Lecture 2: Fingerprint recognition

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Fall 2014 University of Notre Dame, IN, USA



Historical background What we observe in fingerprint biometrics? Fingerprint image capture Fingerprint image pre-processing Fingerprint recognition methods Minutiae detection Minutiae matching

Historical background

Lecture 2: Fingerprint recognition Historical background

What we observe in fingerprint biometrics? Fingerprint image capture Fingerprint image pre-processing Fingerprint recognition methods Minutiae detection Minutiae matching

Scientific milestones

- 1. 1684: Nehemian Grew, UK
 - first scientific work on fingerprint structure (description of ridges, valleys and sweat pores)
- 2. 1686: Marcello Malpighi, University of Bologna
 - first classification of fingerprints (definition of similar patterns possible to be grouped)
 - similar work done later by John Purkinji (1823, Poland) and Sir Edward R. Henry (1899, UK)

Scientific milestones

3. 1880: Henry Faulds, Tokio, Japan

- first experiments showing high uniqueness of fingerprints
- first identification of a latent fingerprint left on a bottle (after a theft in Tokio's hospital)
- skill sharing with Charles Darwin and Francis Galton (Darwin's cousin)
- 4. 1888: Sir Francis Galton
 - definition and classification of fingerprint singular points
 - definition of "minutiae" (a.k.a. *Galton's details*)
 - experiments presenting high temporal stability and uniqueness of fingerprints (estimated identification error probability 1:64 billion)
 - "Fingerprints" book: foundations of the methods used presently in biometric systems

Scientific milestones

Criticism of the "Fingerprints" book, New York Times, 1893

"Carried away by his enthusiasm, Mr. Galton declares that these markings «are in some respects the most important of all anthropological data» (...) What Mr. Galton wants to show is that through the prints made by the finger tips we have an absolute method of identification. As to that stupid thing, palmistry, our authority says it has no more significance than the creases on old clothes."

"When one comes to the real practical use of the finger-mark method it seems to have none. If there be any reliance to be put in it as a means of identification it would require an expert having uncommon powers of observation."

"Scientifically, when further treated, the subject may be of minor interest; practically, it has none at all. The book, of course, shows that diligence and hard work which are common to everything Mr. Galton does, but really «the play is not worth the candle»." MR. GALTON ON FINGER PRINTS. FINGER PRINTS. By Fearch Gallen, P. B. S.

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Bertillonage system ...



5. 1880: Alphonse Bertillon, France

 Bertillonage system: lengths of bones + "soft biometrics": height and weight, iris color (<u>not</u> the iris pattern used currently) Biometrics (CSE 40537/60537) Lecture 2: Fingerprint recognition LHistorical background

... and its collapse in 1903



William West and Will West institutionalized at the same time to the same penitentiary in Leavenworth, Kansas, USA. This significantly undermined the *Bertillonage* system reliability.

Source: "History of Fingerprints", INTERPOL, 2009

Application milestones

- 1. 1892: Juan Vucetich, Argentina
 - first criminal case, in which the latent fingerprints were used to proof a crime
- 2. 1910: Edmond Locard, France
 - experiments delivering the number (=12) of matching features required in a court (i.e. defendant is pronounced guilty if at least 12 features match in the sample and reference material)
 - *Exchange Principle*: when committing a crime we always leave something at the crime scene, and take something with us
- 3. 1903–1924: Common acceptance of fingerprints as an authentication method
 - 1903: Scotland Yard starts to use fingerprints
 - 1915: foundation of the *International Association for Identification*
 - 1924: Fingerprint Identification Division becomes part of *Bureau of Investigation*



IAI logo

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What we knew at the beginning of XX century?

- 1. Individual features of the fingerprints are unique in different fingers and stable in time (foundation of fingerprint recognition)
- Fingerprint ridges and valleys can be grouped by similar shapes observed across the human population (foundation of fingerprint classification)

What we observe in fingerprint biometrics?

Lecture 2: Fingerprint recognition

Historical background

What we observe in fingerprint biometrics?

Fingerprint image capture Fingerprint image pre-processing Fingerprint recognition methods Minutiae detection Minutiae matching

What we observe in fingerprint biometrics?

Zooming in the fingerprint surface

- 1. Base elements: ridges and valleys
- 2. Level 1 features: core and singular points
- 3. Level 2 features: minutiae (Galton's details)
- 4. Level 3 features: sweat pores, incipient ridges, warts, scars, creases

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Base elements: ridges and valleys



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Level 1 features: core and singular points



synthetic fingerprints generated by SFINGE

- 1. Singular points
 - whorl, loop, delta
 - we need singular points to classify the fingerprints
- 2. Core
 - the uppermost singular point, or the point where the ridge curvature is the highest (if there is no singular point)
 - we need the core to align fingerprint images (before feature extraction

Detection of singular points

Use of Poincaré index (Kawagoe and Tojo, 1984)



- 1. In general: total rotation along the curve on a gradient field
- 2. In fingerprints: we use directional image to estimate ridge directions and calculate the Poincaré index

Detection of singular points

How to calculate directional image?



1. Calculate a (discrete) gradient field

$$\nabla(x_i, y_i) = [\nabla_x(x_i, y_i), \nabla_y(x_i, y_i)]^T$$

- Replace gradients with orthogonal vectors and forget about their orientation ⇒ directional field
- Average directions of the directional field in some small neighborhood, e.g. 8×8 pixels ⇒ directional image

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What we observe in fingerprint biometrics?

Detection of singular points

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What we observe in fingerprint biometrics?

Detection of singular points

How to calculate the Poincaré index?

- 1. Select random orientation for one, example element of the directional image
- 2. For the remaining elements select the closest orientation to the neighboring element

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What we observe in fingerprint biometrics?

Detection of singular points

How to calculate the Poincaré index?



3. Travel along the closed curve and sum up the rotations

- 0^o no singular points in this location
- 360^o we found the whorl
- 180^{o} we found the loop
- -180^{o} we found the delta

Detection of singular points Other popular methods

- 1. Local properties of ridge pattern: irregularity, curvature, symmetry
 - for instance: ridge irregularity coefficient (Capelli)

$$\rho_{i,j} = 1 - \frac{\left\|\sum_{m}\sum_{n} \mathbf{d}_{m-i,n-j}\right\|}{\sum_{m}\sum_{n} \left\|\mathbf{d}_{m-i,n-j}\right\|}$$

2. Image partitioning (use of quantized ridge orientation)

Henry's classification



Source: N. Yager, A. Amin, *Fingerprint verification based on minutiae features*. Pattern Anal. Applic. vol. 7, pp. 94-113, 2004

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Level 2 features: minutiae (Galton's details)





images found at www.optel.com.pl

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Lecture 2: Fingerprint recognition

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Erg Chebbi desert, Morocco

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Lecture 2: Fingerprint recognition

What we observe in fingerprint biometrics?



Source: freewallpaperspot.com
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What we observe in fingerprint biometrics?



Source: freewallpaperspot.com

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Level 3 features

based on: A. K. Jain, Y. Chen, and M. Demirkus, Pores and Ridges: High-Resolution Fingerprint Matching Using Level 3 Features, PAMI, IEEE, 2007



- 1. Recommended image resolution: 1000 dpi
- 2. Individual features: shape and location of sweat pores, incipient ridges, warts, scars, creases, wrinkles, ridge dots, etc.
- 3. Helpful when only fragmentary fingerprints are available
- 4. Popular in fingerprint liveness detection

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What we observe in fingerprint biometrics?

AFIS vs. biometrics

(AFIS: Automatic Fingerprint Identification System)

- 1. Criminology
 - Huge data sets: current FBI data set gathers more that 200 million dactyloscopy cards (each card contains fingerprints of all 10 fingers)
 - Different quality of samples (latent and fragmentary fingerprints)
 - Identification times: up to an hour

Example: a single person would need 67 years (!) to search a database gathering 1.7 million dactyloscopy cards; an AFIS system solves this task in ... 20 minutes

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- 2. Biometrics
 - Similar quality of samples
 - Identification times: fraction of a second

Lecture 2: Fingerprint recognition

-Fingerprint image capture

Lecture 2: Fingerprint recognition

Historical background What we observe in fingerprint biometri

Fingerprint image capture

Fingerprint image pre-processing Fingerprint recognition methods Minutiae detection Minutiae matching

Image capture methods

- 1. Off-line techniques
 - Digitizing (scanning) of dactyloscopy cards
 - Digitizing (photographing) of latent fingerprints
- 2. On-line techniques
 - Capacitive sensors
 - Optical sensors
 - Piezoelectric (pressure) sensors
 - Thermal sensors
 - Ultrasound sensors
 - Touchless sensors

Digitizing of latent fingerprints Used by criminology experts, not in biometric systems



Magnetic powder (fluorescent)

Image in visible light

Image in UV light (orange filter applied)

Capacitive sensors



- 1. Matrix of capacitors: charge depends on the distance between the fingerprint ridge and the sensor; charge interpreted by an AD converter as 8-bit numbers
- 2. Low cost, but sensitive to noise (dirt, finger moistness)
- 3. Accuracy decreases if not cleaned (contact with sweat and dirt)
- 4. Typical resolution: 300 dpi

Capacitive sensors

Fingerprint image sample



Source: FVC 2002

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Optical sensors



- 1. Total inside reflection (TIR) at the medium boundary (TIR can be observed for angles larger than some critical angle with respect to the normal to the surface)
- 2. Contact of ridges with the prism \Rightarrow no TIR in these locations (hence dark regions for ridges)
- 3. No contact of valleys with the prism \Rightarrow TIR occurs in these locations (hence bright regions for valleys)
- 4. Typical resolution: 400-600 dpi

Optical sensors

Fingerprint image samples



"Flat" impression (sensor: Biometrika FX2000) "Rolled" impression (from nail to nail) (sensor: CrossMatch LS320)

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Optical sensors

Fingerprint image samples



Thumbs prints

Little, ring, middle and index fingerprints

captured in "4-4-2" mode (sensor: L1 TP4100)

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Piezoelectric (pressure) sensors



- 1. Matrix of piezoelectric sensors: pressure interpreted by an AD converter as 8-bit numbers
- 2. Not sensitive to finger moistness (images of wet and dry fingers are almost identical), and total pressure
- 3. Typical resolution: 400 dpi

Piezoelectric (pressure) sensors

Fingerprint image sample



Thermal sensors (example: Atmel AT77C101B FingerChip)



- 1. Measurement of finger swept over the sensor (8×280)
- 2. AD converter compares temperatures in moments t and $t + \Delta$
- 3. Accuracy depends on stability of Δ

Thermal sensors (example: Atmel AT77C101B FingerChip)



- 4. Small sensor (50 μ m) induces high resolution (500 dpi)
- Inverse proportion between sweep speed and accuracy (for typical speed of finger sweep we need more than 500 measurements per second; typical measurement frequency is 2 kHz)

Thermal sensors

Fingerprint image sample



source: Atmel Fingerchip Witepaper

Ultrasound sensors



- 1. Scattering of sound waves on the medium boundary (sensor finger)
- Reading the scattered waves by a transducer moving along a circular trajectory, whose axis is perpendicular to the contact surface (to collect scattered signal at different angles, typically 256 directions)

Ultrasound sensors

(example: Optel, www.optel.com.pl)



- 3. Typical resolution: 250 dpi, once all impulse response are colected, the image is reconstructed in single milliseconds
- 4. May be costly (when compared to capacitive or optical sensors), but difficult to be faked (ultrasound waves can analyse structures underneath the skin)

Ultrasound sensors

Fingerprint image sample



source: www.optel.com.pl

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Commercial fingerprint sensors (examples)



Optical (Identix)

Capacitive (Precise Biometrics and Covetek)



Piezoelectric (BMF/Hitachi)



Thermal (BioOK and Atmel Fingerchip)



Ultrasound (Optel)

Touchless sensors





SAGEM Biometrics 2009, London, UK

- $1.\ 3D$ imaging with CCD sensors
- 2. Transforming of the 3D fingerprint image to the flat image (compliant to ISO/IEC 19794-4)

Touchless sensors

Fingerprint image sample



sensor: MORPHO

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Touchless sensors



MORPHO Biometrics 2010, London, UK

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Touchless sensors



TST Biometrics Biometrics 2010, London, UK

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Fingerprint data representation

- 1. Raw image (not processed) ISO/IEC 19794-4:2005
- 2. Compressed image
 - WSQ (Wavelet Scalar Quantization) IAFIS-IC-0110 (V3), WSQ Gray-scale Fingerprint Image Compression Specification 1997
 - calculation of the wavelet transform
 - quantization of the wavelet coefficients
 - Huffman encoding
 - JPEG, JPEG2000, PNG
 - compressed images used in biometric ID and travel documents (due to interoperability requirement)

Fingerprint data representation

- 3. Use of spectral data representing local image regions ISO/IEC 19794-3:2006
 - cosine transform
 - discrete Fourier transform
 - Gabor transform
- 4. Skeletal image (symbolic representation of ridges) ISO/IEC 19794-8:2006
- 5. Features (e.g. minutiae) ISO/IEC 19794-2:2005

Lecture 2: Fingerprint recognition

LFingerprint image pre-processing

Lecture 2: Fingerprint recognition

Historical background What we observe in fingerprint biometrics

Fingerprint image capture

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Fingerprint recognition methods Minutiae detection Minutiae matching

Distortions

1. Linear and affine deformations

- translations and rotations of a finger (severe for small sensors) example: finger translation by 2mm (imperceptible for a human) yields 40 pixels of shift in the fingerprint image (for typical 500 dpi sensor)
- 2. Nonlinear (elastic) deformations
 - different pressure level
 - mapping of 3D elastic object into 2D flat image
 - main source of within-class variability

Lecture 2: Fingerprint recognition

LFingerprint image pre-processing

Distortions

- 3. Different scanning areas
- 4. Skin conditions and properties (dry, sweaty, injured)
 - · ridges have no physical contact with a sensor
 - incomplete fingerprint images
 - artificial discontinuities and joints of ridges
- 5. Latent fingerprints left on the sensor (impact especially capacitive and optical sensors)
- 6. Limited accuracy of the sensor

Example: skin condition



Source: D. Maltoni, et al. Handbook of Fingerprint Recognition, Second Edition

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LFingerprint image pre-processing

Image enhancement

1. Enhancement of ridges and valleys

- directional and frequency selectivity: Fourier transform, wavelet transforms (e.g. Gabor)
- maximum filter response for directions orthogonal to ridges
- 2. Enhancement of intensity and contrast
 - histogram alignment
 - Laplace filtering

Image enhancement

Example: use of Gabor filtering for enhancement of ridges and valleys



Graphical representation of Gabor filter bank used in fingerprint image enhancement



Original fingerprint image (<u>left</u>) and enhanced fingerprint image (<u>right</u>)

Source: D. Maltoni, *et al.* Handbook of Fingerprint Recognition, Second Edition Biometrics (CSE 40537/60537)

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L-Fingerprint image pre-processing

Image segmentation



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Image segmentation



1. Analysis of image histograms


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Image segmentation



1. Analysis of image histograms



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Image segmentation



1. Analysis of image histograms



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Image segmentation



2. Average variance

In our example:

$$\sigma_1^2 = 2 \ 441.12$$

 $\sigma_2^2 = 131.96$

Modification: variance calculated only in directions orthogonal to ridges

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Lecture 2: Fingerprint recognition

LFingerprint image pre-processing

Image segmentation



3. Analysis of image gradient

- cohesion of gradient directions in ridge areas
- high values of gradient in ridge areas, low in background

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Image segmentation



- 4. Local Fourier spectrum for image energy estimation
- 5. Gabor filters (directional and frequency selectivity)
- 6. Multidimensional metrics (accurate but time-consuming)

Examples:

- variance + intensity + gradient cohesion
- morphological filters + linear classifier

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Lecture 2: Fingerprint recognition

LFingerprint image pre-processing

Image segmentation



Example result of fingerprint image segmentation: Gabor filters and a global threshold were use to recognize 'ridge' and 'background' areas. Lecture 2: Fingerprint recognition

LFingerprint recognition methods

Lecture 2: Fingerprint recognition

Historical background What we observe in fingerprint biometric Fingerprint image capture

Fingerprint image pre-processing

Fingerprint recognition methods

Minutiae detection Minutiae matching

Classification of fingerprint recognition methods

- 1. Matching at level 1
 - local properties of directional images
 - image filtering, wavelet transformation + quantization (building a 'fingerprint code')
 - image (local) correlation

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 - fingerprint image representation as a minutiae map (location and rotation, rarely type)
 - minutiae-base methods significantly prevail over all remaining methods

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 - fingerprint image representation as a minutiae map (location and rotation, rarely type)
 - minutiae-base methods significantly prevail over all remaining methods
- 3. Matching at level 3
 - properties of level 3 features: shape, location, orientation (if makes sense), properties in a wavelet domain

Biometrics (CSE 40537/60537)

Lecture 2: Fingerprint recognition

LFingerprint recognition methods

Do we need non-minutiae methods?

Do we need non-minutiae methods?

- 1. Higher reliability for low quality fingerprint images
- 2. Useful for fragmentary fingerprints
- 3. Additional description of the fingerprints image (higher number of biometric features should help in authentication)

Do we need non-minutiae methods?

- 1. Higher reliability for low quality fingerprint images
- 2. Useful for fragmentary fingerprints
- 3. Additional description of the fingerprints image (higher number of biometric features should help in authentication)

Answer: YES, sometimes they provide the only authentication possibility when minutiae-based methods fail.

Lecture 2: Fingerprint recognition

Minutiae detection

Lecture 2: Fingerprint recognition

Historical background What we observe in fingerprint biometric Eingerprint image capture

Fingerprint image capture

Fingerprint image pre-processing

Fingerprint recognition methods

Minutiae detection

Minutiae matching

How to locate the minutiae?



Minutiae detection

Use of gray scale images

- 1. Ridge tracking (Maio, Maltoni, 1997)
 - Modification 1: adaptive step and binarization threshold (Jiang, Yau, Ser 1999, 2001)
 - Modification 2: simultaneous tracking of a ridge and the neighboring valleys (Liu, Huang, Chan, 2000)
- 2. Gabor wavelet features + nonlinear classification, e.g. nonlinear neural network (Leung, Engeler, Franck, 1990)
- 3. Gaussian Mixture Models for local histograms modeling + (Chang, Fan, 2001)
- 4. Local symmetry of the image (Nilsson, Bigun, 2001)

Minutiae detection

Use of binary images



1. Binary image generation

- use of a global intensity threshold (simple, but low quality)
- use of a local or adaptive intensity threshold (may be preceded by ridge and valley enhancement)
- decomposition of a local histogram in directions orthogonal to ridges (Ratha, Chen, Jain, 1995)
- 2. Ridge tracking (easier than in gray scale image)

Minutiae detection

Use of skeletal images



1. Thinning of the binary image

- solutions inspired by methods used in maps vectorization and handwriting recognition
- popular solutions are based on mathematical morphology (e.g. multiple erosion)

$2. \ \ \text{Smoothing of the skeletal image}$

- removing very short ridges
- removing very short joints
- joining very short ridge breaks

Minutiae detection

Use of skeletal images



3. Simple analysis of neighboring pixels

number of neighboring 'ridge' pixels provides the answer:

- = 1 : ridge ending
- = 2 : ridge (no minutia)
- $\geqslant 3$: bifurcation

Minutiae detection

Use of skeletal images



- 4. Minutiae filtering: removal of 'fake' (excessive) minutiae
 - heuristic methods
 - removing of minutiae located at boundaries
 - removing constellations of minutiae
 - duality of minutiae: simultaneous processing of positive and negative images (Hung, 1993)

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Example minutiae map

Right: minutiae directions compliant to ISO/IEC FDIS 19794-2 (2011)



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Minutiae matching

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Historical background

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Minutiae detection

Minutiae matching

Minutiae matching steps

1. Compensation of linear deformations

 finding a linear mapping between the probe and reference maps of minutiae



2. Compensation of non linear deformations

- popular and easy: setting the tolerance box: a margin of acceptable difference between properties of two minutiae
- more accurate, yet time consuming: surface warping (Capelli, Maio, Maltoni, 2001)
- interesting: use of canonical form of the skeletal images (Senior, Bolle, 2001)

Minutiae matching steps

3. Calculation of the matching score

- popular: number of minutiae that match average number of minutiae in both maps
- modifications: a) in denominator: number of elements in the common set of minutiae maps, b) minutiae weighting depending on their quality)

Minutiae matching

Mathematical definition of the problem

Minutiae sets:

$$\mathcal{T} = \{\mathbf{m}_1, \mathbf{m}_2, \dots, \mathbf{m}_M\}, \quad \mathbf{m}_i = \{x_i, y_i, \theta_i\}, \quad i = 1, \dots, M$$
$$\mathcal{P} = \{\mathbf{m}'_1, \mathbf{m}'_2, \dots, \mathbf{m}'_N\}, \quad \mathbf{m}'_j = \{x'_j, y'_j, \theta'_j\}, \quad j = 1, \dots, N$$

Two minutiae match if:

$$s(\mathbf{m}'_j, \mathbf{m}_i) = \sqrt{(x'_j - x_i)^2 + (y'_j - y_i)^2} \leqslant r_0$$
$$d(\mathbf{m}'_j, \mathbf{m}_i) = \min\left(|\theta'_j - \theta_i|, 360^\circ - |\theta'_j - \theta_i|\right) \leqslant \theta_0$$

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Minutiae matching

Mathematical definition of the problem

Finding a mapping function:

$$f: \mathbf{m}'_j \mapsto \mathbf{m}''_j$$
$$\mathbf{m}'_j = \{x'_j, y'_j, \theta'_j\}, \quad \mathbf{m}''_j = \{x''_j, y''_j, \theta'_j + \theta\}, \quad j = 1, \dots, N$$

typically only shift and rotation are used, that is:

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

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Minutiae matching

Mathematical definition of the problem

Aim function:

$$\max_{\Delta x, \Delta y, \theta, p} \sum_{i=1}^{N} h\Big(f_{\Delta x, \Delta y, \theta}(\mathbf{m}'_{p(i)}), \mathbf{m}_i\Big)$$

where

$$h(\mathbf{m}_{j}'',\mathbf{m}_{i}) = \begin{cases} 1 & \text{if } s(\mathbf{m}_{j}'',\mathbf{m}_{i}) \leqslant r_{0} \text{ and } d(\mathbf{m}_{j}'',\mathbf{m}_{i}) \leqslant \theta_{0} \\ 0 & \text{otherwise} \end{cases}$$

and p defines the minutiae correspondence in the maps ${\mathcal T}$ i ${\mathcal P}.$

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Minutiae matching

Mathematical definition of the problem

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Mathematical definition of the problem

Remarks on p function:

• p(i) = j does not mean that two minutiae "match" in h sense

Minutiae matching

Mathematical definition of the problem

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- p(i) = j when $\mathbf{m}_i \in \mathcal{T}$ has a correspondent minutia $\mathbf{m}_j' \in \mathcal{P}$

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- *p* is a bijection: each minutia m'_j ∈ P has a single correspondent minutia m_i ∈ T (and minutiae that have no correspondence are skipped)
- in practice *p* is unknown, and brute-force solutions (checking every minutiae pair) yield exponential calculation times

Compensation of linear deformations

Example approach: use of Hough transform

- 1. Popular and fast
- 2. Converts point-pattern matching problem into detecting peaks in the so called **Hough space** or **parameter space**

in fingerprint matching: location, rotation and scale of the minutiae maps

3. Independent 'experts' vote for their best combination of discretized parameter values

each 'expert' increases elements in the discretized parameter space, the so called **accumulator space**, depending on its 'expertise'

4. Maximum element of the accumulator space suggests the winning combination of the discretized parameters

Compensation of linear deformations

Example approach: use of Hough transform

Assumptions:

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Compensation of linear deformations

Example approach: use of Hough transform

Assumptions:

• transformation defined by the quadruple $(\Delta x, \Delta y, \theta, s)$: shift, rotation and scale
Example approach: use of Hough transform

Assumptions:

- transformation defined by the quadruple $(\Delta x, \Delta y, \theta, s)$: shift, rotation and scale
- we use discretized values of $\Delta x, \Delta y, \theta, s$, namely: $\Delta x^+, \Delta y^+, \theta^+$ oraz s^+

Example approach: use of Hough transform

Incrementation of the accumulator space elements:

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Example approach: use of Hough transform

Incrementation of the accumulator space elements: $\mathbf{A}[\Delta x^+, \Delta y^+, \theta^+, s^+] = 0 \text{ for all } \Delta x^+, \Delta y^+, \theta^+ \text{ and } s^+$ for every \mathbf{m}_i , for every \mathbf{m}'_j , for every θ^+ if $d(\theta'_j + \theta^+, \theta_i) \leq \theta_0$

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

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$$\Delta x^+ = \text{quantization}(\Delta x), \ \Delta y^+ = \text{quantization}(\Delta y)$$
$$\mathbf{A}[\Delta x^+, \Delta y^+, \theta^+, s^+] = \mathbf{A}[\Delta x^+, \Delta y^+, \theta^+, s^+] + 1$$

Example approach: use of Hough transform

Winning combination of the discretized parameters:

$$(\Delta x^*, \Delta y^*, \theta^*, s^*) = \operatorname*{argmax}_{\Delta x^+, \Delta y^+, \theta^+, s^+} \mathbf{A}(\Delta x^+, \Delta y^+, \theta^+, s^+)$$

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Useful modifications:

- 1. Simultaneous, weighted incrementation of ${f A}(\Delta x^+,\Delta y^+,\theta^+,s^+)$ and its neighbors
- 2. Use of parallel computing (parallelization of Hough transform is very easy)
- 3. Coarse-to-fine approaches

End of week remainders

- 1. Solve the quiz #2
 - deadline: Monday, Sept. 15, 11:00 AM
- 2. Attend the practical class on Monday, Sept. 15
 - bring an USB Flash or external hard drive to the class, it will be required to copy your biometric data and MATLAB programs (the package should not exceed 20 MB)
 - your biometric data will not be posted to any webpage due to security reasons