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Fingerprint Recognition

Basics and Recent Advances

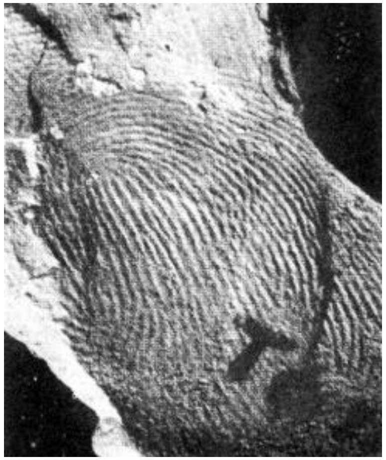
Outline

- State-of-the-art
  - Image acquisition and fake detection
  - Feature extraction
  - Matching approaches
  - FVC competitions

- New directions
  - Hot topics
  - MCC: a novel local matching approach
  - Enhancement of latent fingerprints
  - FVC-onGoing
  - Generation of synthetic fingerprint images: the SFinGe approach

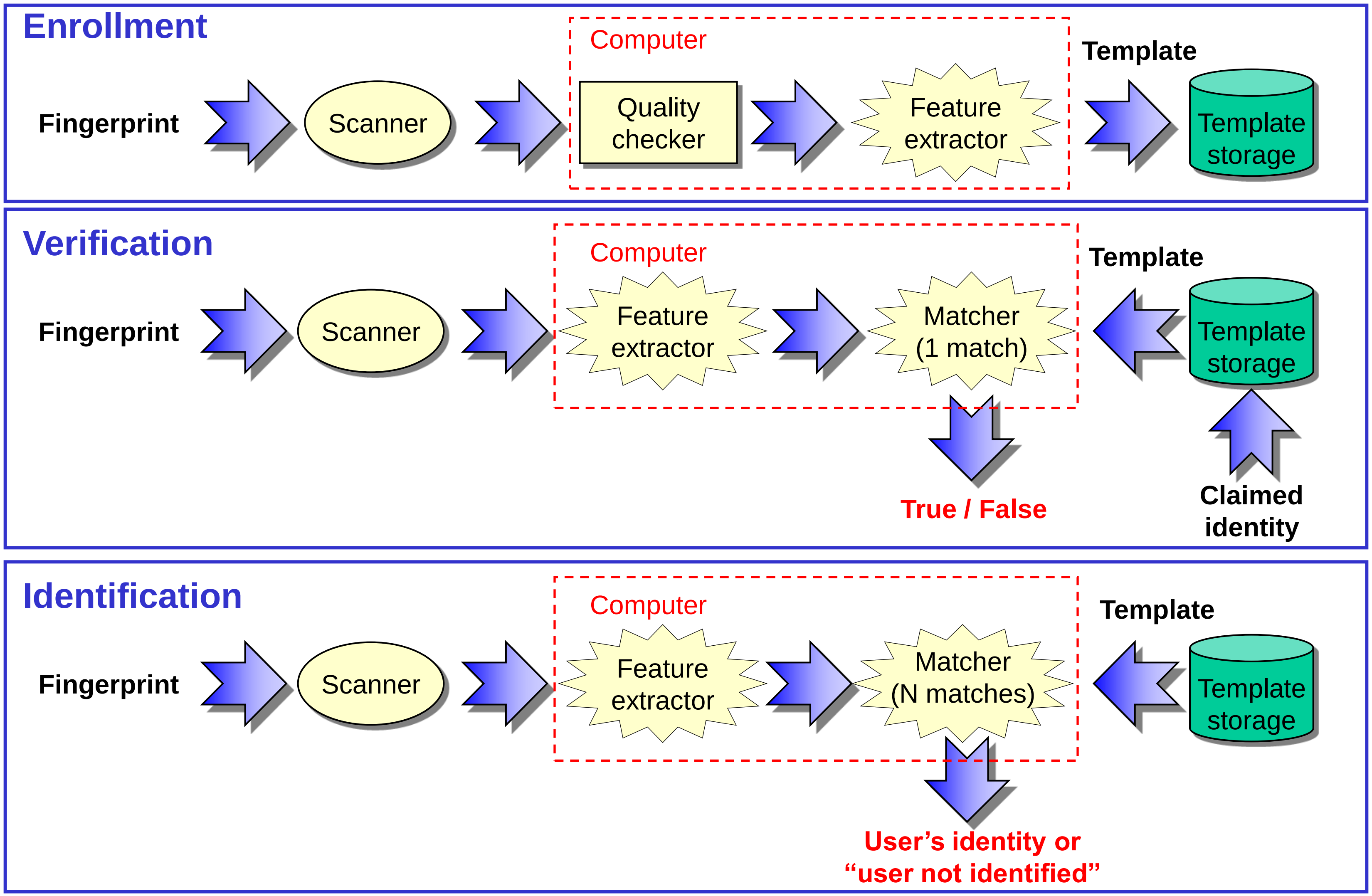
Why fingerprints?

- Highly distinctive and unique
- Do not change during the lifetime of a person
- Publicly accepted as reliable (evidence in a court of law)
- Identical twins have different fingerprints



An impression on a Palestinian lamp (400 B.C.)

Fingerprint recognition system



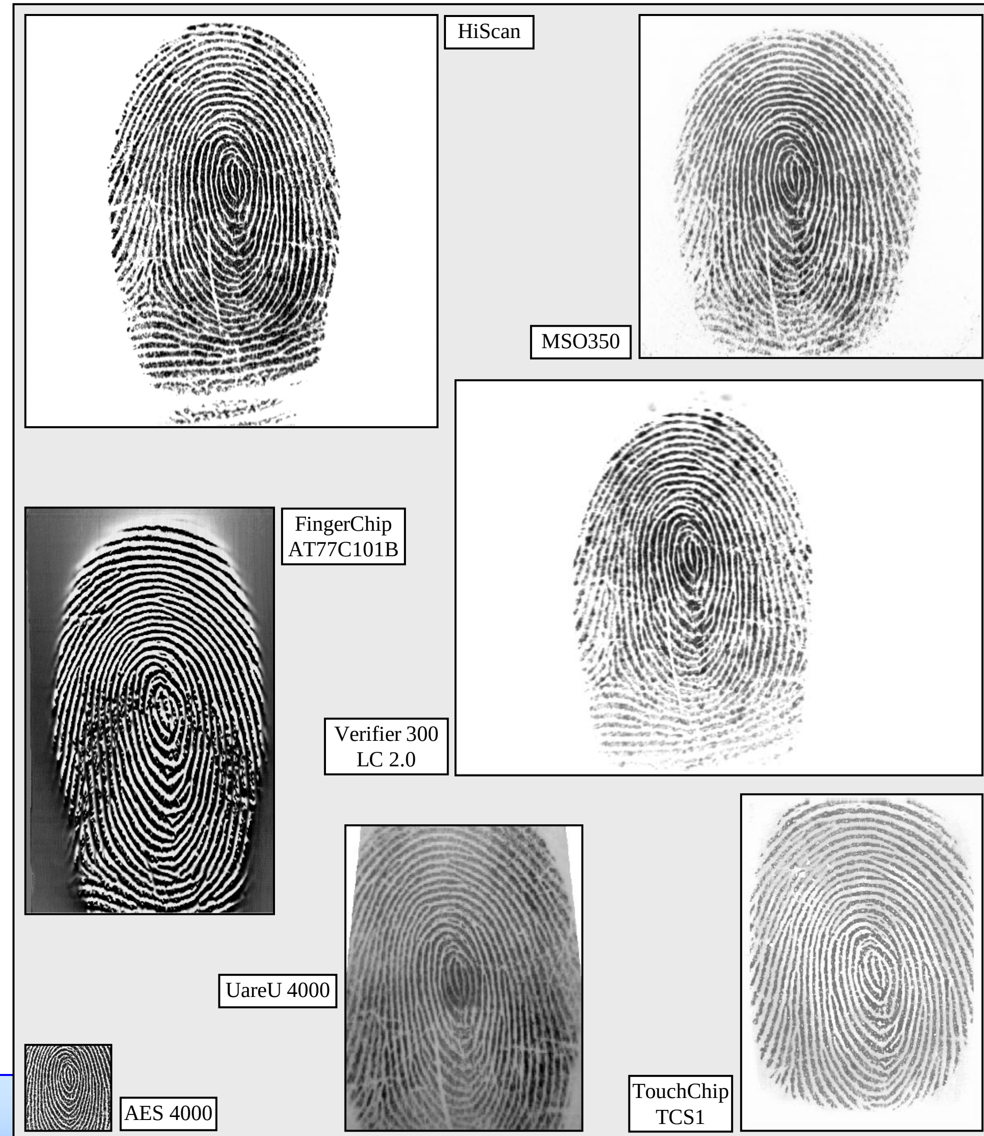
Fingerprint acquisition

- Off-line acquisition
  - Ink technique
  - Latent fingerprints

- On-line acquisition
  - Optical sensors
  - Silicon-based sensors
  - ...

On-line fingerprint scanners – single finger

	Technology	Company	Model	Dpi	Area (h×w)	PIV IQS compliant
Optical	FTIR	Biometrika www.biometrika.it	HiScan	500	1"×1"	√
Optical	FTIR	Crossmatch www.crossmatch.net	Verifier 300 LC 2.0	500	1.2"×1.2"	
Optical	FTIR	Digital Persona www.digitalpersona.com	UareU4000	512	0.71"×0.57"	
Optical	FTIR	L-1 Identity www.identix.com	DFR 2100	500	1.05"×1.05"	√
Optical	FTIR	Sagem www.morpho.com	MSO350	500	0.86"×0.86"	√
Optical	FTIR	Secugen www.secugen.com	Hamster IV	500	0.66"×0.51"	√
Solid-state	Capacitive	Upek www.upek.com	TouchChip TCS1	508	0.71"×0.50"	√
Solid-state	Thermal (sweep)	Atmel www.atmel.com	FingerChip AT77C101B	500	0.02"×0.55"	
Solid-state	Electric field	Authentec www.authentec.com	AES4000	250	0.38"×0.38"	
Solid-state	Piezoelectric	BMF www.bm-f.com	BLP-100	406	0.92"×0.63"	

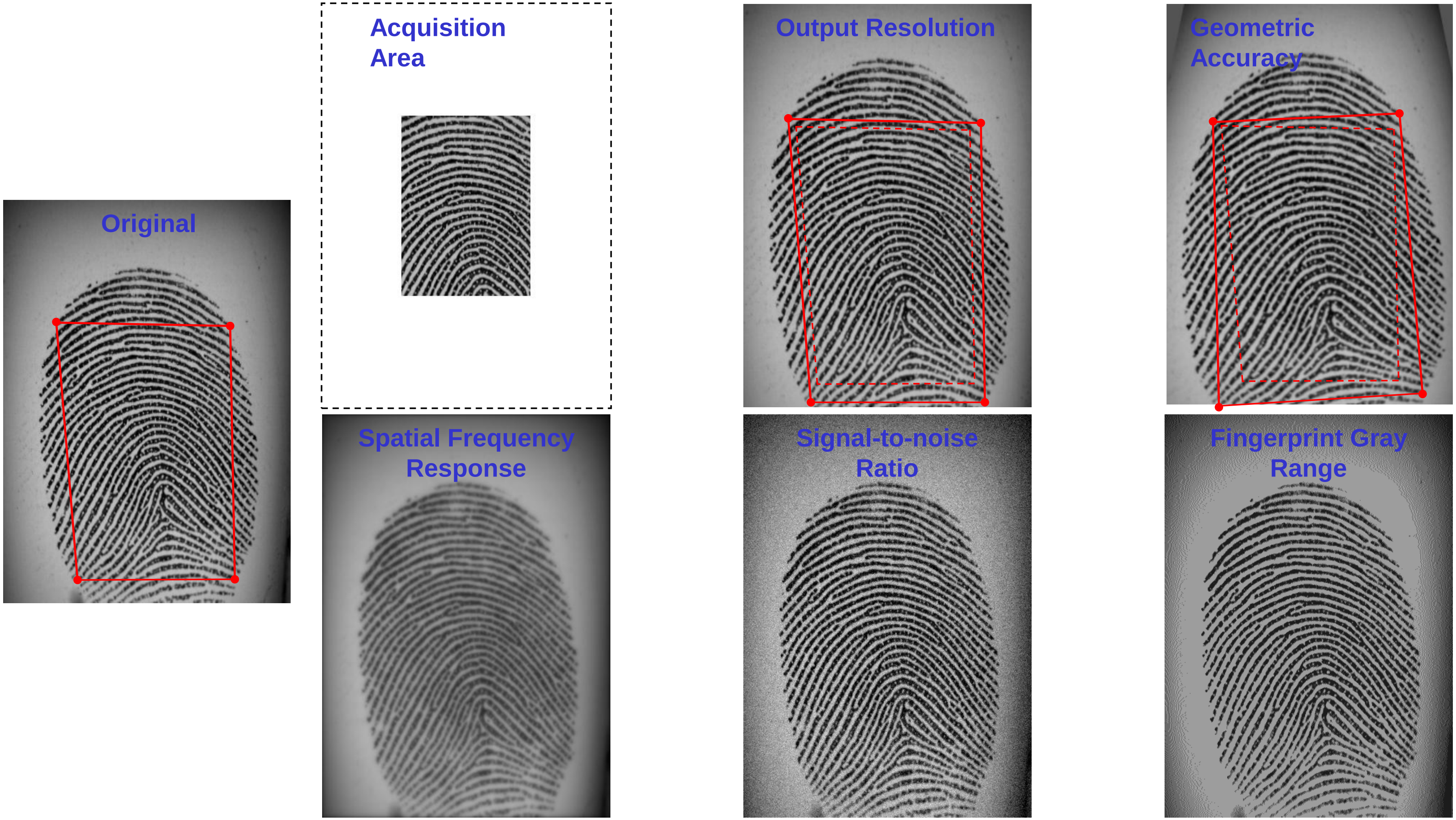


On-line fingerprint scanners – multi finger

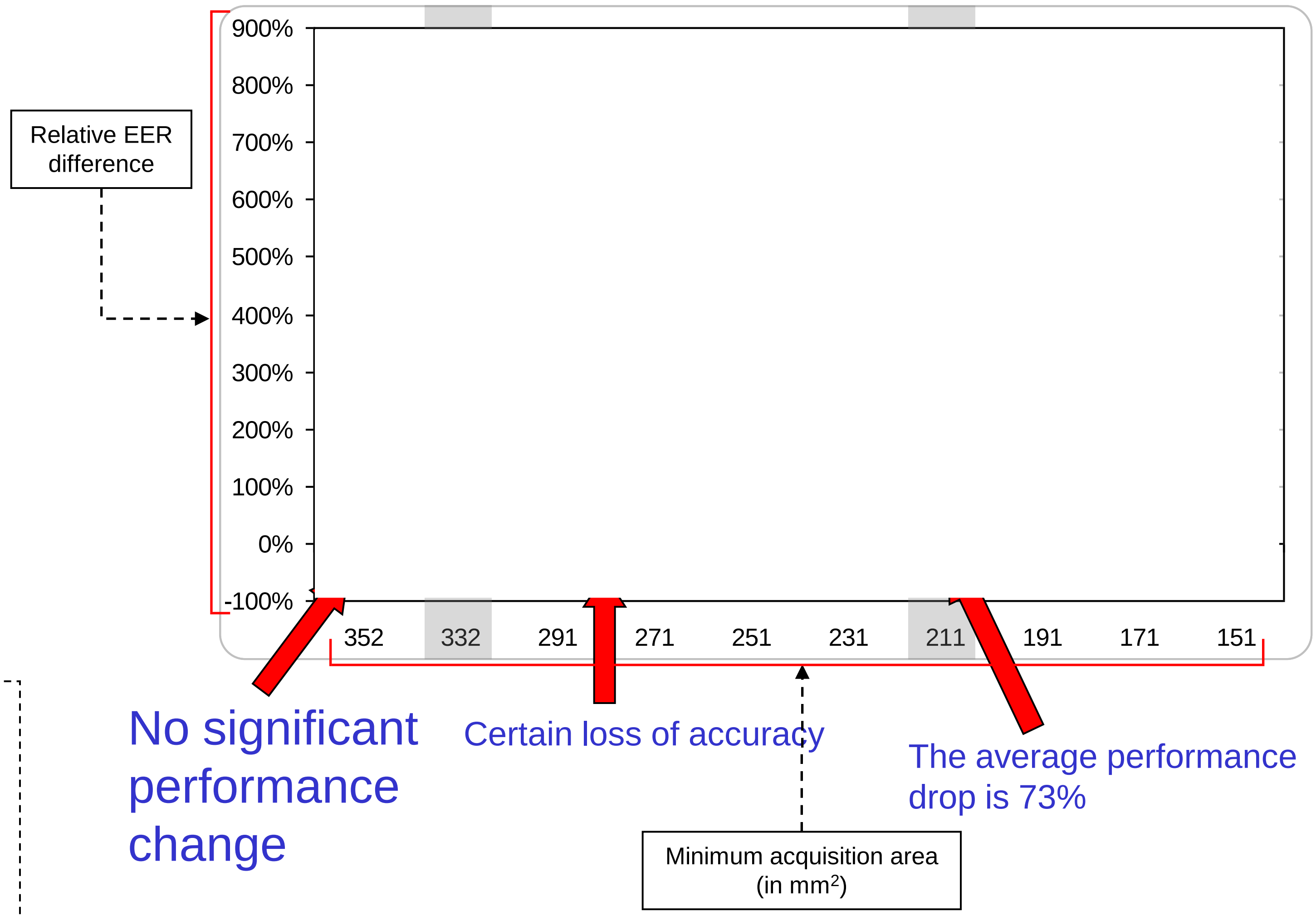
	Technology	Company	Model	Dpi	Area (h×w)	IAFIS IQS compliant
Optical	FTIR	Crossmatch www.crossmatch.net	L SCAN 1000	1000	3.0"×3.2"	√
	FTIR	L-1 Identity www.l1id.com	TouchPrint 4100	500	3.0"×3.2"	√
	FTIR	Papillon www.papillon.ru	DS-30	500	3.07"×3.38"	√

“Operational” quality of fingerprint scanners

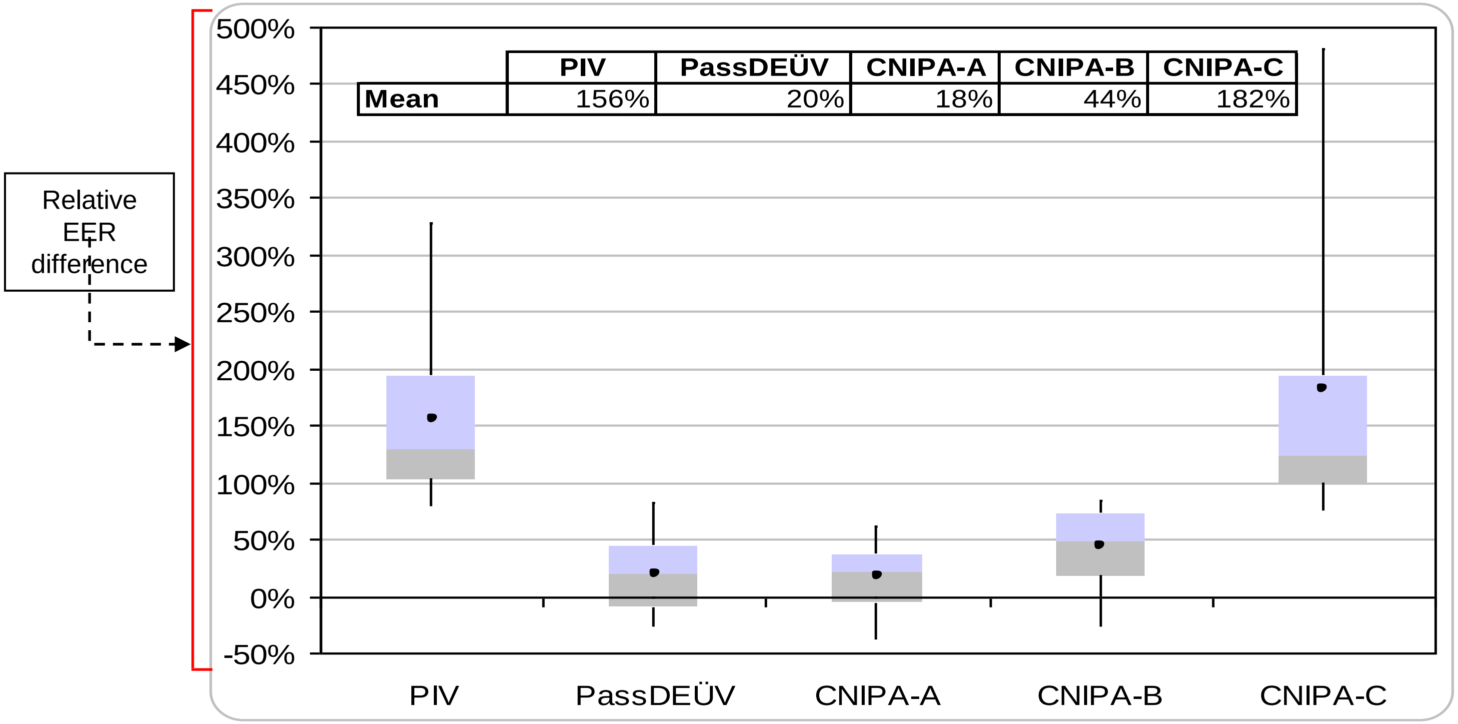
main quality parameters



The most important parameter is Acquisition area



Certification of scanners & classes of quality



	PIV	PassDEÜV	CNIPA-A	CNIPA-B	CNIPA-C
Mean	156%	20%	18%	44%	182%

- Cappelli R., Ferrara M. and Maltoni D., “On the Operational Quality of Fingerprint Scanners”, IEEE Transactions on Information Forensics and Security, vol. 3, no. 2, pp. 192-202, 2008.
- A. Alessandroni, R. Cappelli, M. Ferrara and D. Maltoni, "Definition of Fingerprint Scanner Image Quality Specifications by Operational Quality", in proceedings European Workshop on Biometrics and Identity Management (BIOID 2008), Roskilde, Denmark, May 2008.

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...

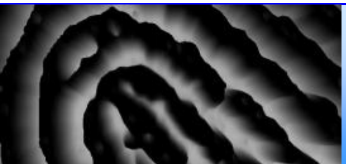
Fake detection

- Making a fake finger is not easy, but with the right knowledge and the appropriate materials ...
  - Much more easy with cooperation of the user
  - Typical materials:
    - Gelatin, Silicone, Latex.

Gelatine Finger

Silicone Finger

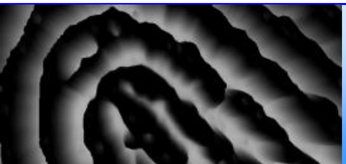
Latex Finger



Fake detection (2)

- The potential weakness of commercial fingerprint scanners has been highlighted in some works:
  - Fingerprint recognition–don't get your fingers burned [Van der Putte, Keuning, 2000]
  - Impact of artificial "gummy" fingers on fingerprint systems [Matsumoto, 2002]
  - …
  - Fake Finger Detection by Skin Distortion Analysis [A. Antonelli, R. Cappelli, D. Maio and D. Maltoni - IEEE Transactions on Information Forensics and Security, 2006]

- Possible measures
  – Intrinsic properties of a live person
    - Physical (e.g. elasticity), Electrical (e.g. resistance), Visual (e.g. color), …
  – Signals generated involuntarily
    - Pulsation, Blood pressure, Perspiration, …
  – Voluntary/involuntary response to stimuli



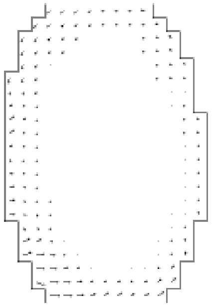
Fake finger detection by distortion analysis

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

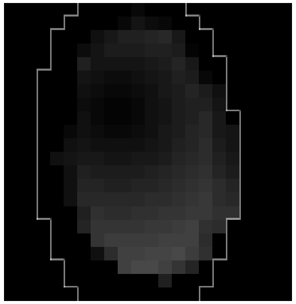
Real finger

Fake finger

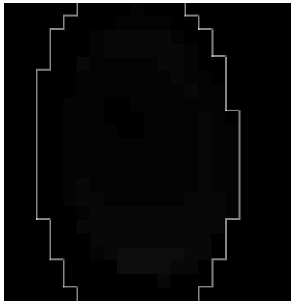
Source frame



Optical Flow



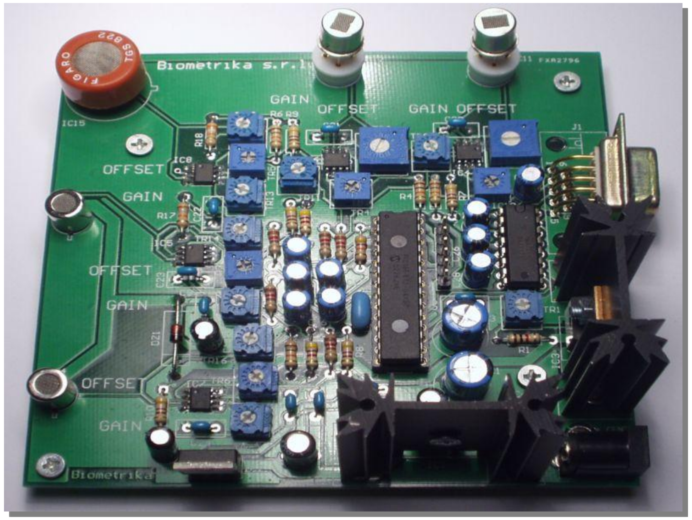
Distortion Map

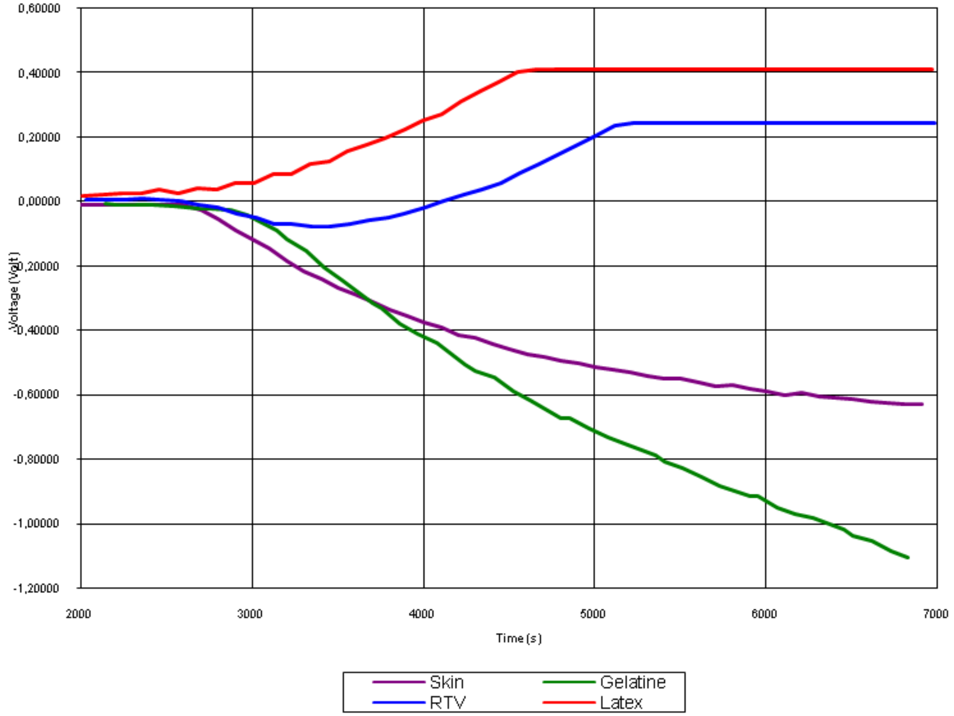


Integrated DM

DistortionCode

Fake finger detection by odor analysis

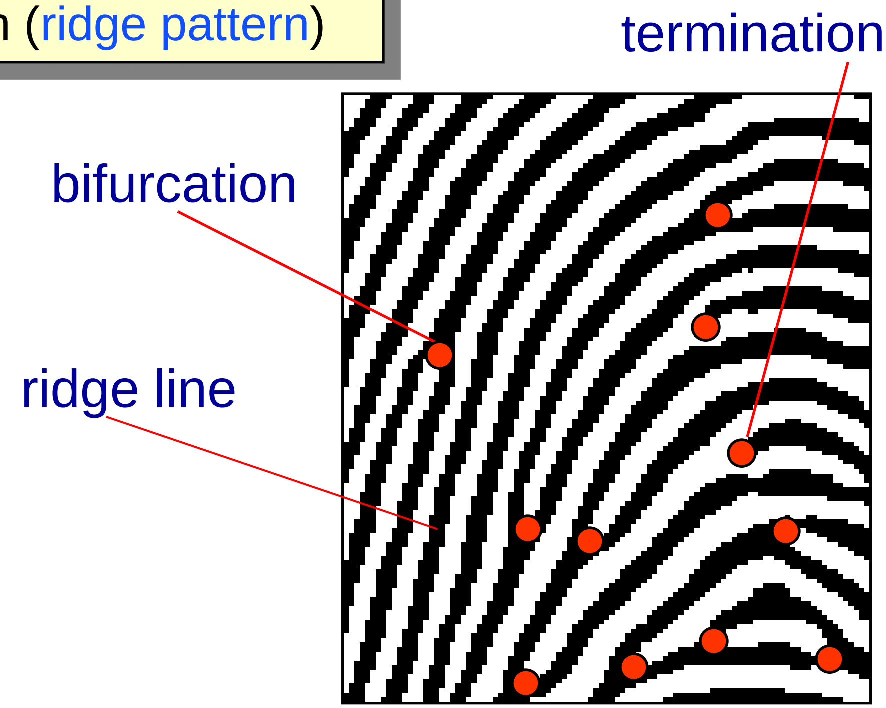




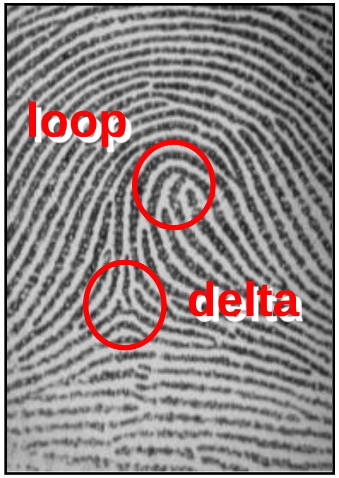
- The idea:
  - Using one or more odor sensors (*electronic noses*) to detect materials usually adopted to make fake fingers
    - Electronic nose: array of chemical sensors designed to detect and discriminate complex odors

Fingerprint anatomy (1)

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

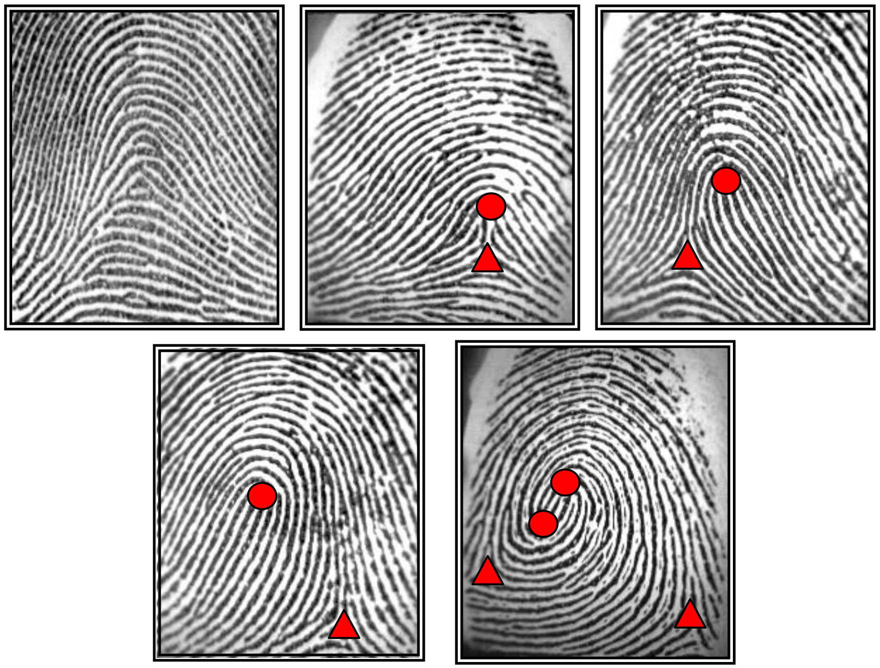


Sometimes the ridge lines produce local macro-singularities, called whorl (O), loop (U) and delta (Δ)

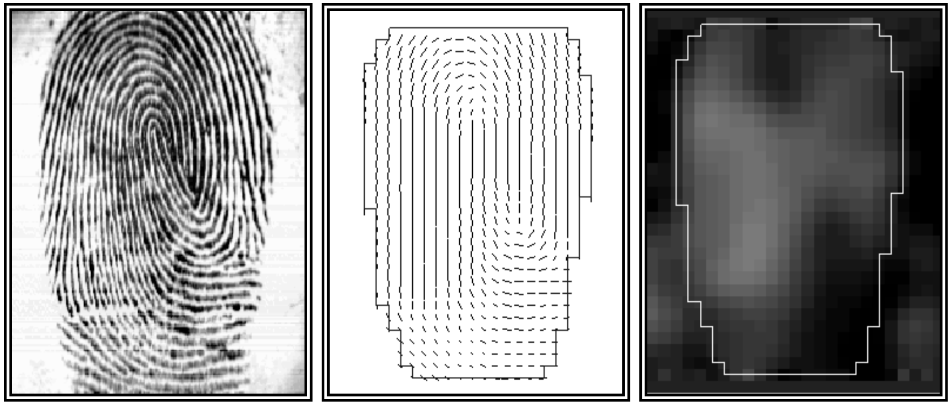


The minutiae, or Galton's characteristics, are determined by the termination or the bifurcation of the ridge lines

Fingerprint anatomy (2)



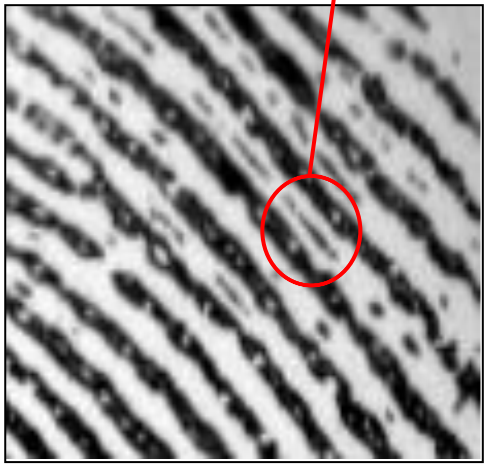
The five main fingerprint classes

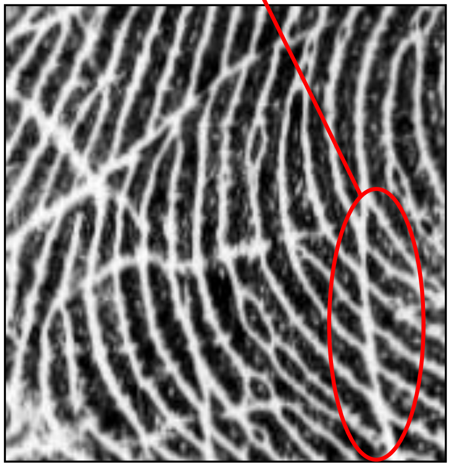


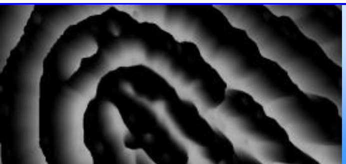
- The ridge-line flow can be effectively described by a directional map
- The ridge line density can be summarized by using a density map

Fingerprint anatomy (3)

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

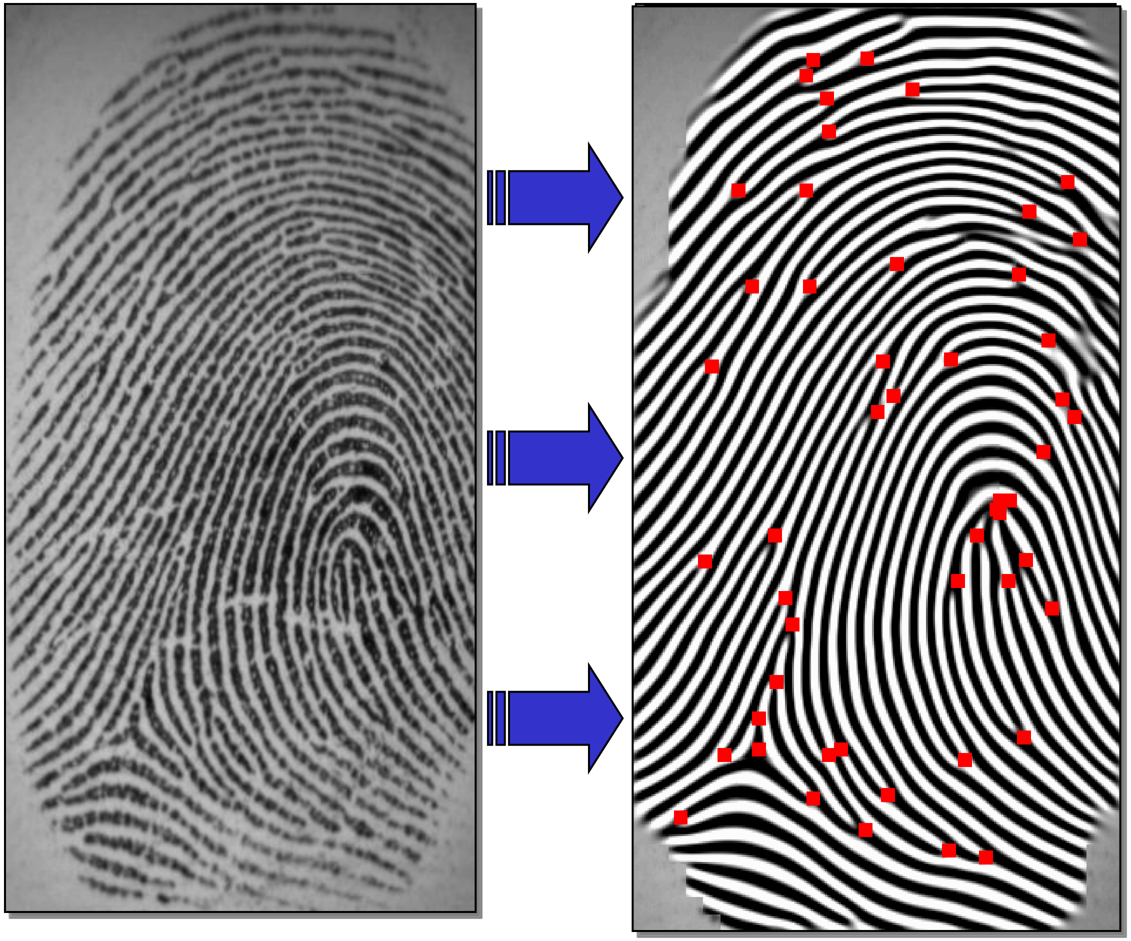


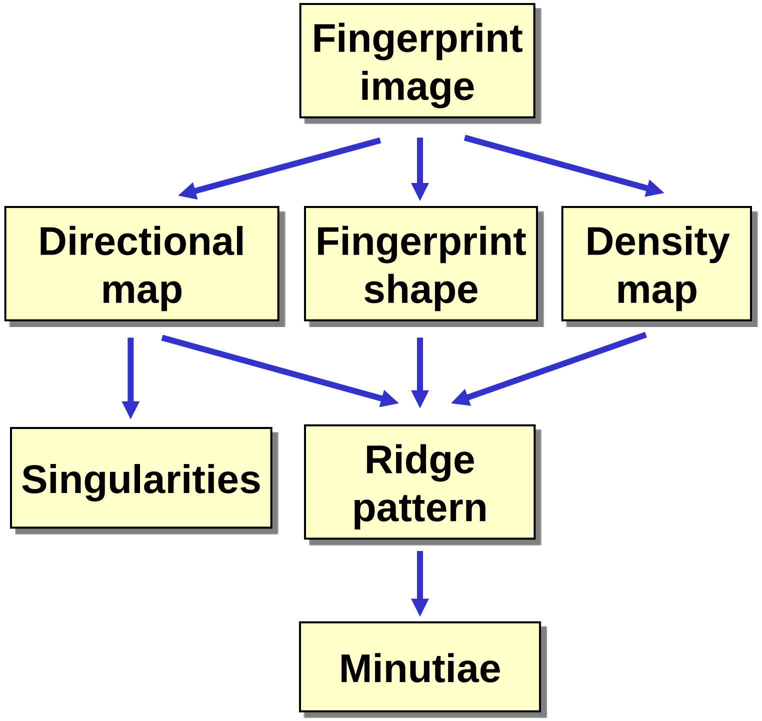




Fingerprint anatomy (4)

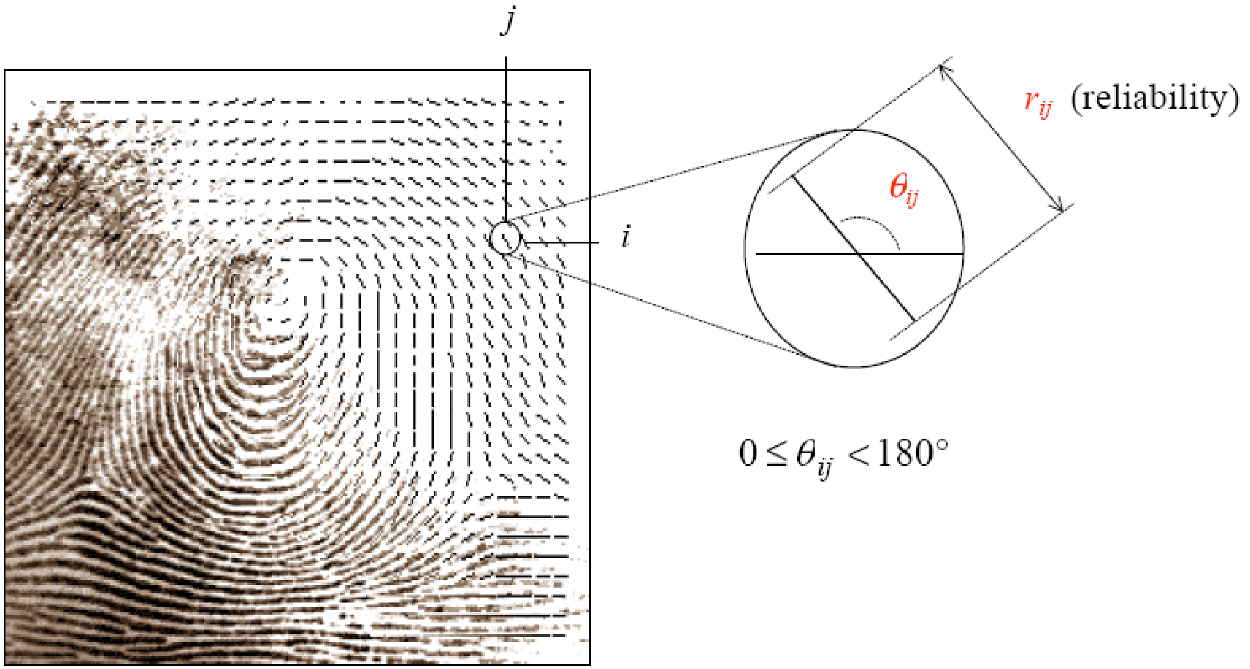
Feature extraction steps



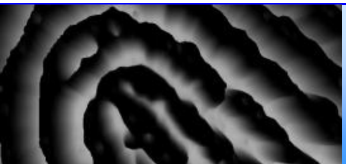


Local ridge orientation (1)

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



The simplest and most natural approach for extracting local ridge orientation is based on computation of gradient phase angles (problems of non-linearity and circularity).



Local ridge orientation (2)

- Robust computation (based on local averaging of gradient estimates) as proposed by Kass and Witkin (1987), Bigun and Granlund (1987), G.:Donahue and Rokhlin (1993), Chen, and Jain (1995), and Bazen and Gerez (2002):

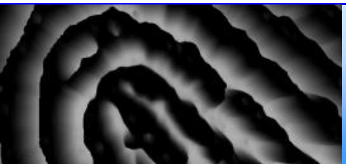
$$\theta_{ij} = 90^\circ + \frac{1}{2}\,\mathrm{atan2}\left(2G_{xy}, G_{xx} - G_{yy}\right),$$

$$G_{xy} = \sum_{h=-8}^{8}\sum_{k=-8}^{8} \nabla_x\left(x_i + h, y_j + k\right)\cdot \nabla_y\left(x_i + h, y_j + k\right),$$

$$G_{xx} = \sum_{h=-8}^{8}\sum_{k=-8}^{8} \nabla_x\left(x_i + h, y_j + k\right)^2,$$

$$G_{yy} = \sum_{h=-8}^{8}\sum_{k=-8}^{8} \nabla_y\left(x_i + h, y_j + k\right)^2,$$

where ∇x and ∇y are the *x*- and *y*-gradient components computed through 3 $\times$ 3 Sobel masks, and atan2(*y*,*x*) calculates the arctangent of the two variables *y* and *x*: it is similar to calculating the arctangent of *y*/*x*, except that the signs of both arguments are used to determine the quadrant of the result.



Smoothing local orientations

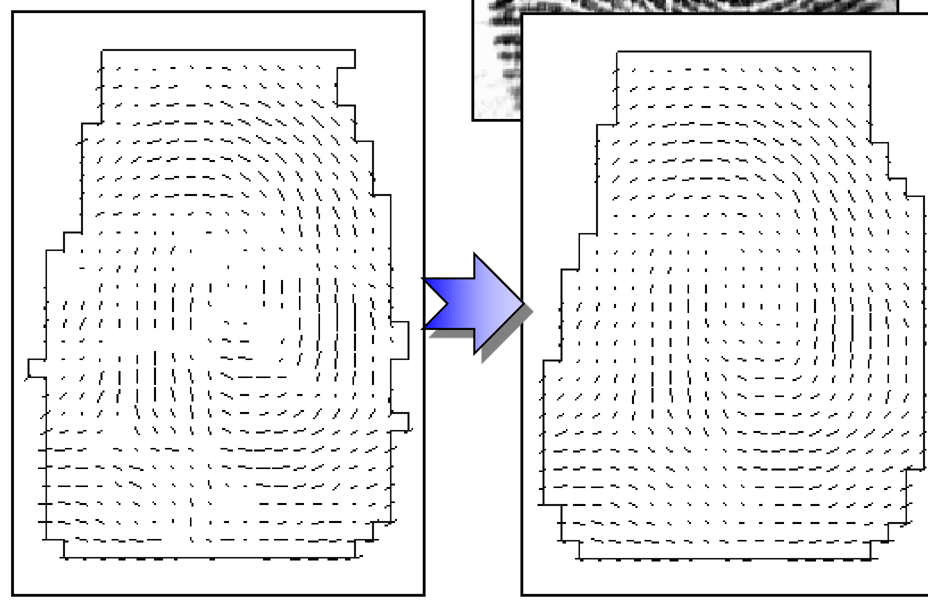
What is the average orientation between 5 and 175° ? and between 0 and 90° ?

a simple but elegant solution is to double the angles; each element is encoded by the vector:

$$\mathbf{d}_{ij} = \left[r_{ij} \cdot \cos 2\theta_{ij}, r_{ij} \cdot \sin 2\theta_{ij} \right],$$

averaging the angles in a local $n \times n$ window, is performed by separately averaging the two (x and y) components:

$$\bar{\mathbf{d}} = \left[\frac{1}{n^2} \sum_{i,j} r_{ij} \cdot \cos 2\theta_{ij}, \frac{1}{n^2} \sum_{i,j} r_{ij} \cdot \sin 2\theta_{ij} \right]$$



Orientation extraction algorithms

- **Local Analysis**: each orientation is estimated by using image information (pixels) from a local window.
  - Gradient
  - Slit-Based (Slit [Oliveira07])
  - Frequency Domain (STFT [Govindaraju07])
  - Tracing Based (Line-sensor [Gottschlich09])

- **Global Analysis**: each orientation is estimated according to a global modeling function.
  - Geometric Models (need singular points)
  - Global Approximation (FOMFE [Wang07], Legendre Polynomials [Ram10])
  - Learning Based (AFROM [Ram09])

Systematic comparison can be found in:

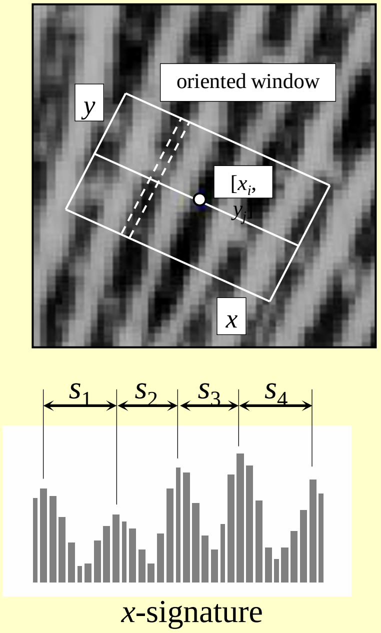
F. Turroni, D. Maltoni, R. Cappelli and D. Maio, "Improving Fingerprint Orientation Extraction", IEEE Transactions on Information Forensics and Security, vol.6, no.3, pp.1002-1013, September 2011.

Local ridge frequency (1)

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

- Counting-based approach (Hong, Wan, and Jain (1998)):
- Variation-based approach (Maio and Maltoni (1998a))
- Estimation in the Fourier domain (Kovacs, Rovatti, and Frazzoni (2000)):

Counting-based approach

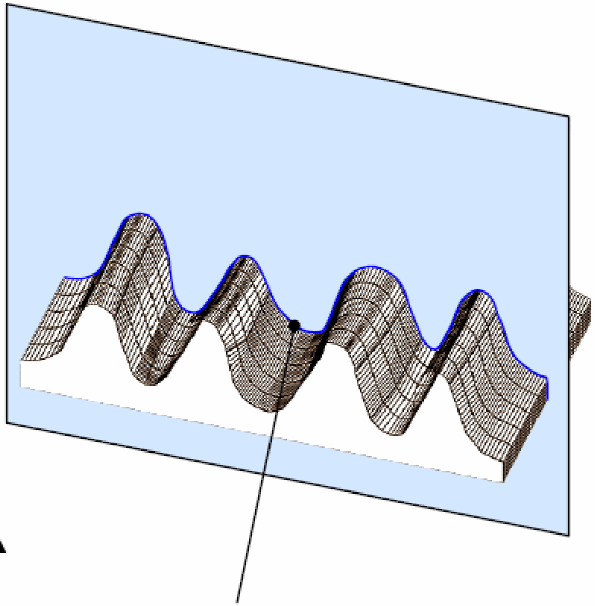


$$f_{ij} = \frac{4}{s_1 + s_2 + s_3 + s_4}$$

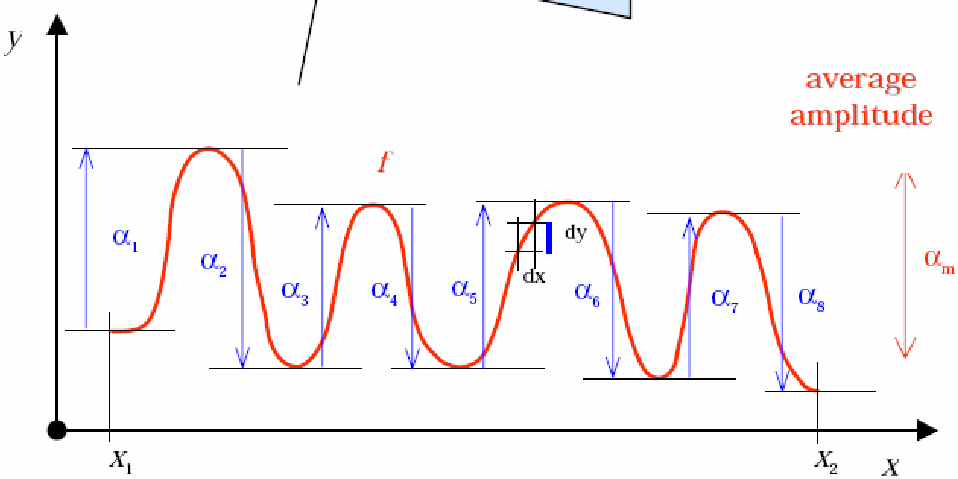
Local ridge frequency (2)

Variation-based approach

Maio and Maltoni (1998a)



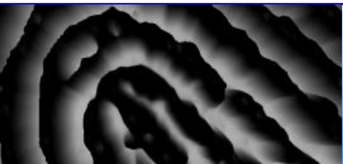
the ridge-line local density corresponds to the frequency ν of f, that is the number of periods per unit length



Variation of f

$$V(f) = \int_{x_1}^{x_2} \left| \frac{df(x)}{dx} \right| \cdot dx = \int_{x_1}^{x_2} \left| \frac{dy}{\cancel{dx}} \cdot \cancel{dx} \right| = \alpha_1 + \alpha_2 + \dots \alpha_8$$

$$V(f) = (x_2 - x_1) \cdot 2\nu \cdot \alpha_m \quad \Rightarrow \quad \boxed{\nu = \frac{V(f)}{2\,(x_2 - x_1) \cdot \alpha_m}}$$

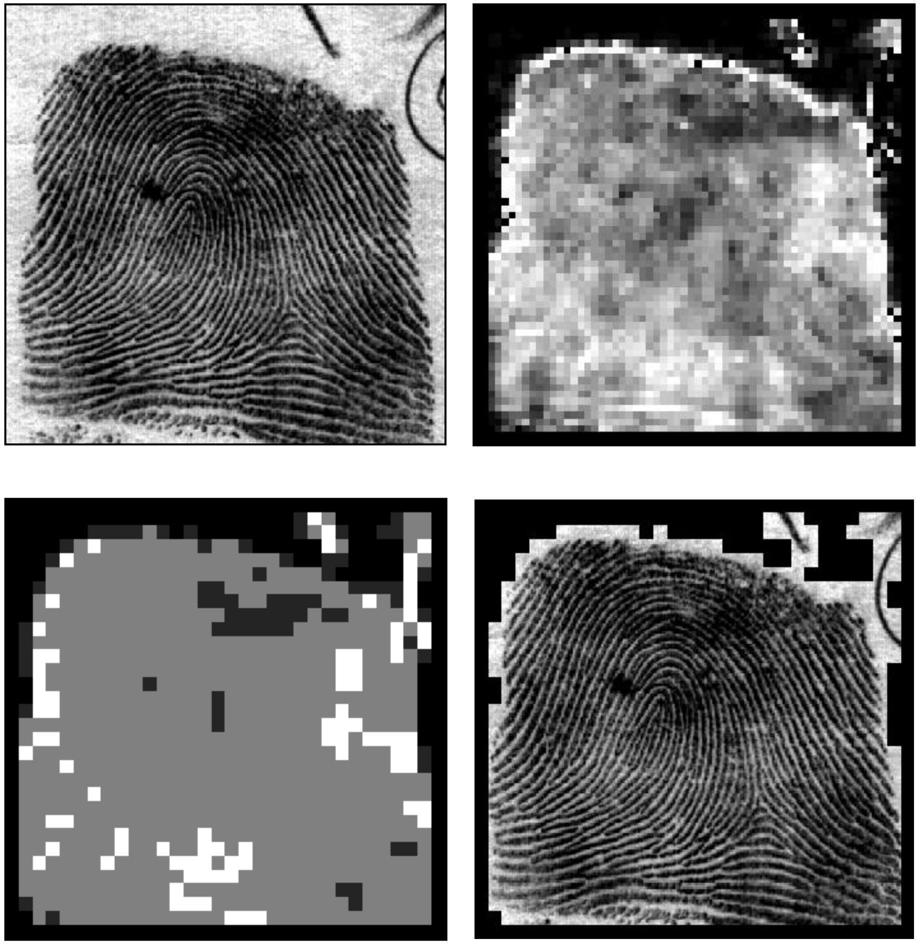


Segmentation

- The term *segmentation* is used to denote the separation of fingerprint area (foreground) from the image background.

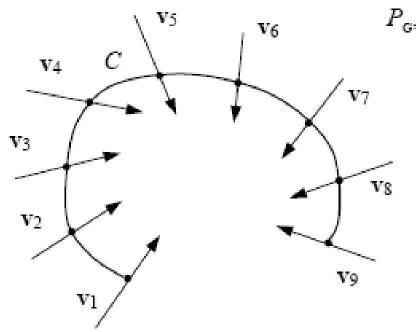
- Foreground and background are discriminated by the presence of a striped and oriented pattern in the foreground and of an isotropic pattern in the background.

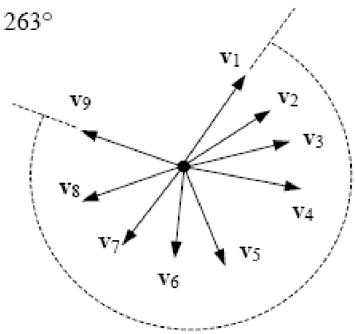
- How to measure anisotropy ?
  - presence of a well defined peak in a local histogram of orientations (Mehtre et al. (1987))
  - variance of the gray-levels in direction orthogonal to the gradient (Ratha, Chen, and Jain (1995))
  - magnitude of the gradient (Maio and Maltoni (1997))
  - combination of more features (Bazen and Gerez (2001b))



Singularity detection (1)

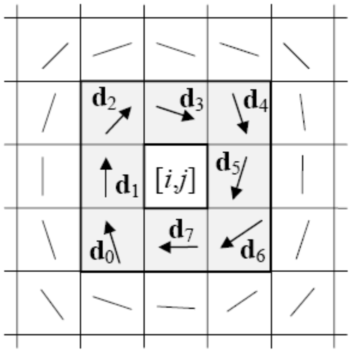
The best-known method is based on Poincaré index (Kawagoe and Tojo (1984)).



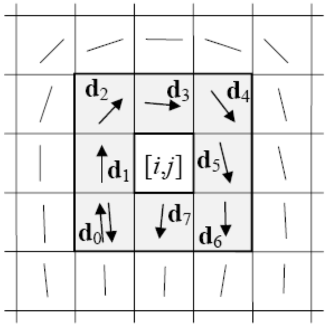


The Poincaré index $P_{G,C}(i,j)$ at $[i,j]$ is computed as:

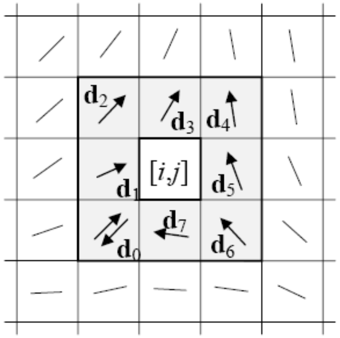
- The (closed) curve C is an ordered sequence of orientations, such that $[i,j]$ is an internal point
- $P_{G,C}(i,j)$ is computed by algebraically summing the orientation differences between adjacent elements of C. Summing orientation differences requires a direction (among the two possible) to be associated at each orientation. *A solution to this problem is to randomly select the direction of the first element and assign the direction closest to that of the previous element to each successive element.*



$P_{G,C}(i,j) = 360°$
whorl

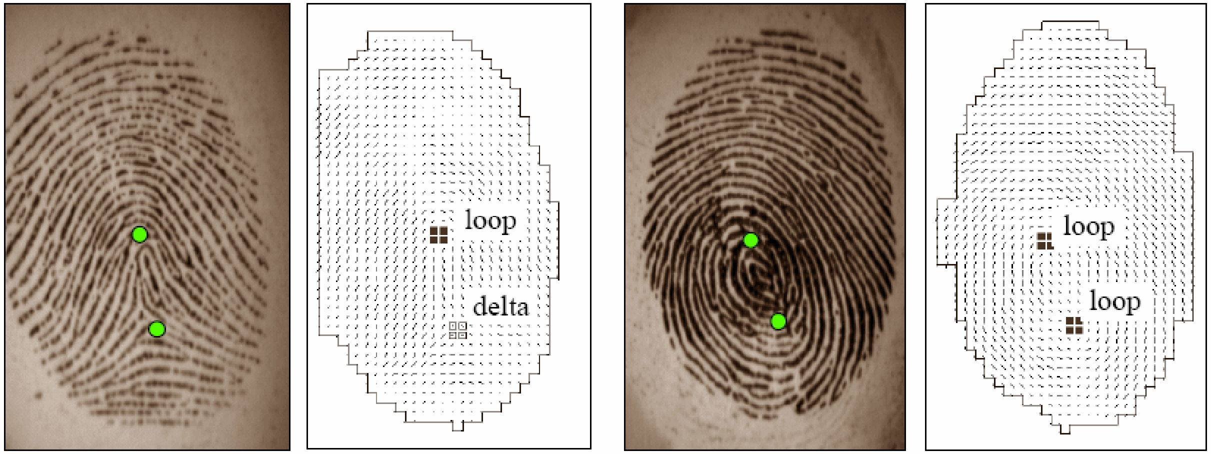


$P_{G,C}(i,j) = 180°$
loop

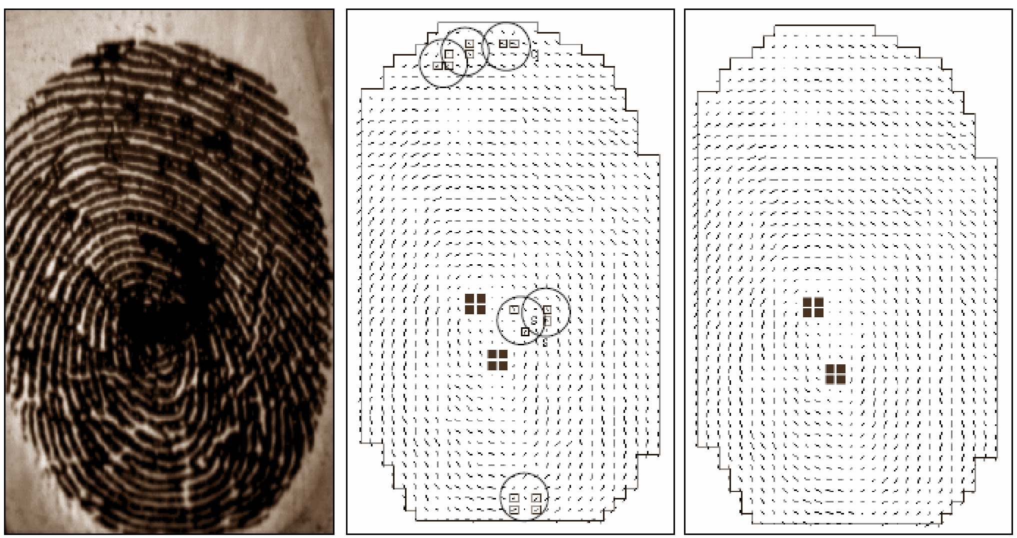


$P_{G,C}(i,j) = -180°$
delta

Singularity detection (2)



Smoothing of local orientation is necessary to control noise.



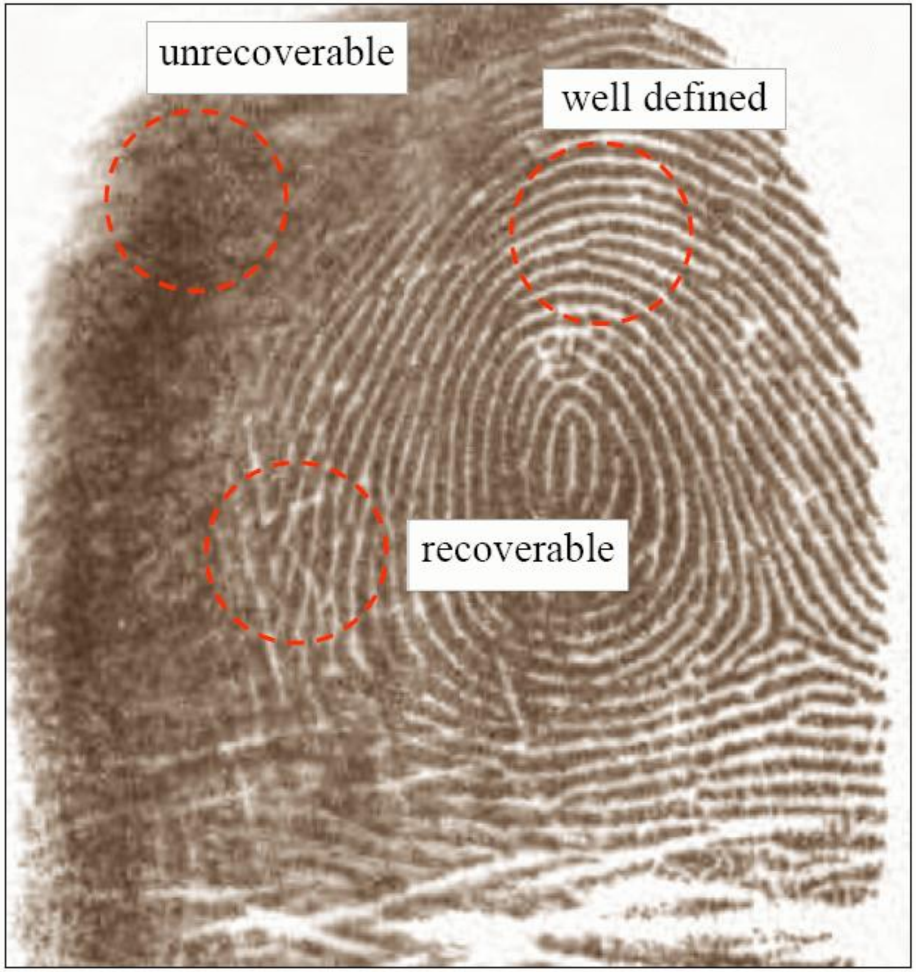
How much smoothing ?

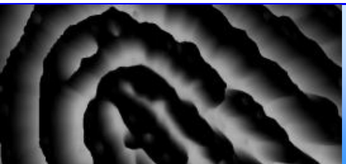
➔Iteratively smooth until a valid number of singularities is detected
Karu and Jain (1996)

Enhancement (1)

- Aimed at **improving the quality** of **recoverable regions** to simplify successive stages

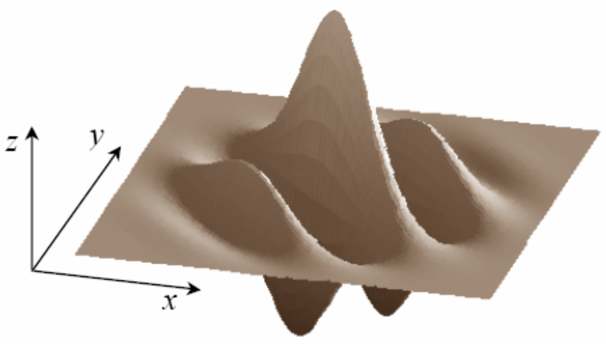
Good medium poor

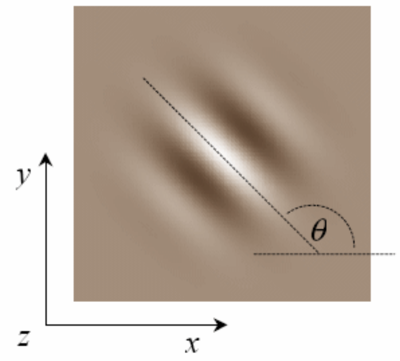




Enhancement (2)

Best results with contextual filters (e.g. Gabor filters).

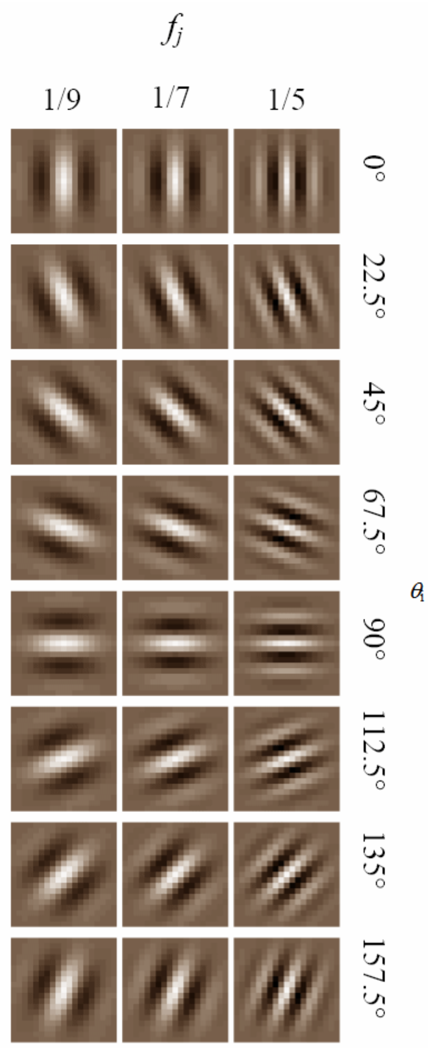


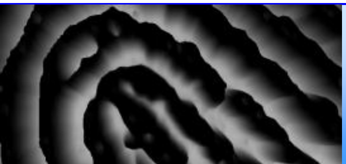


$$g(x, y : \theta, f) = \exp\left\{ -\frac{1}{2}\left[\frac{x_\theta^{\;2}}{\sigma_x^{\;2}} + \frac{y_\theta^{\;2}}{\sigma_y^{\;2}} \right] \right\} \cdot \cos(2\pi f \cdot x_\theta),$$

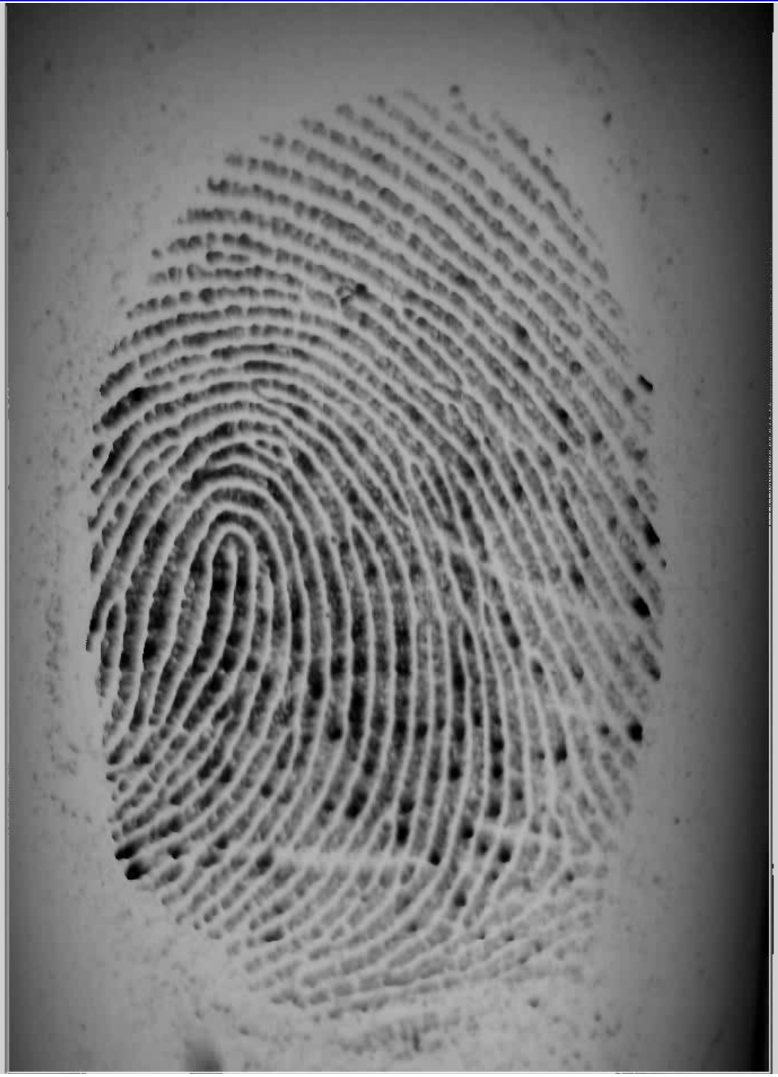
$$\begin{bmatrix} x_\theta \\ y_\theta \end{bmatrix} = \begin{bmatrix} \cos(90^\circ - \theta) & \sin(90^\circ - \theta) \\ -\sin(90^\circ - \theta) & \cos(90^\circ - \theta) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \sin\theta & \cos\theta \\ -\cos\theta & \sin\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Each pixel $[x,y]$ of the image is convolved with the filter $g_{ij}(x,y)$ such that θ_i is the discretized orientation closest to θ_{xy} and f_j is the discretized frequency closest to f_{xy}.





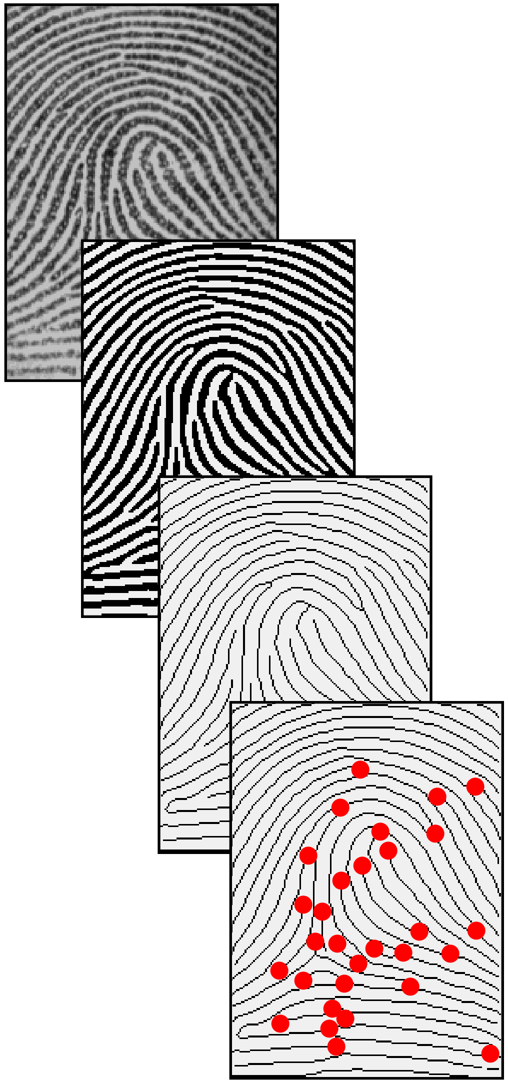
Enhancement (3)



Automatic minutiae detection

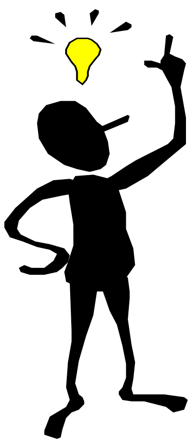
- An extremely important task: a lot of research has been devoted to this topic.

- Traditional approach:
  1. **Binarization**: the fingerprint gray-scale image is converted into a binary image
  2. **Thinning**: the binary image is submitted to a thinning stage (the ridge-line thickness is reduced to one pixel)
  3. **Detection**: a simple image scan allows to detect the pixels that correspond to minutiae

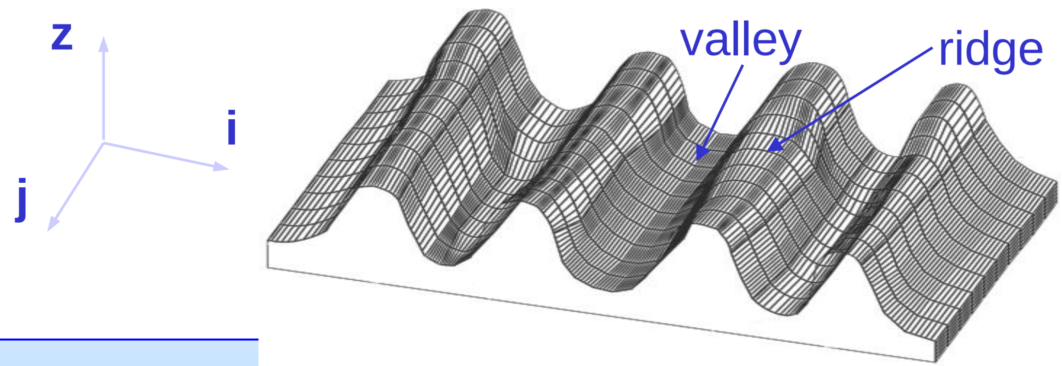


Direct gray-scale minutiae detection (1)

- Problems of the binarization-based approaches:
  - a **significant amount of information** may be **lost** during the binarization process
  - binarization and thinning are **time-consuming**
  - thinning may introduce a large number of **spurious minutiae**
  - most of the binarization techniques proved to be unsatisfactory when applied to low-quality images

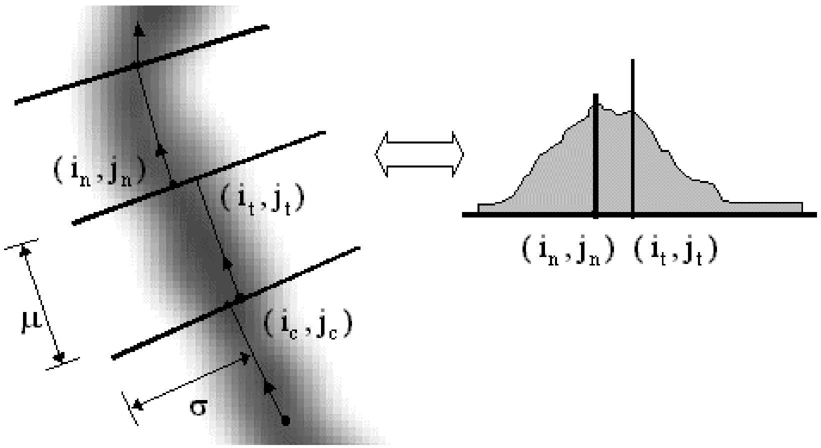


Follow the ridge lines on the gray-scale image, by “sailing” according to the local orientation of the ridge pattern

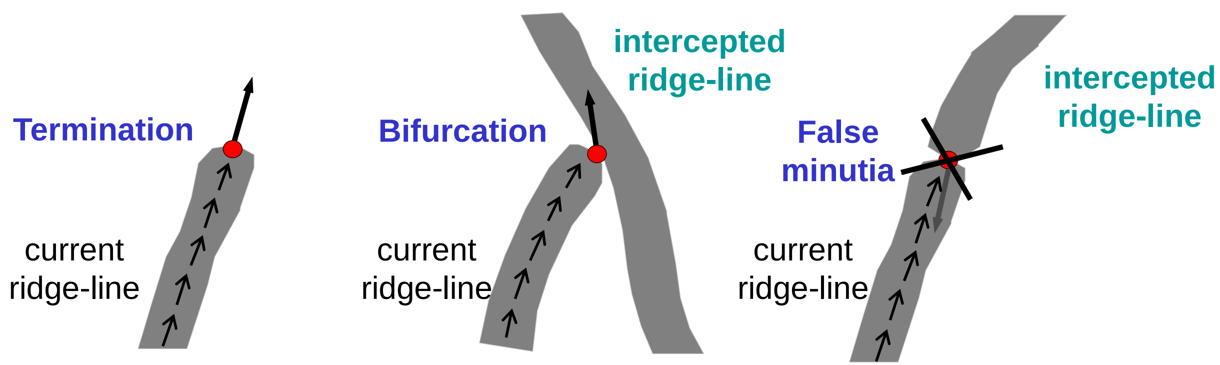


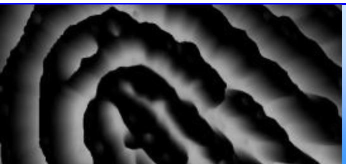
Direct gray-scale minutiae detection (2)

A ridge-line is made of a set of points that are the local maxima with respect to the direction orthogonal to the ridge-line itself

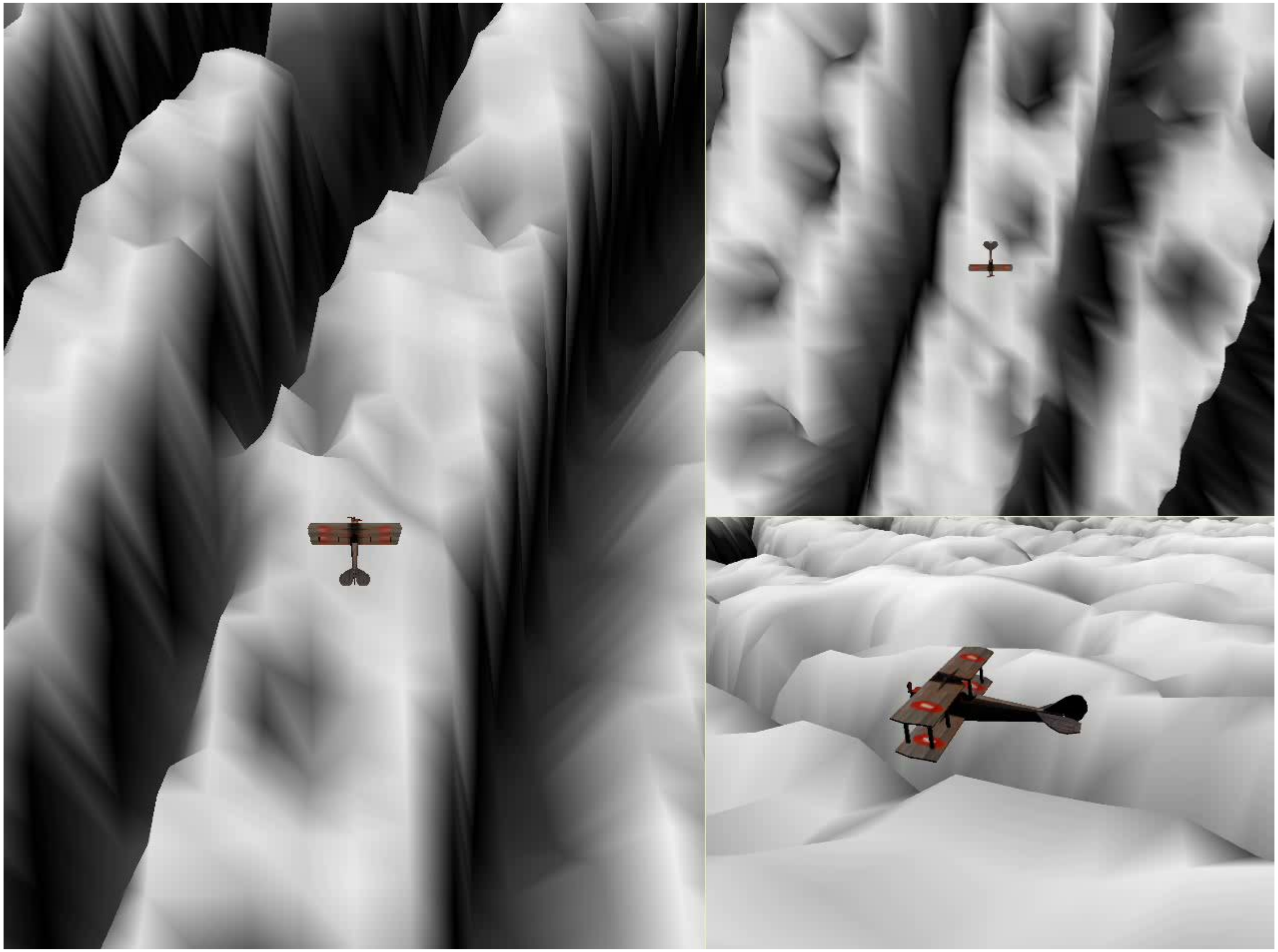


A set of starting points is determined (according to a square-mesh grid superimposed to the image); for each point, the algorithm find the nearest ridge-line and follows it until a bifurcation or a termination is reached.





Direct gray-scale minutiae detection - Demo



Fingerprint recognition

- Finding the similarity between two fingerprints

Same finger

Same finger

Different fingers

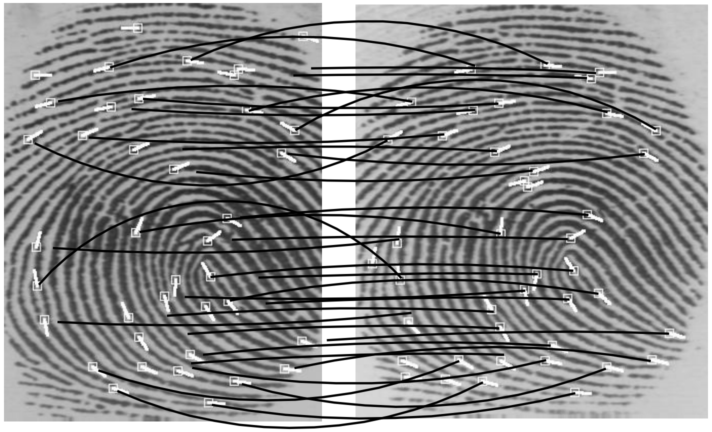
Different fingers

Fingerprint recognition: main challenges

- High displacement and/or rotation
  - Small overlap between the template and the input fingerprints. This problem is particularly serious for *small-area sensors*. A finger displacement of just 2 mm (imperceptible to the user) results in a translation of about 40 pixels in a fingerprint image scanned at 500 dpi.
- Non-linear distortion
  - The act of sensing maps the three-dimensional shape of a finger onto the two-dimensional surface of the sensor. This results in a non-linear distortion in successive acquisitions of the same finger due to skin plasticity.
- Different pressure and skin condition
  - Non uniform finger pressure, dryness of the skin, skin disease, sweat, dirt, grease, and humidity in the air.
- Feature extraction errors
  - Feature extraction algorithms are imperfect and often introduce measurement errors, in particular in *low-quality fingerprint images*

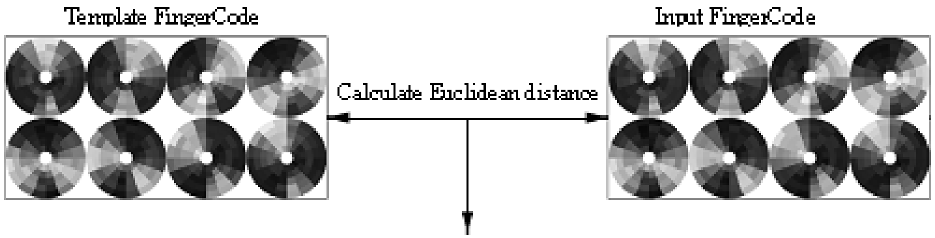
Fingerprint matching approaches (1)

- Minutiae-based matching
  - The most popular and widely used technique. Minutiae-based matching consists in finding the alignment that results in the maximum number of minutiae pairings.



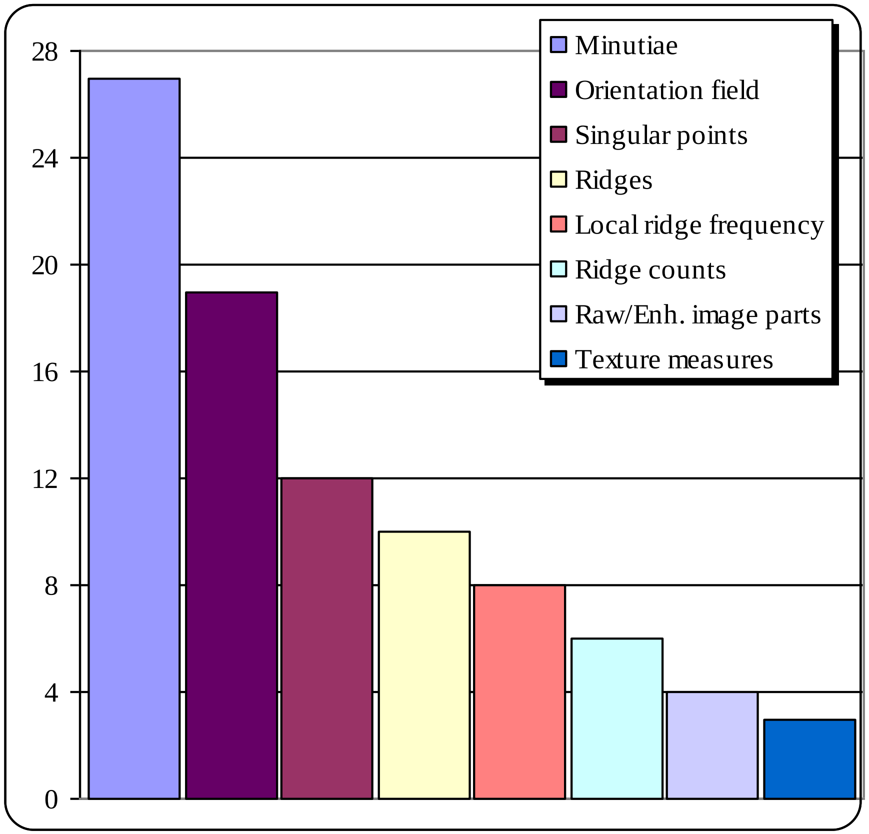
- Correlation-based matching
  - Two fingerprints are superimposed and the correlation between corresponding pixels is computed for different alignments.

- Ridge feature-based matching
  - Other features of the fingerprint ridge pattern (e.g., *local orientation* and *frequency*, *ridge shape*, *texture information*) may be extracted more reliably than minutiae in *low-quality images*.

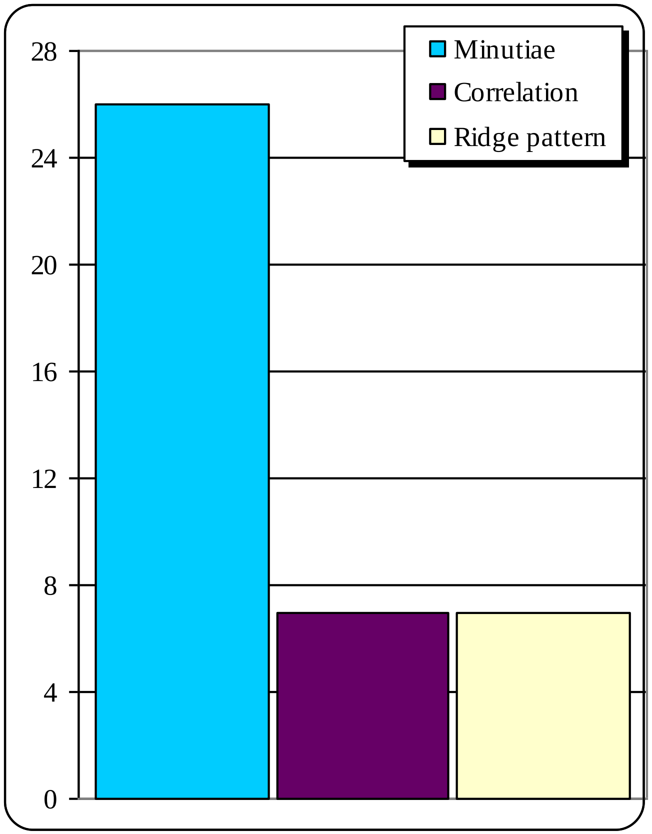


Fingerprint matching approaches (2)

State of the art algorithms: features extracted and matching approaches adopted (source: 29 algorithms from FVC2004)



Features extracted



Matching approaches

Minutiae-based matching: Problem formulation

$$\mathbf{T} = \{\mathbf{m}_1, \mathbf{m}_2, \ldots, \mathbf{m}_m\} \quad \mathbf{m}_i = \{x_i, y_i, \theta_i\} \quad i = 1..m$$
$$\mathbf{I} = \{\mathbf{m}'_1, \mathbf{m}'_2, \ldots, \mathbf{m}'_n\} \quad \mathbf{m}'_j = \{x'_j, y'_j, \theta'_j\} \quad j = 1..n,$$

the two sets of minutiae corresponding to the Template and the Input

$$\underset{\Delta x, \Delta y, \theta, P}{\text{maximize}} \sum_{i=1}^{m} mm\left(map_{\Delta x, \Delta y, \theta}\left(\mathbf{m}'_{P(i)}\right), \mathbf{m}_i\right)$$

maximize the number of minutiae mates between template and "aligned" Input

$$mm\left(\mathbf{m}''_j, \mathbf{m}_i\right) = \begin{cases} 1 & sd\left(\mathbf{m}''_j, \mathbf{m}_i\right) \le r_0 \quad \text{and} \quad dd\left(\mathbf{m}''_j, \mathbf{m}_i\right) \le \theta_0 \\ 0 & \text{otherwise.} \end{cases}$$

$$dd\left(\mathbf{m}'_j, \mathbf{m}_i\right) = \min\left(\left|\theta'_j - \theta_i\right|, 360° - \left|\theta'_j - \theta_i\right|\right)$$
$$sd\left(\mathbf{m}'_j, \mathbf{m}_i\right) = \sqrt{\left(x'_j - x_i\right)^2 + \left(y'_j - y_i\right)^2}$$

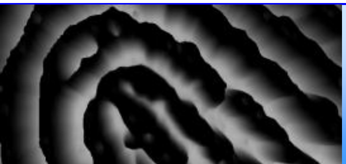
the two minutiae can be paired

$P(i)$ is an unknown function that determines the pairing between **I** and **T** minutiae:

1. $P(i) = j$ indicates that the mate of the $\mathbf{m}_i$ in **T** is the minutia $\mathbf{m}'_j$ in **I**;
2. $P(i) = \text{null}$ indicates that minutia $\mathbf{m}_i$ in **T** has no mate in **I**;
3. a minutia $\mathbf{m}'_j$ in **I**, such that $\forall\ i = 1..m,\ P(i) \neq j$ has no mate in **T**;
4. $i = 1..m,\ \ k = 1..m,\ \ i \neq k \ \Rightarrow\ P(i) \neq P(k)$ or $P(i) = P(k) = \text{null}$ (each minutia in **I** is associated with a maximum of one minutia in **T**).

$$map_{\Delta x, \Delta y, \theta}\left(\mathbf{m}'_j = \{x'_j, y'_j, \theta'_j\}\right) = \mathbf{m}''_j = \{x''_j, y''_j, \theta'_j + \theta\}$$

$$\begin{bmatrix} x''_j \\ y''_j \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x'_j \\ y'_j \end{bmatrix} + \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$



Global minutiae matching (1)

... an Hough transform-based approach (Ratha et al. (1996))

The space of transformations consists of quadruples (Δx, Δy, θ, s), where each parameter is discretized (denoted by the symbol $^+$) into a finite set of values:

$$\Delta x^+ \in \{\Delta x_1^+, \Delta x_2^+, \ldots, \Delta x_a^+\} \quad \Delta y^+ \in \{\Delta y_1^+, \Delta y_2^+, \ldots, \Delta y_b^+\},$$
$$\theta^+ \in \{\theta_1^+, \theta_2^+, \ldots, \theta_c^+\} \quad s^+ \in \{s_1^+, s_2^+, \ldots, s_d^+\}.$$

At the end of the accumulation process, the best alignment transformation (Δx^*, Δy^*, θ^*, s^*) is then obtained as

$$(\Delta x^*, \Delta y^*, \theta^*, s^*) = arg \max_{\Delta x^+, \Delta y^+, \theta^+, s^+} \mathbf{A}[\Delta x^+, \Delta y^+, \theta^+, s^+]$$

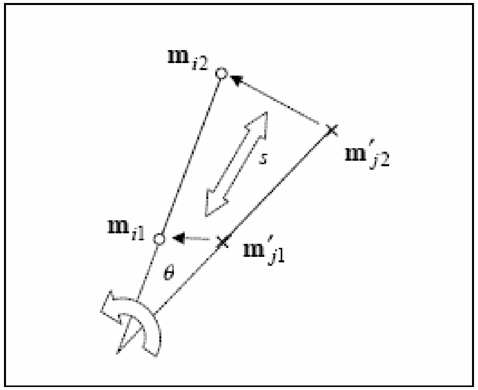
Computational complexity: $O(m \times n \times c \times d)$

for each $\mathbf{m}_i$, $i = 1..m$
  for each $\mathbf{m}'_j$, $j = 1..n$
    for each $\theta^+ \in \{\theta_1^+, \theta_2^+, \ldots, \theta_c^+\}$
      if $dd(\theta'_j + \theta^+, \theta_i) < \theta_0$
        for each $s^+ \in \{s_1^+, s_2^+, \ldots, s_d^+\}$
          {$\begin{bmatrix}\Delta x \\ \Delta y\end{bmatrix} = \begin{bmatrix}x_i \\ y_i\end{bmatrix} - s^+ \cdot \begin{bmatrix}\cos\theta^+ & -\sin\theta^+ \\ \sin\theta^+ & \cos\theta^+\end{bmatrix}\begin{bmatrix}x'_j \\ y'_j\end{bmatrix}$
          Δx^+, Δy^+ = quantization of Δx, Δy to the nearest bin
          $\mathbf{A}[\Delta x^+, \Delta y^+, \theta^+, s^+] = \mathbf{A}[\Delta x^+, \Delta y^+, \theta^+, s^+] + 1$
          }

Global minutiae matching (2)

Several variants of the above algorithm:

- scale is often fixed to 1 (3-dimensional search space instead of 4-dimensional search space)
- considering two pairs of minutiae, rotation and scale parameters can be derived independently of the translation (Chang et al. (1997)) ...



from the pairing of two minutiae in I with two minutiae in T it is possible to derive scale and rotation...

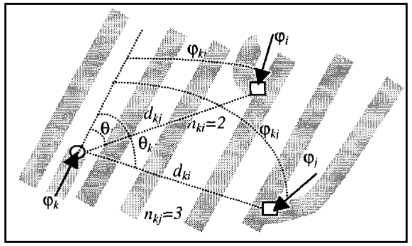
Local minutiae matching

Local minutiae matching *consists of comparing two fingerprints according to local minutiae structures.*

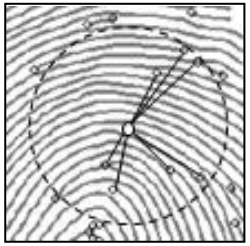
Local structures *are characterized by attributes that are invariant with respect to global transformations (e.g., translation, rotation, etc.) and therefore are suitable for matching without any a priori global alignment.*

Matching local minutiae structures *is usually* ***faster*** *and* ***more robust*** *to distortion, but* ***less distinctive****.*

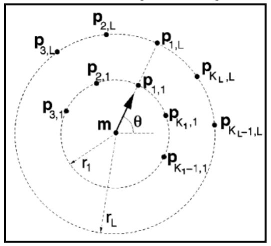
Jiang (2000)



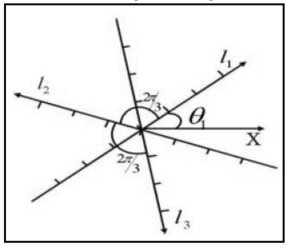
Ratha (2000)



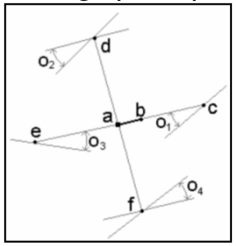
Tico (2003)



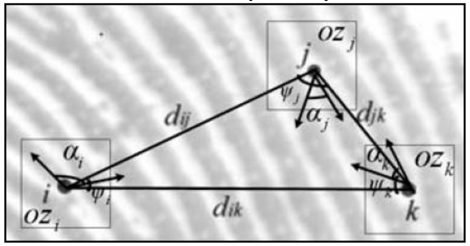
Qi (2004)



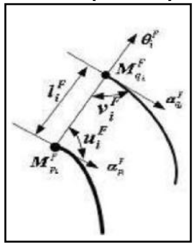
Ng (2004)



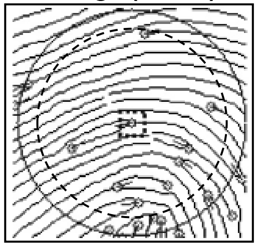
Chen (2005)

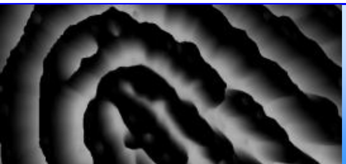


He (2006)



Feng (2008)



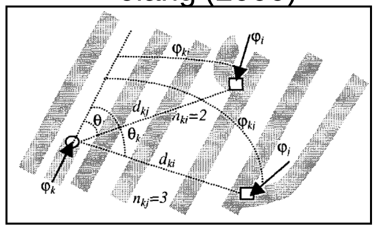


Families of local structures

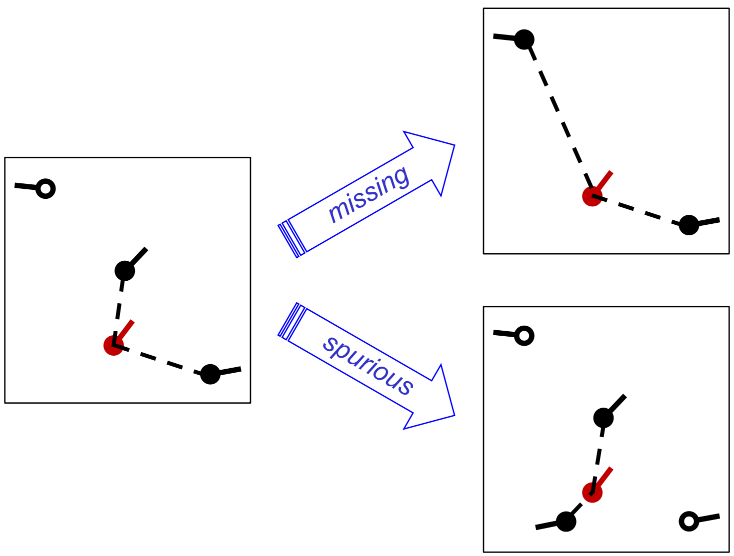
Nearest neighbour-based structures:

the neighbors of the central minutia are formed by its *K* spatially closest minutiae. This leads to *fixed-length descriptors* that can be usually matched very efficiently.

Jiang (2000)

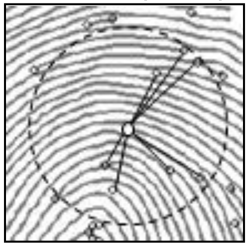


Drawback: the possibility of exchanging nearest neighbour minutiae due to missing or spurious ones.



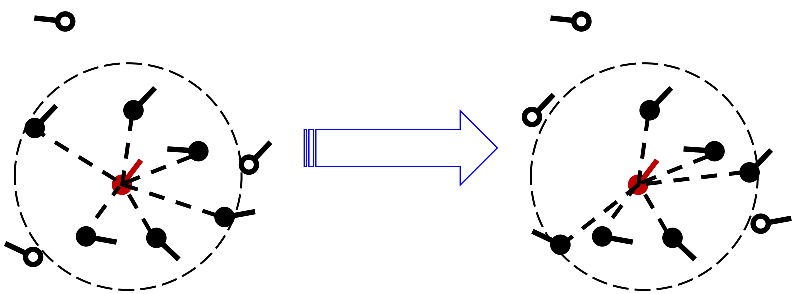
Fixed radius-based structures:

Ratha (2000)



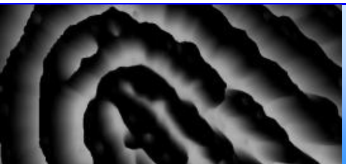
the neighbors are defined as all the minutiae that are closer than a given radius R from the central minutia. The *descriptor length is variable* and depends on the local minutiae density; this can lead to a more complex local matching; however, in principle, missing and spurious minutiae can be better tolerated.

Drawback: border errors. Minutiae close to the local region border in one of the two fingerprints can be mismatched because of different local distortion or location inaccuracy that cause the same minutiae to move out of the local region in the second fingerprint.



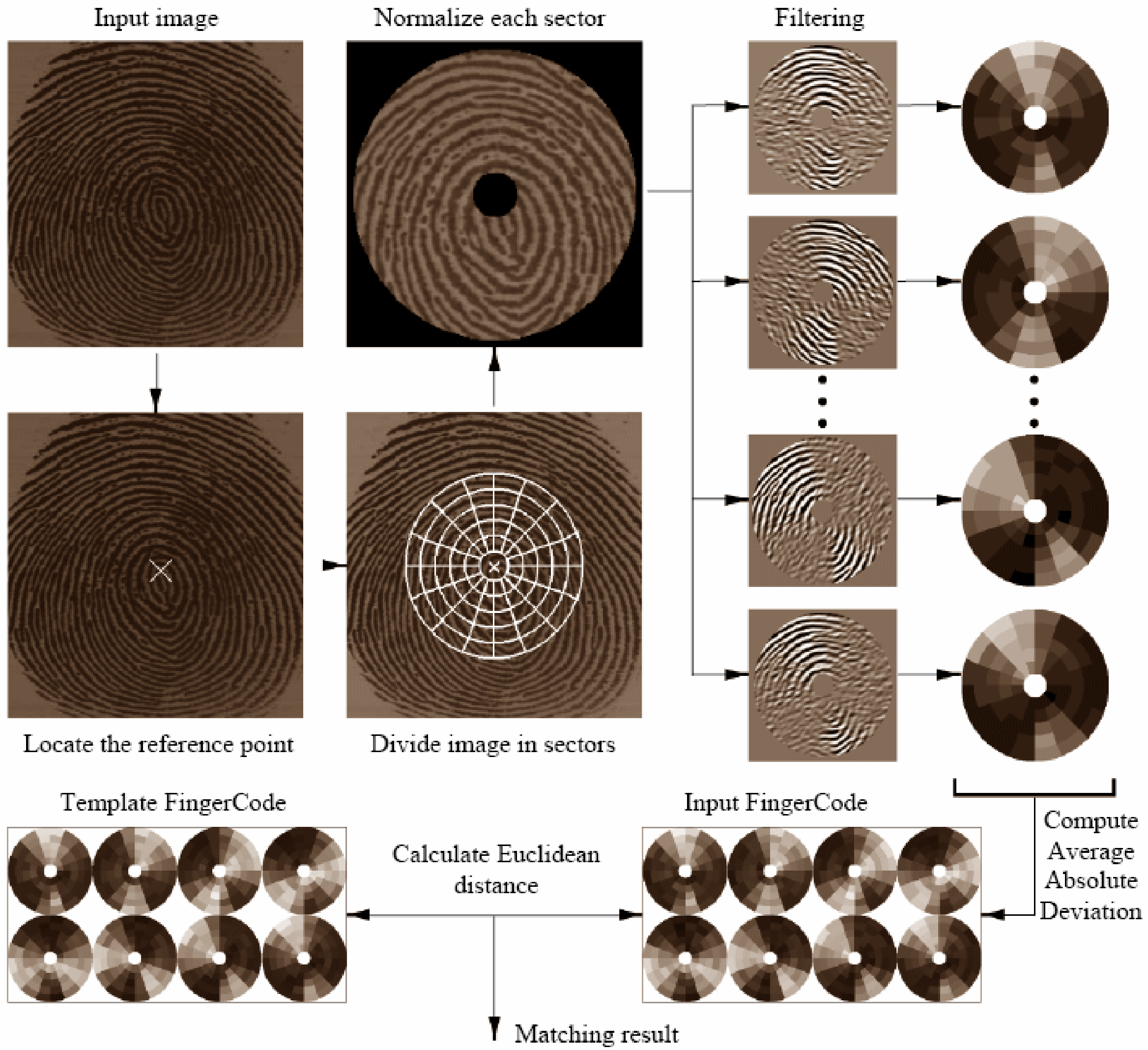
Ridge feature-based matching

- Why other features and not simply minutiae ?
  - reliably extracting minutiae from poor quality fingerprints is very difficult
  - minutiae extraction is time consuming
  - a fixed-length invariant feature code is useful for “indexing” fingerprint databases
  - additional features may be used in conjunction with minutiae (and not as an alternative) to increase system accuracy and robustness
- The most commonly used alternative features are:
  1. size of the fingerprint and shape of the external fingerprint silhouette;
  2. number, type, and position of singularities;
  3. spatial relationship and geometrical attributes of the ridge lines (Xiao and Bian (1986) and Kaymaz and Mitra (1992));
  4. shape features (Takeda et al. (1990) and Ceguerra and Koprinska, 2002);
  5. global and local texture information;
  6. sweat pores (Stosz and Alyea, 1994);
  7. fractal features (Polikarpova, 1996).



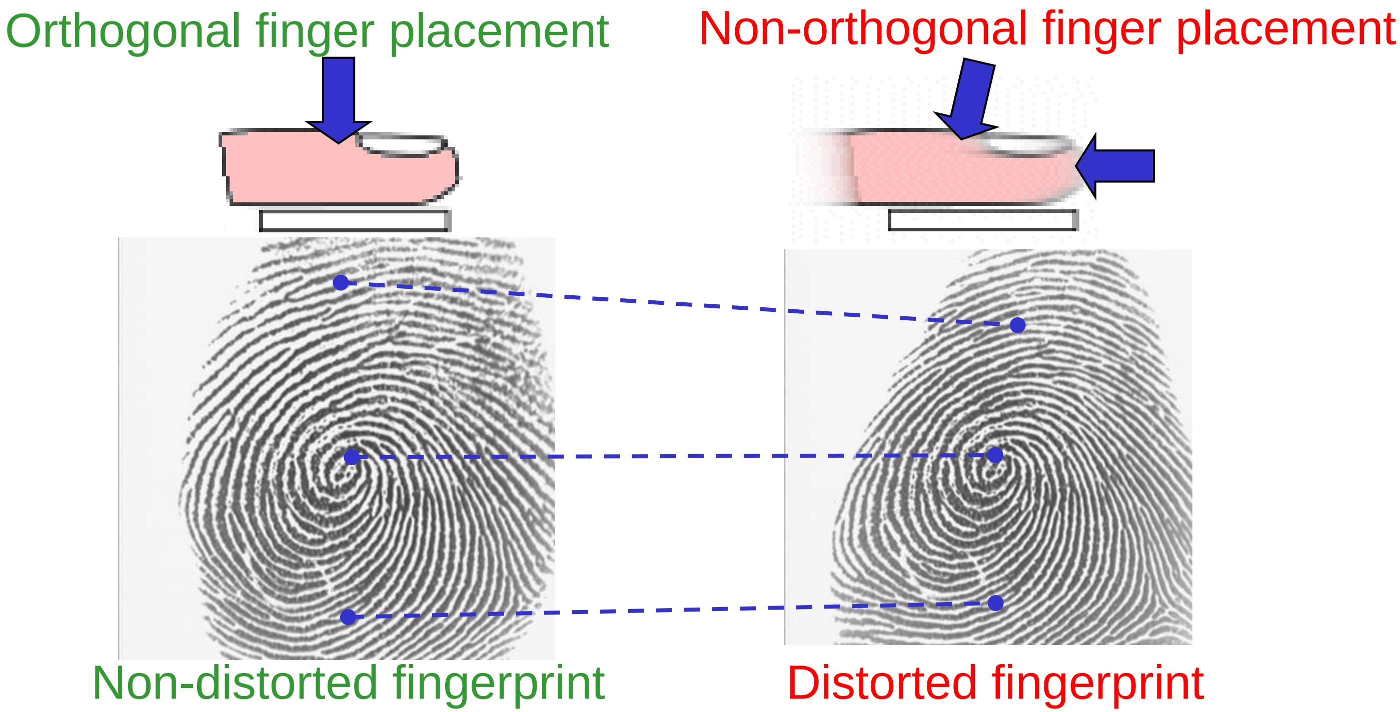
Texture-based matching

FingerCode approach (Jain et al. (2000))



Skin distortion

One of the main factors that contribute to make substantially different the impressions of a given finger is skin distortion



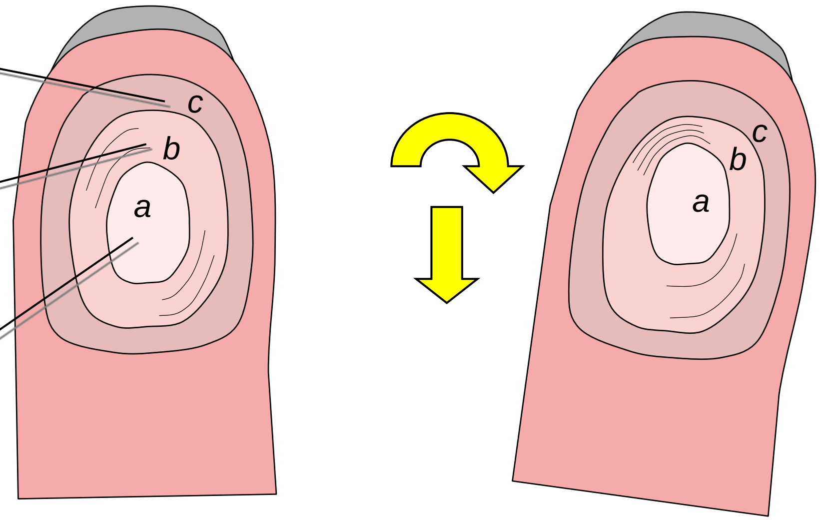
Skin distortion model (1)

The finger pressure against the sensor is not uniform, but decreases moving from the center towards the borders.

external region:
skin moved

transitional region:
skin distorted

close-contact region:
skin not moved



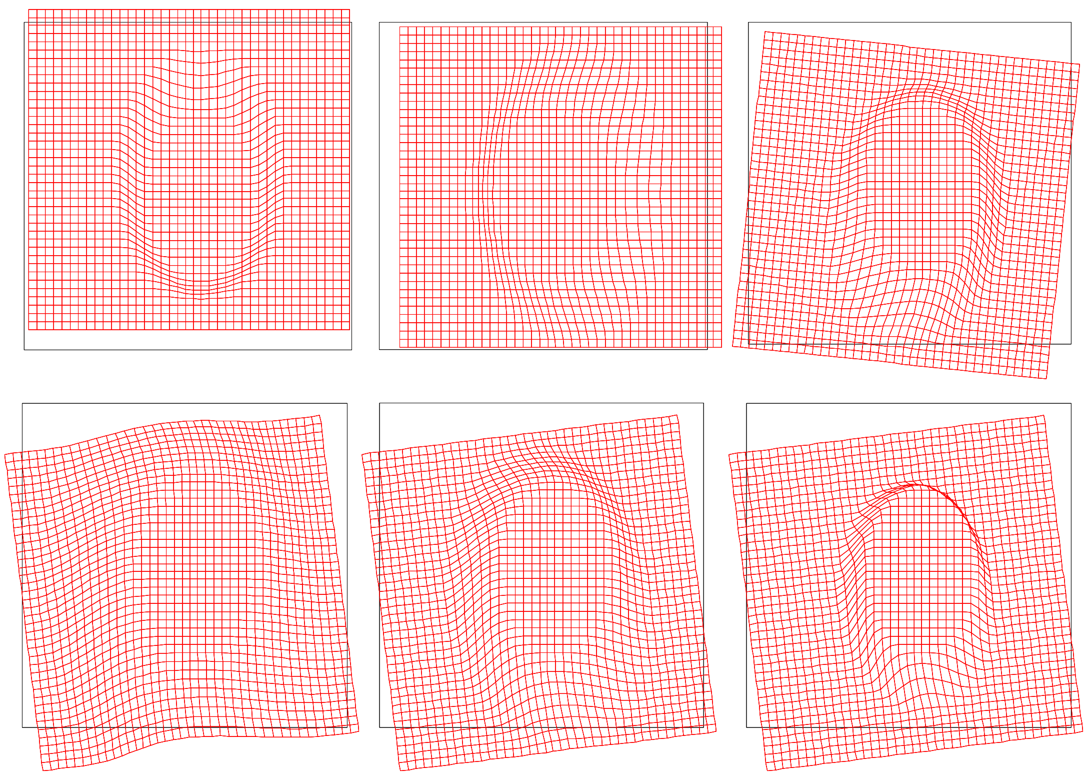
a) close-contact region, where the high pressure and the surface friction does not allow any skin slippage

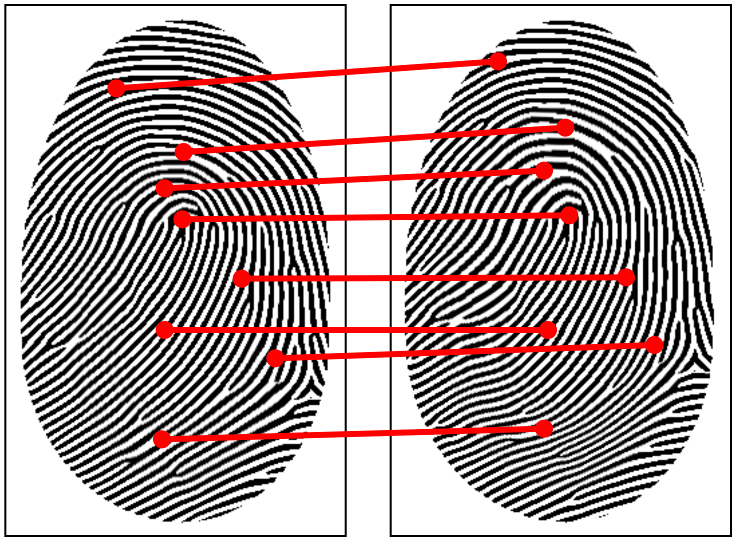
c) external region, where the low pressure allows the skin to be dragged by the finger movement

b) transitional region where an elastic distortion is produced to smoothly combine regions *a* and *c*

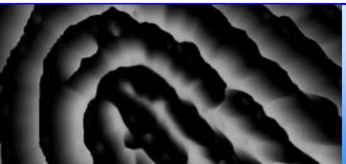
Skin distortion model (2)

$$distortion : \Re^2 \rightarrow \Re^2 \, , \;\; distortion(\mathbf{v}) = \mathbf{v} + \Delta(\mathbf{v}) \cdot brake(shapedist_a(\mathbf{v}), k)$$





Original image   Distorted image

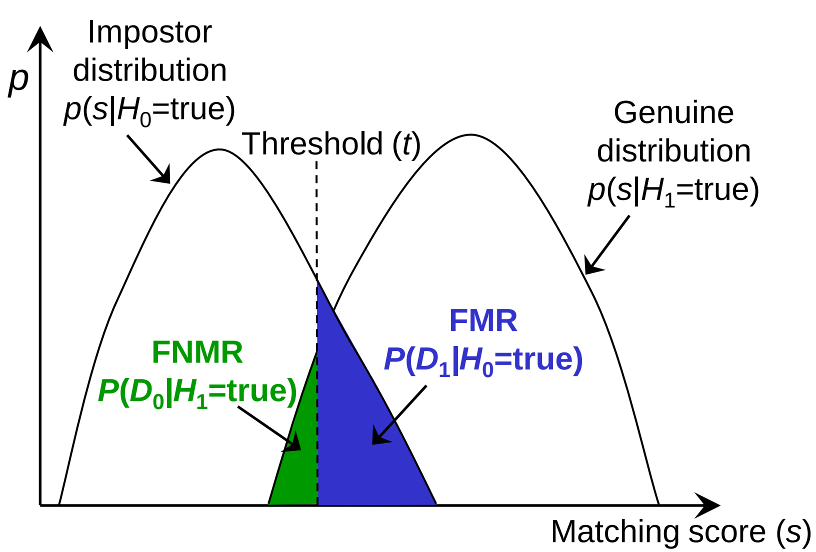


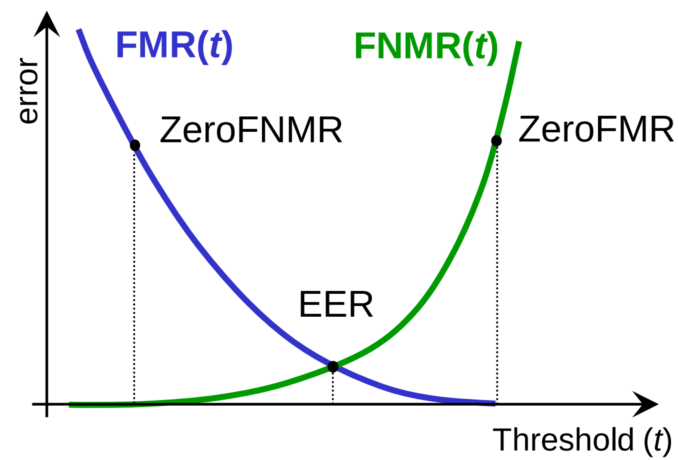
Performance evaluation: errors

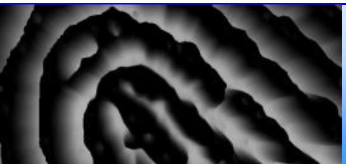
- False Match (in positive recognition often called False Acceptance)
  - mistaking biometric measurements from two different persons to be from the same person
- False Non-Match (in positive recognition often called False Rejection)
  - mistaking two biometric measurements from the same person to be from two different persons

Hypotheses:
H_0: different person
H_1: same persons

Possible decisions:
D_0: different person
D_1: same persons







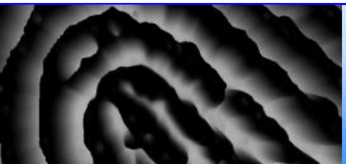
Fingerprint Verification Competitions

Algorithms are provided as binary executable programs, compliant to a given I/O protocol

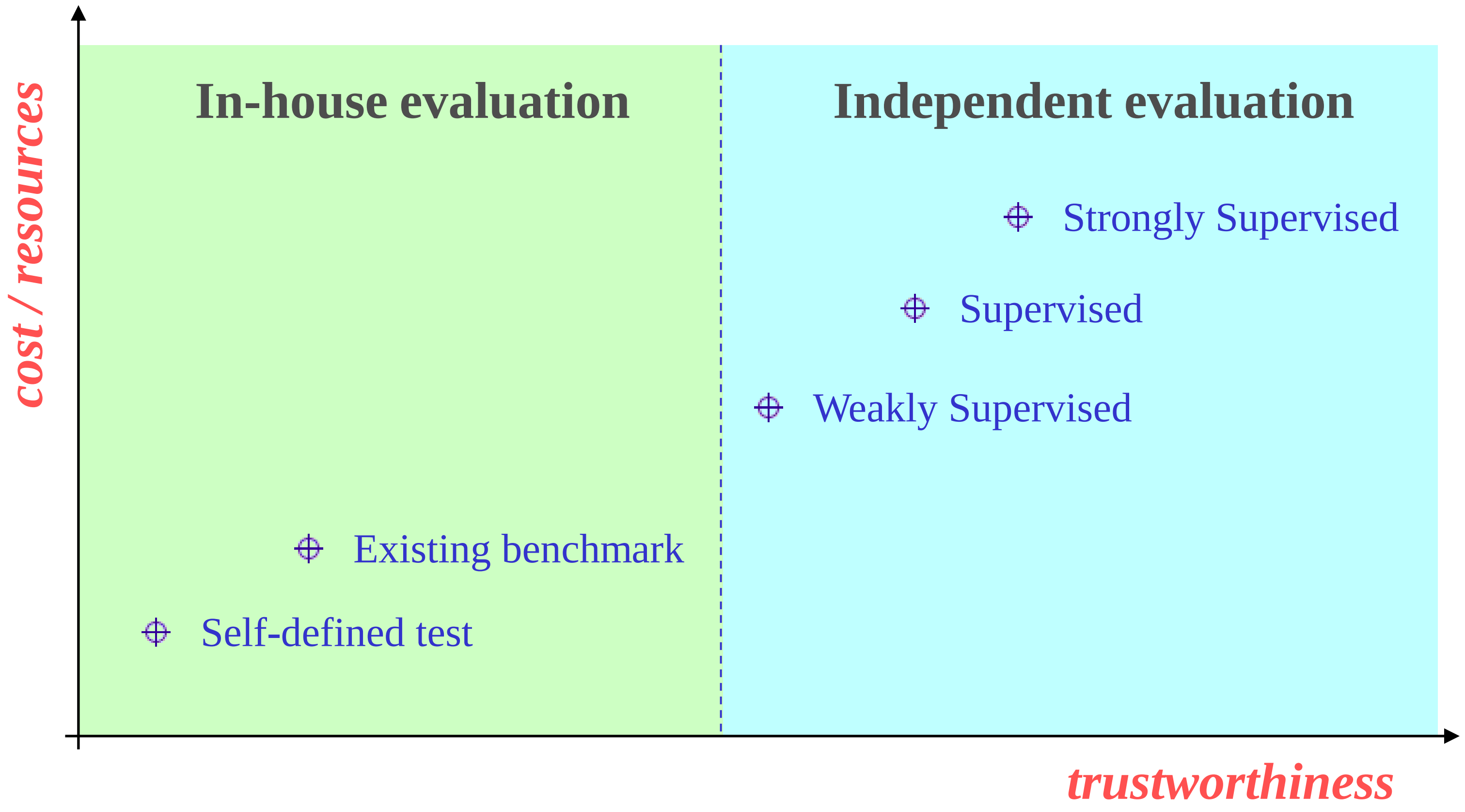
- FVC is a technology evaluation of algorithms
  - Not complete systems, but only algorithms
  - Not a performance evaluation in a real application
- Main aims
  - Track the state-of-the-art in fingerprint recognition
  - Provide updated benchmarks and a testing protocol for fair and unambiguous evaluation of fingerprint verification algorithms

FVC Competitions – Summary

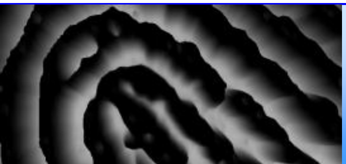
	FVC2000	FVC2002	FVC2004	FVC2006
Participants registered	**25**	**48**	**110**	**150**
Actual participants	**10**	**28**	**43**	**53**
Algorithms evaluated	**11**	**31**	**41 (*Open*)** **26 (*Light*)**	**44 (*Open*)** **26 (*Light*)**
Website accesses	~60,000	~60,000	~60,000	~20,000
E-mails exchanged	>500	>700	>900	>800
Databases	4 (set A: 100x8 fingerprints, set B: 10x8 fingerprints)			4 (set A: 140x12 fingerprints, set B: 10x12 fingerprints)



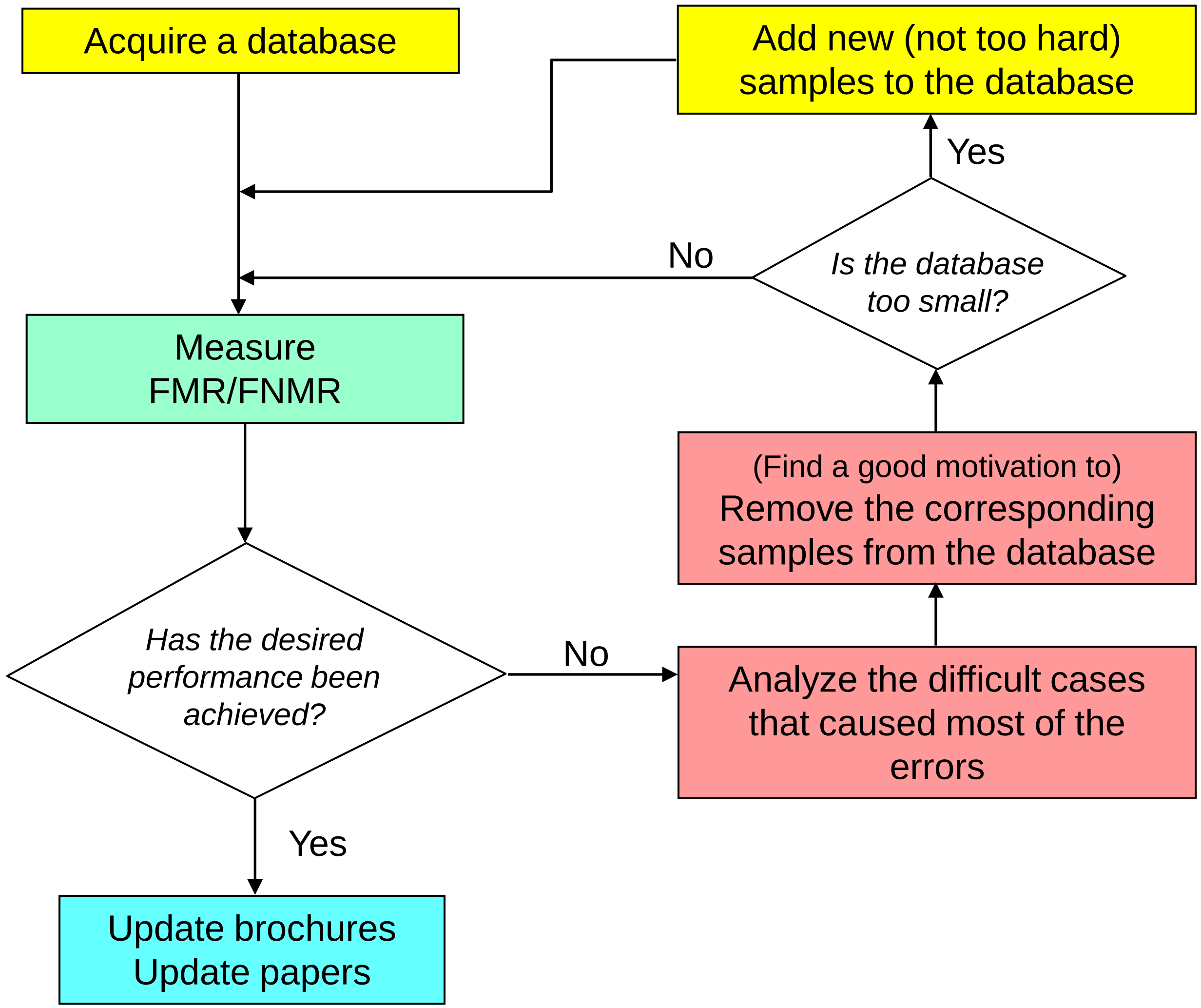
Technology evaluations



For details see: See R. Cappelli, D. Maio, D. Maltoni, J.L. Wayman and A.K. Jain, Performance Evaluation of Fingerprint Verification Systems, IEEE Transactions on Pattern Analysis Machine Intelligence, vol.28, no.1, pp.3-18, January 2006.

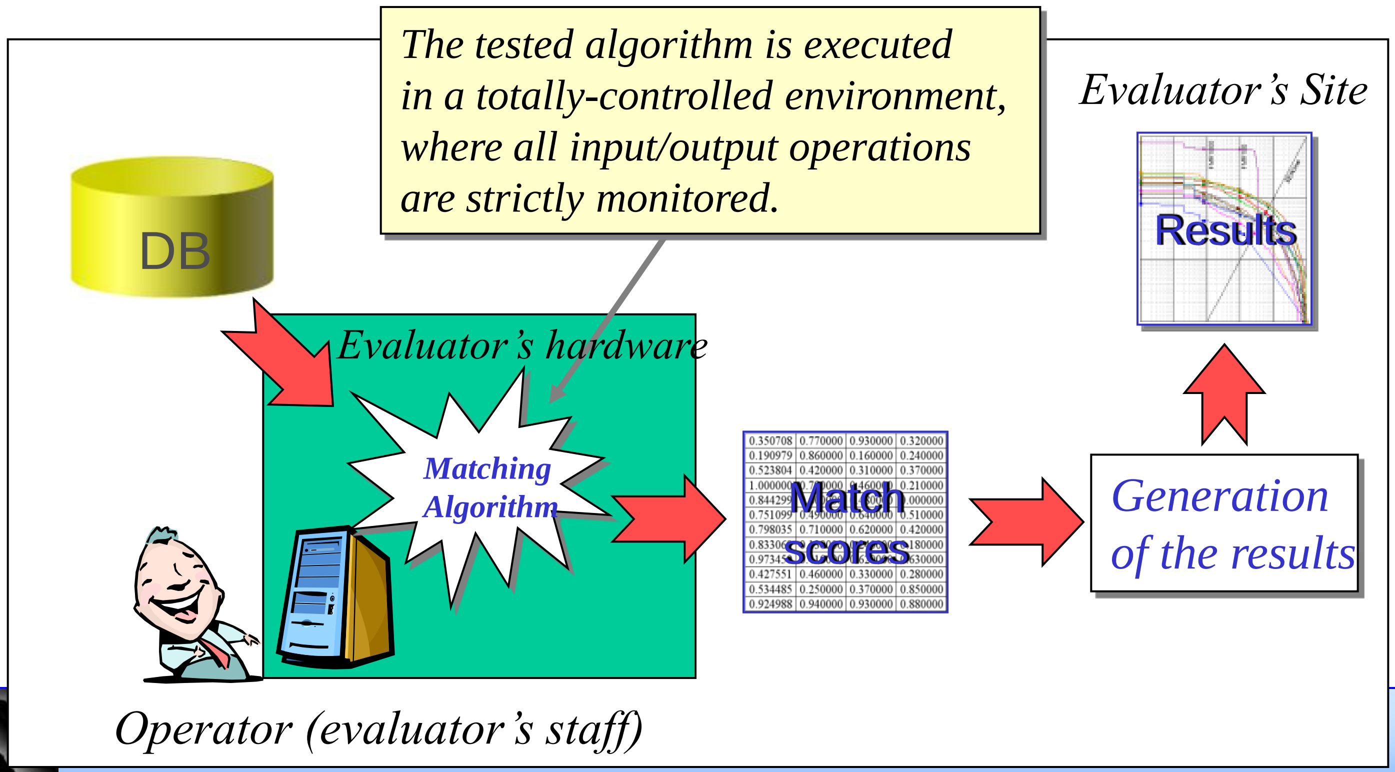


The risk of in-house testing with self-defined protocols



FVC Testing procedure

- **Database**: sequestered data
- **Protocol**: software components compliant to a given input/output protocol are tested on the evaluator’s hardware
- **Results**: generated by the evaluator from the matching scores obtained during the test



End of part one: state-of-the-art

New directions (1)

- Nowadays research on fingerprints is particularly active on:
  - Fast fingerprint matching and indexing (millions of fingerprints)
    - new very large AFIS: Indian UIDAI (enrolling 1.2 billions residents), European BMS (for the new Visa Information System)
    - increasing demand for low cost AFIS from emerging countries.
    - MCC (Minutiae Cylinder Code)
  - Exploiting extended fingerprint features
    - NIST CDEFFS (Committee to Define an Extended Fingerprint Feature Set)
    - do third level features help match fingerprint fragments and/or latents? see [NISTIR 7775].
  - Robust orientation modeling
    - only global models can predict local orientations on very noisy regions.
    - adaptive techniques (fusion of local and global approaches)

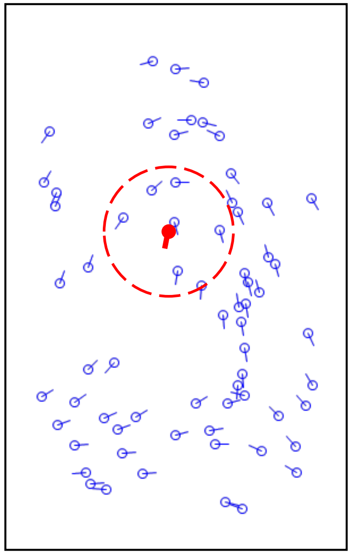
New directions (2)

- continue …
  - – Automated and semi-automated latent processing and matching
    - new semi-automated techniques for feature extraction
    - BioLab approach
  - – Learning based methods
    - Humans still outperform computers in fingerprint feature extraction on very low quality fingerprints
    - Can learning-based methods help improve machine capabilities?
  - – Template protection techniques
    - Aim: avoid disclosure of personal data, making compromised templates revocable.
    - Several approaches proposed but still not mature
    - FVC-onGoing benchmark and MCC based technique.

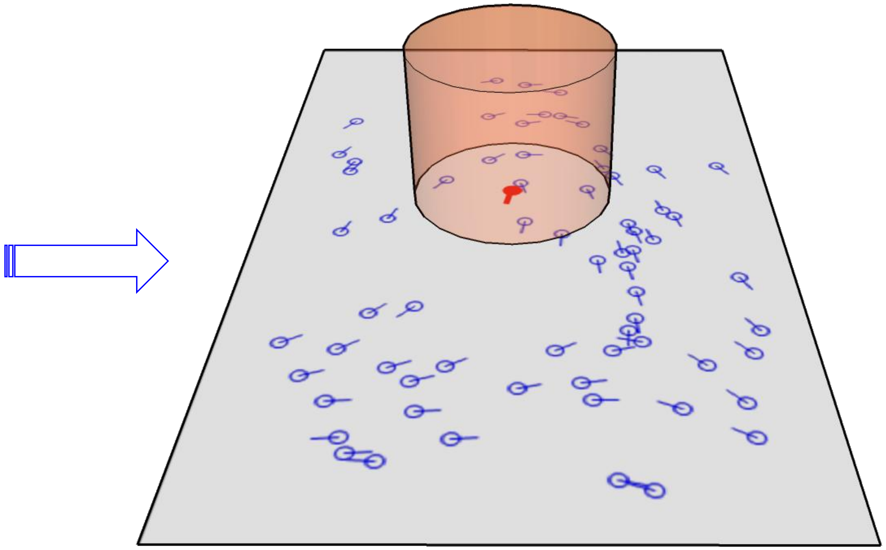
MCC: a new local matching approach

- Fixed radius structure;
- Fixed-length descriptors;
- Fast and simple matching phase;
- Matching algorithm compliant to ISO/IEC 19794-2 (2005);
- Portable on inexpensive secure platforms.

Traditional local structure

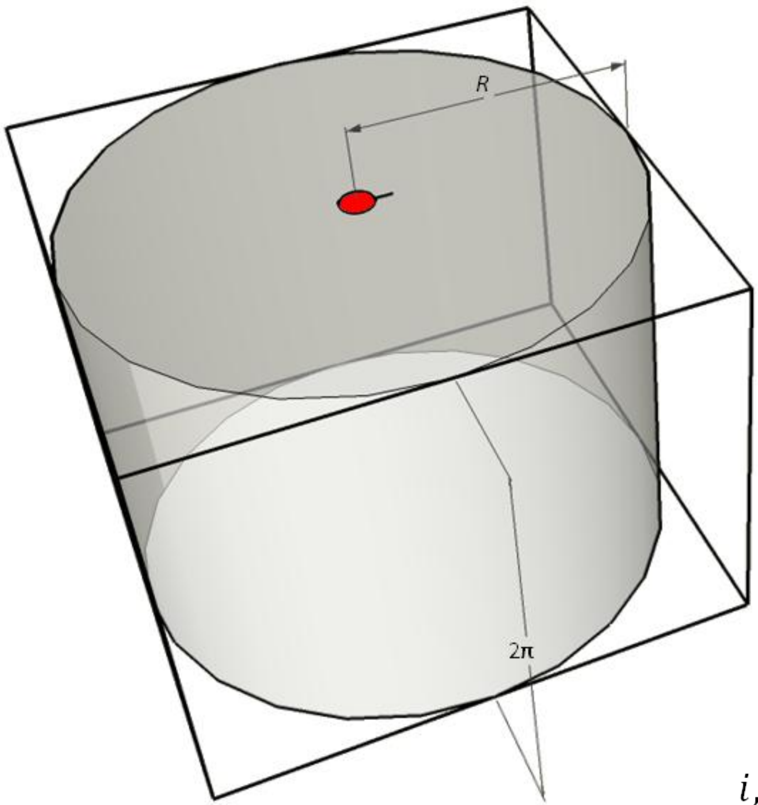


MCC: a new 3D local structure



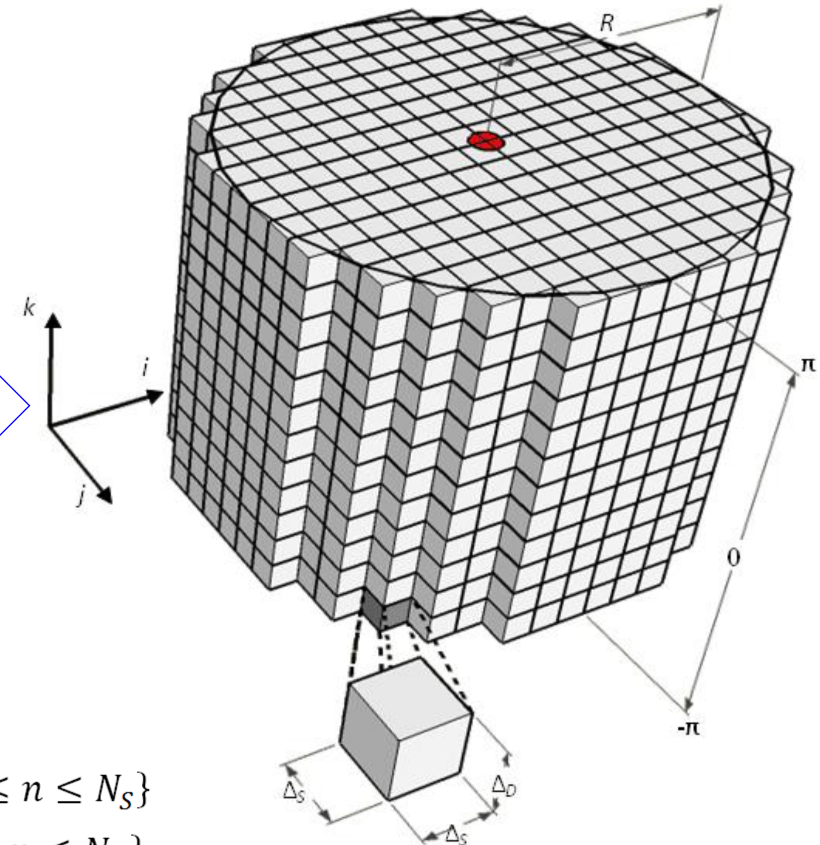
MCC: Minutia Cylinder Code [Patent pending ITBO2009A000149]

MCC: the cylinder local structure



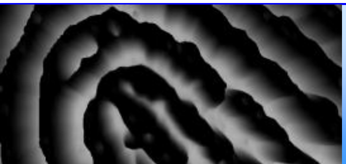
$$\Delta_S = \frac{2 \cdot R}{N_S}$$

$$\Delta_D = \frac{2\pi}{N_D}$$

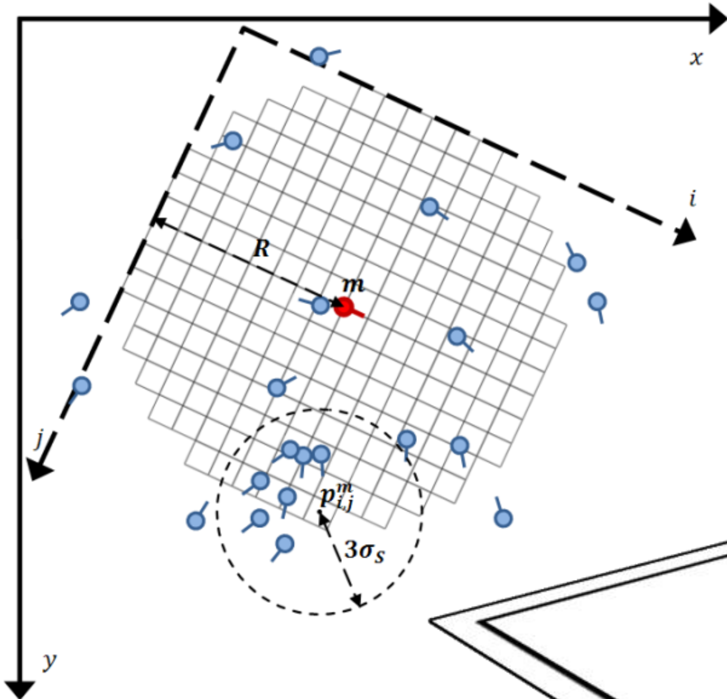


$$i, j \in I_S = \{n \in \mathbb{N}, 1 \le n \le N_S\}$$

$$k \in I_D = \{n \in \mathbb{N}, 1 \le n \le N_D\}$$

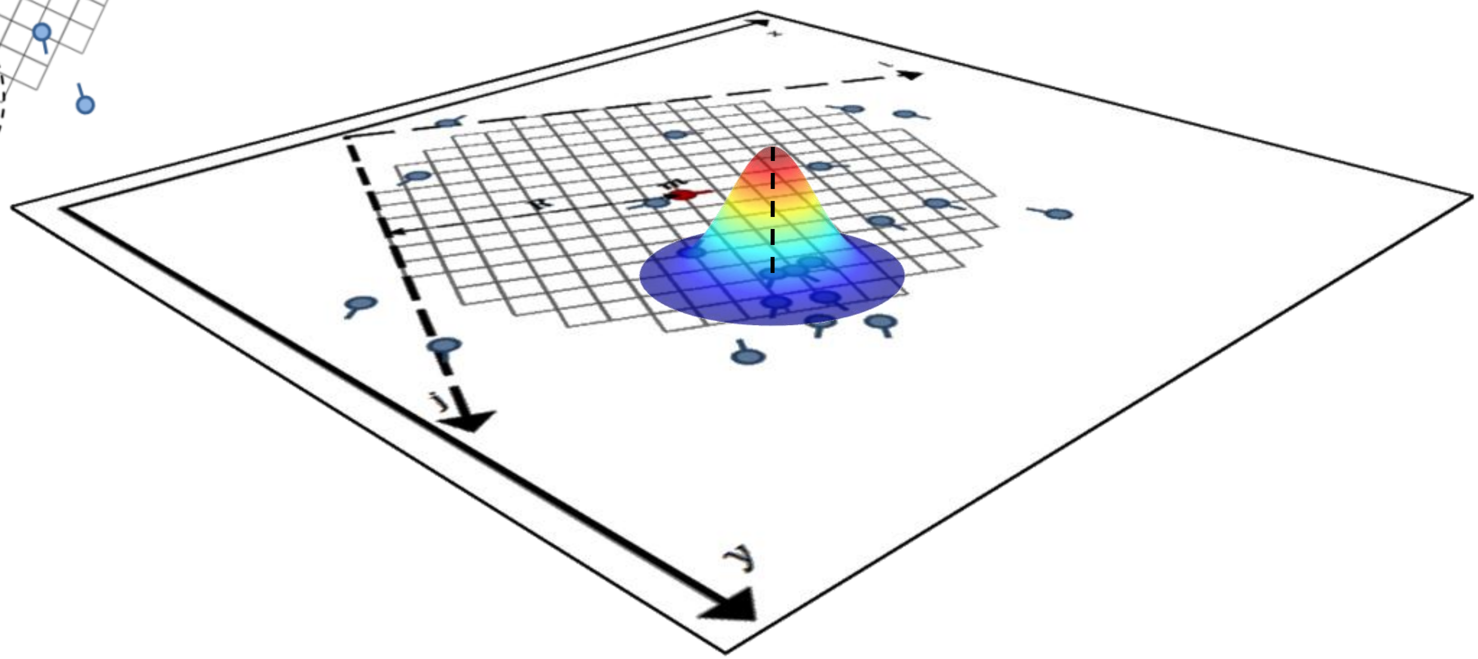


MCC: the spatial contribution

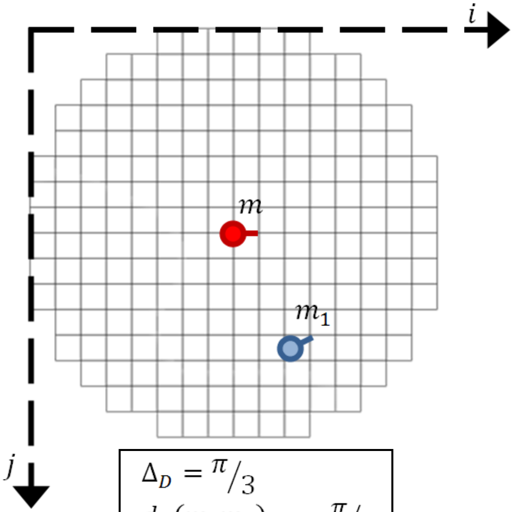


$$C^S_m\left(m_t, p^m_{i,j}\right) = G_S\left(\boxed{d_S\left(m_t, p^m_{i,j}\right)}\right)$$

$$\boxed{G_S(t) = \frac{1}{\sigma_S\sqrt{2\pi}}\, e^{\left(-\frac{t^2}{2\sigma_S^2}\right)}}$$



MCC: the directional contribution

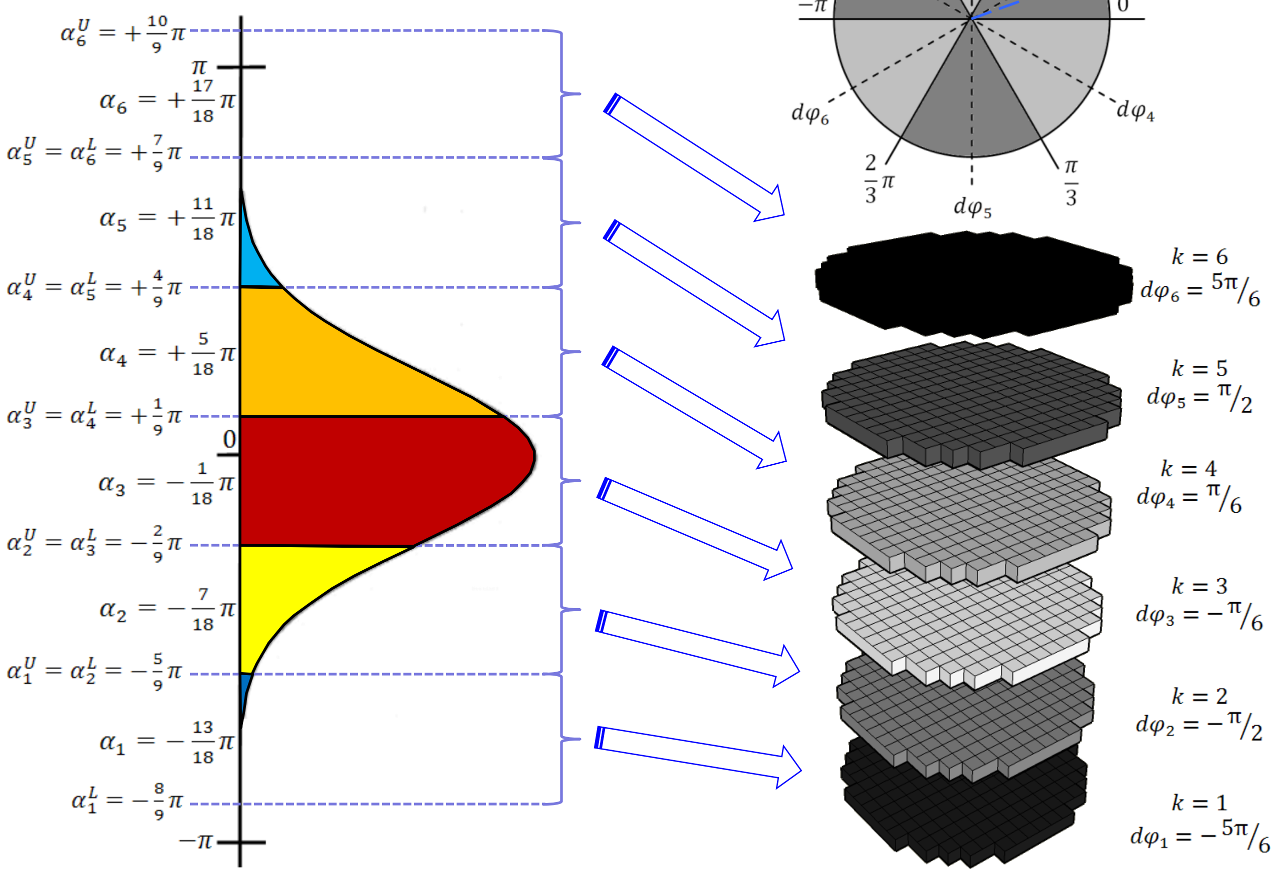


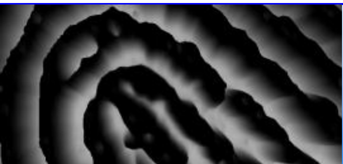
$$\Delta_D = \pi/3$$
$$d_\theta(m, m_1) = -\pi/9$$

$$C_m^D(m_t, d\varphi_k) = G_D\left(\boxed{d\phi\left(d\varphi_k, d_\theta(m, m_t)\right)}\right)$$

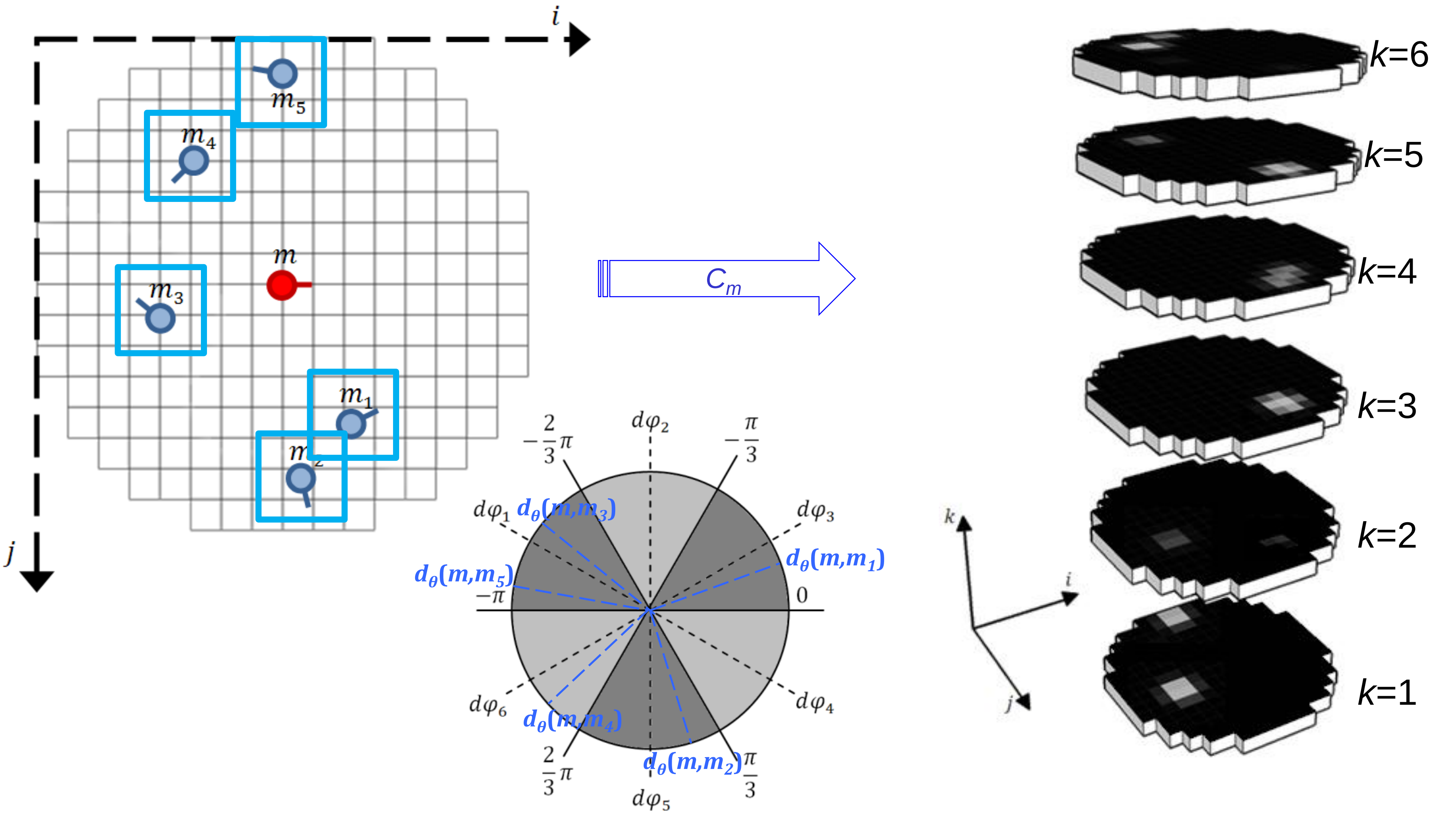
$$\alpha_k = d\phi\left(d\varphi_k, -\pi/9\right)$$
$$\alpha_k^L = \alpha_k - \pi/6$$
$$\alpha_k^U = \alpha_k + \pi/6$$

$$G_D(\alpha) = \frac{1}{\sigma_D\sqrt{2\pi}} \int_{\alpha-\frac{\Delta_D}{2}}^{\alpha+\frac{\Delta_D}{2}} e^{-\frac{t^2}{2\sigma_D^2}}\, dt$$

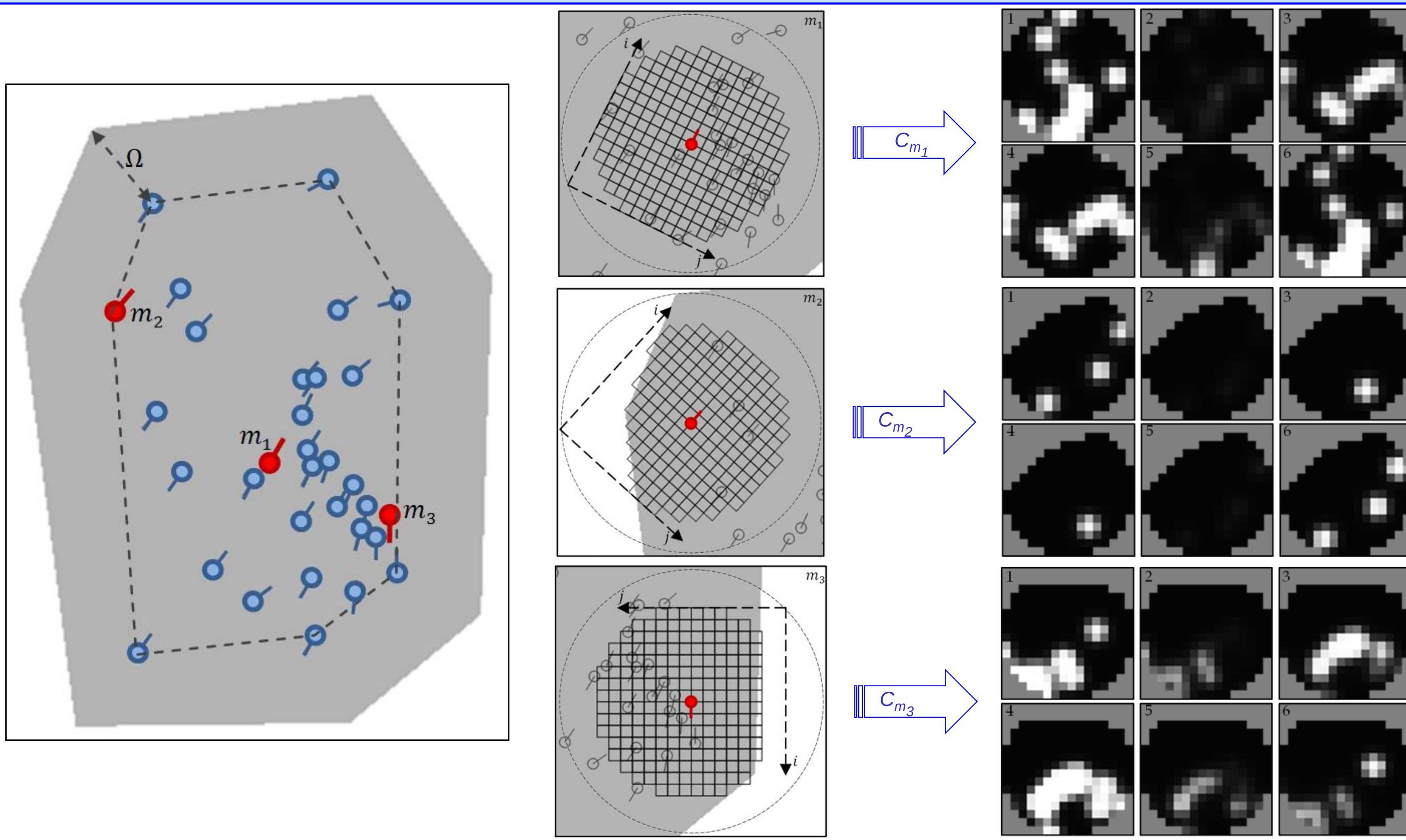




MCC: example of a cylinder

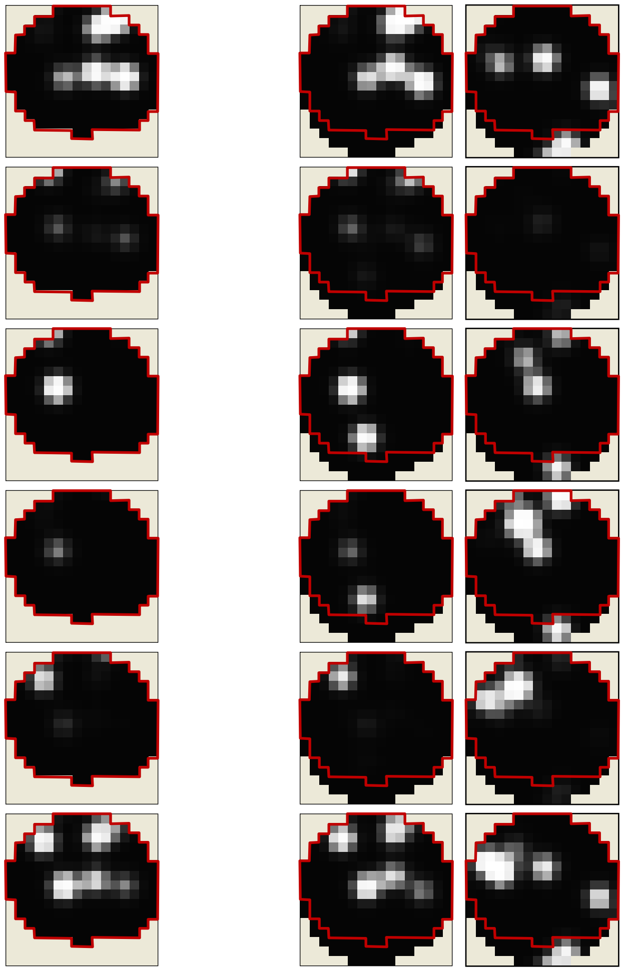


MCC: example of a template



MCC: the similarity between two cylinders

C_a C_b C_c



$$\mathbf{c}_m[lin(i,j,k)] = C_m(i,j,k)$$

$$lin(i,j,k) = (k-1)\cdot(N_S)^2 + (j-1)\cdot N_S + i$$

$$\mathbf{c}_{a|b}[t] = \begin{cases} \mathbf{c}_a[t] & \text{if } \mathbf{c}_a[t] \text{ and } \mathbf{c}_b[t] \text{ are } \mathit{matchable} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbf{c}_{b|a}[t] = \begin{cases} \mathbf{c}_b[t] & \text{if } \mathbf{c}_b[t] \text{ and } \mathbf{c}_a[t] \text{ are } \mathit{matchable} \\ 0 & \text{otherwise} \end{cases}$$

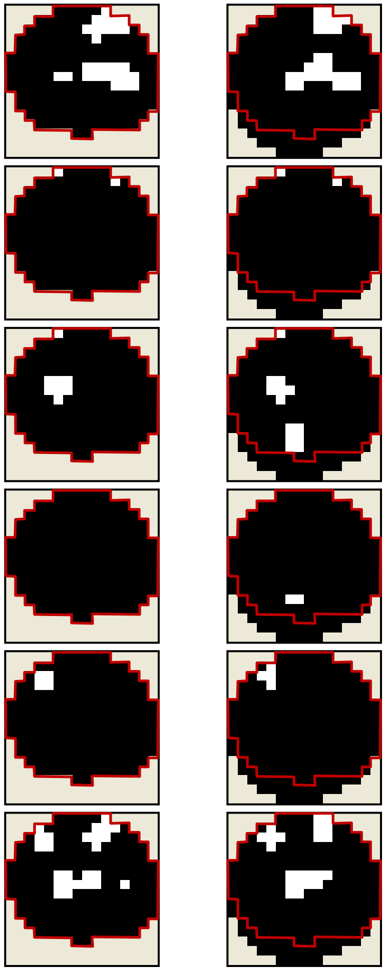
$$\boxed{\gamma(a,b) = \begin{cases} 1 - \dfrac{\|\mathbf{c}_{a|b} - \mathbf{c}_{b|a}\|}{\|\mathbf{c}_{a|b}\| + \|\mathbf{c}_{b|a}\|} & \text{if } C_a \text{ and } C_b \text{ are } \mathit{matchable} \\ 0 & \text{otherwise} \end{cases}}$$

$\gamma(a,b)=0.75$

$\gamma(a,c)=0.38$

MCC: bit-based implementation

C_a C_b



The cell value:

$$\Psi_{Bit}(v) = \begin{cases} 1 & \text{if } v \geq \mu_\Psi \\ 0 & \text{otherwise} \end{cases}$$

The similarity between two cylinders:

$$\mathbf{c}_m[lin(i,j,k)] = \begin{cases} 1 & \text{if } C_m(i,j,k) = 1 \\ 0 & \text{otherwise} \end{cases}$$

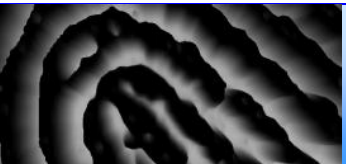
$$\hat{\mathbf{c}}_m[lin(i,j,k)] = \begin{cases} 1 & \text{if } C_m(i,j,k) \neq invalid \\ 0 & \text{otherwise} \end{cases}$$

$$\hat{\mathbf{c}}_{ab} = \hat{\mathbf{c}}_a \text{AND } \hat{\mathbf{c}}_b$$

$$\mathbf{c}_{a|b} = \mathbf{c}_a \text{ AND } \hat{\mathbf{c}}_{ab} \text{ , } \mathbf{c}_{b|a} = \mathbf{c}_b \text{ AND } \hat{\mathbf{c}}_{ab}$$

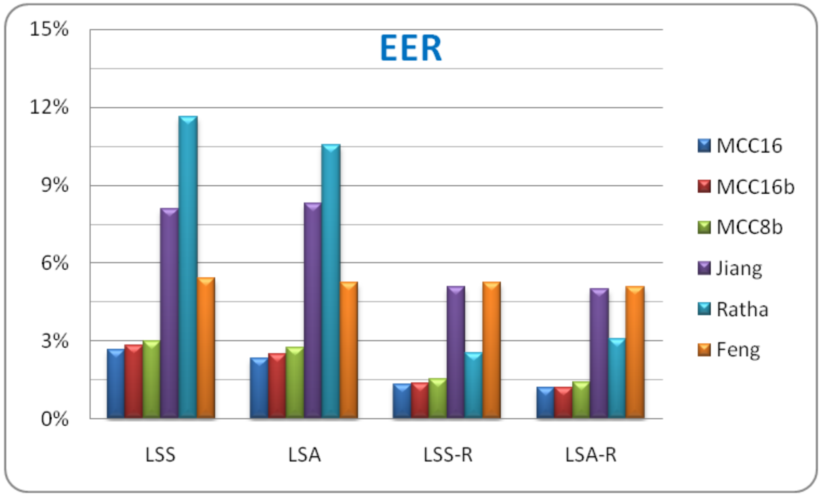
$$\gamma_{Bit}(a,b) = \begin{cases} 1 - \frac{\left\|\mathbf{c}_{a|b} \text{ XOR } \mathbf{c}_{b|a}\right\|}{\left\|\mathbf{c}_{a|b}\right\| + \left\|\mathbf{c}_{b|a}\right\|} & \text{if } C_a \text{ and } C_b \text{ are } matchable \\ 0 & \text{otherwise} \end{cases}$$

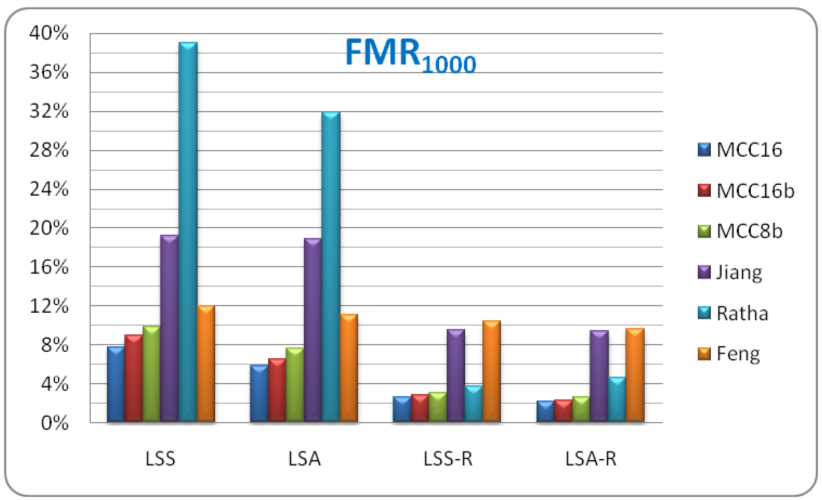
$\gamma_{Bit}(a,b)=0.63$



MCC: experimental evaluation

Accuracy





Efficiency

AVERAGE MATCHING TIMES OVER ALL DATASETS (MILLISECONDS)

	T_{cs}	T_{ls}	T_{gs}			
			LSS	LSA	LSS-R	LSA-R
MCC16	21.0	21.0	0.5	4.3	2.7	4.7
MCC16b	17.3	1.2	0.5	4.3	2.8	4.7
MCC8b	4.2	$\boxed{0.3}$	$\boxed{0.5}$	4.2	2.9	4.8
Jiang	1.0	0.8	0.4	4.3	2.6	4.1
Ratha	1.0	250.7	0.5	4.3	2.8	4.4
Feng	0.2	12.3	0.5	2.4	2.8	3.1

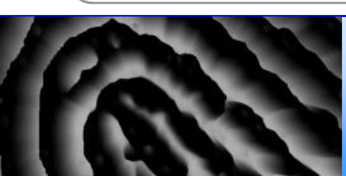
C#: 0.8ms

C+SSE3: 0.007ms

>500.000 matches/s on a quad core

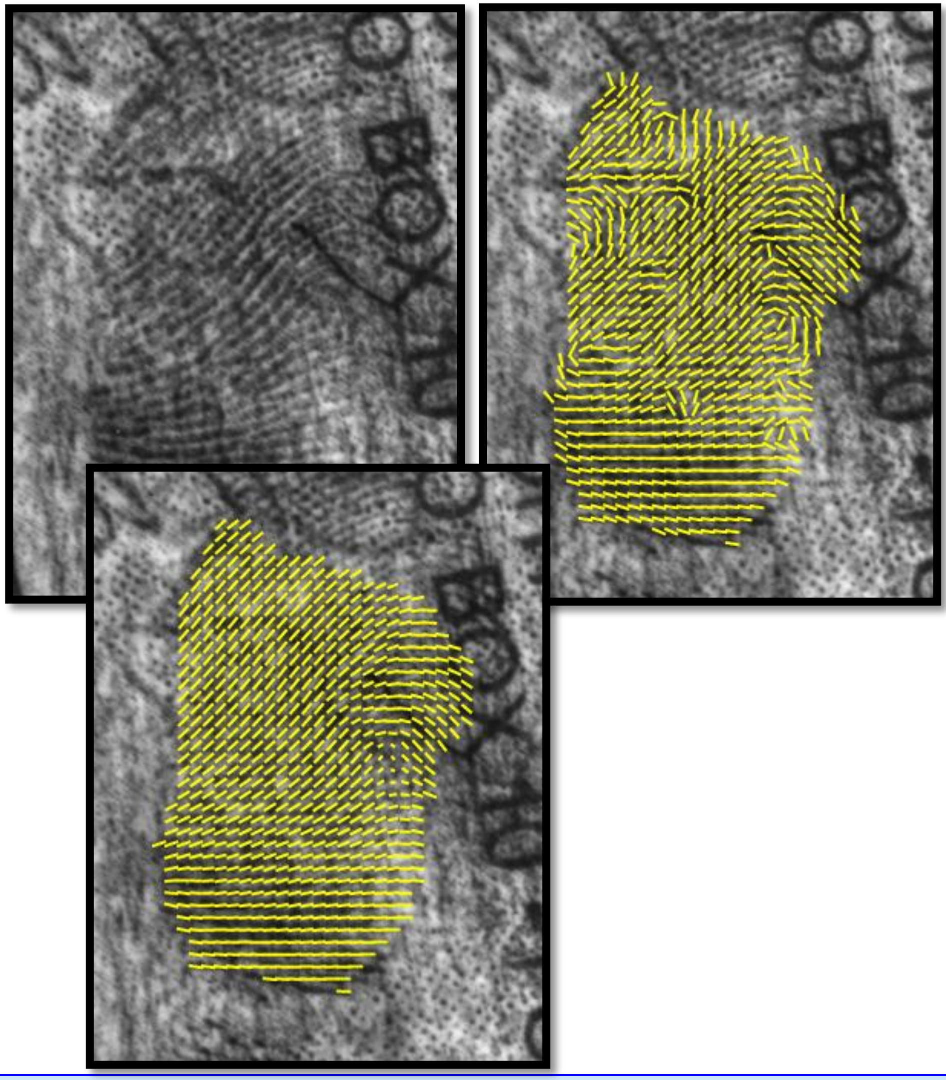
A... R ALL

				...rmat	
	Size	Size	Ratio	Size	Ratio
MCC16	209253	103766	202%	104595	200%
MCC16b	7630	1457	524%	1642	465%
MCC8b	1913	605	316%	655	292%
Jiang	1068	608	176%	647	165%
Ratha	26543	19487	136%	20046	132%
Feng	1428	567	252%	614	233%

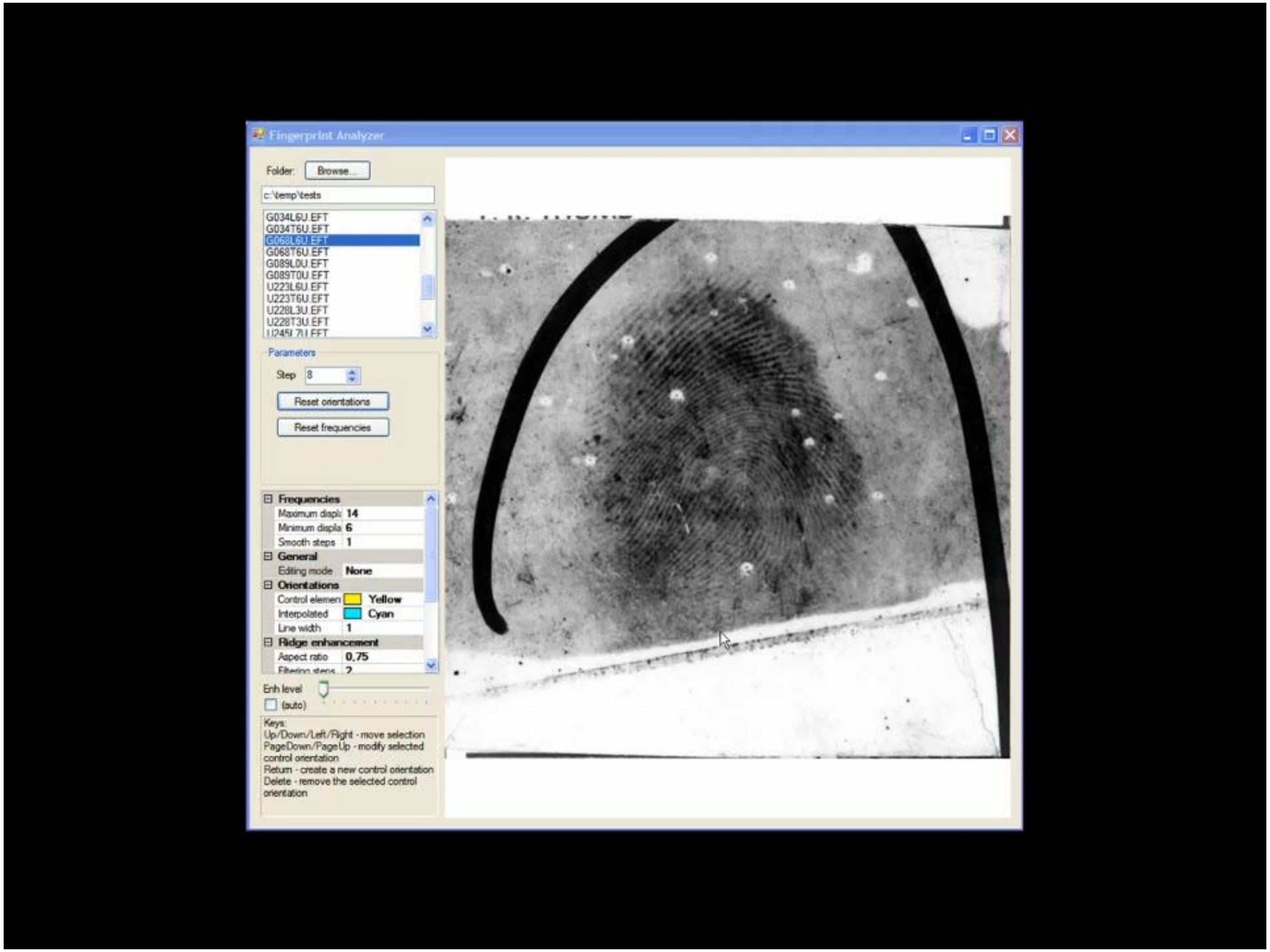


Enhancement of latent fingerprints

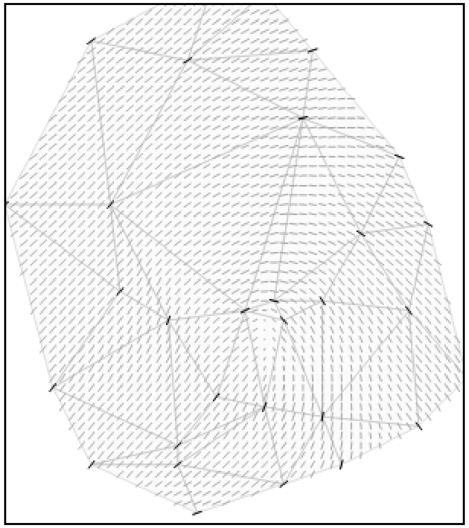
- A very challenging task
- How to (automatically) estimate the context?
  - Can local orientations and frequencies be reliably computed on very low-quality fingerprints?
  - Regularization techniques and global orientation models may help to find a solution, but the problem is still open.

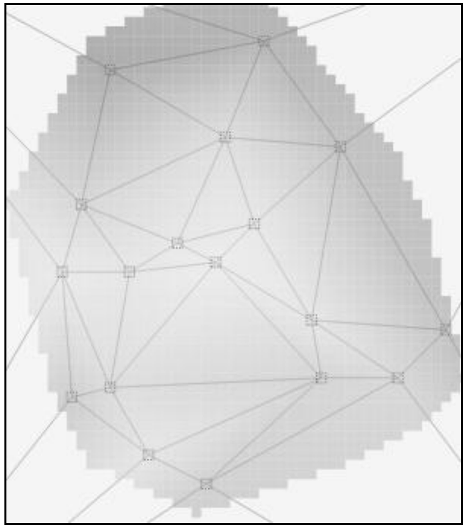


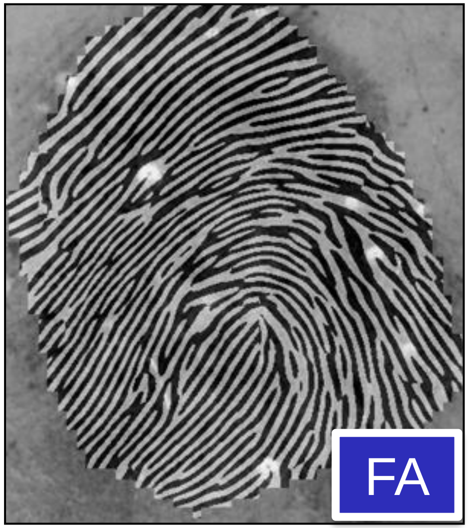
A semi-automatic approach

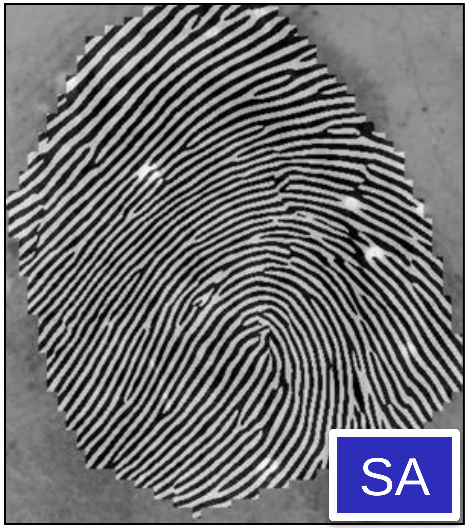


Example: a NIST DB27 “good” latent image

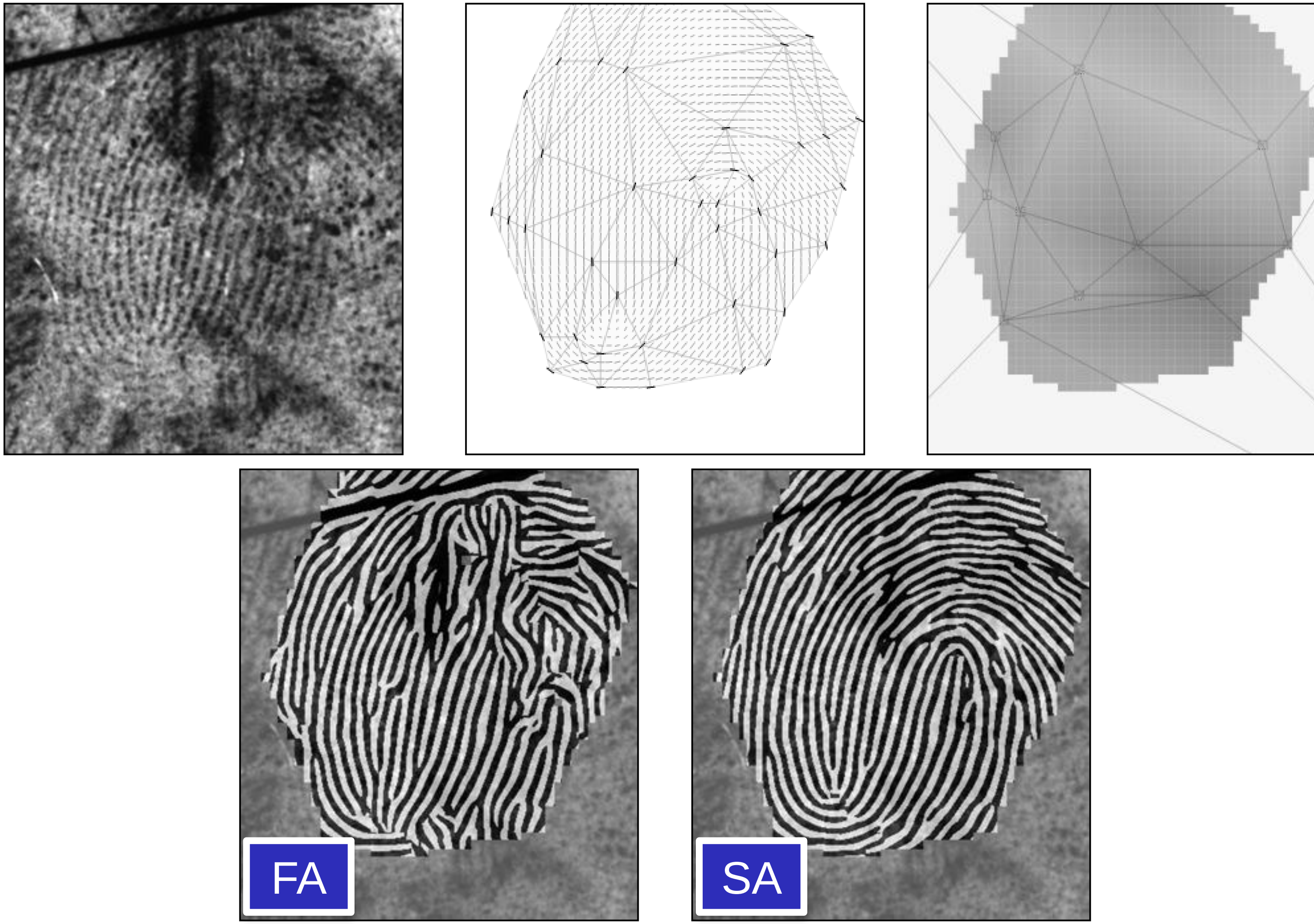




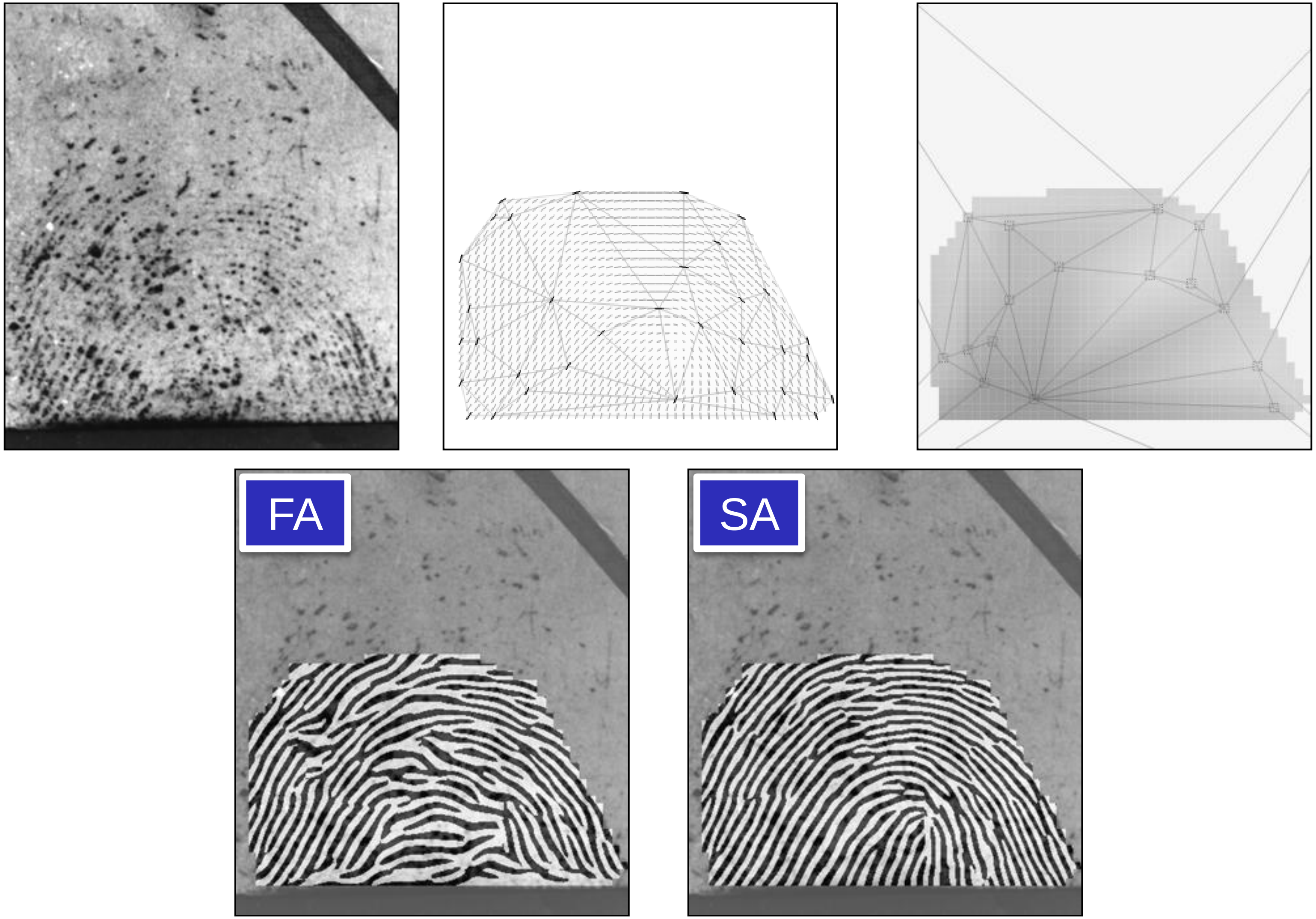




Example: a NIST DB27 “bad” latent image



Example: a NIST DB27 “ugly” latent image

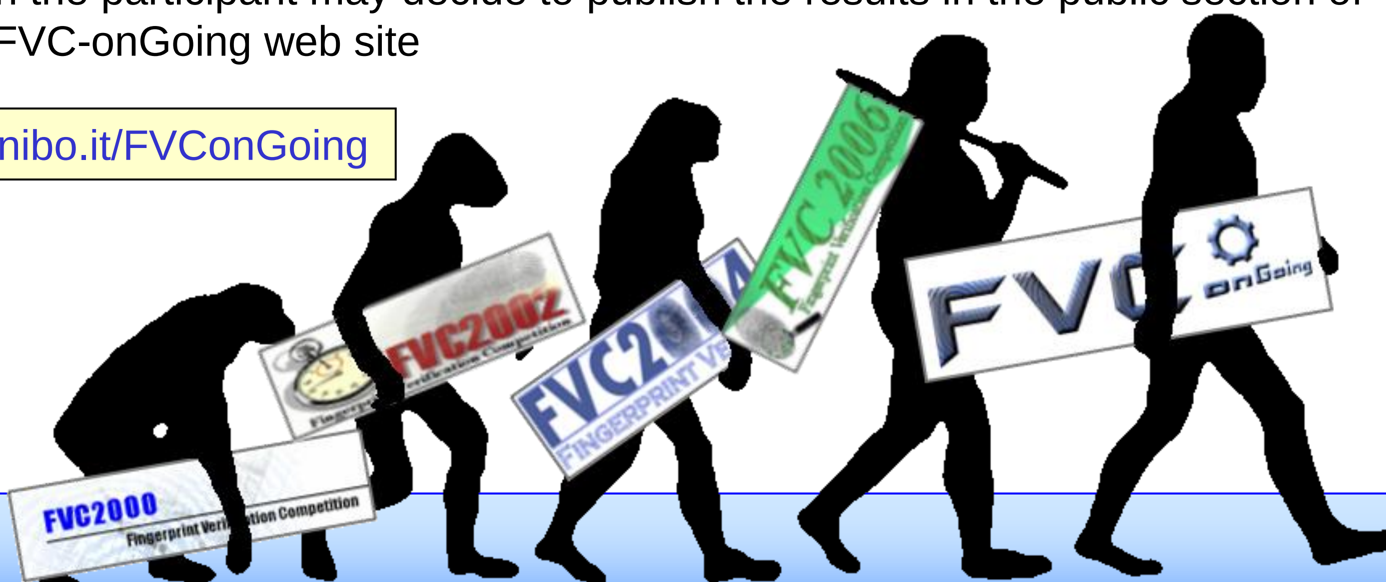


FVC-onGoing

started June 2009

- Web-based automatic evaluation of fingerprint recognition algorithms
  - Participants can be: companies, academic research groups, or independent developers
  - Algorithms are tested on sequestered datasets and results are reported using well-known performance indicators and metrics
  - Fully automated:
    1. The system automatically tests the algorithm submitted by a participant
    2. The participant sees the results in its “private area”
    3. Then the participant may decide to publish the results in the public section of the FVC-onGoing web site

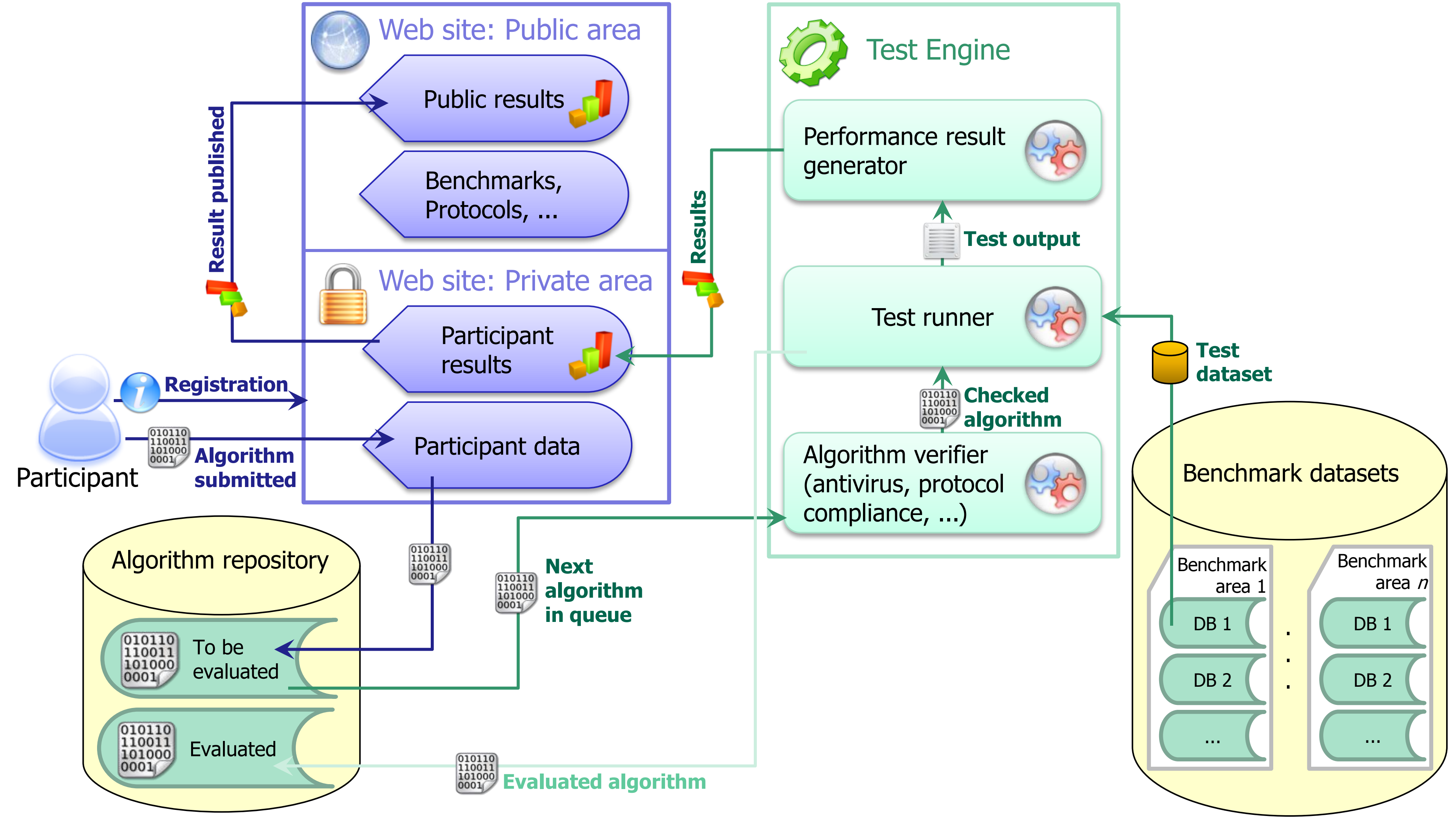
http://biolab.csr.unibo.it/FVConGoing



What's new in FVC-onGoing

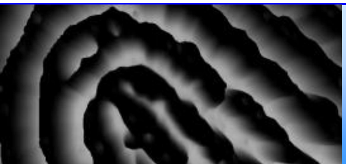
- Previous FVC initiatives were organized as "competitions"
  - Specific calls and Fixed time frames
- FVC-onGoing is:
  - An "on going competition" always open to new participants
    - Datasets will remain sequestered
  - An evolving online repository of benchmarks, evaluation metrics and results
    - However the benchmark datasets will not evolve over time; in case new datasets will be added in the future, they will form a different benchmark (or a new version of an existing one)
- Not only limited to fingerprint verification algorithms:
  - Ad hoc benchmarks for testing specific modules of fingerprint verification systems will be available, for instance:
    - Orientation Image Estimation
    - Minutiae Extraction

FVC-onGoing: Workflow

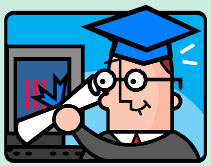
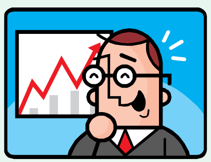
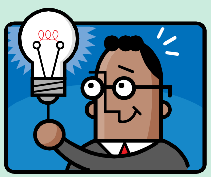


Currently available benchmarks

Area	Benchmark	Description
 **FV** Fingerprint Verification	FV-TEST	A simple dataset useful to test algorithm compliancy with the testing protocol
	FV-STD-1.0	Fingerprint images acquired in operational conditions using high-quality optical scanners
	FV-HARD-1.0	Difficult cases (noisy images, distorted impressions, etc.): more challenging
 **FMISO** Fingerprint ISO Template Matching	FMISO-TEST	A simple dataset useful to test algorithm compliancy with the testing protocol
	FMISO-STD-1.0	Fingerprint images acquired in operational conditions using high-quality optical scanners
	FMISO-HARD-1.0	Difficult cases (noisy images, distorted impressions, etc.): more challenging
 **FOE** Fingerprint Orientation Extraction	FOE-TEST	A simple dataset useful to test algorithm compliancy with the testing protocol
	FOE-STD-1.0	Orientation extraction benchmark on fingerprints with orientation ground-truth manually labeled using an ad-hoc software tool. Good-quality and bad-quality datasets.

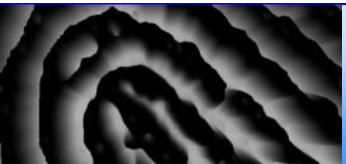


Current status

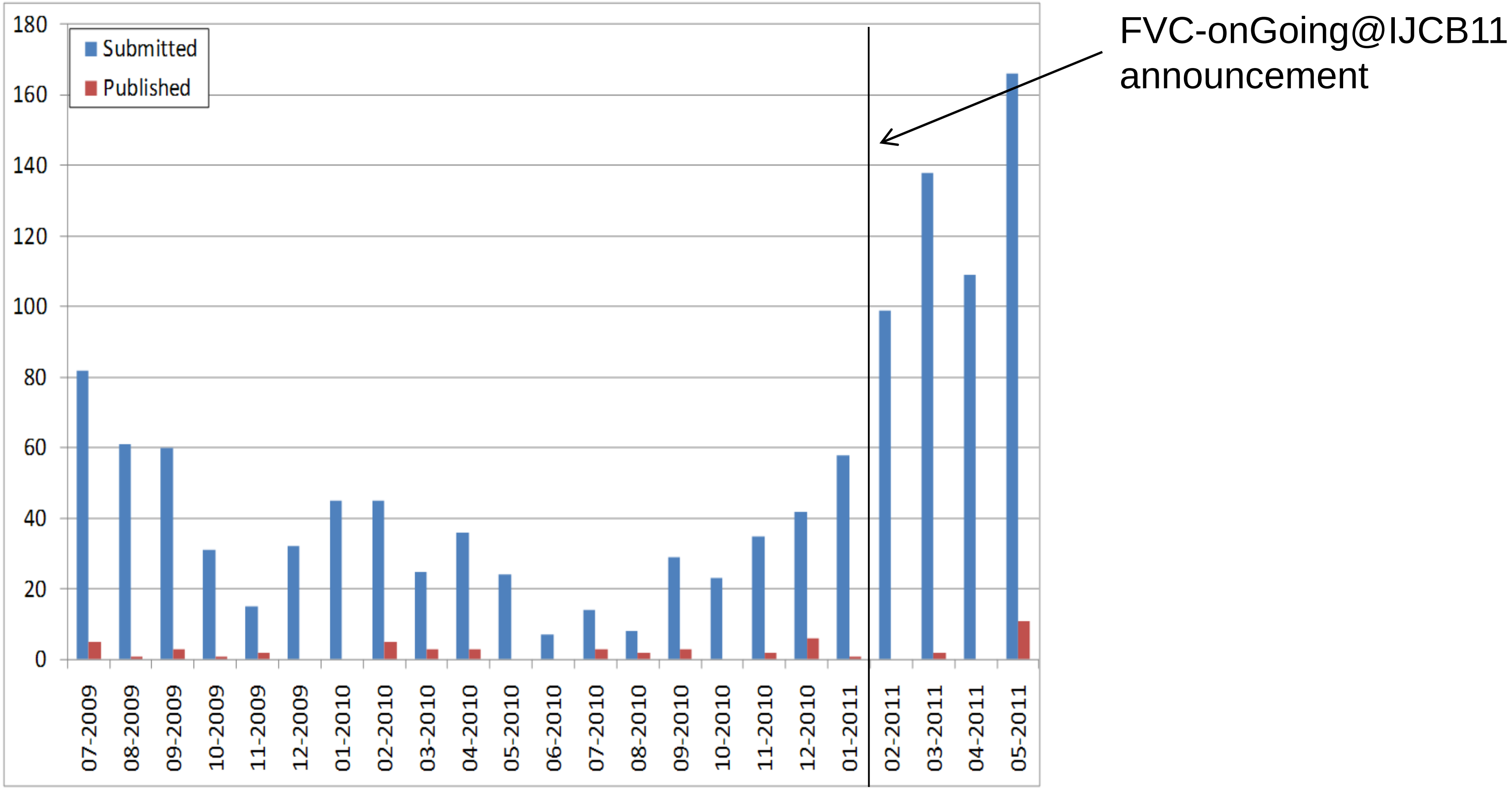
Registered Participants (389)		Dec 2011
	Academic Research Groups	63
	Companies	84
	Independent Developers	242

Algorithm Evaluated		Dec 2011
	Fingerprint Verification	664
	Fingerprint ISO Template Matching	761

Results Published		Dec 2011
	Fingerprint Verification	30
	Fingerprint ISO Template Matching	27



Submitted vs Published



FV: Fingerprint Verification

Benchmark FV-STD-1.0:

Published on	Benchmark	Participant	Type	Algorithm	Version	EER ▲	FMR1000	FMR10000	Show details
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%	
15/05/2011	FV-STD-1.0	AA Technology Ltd.	Company	EMB9200	2.3	0,176%	0,188%	0,303%	
20/07/2009	FV-STD-1.0	Neurotechnology	Company	MM_FV	3.0	0,281%	0,386%	0,581%	
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%	
15/07/2009	FV-STD-1.0	Secuest Inc.	Company	STAR	1.0	1,265%	2,504%	4,026%	
24/06/2009	FV-STD-1.0	jFinger Co., Ltd.	Company	JF_FV	V1.21a	1,618%	2,872%	4,545%	
25/08/2010	FV-STD-1.0	Robert Važan	Independent Developer	SourceAFIS	1.1	3,649%	7,266%	10,905%	
14/05/2011	FV-STD-1.0	Yanbing Zhang & Bao Feng Lan	Independent Developer	MiraFinger	2.2	6,701%	67,475%	84,488%	

FV: Fingerprint Verification (2)

Benchmark FV-HARD-1.0:

Published on	Benchmark	Participant	Type	Algorithm	Version	EER ▲	FMR1000	FMR10000	Show details
29/08/2011	FV-HARD-1.0	Tiger IT Bangladesh	Company	TigerAFIS	1.2ec10	0,687%	1,077%	1,781%	
15/05/2011	FV-HARD-1.0	AA Technology Ltd.	Company	EMB9200	2.3	0,700%	1,247%	1,817%	
31/08/2011	FV-HARD-1.0	AA Technology Ltd.	Company	EMB9300	1.1	0,722%	1,092%	1,542%	
14/09/2010	FV-HARD-1.0	Green Bit S.p.A	Company	GBFRSW	1.3.2.0	0,735%	1,444%	2,355%	
14/05/2011	FV-HARD-1.0	Institute of Automation, Chinese Academy of Sciences	Academic Research Group	MntModel	1.0	1,257%	2,795%	4,436%	
20/07/2009	FV-HARD-1.0	Neurotechnology	Company	MM_FV	3.0	1,528%	3,043%	4,079%	
15/05/2011	FV-HARD-1.0	UnionCommunity	Company	Triple_M	1.1	2,021%	4,420%	8,447%	
26/08/2010	FV-HARD-1.0	Robert Važan	Independent Developer	SourceAFIS	1.1	6,769%	13,954%	16,310%	

FMISO: Fingerprint ISO Template Matching

Benchmark FMISO-STD-1.0:

Published on	Benchmark	Participant	Type	Algorithm	Version	EER ▲	FMR1000	FMR10000	Show details
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%	
15/12/2010	FMISO-STD-1.0	Suprema, Inc.	Company	SFCore	1.0	0,258%	0,346%	0,639%	
12/10/2009	FMISO-STD-1.0	Tiger IT Bangladesh	Company	Tiger ISO	0.1	0,317%	0,447%	0,866%	
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%	
02/04/2010	FMISO-STD-1.0	id3 Semiconductors	Company	Fingerprint Matcher ISO	1.0	0,559%	0,783%	1,147%	
22/07/2010	FMISO-STD-1.0	Biometric System Laboratory	Academic Research Group	MCC (Baseline)	1.1	0,570%	0,884%	1,331%	
26/09/2009	FMISO-STD-1.0	APRO TECHNOLOGY (BANGKOK) CO., LTD.	Company	APF_FMISO	1.1	0,582%	0,801%	1,057%	
20/07/2009	FMISO-STD-1.0	Neurotechnology	Company	MM_FMISO	3.0	0,598%	0,801%	1,234%	
30/11/2010	FMISO-STD-1.0	Communik8 Ltd	Company	Authentik8	1.0	1,017%	2,475%	10,473%	
15/09/2010	FMISO-STD-1.0	Robert Važan	Independent Developer	SourceAFIS	1.3	1,334%	2,002%	2,900%	

FMISO: Fingerprint ISO Template Matching (2)

Benchmark FMISO-HARD-1.0:

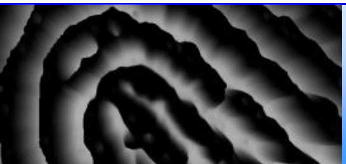
Published on	Benchmark	Participant	Type	Algorithm	Version	EER ▲	FMR1000	FMR10000	Show details
26/12/2011	FMISO-HARD-1.0	NITGen&Company	Company	Nitgen_ISO	1.0	1,089%	4,379%	6,082%	
24/03/2011	FMISO-HARD-1.0	UnionCommunity	Company	Triple_M_ISO	1.2	1,103%	3,157%	7,878%	
15/05/2011	FMISO-HARD-1.0	AA Technology Ltd.	Company	EMB9200	2.41	1,113%	2,076%	3,282%	
15/12/2010	FMISO-HARD-1.0	Suprema, Inc.	Company	SFCore	1.0	1,407%	2,697%	4,570%	
14/05/2011	FMISO-HARD-1.0	Institute of Automation, Chinese Academy of Sciences	Academic Research Group	MntModel	1.0	1,588%	2,821%	3,965%	
22/07/2010	FMISO-HARD-1.0	Biometric System Laboratory	Academic Research Group	MCC (Baseline)	1.1	2,315%	4,876%	6,206%	
09/03/2010	FMISO-HARD-1.0	id3 Semiconductors	Company	Fingerprint Matcher ISO	1.0	2,400%	4,260%	6,605%	
20/07/2009	FMISO-HARD-1.0	Neurotechnology	Company	MM_FMISO	3.0	2,430%	4,607%	6,139%	
26/09/2009	FMISO-HARD-1.0	APRO TECHNOLOGY (BANGKOK) CO., LTD.	Company	APF_FMISO	1.1	2,552%	4,581%	5,963%	

What can we learn?

Characteristics of algorithms published on FV area:

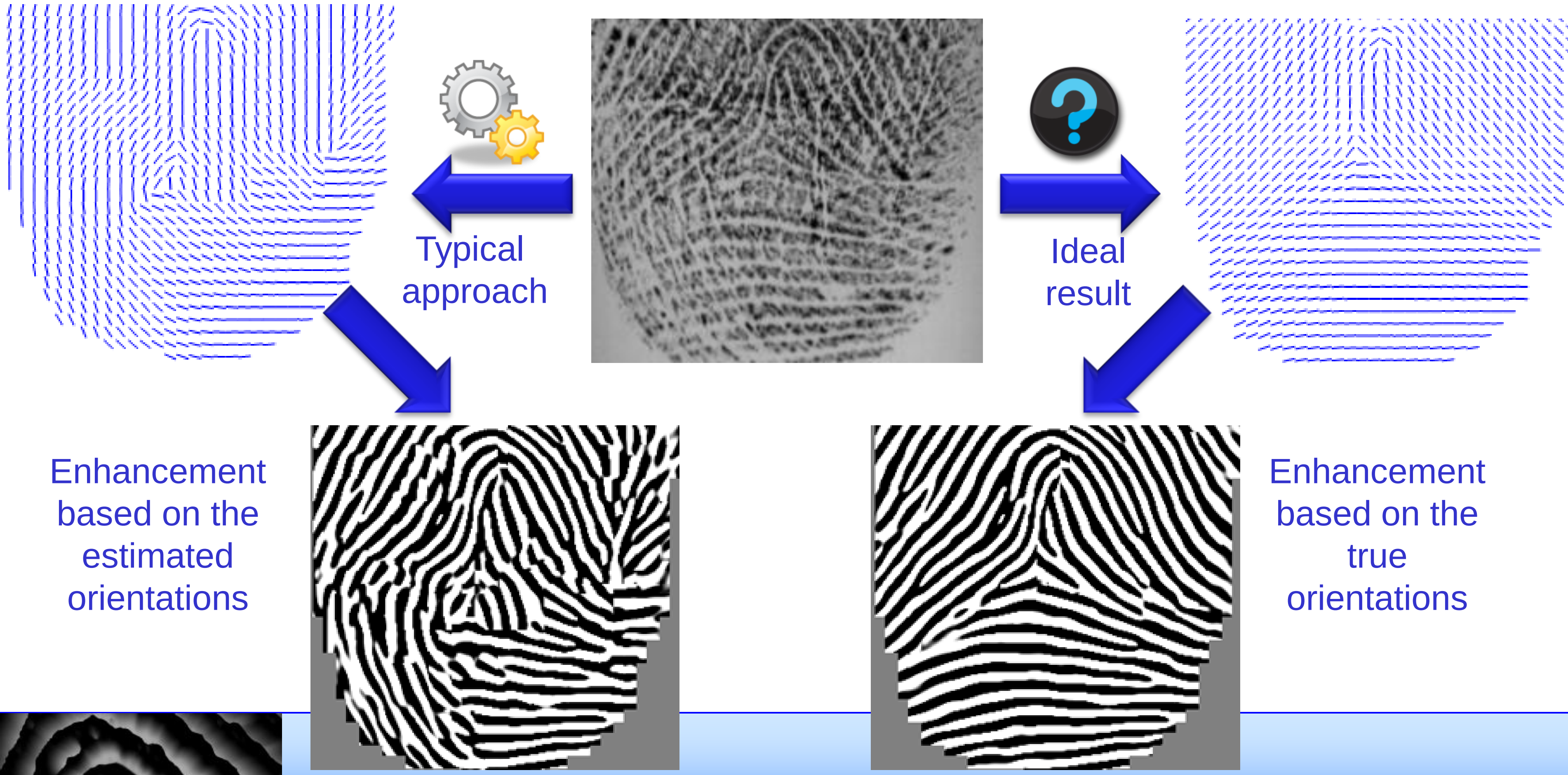
	Algorithm			EMB9200 2.3	Triple_M 1.1	MntModel 1.0	MiraFinger 2.2	GBFRSW 1.3.2.0	SourceAFIS 1.1	MM_FV 3.0	STAR 1.0	JF_FV 1.21a
Preprocessing	Segmentation			X	X	X		X	X	X	X	X
	Enhancement			X	X	X			X	X	X	X
	Binarization			X	X	X		X	X	X	X	X
Feature Used	Minutiae			X	X	X	X	X	X	X	X	X
	Singular Points									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



New Benchmark: Fingerprint Orientation Extraction

- Challenge: Estimation of local orientations in low-quality images
  - A <u>fundamental</u> step in fingerprint analysis and recognition



Evaluating Fingerprint Orientation Extraction

- How the benchmark works:
  - Participants’ algorithms are required to extract local orientations from fingerprint images and to save them into a specific format.
  - The extracted orientations are compared to the **ground-truth** in order to assess the algorithm accuracy.

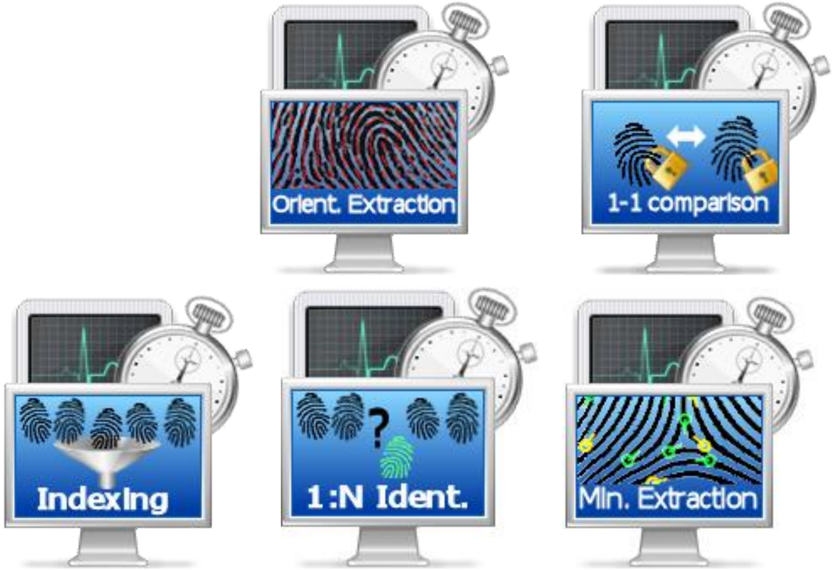

Fingerprint


Ground truth


Extracted


Errors

The next steps

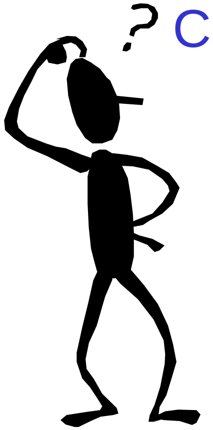


- Recently-added benchmark areas
  - Fingerprint Orientation Extraction
  - Secure-Template Fingerprint Verification
- New benchmark areas planned
  - Fingerprint Indexing
  - Fingerprint Identification (1:N)
  - Minutiae extraction accuracy
- New benchmarks with synthetic datasets
  - Large datasets for Fingerprint Orientation Extraction (orientation ground-truth can be automatically generated by SFinGe)
  - Datasets for Minutiae Extraction Accuracy (minutiae ground-truth automatically generated by SFinGe)

SFinGe (the Italian for Sphinx, pron. *sphin-je*)

A software able to synthetically (randomly) generate large databases of realistic fingerprint images with ground truth data (minutiae, local orientations, …)

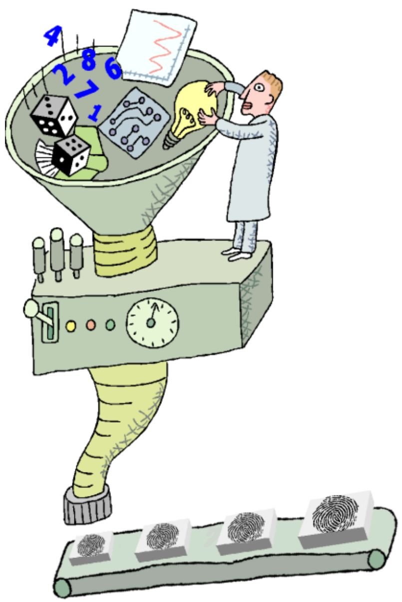
Synthetic fingerprint generation



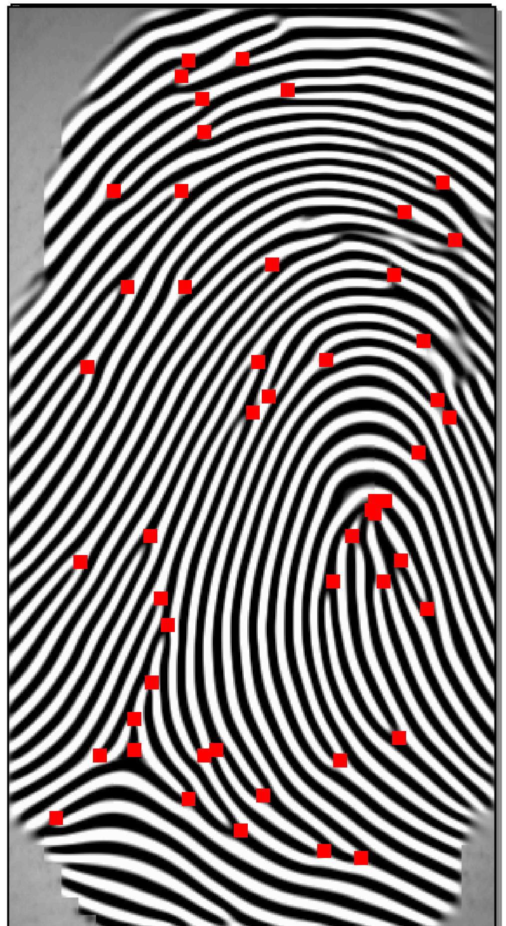
Collecting large databases of fingerprint images is:

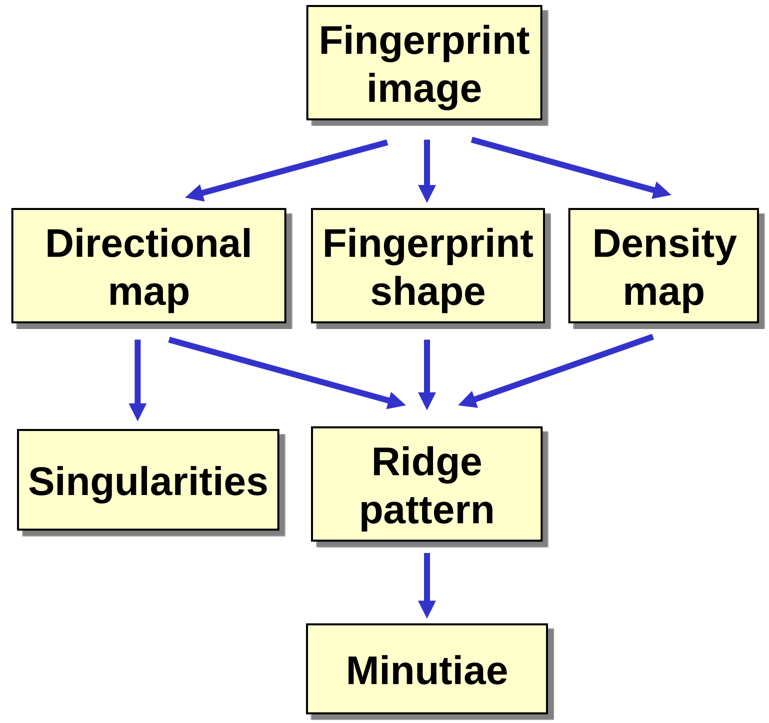
- expensive both in terms of money and time
- boring for both the people involved and for the volunteers, which are usually submitted to several acquisition sessions at different dates
- problematic due to the privacy legislation which protects such personal data

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

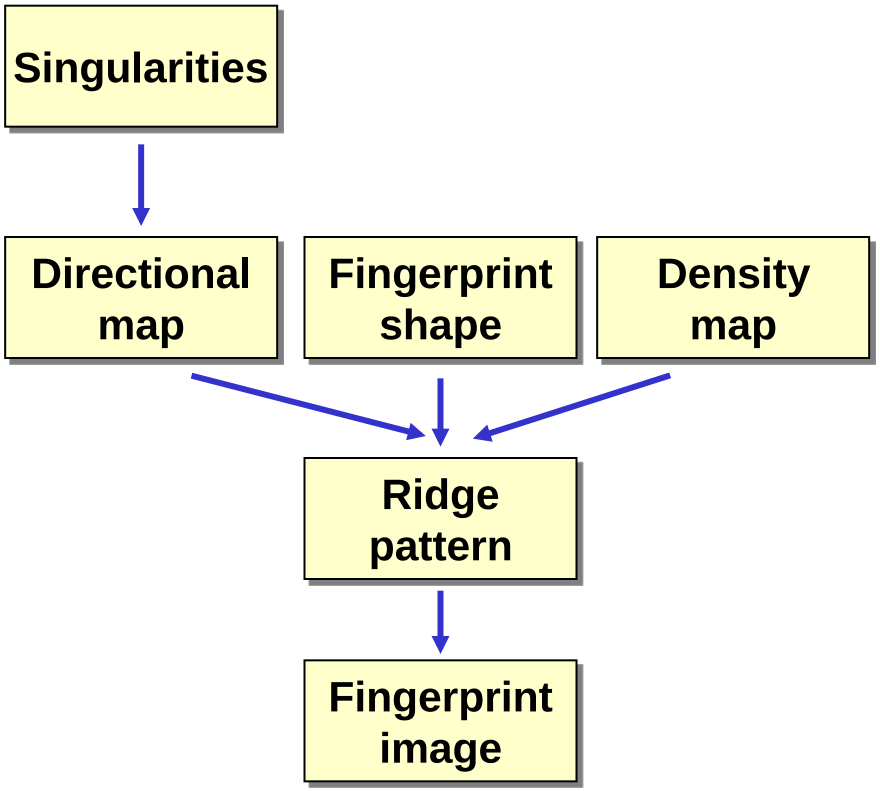


Typical feature extraction from a real fingerprint

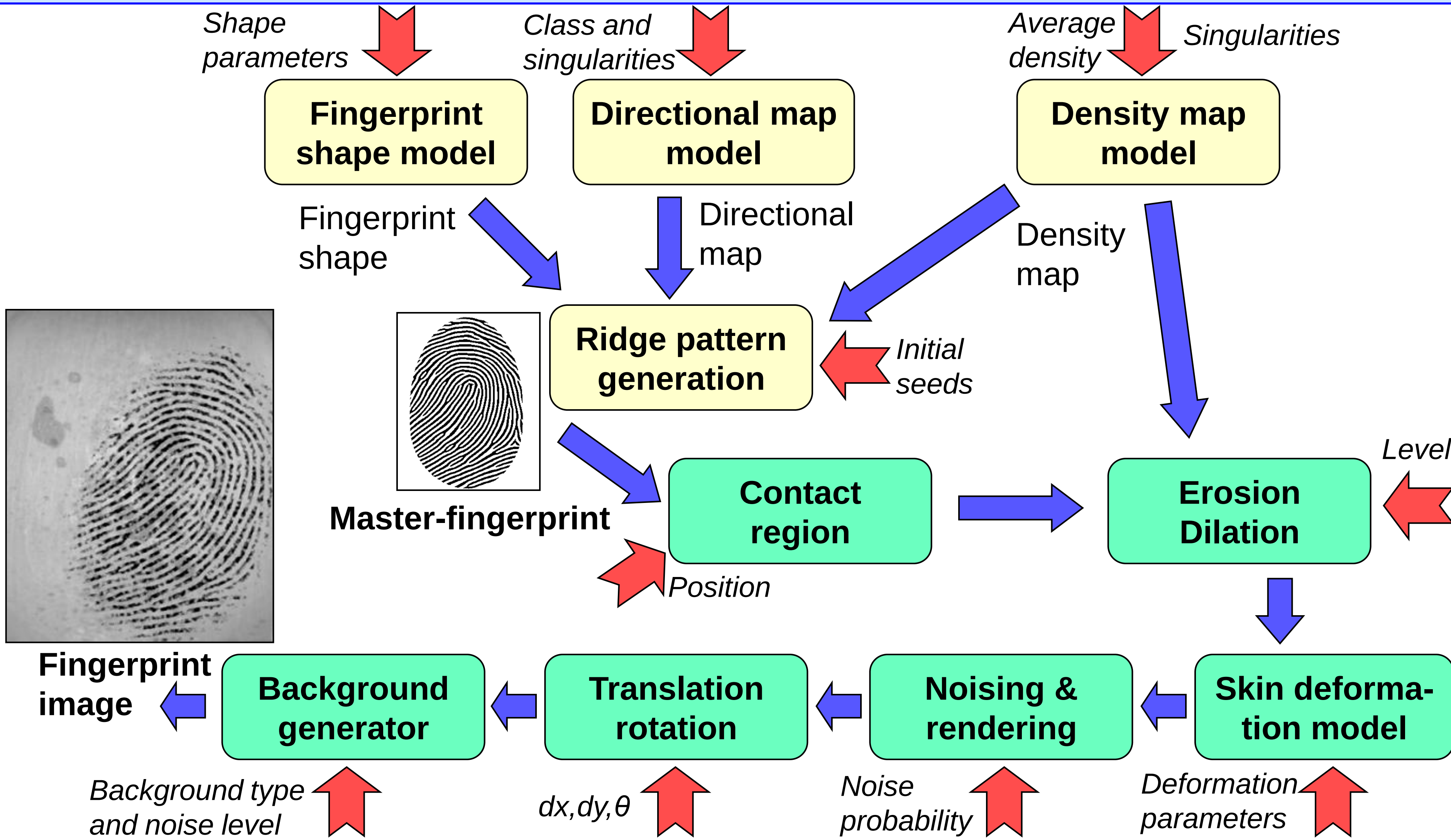




How SFinGe works (2)



How SFinGe works (3)

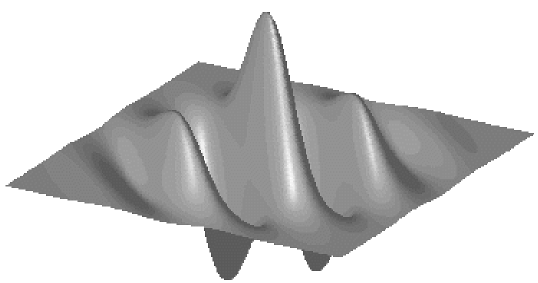


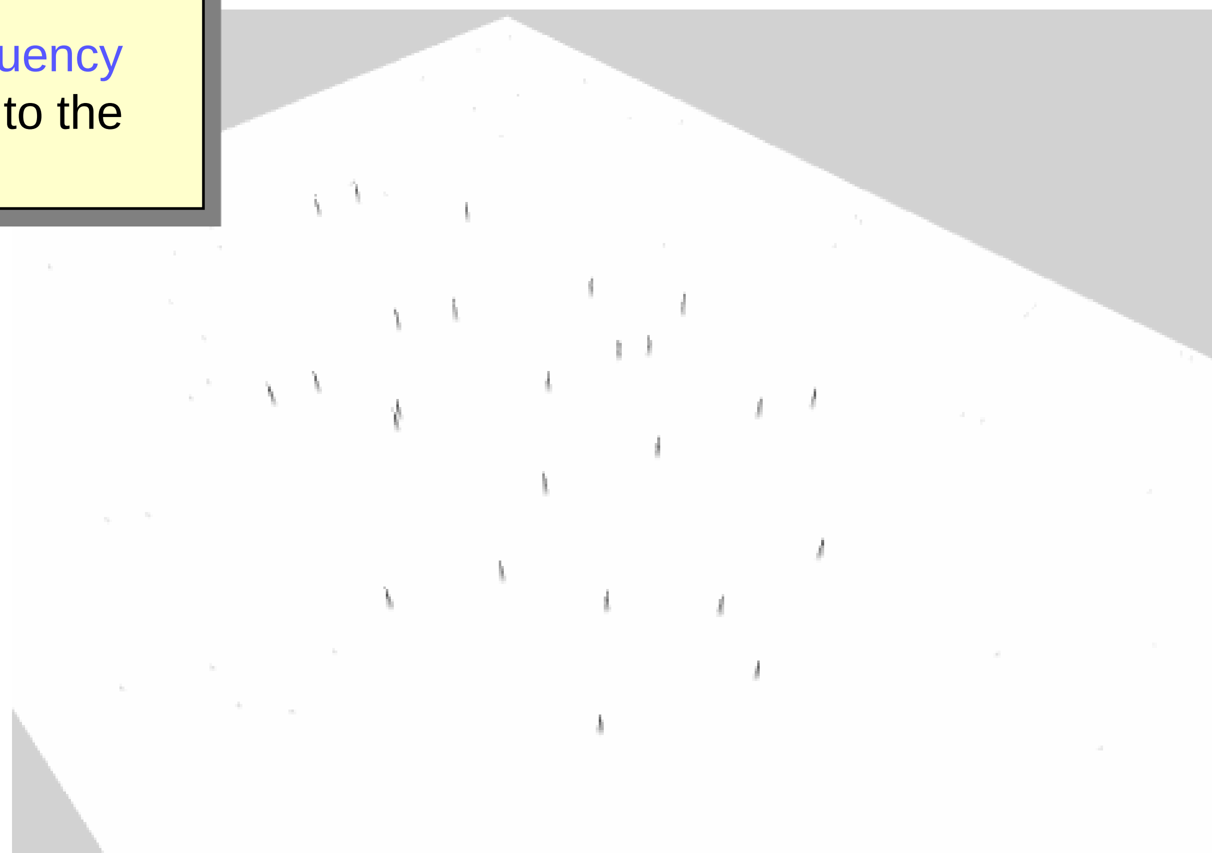
Ridge pattern generation

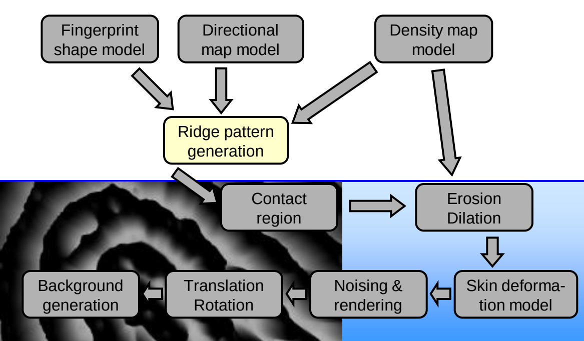
Gabor-like filters are iteratively applied to an initially-white image, enriched with few random points.

The filters orientation and frequency are locally adjusted according to the directional and density maps.

Realistic minutiae appear at random positions

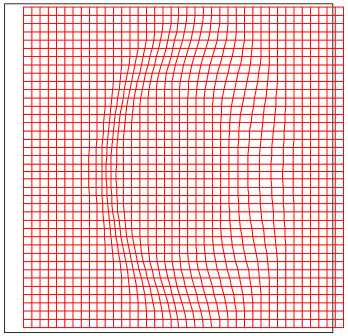


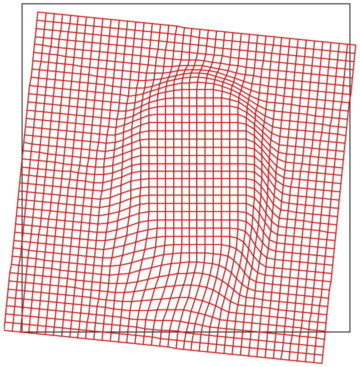


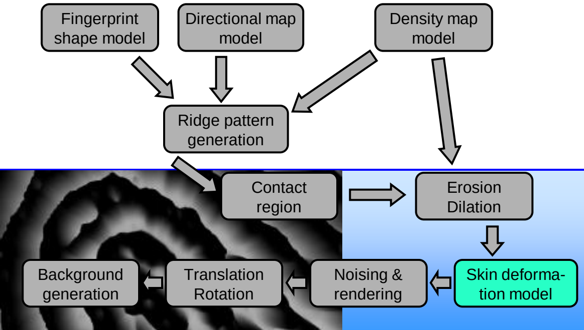


Simulating skin distortion

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





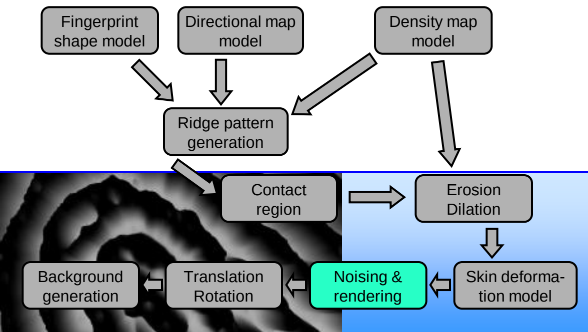


Noising and rendering

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

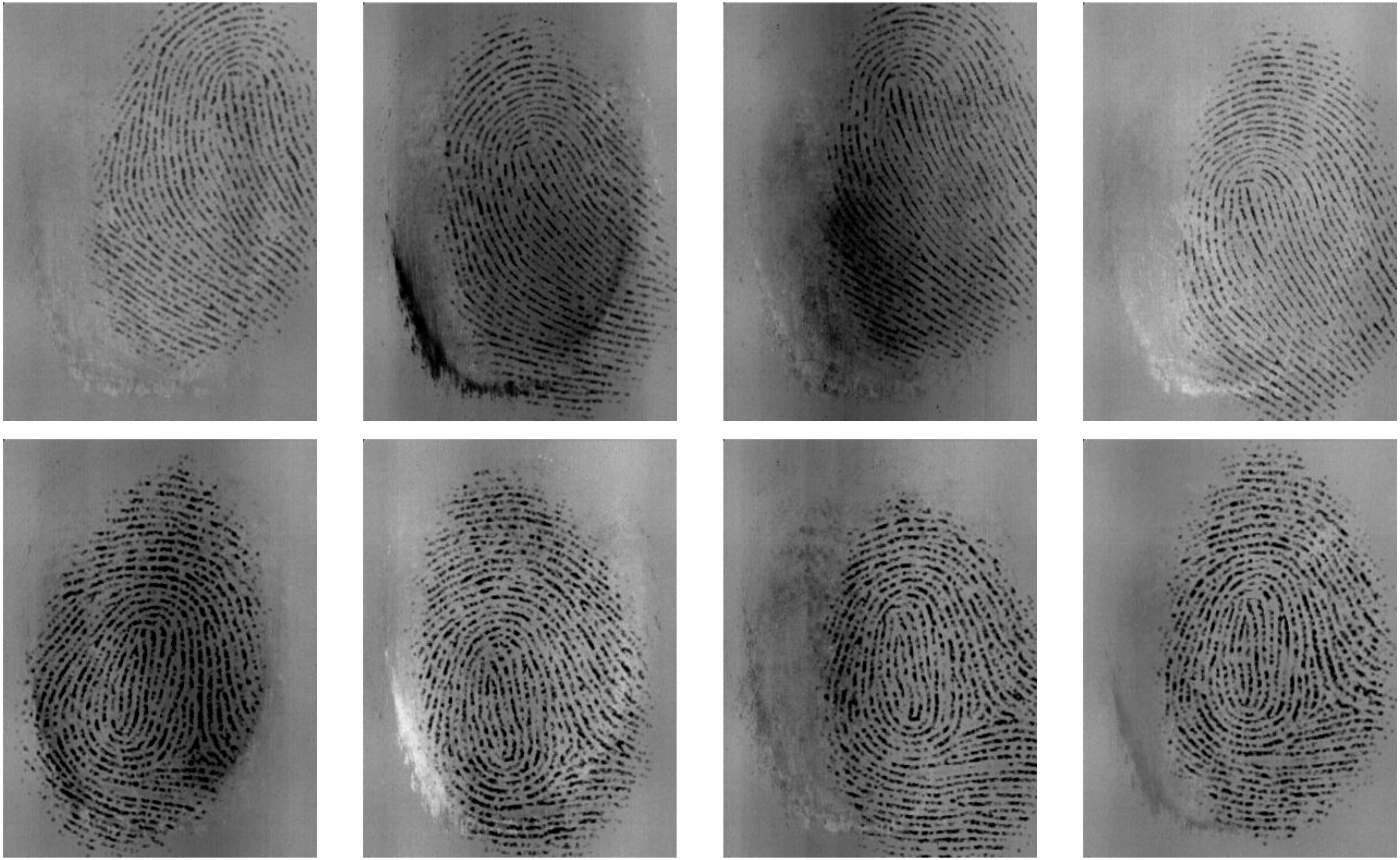
SFinGe adds specific noise and applies an ad-hoc smoothing process to simulate real-fingerprints irregularities



Examples


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

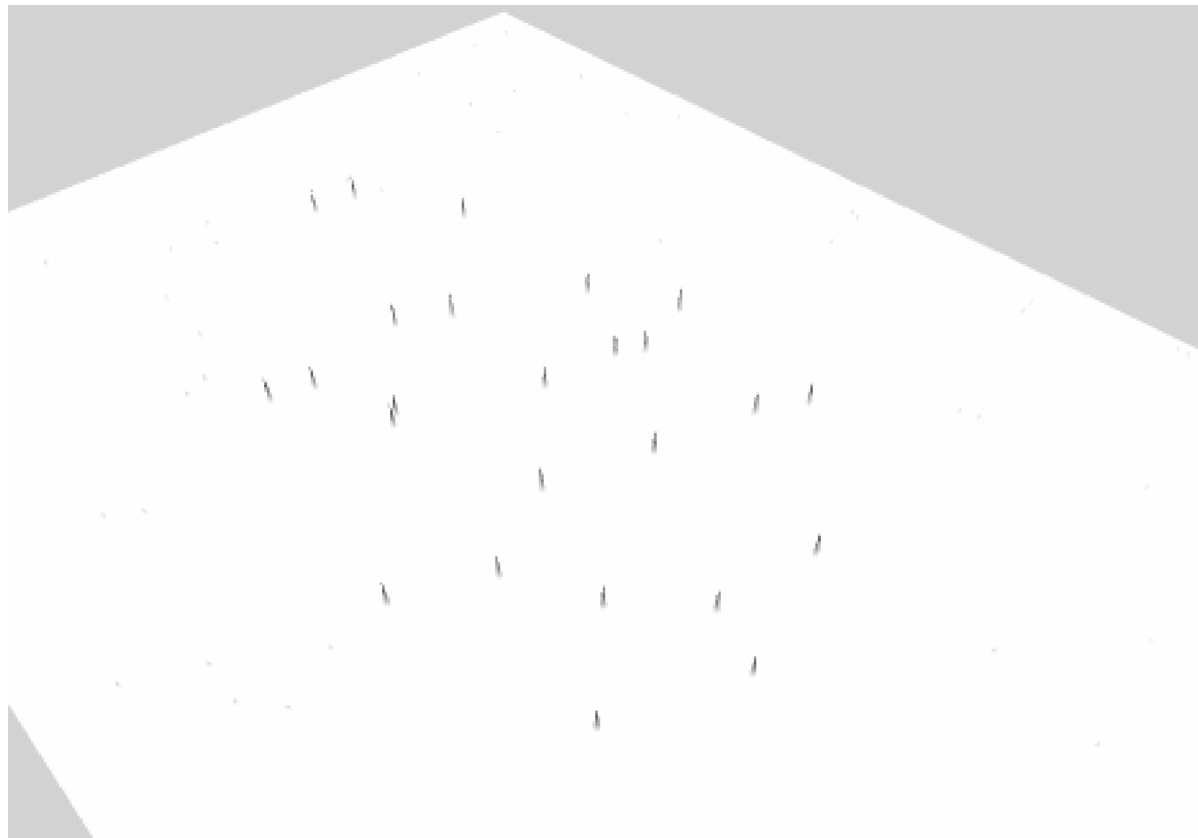
Examples (2)



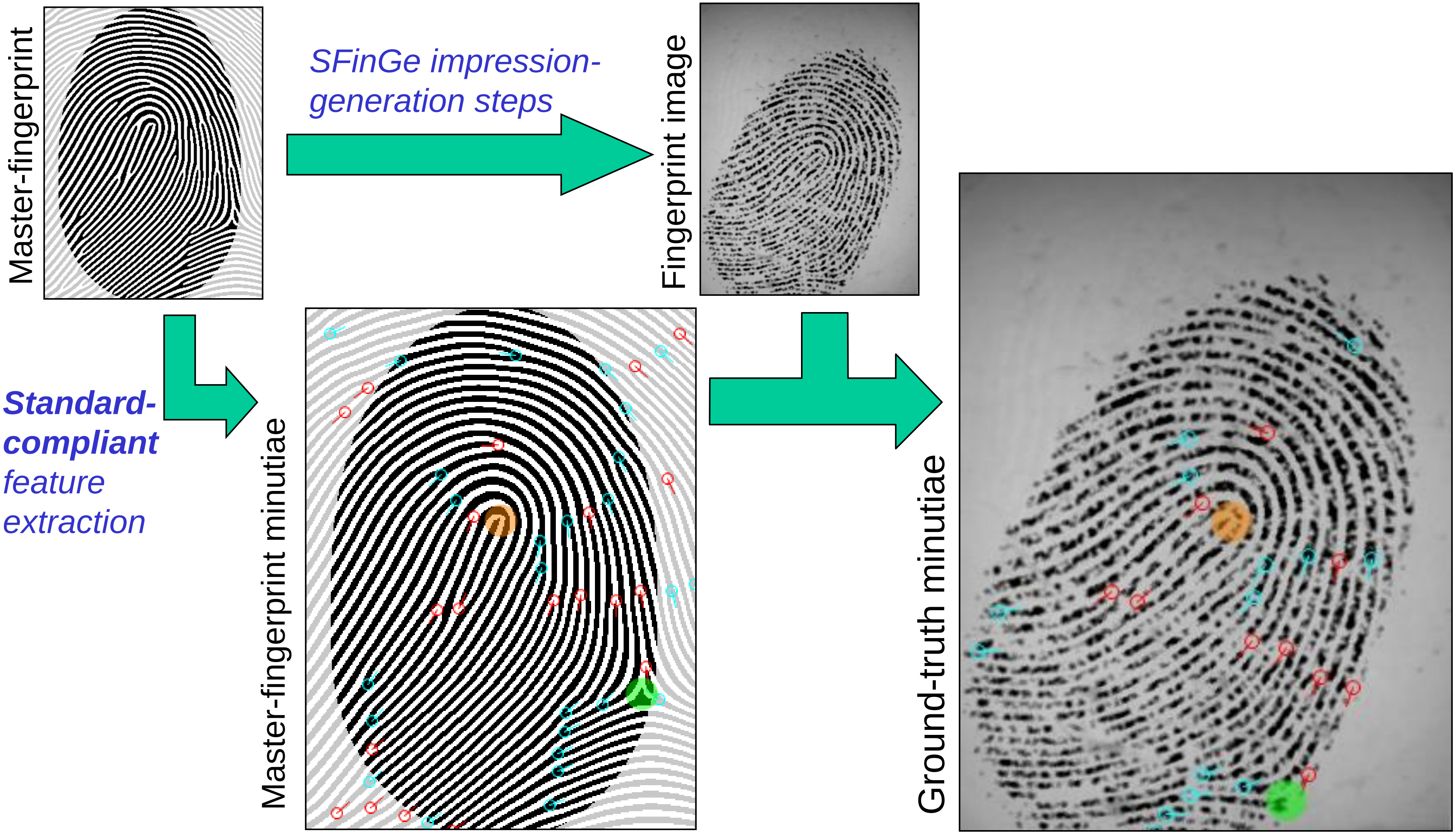
SFinGe: generation of minutiae ground-truth

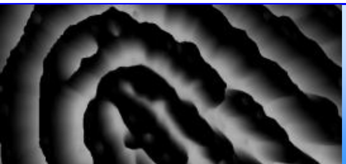
SfinGe "master fingerprints" are "ideal" fingerprint patterns

SfinGe "master fingerprints" are well-suited for applying the precise minutiae extraction procedures that are being proposed as ANSI and ISO standards.



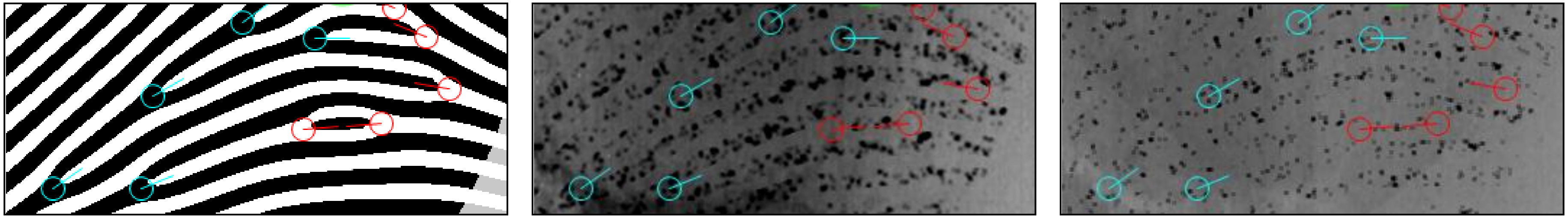
Automatic generation of the *ground-truth*





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)

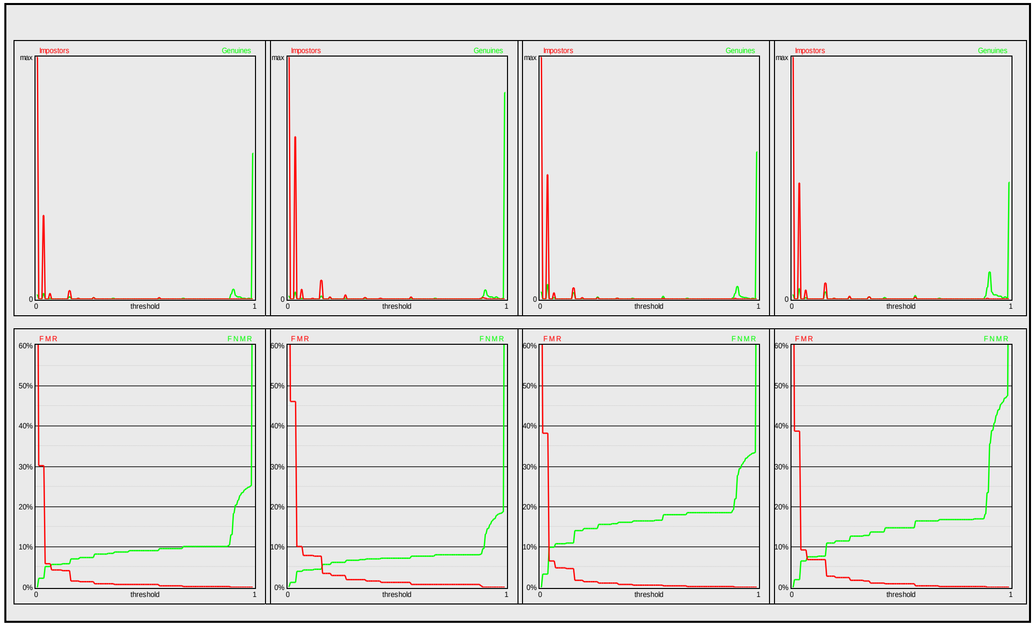
FVC2000

Fingerprint Verification Competition

A test has been performed in conjunction with FVC2000, where one of the four DB used (DB4) was synthetically generated by SFinGe:

- The participant algorithms performed on DB4 similarly to the other DBs
- The genuine/impostor distributions and the ROC curves are also very close

DB1 (real) **DB2 (real)** **DB3 (real)** **DB4 (Synthetic)**



This proves that the main inter-class and intra-class variation of fingerprints in nature are well captured by SFinGe

SFinGe validation (3)

FVC2002 Fingerprint Verification Competition

A more systematic analysis was performed on FVC2002 results.

$$RRD_i^{(j)} = \frac{\left|R_{i1}^{(j)} - R_{i2}^{(j)}\right| + \left|R_{i1}^{(j)} - R_{i3}^{(j)}\right| + \left|R_{i2}^{(j)} - R_{i3}^{(j)}\right|}{3}$$

is the average ranking difference of algorithm i according to indicator j, among the three real databases; indicates how stable is the performance of algorithm i (according to indicator j) over the three databases

$$SRD_i^{(j)} = \frac{\left|R_{i4}^{(j)} - R_{i1}^{(j)}\right| + \left|R_{i4}^{(j)} - R_{i2}^{(j)}\right| + \left|R_{i4}^{(j)} - R_{i3}^{(j)}\right|}{3}$$

is the average ranking difference of algorithm i according to indicator j, between the synthetic database and each of the real database; denotes the amount of variation between synthetic and real databases

SFinGe validation (4)

The results are quite surprising !

The difference between DB4 (the synthetic DB) and the others are even smaller than the inter-difference among the three real databases.

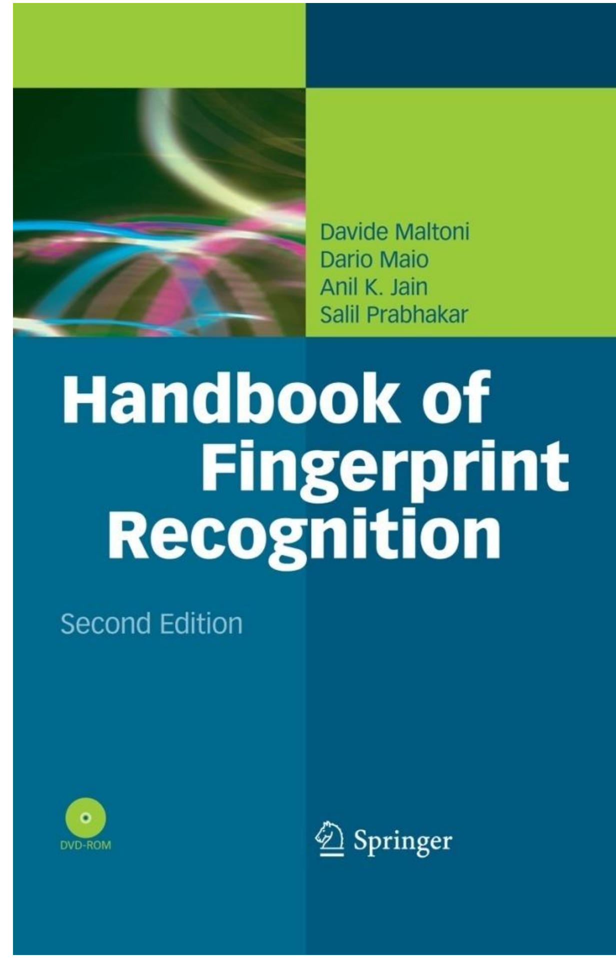
	EER		*ZeroFMR*		*FMR1000*		*FMR100*	
	$RRD_i^{(1)}$	$SRD_i^{(1)}$	$RRD_i^{(2)}$	$SRD_i^{(2)}$	$RRD_i^{(3)}$	$RD_i^{(3)}$	$RD_i^{(4)}$	$RD_i^{(4)}$
Average	2.84	2.65	3.14	2.74	2.58	2.58	2.69	2.59
Max	8.67	11.33	11.33	7.67	7.33	5.67	8.00	10.67
Min	0.00	0.00	0.67	0.33	0.00	0.33	0.00	0.33
St. Dev.	2.51	2.43	2.35	1.76	1.94	1.45	2.15	2.36

Handbook of Fingerprint Recognition

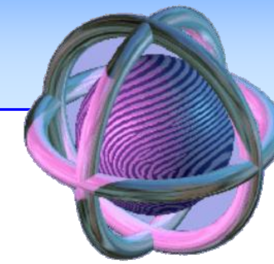
- The book includes results of BioLab research and provides an updated snapshot of the current state-of-the-art in fingerprint recognition.
- More details on the topics of this lecture can be found in this book.

The second edition (a major update) has been recently published by Springer

http://bias.csr.unibo.it/maltoni/handbook



References



- Web sites
  - http://biolab.csr.unibo.it (BioLab web site)
  - http://biolab.csr.unibo.it/FVConGoing (FVC-onGoing web site)

- Books

  - *Handbook of Fingerprint Recognition (Second Edition)*, by D. Maltoni, D. Maio, A.K. Jain and S. Prabhakar, Springer, 2009.
  - *Biometric Systems - Technology, Design and Performance Evaluation* by J.L. Wayman, A.K. Jain, D. Maltoni and D. Maio (Eds), Springer, 2005.

- Selected (recent) papers :

  - R. Cappelli, D. Maio, D. Maltoni, J.L. Wayman and A.K. Jain, *Performance Evaluation of Fingerprint Verification Systems*, IEEE Trans. on PAMI, 2006.
  - R. Cappelli, A. Lumini, D. Maio and D. Maltoni, *Fingerprint Image Reconstruction from Standard Templates*, IEEE Trans. on PAMI, 2007.
  - R. Cappelli, M. Ferrara and D. Maltoni, *On the Operational Quality of Fingerprint Scanners*, IEEE Trans. on IFS, 2008.
  - R. Cappelli and D. Maltoni, *On the Spatial Distribution of Fingerprint Singularities*, IEEE Trans. on PAMI, 2009.
  - R. Cappelli, M. Ferrara and D. Maltoni, *Minutia Cylinder-Code: a new representation and matching technique for fingerprint recognition*, IEEE Trans. on PAMI 2010.
  - R. Cappelli, M. Ferrara and D. Maltoni, *Fingerprint Indexing based on Minutia Cylinder-Code*, IEEE Trans. on PAMI, 2011.
  - R. Cappelli, M. Ferrara and D. Maio, *Candidate List Reduction based on the Analysis of Fingerprint Indexing Scores*, IEEE Trans. on IFS, to appear.
  - F. Turroni, D. Maltoni, R. Cappelli and D. Maio, "*Improving Fingerprint Orientation Extraction*, IEEE Trans. on IFS, 2011.
  - R. Cappelli, *Fast and Accurate Fingerprint Indexing based on Ridge Orientation and Frequency,* IEEE Trans. on SMC-B, to appear.