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Introduction to Biometrics

Deep Learning in Biometrics

Ruggero Donida Labati

Academic year 2020/2021



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Content

1. Introduction to the course
2. Basic concepts on biometrics
3. Biometric recognition process
4. Fingerprint
5. Face
6. Iris
7. Performance evaluation of biometric systems
8. Preview of the next lecture
9. Summary



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1. Introduction to the Course



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Program

- 1) Date: Tuesday, November 24, 2020
Time: 10:00-13:00
Introduction to Biometrics
- 2) Date: Thursday, November 26, 2020
Time: 10:00-13:00
Machine Learning in Biometrics
- 3) Date: Tuesday, December 1, 2020
Time: 11:00-13:00
Deep Learning in Biometrics
- 4) Date: Tuesday, December 1, 2020
Time: 14:00-16:00
Deep Learning in Biometrics



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Contacts



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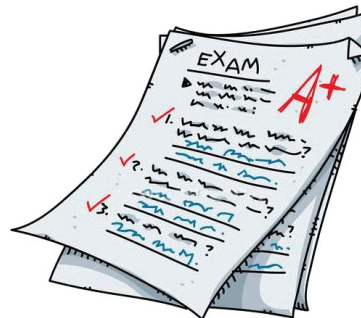


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Exam

- Project or literature survey on a topic of the course
- The topic must be decided with the teacher of this course



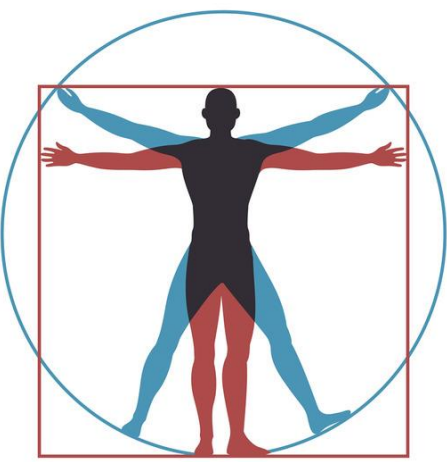
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2. Basic concepts on biometrics




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Biometrics

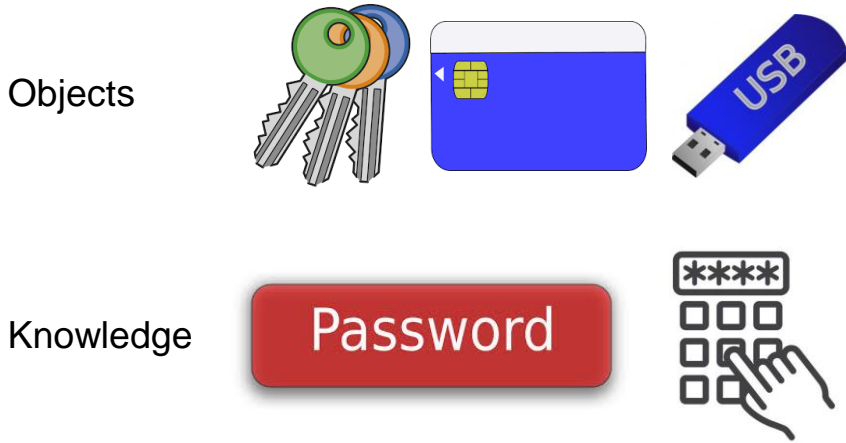
Biometrics is defined by the International Organization for Standardization (ISO) as **“the automated recognition of individuals based on their behavioral and biological characteristics”**



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Traditional Identity Recognition Methods

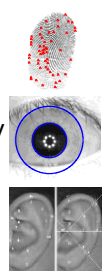


Biometric Traits

• Biometrics:

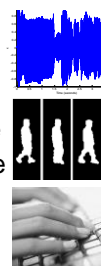
- physiological

- fingerprint
- iris
- hand geometry
- palmprint
- palmevein
- ear
- ECG
- DNA



- behavioral

- voice
- gait
- signature
- keystroke



Applications (1/3)



Border control



Disney world



2004 Summer Olympics

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Applications (2/3)



Shops

```
* Type ID
* Swipe ID
* Select payment
  -OR-
* Pay cashier
Cred Debitl EBT I
```



ATM



Surveillance

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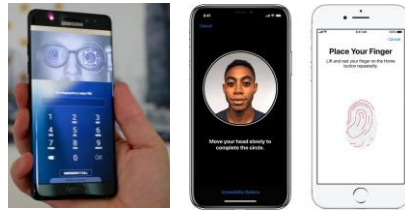
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Applications (3/3)



LiveGrip™
Advanced Biometrics, Inc



Smartphones



Hitachi - grip-type finger vein authentication

<http://www.hitachi.com>

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Characteristics of Biometric Traits

- Human characteristic
 1. Universality
 2. Distinctiveness
 3. Permanence
 4. Collectability

- Technology
 1. Performance
 2. Acceptability
 3. Circumvention



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Qualitative Evaluation of Biometric Traits

Trait	Univ.	Uniq.	Perm.	Coll.	Perf.	Acc.	Circ.
Face	H	L	M	H	L	H	L
Fingerprint	M	H	H	M	H	M	H
Hand geometry	M	M	M	H	M	M	M
Keystrokes	L	L	L	M	L	M	M
Hand vein	M	M	M	M	M	M	H
Iris	H	H	H	M	H	L	H
Retinal scan	H	H	M	L	H	L	H
Signature	L	L	L	H	L	H	L
Voice	M	L	L	M	L	H	L
Facethermograms	H	H	L	H	M	H	H
Odor	H	H	H	L	L	M	L
DNA	H	H	H	L	H	L	L
Gate	M	L	L	H	L	H	M
Ear	M	M	H	M	M	H	M

A. Jain, A. Ross, and S. Prabhakar, "An introduction to biometric recognition," IEEE Trans. on Circuits and Systems for Video Technology, vol. 14, no. 1, pp. 4–20, Jan. 2004.

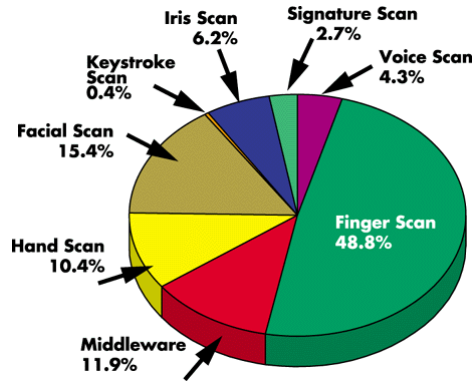
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Biometric Traits in Real Applications



International Biometric Group, New York, NY; 1.212

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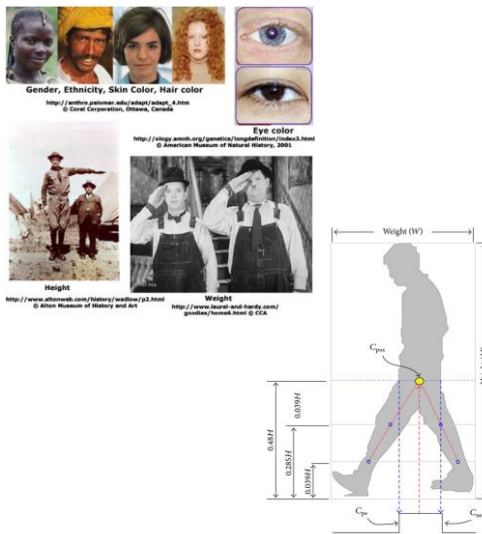


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Soft Biometrics

- Soft biometric traits are characteristics that provide some information about the individual, but lack the distinctiveness and permanence to sufficiently differentiate any two individuals
- Continuous or discrete



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3. Biometric Recognition Process



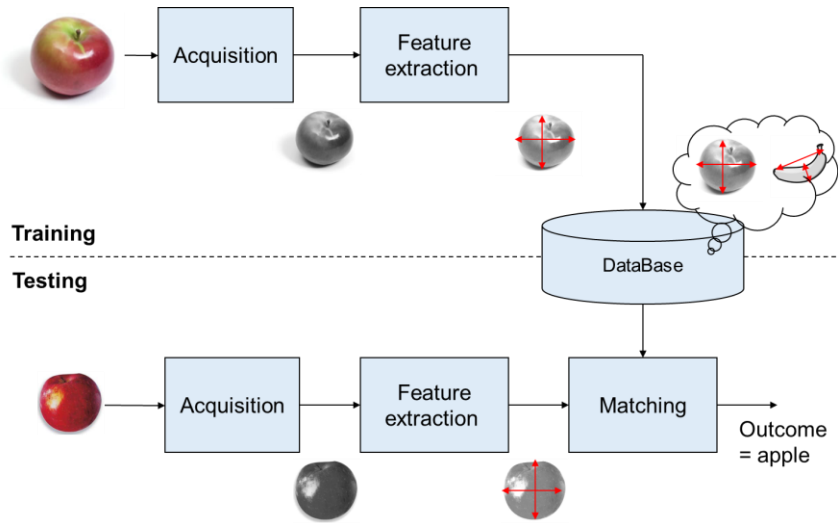
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Pattern Recognition Systems



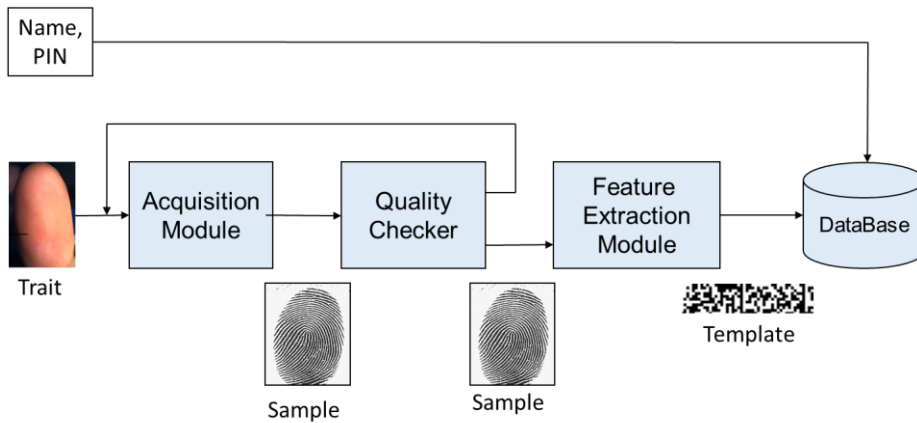
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Enrollment



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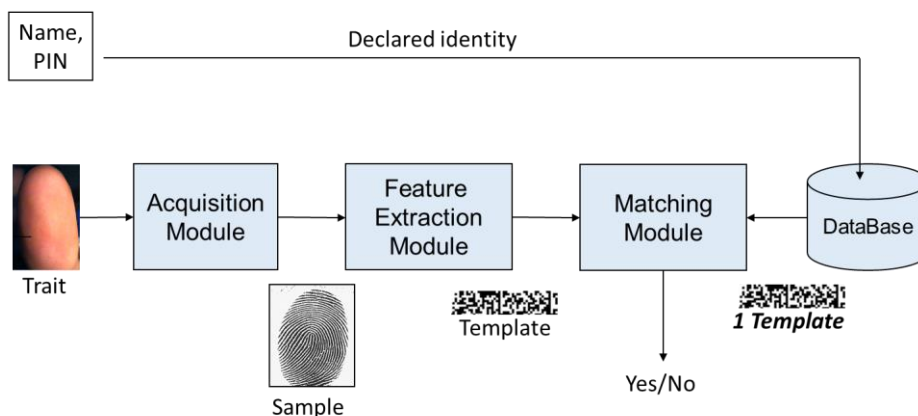
Verification / Identification

- Verification
 - The verification involves confirming or denying a person's claimed identity

- Identification
 - In the identification mode, the biometric system has to establish a person's identity by comparing the acquired biometric data with the information related to a set of individuals, performing a one-to-many comparison
 - Positive
 - Negative

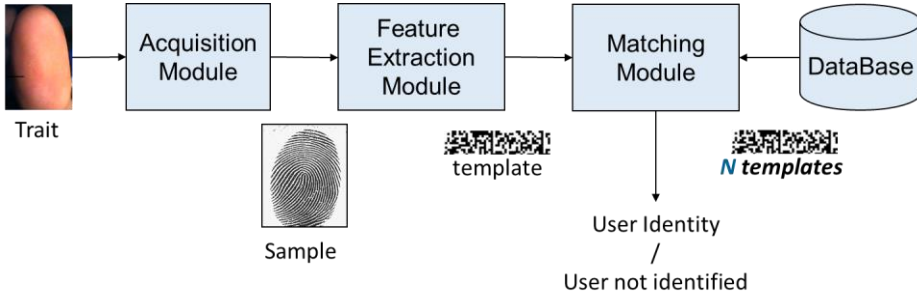
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Verification



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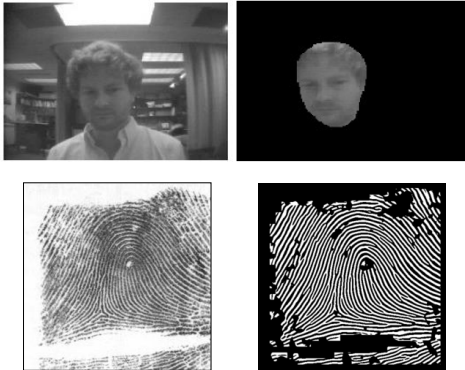
Identification



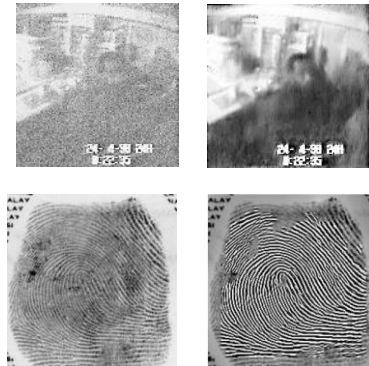
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Preprocessing

Segmentation



Enhancement



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Feature Extraction

- Different Methods
 - biometric trait
 - biometric system
 - local / global
- Computes a **template** from a **sample**
 - Sample = input multidimensional signal
 - One-dimensional signal
 - Image
 - 3D model
 - Video
 - Template = abstract and compact representation of the distinctive characteristics of the sample

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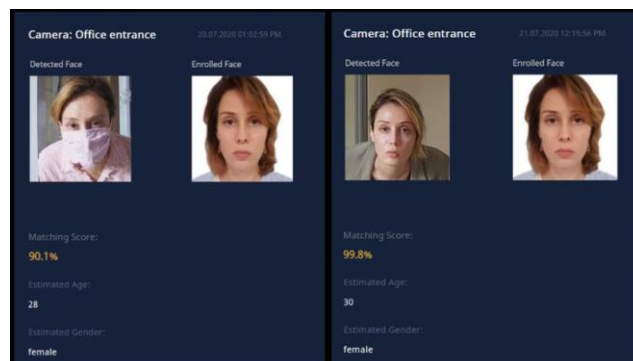


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Matching

- Computes the **matching score** between two templates
 - Distance
 - Similitude



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Genuine and Impostor Comparisons

Genuine comparison



Impostor comparison



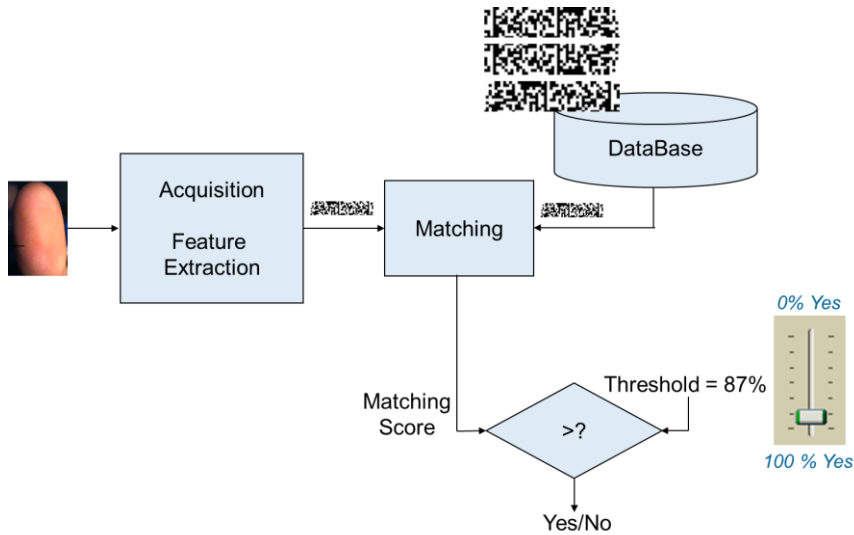
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Decision



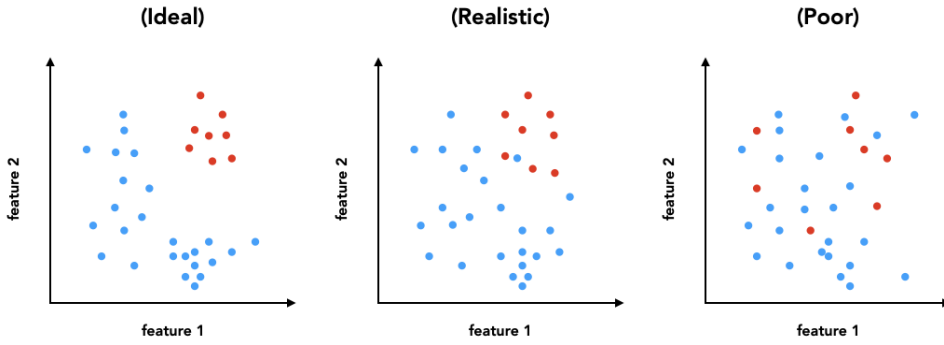
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Pattern Recognition: 2D Feature Space



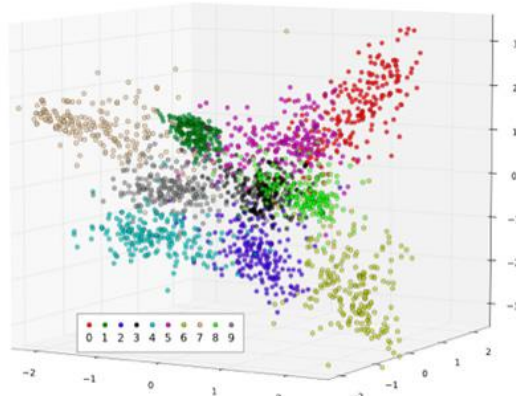
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Pattern Recognition: 3D Feature Space



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Interclass Similitude and Intraclass Variability

Interclass similitude

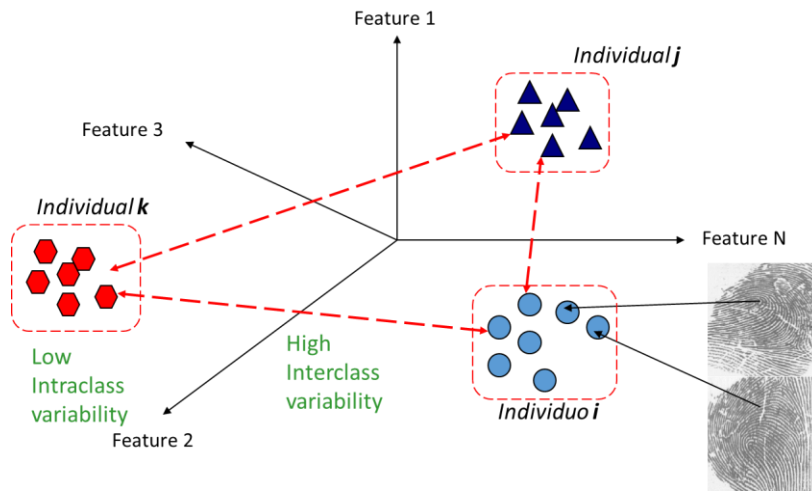


intraclass variability



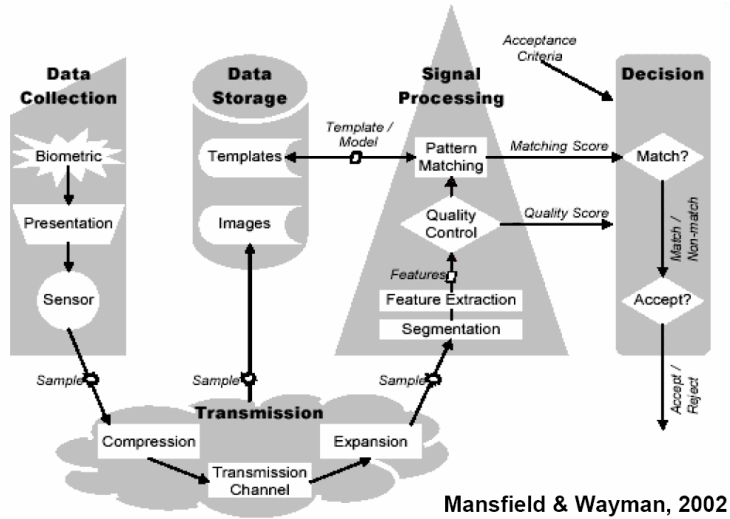
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Pattern Recognition and Biometrics



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Modules of Biometric Systems



4. Fingerprint



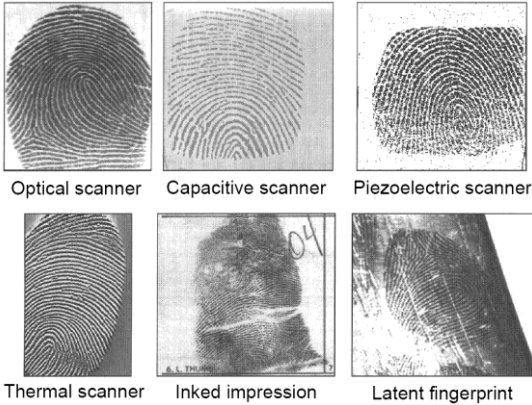
Fingerprint

- A fingerprint in its narrow sense is an impression left by the friction ridges of a human finger
- One of the most used traits in biometric applications
 - High durability
 - High distinctivity
- The more mature biometric trait



Fingerprint Images

Sensors

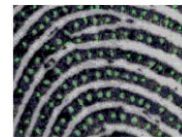
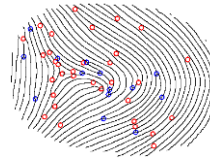


Finger placements



Levels of Analysis

- **Level 1:** the overall global ridge flow pattern
- **Level 2:** points of the ridges, called minutiae points
- **Level 3:** ultra-thin details, such as pores and local peculiarities of the ridge edges



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Level 1: Local Ridge Orientation

- Usually from 0° to 180°
- Evaluation of the gradient orientation in squared regions
For each local region, the ridge orientation is considered as the mean of the angular values of the pixels



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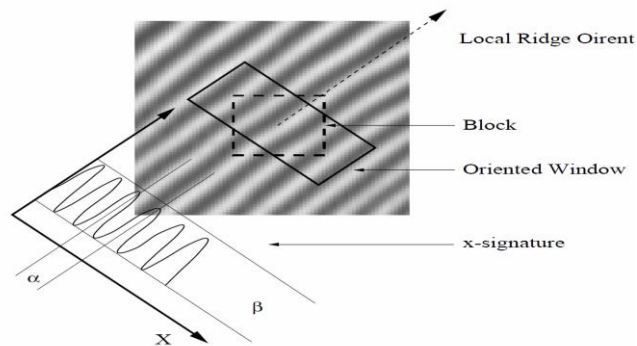


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Level 1: Local Ridge Frequency

- Global or map
- x-signature



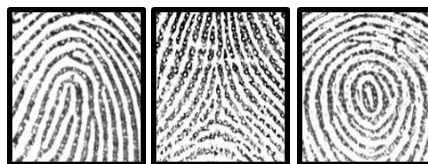
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Level 1: Singular Regions



Loop

Delta

Whorl

- Pointcaré algorithm
- The northern loop is usually considered as the core point

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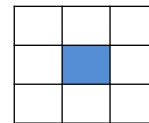
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Level 1: Pointcaré Algorithm

- Let G be a vector field and C be a curve immersed in G , then the Poicaré index $P_{G,C}$ is defined as the total rotation of the vectors of G along C

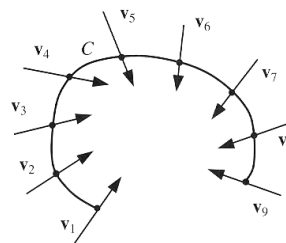
- Considering eight near elements d_k ($k = 0 \dots 7$)

$$P_{G,C}(i, j) = \sum_{k=0 \dots 7} \text{angle}(d_k, d_{(k+1) \bmod 8})$$



- Classification

- 0° = the point is not a singular point;
- 360° = whorl region;
- 180° = core point;
- -180° = delta point.



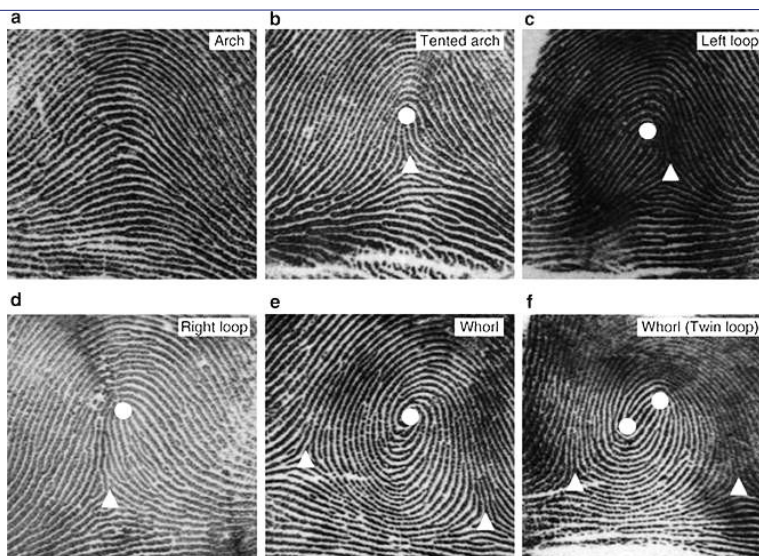
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Level 1: Classification of the Ridge Pattern



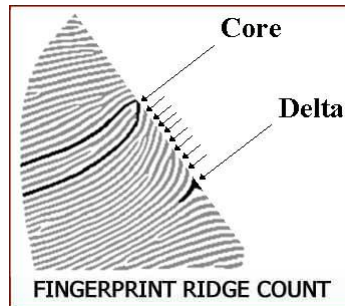
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Level 1: Ridge Count



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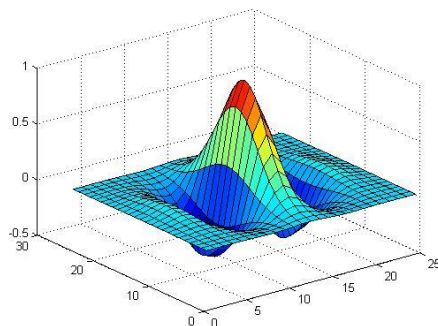


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Level 1: Gabor Filters (1/2)

- Evaluates both frequency and space



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Level 1: Gabor Filters (2/2)

The even-symmetric Gabor filter has the general form

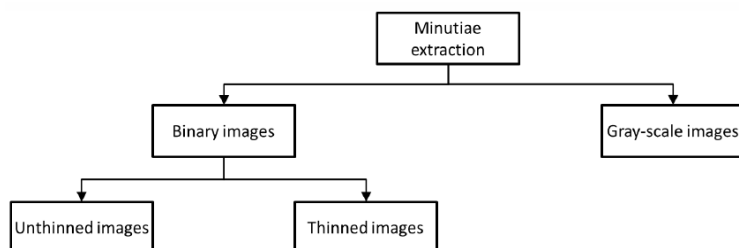
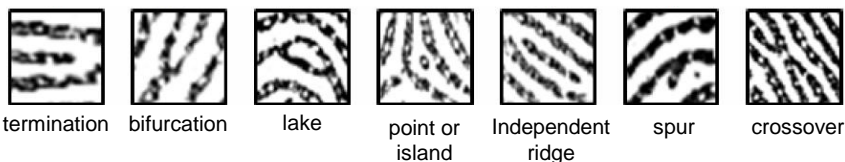
$$h(x, y : \phi, f) = \exp \left\{ -\frac{1}{2} \left[\frac{x_\phi^2}{\sigma_x^2} + \frac{y_\phi^2}{\sigma_y^2} \right] \right\} \cos(2\pi f x_\phi),$$

$$x_\phi = x \cos(\phi) + y \sin(\phi)$$

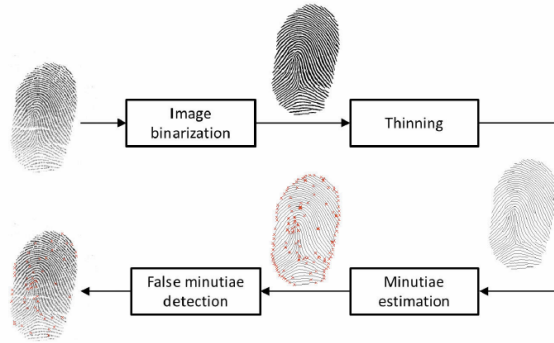
$$y_\phi = -x \sin(\phi) + y \cos(\phi)$$

where Φ is the orientation of the Gabor filter, f is the frequency of a sinusoidal plane wave, and σ_x and σ_y are the space constants of the Gaussian envelope along x and y axes, respectively.

Level 2: Minutiae



Level 2: Minutiae Extractor



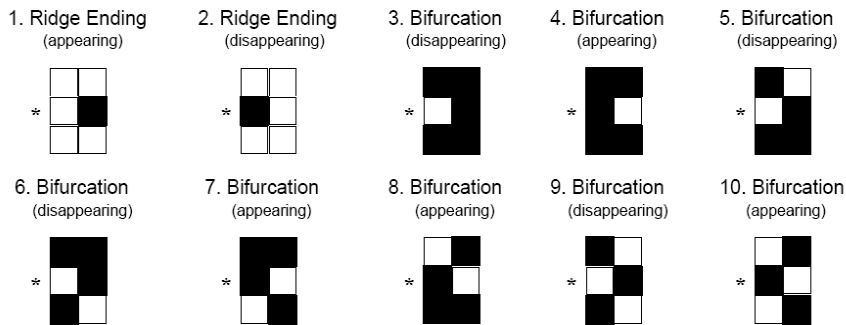
Crossing number: 8 neighborhood of the pixel p

$$CN(p) = \frac{1}{2} \sum_{k=1}^8 |n_k - n_{((k+1) \bmod 8)}|$$

If $CN(p) = 1$ or $CN(p) = 3$, p is a minutia



Level 2: Minutia Patterns

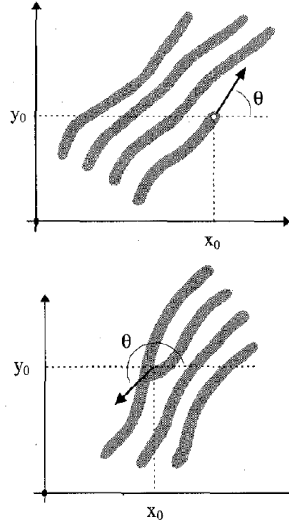


Level 2: Ridge Following

```

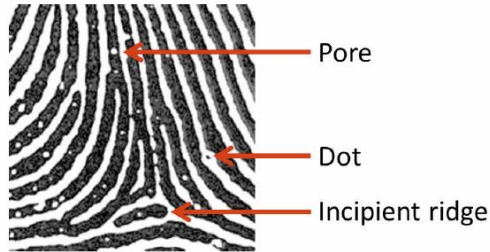
find_minutia ( i_s, j_s )
{
  esc := false ;
  (i_c, j_c) := nearest_ridge_line_maximum
  (i_s, j_s) ;
  if ((i_c, j_c) ∈ discovered_ridge_lines
  (T)) then esc := true ;
  if (¬ esc)
  {
    φ_c := tangent_direction_in (i_c, j_c) ;
    ridge_line_following (i_c, j_c, φ_c) ;
    if (termination ∨ excessive
    bending) then
      { // termination_minutia has
      been found
      store_termination_minutia ; }
    if (intersection) then
      { // bifurcation_minutia may
      exist
      if (intersection_point_is
      valid) then
        store_bifurcation_minutia
      else delete_false_termination
      minutia ;
      }
    store_polygonal ( T ) ;
    // Perform similar operations in
    direction φ_c + π ;
    ridge_line_following (i_c, j_c, φ_c + π)
  }
  ...
}

```

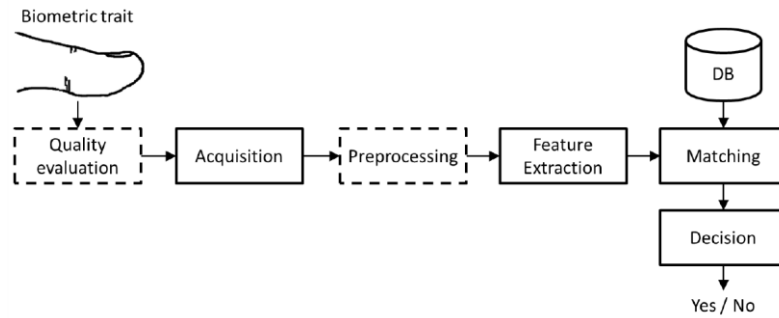


Level 3

- Minimum resolution of 800 DPI



The Biometric Recognition Process



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Acquisition



Latent



Inked and rolled



Live scan

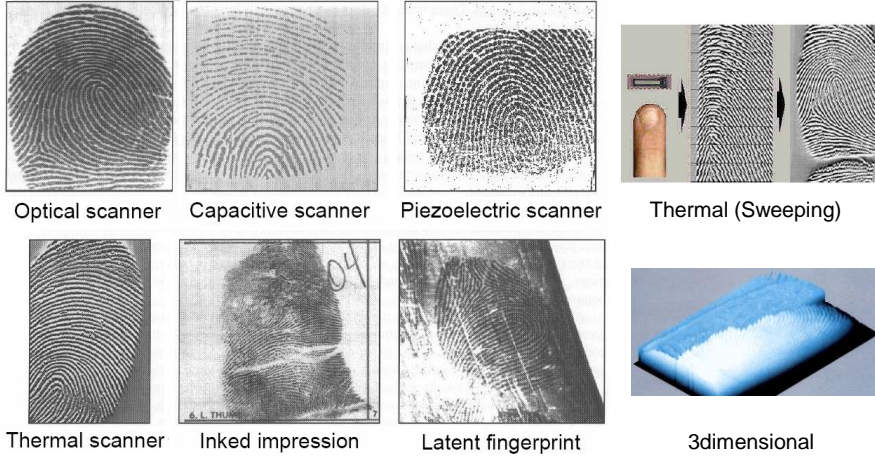
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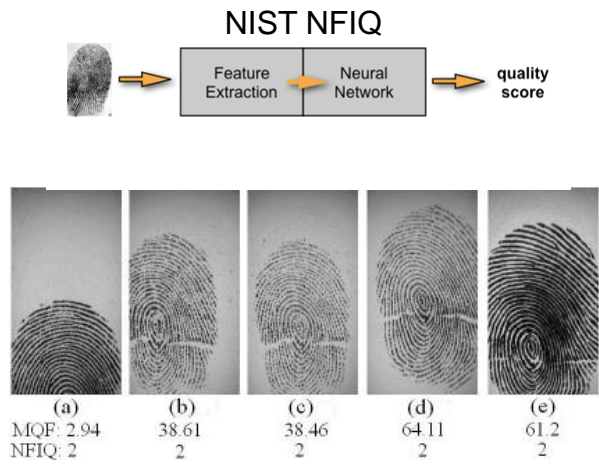
52

Images



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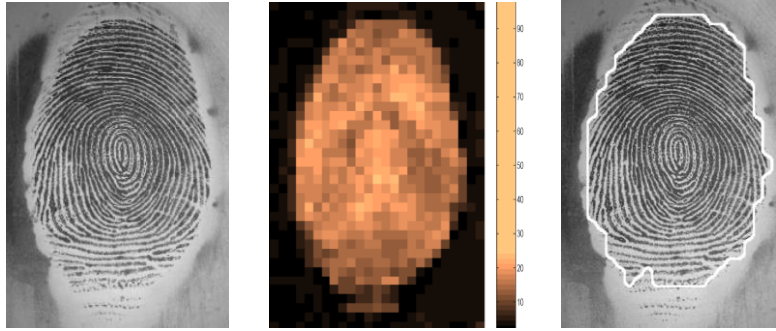
Quality Evaluation (1/2)



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Preprocessing: Segmentation

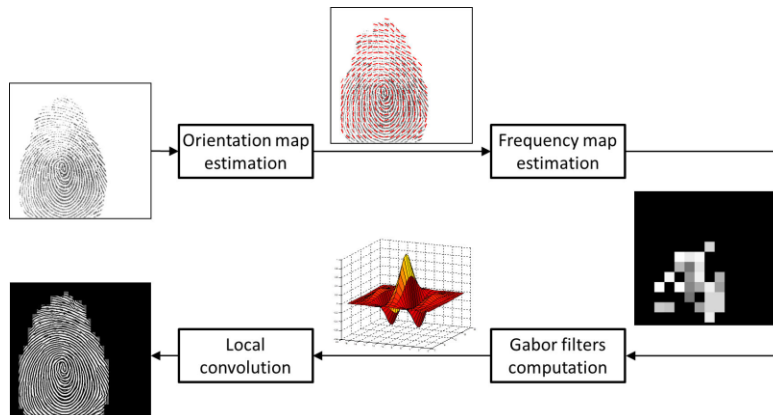
- Local standard deviation (16 X 16 pixels)



55

Preprocessing: Enhancement

- Contextual filtering



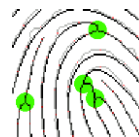
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Minutiae-based Matching

- Two minutiae are considered as correspondent if their spatial distance s_d and direction difference d_d are less than fixed thresholds

$$s_d(m'_j, m_i) = \sqrt{(x'_j - x_i)^2 + (y'_j - y_i)^2}$$

$$d_d(m'_j, m_i) = \min(|\theta'_j - \theta_i|, (360 - |\theta'_j - \theta_i|))$$



- Non-exact point pattern matching
 - Roto-translations
 - Non-linear distortions
 - False minutiae
 - Missed minutiae
 - Non constant number of minutiae



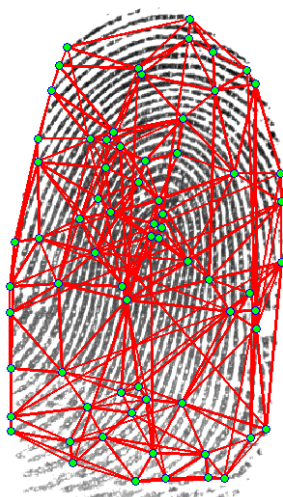
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Minutiae-based Matching: Delaunay Triangulation



• Features

- Side lengths of the triangles

$$L(i, 1) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

$$L(i, 2) = \sqrt{(x_1 - x_3)^2 + (y_1 - y_3)^2}$$

$$L(i, 3) = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2}$$

- Greater angles

$$\alpha(i, 1) = \frac{L(i, 1)^2 + L(i, 2)^2 - L(i, 3)^2}{2 \cdot L(i, 1) \cdot L(i, 2)}$$

- Incenters

- Minutiae features (x, y, θ)

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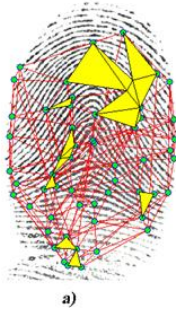
58

Minutiae-based Matching: Delaunay Triangulation (1/2)

- Method A

$$|L_B(j) - L_A(i)| < s_L,$$

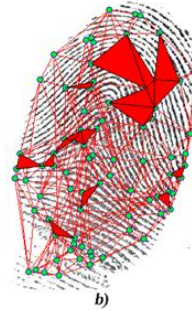
$$|\vartheta_B(j) - \vartheta_A(i)| < s_O,$$



- Method B

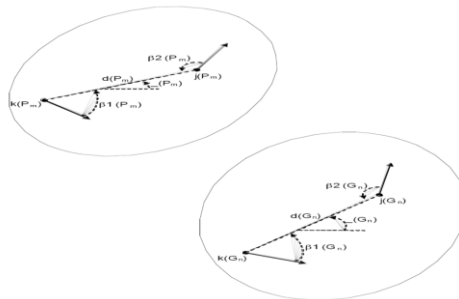
$$|L_B(j) - L_A(i)| < s_L,$$

$$|\vartheta_B(j) - \vartheta_A(i)| < s_O,$$

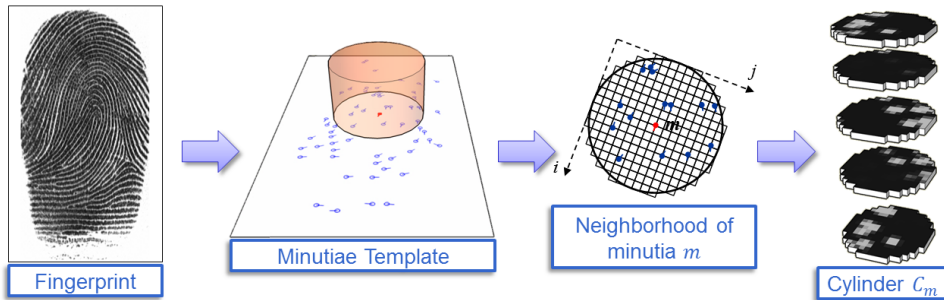


Minutiae-based Matching: NIST Bozhorth 3

- Step 1: Construction of Intra-Fingerprint Minutiae Comparison Tables
- Step 2: Construction of Inter-Fingerprint Compatibility Table
- Step 3: Traverse Inter-Fingerprint Compatibility Table constructed in second step

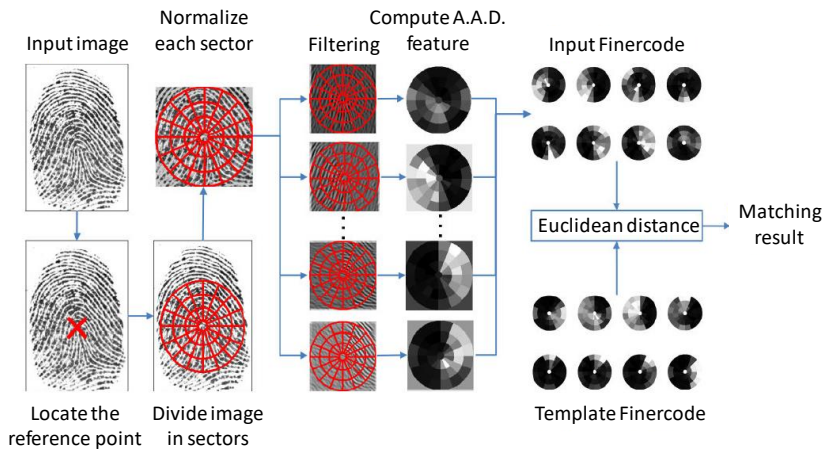


Other Minutiae-based Recognition Methods: Cylindercode



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Other Recognition Methods: Fingercode



[1] A. K. Jain, et al., "Filterbank-based fingerprint matching,"
 IEEE Transactions on Image Processing, 2000.



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5. Iris

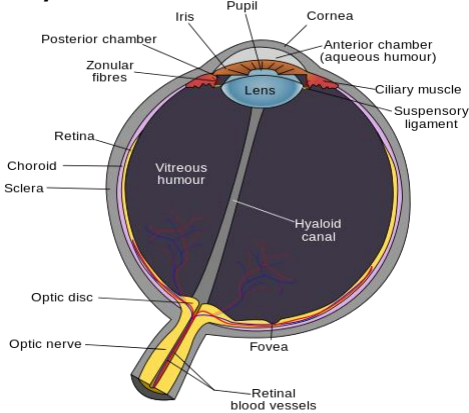


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Iris Biometric Trait

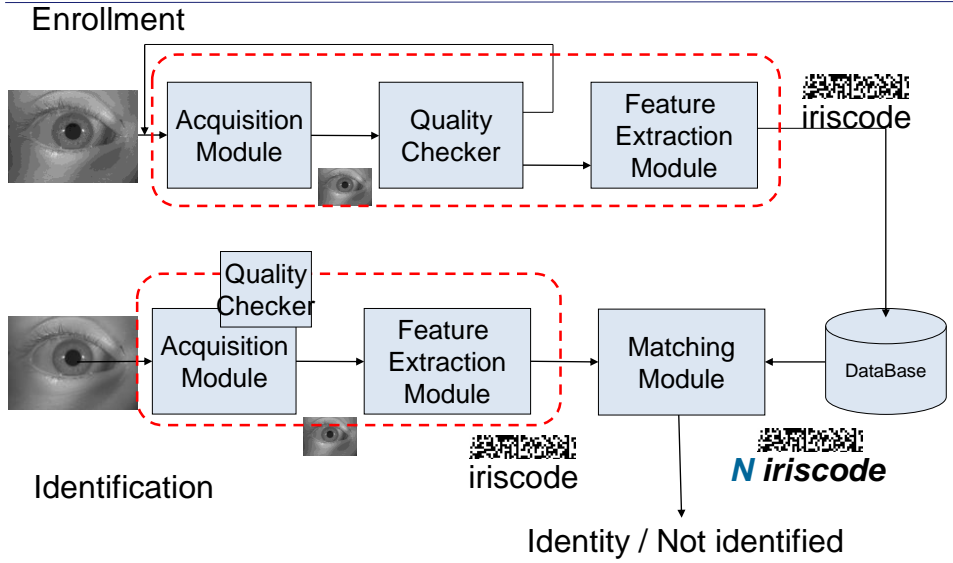


The colored ring around the pupil of the eye is called the Iris

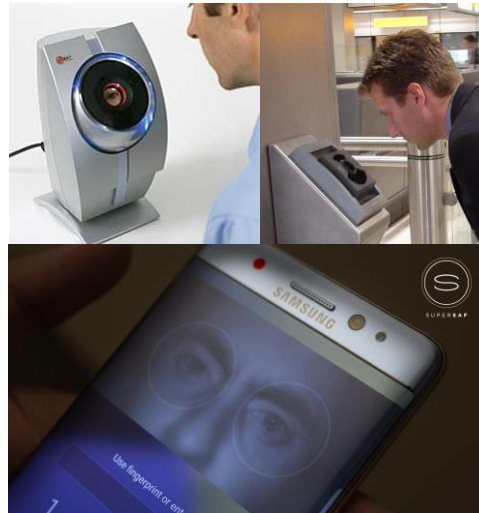


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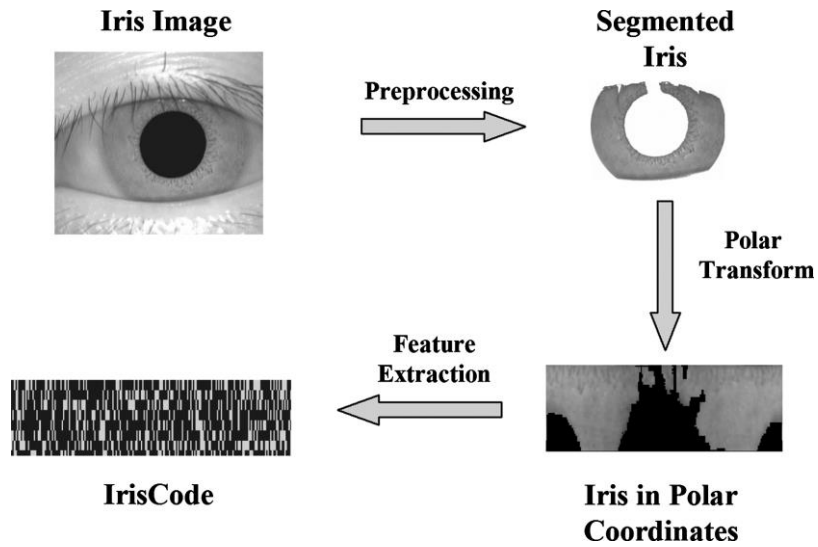
Iris-based Identification



Iris Scanners



How Iris Recognition Works



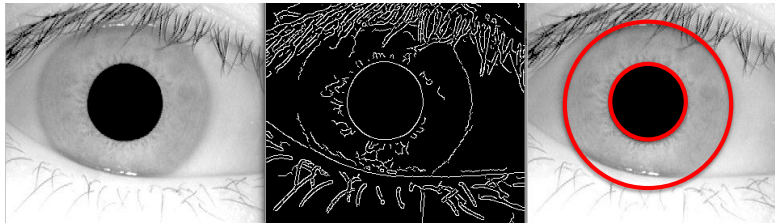
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Iris Segmentation Using Hough Transform



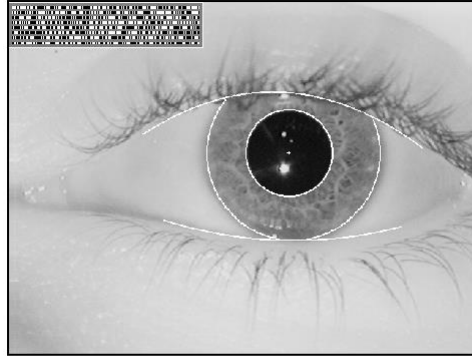
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Iris Segmentation Using Daugman's Method



$$\max_{(r, \theta_0, \theta_1)} \left| G_\sigma(r) * \frac{\partial}{\partial r} \int_{\theta_0, \theta_1} \frac{I(x, y)}{2\pi r} d\theta \right|$$

Localizing iris boundaries by differential operators

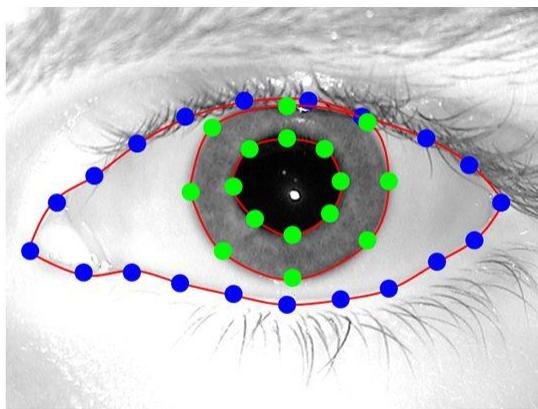
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Iris Segmentation Using Active Contours



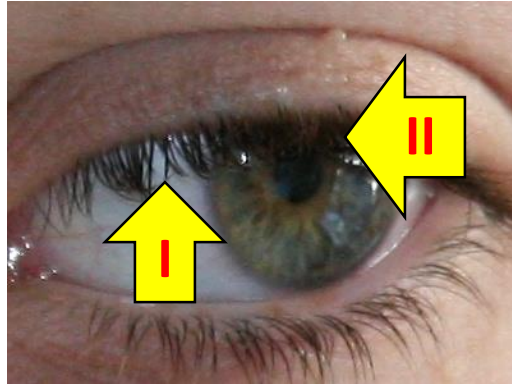
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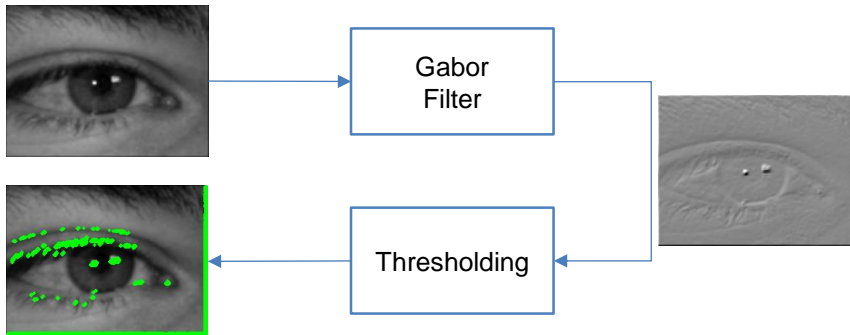
Eyelids and Eyelashes



I = separable eyelashes

II = not-separable eyelashes

Separable Eyelashes



$$g(x, y) = K \exp(-\pi(a^2(x - x_0)^2 + b^2(y - y_0)^2)) \exp(j(2\pi F_0 (x \cos \omega_0 + y \sin \omega_0) + P))$$

$$L_1(x, y) = \begin{cases} 1 & \text{if } |I(x, y) * \text{Re}(g(x, y))| > t_3 \\ 0 & \text{else} \end{cases}$$

$$t_3 = k \max(|I_r(x, y) * g(x, y)|)$$

Non-separable Eyelashes and Reflections

1) $L_2(x, y) = \begin{cases} 1 & \text{if } \text{var}(I(x, y)) > t_4 \\ 0 & \text{else} \end{cases}$

2) $L_3(x, y) = \text{erode}(L_2(x, y), S)$

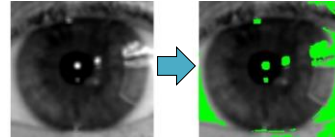
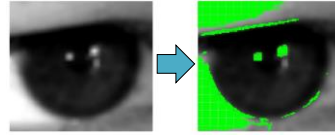
3) $L_4(x, y) = \begin{cases} 1 & \text{if } I(x, y) > t_5 \\ 0 & \text{else} \end{cases}$

4) $L_5 = L_3 \text{ OR } L_4$

5) Starting from an initial set of points L_5 , we apply an iterative region growing technique based on the following

$$\mu + \beta\sigma < I(x, y)$$

where μ and σ are the local mean and standard deviation of $I(x, y)$ processed in a 3×3 matrix centered in the point x, y and β is a fixed threshold .



Iris Normalization: Motivation



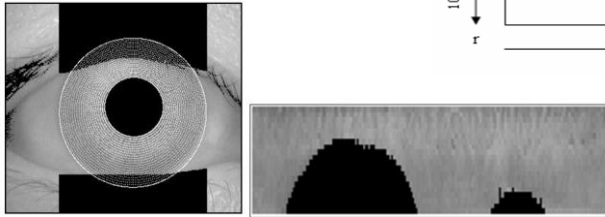
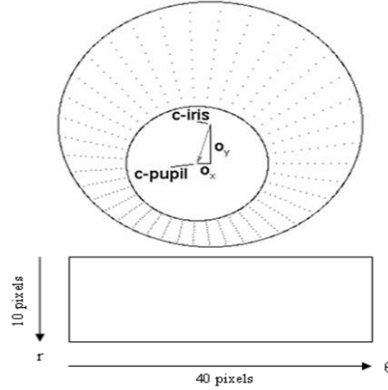
Iris Normalization: Rubber Sheet Model

$$r' = \sqrt{\alpha\beta} \pm \sqrt{\alpha\beta^2 - \alpha - r_1^2}$$

with

$$\alpha = o_x^2 + o_y^2$$

$$\beta = \cos\left(\pi - \arctan\left(\frac{o_y}{o_x}\right) - \theta\right)$$



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Iriscode (1/2)

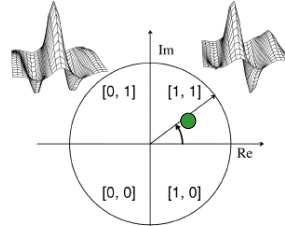
$$h_{\{Re, Im\}} = \text{sgn}\{Re, Im\} \int_{\rho} \int_{\phi} I(\rho, \phi) e^{-i\omega(\theta_0 - \phi)} \cdot e^{-(r_0 - \rho)^2 / \alpha^2} e^{-(\theta_0 - \phi)^2 / \beta^2} \rho d\rho d\phi$$

"The detailed iris pattern is encoded into a 256-byte "IrisCode" by demodulating it with 2D Gabor wavelets, which represent the texture by phasors in the complex plane. Each phasor angle (Figure) is quantized into just the quadrant in which it lies for each local element of the iris pattern, and this operation is repeated all across the iris, at many different scales of analysis"*

J. Dougman



Phase-Quadrant Demodulation Code (*)



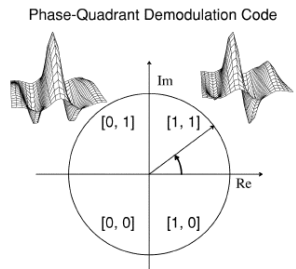
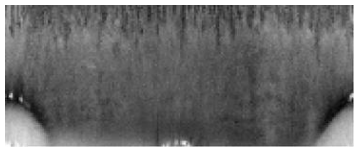
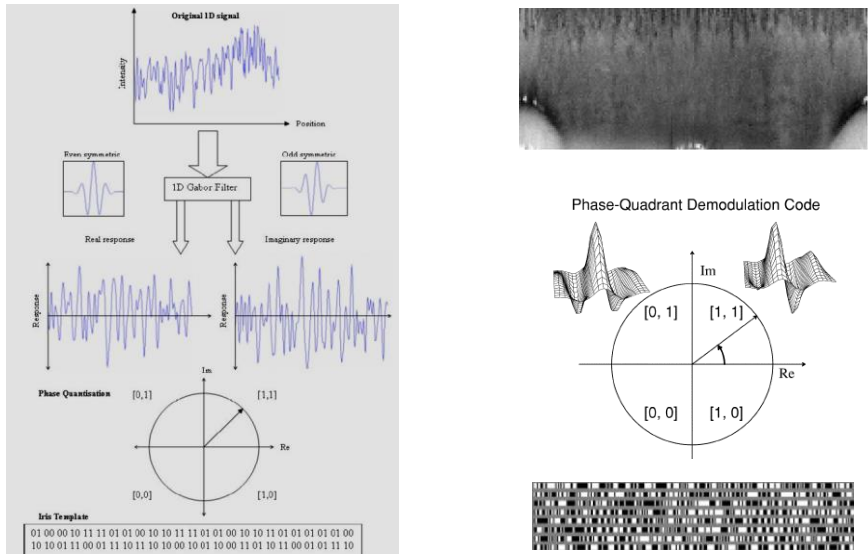
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Iriscode (2/2)



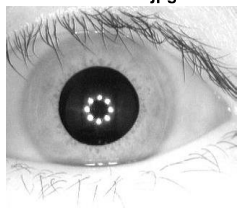
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Iriscode Matching


$$HD = \frac{\|(codeA \otimes codeB) \cap maskA \cap maskB\|}{\|maskA \cap maskB\|}$$

Matching Score = 0.26848

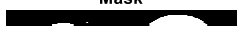
S1001L03.jpg



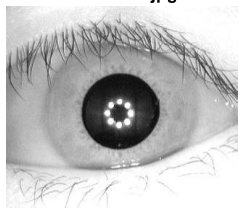
Iriscode




Mask



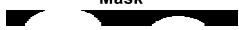
S1001L05.jpg



Iriscode



Mask




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6. Face

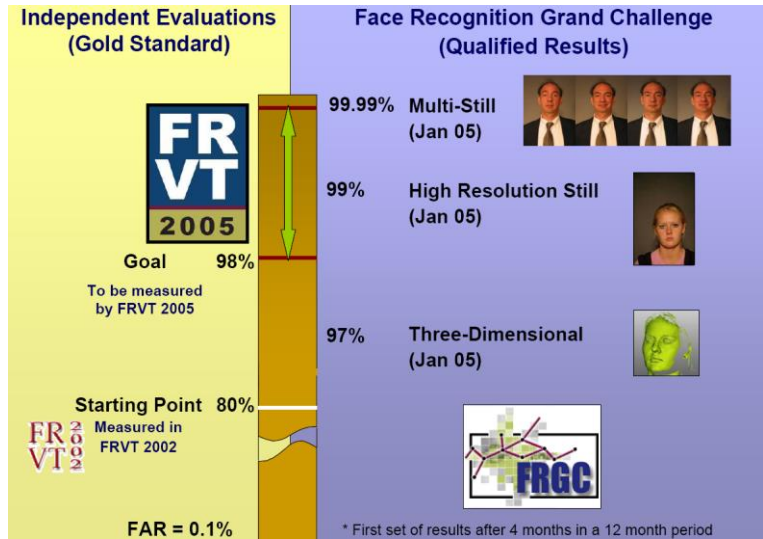


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Face Recognition Using Still Images



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Face Acquisition Sensors

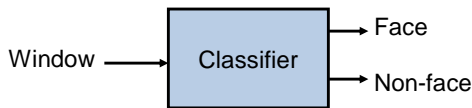
- Cameras (a)
- Webcams
- Scanners for off-line acquisitions
- Termocameras (b)
- Multispectral devices (c,d,e,f)



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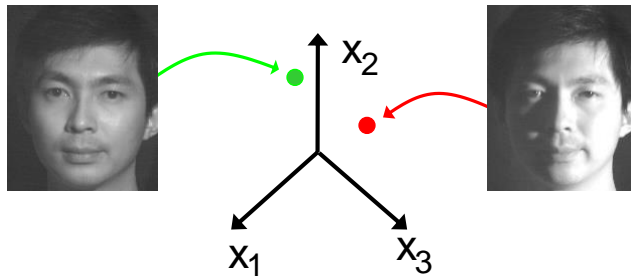
Face Detection

- Scan window over image
- Classify window as either:
 - Face
 - Non-face



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Images as Features



- Consider an n -pixel image to be a point in an n -dimensional space, $\mathbf{x} \in \mathbf{R}^n$.
- Each pixel value is a coordinate of \mathbf{x} .

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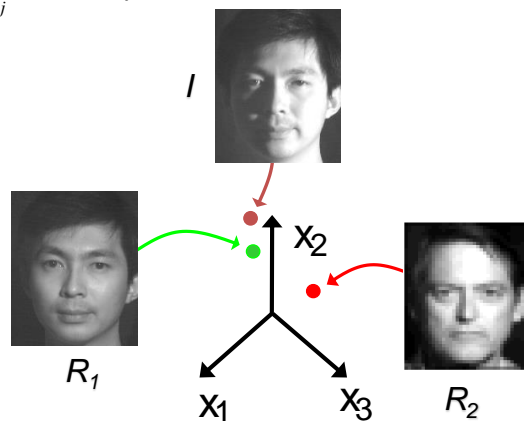
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Nearest Neighbor Classifier

$\{R_j\}$ are set of training images.

$$ID = \arg \min_j \text{dist}(R_j, I)$$



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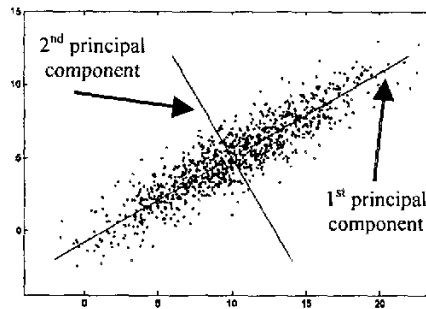


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Eigenfaces

- Use Principle Component Analysis (PCA) to reduce the dimensionality



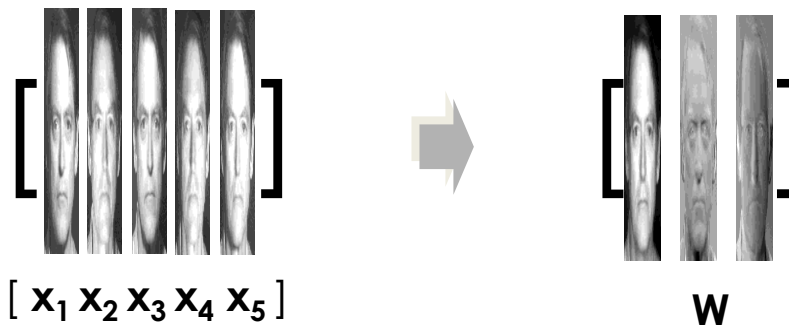
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Eigenfaces (2)



- Construct data matrix by stacking vectorized images and then apply Singular Value Decomposition (SVD)

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Eigenfaces (2)

- Modeling
 - Given a collection of n labeled training images
 - Compute mean image and covariance matrix
 - Compute k Eigenvectors (note that these are images) of covariance matrix corresponding to k largest Eigenvalues
 - Project the training images to the k -dimensional Eigenspace
- Recognition
 - Given a test image, project to Eigenspace
 - Perform classification to the projected training images



Problems of PCA

- Projection may suppress important detail
 - smallest variance directions may not be unimportant
- Method does not take discriminative task into account
 - typically, we wish to compute features that allow good discrimination
 - not the same as largest variance



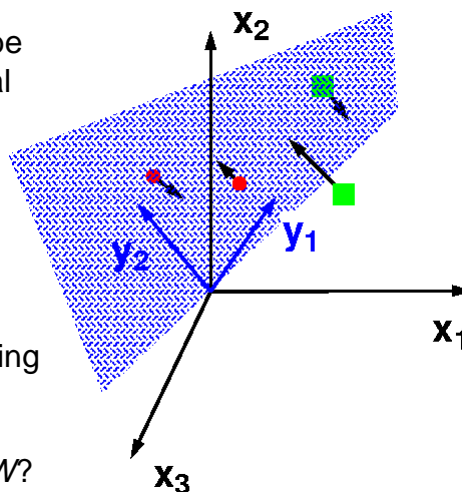
Fisherfaces

- An n -pixel image $\mathbf{x} \in \mathbf{R}^n$ can be projected to a low-dimensional feature space $\mathbf{y} \in \mathbf{R}^m$ by

$$\mathbf{y} = \mathbf{W}\mathbf{x}$$

where \mathbf{W} is an n by m matrix.

- Recognition is performed using nearest neighbor in \mathbf{R}^m .
- How do we choose a good \mathbf{W} ?



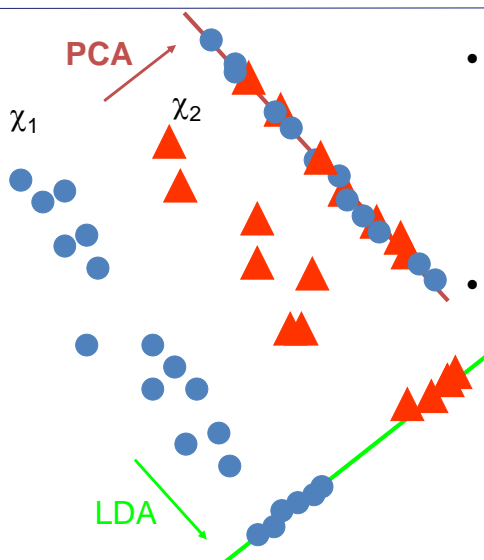
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PCA and LDA



- PCA (Eigenfaces)

$$\mathbf{W}_{PCA} = \arg \max_{\mathbf{W}} |\mathbf{W}^T \mathbf{S}_T \mathbf{W}|$$

Maximizes projected total scatter

- Fisher's Linear Discriminant

$$\mathbf{W}_{fld} = \arg \max_{\mathbf{W}} \frac{|\mathbf{W}^T \mathbf{S}_B \mathbf{W}|}{|\mathbf{W}^T \mathbf{S}_W \mathbf{W}|}$$

Maximizes ratio of projected between-class to projected within-class scatter

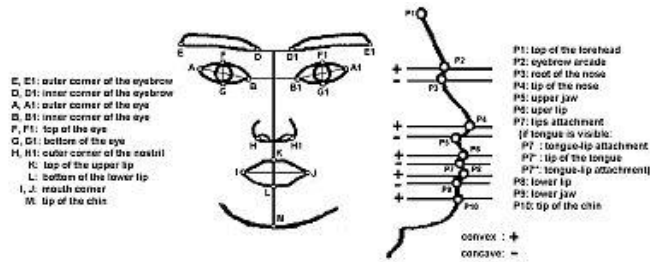
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Face Recognition Based on Fiducial Points



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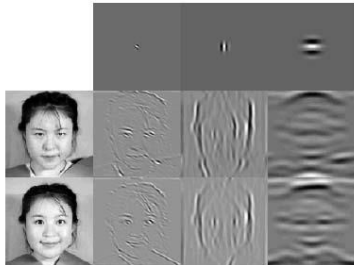


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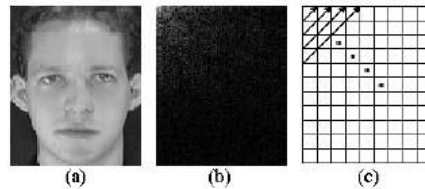
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Examples of Other Features

Gabor wavelet



Discrete cosine transform



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7. Evaluation of biometric systems



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Evaluation Strategies

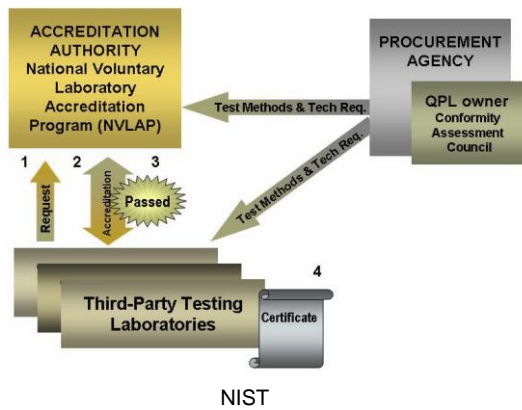
Technology



Scenario

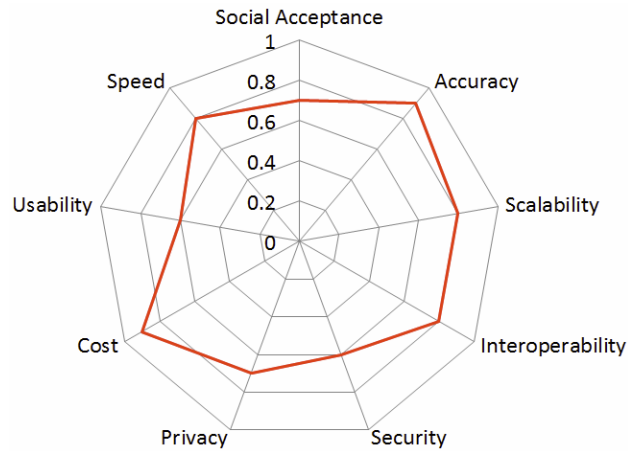


Operational



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Aspects to be Evaluated



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Accuracy Evaluation: Genuine and Impostor Scores

Genuine scores

$$S(X_{1_1}, X_{1_2}) = 0.7$$

$$S(X_{1_1}, X_{1_3}) = 0.8$$

$$S(X_{2_1}, X_{2_2}) = 0.4$$

$$S(X_{2_1}, X_{2_3}) = 0.5$$

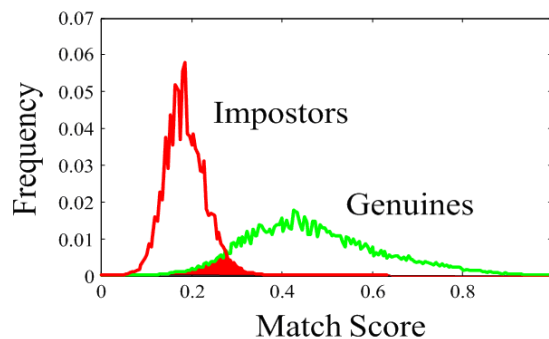
Impostor scores

$$S(X_{1_1}, X_{3_2}) = 0.11$$

$$S(X_{4_1}, X_{3_1}) = 0.21$$

$$S(X_{5_2}, X_{1_2}) = 0.001$$

$$S(X_{2_2}, X_{1_2}) = 0.19$$



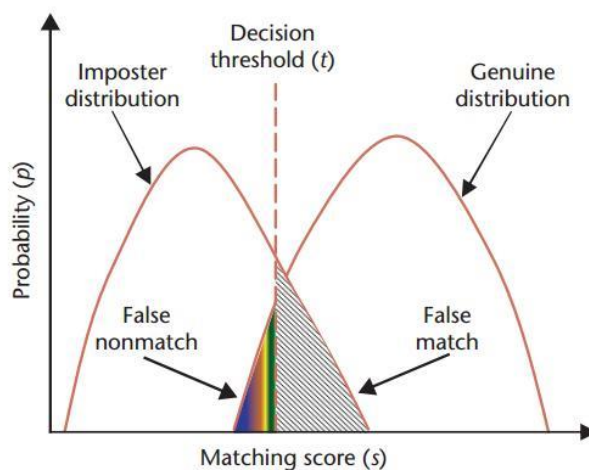
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Decision Threshold



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Accuracy evaluation: FMR and FNMR

- **False match rate (FMR):** the probability that the system incorrectly matches the input pattern to a non-matching template in the database. It measures the percent of invalid inputs that are incorrectly accepted.
Type 1 error
- **False non-match rate (FNMR):** the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs that are incorrectly rejected.
Type 2 error

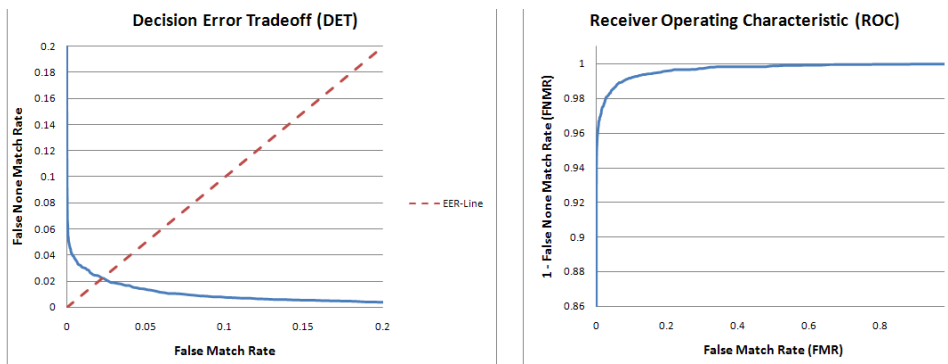
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Accuracy Evaluation: DET and ROC



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Accuracy Evaluation: Other Figures of Merit

- **Equal error rate (EER):** the ideal point in which $FMR = FNMR$
- **False acceptance rate (FAR):** similar to FMR, but used for the complete biometric system (not only the algorithms)
- **False rejection rate (FRR):** similar to FNMR, but used for the complete biometric system (not only the algorithms)
- **Failure to acquire (FTA)**
- **Failure to enroll (FTE)**

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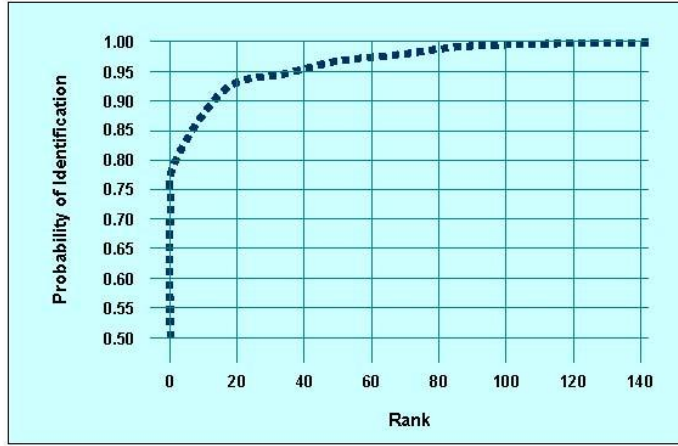


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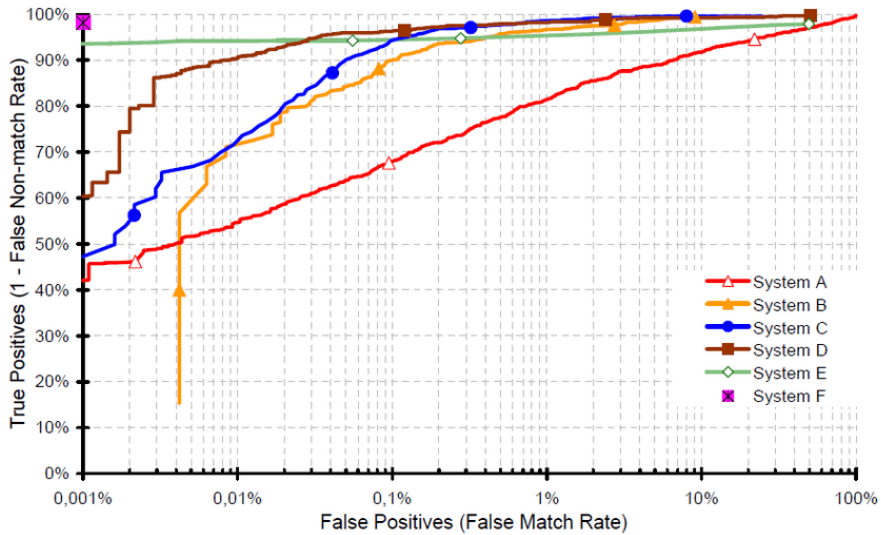
Accuracy Evaluation: Identification

Cumulative Match Characteristic



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Accuracy Evaluation: Selection of the Best Method



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8. Preview of the next lecture



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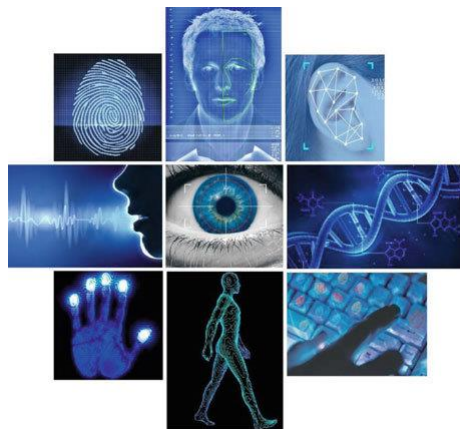


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Research trends

- Accuracy
- Robustness
- Security
- Etc.



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Machine learning

- Introduction
- Feedforward neural networks
- Overfitting
- Introduction to deep learning



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9. Summary



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Summary

1. Introduction to the course
2. Basic concepts on biometrics
3. Biometric recognition process
4. Fingerprint
5. Face
6. Iris
7. Performance evaluation of biometric systems
8. Preview of the next lecture



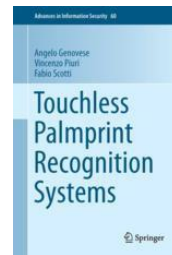
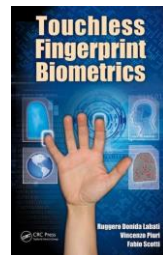
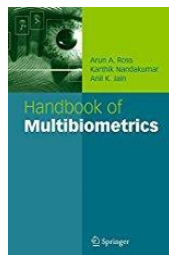
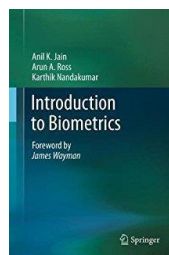
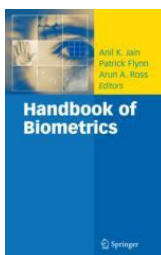
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Thank you!



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