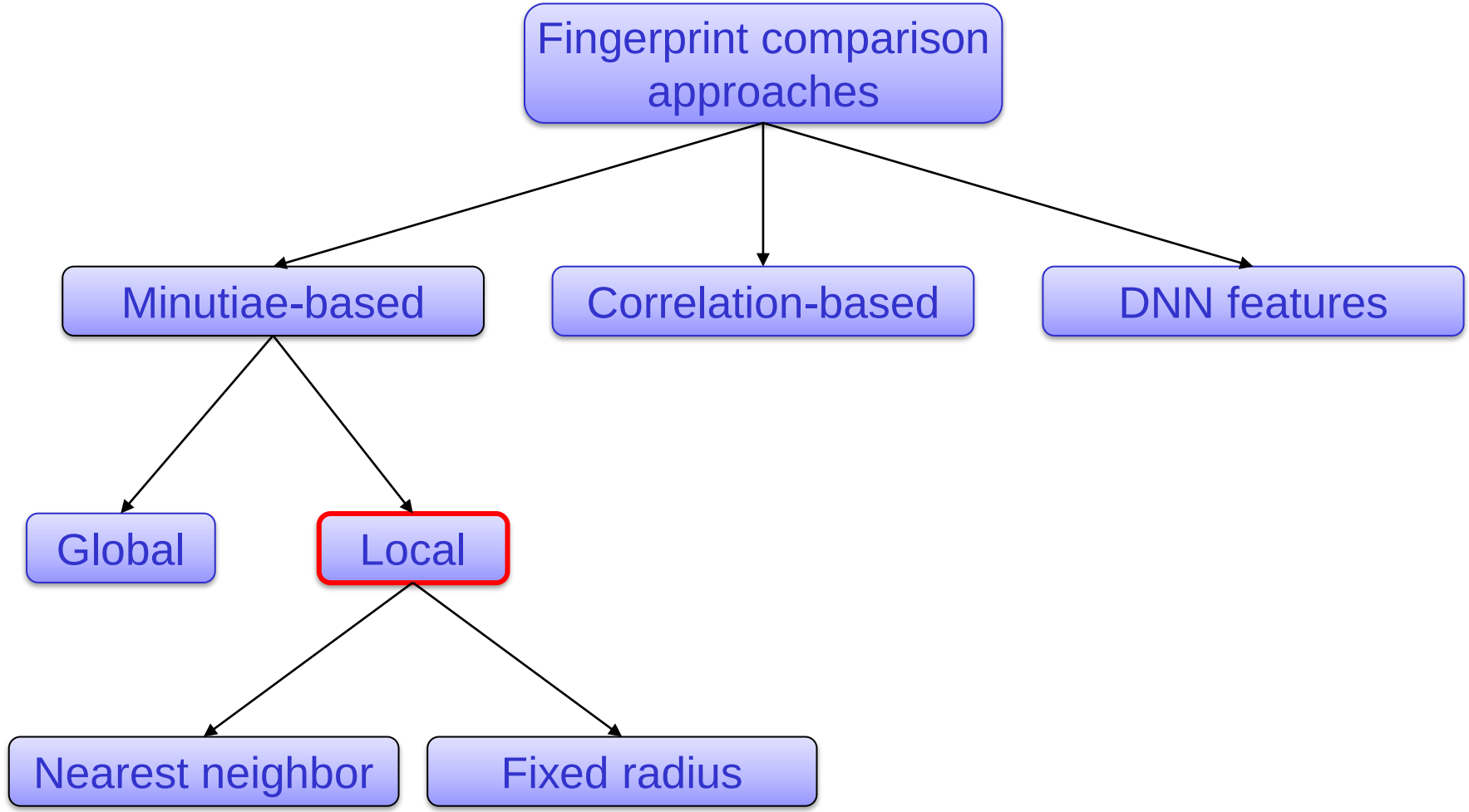
Local minutiae-based approaches (1)

The objective of local minutiae-based approaches is to pair minutiae using local minutiae features invariant to global transformations without a pre-alignment step. Usually they are based on the following steps:

1. for each minutia local features are computed from local minutiae neighborhoods.
2. the minutiae are paired according to local features (fast, robust to distortion but less distinctive).
3. a consolidation step is performed to verify if local matches hold at global level.

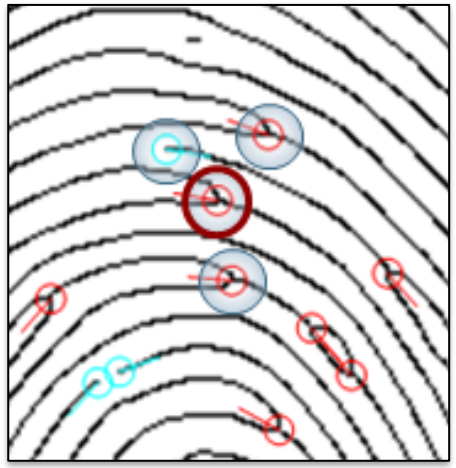


Local minutiae-based approaches (2)



Nearest-neighbor-based local structures

The neighbors of the central minutia are formed by its *K* closest minutiae.

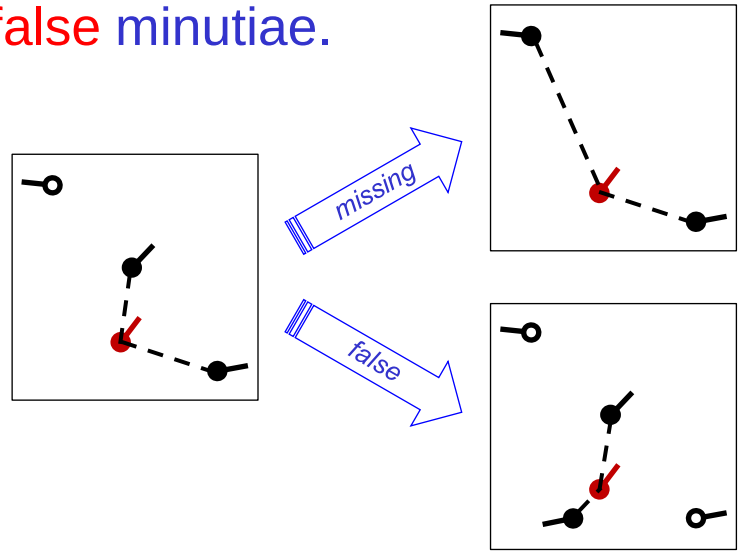


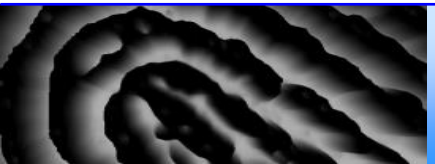
Advantages

- fixed-length descriptors that can be compared very efficiently.

Drawbacks

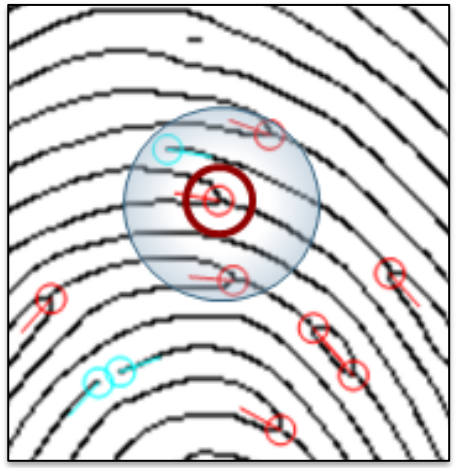
- possibility of exchanging nearest neighbor minutiae due to missing or false minutiae.





Fixed-radius-based local structures

The neighbors are defined as all the minutiae that are closer than a given radius R from the central minutia.

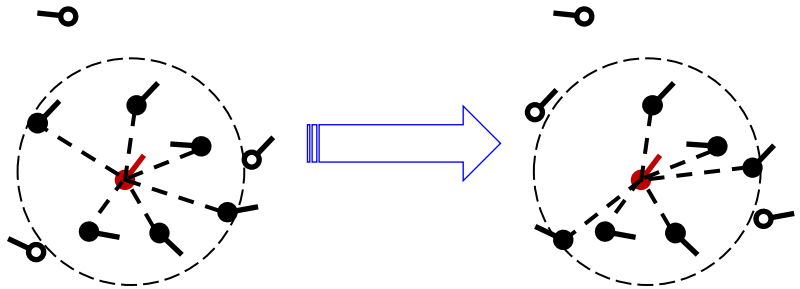


Advantages

- missing and false minutiae are better tolerated.

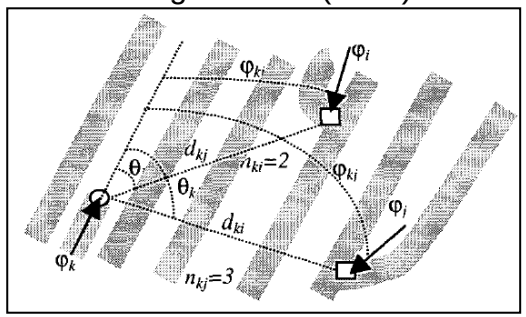
Drawbacks

- the descriptor length is variable and depends on the local minutiae density leading to a more complex comparison.
- minutiae close to the border can be mismatched because of different local distortion or location inaccuracy.

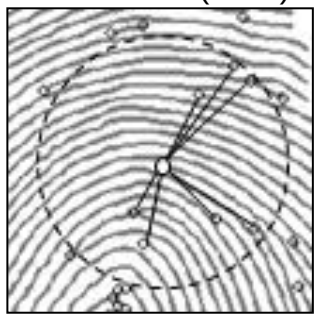


Local structures: examples

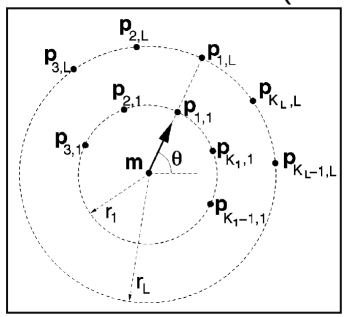
Jiang and Yau (2000)



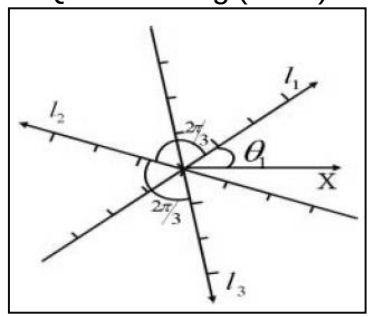
Ratha et al. (2000)



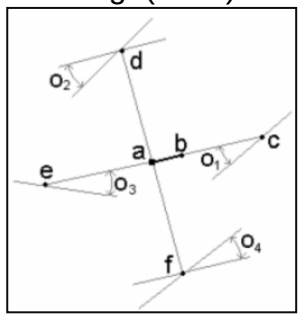
Tico and Kuosmanen (2003)



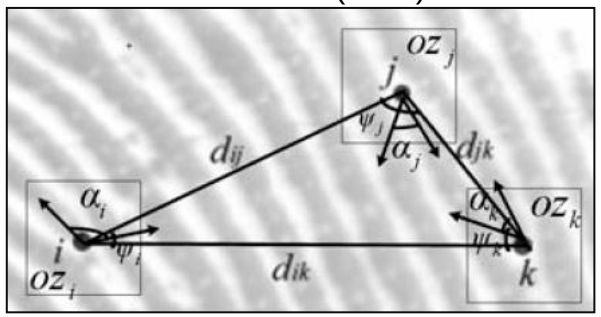
Qi and Wang (2004)



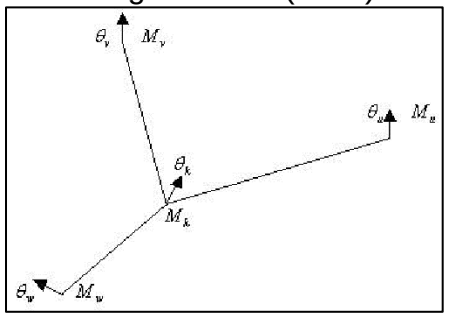
Ng (2004)



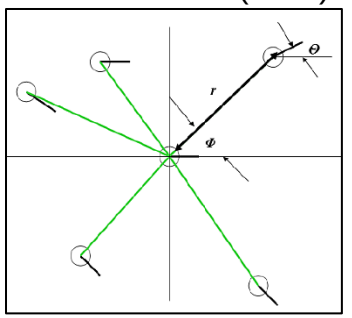
Chen et al. (2005)



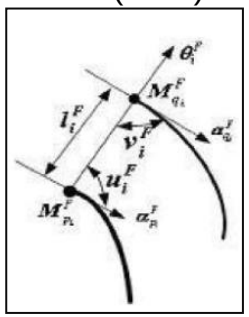
Deng and Huo (2005)



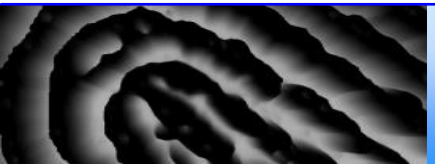
Chikkerur et al. (2006)



He (2006)



Feng (2008)

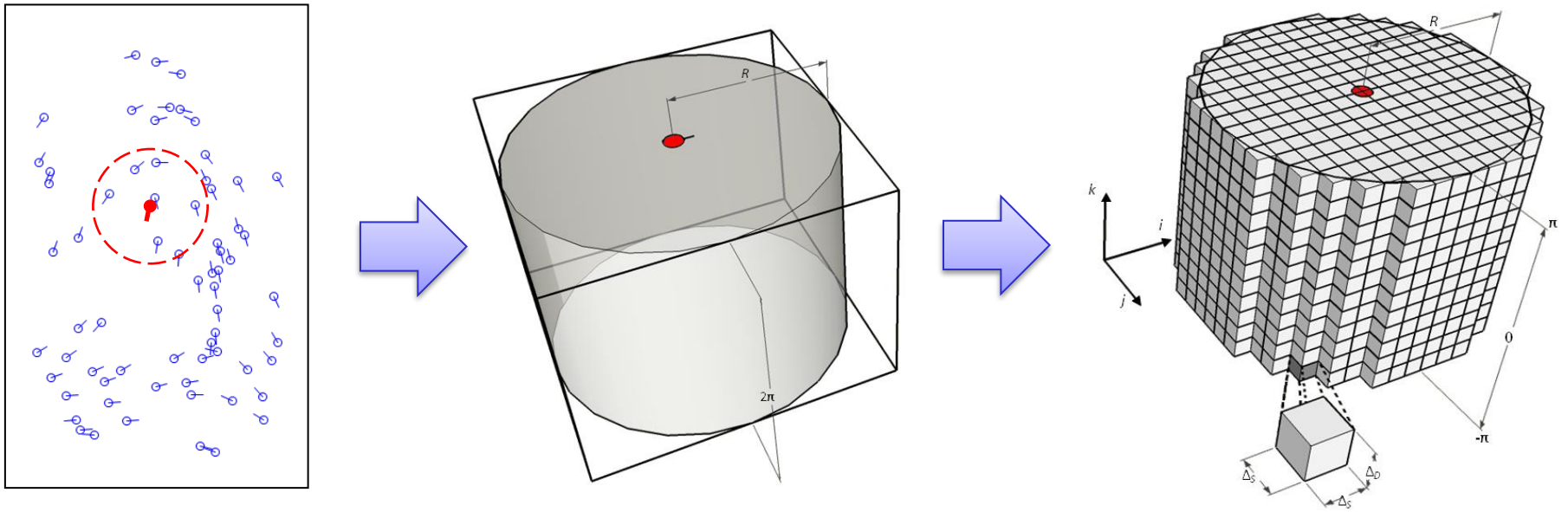


Minutia Cylinder-Code (MCC) (1)

R. Cappelli, M. Ferrara and D. Maltoni, "Minutia Cylinder-Code: a new representation and matching technique for fingerprint recognition", *IEEE tPAMI* 2010.

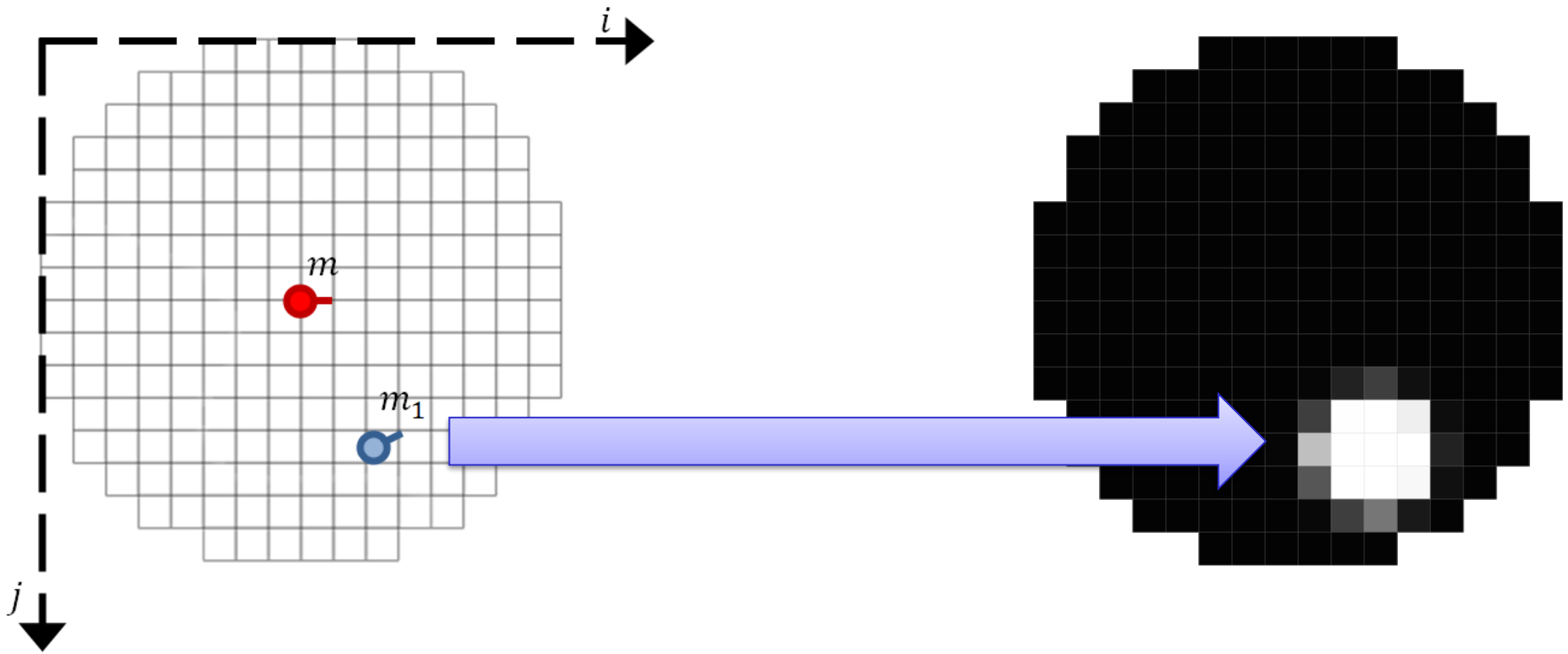
Main advantages:

- fixed radius structure;
- fixed-length descriptors;
- tolerates local distortion and small feature extraction errors;
- bit-oriented coding;
- fast and simple local structure comparison phase;



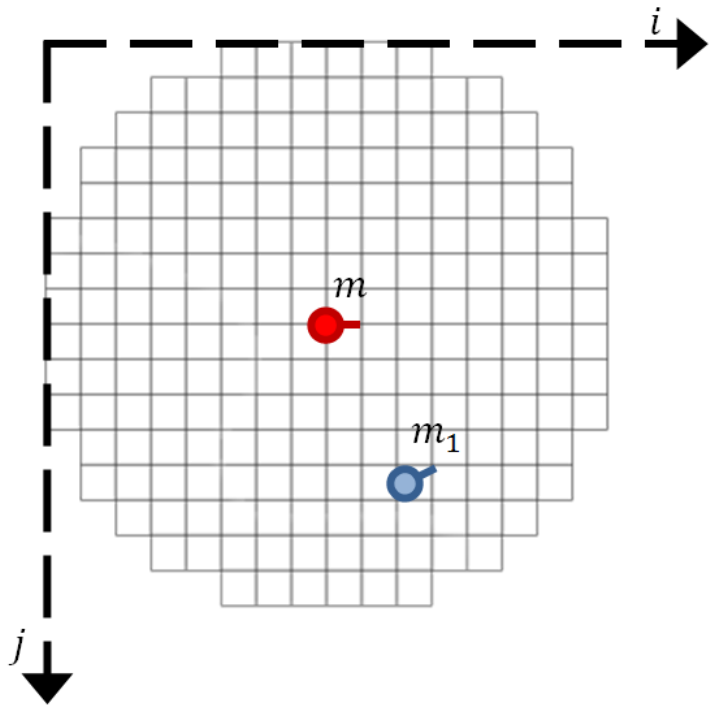
Minutia Cylinder-Code (MCC) (2)

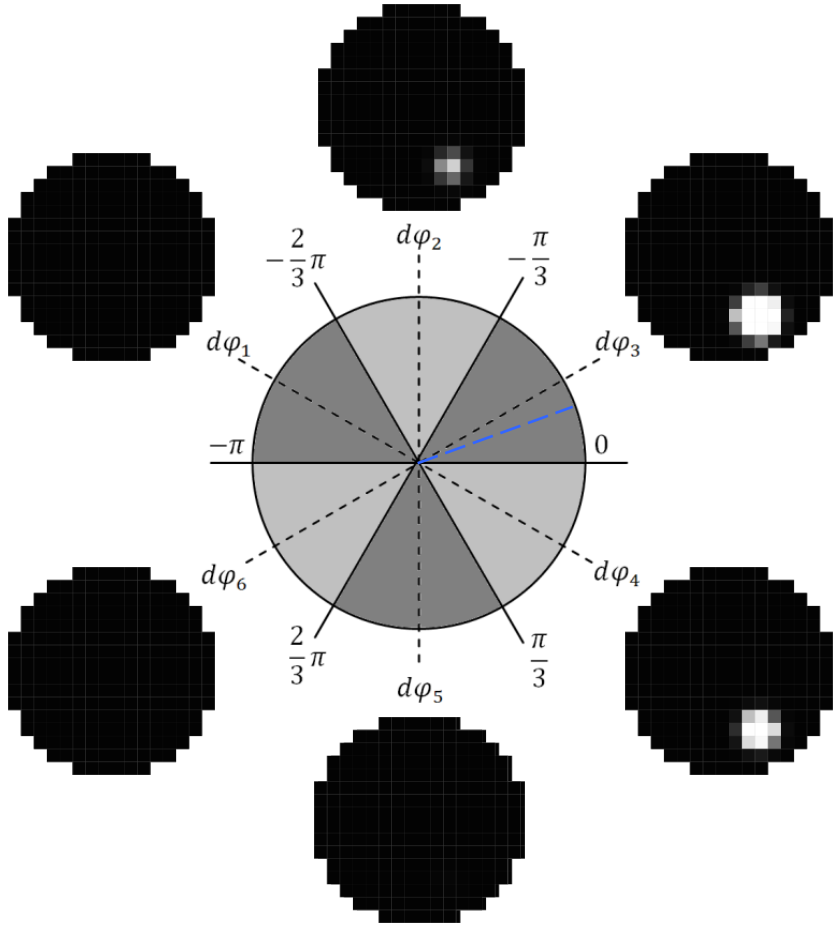
The spatial contribution of the neighbor minutia is spread over cells near its position.



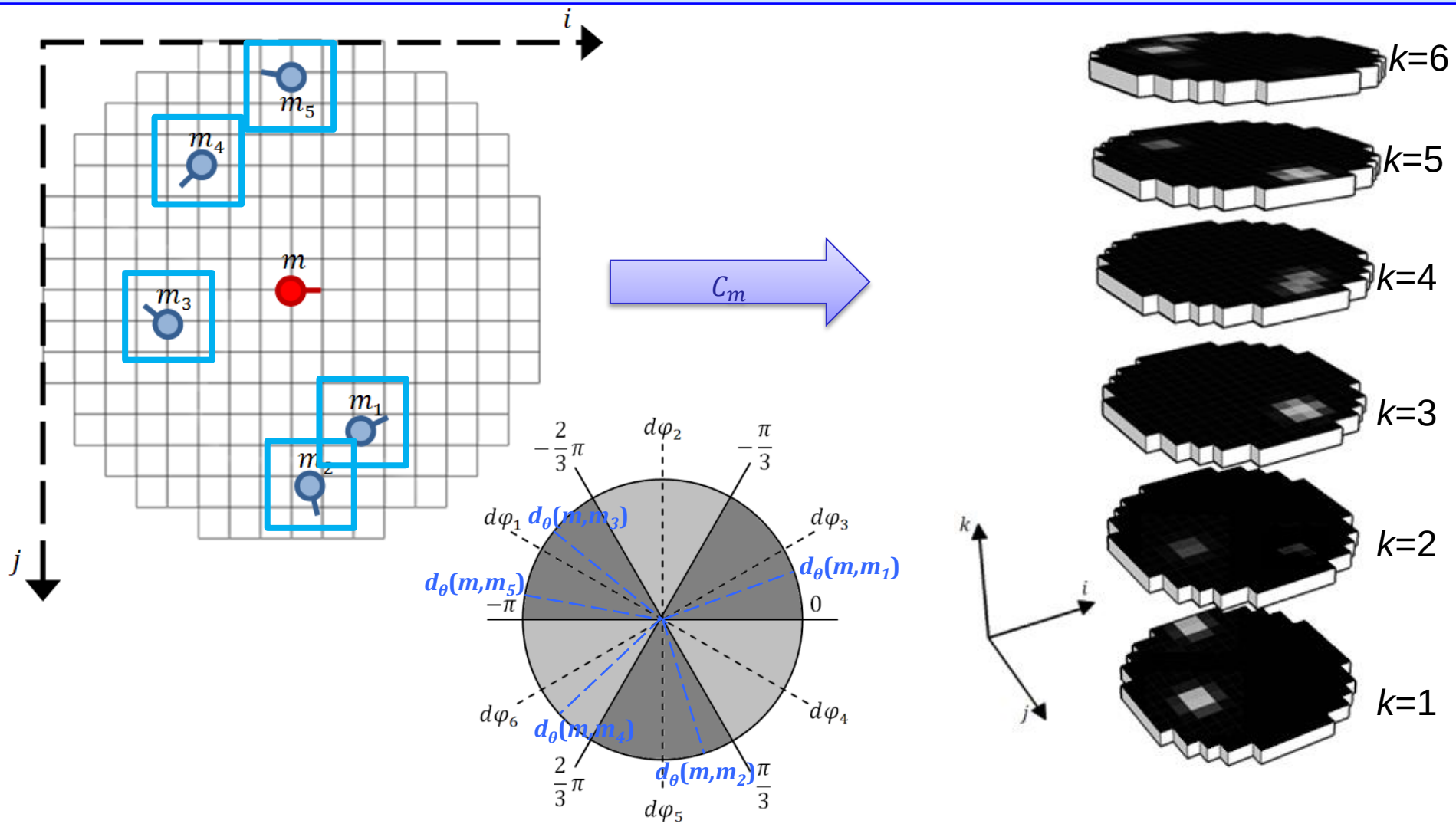
Minutia Cylinder-Code (MCC) (3)

The directional contribution depends on the angle differences.



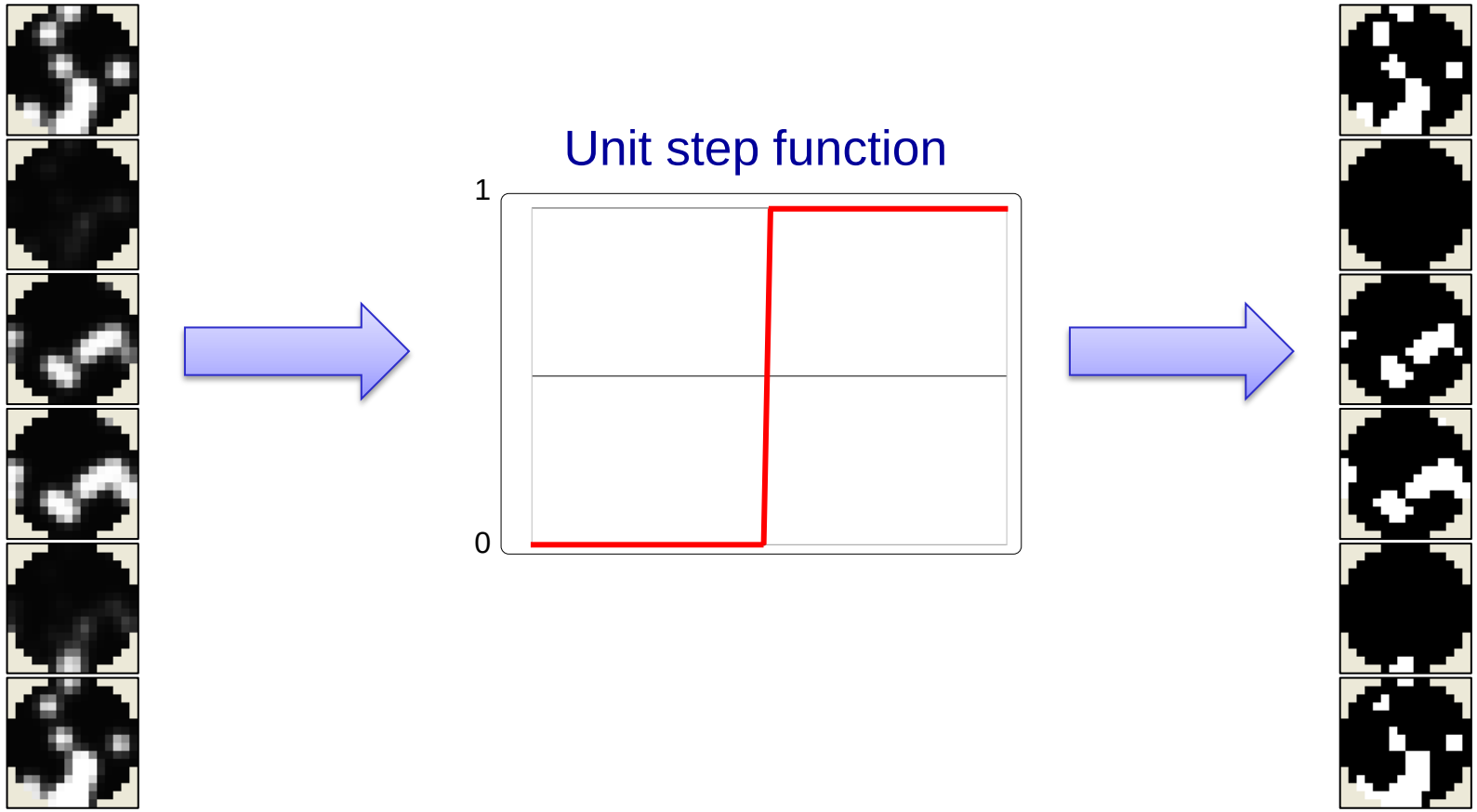


Minutia Cylinder-Code (MCC) (4)

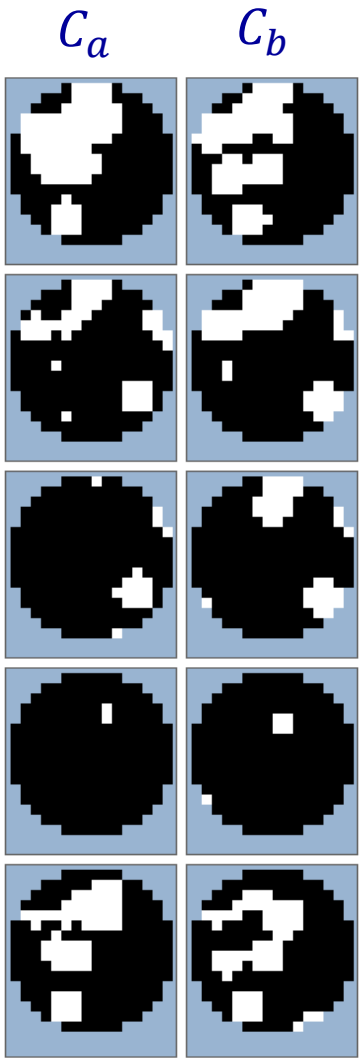


Minutia Cylinder-Code (MCC) (5)

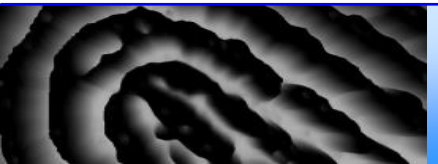
The cylinders can be conveniently converted into bit vectors by applying a unit step function.



Minutia Cylinder-Code (MCC) (6)



$$\gamma(a,b) = 1 - \frac{\|C_a \text{ XOR } C_b\|}{\|C_a\| + \|C_b\|} = 0.64$$

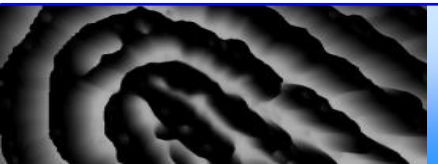


Minutia Cylinder-Code (MCC) (7)

MCC speed performance

Test: 100 identification queries on a 1M database

Version	System configuration	Comparisons per second
MCC SDK Single core, no SSE optimizations Download: http://biolab.csr.unibo.it/mccsdk.html	Intel CPU E5-2650 @ 2GHz, 64-bit O.S.	18,000
SSE4 Optimized for CPU	Intel CPU E5-2650 @ 2GHz, 64-bit O.S. 2 processors, 32 cores	7 Millions
GPU (CUDA) and CPU Optimized	Intel CPU E5-2650 @ 2GHz, 64-bit O.S. 2 processors, 32 cores 4 Nvidia Tesla C2075 GPUs	42 Millions
GPU (CUDA) and CPU Optimized	Intel CPU Xeon E5-1660 @ 3.2GHz, 64-bit O.S. 1 processor, 8 cores 1 Nvidia Titan RTX GPU	117 Millions



Fingerprint Verification Competitions (FVC)

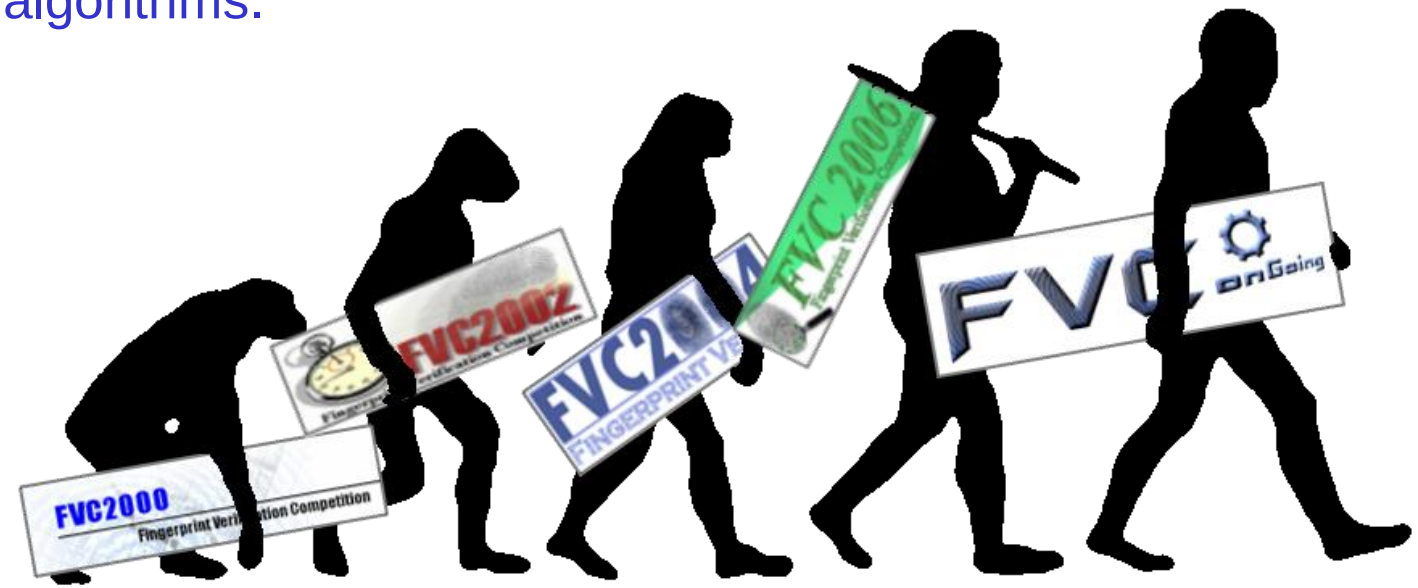
FVC was born in 2000 as a strongly supervised evaluation for fingerprint verification algorithms, to:

- track the state-of-the-art;
- provide benchmarks and testing protocols for a fair evaluation.

	FVC2000	FVC2002	FVC2004	FVC2006
# Participants registered	25	48	110	150
# Algorithms evaluated	11	31	67	70
# Databases	3 real, 1 synthetic			
# Fingers per database	100			140
# Samples per finger	8			12

FVC-onGoing (1)

In 2009 started FVC-onGoing, a fully automated web-based evaluation system always open to new participants and new algorithms.



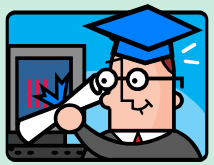
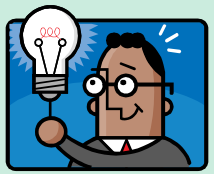
Not only limited to fingerprint verification algorithms but also for:

- other fingerprint modules (e.g., local orientation extraction, fingerprint indexing)
- other biometric problems (e.g., palmprint verification, face morphing detection)

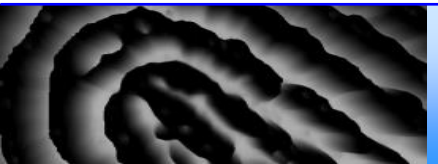
http://biolab.csr.unibo.it/fvcongoing

FVC-onGoing (2)

Statistics - updated May 2020:

Registered Participants (1658)		
	Academic Research Groups	275
	Companies	269
	Independent Developers	1114

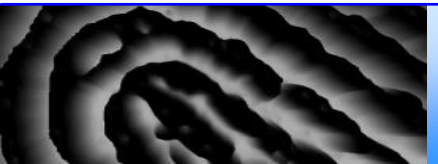
Fingerprint Benchmark Area	Algorithms Evaluated (5539)	Algorithms Published (204)
Fingerprint Verification	2028	74
Fingerprint ISO Template Matching	2630	98
Fingerprint Orientation Extraction	610	14
Fingerprint Indexing	211	10
Secure Template Fingerprint Verification	60	8



FV: Fingerprint Verification

Benchmark FV-STD-1.0 (Top Algorithms @ May 2020):

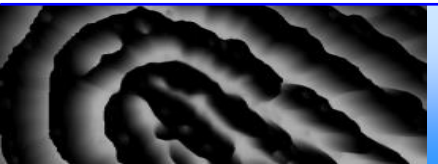
Published on	Benchmark	Participant	Type	Algorithm	Version	EER ▲	FMR_{1000}	FMR_{10000}	Show details
01/05/2020	FV-STD-1.0	Neurotechnology	Company	MM_FV	12.0	0.010 %	0.000 %	0.022 %	
27/07/2017	FV-STD-1.0	Beijing Hisign Bio-info Institute	Company	HXKJ	2.4	0.022 %	0.007 %	0.036 %	
29/08/2011	FV-STD-1.0	Tiger IT Bangladesh	Company	TigerAFIS	1.2ec	0.108 %	0.115 %	0.242 %	
14/09/2010	FV-STD-1.0	Green Bit S.p.A	Company	GBFRSW	1.3.2.0	0.118 %	0.155 %	0.519 %	
31/08/2011	FV-STD-1.0	AA Technology Ltd.	Company	EMB9300	1.1	0.142 %	0.159 %	0.220 %	
17/10/2016	FV-STD-1.0	Decatur Industries, Inc.	Company	Decatur	1.2	0.158 %	0.213 %	0.372 %	
15/05/2011	FV-STD-1.0	AA Technology Ltd.	Company	EMB9200	2.3	0.176 %	0.188 %	0.303 %	
15/01/2015	FV-STD-1.0	GenKey Netherlands BV	Company	BioFinger	1.0	0.249 %	0.267 %	0.375 %	
14/05/2011	FV-STD-1.0	Institute of Automation, Chinese Academy of Sciences	Academic Research Group	MntModel	1.0	0.293 %	0.512 %	1.209 %	
15/05/2011	FV-STD-1.0	UnionCommunity	Company	Triple_M	1.1	0.418 %	0.859 %	1.977 %	
20/05/2020	FV-STD-1.0	Beijing Bata Technolgy Co. Ltd.	Company	Bata-FP	2.0	0.432 %	0.595 %	0.869 %	
23/07/2019	FV-STD-1.0	Vsoft	Company	BioPass Finger	2.4	0.588 %	1.017 %	1.894 %	
20/02/2015	FV-STD-1.0	ru zhou	Independent Developer	AllStar	1.0	0.613 %	0.938 %	1.396 %	



FMISO: Fingerprint ISO Template Matching

Benchmark FMISO-STD-1.0 (Top Algorithms @ May 2020):

Published on	Benchmark	Participant	Type	Algorithm	Version	EER ▲	FMR_{1000}	FMR_{10000}	Show details
12/06/2014	FMISO-STD-1.0	Neurotechnology	Company	MM_FMISO	5.1	0.194 %	0.328 %	0.776 %	
15/05/2011	FMISO-STD-1.0	AA Technology Ltd.	Company	EMB9200	2.41	0.234 %	0.292 %	0.444 %	
24/03/2011	FMISO-STD-1.0	UnionCommunity	Company	Triple_M_ISO	1.2	0.234 %	0.361 %	0.620 %	
22/09/2015	FMISO-STD-1.0	Xiamen Toyonway Intellectual Technology Co. Ltd, China	Company	TW2F_ISO	0.2	0.252 %	0.314 %	0.556 %	
15/12/2010	FMISO-STD-1.0	Suprema, Inc.	Company	SFCore	1.0	0.258 %	0.346 %	0.639 %	
09/03/2014	FMISO-STD-1.0	Tiger IT Bangladesh	Company	TigerAFIS	v1.2-ISO/MINEX	0.296 %	0.422 %	0.837 %	
17/10/2016	FMISO-STD-1.0	Decatur Industries, Inc.	Company	Decatur	1.3.2	0.300 %	0.415 %	0.700 %	
12/10/2009	FMISO-STD-1.0	Tiger IT Bangladesh	Company	Tiger ISO	0.1	0.317 %	0.447 %	0.866 %	
05/12/2019	FMISO-STD-1.0	Beijing Hisign Bio-info Institute	Company	HXKJ	3.05	0.342 %	0.437 %	0.617 %	
31/12/2015	FMISO-STD-1.0	BKIC Laboratory - Hanoi University of Science and Technology	Academic Research Group	BKAFIS	0.4	0.346 %	0.491 %	0.696 %	
14/05/2011	FMISO-STD-1.0	Institute of Automation, Chinese Academy of Sciences	Academic Research Group	MntModel	1.0	0.380 %	0.505 %	0.819 %	
18/07/2012	FMISO-STD-1.0	id3 Technologies	Company	Fingerprint Matcher ISO	2.0.1	0.392 %	0.592 %	0.801 %	
20/02/2014	FMISO-STD-1.0	Biometric System Laboratory	Academic Research Group	MCC (Baseline)	1.4	0.411 %	0.602 %	0.999 %	

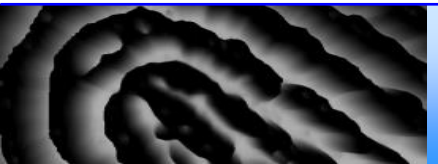


What can we learn?

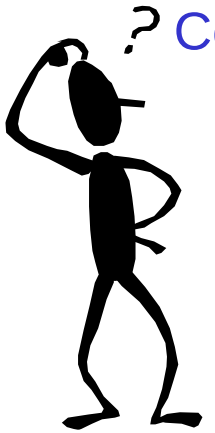
Characteristics of algorithms published on FV area:

	Algorithm			EMB9200 2.3	Triple_M 1.1	MntModel 1.0	MiraFinger 2.2	GBFRSW 1.3.2.0	SourceAFIS 1.1	MM_FV 3.0	STAR 1.0	JF_FV 1.21a
Preprocessing	Segmentation			X	X	X		X	X	X	X	X
	Enhancement			X	X	X			X	X	X	X
	Binarization			X	X	X		X	X	X	X	X
Feature Used	Minutiae			X	X	X	X	X	X	X	X	X
	Singular Points									X	X	X
	Ridge Shape							X				
	Ridge Counts			X						X		
	Orientation Field			X	X	X		X		X	X	X
	Local Ridge Frequency				X			X		X	X	
	Texture						X				X	
Matching	Matching Strategy	Minutiae-Based	Local	X	X	X	X	X	X	X	X	X
			Global	X	X	X		X	X	X	X	X
		Based on Geometry Ridge Features						X				X
	Alignment Model	Displacement		X	X	X	X	X	X	X	X	X
		Rotation		X	X	X	X	X	X	X	X	X
		Scale					X				X	X
		Non-linear Distortion		X	X		X	X		X	X	

For the most effective algorithms
enhancement / binarization based on contextual filtering
alignment mainly relies on minutiae
matching with multiple features (minutiae, frequency, orientation)
minutia alignment/matching with two stage: local matching + global consolidation



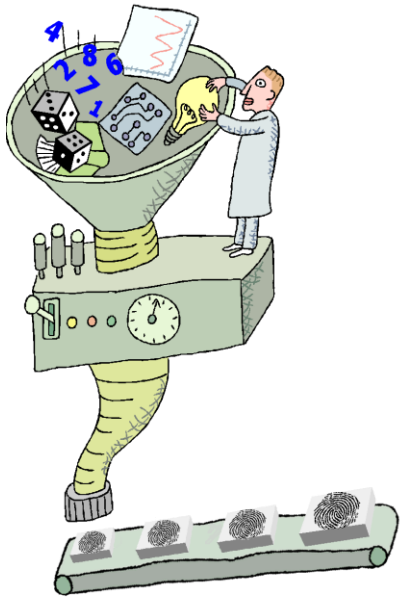
Synthetic fingerprint generation

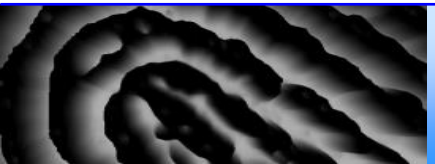


Collecting large databases of fingerprint images is:

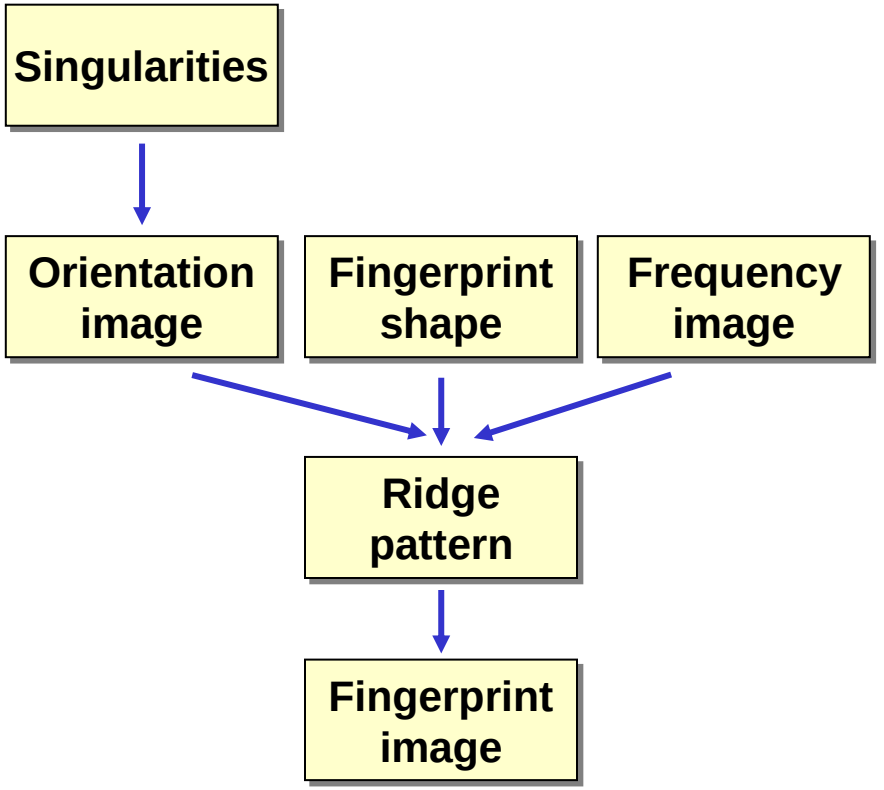
- expensive both in terms of money and time
- boring for both the people involved and for the volunteers, which are usually submitted to several acquisition sessions at different dates
- problematic due to the privacy legislation which protects such personal data

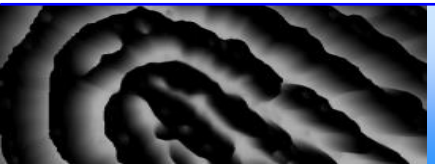
A method able to *artificially* generate realistic fingerprint-images could be used in several contexts to avoid collecting databases of real fingerprints



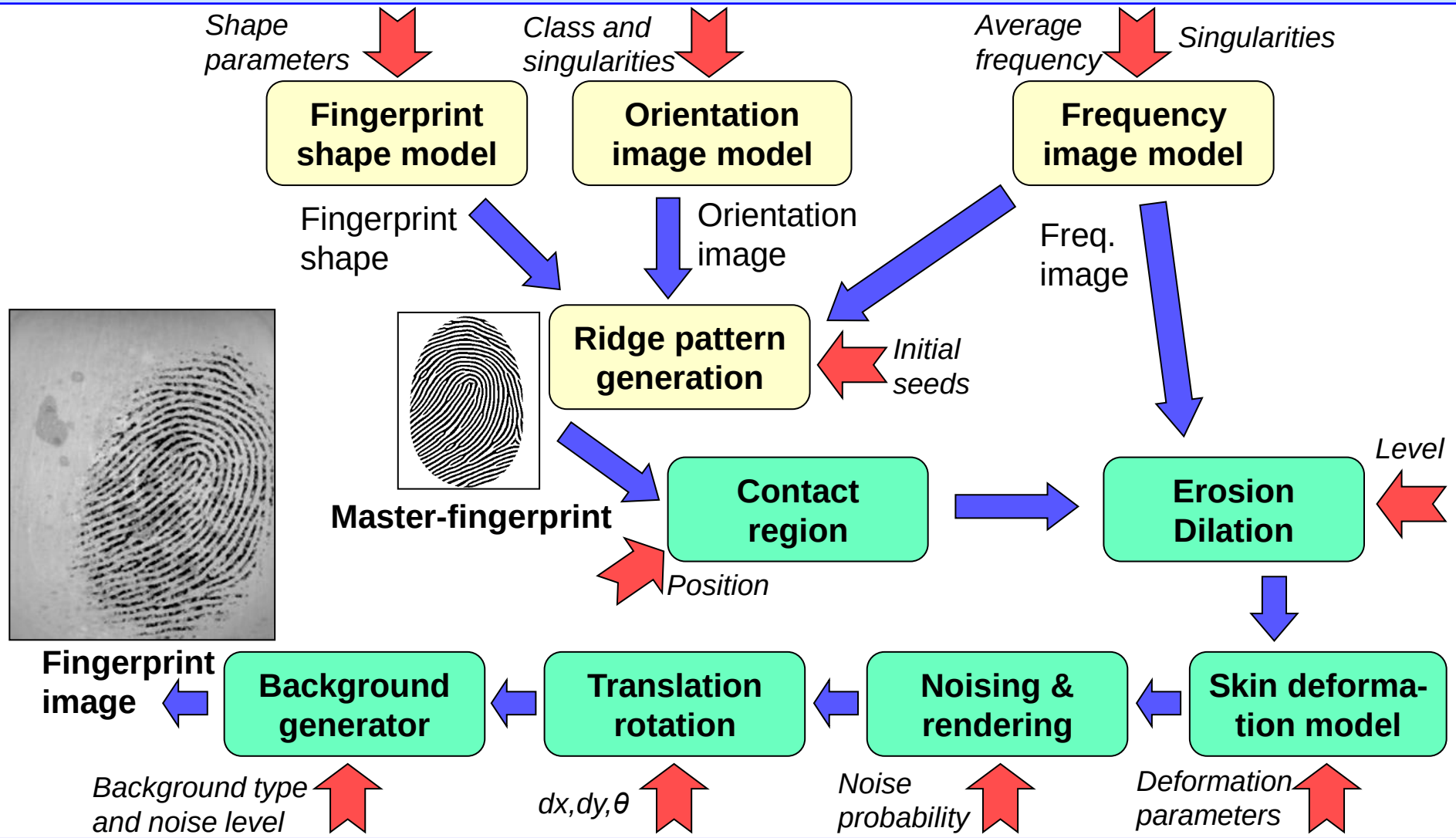


How SFinGe works (1)





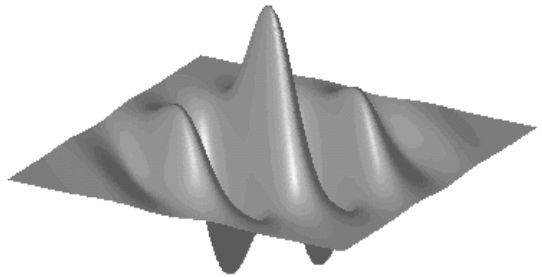
How SFinGe works (3)



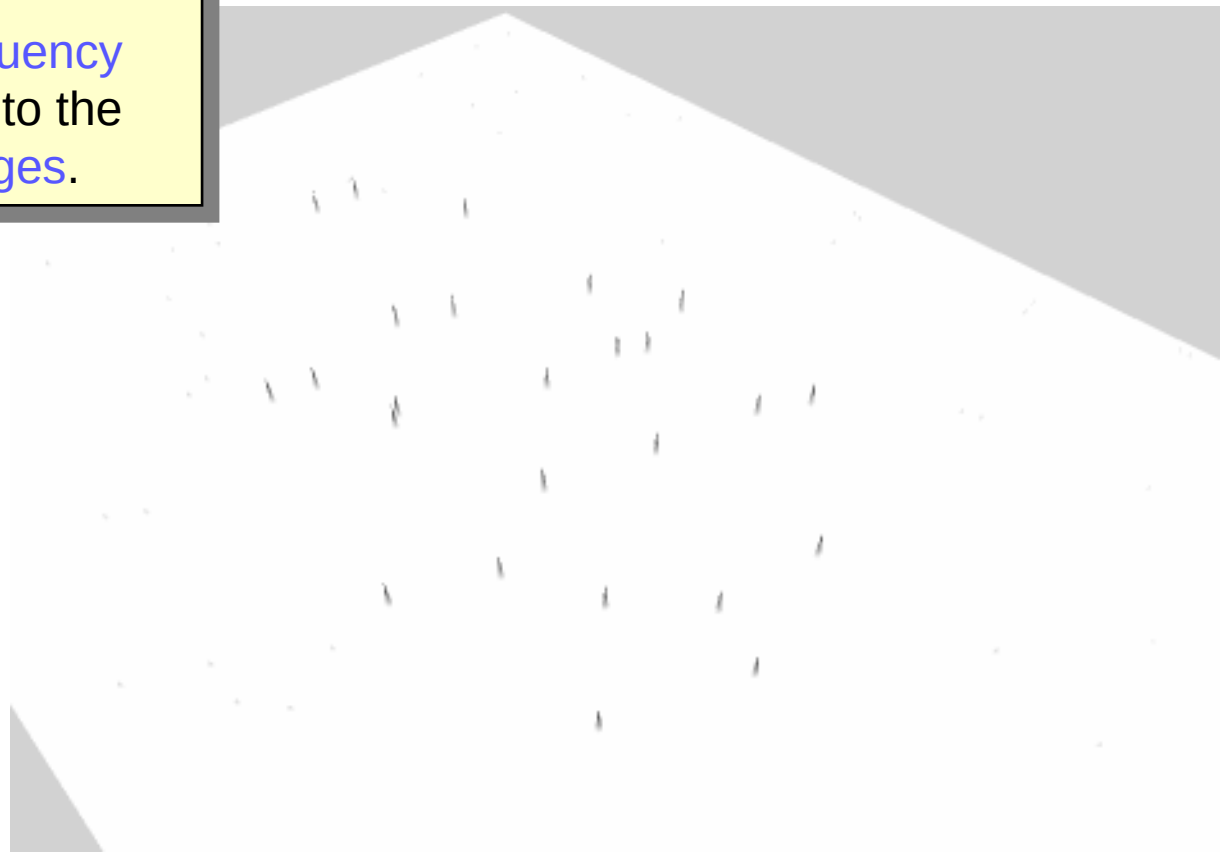
Ridge pattern generation

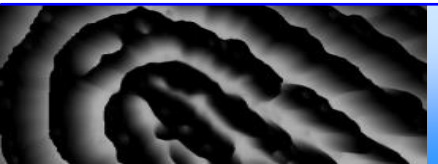
Gabor-like filters are iteratively applied to an initially-white image, enriched with few random points.

The filters orientation and frequency are locally adjusted according to the orientation and frequency images.



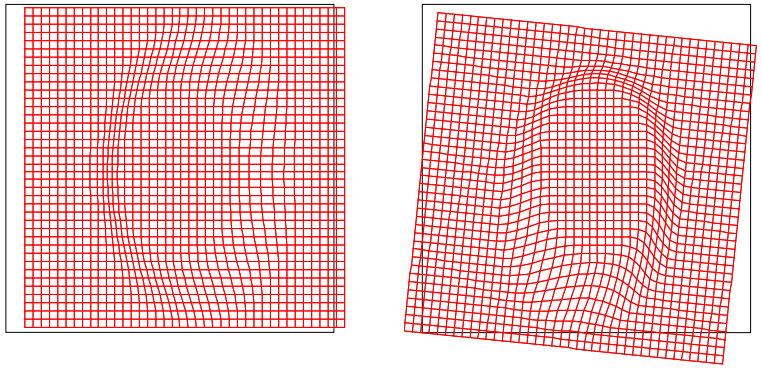
Realistic minutiae appear at random positions

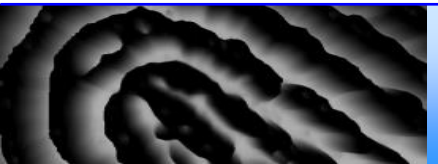




Simulating skin distortion

The skin distortion model is applied to randomly generate realistic impressions of the same “synthetic finger”



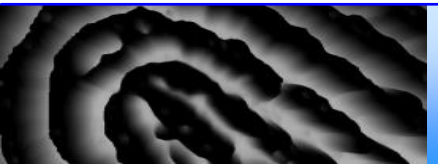


Noising and rendering

Several factors contribute to deteriorate the quality of real fingerprints:

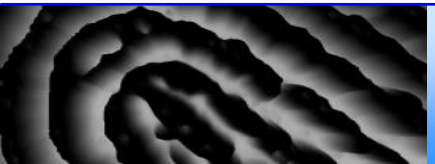
- irregularity of the ridges and their different contact with the sensor surface
- small cuts or abrasions on the fingertip
- presence of small pores within the ridges

SFinGe adds specific noise and applies an ad-hoc smoothing process to simulate real-fingerprints irregularities

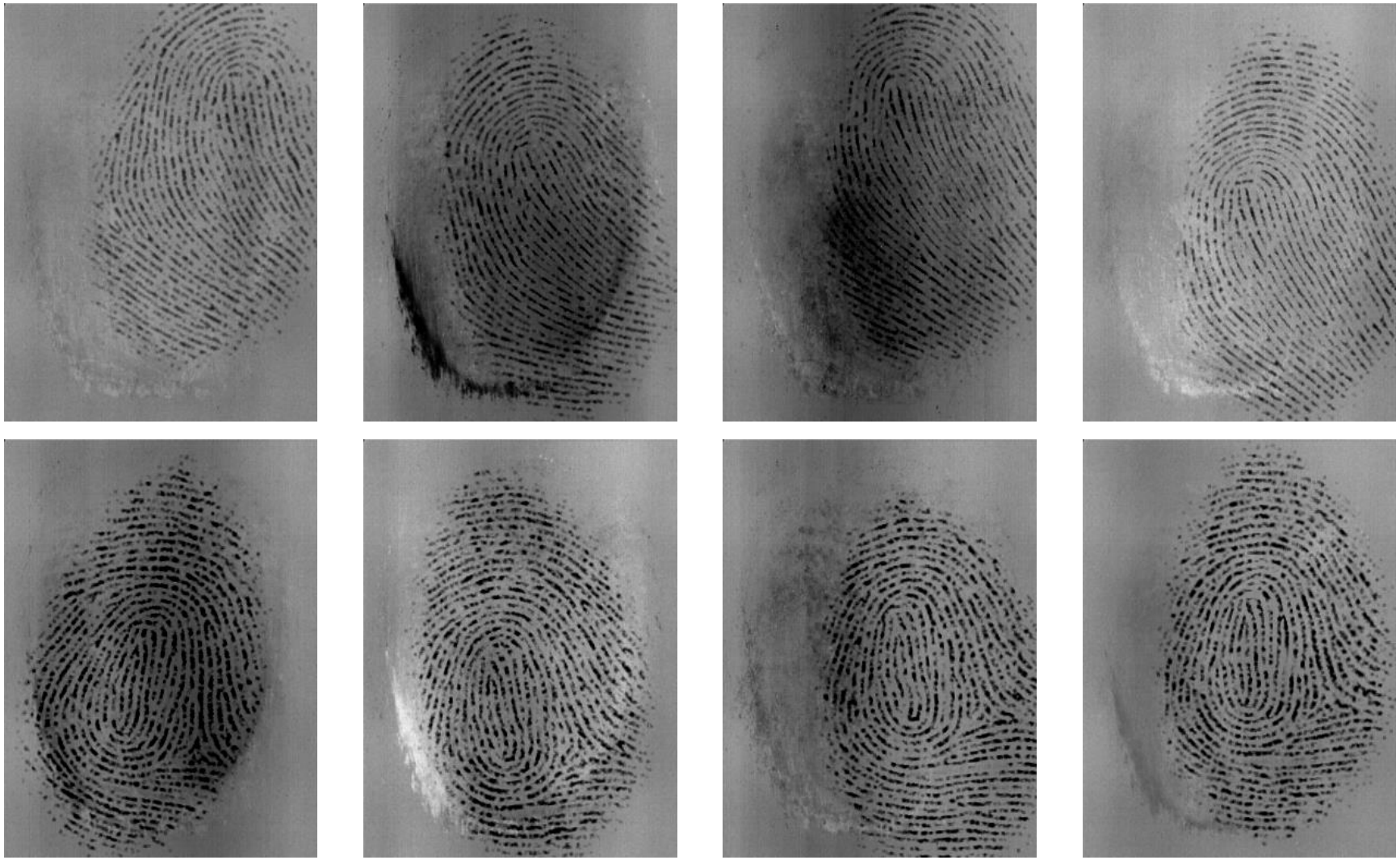


Examples


Generated by Sfinge - © 2000 BioLab
University of Bologna - ITALY

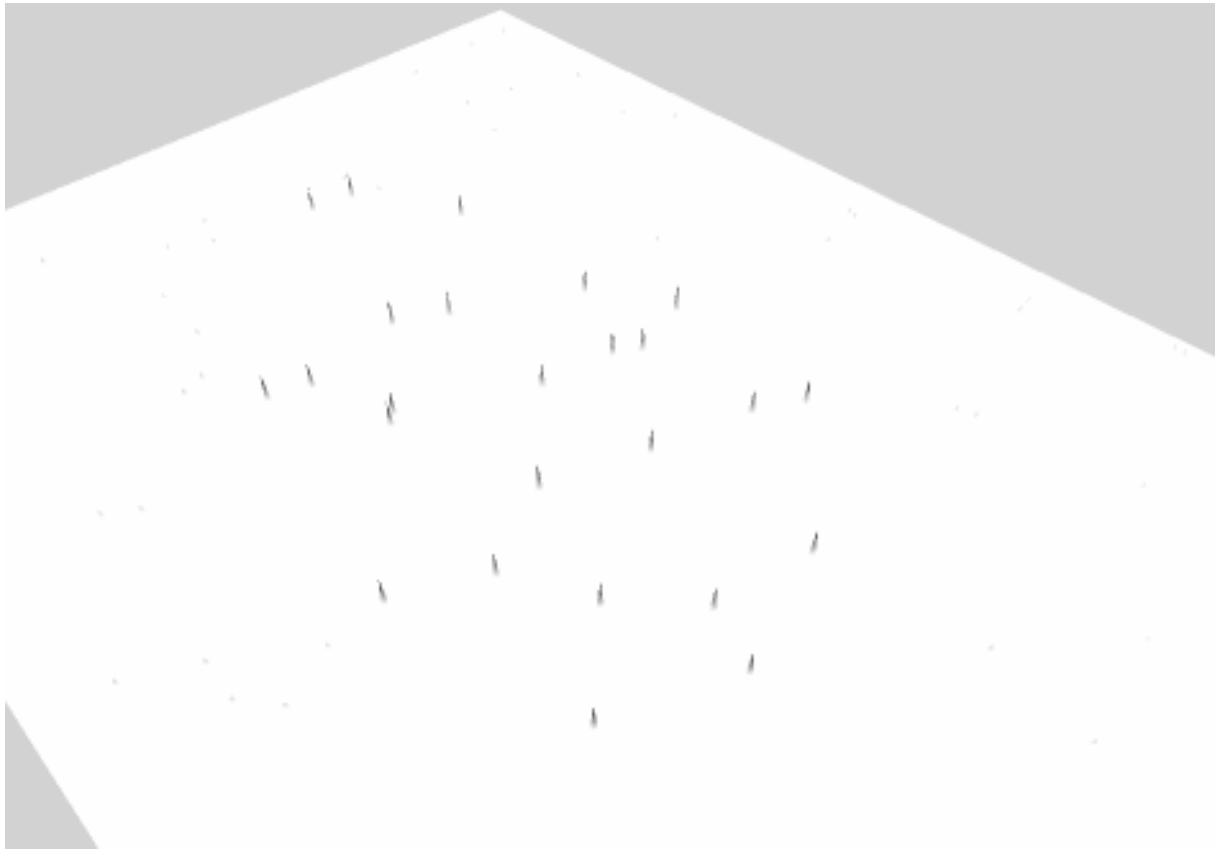


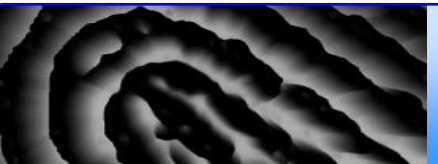
Examples (2)



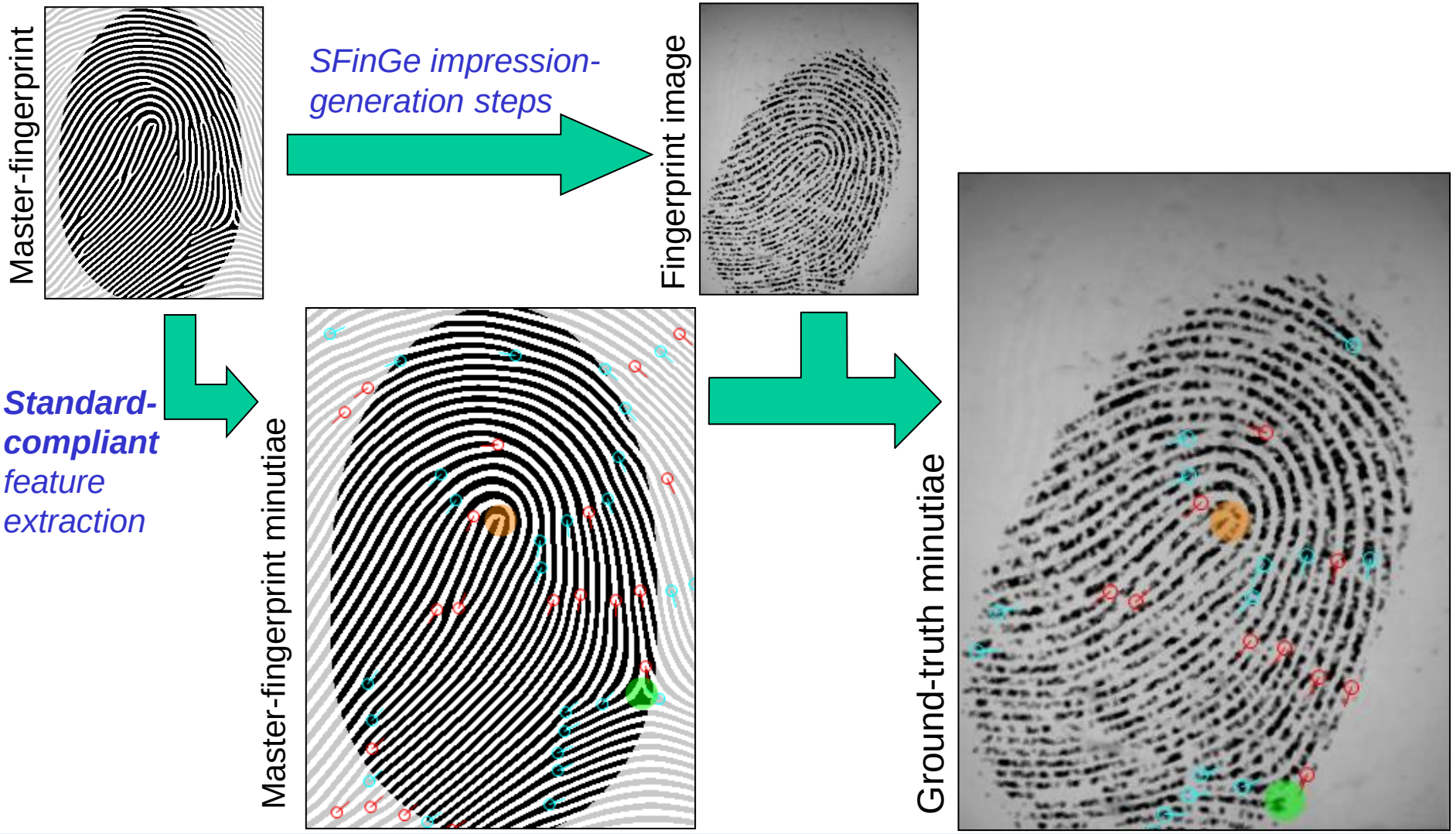
SFinGe: generation of minutiae ground-truth

SfinGe “master fingerprints” are “ideal” fingerprint patterns: well-suited for applying the precise minutiae extraction procedures defined in ANSI and ISO standards.



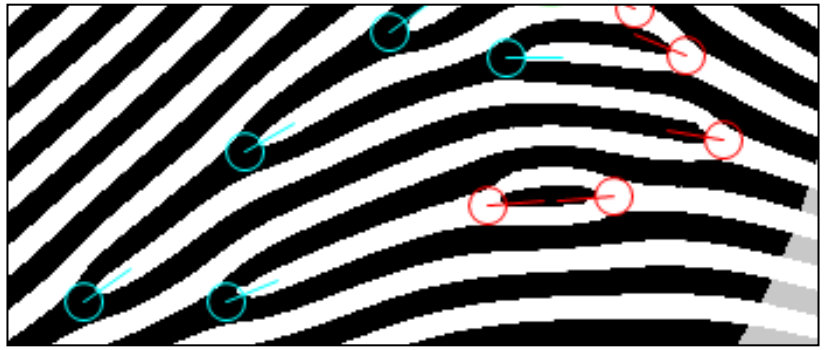


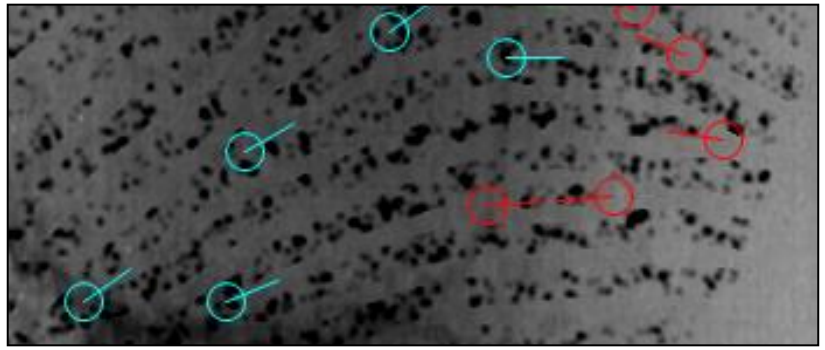
Automatic generation of the ground-truth

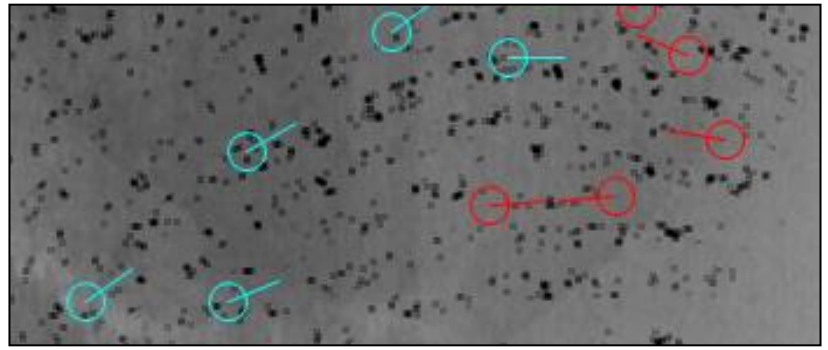


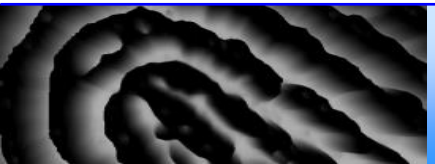
Advantages of SFinGe minutiae ground-truth

- Automatic generation of large fingerprint databases with ground-truth minutiae
  - Features can be extracted by applying the standard procedures easily and without ambiguities (extraction occurs on a binary image without noise)
- The main fingerprint characteristics can be controlled
  - e.g. Fingerprint class, ridge line density, finger placement, skin distortion, fingerprint quality, ...
  - Datasets to test the impact of a given parameter (e.g. fingerprint quality) can be easily generated
- The ground truth is always unique and sound, even when the quality of the final image is very low









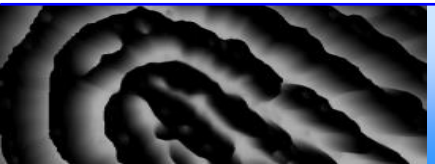
SFinGe validation (1)

Fingerprint images generated by SFinGe appear very realistic

About 90 people (many of them having a good background in fingerprint analysis) have been asked to find a synthetic fingerprint image among 4 images (3 of which were real fingerprints).
The synthetic image proved to be not distinguishable from the others

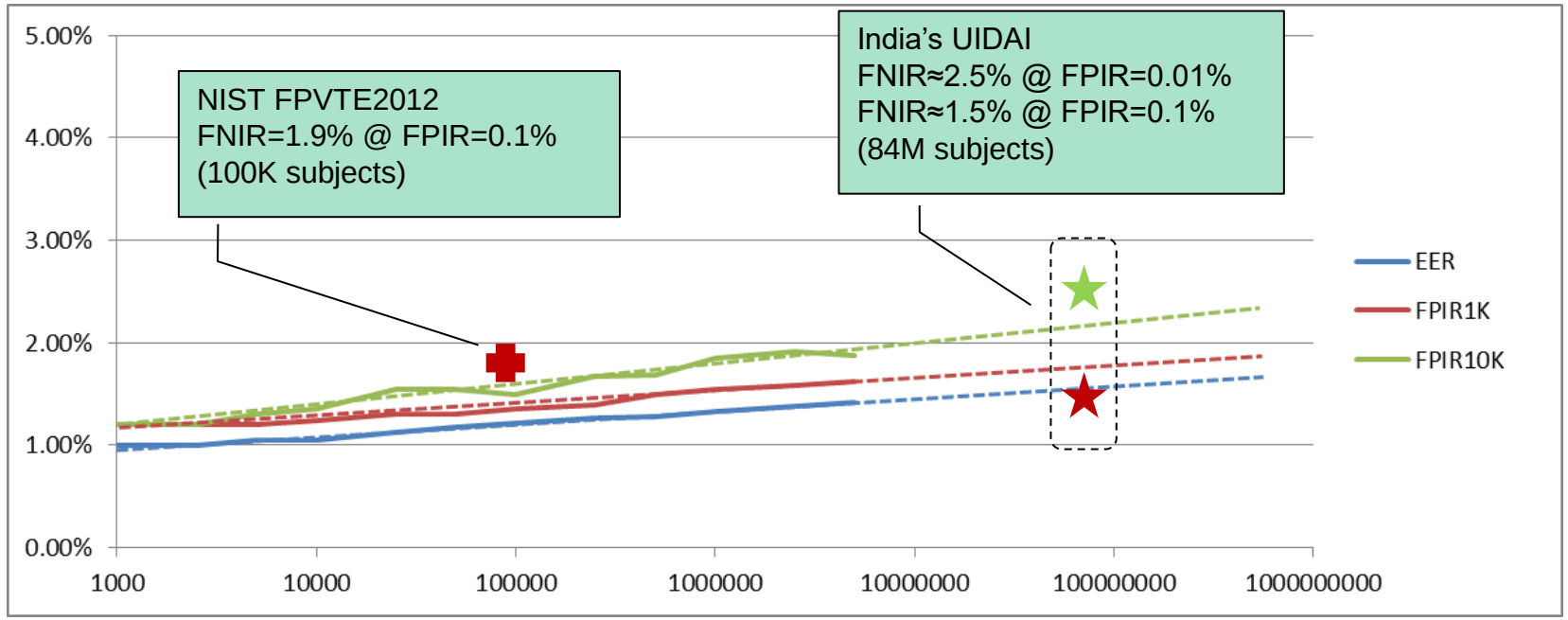
A B C D

Poll results	
A	23%
B	27%
C	21%
D	29%



SFinGe validation (2)

Predicting fingerprint identification accuracy with synthetic data [Fidelity Project – EU]



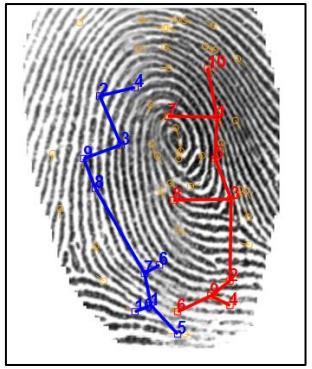
20K queries (10K mates, 10K non-mates)

For this experiment: ≈ 200 billion fingerprint comparisons (carried out on a single PC in less than 11 hours, thanks to other Fidelity developments)

Main challenges

Nowadays research on fingerprints is mainly active on:

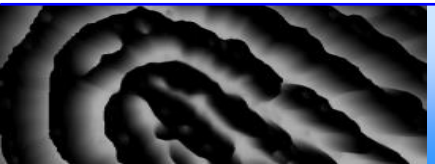
Double-identity fingerprints



Fake fingerprints

Altered fingerprints

Latent fingerprints



Fake fingerprints

The idea of using fake fingerprints to fool biometric recognition is not new.

Diamonds are Forever
(1971)

Bond goes undercover as Peter Franks, a diamond smuggler...

How to make a fake fingerprint?

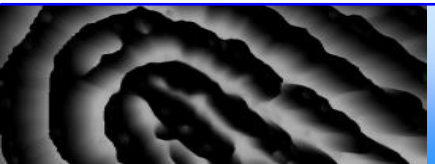
Making a fake finger is not easy, but it is possible with the right knowledge and the appropriate materials.

1) Press the finger into a putty-like material

2) Negative mold of the fingerprint

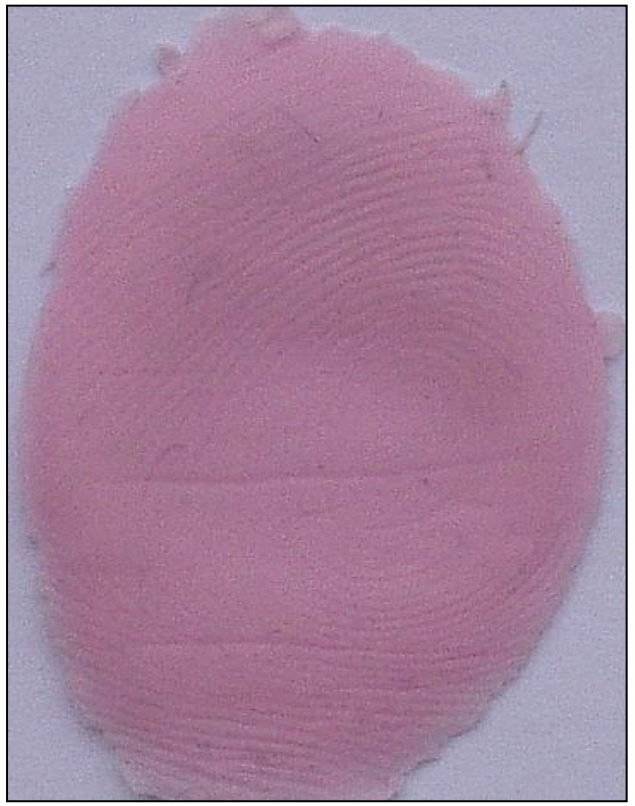
3) Pour the gelatine onto the mold

4) Fake fingerprint



Examples

Gelatine



Silicone

Latex

Fake finger detection by distortion analysis

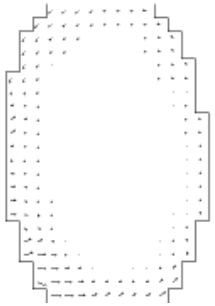
A. Antonelli, R. Cappelli, D. Maio and D. Maltoni, "Fake Finger Detection by Skin Distortion Analysis", *IEEE tIFS*, 2006.

The user is required to place a finger onto the scanner surface and to apply some pressure while rotating the finger

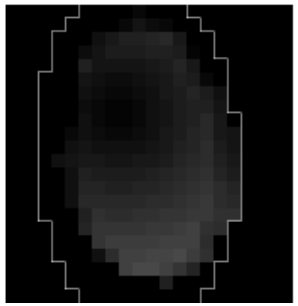
Real finger

Fake finger

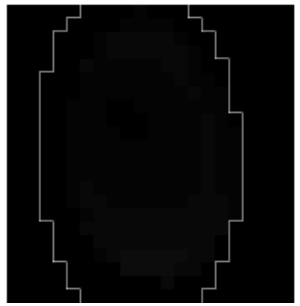
Source frame



Optical Flow



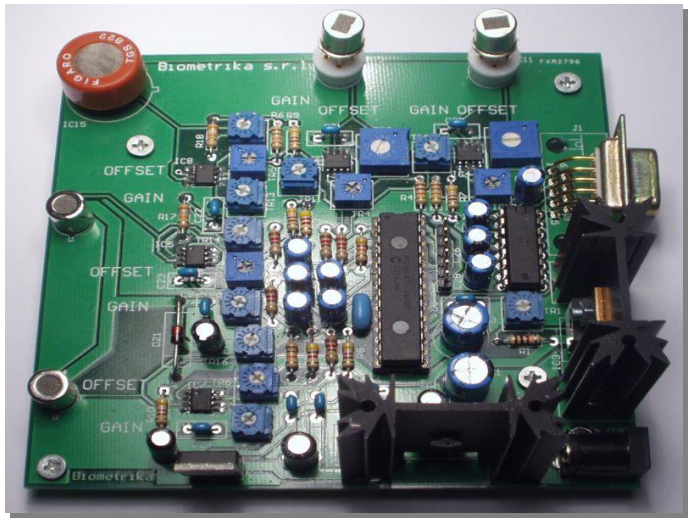
Distortion Map

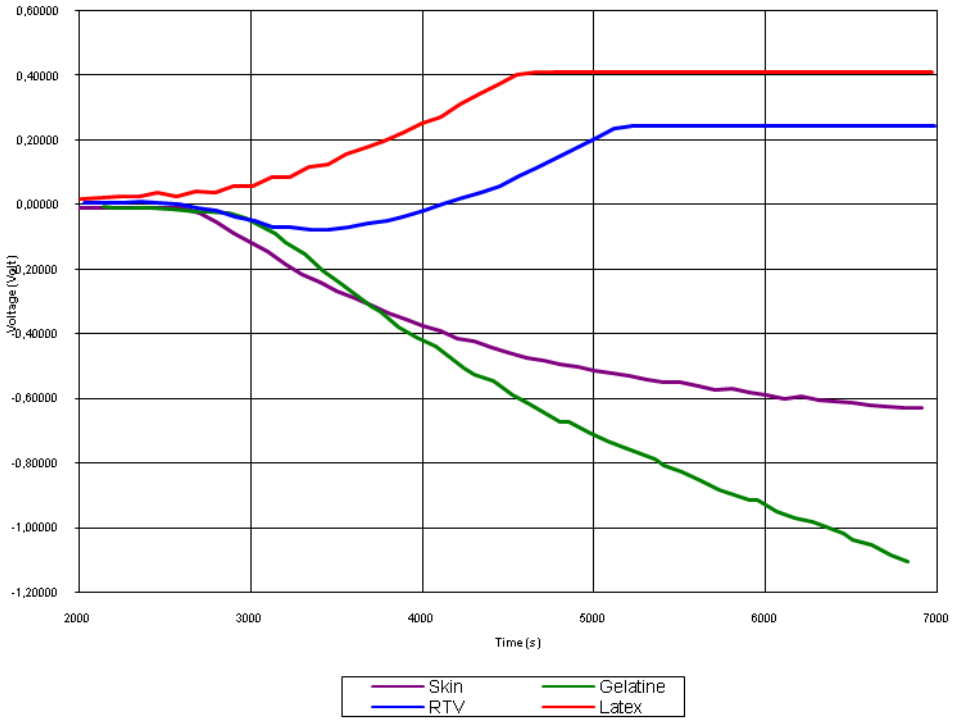


Integrated DM

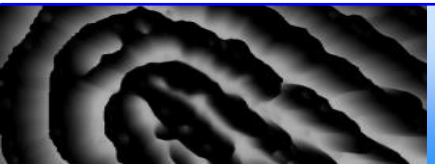
DistortionCode

Fake finger detection by odor analysis





- The idea:
  - Using one or more odor sensors (*electronic noses*) to detect materials usually adopted to make fake fingers
    - Electronic nose: array of chemical sensors designed to detect and discriminate complex odors



Solutions & Open issues

Current solutions

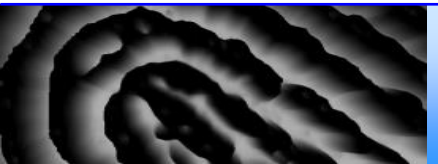
Fake finger detection methods based on properties of a live finger:

- temperature
- electrical conductivity
- skin elasticity
- skin color
- odor
- optical properties
- sub-surface properties
- pulsation
- blood pressure
- perspiration
- texture

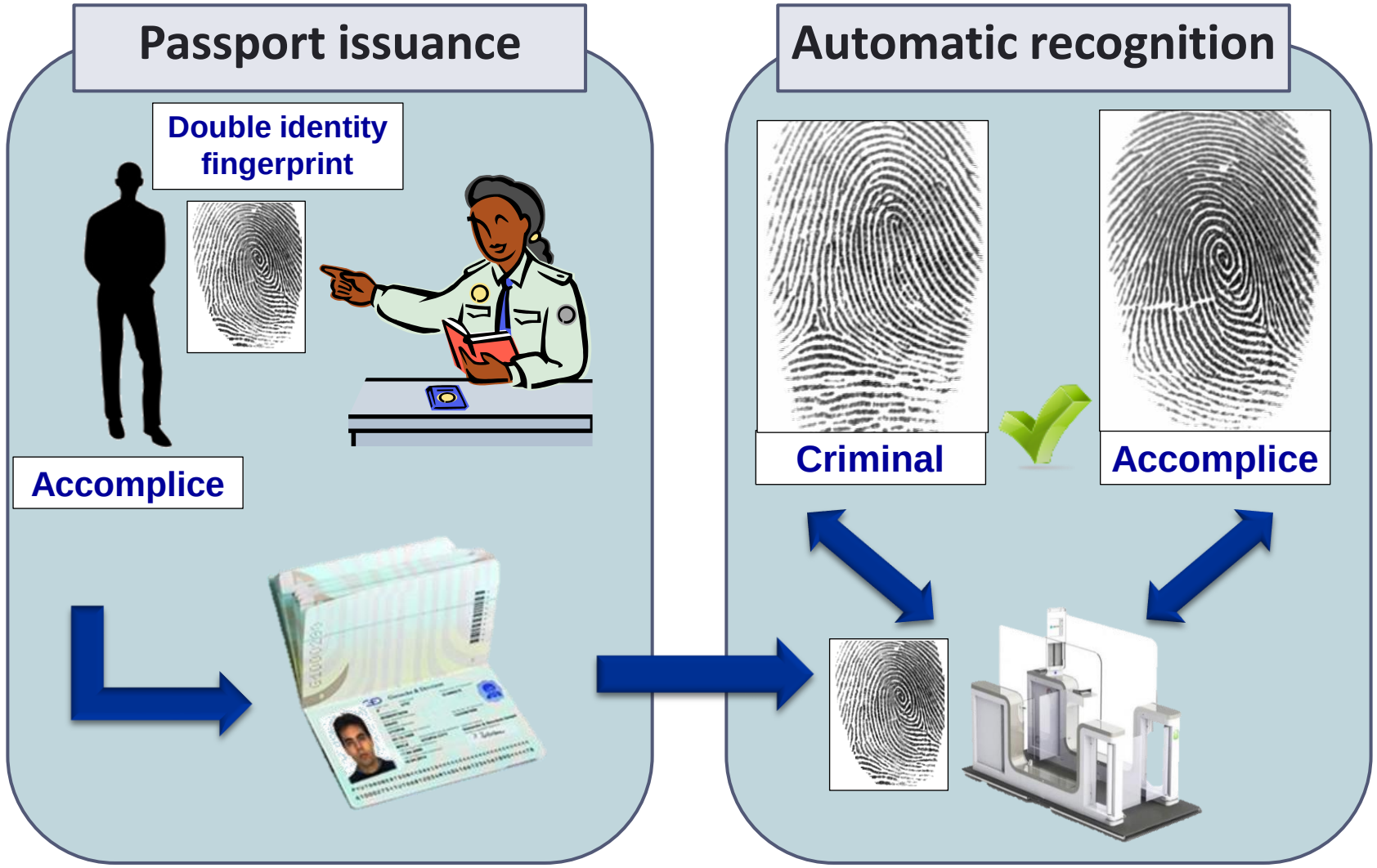
Since 2009, an independent competition called LivDet compares biometric liveness detection approaches: it is organized every two years.

Open issues

If the fake detection approach used by a fingerprint system is known, it is quite easy to imagine a fake finger attack able to fool that specific system.



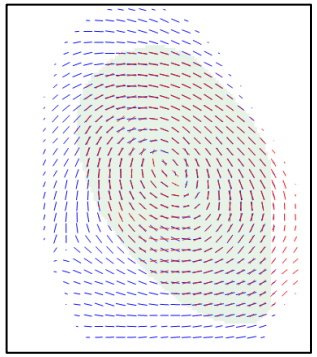
Double-identity fingerprint attack



Double-identity fingerprint generation

1. Fingerprint selection

2. Local orientations



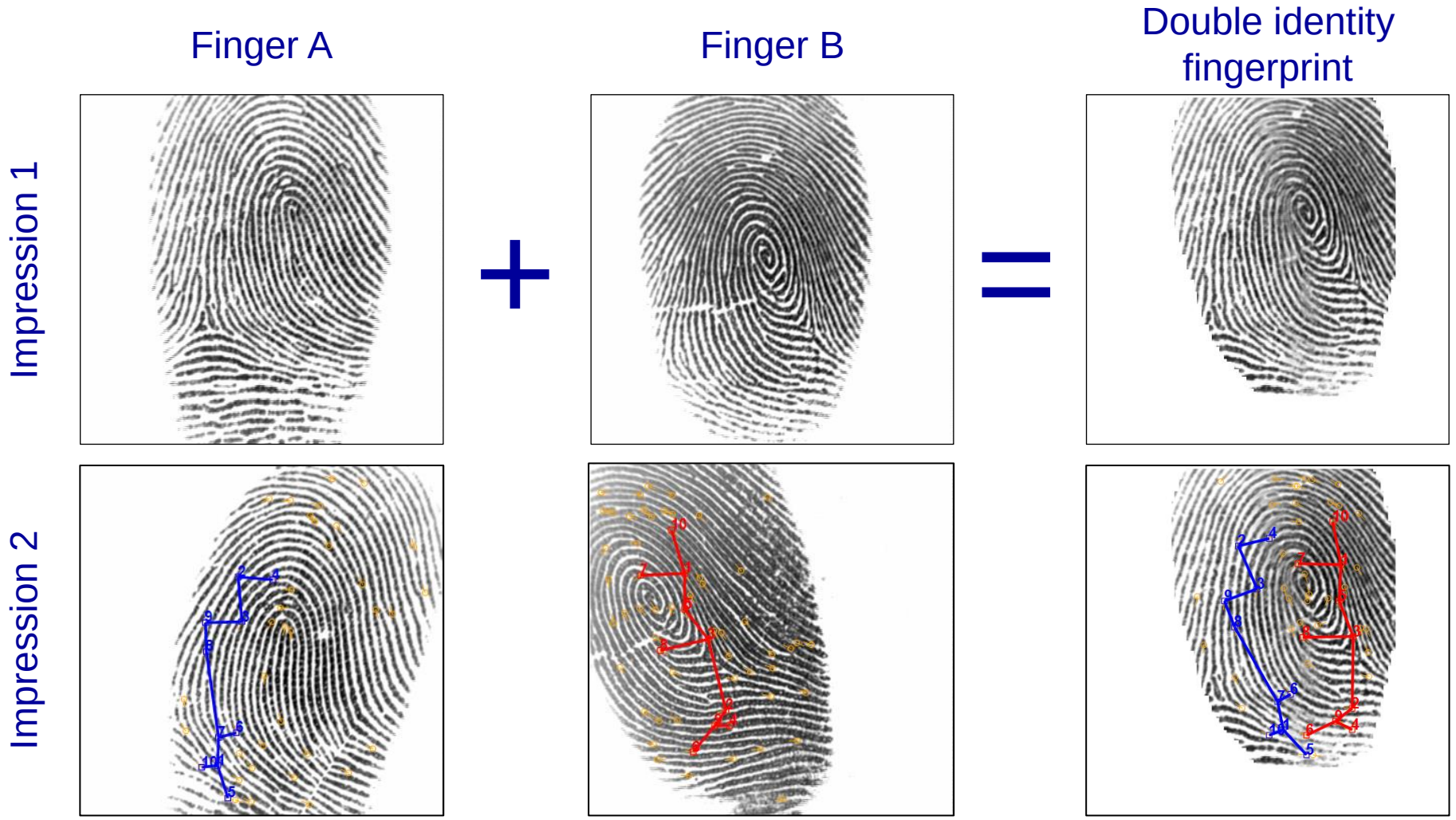
3. Best alignment

4. Fingerprint superimposition

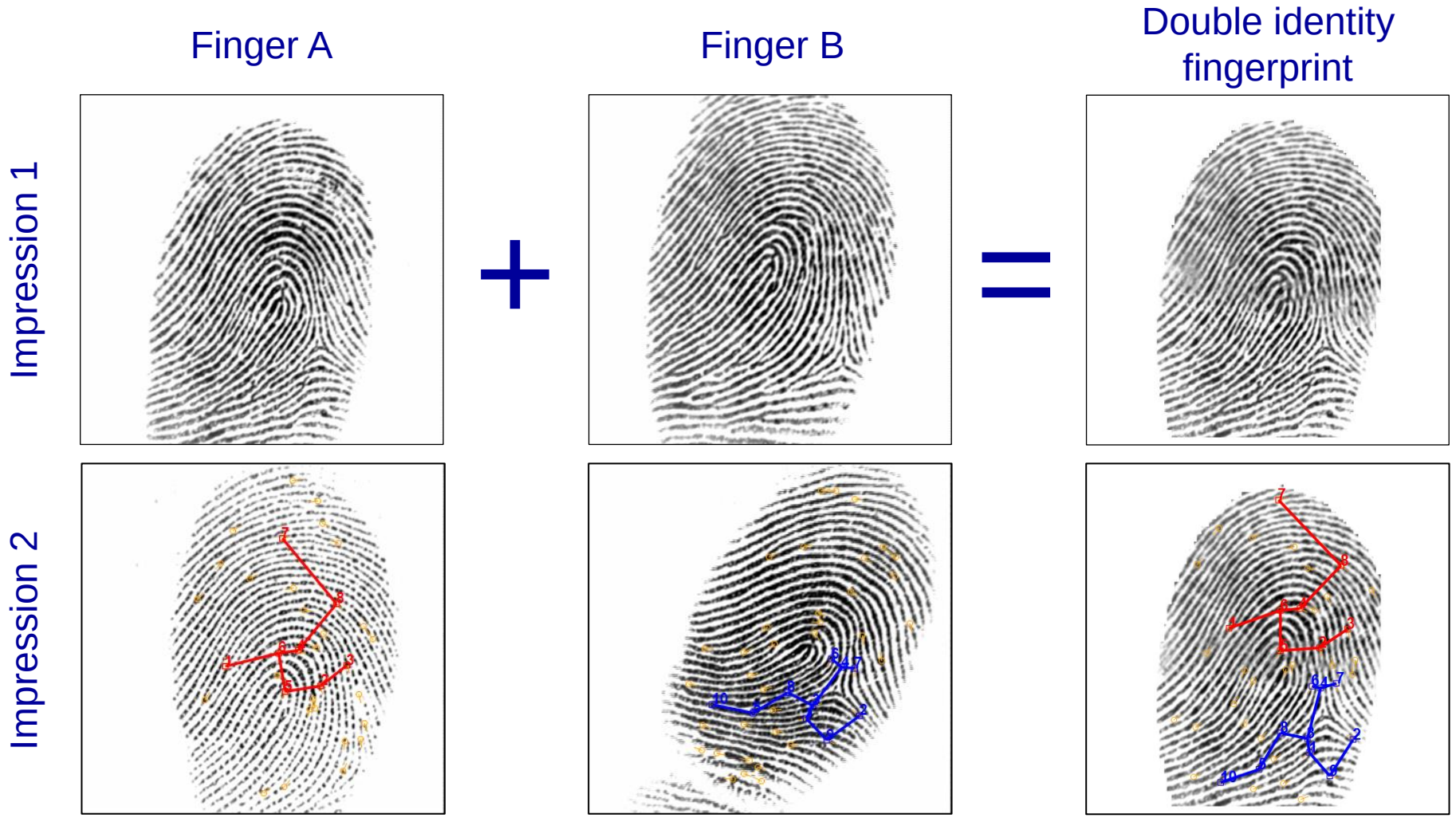
5. Optimal cutline

6. Fingerprint generation

Examples (1)

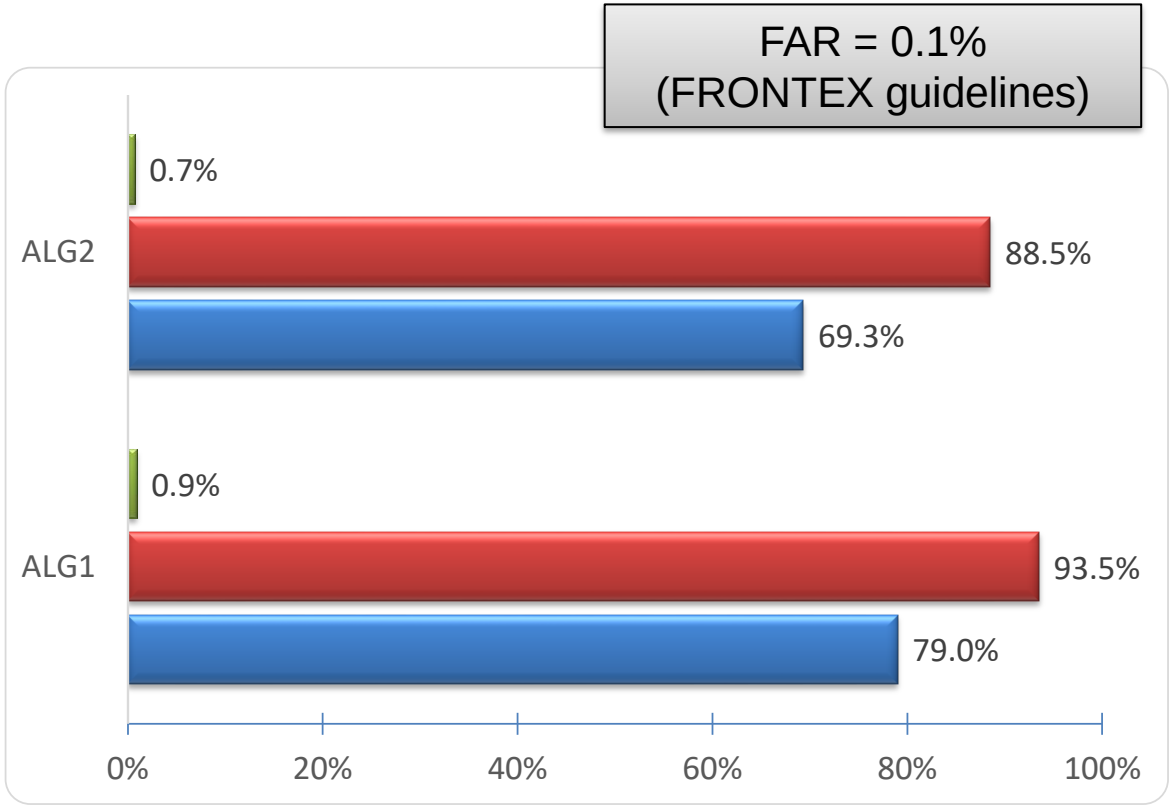

Finger A
Finger B
Double identity fingerprint
Impression 1
Impression 2

Examples (2)


Finger A
Finger B
Double identity fingerprint
Impression 1
Impression 2

Double-identity fingerprint experiments

Experiments have been conducted with two state-of-the-art fingerprint recognition algorithms on the FVC2002 DB1A database, containing 800 fingerprints from 100 fingers (8 impressions per finger) by performing 1400 attack attempts.



Current solutions

None

Open issues

- Double identity fingerprint detection methods
- Fingerprint recognition approaches able to deal with double identity attack

Why altered fingerprints?

Criminals, to avoid identification, can irreversibly alter their fingerprints.

Transplanted

Bitten

Burnt with acid

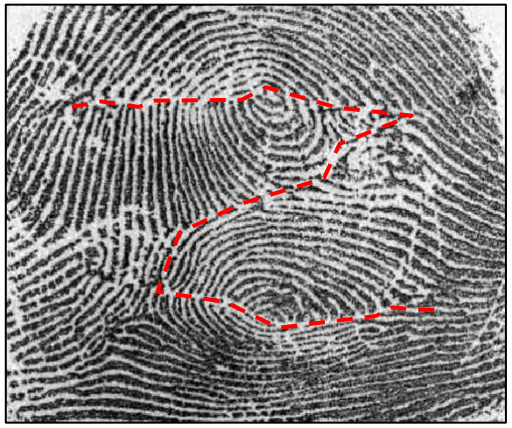
Surgically altered

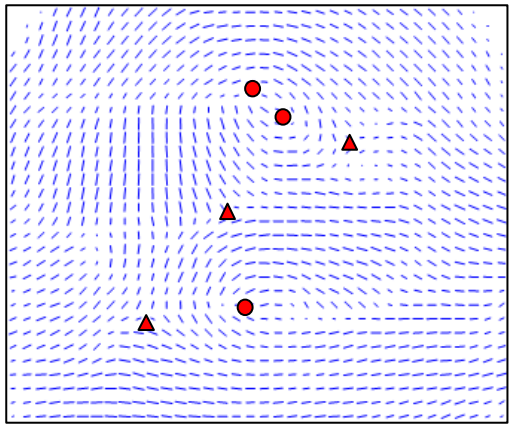
Alterations

The alterations can be classified into three categories, according to the resulting fingerprint pattern and not to the alteration process applied.

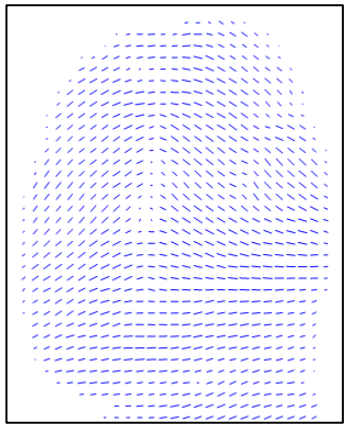
Obliteration

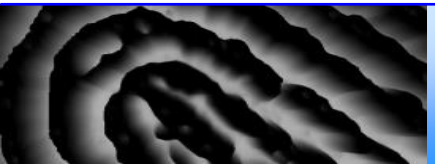
Distortion





Imitation





Solutions & Open issues

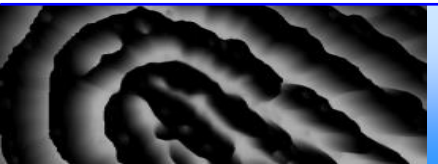
Current solutions

Altered fingerprint detection methods based on:

- ridge quality map
- singularity pattern analysis
- scar detection
- local orientation map analysis
- minutiae distribution analysis

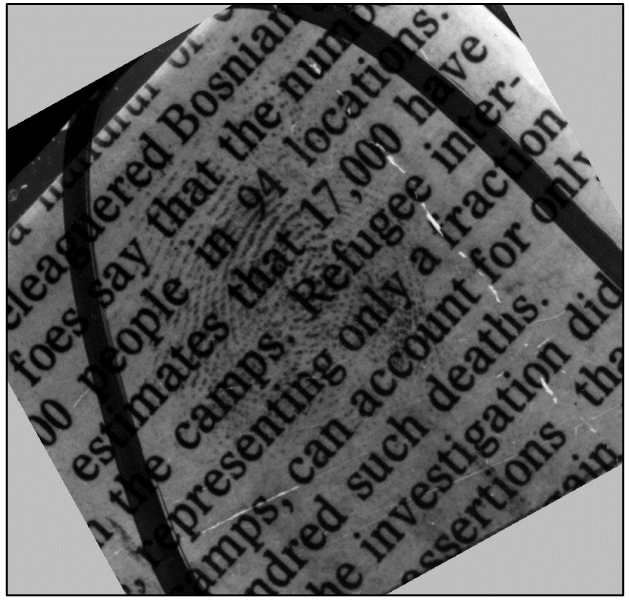
Open issues

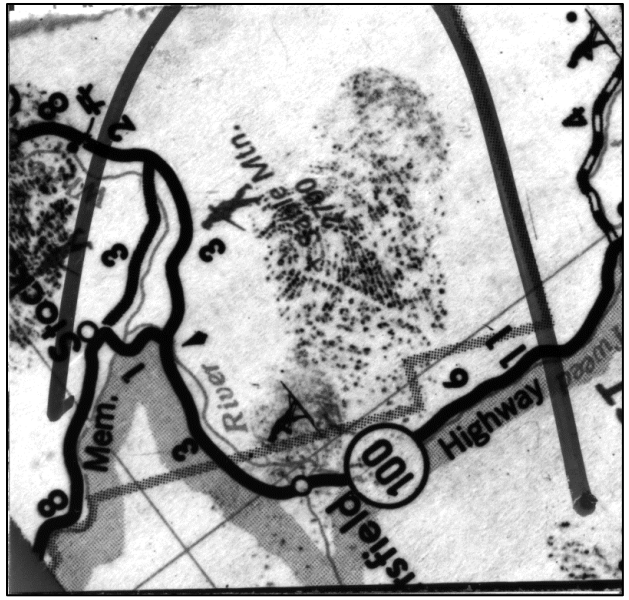
- reconstruct original fingerprint from the given altered one
- compare altered fingerprints to original ones



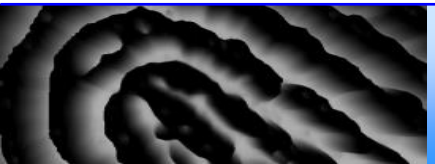
What is a latent fingerprint?

A latent fingerprint is an invisible fingerprint left on a surface by deposits of oils and/or perspiration from the finger. Usually it can be detected with the application of chemical or physical methods.





The key problem is reliably estimating the context (local orientations and frequencies)



Automatic latent processing

- Fully automatic ("lights-out") and highly accurate latent matching is one the major objectives of FBI's Next Generation Identification (NGI) program.
  - Automatic Minutiae extraction on noisy fingerprints is still a problem
    - Segmentation
    - Orientation and Frequency Estimation

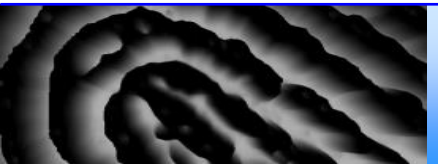
K. Cao and A. K. Jain, "Automated Latent Fingerprint Recognition", IEEE tPAMI, 2018

- Machine learning techniques are being introduced:

  2012…2014: dictionary-based techniques to estimate orientation field

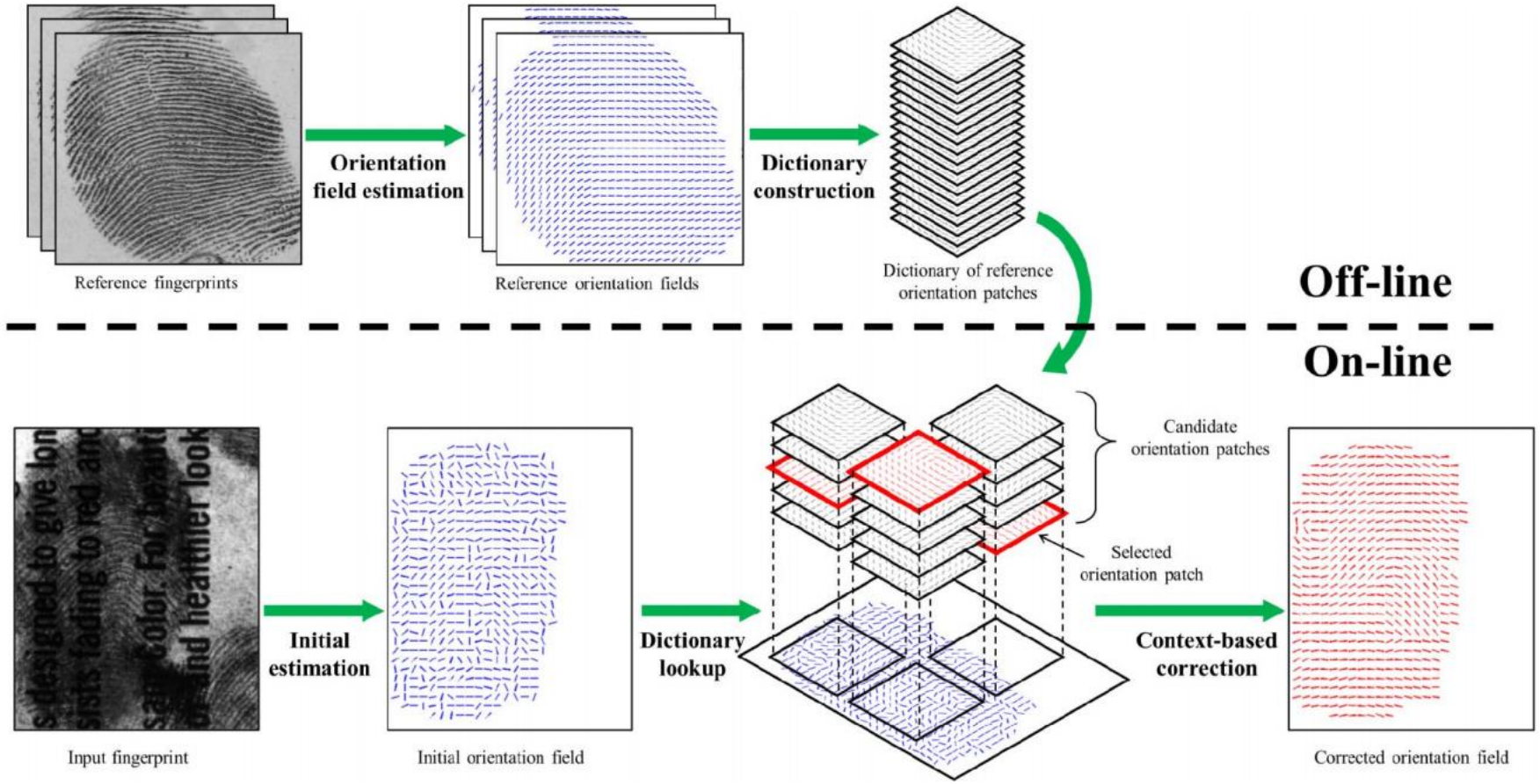
  2014…2020: deep learning approaches:

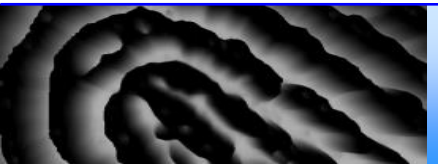
  - CNN (Convolutional Neural Networks) for orientation extraction, minutiae extraction, minutiae filtering and minutiae descriptors.
  - Autoencoders (denoising), GAN (Generative Adversarial Networks)



Global orientation dictionary

J. Feng, J. Zhou, and A. K. Jain, "Orientation Field Estimation for Latent Fingerprint Enhancement", IEEE Trans. PAMI, 2013.



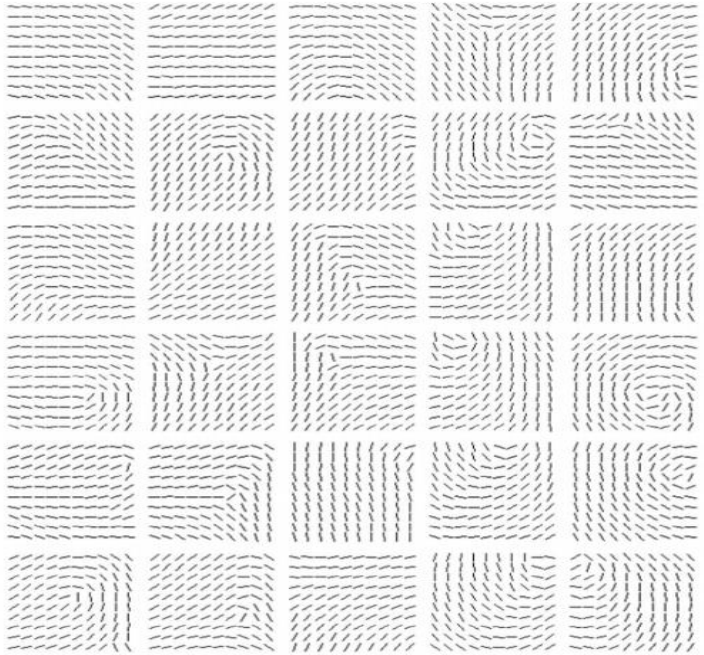


Ridge structure dictionary

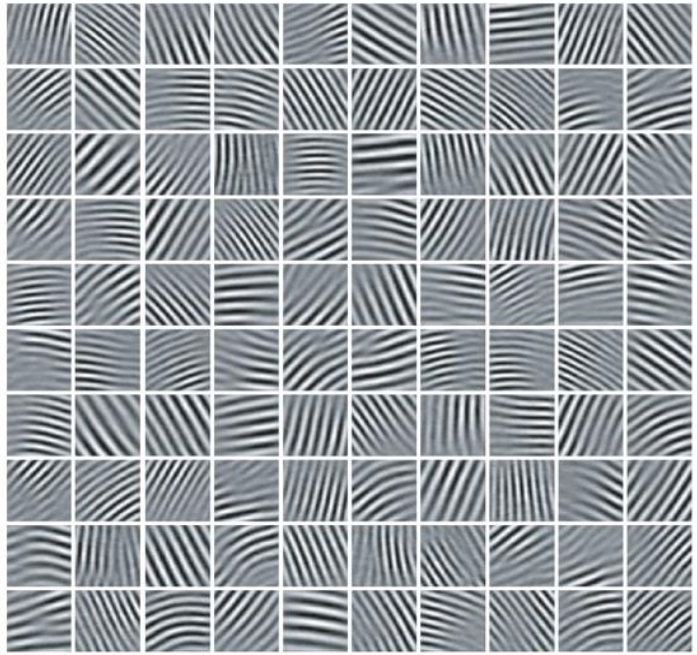
K. Cao, E. Liu, A. K. Jain, "Segmentation and Enhancement of Latent Fingerprints: A Coarse to Fine Ridge Structure Dictionary", IEEE Trans. PAMI, 2014.

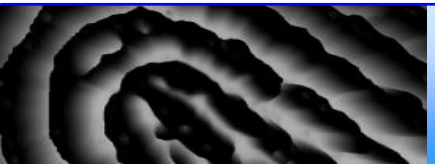
Ridge-frequency can be estimated as well.

Orientation patches



Ridge structure patches





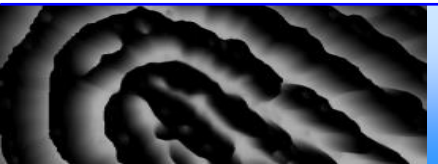
Solutions & Open issues

Current solutions

- Semi-automatic tools supervised by human experts.
- Techniques based on prior knowledge of fingerprint structure.
- Novel approaches based on convolutional neural networks.

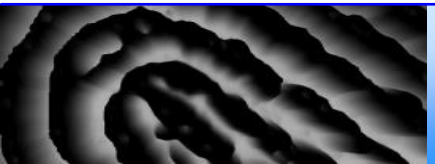
Open issues

Fully automatic (“lights-out”) and highly accurate latent comparison remains one the major objectives of FBI’s Next Generation Identification (NGI) program.



Thank you for your attention

http://biolab.csr.unibo.it
raffaele.cappelli@unibo.it



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Book

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Fingerprint acquisition

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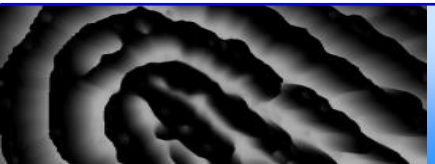

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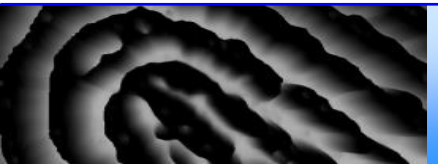

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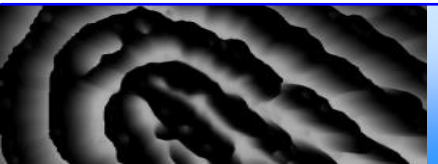

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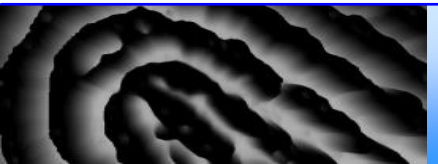

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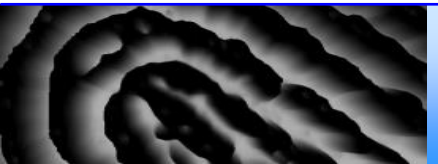

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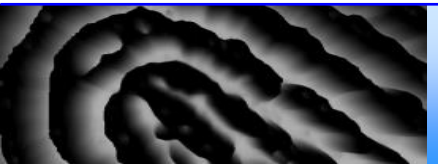

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