Fingerprint Recognition

IDEMIA

10/5/2020

Fingerprint recognition

1. Fingerprint recognition, history and context : what you know

What you know about fingerprints

Good quality fingerprint

Bad quality fingerprint

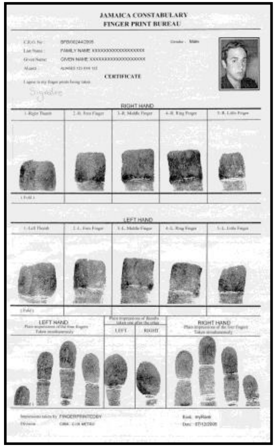
Passport

Used by the FBI to identify criminals in a cool way !

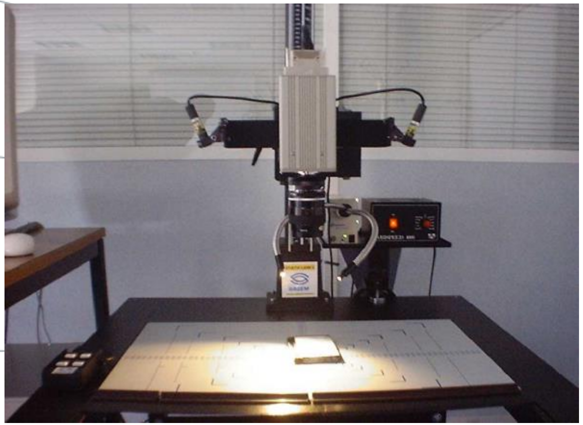
1. Fingerprint recognition, history and context : devices

What it actually includes

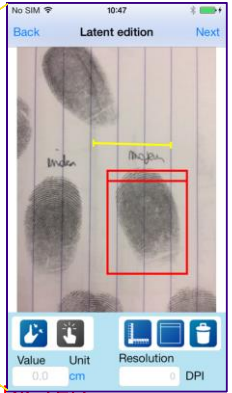
Latent fingerprints



10print files



Laboratory acquisition workstation



LIVESCAN DEVICES

OEM MODULES

ACCESS CONTROL TERMINALS

1. Fingerprint recognition, history and context : brief history

History of fingerprint recognition

- BC: babylon used fingerprints
- 7th century : Chinese people used fingerprints as signature
- 1686: description of pattern
- 1877: Herschel : uniqueness and identification
- 1892: Galton classification system
- 1902: Scheffer Henri Leon case by Bertillon
- 1924: Inauguration of the FBI system (810.000 fingerprints)
- 1960: FBI system: 75.000.000 fingerprints

1. Fingerprint recognition: Principles of biometric identification

Immutability

Do not change naturally during the life of a person

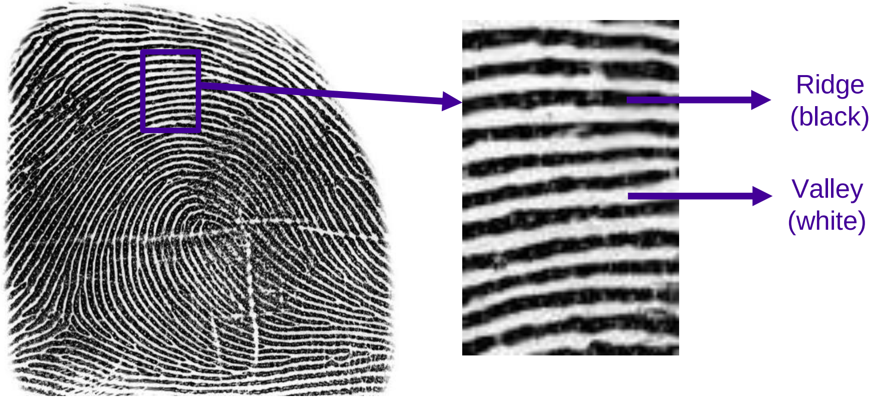
Uniqueness

No two people have ever been found to be identical

2. Fingerprint images: ridges, valleys, cores and deltas

Ridges and valleys

- Ridge width: 0,100mm – 0,300mm
- Ridge-valley periodicity: ~0,500mm



Full fingerprint

Singularities

- Loop: maximum curvature
- Whorl: 2 loops facing each other
- Delta: 3 ridges directions converging to a single point

Whorl

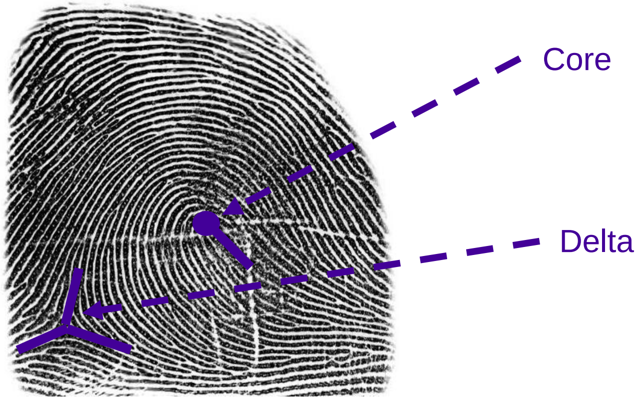
Whorl

Delta

2. Fingerprint images: level 1 information

One image to be recognized among all

- Level 1 information: Pattern
- 4 principal patterns (derived from cores/deltas):



Left loop (~30%)
Core on the left, Delta on the right

Right loop (~30%)
Core on the right, Delta on the left

Whorl (~35%)
2 Cores (up and down), 2 Deltas

Arch (~5%)
No core, no delta

2. Fingerprint images: level 1 information

In-between patterns

- The pattern space is continuous

Double-loop (close to whorl)

Whorl abnormality

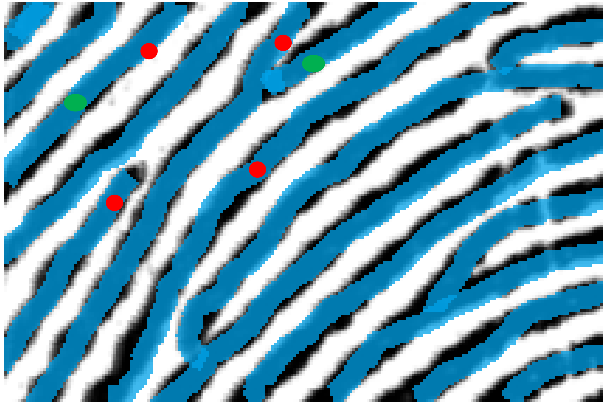
Mini-loop (~arch)

…

2. Fingerprint images: level 2 information

One image to be recognized among all

- Level 2 information: Characteristic points: minutiaes, cores, deltas

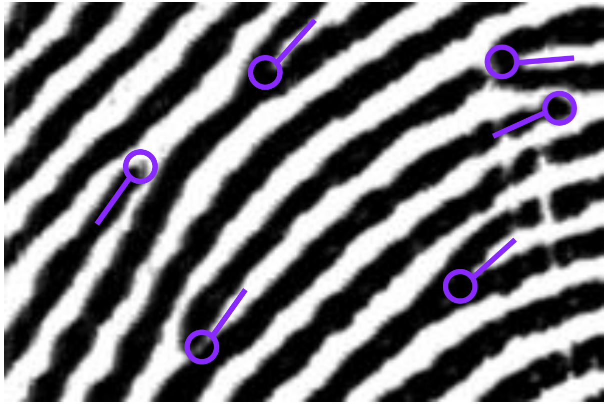


Ridge

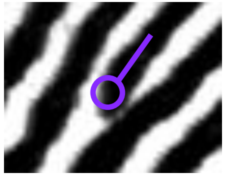
A ridge which ends abruptly

A ridge which divides into 2 ridges

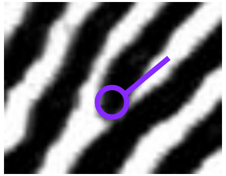
Data representation



For robustness



If detected as ridge ending

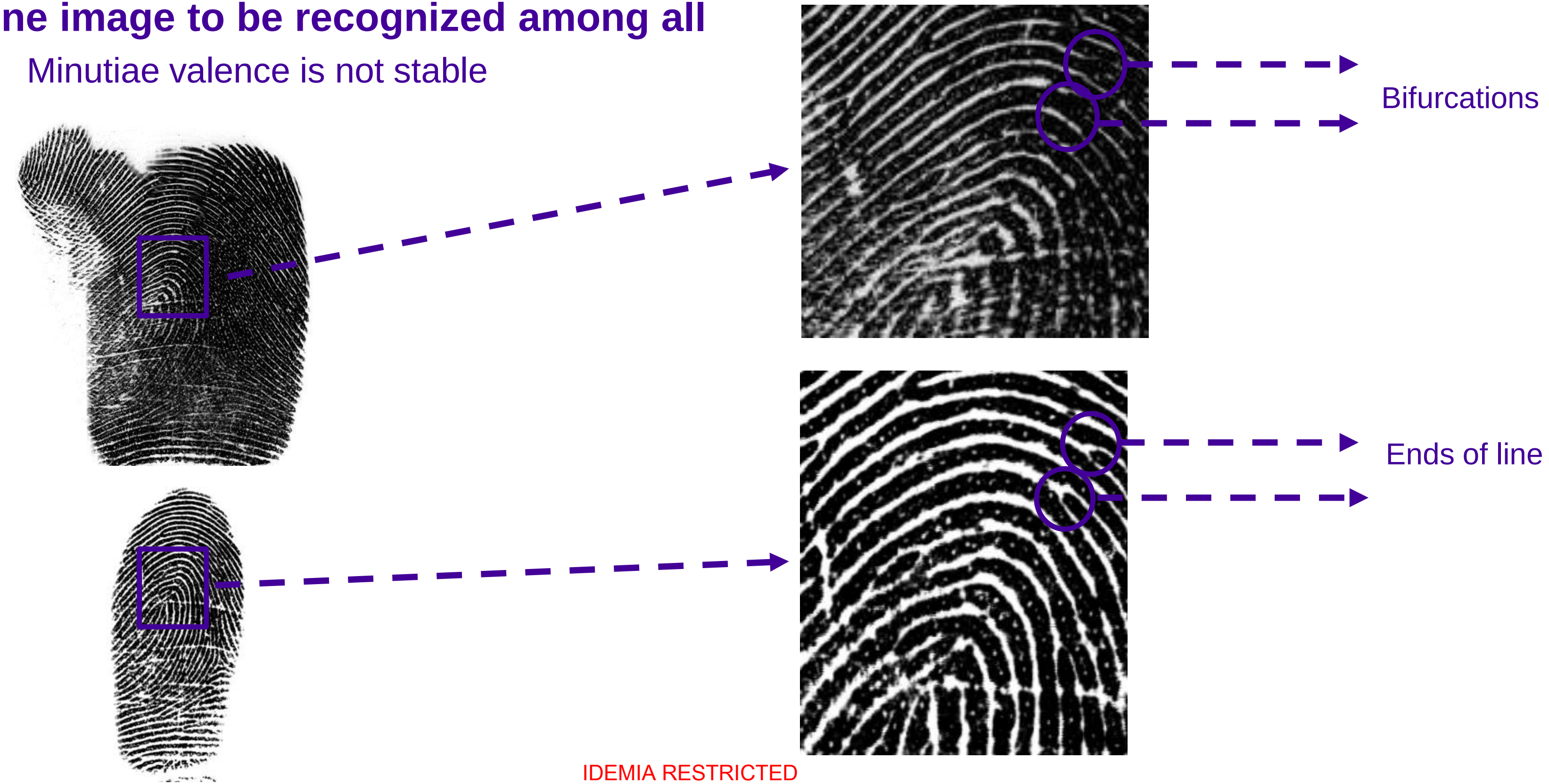


If detected as ridge bifurcation

2. Fingerprint images: level 2 information

One image to be recognized among all

- Minutiae valence is not stable



2. Fingerprint images: level 2 information

One image to be recognized among all

- Additionnal minutiae types

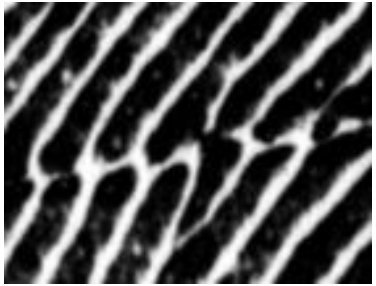
Island

Spur

Lake

Independent ridge

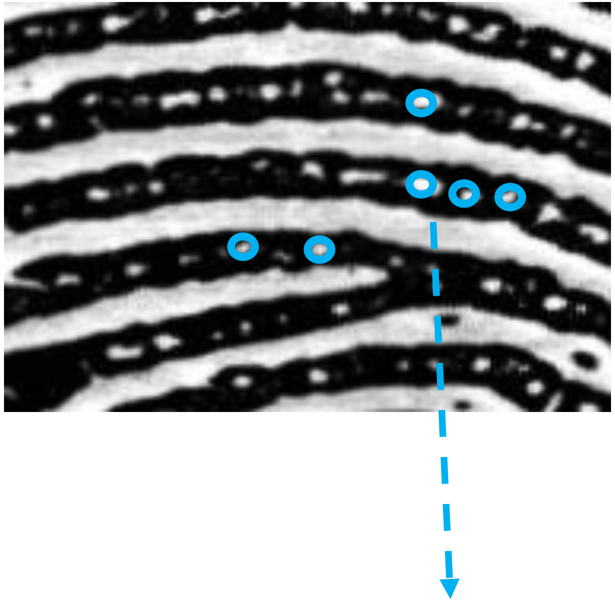
- Impact of scars ➔ minutiae extractor algorithm needs to be robust



2. Fingerprint images: level 3 information

One image to be recognized among all

- Level 3 information: Pores, ridge shape, incipient ridges, scars, creases, deformations…

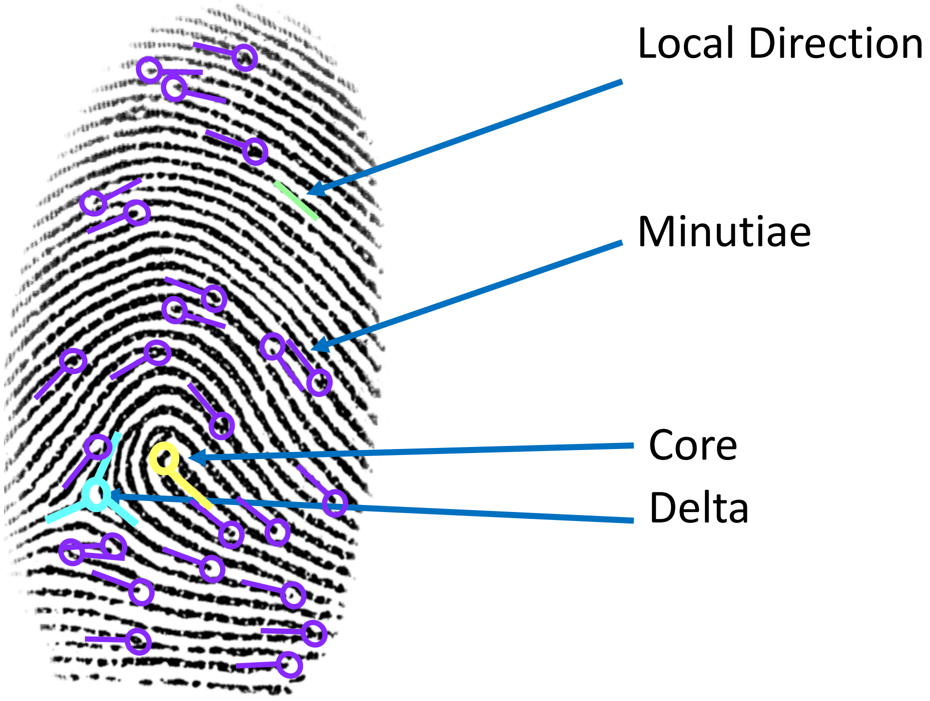


But pores are not consistent with acquisitions
This example: same finger, same day, different sensor

2. Fingerprint images: all included

One image to be recognized among all

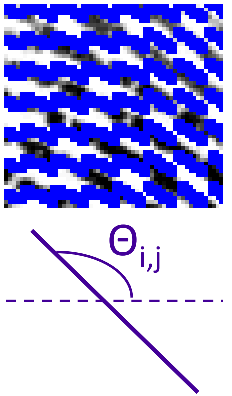
- All included



3. Characteristics extraction

a. Ridge orientation
b. Ridge frequency
c. Segmentation
d. Core/Delta detection
e. Enhancement
f. Minutiae detection
g. Ridge count
h. Fingerprint quality

3. Characteristics extraction: a) Ridge Orientation



To extract minutiae, you need to extract first the local orientation

- At pixel [x,y], local ridge orientation $\theta_{x,y}$ is in [0… 180°] (no direction)
- Orientation image is usually downsampled
- ➔ node [i,j] of the orientation image has $\theta_{i,j}$ orientation located over pixel $[x_i,y_j]$

Methods

- Gradient based methods
- Projection based methods
- Frequency domain methods
- Final step : regularization

3. Characteristics extraction: a) Ridge Orientation

Gradient based methods

- To estimate standard gradient, use of convolutionnal masks (Prewitt, Sobel…) to estimate ∇x and ∇y, then arctangent of $\nabla y / \nabla x$ ratio

$$\mathbf{G_x} = \begin{bmatrix} +1 & 0 & -1 \\ +1 & 0 & -1 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \quad \mathbf{G_y} = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * \mathbf{A}$$

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \quad \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * \mathbf{A}$$

Can be decomposed as averaging and diffentiation

$$\begin{bmatrix} +1 & 0 & -1 \\ +1 & 0 & -1 \\ +1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \begin{bmatrix} +1 & 0 & -1 \end{bmatrix}$$

$$\mathbf{G}_x = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} * \left(\begin{bmatrix} +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \right)$$

Prewitt

$$\mathbf{G} = \sqrt{\mathbf{G}_x{}^2 + \mathbf{G}_y{}^2}$$

$$\mathbf{\Theta} = \operatorname{atan2}(\mathbf{G}_y, \mathbf{G}_x)$$

Sobel

3. Characteristics extraction: a) Ridge Orientation

Gradient based methods

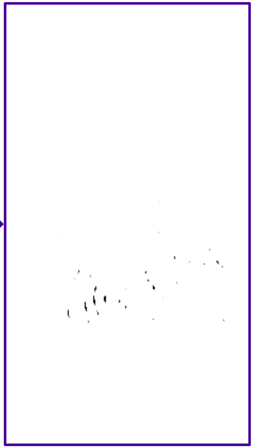
- To extract characteristics : set of filters with different frequencies and orientations
- Gabor filters :

$$G_c[i,j] = Be^{-\frac{(i^2+j^2)}{2\sigma^2}} \cos(2\pi f(i\cos\theta + j\sin\theta))$$

$$G_s[i,j] = Ce^{-\frac{(i^2+j^2)}{2\sigma^2}} \sin(2\pi f(i\cos\theta + j\sin\theta))$$

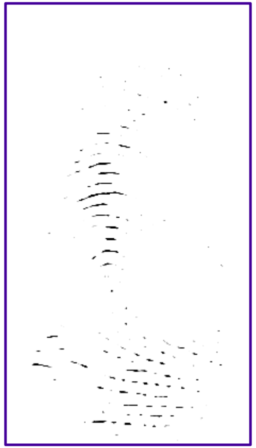
f: frequency
ϑ: orientation
σ: region size

Input image

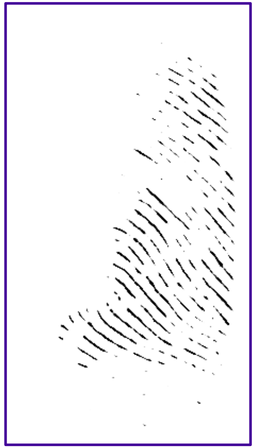


Gabor 0°

Gabor 45°



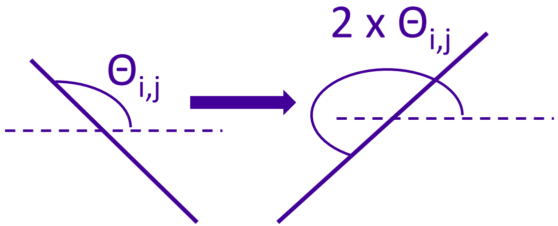
Gabor 90°



Gabor 135°

3. Characteristics extraction: a) Ridge Orientation

Gradient based methods



- With a gradient estimation, we get $\boldsymbol{\theta = atan2(\nabla_y, \nabla_x)}$
- However, 0° and 179° are not quasi-opposites in our 180°-modulo definition
- ➔ Double angle to find twice the angle, and finally divide by 2
- $\boldsymbol{estimated\ orientation: (1) d = [r.cos(2\theta), r.sin(2\theta)]}$

  Where r is the gradient response intensity (for example $\boldsymbol{r} = ||\boldsymbol{\nabla x, \nabla y}||^2$)

- However (bis), gradient estimation in one point is very susceptible to noise
- ➔ Average on a window W of size n x n
- $\boldsymbol{robust\ estimated\ orientation: (2) d} = \left[\frac{\boldsymbol{1}}{\boldsymbol{n}^2}\sum_W r.\cos(2\theta)\ , \frac{\boldsymbol{1}}{\boldsymbol{n}^2}\sum_W r.\sin(2\theta)\right]$

3. Characteristics extraction: a) Ridge Orientation

Gradient based methods

- However (ter), 2 vectors facing each other are canceled, whatever its orientation
- ➔ we use both directions
- $(3)\boldsymbol{\theta_{ij} = 90° + \frac{1}{2} atan2(2G_{xy}, G_{xx} - G_{yy})}$

with $G_{xy} = \sum_{h=-S}^{S} \sum_{k=-S}^{S} \nabla_x(x_i + h, y_j + k)\nabla_y(xi + h, yj + k)$

$G_{xx} = \sum_{h=-S}^{S} \sum_{k=-S}^{S} \nabla_x(xi + h, yj + k)^2$

$G_{yy} = \sum_{h=-S}^{S} \sum_{k=-S}^{S} \nabla_y(xi + h, yj + k)^2$

Ratha, Chen, and Jain (1995)

➔ *Estimate dominant ridge orientation on a (2S+1)x(2S+1) window centered at [x_i,y_j]*

∇_x and ∇_y can be estimated via Sobel masks (or other methods)

3. Characteristics extraction: a) Ridge Orientation

Gradient based methods

- From $(3)\boldsymbol{\theta_{ij}} = \mathbf{90°} + \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{atan}\mathbf{2}(\mathbf{2}\boldsymbol{G_{xy}}, \boldsymbol{G_{xx}} - \boldsymbol{G_{yy}})$
- We can define the confidence value by the norm of the sum of orientation vectors ➔ [0,1], close to 1 when all vectors are in the same direction
- $(\mathbf{4})\boldsymbol{coherence}(\boldsymbol{\theta_{ij}}) = \boldsymbol{x} = \frac{|\sum_W \boldsymbol{d}|}{\sum_W |\boldsymbol{d}|} = \frac{\sqrt{(\boldsymbol{G_{xx}} - \boldsymbol{G_{yy}})^2 + 4\boldsymbol{G_{xy}}^2}}{\boldsymbol{G_{xx}} + \boldsymbol{G_{yy}}}$

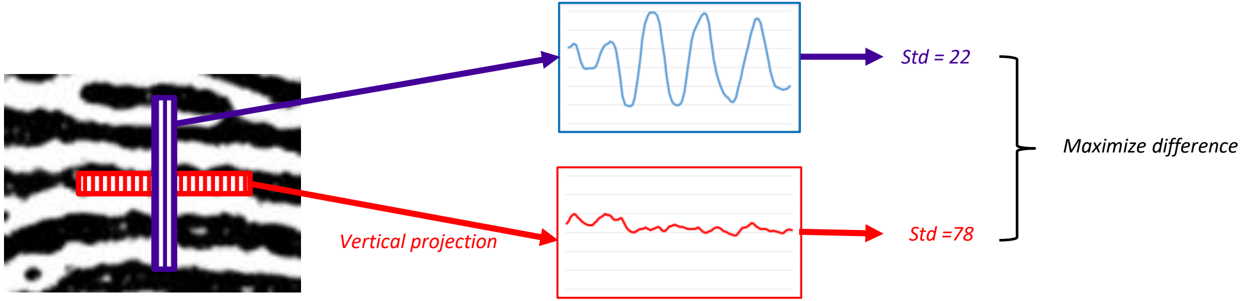
  Kass and Watkins (1987)

- Drawback : derivatives can be close to 0 when in the middle of ridges or valleys
- ➔ look further than 1st degree derivative

3. Characteristics extraction: a) Ridge Orientation

Projection based methods

- Define a fixed set of reference orientations (slits) : $\boldsymbol{S_k = k\frac{\pi}{N}}$, $\quad \mathbf{k = 0 \ldots N-1}$
- ➔ Goal : select the best S_k at all $[x_i,y_j]$, then we have $\boldsymbol{\theta_{ij} = S_{k-opt}}$
- For example, projection of greyscale on given direction vs orthogonal direction



- $k^{*} = \underset{k}{argmax}|stdev(S_k) - stdev(S_{Orth(k)})|, \quad Orth(k) = \left(k + \frac{N}{2}\right) mod[N]$

Oliveira and Leite (2008)

- $k_{opt} = \begin{cases} k^{*} & if\ stdev(S_{k}{}^{*}) < stedev(S_{Orth(_k{}^{*})}) \\ Orth(k^{*}) & Otherwise \end{cases}$

3. Characteristics extraction: a) Ridge Orientation

Frequency domain methods

- Short Time Fourier Transform (STFT) analysis ➔ image divided into blocks
- $F(u,v)$: Fourier Transform of each block, $|F(u,v)|$ spectrum mapped to polar coord. $|F(r,\theta)|$
- Then, probability of given \theta (within the block) is computed as the marginal density function:
- $p(\theta) = \int_r \; p(r,\theta)dr\,, \quad where\; p(r,\theta) = \frac{|F(r,\theta)|}{\iint_{r,\theta}|F(r,\theta)|drd\theta}$
- Then, expected value of θ is computed as previously as :
- $E\{\theta\} = 90° + \frac{1}{2}atan2(\int_\theta \; p(\theta)\sin(2)\,d\theta\,, \int_\theta \; p(\theta)\cos(2)\,d\theta)$

Chikkerur, Cartwright, and Govindaraju (2007)

3. Characteristics extraction: a) Ridge Orientation

Final step: regularization

- Possible inconsistencies in the local orientations
- ➔ use the fingerprint as a whole to regularize it. For example, by a polynomial approach :

$$U = R + iI = \cos(2\theta) + i\sin(2\theta)$$

Modelize orientation map as a complex

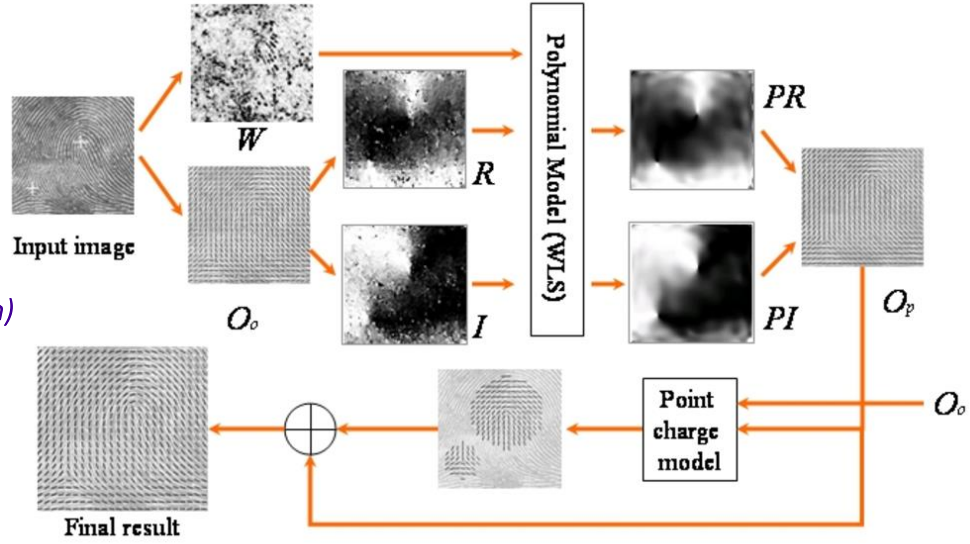
$$\begin{pmatrix} 1 & x & \cdots & x^n \end{pmatrix} \begin{bmatrix} p_{00} & p_{01} & \cdots & p_{0n} \\ p_{10} & p_{11} & \cdots & p_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n0} & p_{n1} & \cdots & p_{nn} \end{bmatrix} \begin{pmatrix} 1 \\ y \\ \vdots \\ y^n \end{pmatrix}$$

Model R and I by bivariate Polynomial Model (PM) (order n)

$$PC_{core} = (H_1, H_2) = \begin{cases} \left(\frac{y-y_0}{r}, \frac{x-x_0}{r}\right) Q & r \le R \\ (0,0) & r > R \end{cases}$$

$$PC_{delta} = (H_1, H_2) = \begin{cases} \left(\frac{y-y_0}{r}, -\frac{x-x_0}{r}\right) Q & r \le R \\ (0,0) & r > R \end{cases}$$

Model Point Charge (PC) model around cores and deltas



Jinwei Gu, Jie Zhou, A Novel model for Orientation Field of Fingerprints, CVPR 2003

3. Characteristics extraction: a) Ridge Orientation

Final step: regularization

- Possible inconsistencies in the local orientations
- ➔ use the fingerprint as a whole to regularize it

$$\alpha_{PC}^{(k)}(x,y) = 1 - \frac{r^{(k)}(x,y)}{R^{(k)}} \qquad \alpha_{PM}(x,y) = \max\left(1 - \sum_{k=1}^{K} \alpha_{PC}^{(k)}, 0\right)$$

Add coefficient so that PC model is preponderent around cores and deltas

$$\begin{pmatrix} R(x,y) \\ I(x,y) \end{pmatrix} = \alpha_{PM} \cdot \begin{pmatrix} PR \\ PI \end{pmatrix} + \sum_{k=1}^{K} \alpha_{PC}^{(k)} \cdot \begin{pmatrix} H_1^{(k)} \\ H_2^{(k)} \end{pmatrix}$$

Combination model for the whole fingerprint's orientation field

➔ Use WLS (weighted Least Square) to approximate polynome

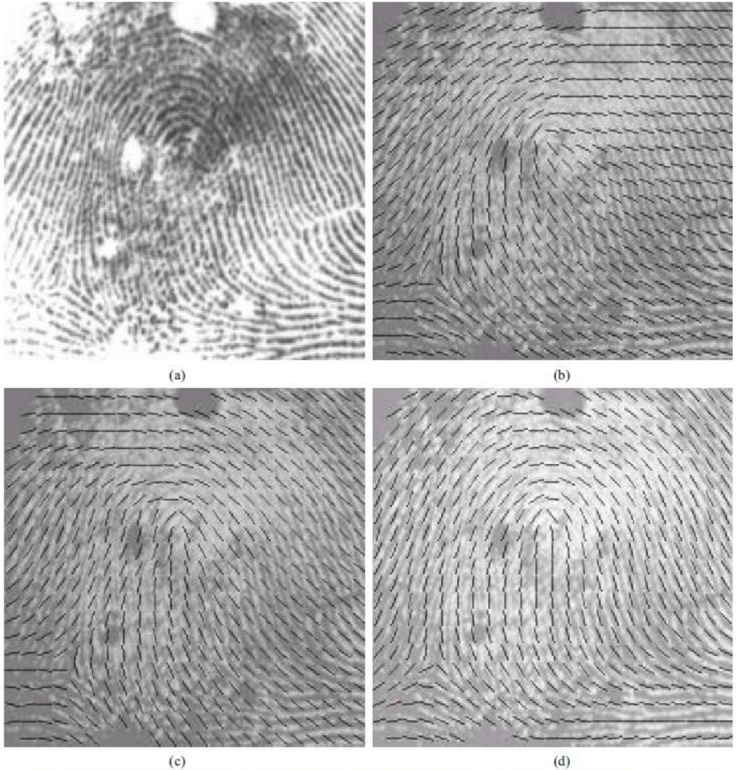


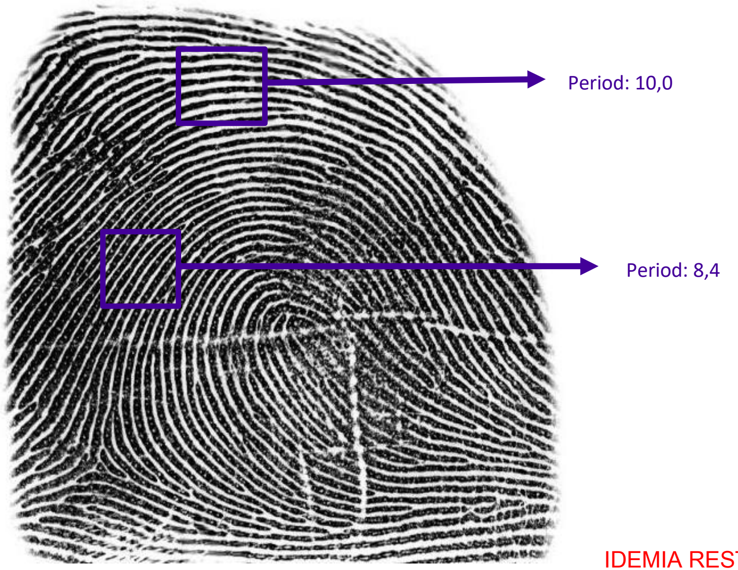
Figure 2. Reconstructed orientation of a poor-quality loop from Set 2 by three models: (a) Original fingerprint, (b) zero-pole, (c) piecewise linear model, and (d) the combination model. Zero-pole roughly describes the orientation. Piecewise linear model fails in the places far from the singular points, such as the left and the right bottom part in (c) compared with (d).

Jinwei Gu, Jie Zhou, A Novel model for Orientation Field of Fingerprints, CVPR 2003

3. Characteristics extraction: b) Ridge Frequency

Frequency estimation

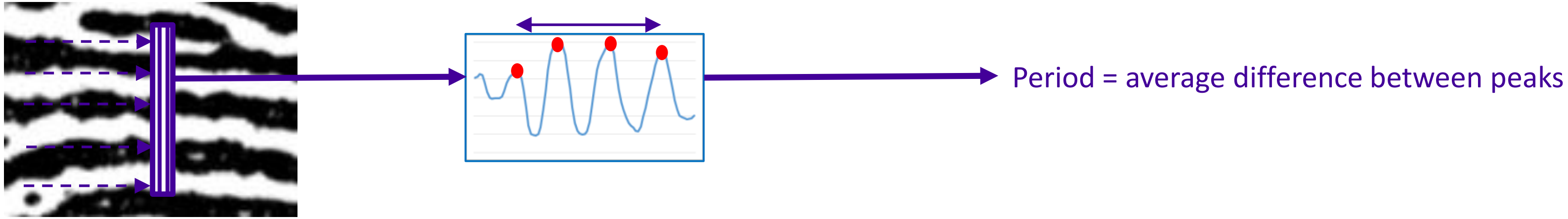
- Frequency: number of ridges per unit length at a given point along the orthogonal ridge direction
- Periodicity usually between 8 and 11 pixels @500dpi, not uniform on the whole finger
- Very valuable information to extract squeleton and, later, minutiae



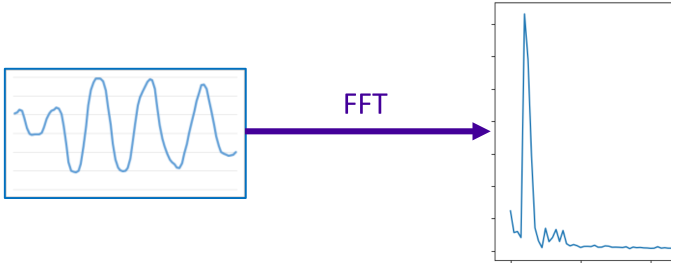
3. Characteristics extraction: b) Ridge Frequency

Projection on the orientation axis

- Average difference between peaks



- Modelisation as a sinusoidal shape (maxima in the fourier power spectrum)



3. Characteristics extraction: c) Segmentation

Confidential / Restricted / Public
Presentation or part title

Segmentation

- Delimitation of fingerprint area

$$Mean = \sum_W I$$

$$Var = \sum_W (I - Mean)^2$$

$$Coh = \frac{|\sum_W (G_{s,x}, G_{s,y})|}{\sum_W |(G_{s,x}, G_{s,y})|} = \frac{\sqrt{(G_{xx} - G_{yy})^2 + 4G_{xy}^2}}{G_{xx} + G_{yy}}$$

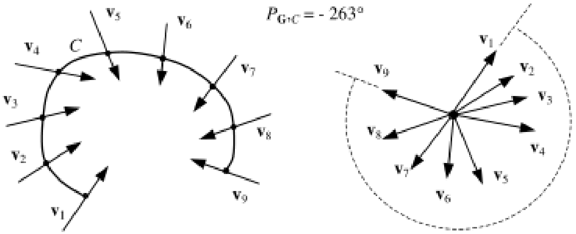
Use of mean, variance and covariance
Bazen and Gerez, ProRISC 2001, Workshop on Circuits, Systems and Signal Processing, Veldhoven, Netherlands, November 2001

- Most methods : fuse all previously extracted information (frequency, orientation, variance…)

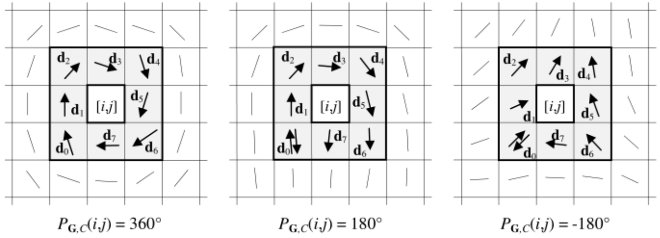
3. Characteristics extraction: d) Core and delta detection

Core and delta : singularities

- Core : maximum of curvature
- Delta : three different orientations converging to the same point
- Poincaré index (Kawagoe and Tojo, 1984) : total rotation of orientation vectors around a point



$$P_{\mathbf{G},C}(i,j) = \sum_{k=0..7} angle\left(\mathbf{d}_k, \mathbf{d}_{(k+1) \bmod 8}\right).$$



Whorl — Loop — Delta

$$P_{\mathbf{G},C}(i,j) = \begin{cases} 0° & \text{if } [i,j] \text{ does not belong to any singular region} \\ 360° & \text{if } [i,j] \text{ belongs to a whorl type singular region} \\ 180° & \text{if } [i,j] \text{ belongs to a loop type singular region} \\ -180° & \text{if } [i,j] \text{ belongs to a delta type singular region.} \end{cases}$$

Maltoni, Maio, Jain, Prabhakar, Handbook of Fingerprint Recognition

3. Characteristics extraction: e) Enhancement

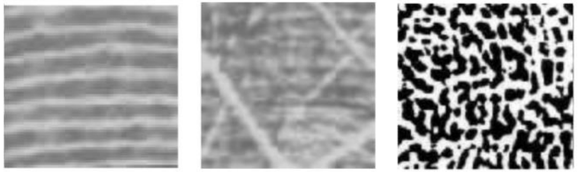
Enhancement

- Goal: improve ridges clarity and thus image quality to make minutiae extraction an easier task
- Usual issues:
  - Ridges not continuous
  - Parallel ridges not separated
  - Cuts, creases, bruises

Average quality

Bad quality

Very bad quality



(a) (b) (c)

Figure 3: Fingerprint regions; (a) well-defined region; (b) recoverable corrupted region; (c) unrecoverable corrupted region.

Fingerprint Image Enhancement, Algorithm and Performance Evaluation, Hong, Wan, Jain

3. Characteristics extraction: e) Enhancement

Pixel-wise enhancement

- New pixel value depends on old pixel value and global parameters
- Results not satisfying enough for fingerprint image enhancement but contrast stretching, histogram manipulation and normalization are effective as first step enhancement

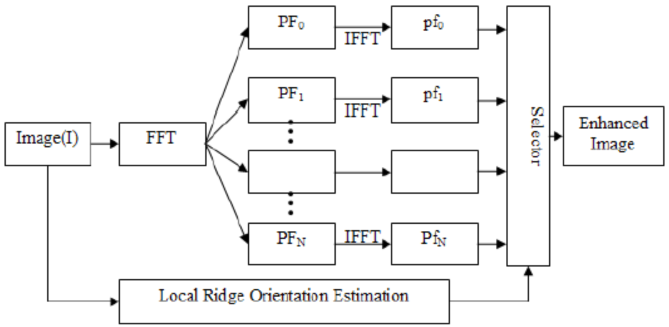
$$\mathcal{G}(i,j) = \begin{cases} M_0 + \sqrt{\frac{VAR_0(\mathcal{I}(i,j)-M)^2}{VAR}}, & \text{if } \mathcal{I}(i,j) > M \\ M_0 - \sqrt{\frac{VAR_0(\mathcal{I}(i,j)-M)^2}{VAR}}, & \text{otherwise,} \end{cases}$$

Fingerprint Image Enhancement, Algorithm and Performance Evaluation, Hong, Wan, Jain

3. Characteristics extraction: e) Enhancement

Contextual filtering

- « Contextual »: filter characteristics change according to the local context (ridge orientation and frequency)



Fingerprint Enhancement Using STFT Analysis, Chikkerur, Cartwright, Govindaraju, Center for Unified Biometrics and Sensors, University at Buffalo, NY, USA

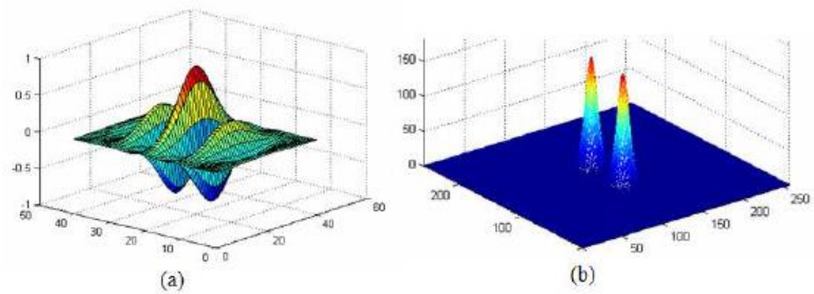


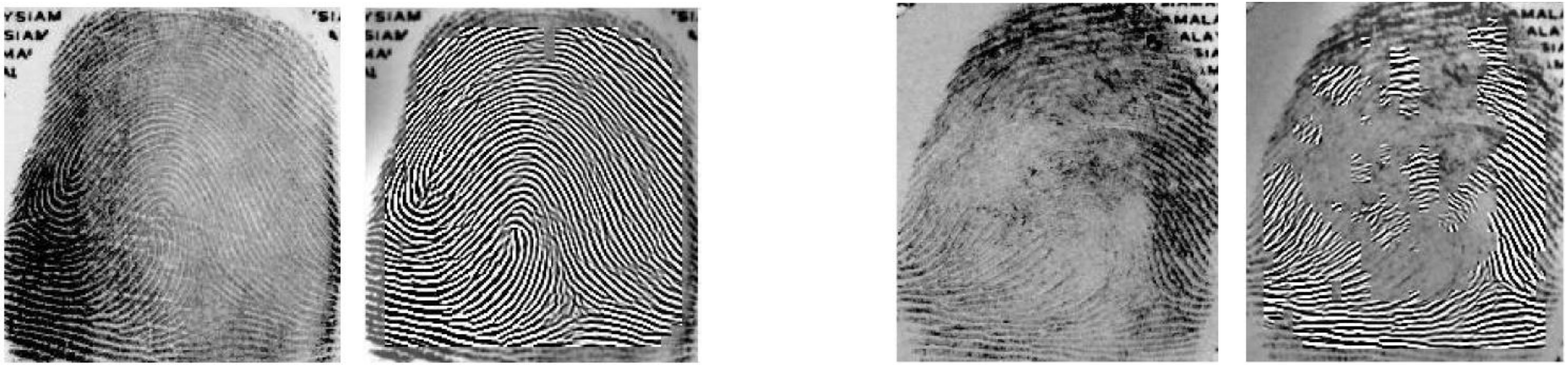
Fig. 3. (a)Real part of the gabor (b) The Fourier spectrum of the Gabor kernel showing the localization in the frequency domain

- Choose reconstructed orientation according to Ridge Orientation Estimation

3. Characteristics extraction: e) Enhancement

Contextual filtering

- Image examples:

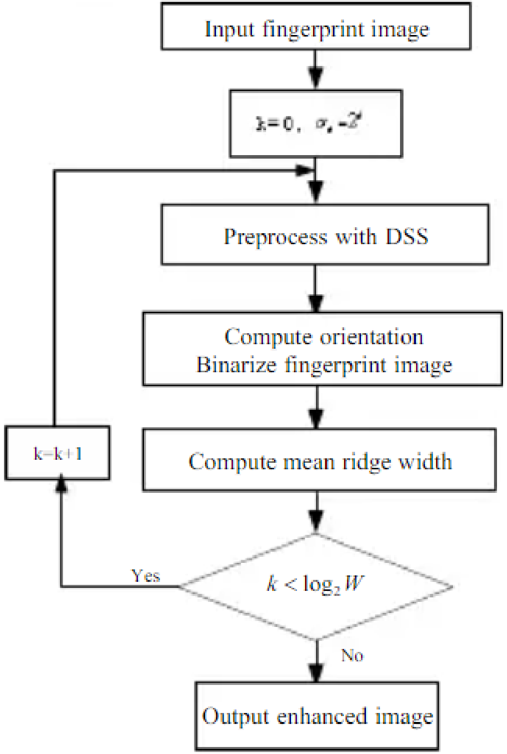


Fingerprint Image Enhancement: Algorithm and Performance Evaluation, Hong, IEEE, 1998

3. Characteristics extraction: e) Enhancement

Multi-resolution filtering

- Image is decomposed into different frequency bands
- Main advantage: remove noise from fingerprint images
  - At higher levels : the rough ridge-valley flow is cleaned, gaps are closed
  - At lower levels (higher frequencies): finer details are preserved

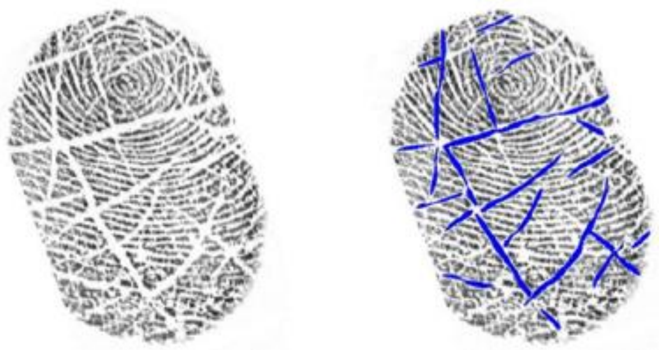


Fingerprint Enhancement with Dyadic Scale-Space, Cheng, Tian, Zhang, Chinese Academy of Science

3. Characteristics extraction: e) Enhancement

Crease detection and removal

- To improve ridge continuity and links between minutiae
- Can be risky if image very creased (crease frequency can take over original signal frequency)



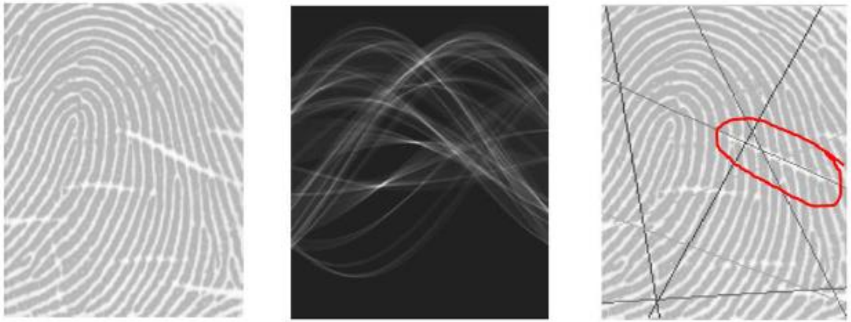


Figure 2.3: Application of Hough transform on fingerprint images[15] (a) Original image, (b) Hough transform Space (c) Line detected after applying Hough transform.

Analysis and detection of fingerprint creases, O.P. Laseinde, WVU, 2012

3. Characteristics extraction: f) Minutiae detection

Minutiae detection

- Used by almost certainly all automatic systems for fingerprint recognition
- Most methods require the fingerprint gray-scale image to be converted into a **binary image**
- After thinning, this becomes a **skeleton image**
- Then, a simple pixel corresponding to minutiae analysis is performed

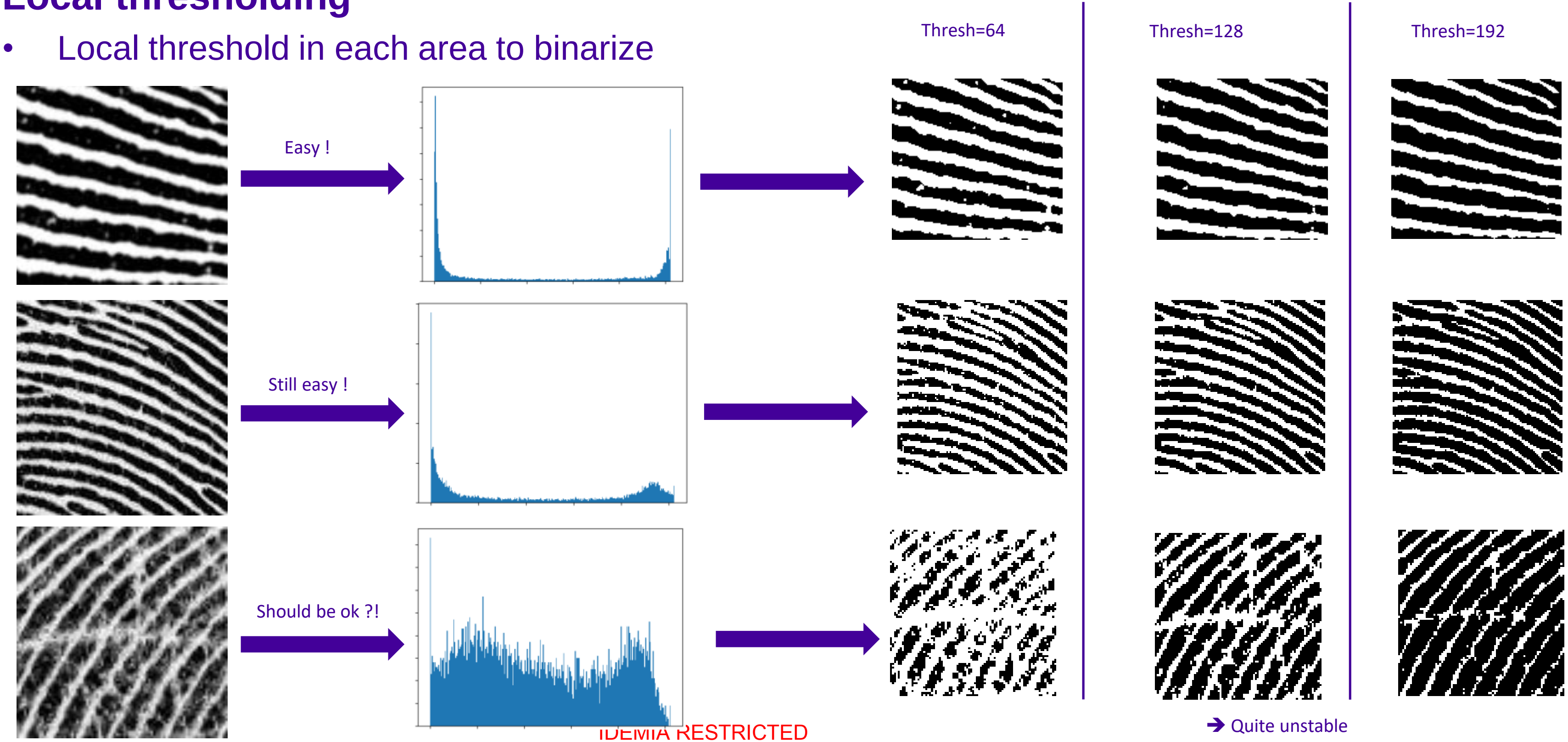
Input image | Binarized image | Thinned image | Thinned image + minutiae

Different Techniques used in the process of feature extraction from fingerprint, T.Patil, S.Nandusekar, International journal of innovations in engineering research and technology, 2019

3. Characteristics extraction: f) Minutiae detection

Local thresholding

- Local threshold in each area to binarize



➔ Quite unstable

3. Characteristics extraction: f) Minutiae detection

Thinning

- Vastly researched (character recognition, document analysis, map drawing…)
- Main objective: conserve connectivity

Fig. 1.

$$\chi = \sum_{k=1}^{8} |\gamma(k+1) - \gamma(k)|,$$

4	3	2
5		1
6	7	8

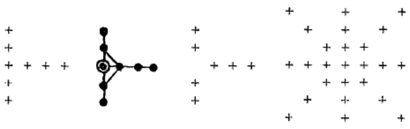
X is excluded of the pattern if either one of these is true:

1. $\chi = 0$, 2 or 4
2. $\sum_{k=1}^{8}\gamma(k) \neq 1$ (i.e. the element must have no, or at least two, neighbors in the pattern)
3. $\gamma(1)\wedge\gamma(3)\wedge\gamma(5) = 0$
4. $\gamma(1)\wedge\gamma(3)\wedge\gamma(7) = 0$
5. If $\chi = 4$ then in addition either condition (a) or (b) must hold:

a. $\{\gamma(1)\wedge\gamma(7) = 1\}$
&
$\{\gamma(2)\vee\gamma(6) = 1\}$
&
$\{\gamma(3)\&\gamma(4)\&\gamma(4)\&\gamma(5)\&\gamma(8) = 0\}$
Where & stands for the word *and*.

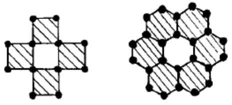
b. $\{\gamma(1)\wedge\gamma(3) = 1\}$
&
$\{\gamma(4)\vee\gamma(8) = 1\}$
&
$\{\gamma(2)\&\gamma(5)\gamma(6)\&\gamma(7) = 0\}$

Fig. 2.



a b c d

Fig. 3.



a b

Thinning algorithms on rectangular, hexagonal, and triangular arrays, E.S. Deutsch, University of Maryland

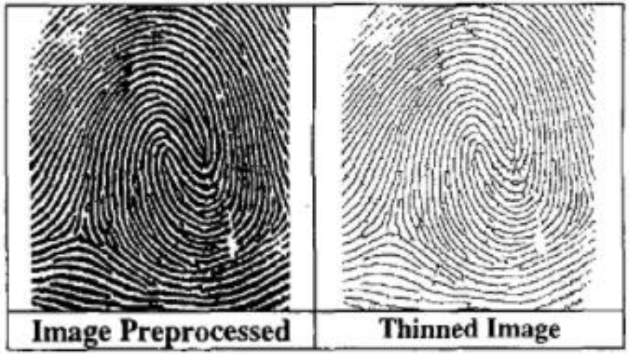


Fig. 2.

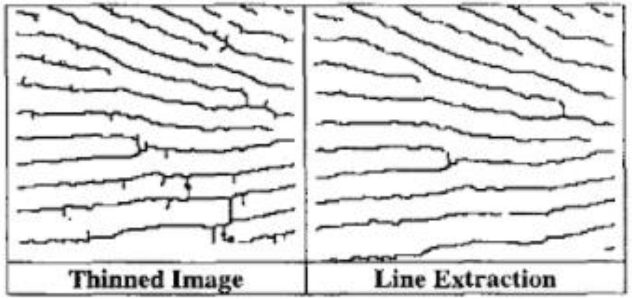


Fig. 3. Zoom in of the final results obtained

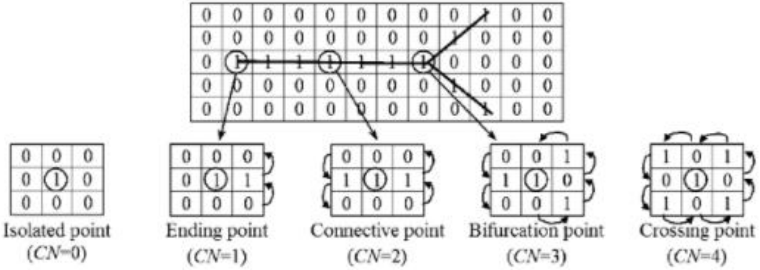
Fingerprints Thinning Algorithm, V.Espinosa-Duro, Polytechnic University of Catalonia

3. Characteristics extraction: f) Minutiae detection

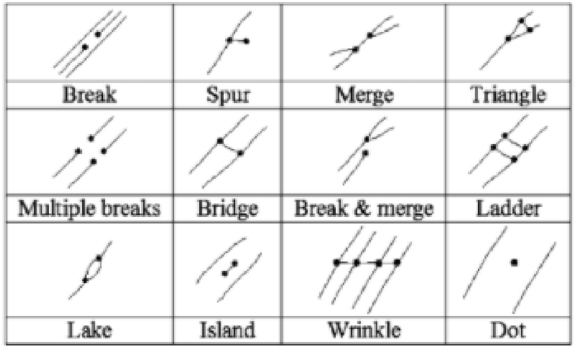
From skeleton to minutiae

- Simple pixel by pixel analysis of the skeleton

CN	Property
0	Isolated point
1	Ending point
2	Connective point
3	Bifurcation point
4	Crossing point



- Removal of false minutiae

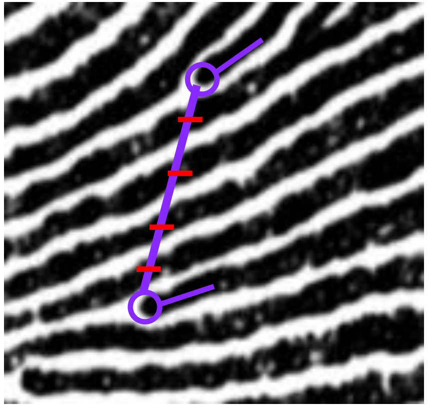


Preprocessing and postprocessing for skeleton-based fingerprint minutiae extraction, Zhao, Tang, The Chinese University of Hong Kong, Shatin, NT, Hong Kong, 2006

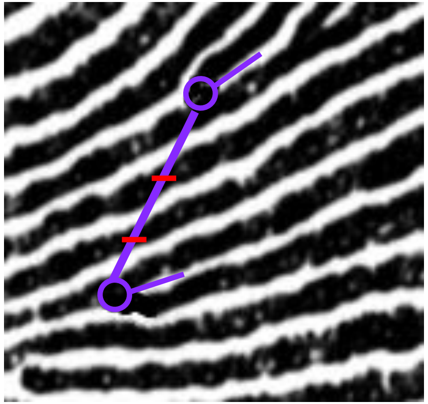
3. Characteristics extraction: g) Ridge count

Ridge count

- Number of ridges between 2 minutiae
- Goal: Use ridge-level information in addition to minutiae to help matching, but still quantified and fast to use
- Possible risks : minutiae valence instability



Ridge count = 4



Ridge count = … 2 ?

3. Characteristics extraction: h) Fingerprint quality

Fingerprint image quality

- Can have multiple significations
- General convention: « matchability » of the image:
  - Number of minutiae
  - Surface of the fingerprint
  - Quality of contrast of the image
  - Number of cores and deltas
- Main use: ok or not during enrolment

(a) (b) (c) (d)

Fingerprint images of different quality. The quality decreases from left to right. (a) Good quality image with high contrast between the ridges and valleys (b) Insufficient dis- tinction between ridges and valleys in the center of the image (c) Dry print

Chikkerur, Cartwright, and Govindaraju (2007)

4. Fingerprint matching

Being able to say that all these fingerprints are from the same finger

4. Fingerprint matching

a. Minutiae based methods

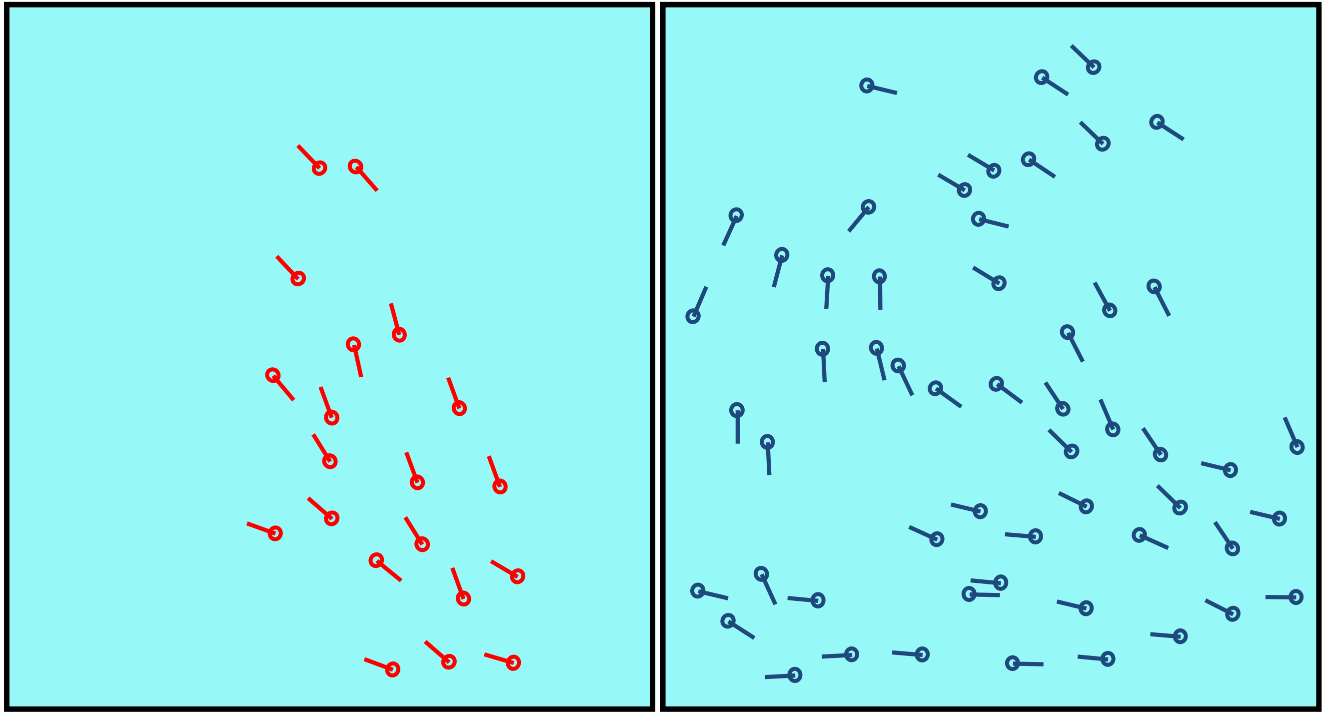
b. Global matching versus local matching

c. Non-minutiae Feature-based methods

d. System performances

4. Fingerprint matching: a) Minutiae based methods

Minutiae based methods



Latent search

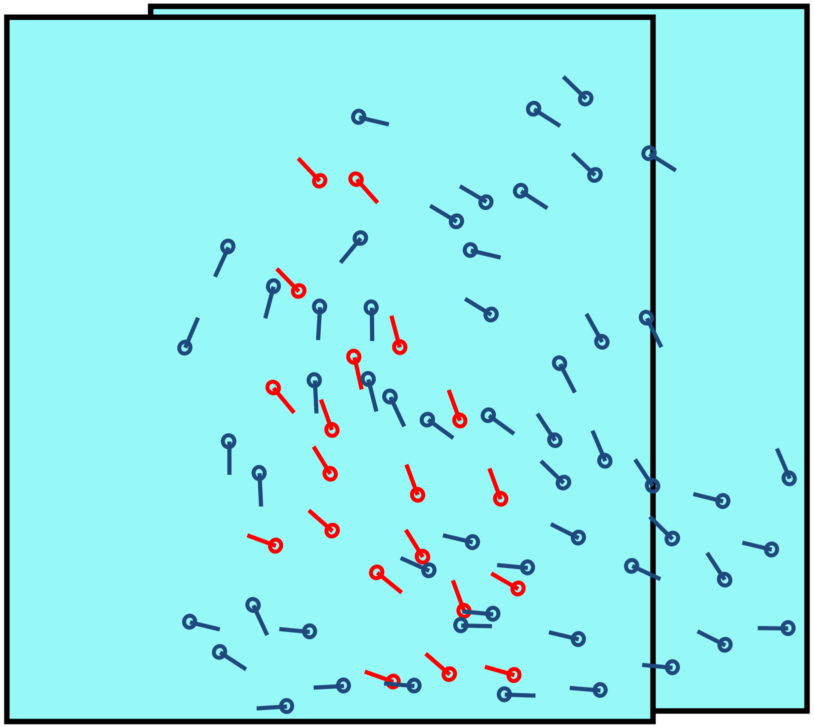
Reference in candidate database

IDEMIA RESTRICTED

4. Fingerprint matching: a) Minutiae based methods

Minutiae based methods:

Translation

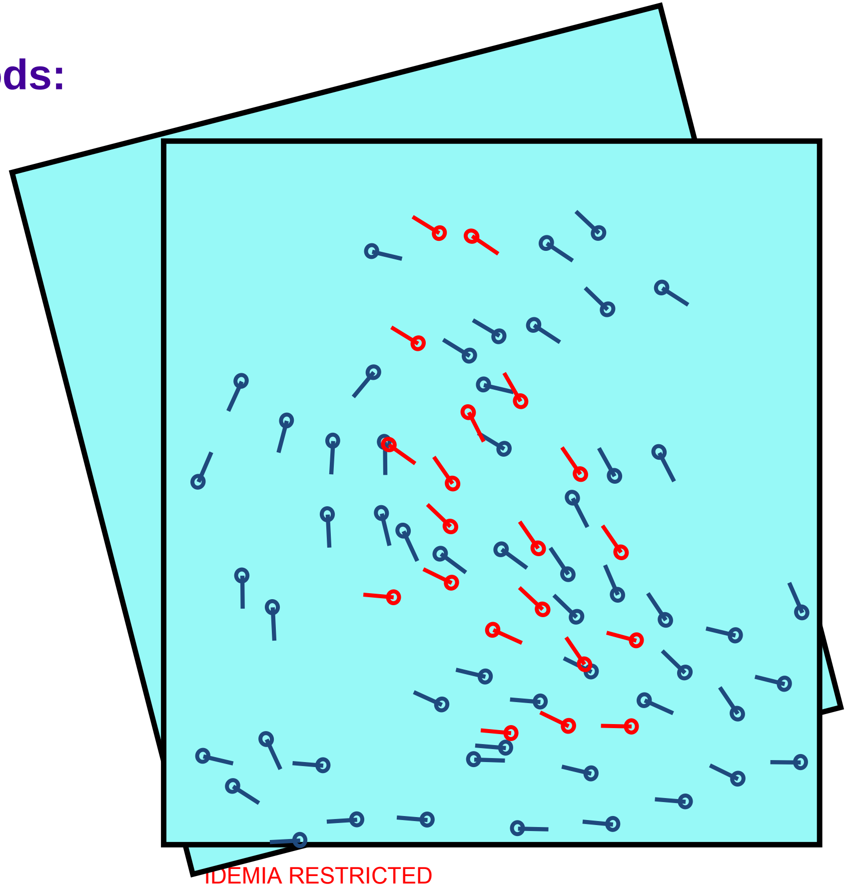


IDEMIA RESTRICTED

4. Fingerprint matching: a) Minutiae based methods

Minutiae based methods:

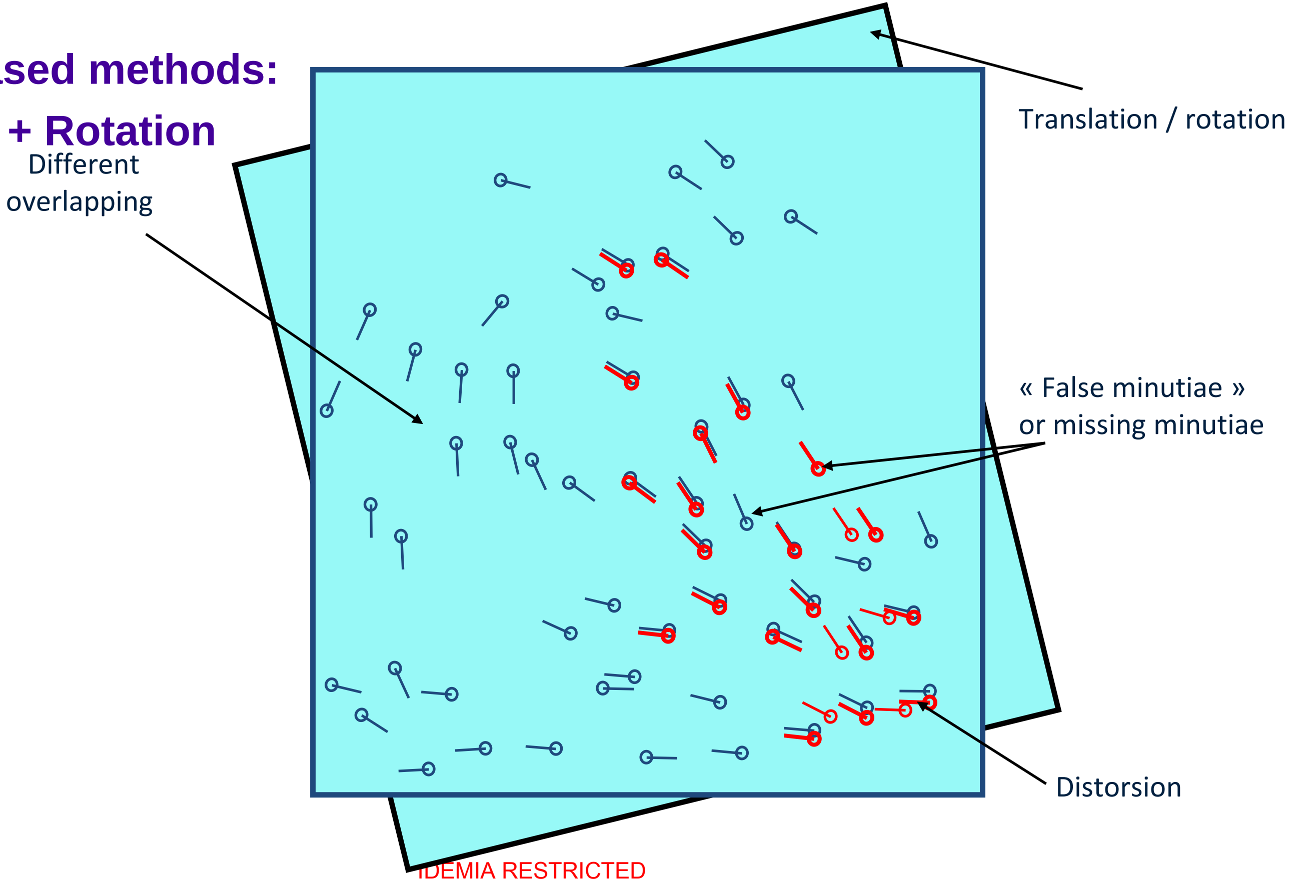
Rotation



4. Fingerprint matching: a) Minutiae based methods

Minutiae based methods:

Translation + Rotation



4. Fingerprint matching: a) Minutiae based methods

Problem formulation

- Point cloud matching ; Minutiae $m = \{x, y, \theta\}$
- Template image : $T = \{\boldsymbol{m}_1, \boldsymbol{m}_2, .., \boldsymbol{m}_m\}$, $\boldsymbol{m}_i = \{x_i, y_i, \theta_i\}$, $i = 1 \dots m$ $(number\ of\ minutiae\ in\ T)$
- Input image: $I = \{\boldsymbol{m'}_1, \boldsymbol{m'}_2, .., \boldsymbol{m'}_n\}$, $\boldsymbol{m'}_j = \{x'_j, y'_j, \theta'_j\}$, $j = 1 \dots n$ $(number\ of\ minutiae\ in\ I)$
- A minutia m’j in I and minutia mi in T are considered matching if:
- $sd(\boldsymbol{m'}_j, \boldsymbol{m}_i) = \sqrt{(x'_j - x_i)^2 + (y'_j - y_i)^2} \leq r_0$
- $dd(\boldsymbol{m'}_j, \boldsymbol{m}_i) = \min(|\theta'_j - \theta_\mathrm{i}|, 360° - |\theta'_j - \theta_\mathrm{i}|) \leq \theta_0$
- Alignment to take into consideration:
  - Rotation and translation
- Then, to be more precise:
  - Scale and distorsion

4. Fingerprint matching: a) Minutiae based methods

Transformation

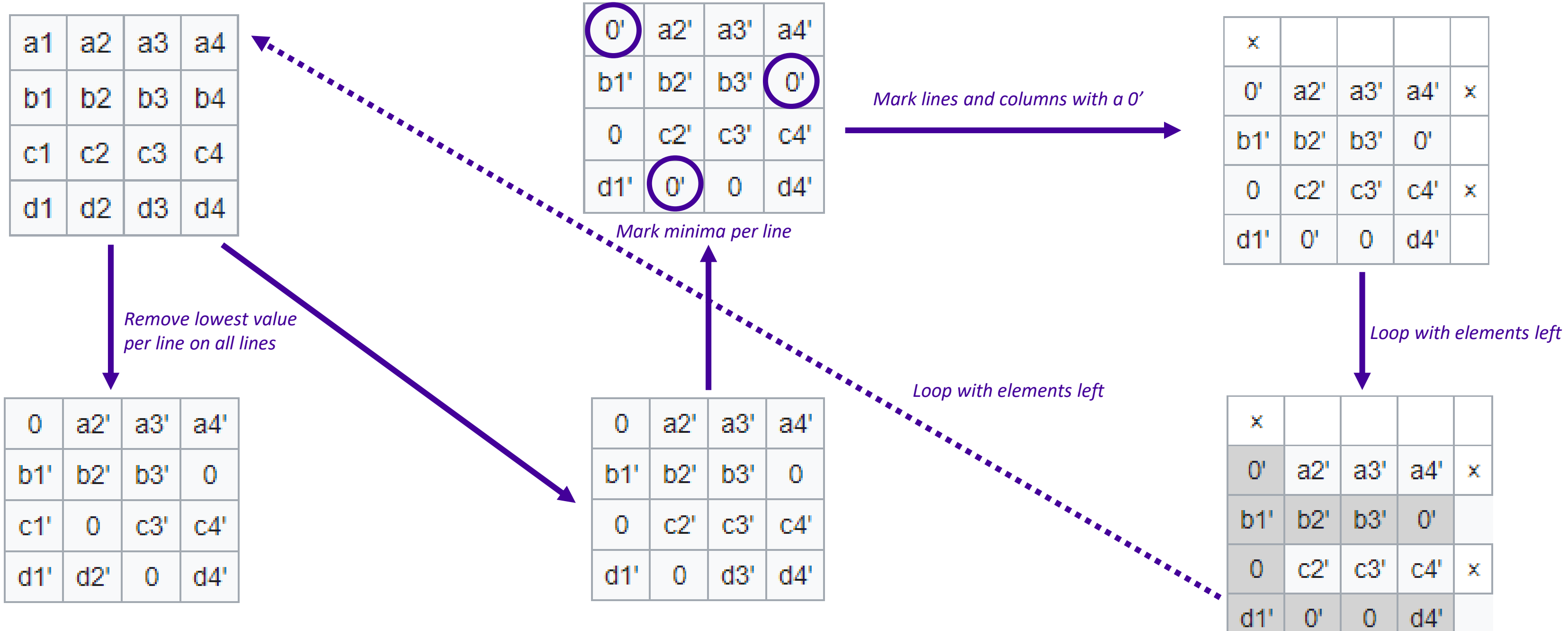
- Let *map()* be the function that maps a **m'**$_j$ minutiae (from **I**) into **m''**$_j$ according to the geometrical tranformation composed of displacement : $[\Delta x, \Delta y]$ and a rotation θ
- $map_{\Delta x \Delta y, \theta}(\boldsymbol{m'}_j = \{x'_j, y'_j, \theta'_j\}) = \boldsymbol{m''}_j = \{x''_j, y''_j, \theta'_j + \theta\}$, where
- $\begin{bmatrix} x''_j \\ y''_j \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x'_j \\ y'_j \end{bmatrix} + \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$
- Let mm() be an indicator of 2 minutiae matching :
- $mm(\boldsymbol{m''}_j, \boldsymbol{m}_i) = \begin{cases} 1, & sd(\boldsymbol{m''}_j, \boldsymbol{m}_i) < r_0 \; and \; dd(\boldsymbol{m''}_j, \boldsymbol{m}_i) < \theta_0 \\ 0, & otherwise \end{cases}$
- Then the problem becomes:
- $\boxed{maximize_{\Delta x \Delta y, \theta, P} \sum_{i=0}^{m} mm(map_{\Delta x \Delta y, \theta}(\boldsymbol{m'}_{P(i)}), \boldsymbol{m}_i)}$ *P: unknown pairing function*

Loop with elements left

4. Fingerprint matching: a) Minutiae based methods

Minutiae association

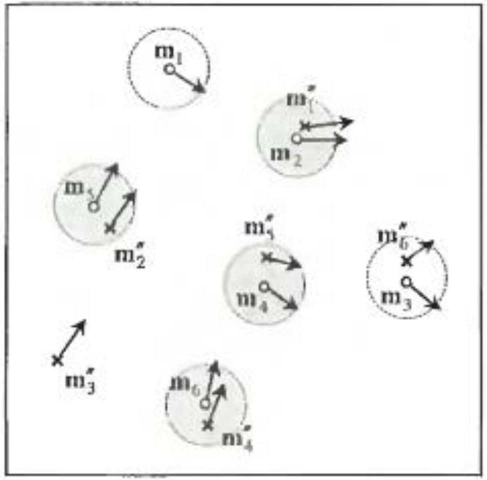
- Given a transformation, associating minutiae can be achieved with Hungarian assignement algorithm (polynomial computational time)



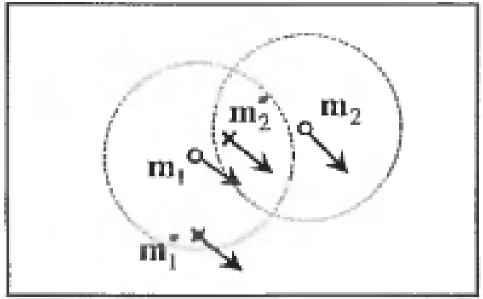
4. Fingerprint matching: a) Minutiae based methods

Minutiae association

- *P* is not well defined (multiple associations possible for one minutiae)
- Brute force search is very heavy computionnaly
- Score similarity: $score = \frac{k}{(n+m)/2}$, k: number of associated minutiae



Example of minutiae association



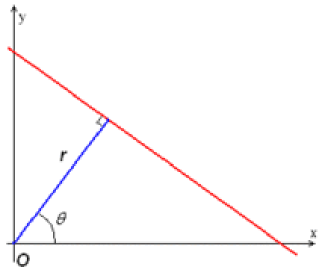
If m_1 is associated with m''_2 (the closest), m_2 remains unassociated
But if m_1 is associated with m''_1, m_2 can be associated with m''_2, and maximizes optimization

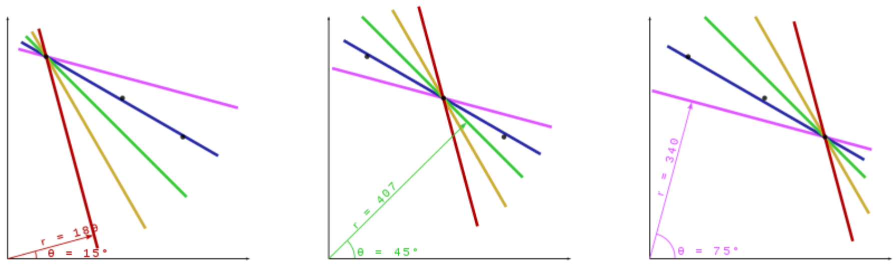
Maltoni, Maio, Jain, Prabhakar, Handbook of Fingerprint Recognition

4. Fingerprint matching: a) Minutiae based methods

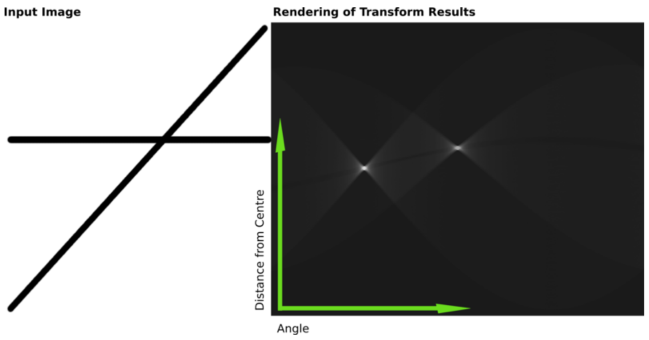
Hough transform-based method

- 1-pass on data to vote in sub-space representation
- Example with line detection:
- Vote for all (r, θ)possible that can pass through a given point





Votes for line detection based on 3 points

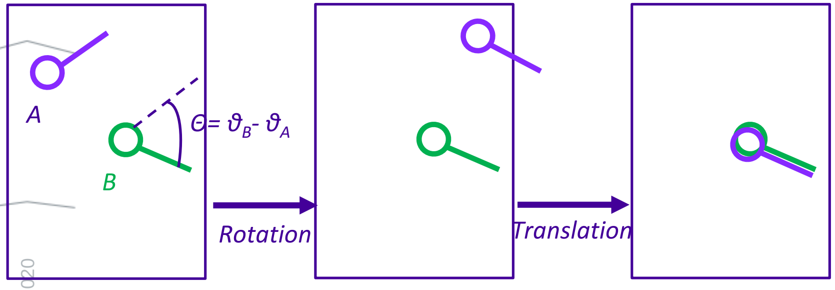


Transform of points in line

4. Fingerprint matching: a) Minutiae based methods

Hough transform-based method

- On minutiae:
- For each pair of minutiae: vote
- Only 1 possible rotation-translation for a pair of $(\{x_i, yi, \theta_i\}\ , \{x'_j, y'_j, \theta'_j\})$



- For more robustness, vote on neighbors as well

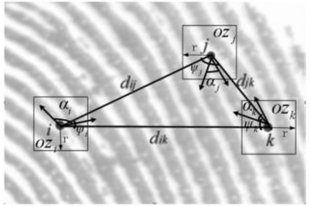
$maxMPS = 0$ // maximum Matching Pair Support
for each $\mathbf{m}_{i1}$, $i1 = 1..m$
for each $\mathbf{m}'_{j1}$, $j1 = 1..n$ // $\mathbf{m}_{i1}, \mathbf{m}'_{j1}$ is the current pair for which MPS has be to estimated
{ Reset $\mathbf{A}$ // the accumulator array
for each $\mathbf{m}_{i2}$, $i2 = 1..m,\ i2 \neq i1$
for each $\mathbf{m}'_{j2}$, $j2 = 1..n,\ j2 \neq j1$
{ θ, s are computed from $\overline{\mathbf{m}_{i2}\mathbf{m}_{i1}}$, $\overline{\mathbf{m}'_{j2}\mathbf{m}'_{j1}}$ according to Equations (9) and (10)
θ^+, s^+ = quantization of θ, s to the nearest bins
$\mathbf{A}[\theta^+, s^+] = \mathbf{A}[\theta^+, s^+] + 1$
}
$MPS = \max_{\theta^+, s^+} \mathbf{A}[\theta^+, s^+]$
if $MPS \geq maxMPS$
{ $maxMPS = MPS$
$(\theta^*, s^*) = arg \max_{\theta^+, s^+} \mathbf{A}[\theta^+, s^+]$
Principal pair $= (\mathbf{m}_{i1}, \mathbf{m}'_{j1})$
}
}

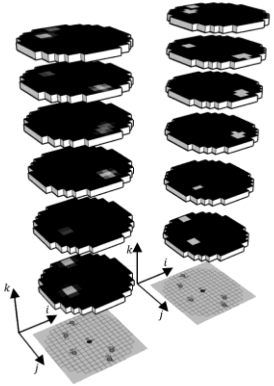
Maltoni, Maio, Jain, Prabhakar, Handbook of Fingerprint Recognition

4. Fingerprint matching: b) Global matching versus local matching

Local matching methods

- Local structures (neighbors, fixed-radius, triangles, textures,…)





MCC, Maltoni

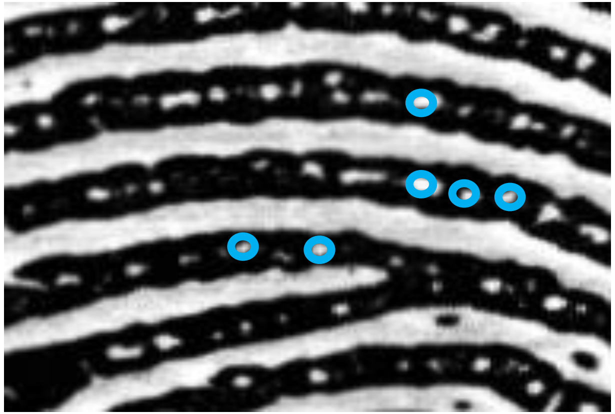
- Handling distortion (warping, clustering, normalization)

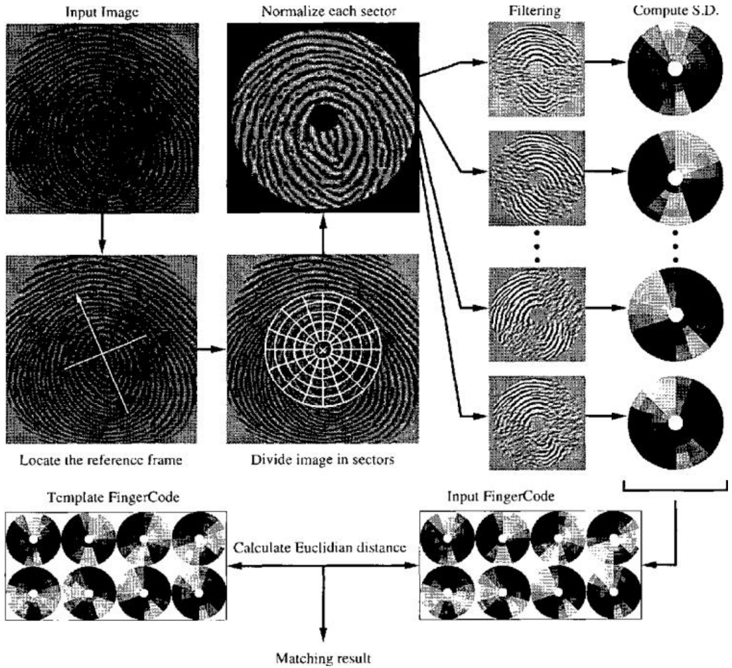
White-box evaluation of fingerprint matchers: robustness to minutiae perturbations, A. Grosz, J.J. Engelsma, N.G. Paulter, A.K. Jain

4. Fingerprint matching: c) Non minutiae-based methods

Non minutiae-based methods

- FingerCode
- Relationship between ridges
- Level 3 features (pores, creases, …)



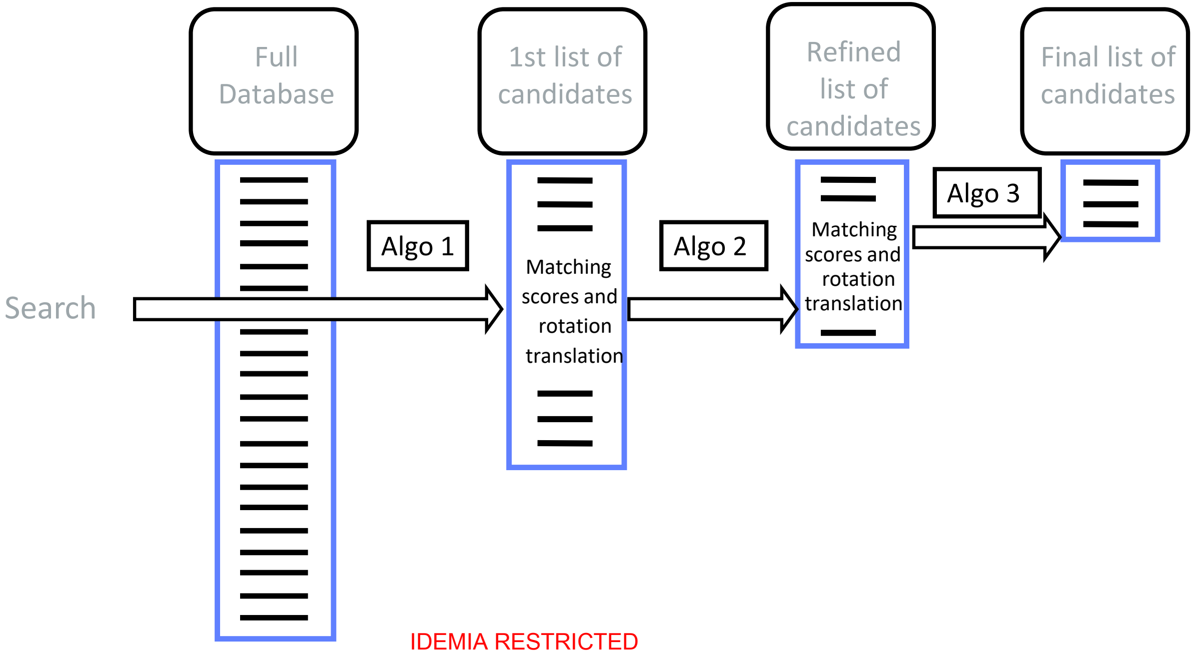


FingerCode approach, A.K. Jain and al, 2000

4. Fingerprint matching: d) System performances

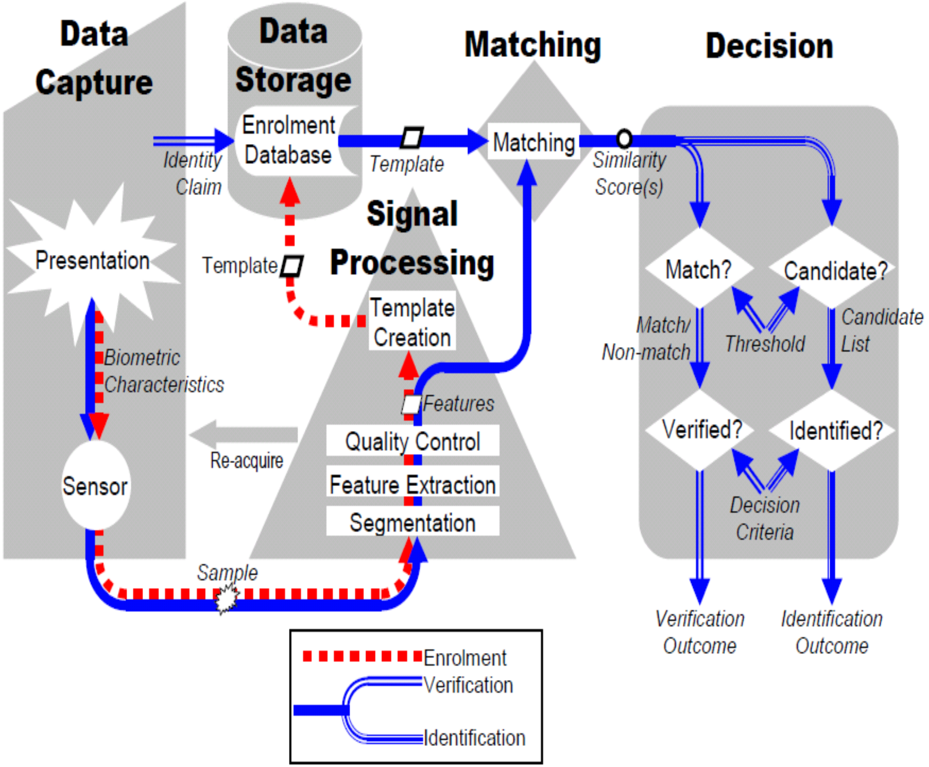
Matching an entire database

- The basic approach is repeated several times with different algorithms
- Each algorithm refines the precedent output



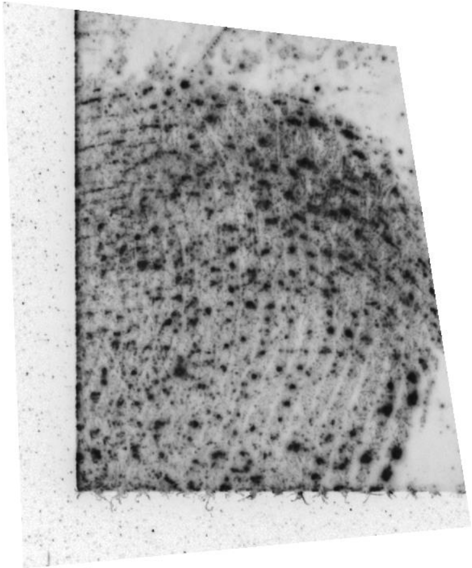
4. Fingerprint matching: d) System performances

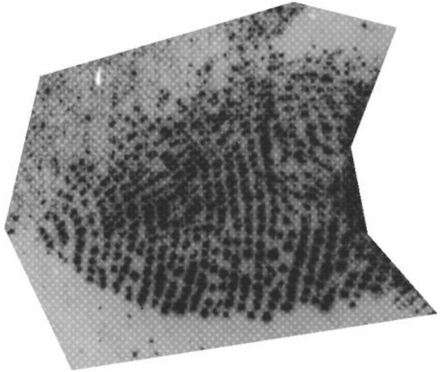
Complete system

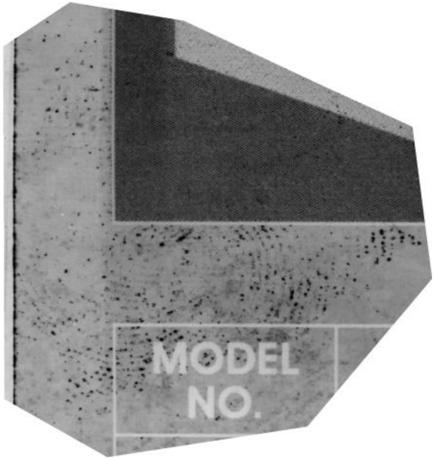


4. Fingerprint matching: d) System performances

The real challenge: latents !



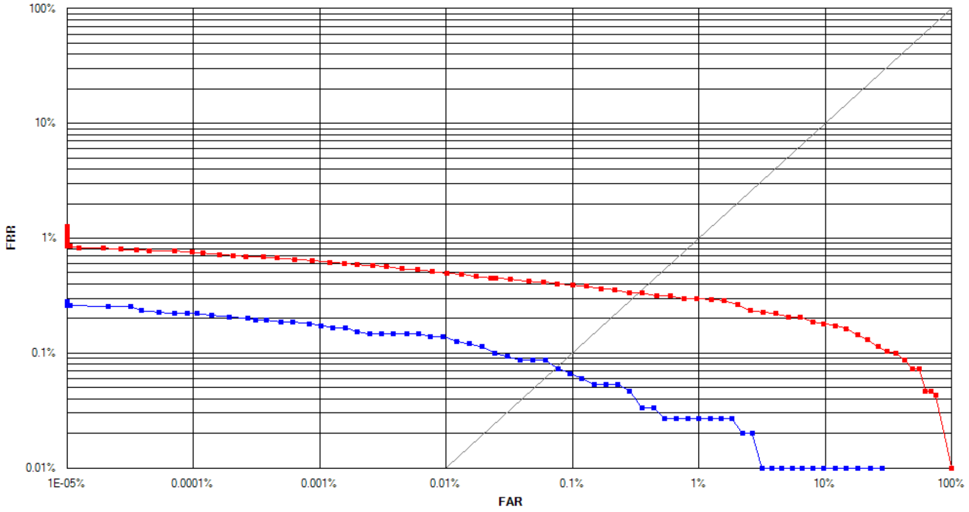




5. Systems

1 to 1 versus 1 to N systems:

- 1 to 1: authentification
- 1 test = 1 image versus 1 template



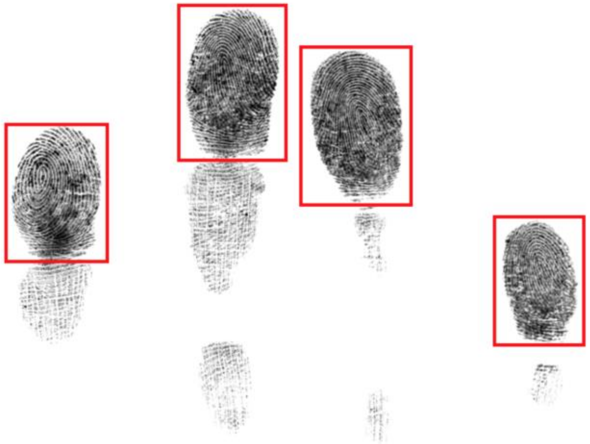
MegaMatcher On Card 11.2 fingerprint template verification algorithm tested on a subset of SONATEQ Fingerprint Database SQ FDB1-75TS1:
Maximized speed configuration;
Maximized accuracy configuration.

- 1 to N: identification:
- 1 test = 1 request against a database (size N)
- ➔ FAR: 0,001% in 1 to 1 would correspond to a FAR=1% in 1 to N with N=1000

5. Systems

Slap segmentation

- Detect and labelize all fingers in an image



Inclined slap

Moisture in the sensor

Images from NIST SlapSegII benchmark

5. Systems

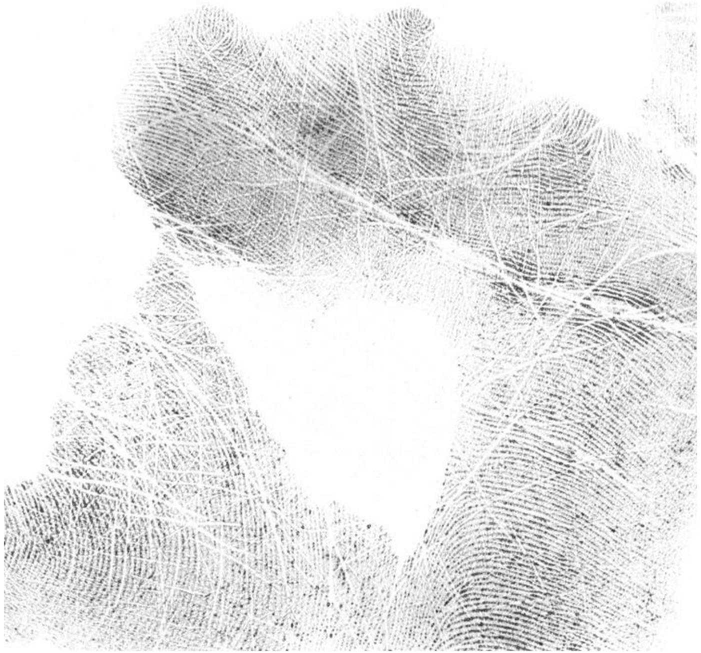
Example of NIST benchmark

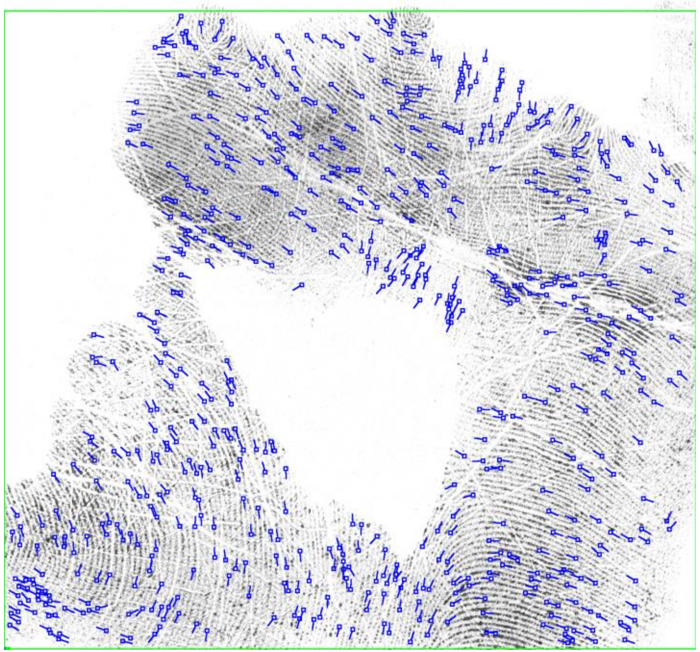
- ELFT-EFS (extended features) benchmark ; 2012

	Latent Subset						
	LA	LB	LC	LD	LE	LF	LG
	Image only	Image + ROI	Image + ROI + Pattern Class + Qual map	Image + Minutiae + Ridge Counts	Image + EFS	Image + EFS + Skeleton	Minutiae + Ridge Counts only
A	63.4	64.1	64.1	65.6	65.6	64.8	40.4
B	57.7	60.1	60.1	67.0	67.0	68.2	47.4
C	59.6	60.1	58.6	66.3	67.2	*n/a*	45.9
D	31.8	23.9	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*
E	44.0	46.9	47.1	46.9	47.1	48.3	0.0

PalmPrint recognition

- A lot more minutiae

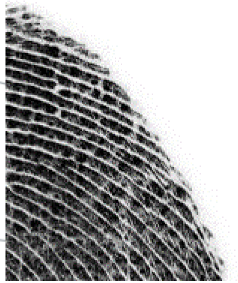


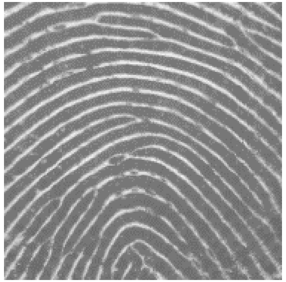


5. Systems

Fingerprint on paiement cards: very challenging

- Very little surface, between 2 and 6 minutiae ➔ need other data
- Embedded platform ➔ ~50KB of code (no CNN !)
- Processor ~100 times slower than standard PC



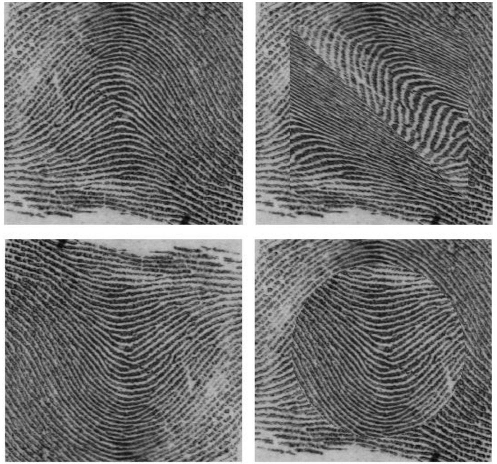


F.CODE
THE FINGERPRINT CARD

5. Systems

Altered fingerprint detection

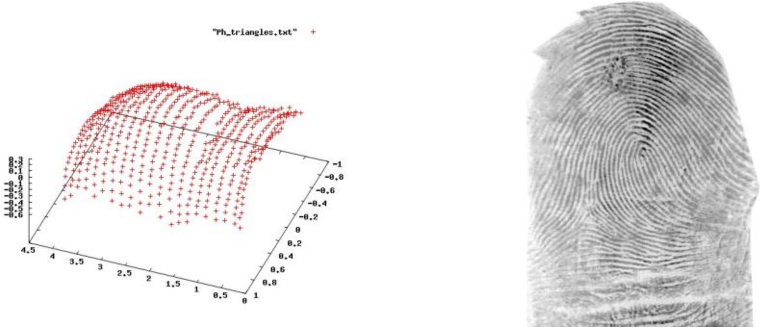
- Used by outlaws to prevent their identification (borders, police)
- 1st level : burn the fingerprint
- 2nd level : (because burned fingers are very suspicious) Cut of finger skin and reattachment in another direction
- Algorithm goal : detect it has been altered



5. Systems

Fingerprint images via cameras

- 3D fingerprint acquisition sensor



3D model and reconstructed fingerprint image via a 3D sensor

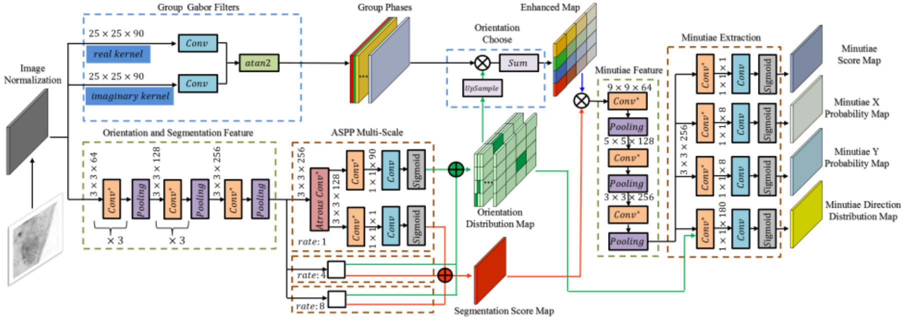
- Direct view (smartphone)

Photo via smartphone sensor

5. Systems

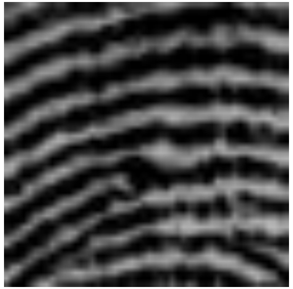
Deep learning

- Obviously, deep learning brings good solutions to classification and detection problems

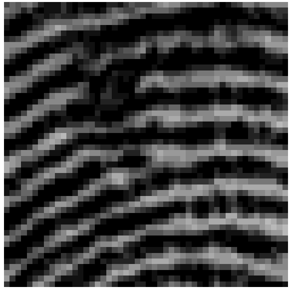


FingerNet, a unified Deep Network for fingerprint minutiae extraction, Y.Tang, F.Gao, J.Feng, Y.Liu

- However, just like irises, fingerprints are structured data ➔ standard approches help a lot



Impossible image in between 2 fingerprint identities



Conclusion: Fingerprints are the best !

- Very diverse types of images (finger, palm, latents, 3D images, …)
- Very diverse environment (image processing, filters, cloud points, structural approaches, …)
- Very diverse algorithms to investigate (segmentation, identification, filtering, …)
- Data optimization for real-time systems
- Millions of images ➔ lots of data to work on
- Civil and police applications
- Many Deep Learning applications
- …

- Who doesn't like koalas ?!