

**Daniel Novák** 

3.10. 2019, Prague

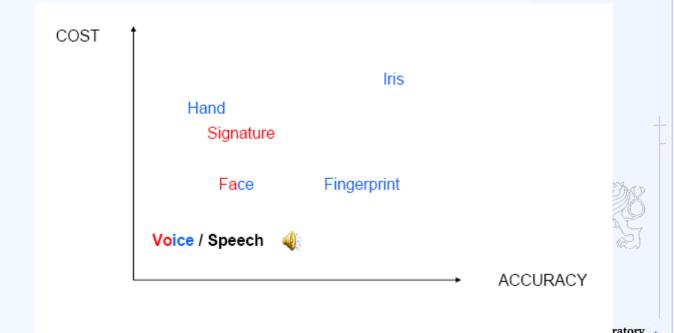
Acknowledgments: Xavier Palathingal, Andrzej Drygajlo, Handbook of Fingerprint Recognition





#### **Outline**

- Introduction to Fingerprint
- History
- Registration
- Enhancement
- Minutiaes detection



Gerstner

# **Fingerprint**

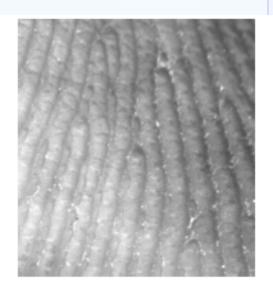
- Fingerprints are "permanent" in that they are formed in the fetal stage, prior to birth, and remain the same throughout lifetime
- The changes can be made by: flexibility from the skin, growing, a dirty finger, scarring, a wound, or a disease of the skin
- They are only weakly determined by genetics, e.g. identical (monozygotic, one egg) twins (the same DNA) have fingerprints that are quite different
- Fingerprints of an individual are "unique"; they indeed are distinctive to a person
- The right definition of a fingerprint is strictly speaking the print (stamp) that a finger left on an object

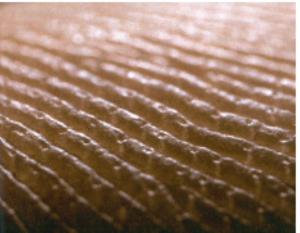




# **Fingerprint**

- The inside surfaces of hands and feet of humans (and, in fact, all primates) contain minute ridges of skin with furrows between each ridge
- The purpose of this skin structure is to:
  - Facilitate exudation of perspiration
  - Enhance sense of touch
  - Providing a gripping surface









# No fingerprint?

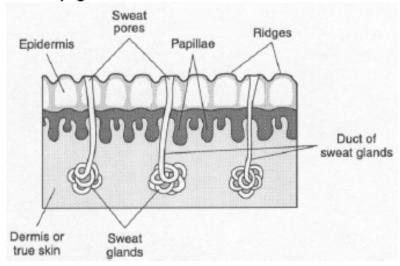
- In very rare cases there are people that do not have prints. Not on their fingers, their palms or their feet. They where born with it or the friction ridges have degenerated during their live
- Approximately 4%
   of fingerprint images
   have been observed
   to have poor ridge
   details





#### **Friction Skin**

- Friction skin differs significantly in structure and function from the skin covering the rest of the body:
  - It is hairless
  - It contains no sebaceous (oil) glands
  - It has a much higher concentration of nerve endings
  - It has a much higher concentration of sweat glands
  - There is a lack of pigmentation







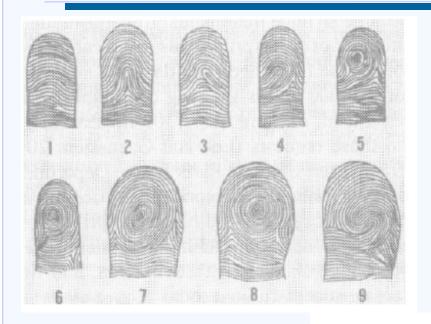
# **History of fingerprints**

- Human fingerprints have been discovered on a large number of archaeological artifacts and historical items
- In 1684, the English plant morphologist, Nehemiah Grew, published the first scientific paper reporting his systematic study on the ridge, furrow, and pore structure
- In 1788, a detailed description of the anatomical formations of fingerprints was made by Mayer.
- In 1823, Purkinji proposed the first fingerprint classification, which classified into nine categories
- Sir Francis Galton introduced the minutae features for fingerprint matching in late 19<sup>th</sup> century
- 1924, an act of U.S. Congress established the Identification Division of the FBI (Federal Bureau of Investigation) with a database of 810 000 fingerprint cards.
   TODAY: 200 mil !!!

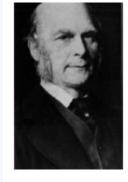


### Purkynje classification & Galton individuality & FBI









2310
THE RESERVE TO SHARE THE PARTY OF THE PARTY
Spellen's Color Sense type road at 20 feet.
So. of Type ? Normal.
D6 Yes
Right Thumb.
1333

# Fingerprints as evidence

- 1892–Juan Vucetich(Argentina) made the first criminal fingerprint identification
- 1914 –Edmond Locard wrote that if 12 points(Galton's details) were the same between two fingerprints, it would suffice as a positive identification.



## ARCHIVES

#### D'ANTHROPOLOGIE CRIMINELLE

DE MÉDECINE LÉGALE

ET DE PSYCHOLOGIE NORMALE ET PATHOLOGIQUE

#### MÉMOIRES ORIGINAUX

#### LA PREUVE JUDICIAIRE PAR LES EMPREINTES DIGITALES

Données physiologiques. — Pratique policière (empreintes fragmentaires; la question des gants; les fausses empreintes). — Nature et valeur de la preuve dactyloscopique. Calcul des chances d'erreur. — Jurisprudence comparée (France, Allemagne, Argentine, Belgique, Etats-Unis, Grande-Bretagne, Italie, Norvège, Portugal, Suisse).

Par EDMOND LOCARD

Docteur en médecine, licencié en droit, Directeur du Laboratoire de Police de Lyon.





# **History of fingerprints**



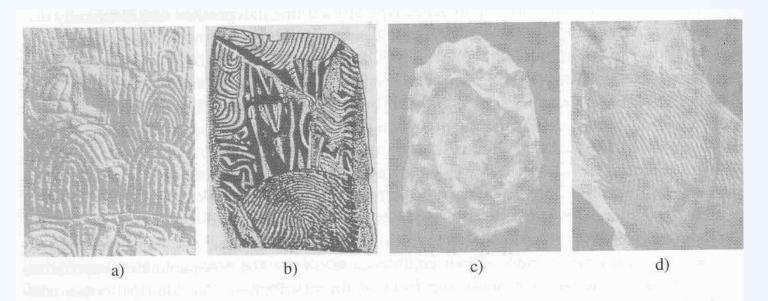


Figure 1.8. Examples of archaeological fingerprint carvings and historic fingerprint impressions a) Neolithic carvings (Gavrinis Island) (Moenssens, 1971); b) standing stone (Goat Island, 2000 B.C.) (Lee and Gaensslen, 2001); c) a Chinese clay seal (300 B.C.) (Lee and Gaensslen 2001); d) an impression on a Palestinian lamp (400 A.D.) (Moenssens, 1971). Although impressions on the Neolithic carvings and the Goat Island standing stones might not be used to indicate identity, there is sufficient evidence to suggest that the Chinese clay seal and impressions on the Palestinian lamp were used to indicate the identity of the providers. Figures courtesy of A. Moenssens, R. Gaensslen, and J. Berry.

# **Formation of fingerprints**

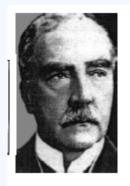
- Fingerprints are fully formed at about **seven months** of fetus development
- General characteristics of the fingerprint emerge as the skin on the fingertip begins to differentiate.
- flow of amniotic fluids around the fetus and its position in the uterus change during the differentiation process
- Thus the cells on the fingertip grow in a microenvironment that is slightly different from hand to hand and finger to finger



# Fingerprint feature extraction

- -Fingerprint pattern, when analyzed at different scales, exhibits different types of features
  - global level delineates a ridge line flow patternSir Edward Henry 1897
  - local level minute details can be identified
  - Very fine level intra-ridge details can be detected

# system Core Gelta Left loop Right loop Whorl Arch Tented arch







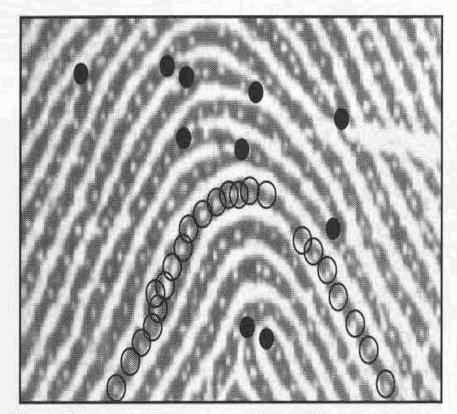
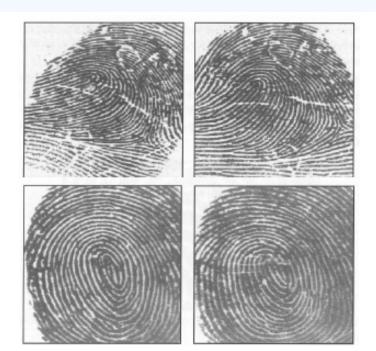


Figure 1.13. Minutiae (black-filled circles) in a portion of fingerprint image; sweat pores (empty circles) on a single ridge line.



# Difficulty in fingerprint matching

- Fingerprint matching is a difficult problem due to large variability in different impressions of the same finger
- Main factors responsible for intra-class variations are: displacement, rotation, partial overlap, non-linear distortion, variable pressure, skin condition, noise and feature extraction errors



Two impressions from the same finger

Two impressions from different fingers





# Fingerprint classification and Indexing

- To reduce the search time and computational complexity
- technique used to assign a fingerprint to one of the several prespecified types
- Only a limited number of categories have been identified, and there are many ambiguous fingerprints

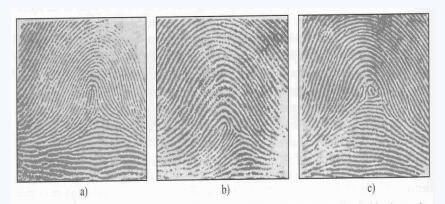
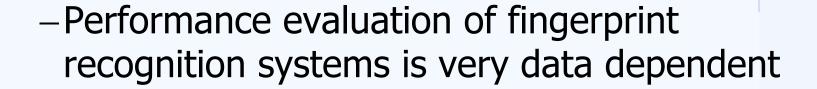


Figure 1.15. Examples of fingerprints that are difficult to classify; a) tented arch; b) a loop; c) a whorl; it seems that all the fingerprints shown here should be in the loop category.





## **Synthetic fingerprints**



—To obtain tight confidence intervals at very low error rates, large databases of images are required and its expensive

 To solve this problem synthetic fingerprint images are introduced, cost reduction





# The main parameters characterizing a fingerprint image are



# Resolution, Area, Number of pixels, Dynamic Range, Geometric Accuracy, Image Quality

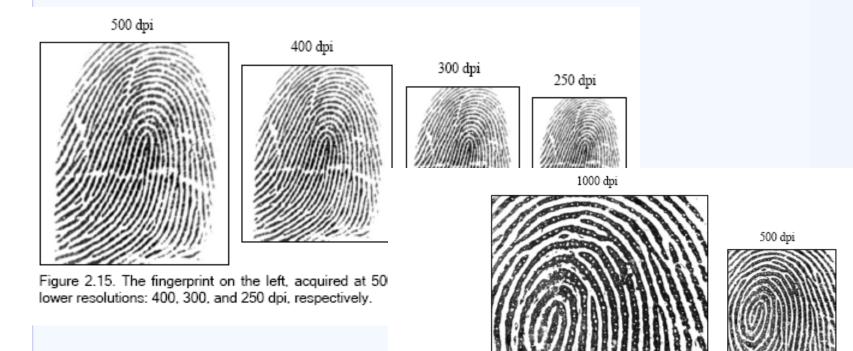


Figure 2.16. The fingerprint portion on the left is acquired at 1000 dpi; sweat pores and other fine details are clearly visible; on the right, the fingerprint portion is sub-sampled at 500 dpi while the fine details are not as clear.

# **Fingerprint images**









Optical scanner

Capacitive scanner Piezoelectric scanner



Thermal scanner



Inked impression



Latent fingerprint





#### **Off-line & On-line fingerprint Acquisition**

 Although the first fingerprint scanners were introduced more than 30 years ago, still ink-technique is used in some applications

Why & What are the advantages?

Because it has the possibility of producing

Rolled impressions

http://crime.about.com/od/police/ss/fingerprints.htm

Latent impressions

- The most important part of a fingerprint scanner is the sensor.
- All the existing scanners belong to one of the 3 families

Optical sensors
Solid state sensors
Ultrasound sensors





tment of Cybernetics, Czech Technical University

# **Rolled & Plain FP**







Figure 2.3. The same finger acquired as a plain impression (on the left) and as a rolled impression (on the right): the portion of the rolled fingerprint corresponding to the plain fingerprint is highlighted.

# **Daktylospopie**

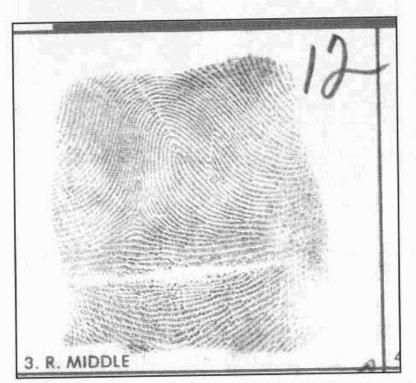


## – Daktyloskopie (Antropometrie)

- -na světě neexistují dva jedinci, kteří mají absolutně shodné obrazce papilárních linií,
- -obrazce papilárních linií jsou po celý život relativně neměnné,
- -obrazce papilárních linií jsou trvale neodstranitelné, pokud není odstraněna zárodečná vrstva pokožky.
- -0.8% zamen, v USA az 2000 pripadu
- -Simon A. Cole, "More Than Zero: Accounting for Error in Latent Fingerprint Identification," *Journal of Criminal Law & Criminology*, Volume 95, Number 3 (Spring 2005), pp. 985-1078.
- 1.Shoda otisků musí být potvrzena dalším hodnotitelem.
- 2.Hodnotitel musí být spolehlivý a prověřený expert.
- 3. Pro určení shody je potřeba velký počet identifikačních rysů.
- 4.Obhájce obžalovaného si může vyžádat dodatečné posouzení shody otisků nezávislým expertem.
- -http://socialecology.uci.edu/faculty/scole



#### **Rolled fingerprint Impressions**



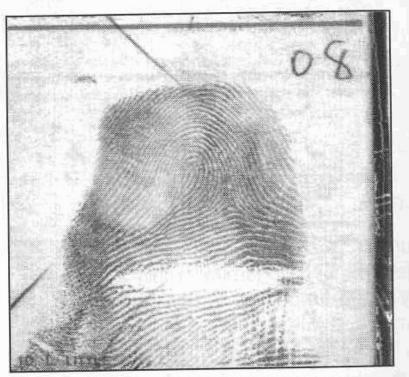


Figure 2.4. Rolled fingerprint images acquired off-line with the ink technique.



#### **Latent fingerprint images**



#### 10 % visible

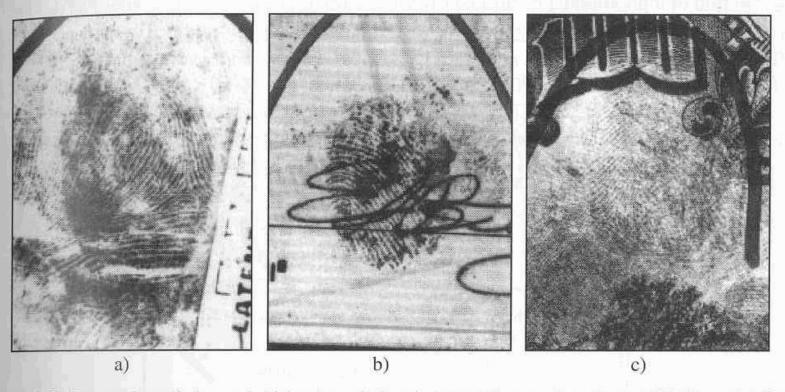


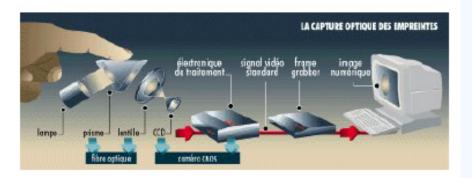
Figure 2.5. Examples of a) good, b) bad, and c) ugly latent fingerprints from NIST Special Database 27 (Garris and McCabe, 2000).



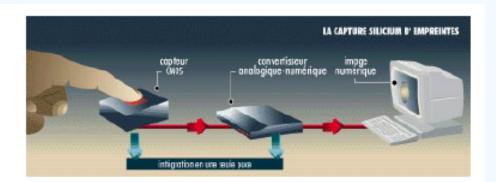
#### Live scan fingerprint sensing

- The most important part of a fingerprint scanner is the sensor.
- All the existing scanners belong to one of the 3 families
   Optical sensors
   Solid state sensors
   Ultrasound sensors

Optical scanner



CMOS scanner

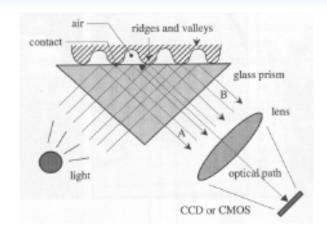




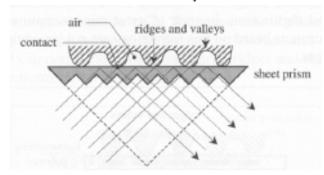


# **Optical sensors**

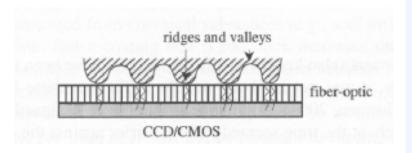




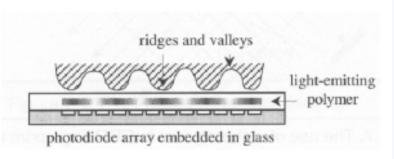
#### Internal reflection optical sensor



Sheet prism optical sensor



#### Sensor based on optical fibers



Electro-optical fingerprint sensor





# **Optical scanner**











Good quality fingerprint

Dry finger

Wet finger

Intrinsically bad fingerprint





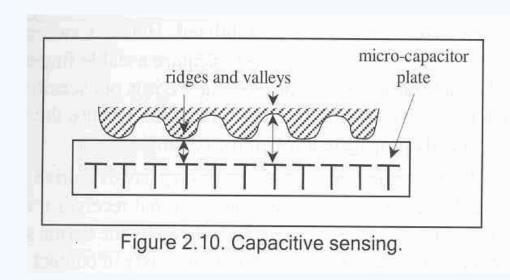
#### **Solid state sensors**

- These are designed to overcome the size and cost problems
- Silicon based sensors are used in this
- Neither optical components nor external CCD/CMOS image sensors are needed
- Four main effects have been produced to convert the physical information into electrical signals
  - Capacitive
  - Thermal
  - Electric field
  - Piezo Electric





## **Capacitive & Piezo- Electric**



- Pressure sensitive sensors
- Produce an electrical signal when mechanical stress is applied to them
- Sensor surface is made up of a non-conducting dielectric material
- •Ridges and valleys are present at different distances from the surface, they result in different amounts of current



#### Thermal sensors & Electric field

- Works based on temperature differentials
- Sensors are made of pyro electric material
- Temperature differential produces an image, but this image soon disappears
  - because the thermal equilibrium is quickly reached and pixel temperature is stabilized
- Solution is sweeping method
- Advantages
  - Not sensitive to ESD
  - Can accept thick protective coating
- Electric field
- Sensor consists of drive ring
- This generates a sinusoidal signal and a matrix of active antennas
- To image a fingerprint, the analogue response of each element in the sensor matrix is amplified, integrated and digitized



#### **Ultrasound sensors**



# Principle is Echography

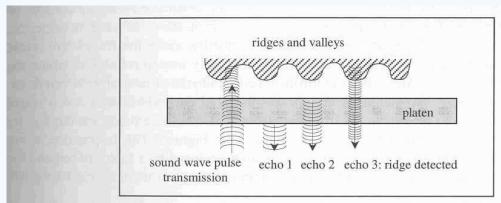


Figure 2.11. The basic principle of the ultrasound technique. Characteristic of sound waves is the ability to penetrate materials, giving a partial echo at each impedance change.

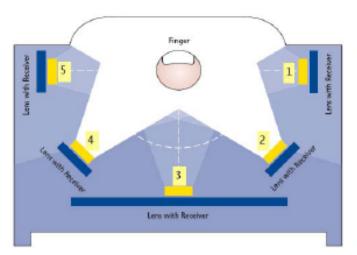
- Advantages of Ultrasound sensors
   Good Quality images
- Disadvantages
   Scanner is large
   Mechanical parts are quite expensive



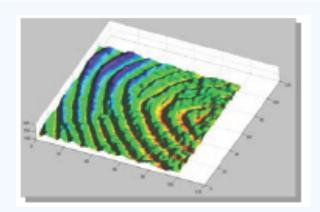


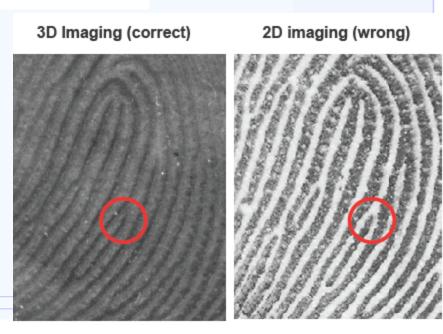
# **Touchless sensor: TBS – Surround Imager**











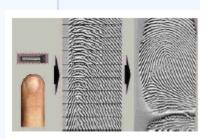
#### **Touch Vs Sweep**

- Drawbacks of Touch method
  - Sensor can become dirty
  - Visible latent fingerprints remains on the sensor
  - Rotation of the fingerprint may be a problem
  - Strict trade-off between the cost and the size of the sensing area

#### **Advantages and drawbacks of Sweeping Method**

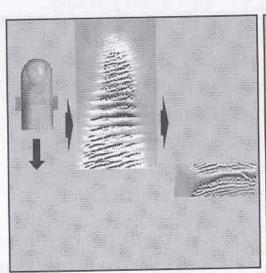
- Equilibrium is continuously broken when sweeping, as ridges and valleys touch the pixels alternately, introducing a continuous temperature change
- Sensors always look clean
- No latent fingerprints remain
- No rotation

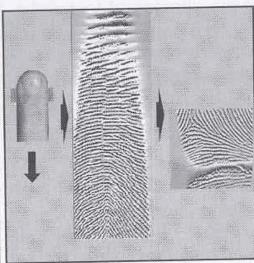
- Novice user may encounter difficulties
- Interface must be able to capture a sufficient number of fingerprint slices
- Reconstruction of the image from the slices is time consuming



#### **Sweeping Method**







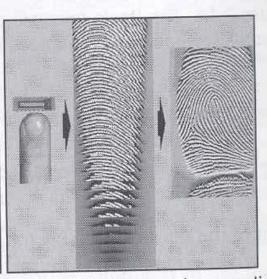


Figure 2.12. As the user sweeps her finger on the sensor, the sensor delivers new image slices, which are combined into a two-dimensional image.





#### Algorithm for fingerprint recognition from the slices

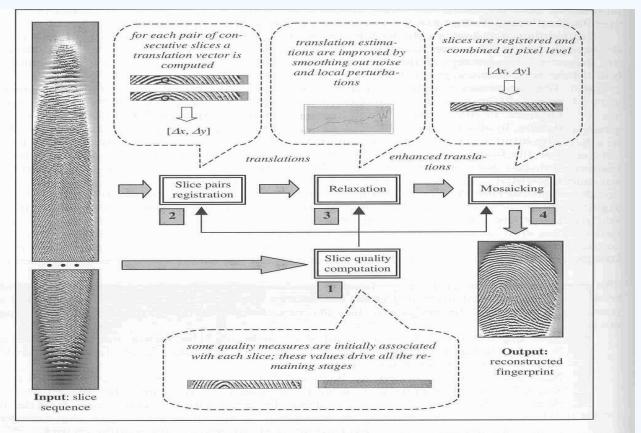


Figure 2.13. An algorithm for fingerprint reconstruction from slices. All the steps are performed sequentially on the whole set of slices. The output of the slice pair registration is a set of translation estimates that are globally enhanced by the relaxation step. These improved estimates drive the mosaicking phase in order to reconstruct the whole fingerprint image.

- Main stages are
- Slice quality computation
- Slice pair registration
- Relaxation
- Mosaicking









igure 2.14. Fingerprint images of the same finger with ideal skin condition as acquired by diferent commercial scanners. Images are reported with right proportions: a) Biometrika FX2000, b) Digital Persona UareU2000, c) Identix DFR200, d) Ethentica TactilSense T-FPM, e) STdicroelectronics TouchChip TCS1AD, f) Veridicom FPS110, g) Atmel FingerChip AT77C101B, b) Authentec AES4000.







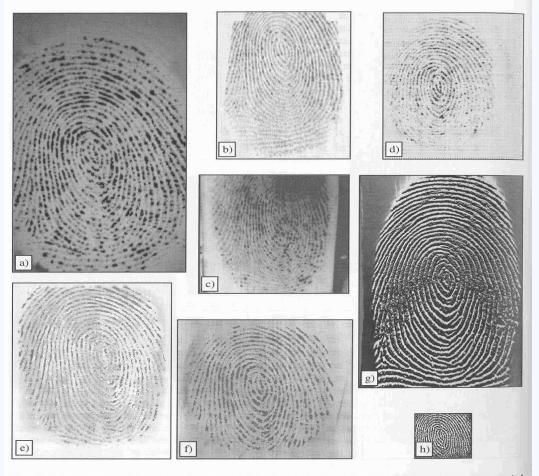


Figure 2.15. Fingerprint images of the same dry finger as acquired by different commercial scanners. Images are reported with right proportions: a) Biometrika FX2000, b) Digital Persona UareU2000, c) Identix DFR200, d) Ethentica TactilSense T-FPM, e) ST-Microelectronics TouchChip TCS1AD, f) Veridicom FPS110, g) Atmel FingerChip AT77C101B, h) Authentec AES4000.









Figure 2.16. Fingerprint images of the same wet finger as acquired by different commercial scanners. Images are reported with right proportions: a) Biometrika FX2000, b) Digital Persona UareU2000, c) Identix DFR200, d) Ethentica TactilSense T-FPM, e) ST-Microelectronics TouchChip TCS1AD, f) Veridicom FPS110, g) Atmel FingerChip AT77C101B, h) Authentec AES4000.







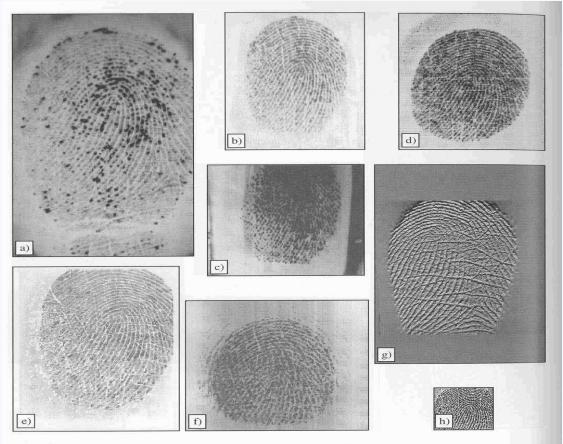


Figure 2.17. Fingerprint images of the same poor quality finger as acquired by different commercial scanners. Images are reported with right proportions: a) Biometrika FX2000, b) Digital Persona UareU2000, c) Identix DFR200, d) Ethentica TactilSense T-FPM, e) ST-Microelectronics TouchChip TCS1AD, f) Veridicom FPS110, g) Atmel FingerChip AT77C101B, h) Authentec AES4000.



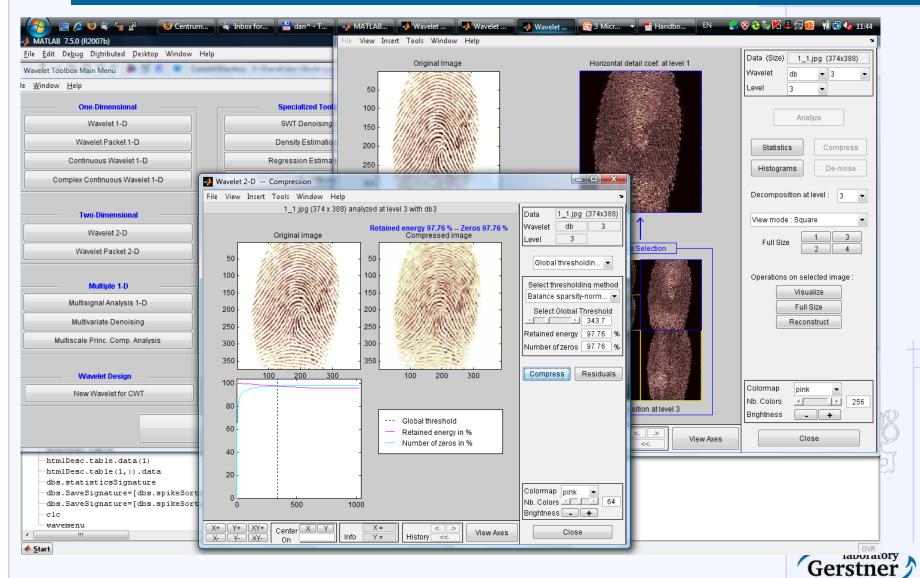


### **Storing and Compressing fingerprint images**

- Each fingerprint impression produces an image of 768 x 768 ( when digitized at 500 dpi)
- In AFIS applications, this needs more amount of memory space to store these images
- Neither lossless methods or JPEG compression techniques are satisfactory
- A new compression technique called Wavelet Scalar Quantization (WSQ) is introduced to compress the images



# DEMO, wavemenu





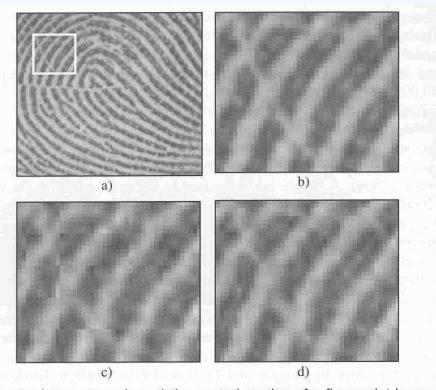


Figure 2.21. Fingerprint compression: a) the central section of a fingerprint image scanned at 500 dpi resolution; b) the marked portion of the image in a); c) the marked portion of the image in a) after the image was compressed using a generic JPEG (www.jpeg.org) image compression algorithm; and d) the marked portion of the image in a) is shown after the image was compressed using the WSQ compression algorithm. Both JPEG and WSQ examples used a compression ratio of 1:12.9; JPEG typically introduces blocky artifacts and obliterates detailed information. Images courtesy of Chris Brislawn, Los Alamos National Laboratory.





# **Enhancement, and Minutias Detection I**

**Daniel Novák** 

3.10.2019, Prague

Acknowledgments: Xavier Palathingal, Andrzej Drygajlo, Handbook of Fingerprint Recognition





Interleaved ridges and valleys

Ridge width: 100µm

300 µm

Ridge-valley cycle:

500 µm

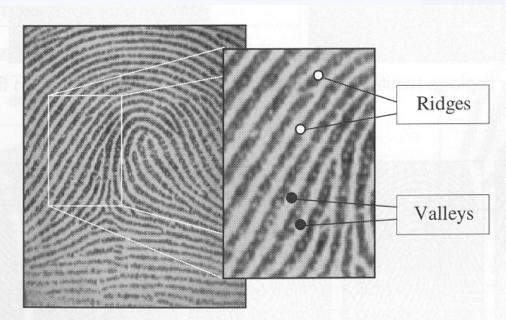


Figure 3.1. Ridges and valleys on a fingerprint image.

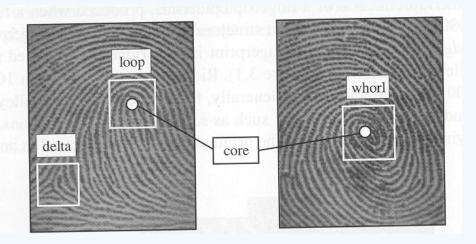




### **A Global Look**

**Singularities:** In the global level the fingerprint pattern shows some distinct shapes

- Loop ( )
- Delta (Δ)
- Whorl (O)...Two facing loop



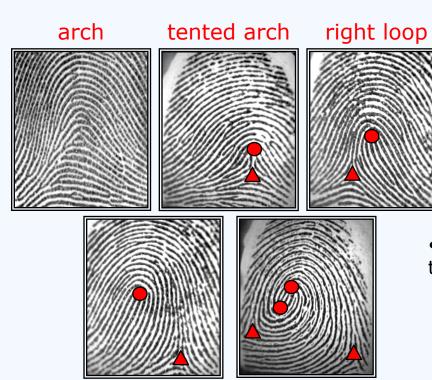
#### Core:

- •A reference point for the alignment.
- •The northmost loop type singularity.
- •According to Henry(1900), it is the northmost point of the innermost ridgeline.
- Not all fingerprints have a core (Arch type fingerprints)





Singular regions are commonly used for fingerprint classification:



whorl

left loop

- •Tzv Henryho systém, rozděluje otisky do pěti tříd
  - Závit (whorl)
  - •Levá a pravá smyčka (loop)
  - Oblouk (arch)
  - Špičatý oblouk (tented arch)





### **Local Look**

Minutia: Small details. Discontinuties in the ridges. (Sir Francis Galton)

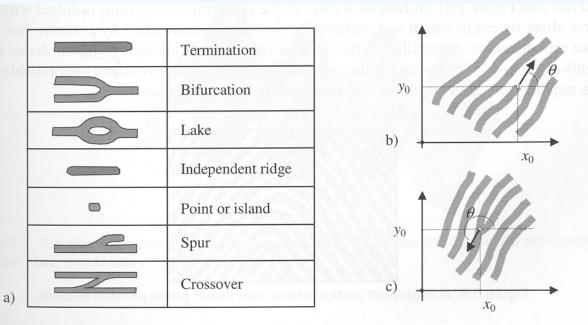


Figure 3.4. a) The most common minutiae types; b) a termination minutia:  $[x_0, y_0]$  are the minutia coordinates;  $\theta$  is the angle that the minutia tangent forms with the horizontal axis; c) a bifurcation minutia:  $\theta$  is now defined by means of the termination minutia corresponding to the original bifurcation that exists in the negative image.





### **Terminologie**

- Papilarni linie
- Vyvýšeniny (ridge)+ prohlubeniny (furrow)
- Charakteristické body
  - Kritické (singulární) body globálně význačné body
    - Jádro
    - Delty
  - Markanty (Minutiaes) lokálně význačné body
    - Rozvětvení (bifurcation)
    - Zakončení (ridge ending)
    - Krátké hrany (short ridge)
    - Překřížení (crossover, bridge)
    - Krátké rozvětvení (spur)
    - Očka (ridge enclosures)





### **Local Look**

Ridge ending / ridge bifurcation duality

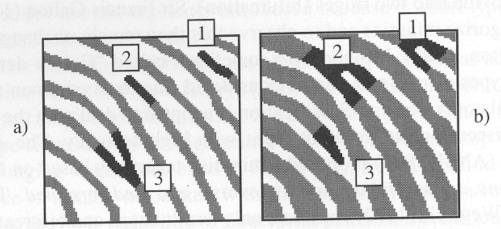


Figure 3.5. The termination/bifurcation duality on a) a binary image and b) its negative image.





### **Local Look**

### **Sweat Pores**

- High resolution images (1000 dpi)
- Size 60-250 μm
- Highly distinctive
- Not practical (High resolution, good quality images)





Figure 3.6. A fingerprint portion where skin sweat pores are well evident.

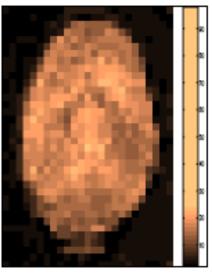


### **Segmentation**









Variance image



Segmented image

Segmentation is the process of isolating foreground from background:

- Image block (16x16 pixels) decomposition
- Thresholding using variance of gradient for each block



# Segmentation

- Separating FP from background
- Straited patterns: no thresholding, striped and oriented pattern & isotropic pattern without orientation
- Segmentation Methods (16x16 block)
  - Variance orthogonal to the ridge direction [Ratha95]
    - Assumption: fingerprint area will exhibit high variance, where as the background and noisy regions will exhibit low variance.
    - Variance can also be used as the quality parameter of the regions.
      - High variance (high contrast): good quality
      - Low variance (low contrast): poor quality
    - Average magnitude of gradient in blocks
      - Fp1 = segmentimage(Fp1);





# **Enhancement, and Minutias Detection II**

**Daniel Novák** 

10.11, 2015, Prague

Acknowledgments: Xavier Palathingal, Andrzej Drygajlo, Handbook of Fingerprint Recognition



- Average orientation around indices i,j
- Unoriented directions
- Weighted (r<sub>ij</sub>)

- $\nabla f = \left(\frac{\partial f}{\partial x_1}, \dots, \frac{\partial f}{\partial x_n}\right).$
- Gradient, maximum pixel-intensity change, arctan gy/gx

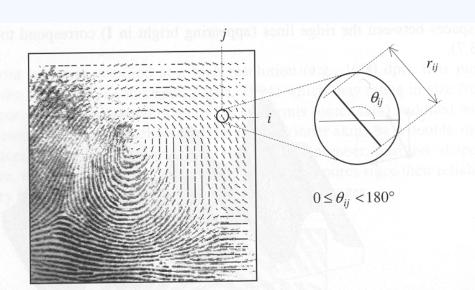


Figure 3.8. A fingerprint image faded into the corresponding orientation image computed over a square-meshed grid of size 16×16. Each element denotes the local orientation of the fingerprint ridges; the element length is proportional to its reliability.







### -Simple Approach

- Gradient with Sobel or Prewitt operators
- Θ<sub>ij</sub> is orthogonal to the direction of the gradient

$$M_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad M_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$M_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad M_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

### Drawbacks:

Non-linear and discontinuous around 90 A single estimate is sensitive to noise Circularity of angles: Averaging is not possible Averaging is not well defined.





Averaging Gradient Estimates
(Kass, Witkin 1987)  $d_{ii} = [r_{ii}, \cos 2\theta_{ii}, r_{ii} \sin 2\theta_{ii}]$ 

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

$$r = \nabla_x^2 + \nabla_y^2$$

(2)





### Effect of averaging

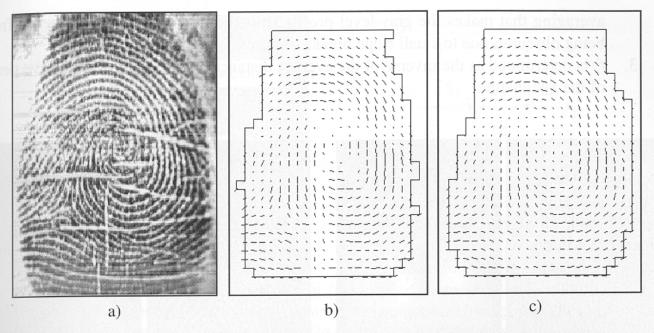


Figure 3.9. a) A poor quality fingerprint image; b) the orientation image of the fingerprint in a) is computed through the Donahue and Rokhlin (1993) method; the orientation of several elements is clearly inconsistent and a regularization step appears necessary; c) the orientation image is the result of the local averaging of each element in b) in its  $3 \times 3$  window according to Equation (2).





## **Orientation field**



An orientation is calculated for each 16x16 block

- Compute the gradient of the smoothed block.  $G_x(i,j)$  and  $G_y(i,j)$  using 3x3 Sobel Masks
- Obtain the dominant direction in the block using the following equation:

$$\theta_d = \frac{1}{2} tan^{-1} \left( \begin{array}{c} \sum_{i=1}^{16} \sum_{j=1}^{16} 2G_x(i,j)G_y(i,j) \\ \frac{1}{16} \sum_{i=1}^{16} \sum_{j=1}^{16} (G_x(i,j)^2 - G_y(i,j)^2) \end{array} \right), G_x \neq 0 \text{ and } G_y \neq 0$$
 (1)

$$G_{xy} = \sum_{h=-8}^{8} \sum_{k=-8}^{8} \nabla_{x} (x_{i} + h, y_{j} + k) \cdot \nabla_{y} (x_{i} + h, y_{j} + k) ,$$

$$G_{xx} = \sum_{h=-8}^{8} \sum_{k=-8}^{8} \nabla_{x} (x_{i} + h, y_{j} + k)^{2} ,$$

$$G_{yy} = \sum_{h=-8}^{8} \sum_{k=-8}^{8} \nabla_{y} (x_{i} + h, y_{j} + k)^{2} ,$$

$$G_{yy} = \sum_{h=-8}^{8} \sum_{k=-8}^{8} \nabla_{y} (x_{i} + h, y_{j} + k)^{2} ,$$

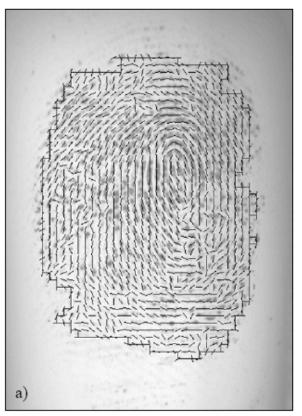
$$G_{yy} = \sum_{h=-8}^{8} \sum_{k=-8}^{8} \nabla_{y} (x_{i} + h, y_{j} + k)^{2} ,$$

- DEMO: Fp1 = computeorientationarray(Fp1);
- Gradient is computed by (standard): [fx, fy] = gradient(double(im));
- Block 10x10



## **Example: Orientation field**





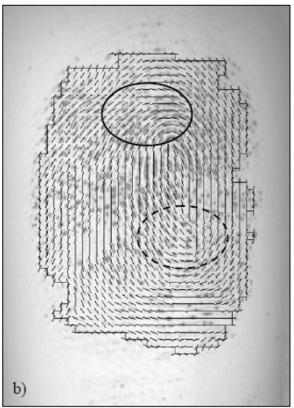
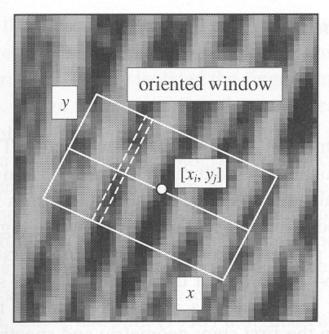


Figure 3.12. a) Estimation of local ridge orientation in a fingerprint through the gradient-based approach corresponding to Equation (3): in the noisy regions the estimation is unreliable; b) two iterations of local (3x3) smoothing are applied, resulting in a more consistent representation; it is worth noting that while the smoothing recovered the correct orientation at several places (e.g., inside the solid circle), it altered the average orientation inside the region denoted by the dashed circle where incorrect orientations were dominating the correct one.

### **Estimation of Local Ridge Frequency**





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

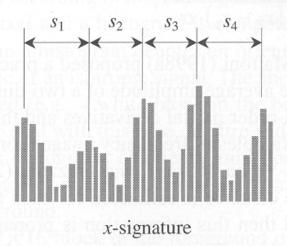


Figure 3.11. An oriented window centered at  $[x_i, y_j]$ ; the dashed lines show the pixels whose gray-levels are accumulated for a given column of the *x*-signature (Hong, Wan, and Jain, 1998). The *x*-signature on the right clearly exhibits five peaks; the four distances between consecutive peaks are averaged to determine the local ridge frequency.



### **Estimation of Local Ridge Frequency**



### Simple Algorithm

- 1) 32x16 oriented window centered at  $[x_i, y_i]$
- 2) The x-signature of the grey levels is obtained
- 3) f<sub>ii</sub> is the inverse of the average distance

To handle noise interpolation and/or low pass filtering is applied.

**DEMO:** Fp1 = computelocalfrequency(Fp1, Fp1.imOriginal);



### **Estimation of Local Ridge Frequency**



### Examples of frequency maps

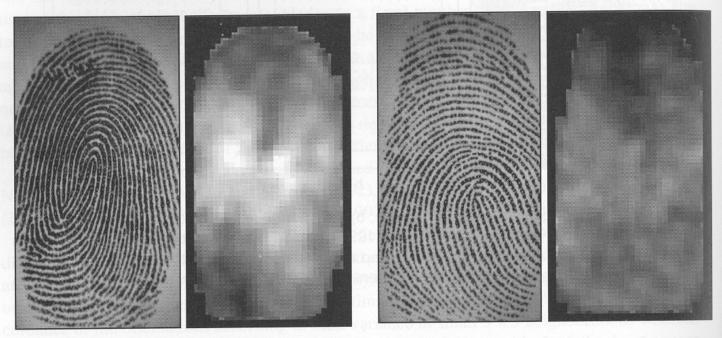


Figure 3.10. Two fingerprint images and the corresponding frequency image computed with the method proposed by Maio and Maltoni (1998a). A local  $3 \times 3$  averaging is performed after frequency estimation to reduce noise. Light blocks denote higher frequencies. It is quite evident that significant changes may characterize different fingerprint regions and different average frequencies may result from different fingers.



### **Contextual Filters**

- The most widely used technique for fingerprint image enhancement
- Conventional image filtering a single filter is used for convolution throughout
- Contextual filtering filter characteristics change according to local context
- Several types of contextual filters proposed
- Indented behavior
  - 1)provide a low-pass [averaging] effect along the ridge direction.
     Linking small gaps and filling impurities due to noise
  - 2)perform a band pass [differentiating] in the direction orthogonal to the ridges
     Increase discrimination between ridges and valleys





### Method proposed by Hong, Wan, and Jain

- Based on Gabor filters
- Gabor filters have both frequency-selective and orientation-selective properties and have optimal joint resolution in spatial and frequency domains
- A Gabor filter is defined by a sinusoidal plane wave tapered by a Gaussian

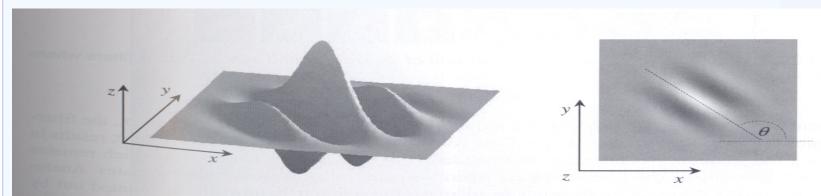


Figure 3.28. Graphical representation (lateral view and top view) of the Gabor filter defined by the parameters  $\theta$  = 135°, f = 1/5, and  $\sigma_x$  =  $\sigma_y$  = 3.







# The even symmetric two-dimensional Gabor filter has the following form:

$$g(x, y: \theta, f) = \exp\left\{-\frac{1}{2}\left[\frac{x_{\theta}^{2}}{\sigma_{x}^{2}} + \frac{y_{\theta}^{2}}{\sigma_{y}^{2}}\right]\right\} \cdot \cos(2\pi f \cdot x_{\theta}), \tag{5}$$

where  $\theta$  is the orientation of the filter, and  $[x_{\theta}y_{\theta}]$  are the coordinates of [x,y] after a clockwise rotation of the Cartesian axes by an angle of  $(90^{\circ}-\theta)$ .

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

Here, f is the frequency of a sinusoidal plane wave and  $\sigma_x$  and  $\sigma_y$  are the standard deviations of the Gaussian envelope along the x and y axes

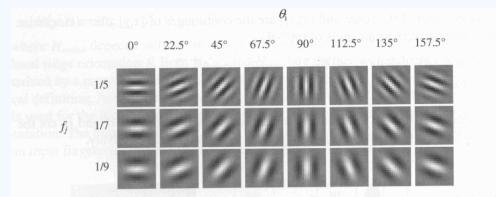




## Method proposed by Hong, Wan, and Jain (cont ..) Gabor Filter



- -4 parameters  $-\theta$ , f,  $\sigma_x$ ,  $\sigma_y$
- The selection of the values  $\sigma_x$  and  $\sigma_y$  involves a tradeoff
- A set  $\{g_{ij}(x,y) \mid i=1...n_0,1..n_f\}$  of filters are priori created and stored , where  $n_0$  is the number of discrete orientations  $\{\theta_i \mid i=1,...n_0\}$  and  $n_f$  the number of discrete frequencies  $\{f_i \mid j=1,...n_f\}$
- Each pixel [x,y] is convolved, with filter  $g_{ij}(x,y)$  such that  $\theta_i$  is the discretized orientation closest to  $\theta_{xy}$  and  $f_j$  is the discretized orientation closest to  $f_{xy}$
- DEMO: Fp1 = enhance2ridgevalley(Fp1);





### Method proposed by Hong, Wan, and Jain (cont ..)

Examples

-Shows the application of Gabor-based contextual filtering on medium and poor quality images

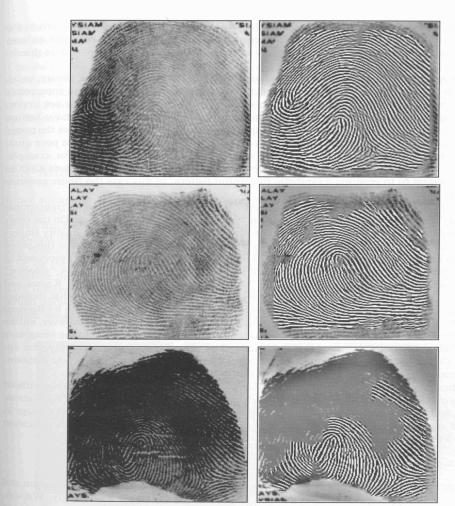


Figure 3.30. Examples of fingerprint enhancement with Gabor filtering as proposed by Hong, Wan, and Jain (1998). On the right, the enhanced recoverable regions are superimposed on the corresponding input images. ©IEEE.

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### **Minutiae Detection**

- Reliable minutiae extraction is extremely important
  - Binarization
  - Thinning
  - Post processing filling holes, linking breaks, removing bridges

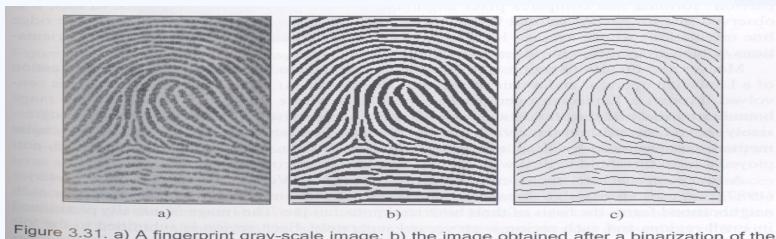


Figure 3.31. a) A fingerprint gray-scale image; b) the image obtained after a binarization of the image in a); c) the image obtained after a thinning of the image in b). Reprinted with permission from Maio and Maltoni (1997). ©IEEE.

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### **Binarization-based methods**

- Simplest method global threshold
  - Local threshold technique
    - Fingerprint specific solutions necessary
    - Binarization is the output of Contextual Filtering: enhance2ridgevalley.m

```
binaryBlkSize = 20;
```

imReconstruct = blkproc(imReconstruct, [binaryBlkSize binaryBlkSize], @binarizeimage);

```
function Iout = binarizeimage(Iin)
level = graythresh(Iin); %Otsu method
Iout = im2bw(Iin, level);
```





### **Threshold computation: Otsu I**



- Otsu's method: N. Otsu (1979). "A threshold selection method from gray-level histograms". IEEE Trans. Sys., Man., Cyber. 9: 62–66
  - http://en.wikipedia.org/wiki/Otsu%27s\_method
  - http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL\_COPIES/MORS
     E/threshold.pdf
- minimizes the intra-class variance for each threshold T lot's of work

$$\sigma_{\mbox{Within}}^2(T) = n_B(T) \sigma_B^2(T) + n_O(T) \sigma_O^2(T)$$

– between-class variance:

$$n_B(T) = \sum_{i=0}^{T-1} p(i)$$

$$n_O(T) = \sum_{i=T}^{N-1} p(i)$$

 $\sigma_B^2(T)$  = the variance of the pixels in the background (below threshold)

 $\sigma_O^2(T)$  = the variance of the pixels in the foreground (above threshold)

$$\sigma_{\text{Between}}^{2}(T) = \sigma^{2} - \sigma_{\text{Within}}^{2}(T)$$

$$= n_{B}(T) \left[\mu_{B}(T) - \mu\right]^{2} + n_{O}(T) \left[\mu_{O}(T) - \mu\right]^{2}$$

where  $\sigma^2$  is the combined variance and  $\mu$  is the combined mean representation of the combined mean representation.

### **Threshold computation: Otsu II**

- Compute histogram and probabilities of each intensity level
- Set up initial  $n_b(0)$  and  $n_o(0)$  and  $\mu_b(0)$ ,  $\mu_o(0)$
- Step through all possible thresholds T=1.... maximum intensity
  - Update  $n_b(T)$ , $n_o(T)$
  - Compute  $\sigma_{\text{between}}(T)$
- Desired threshold corresponds to the maximum  $\sigma_{\text{between}}(T)$





### **Minutiae detection**

- A simple image scan allows the pixel corresponding to minutiae to be detected
- crossing number of a pixel p
- -DEMO: Fp1 = cleanskeleton(Fp1);

$$cn(\mathbf{p}) = \frac{1}{2} \sum_{i=1..8} |val(\mathbf{p}_{i \mod 8}) - val(\mathbf{p}_{i-1})|,$$

where  $\mathbf{p}_0$ ,  $\mathbf{p}_1$ , ...,  $\mathbf{p}_7$  are the pixels belonging to an ordered sequence of pixels defining the 8-neighborhood of  $\mathbf{p}$  and  $val(\mathbf{p}) \in \{0,1\}$  is the pixel value. It is simple to note (Figure 3.36) that a pixel  $\mathbf{p}$  with  $val(\mathbf{p}) = 1$ :

- is an intermediate ridge point if  $cn(\mathbf{p}) = 2$ ;
- corresponds to a termination minutia if  $cn(\mathbf{p}) = 1$ ;
- defines a more complex minutia (bifurcation, crossover, etc.) if  $cn(\mathbf{p}) \ge 3$ .

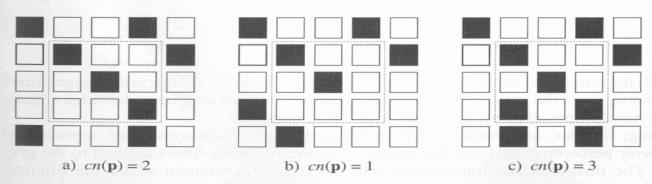


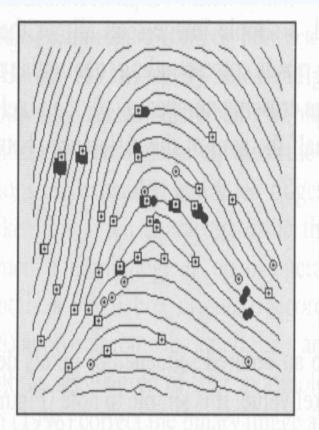
Figure 3.36. a) intra-ridge pixel; b) termination minutia; c) bifurcation minutia.





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### **Examples of minutiae extraction**



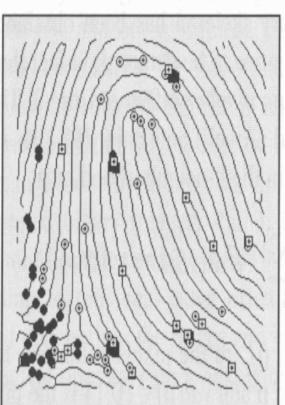
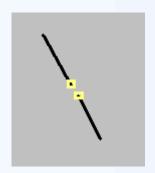


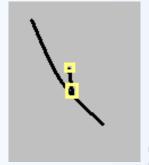
Figure 3.37. Examples of minutiae detection on binary skeletons. White circles and white boxes denote terminations and bifurcations, respectively; black circles and black boxes denote filtered minutiae (see Section 3.9).

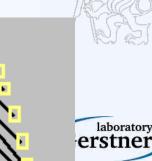
Department of Cybernetics, Czech Technical University

### **Minutiae Filtering**

- Post-processing stage is useful for removing spurious minutiae [already present or introduced by previous steps]
- Two main post-processing types:
  - Structural post-processing
  - Minutiae filtering in the gray-scale domain
- Ridge breaks (insufficient ink or moist)
- Ridge cross-connections (over-ink, over-moist)
- Boundaries







# Example



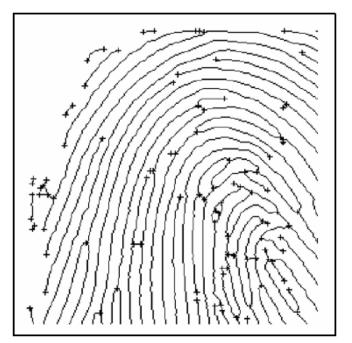




Figure 3.51. Minutiae post-processing according to Farina, Kovacs-Vajna, and Leone (1999). On the right, most of the false minutiae present in the thinned binary image (on the left) have been removed. © Elsevier.

