Classification

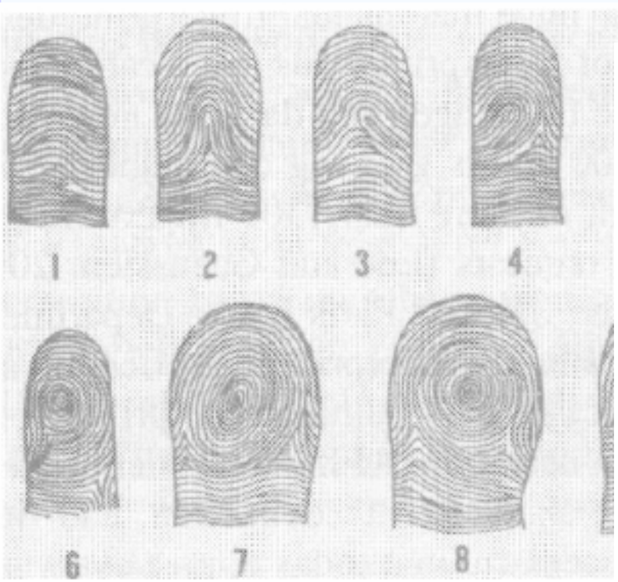
Daniel Novák

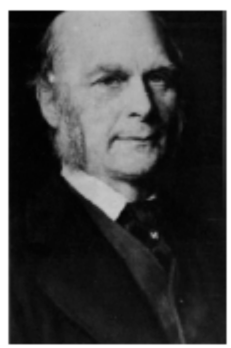
6.12, 2011, Prague

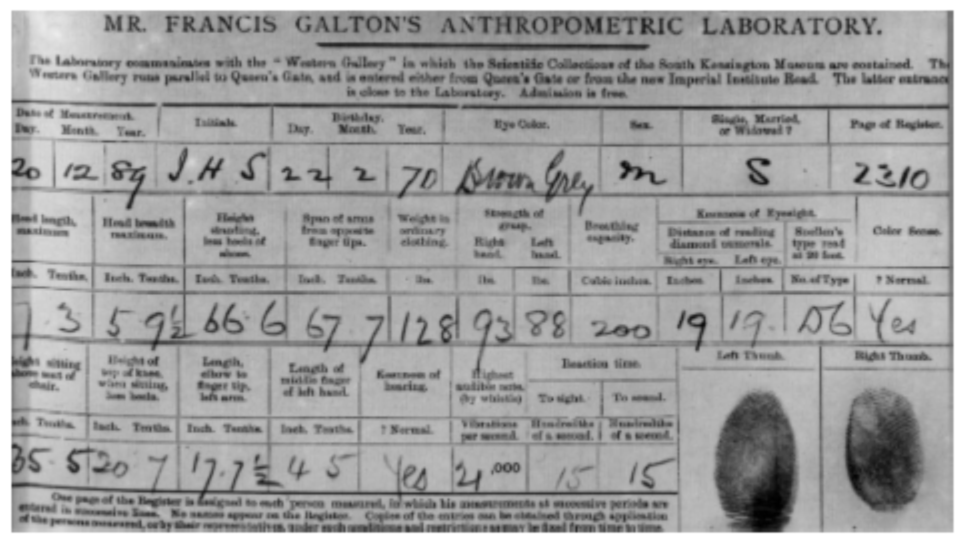
Acknowledgments: Xavier Palathingal, Andrzej Drygajlo, Handbook of Fingerprint Recognition

History

- In 1823, Purkinji proposed the first fingerprint classification, which classified into nine categories: (transverse curve, central longitudinal stria, oblique stripe, oblique loop, almond whorl, spiral whorl, ellipse, circle, and double whorl)
- Sir Francis Galton introduced the minutae features for fingerprint matching in late 19th century







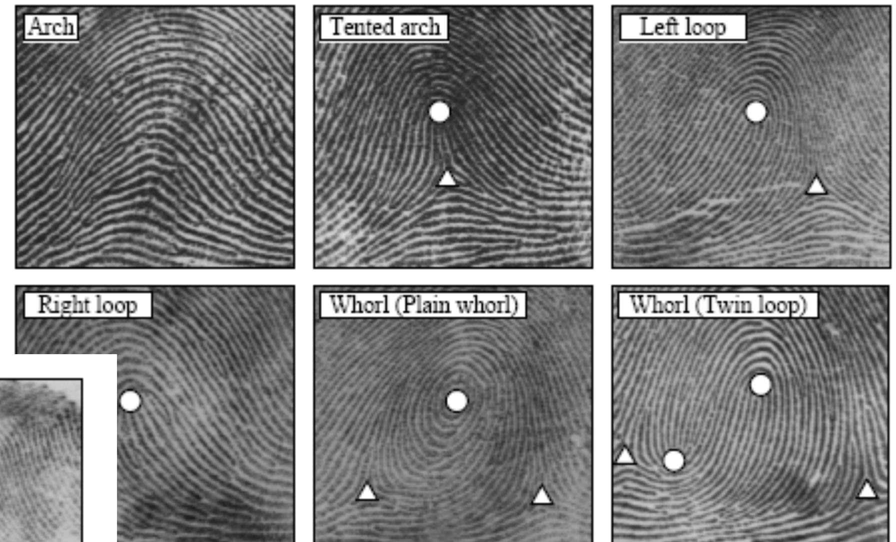
Classes

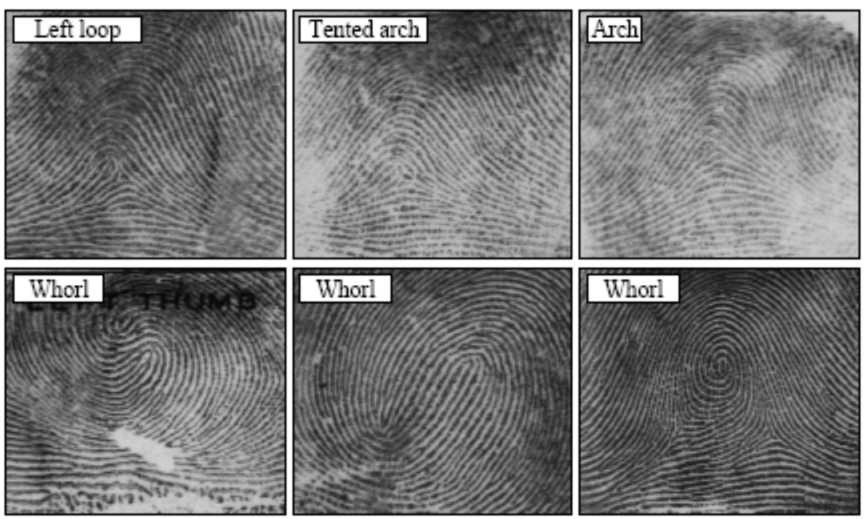
- Arch: 3.7%, tented arch: 2.9%, left loop: 33.8%, right loop: 31.7%, whorl: 27.9%
- Patteren recognition

PROBLEM

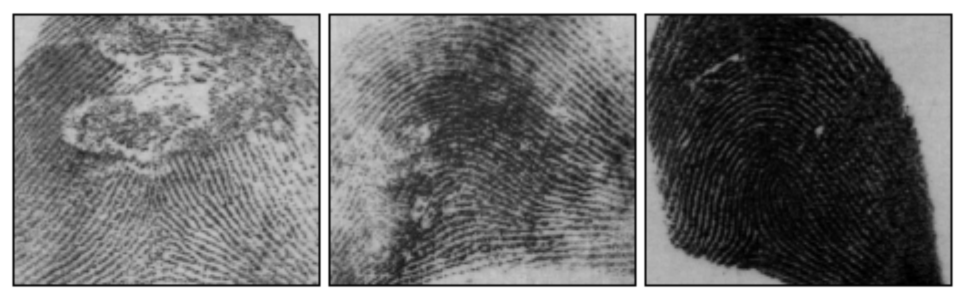
Small-inter class variability

Large intra-class variability



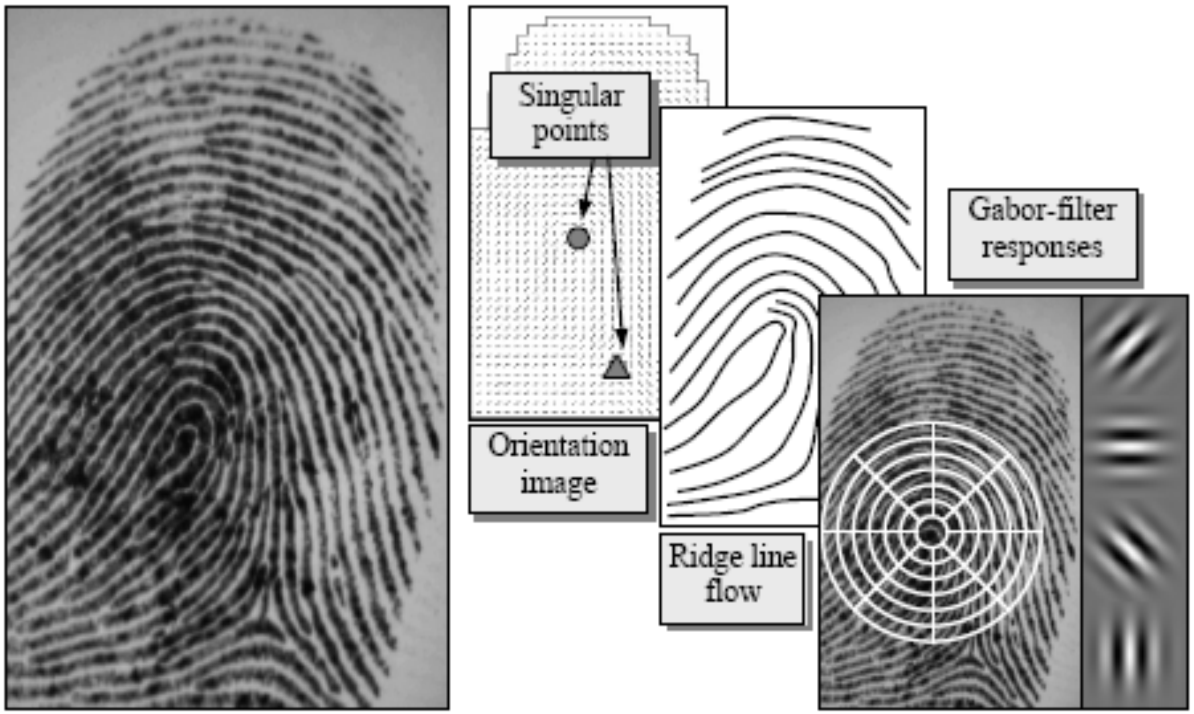


presence of noise



Features

- Based on global features
- Ridge line flow, orientation image, singular point, Gabor filters



Techniques

- Features:
  - O = orientation image
  - S = singularities
  - R = ridge flow,
  - G = Gabor
- classification technique
  - Rb = rule-based
  - Sy = syntactic
  - Str = structural,
  - Sta = statistical
  - Nn = neural network
  - Mc = multiple classifiers

Fingerprint classification approach	*Features*				*Classifier*					
	O	S	R	G	Rb	Sy	Str	Sta	Nn	Mc
Moayer and Fu (1975)	√					√				
Moayer and Fu (1976)	√					√				
Rao and Balck (1980)	√					√				
Kawagoe and Tojo (1984)		√	√		√					
Hughes and Green (1991)	√								√	
Bowen (1992)	√	√							√	
Kamijo, Mieno, and Kojima (1992)	√								√	
Kamijo (1993)	√								√	
Moscinska and Tyma (1993)	√				√				√	
Wilson, Candela, and Watson (1994)	√								√	
Candela et al. (1995)	√		√		√				√	√
Omidvar, Blue, and Wilson (1995)	√								√	
Halici and Ongun (1996)	√								√	
Karu and Jain (1996)		√			√					
Maio and Maltoni (1996)	√						√			
Ballan, Sakarya, and Evans (1997)		√			√					
Chong et al. (1997)			√		√					
Senior (1997)			√				√			
Wei, Yuan, and Jie (1998)	√				√				√	√
Cappelli et al. (1999)	√						√			
Cappelli, Maio, and Maltoni (1999)	√							√		
Hong and Jain (1999)		√	√		√					√
Jain, Prabhakar, and Hong (1999)				√				√	√	√
Lumini, Maio, and Maltoni (1999)	√						√			
Cappelli, Maio, and Maltoni (2000a)	√							√		√
Cho et al. (2000)		√			√					
Bartesaghi, Fernández, and Gómez (2001)		√			√					
Bernard et al. (2001)	√								√	
Marcialis, Roli, and Frasconi (2001)	√			√			√	√	√	√
Pattichis et al. (2001)	√				√				√	√
Senior (2001)	√		√		√		√		√	√
Yao, Frasconi, and Pontil (2001)				√				√		√
Cappelli, Maio, and Maltoni (2002a)	√							√		√
Jain and Minut (2002)			√		√					
Cappelli et al. (2003)	√							√		√
Yao et al. (2003)	√			√			√	√	√	√

Techniques

Fingerprint classification approach	*Features*				*Classifier*					
	O	S	R	G	Rb	Sy	Str	Sta	Nn	Mc
Cappelli and Maio (2004)	√							√		√
Klimanee and Nguyen (2004)	√	√			√					
Senior and Bolle (2004)	√		√		√		√		√	√
Shah and Sastry (2004)								√	√	√
Wang and Xie (2004)	√	√	√		√					
Zhang and Yan (2004)	√	√	√		√					
Park and Park (2005)	√							√		
Neuhaus and Bunke (2005)	√						√			
Tan, Bhanu, and Lin (2005)	√							√		
Min, Hong, and Cho (2006)				√				√		√
Kristensen, Borthen, and Fyllingsnes (2007)				√					√	
Wang and Dai (2007)	√	√			√					
Hong et al. (2008)	√	√		√				√		√
Li, Yau, and Wang (2008)	√	√						√		

Techniques II

- Syntatic: terminal symbols & production rules

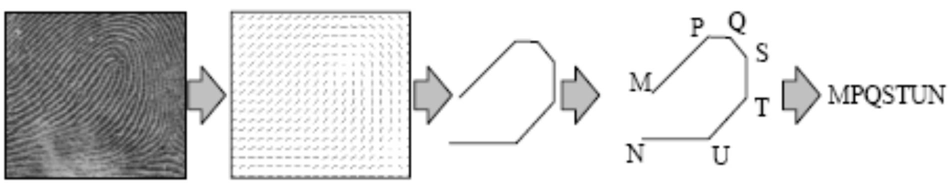
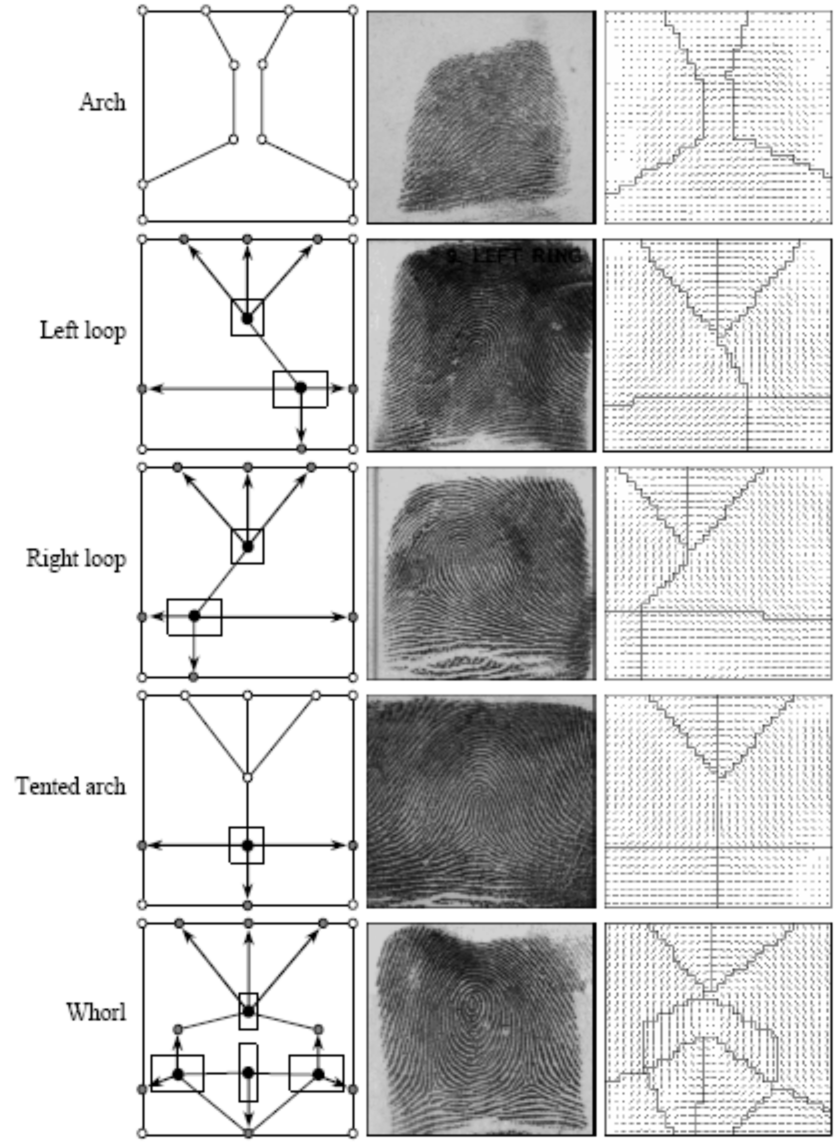


Figure 5.7. A schema of the string-construction approach in Rao and Balck (1980).

- Structural approach
- Statistical
  - Orientation image
  - k-nearest neighbor
  - 30x30 array, 1800 elements
  - PCA (the Karhunen-Loeve) transform

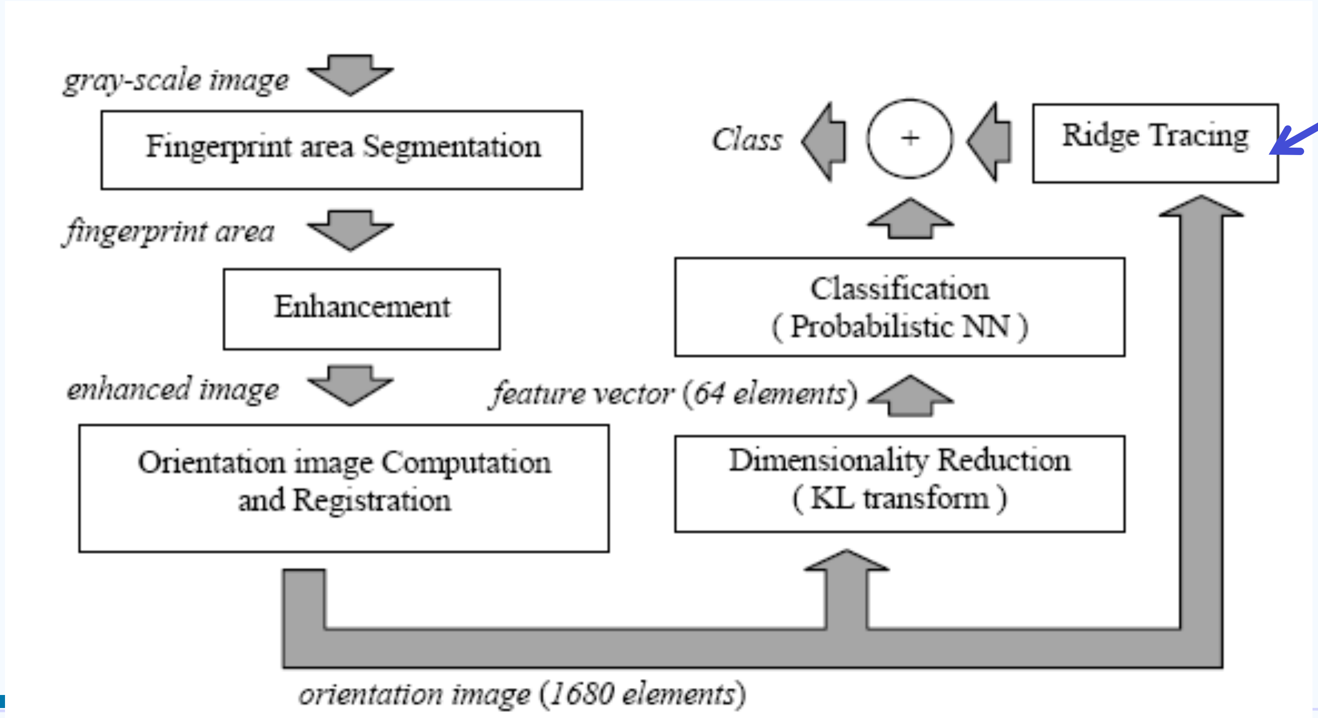
$$\mathbf{d} = \left[r \cdot cos\left(2\theta\right), r \cdot sin\left(2\theta\right)\right].$$



Techniques III

- Multiple classifier-based apparoaches
- PCASYS: Pattern-level Classification Automation systém
- Open Source: http://ffpis.sourceforge.net/
- Developed by NIST: http://www.nist.gov/index.html
  - National Institute of Standards and Technology

Whorl module



Classification Evaluation

- Accuracy
  - Rejection can improve accuracy

$$\text{error rate} = \frac{\text{number of misclassified fingerprints} \times 100}{\text{total number of fingerprints}} \%$$

$$\text{accuracy} = 100\% - \text{error rate}.$$

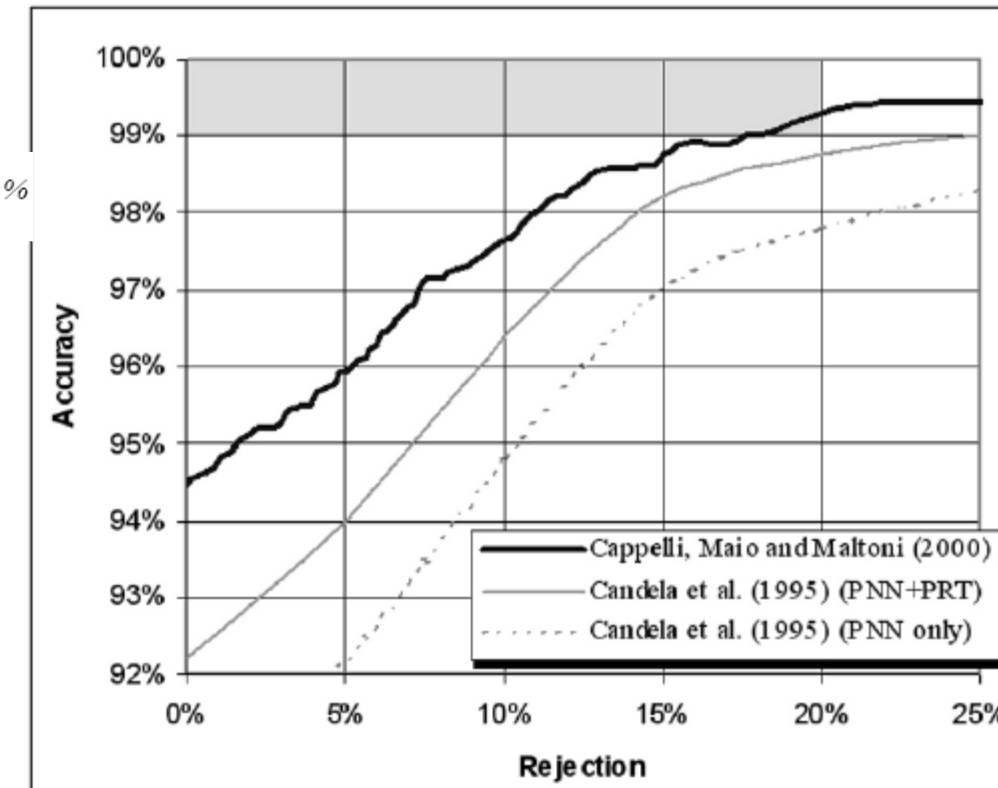
- Penetration rate: time constraint

$$\text{penetration rate} = \frac{\text{number of accessed fingerprints} \times 100}{\text{total number of fingerprints in the database}} \%$$

- Confusion matrix (DB4)

True class	Hypothesized class				
	A	L	R	W	T
A	**420**	6	3	1	11
L	3	**376**	3	9	11
R	5	1	**392**	6	16
W	2	5	14	**377**	1
T	33	18	9	0	**278**

- Rejection can improve accuracy (DB14)
  - Unknown class
  - FBI target
  - **NIST database -DB 4, DB14**



Results on DB4, DB14

- Results on DB4

True class	Hypothesized class				
	A	L	R	W	T
A	**420**	6	3	1	11
L	3	**376**	3	9	11
R	5	1	**392**	6	16
W	2	5	14	**377**	1
T	33	18	9	0	**278**

True class	Hypothesized class			
	A+T	L	R	W
A+T	**782**	10	17	6
L	6	**373**	2	4
R	7	1	**381**	9
W	0	4	7	**391**

Method	Test set	5 classes		4 classes	
		%	*Weighted* (%)	%	*Weighted* (%)
Candela et al. (1995)	Second half	–	–	11.4	6.1
Karu and Jain (1996)	Whole DB	14.6	11.9	8.6	9.4
Senior (1997)	Random 542	–	–	–	8.4
Cappelli, Maio, and Maltoni (1999)	Second half	7.9	6.5	5.5	–
Hong and Jain (1999)	Whole DB	12.5	10.6	7.7	–
Jain, Prabhakar, and Hong (1999)	Second half (*)	10.0	7.0	5.2	–
Marcialis, Roli, and Frasconi (2001)	Second half (*)	12.1	9.6	–	–
Senior (2001)	Second half	–	–	–	5.1
Yao, Frasconi, and Pontil (2001)	Second half (*)	10.7	9.0	6.9	–
Jain and Minut (2002)	Whole DB	–	–	8.8	9.3
Cappelli et al. (2003)	Second half	4.8	3.7	3.7	3.4
Yao et al. (2003)	Second half (*)	10.0	8.1	-	-
Cappelli and Maio (2004)	Second half	7.0	5.9	4.7	5.4
Wang and Xie (2004)	Whole DB	-	-	18.0	-
Zhang and Yan (2004)	Whole DB	15.7	11.0	7.3	8.3
Neuhaus and Bunke (2005)	Second half	19.8	-	-	-
Park and Park (2005)	Second half	9.3	7.9	6.0	-
Tan, Bhanu, and Lin (2005)	Second half	8.4	8.0	6.7	7.5
Min, Hong, and Cho (2006)	Second half (*)	9.6	7.2	-	-
Wang and Dai (2007)	Whole DB	11.5	9.4	-	-
Hong et al. (2008)	Second half (*)	9.2	6.2	5.1	-
Li, Yau, and Wang (2008)	Second half	6.5	7.0	5.0	-

- Results on DB14

Method	Error rate (%)
Candela et al. (1995)	7.8
Wei, Yuan, and Jie (1998)	6.0
Cappelli, Maio, and Maltoni (2000a)	5.6

Biometrics errors

Daniel Novák

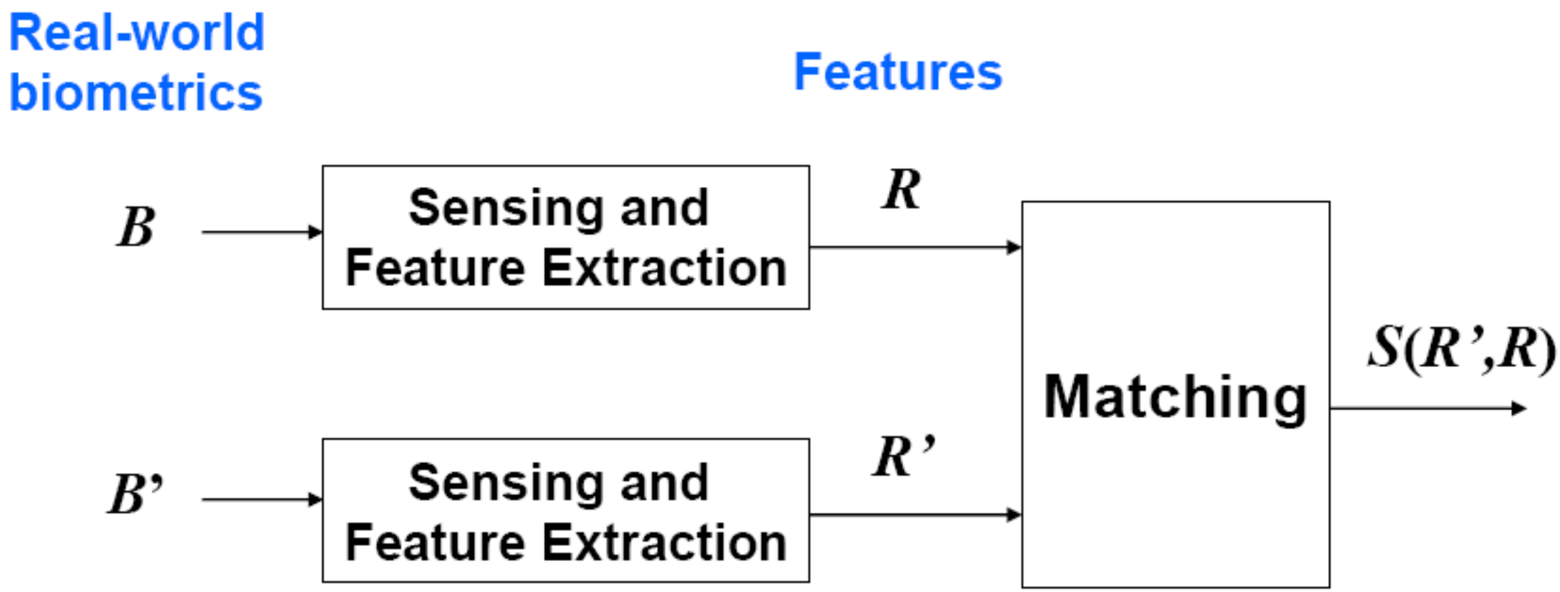
6.12, 2011, Prague

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

Example Iris & Speech

- Example
  - Assume 10’000 customers are signed up for biometric authentication and 1’000 transactions are done weekly
  - Assume best-case biometric verification error of 1 in 1 million (iris)
  - Assume best-case speaker verification error of 1 in 1 hundred
  - How often are customers falsely billed?
- Answer
  - On average 10 people are falsely billed each week
  - On average 100 000 people are falsely billed each week

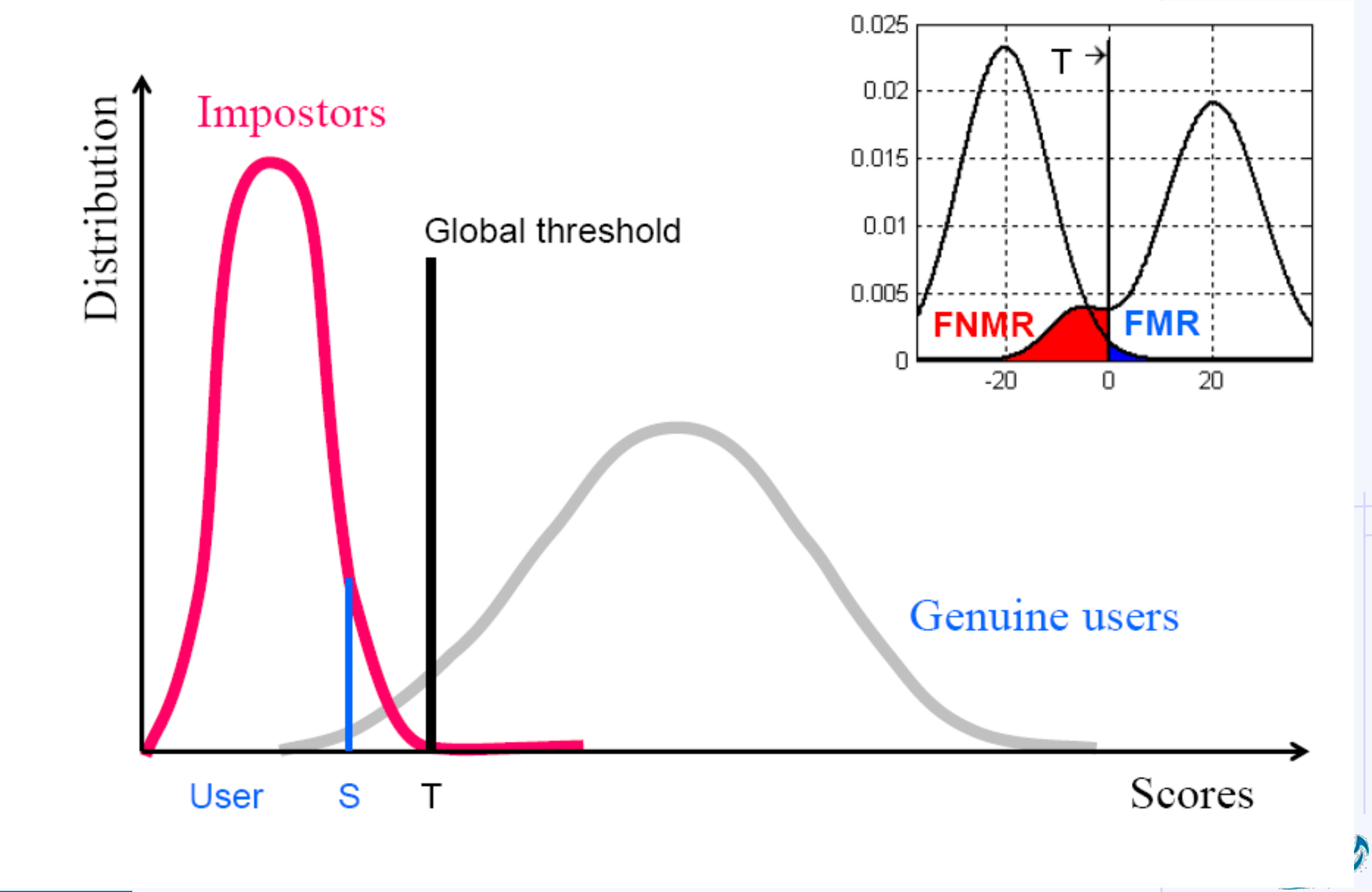
Matching



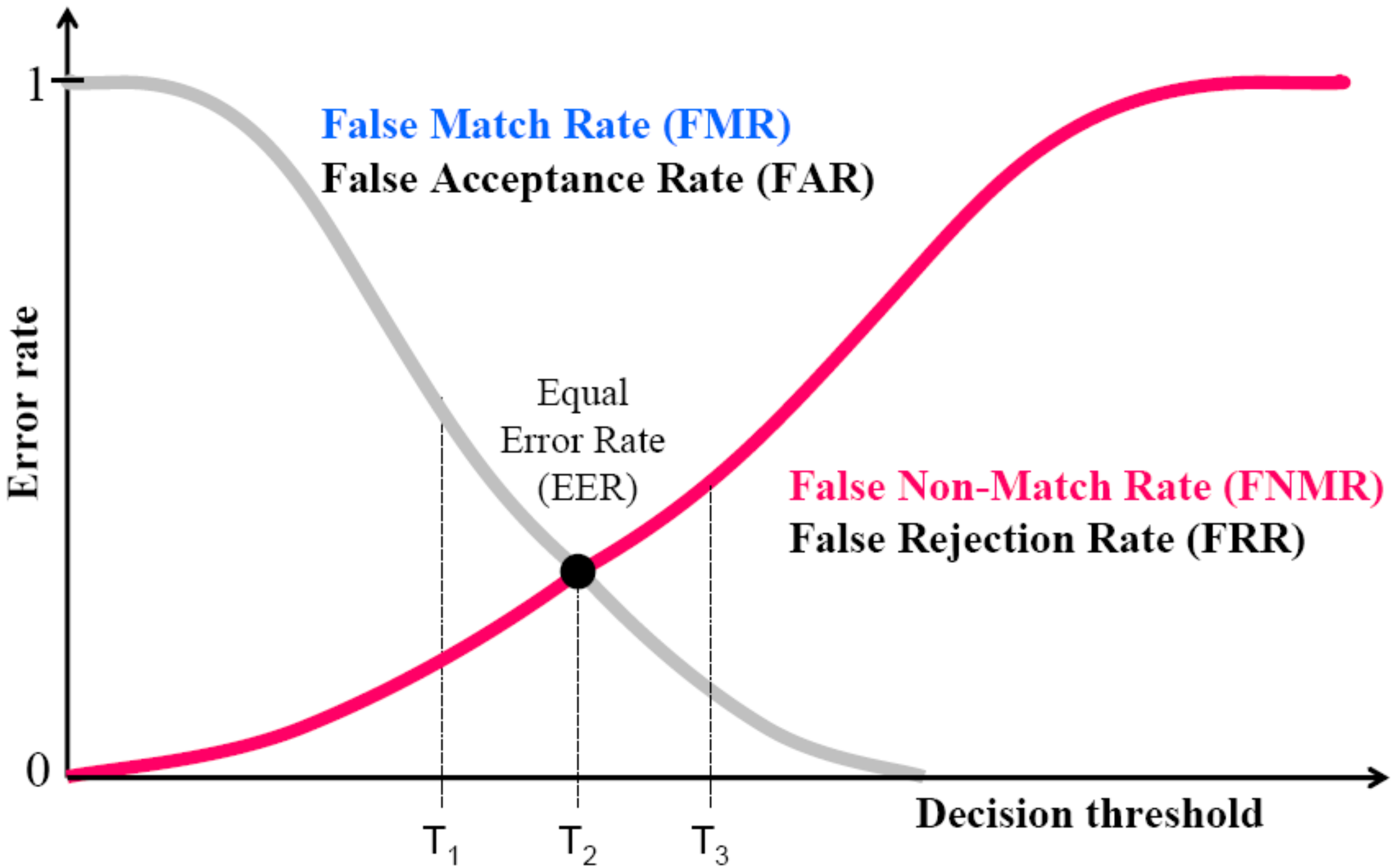
$$\boxed{s(R',R) = s(f_{t'}(B'(t')), f_t(B(t)))}$$

Biometric matching makes a decision by computing a measure of the likelihood that the two input samples from two persons are the « same » and hence that the subjects are the same real-world identity.

Performance evaluation



FMR and FNMR



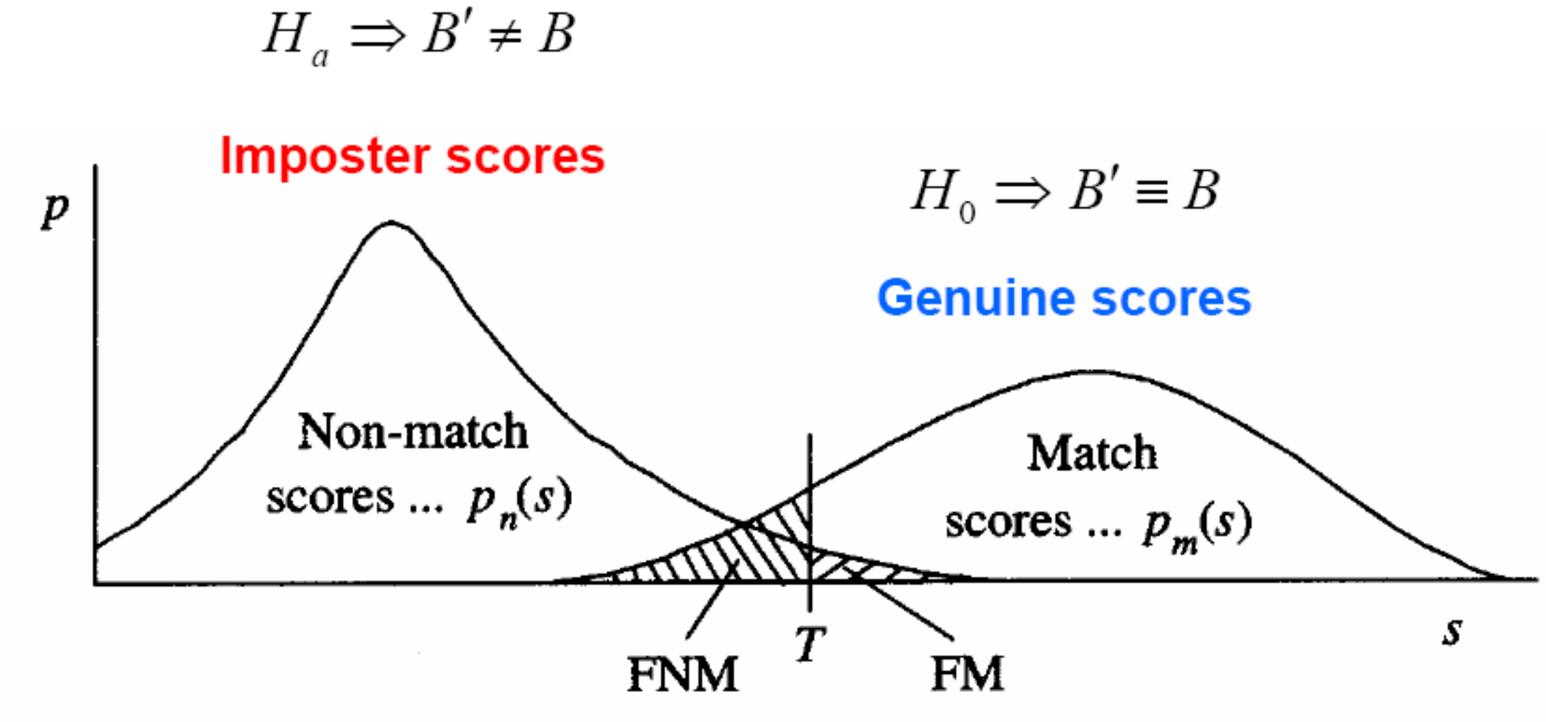
1
0
Error rate
False Match Rate (FMR)
False Acceptance Rate (FAR)
Equal
Error Rate
(EER)
False Non-Match Rate (FNMR)
False Rejection Rate (FRR)
Decision threshold
T1
T2
T3

FA & FR

- **False Accept (FA):** Deciding that a (claimed) identity is a legitimate one while in reality it is an imposter; False Accept Rate (FAR)
- **False Reject (FR):** Deciding that a (claimed) identity is not legitimate when in reality the person is genuine; False Reject Rate (FRR)

- A FA results in security breaches, with an unauthorized person being admitted
- A FR results in convenience problems, since genuinely enrolled identities are denied access to the application

Scores distribution



Given two biometric samples, we can construct two possible hypotheses:

The null hypothesis:	$H_0 \Rightarrow$	the two samples match
The alternate hypothesis:	$H_a \Rightarrow$	the two samples do not match

Two kinds of error

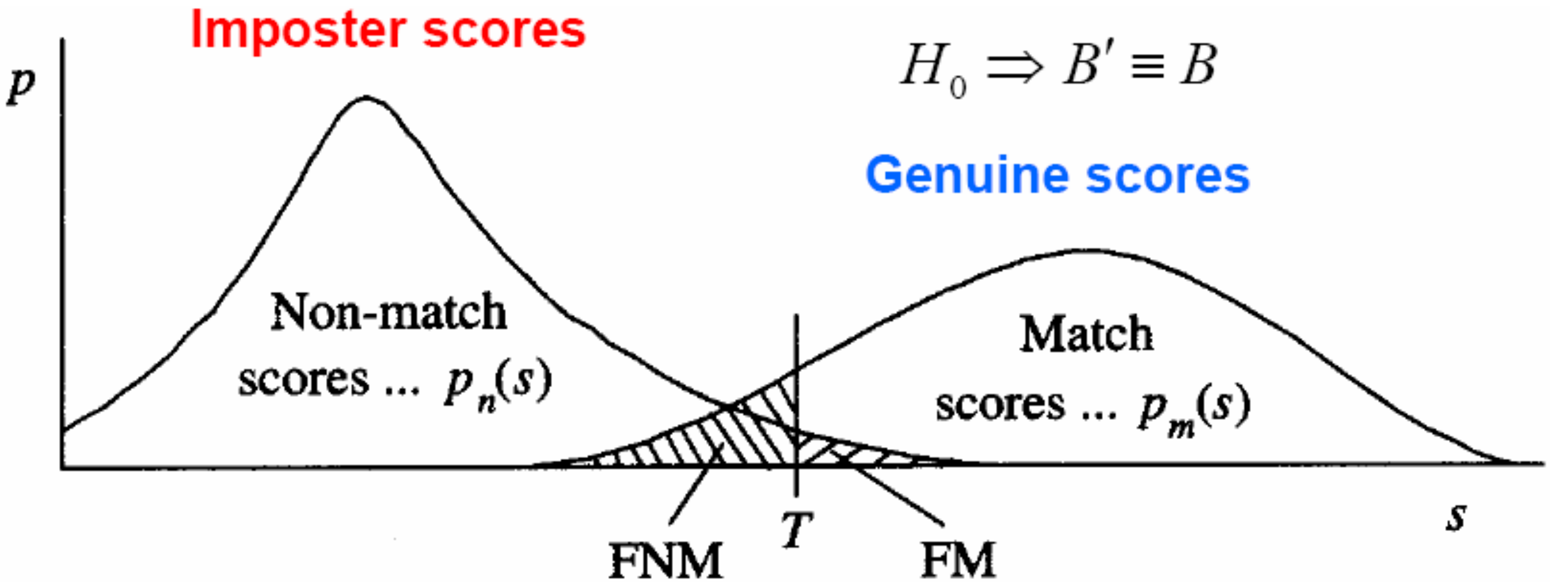
- Verification:

$$\begin{aligned} &\text{Decide } H_0 \text{ is true:} \quad \text{if} \quad s > T, \\ &\text{Decide } H_a \text{ is true:} \quad \text{if} \quad s \leq T. \end{aligned}$$

- Type I Error - False Match (FM): Deciding that two biometrics are from the same identity, while in reality they are from different identities; the frequency with which this occurs is called the False Match Rate (FMR)
- Type II Error – False Non-Match (FNM): Deciding that two biometrics are not from the same identity, while in reality they are from the same identity: the frequency with which this occurs is called the False Non-Match Rate (FNMR)
- Correct Match: correctly deciding that two biometric samples match
- Correct Non-Match: correctly deciding that the samples do not match

Two kinds of error

$$H_a \Rightarrow B' \neq B$$

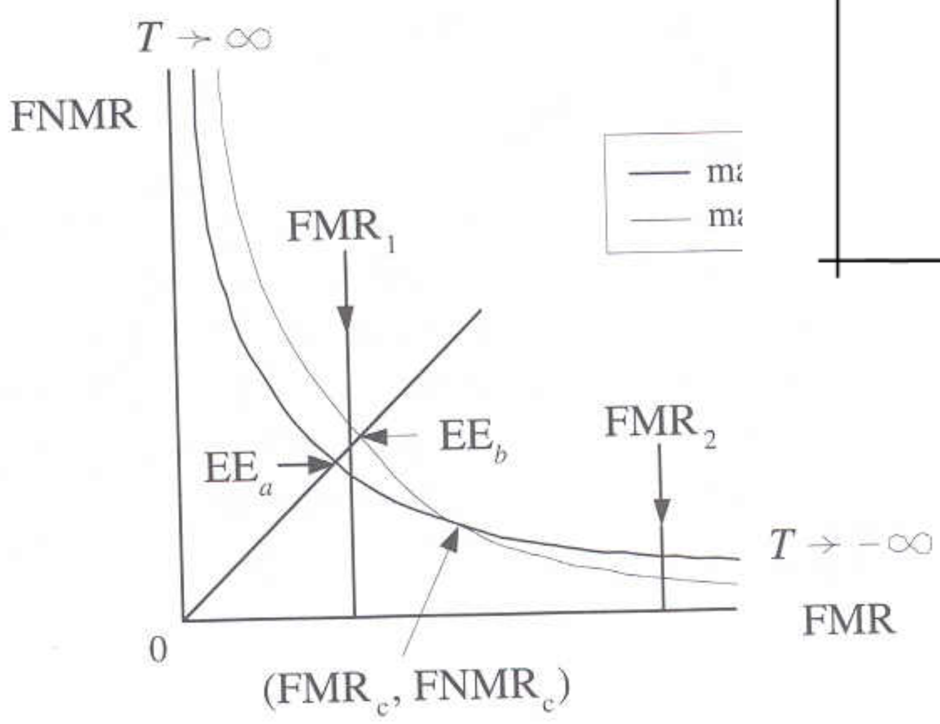


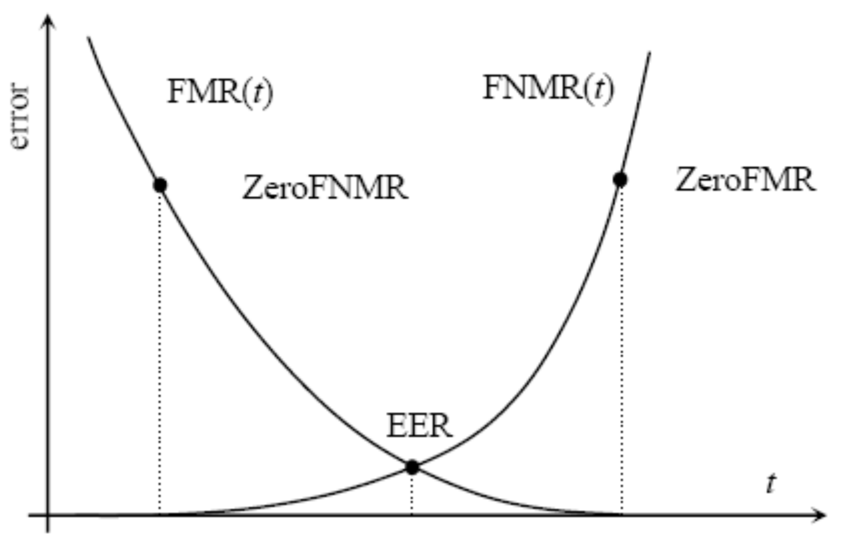
$$\boxed{\mathrm{FNMR}(T) = \int_{s=-\infty}^{T} p_m(s)\,ds}$$

$$\boxed{\mathrm{FMR}(T) = \int_{s=T}^{\infty} p_n(s)\,ds}$$

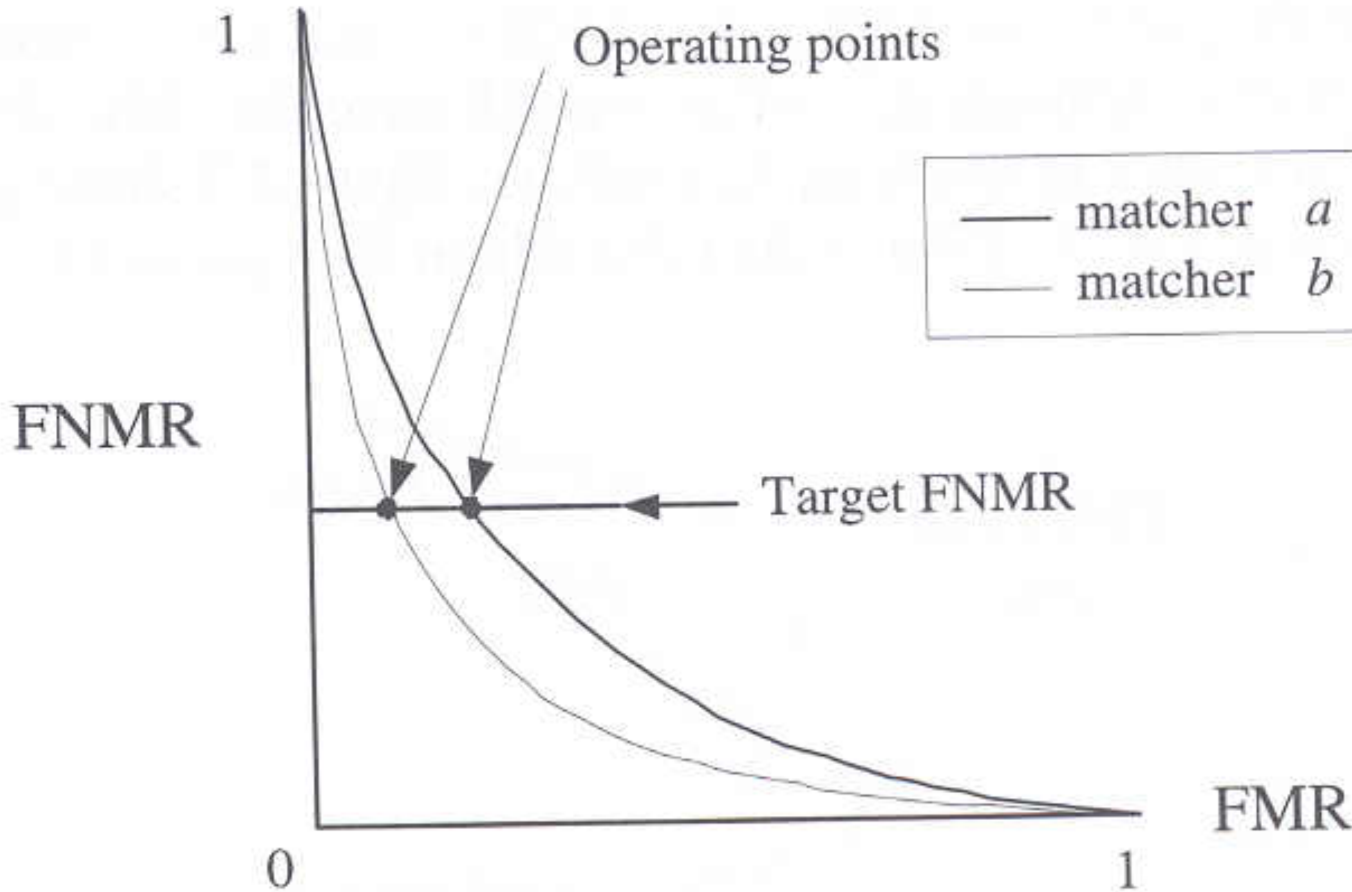
The Equal Error Rate

- ROC:





Using the ROC Curve



Matcher *b* is always better than matcher *a* since for every possible FNMR, its FMR is lower

ROC curve – example on DB1

– 2800 genuine pairs, 4950 imposters pairs

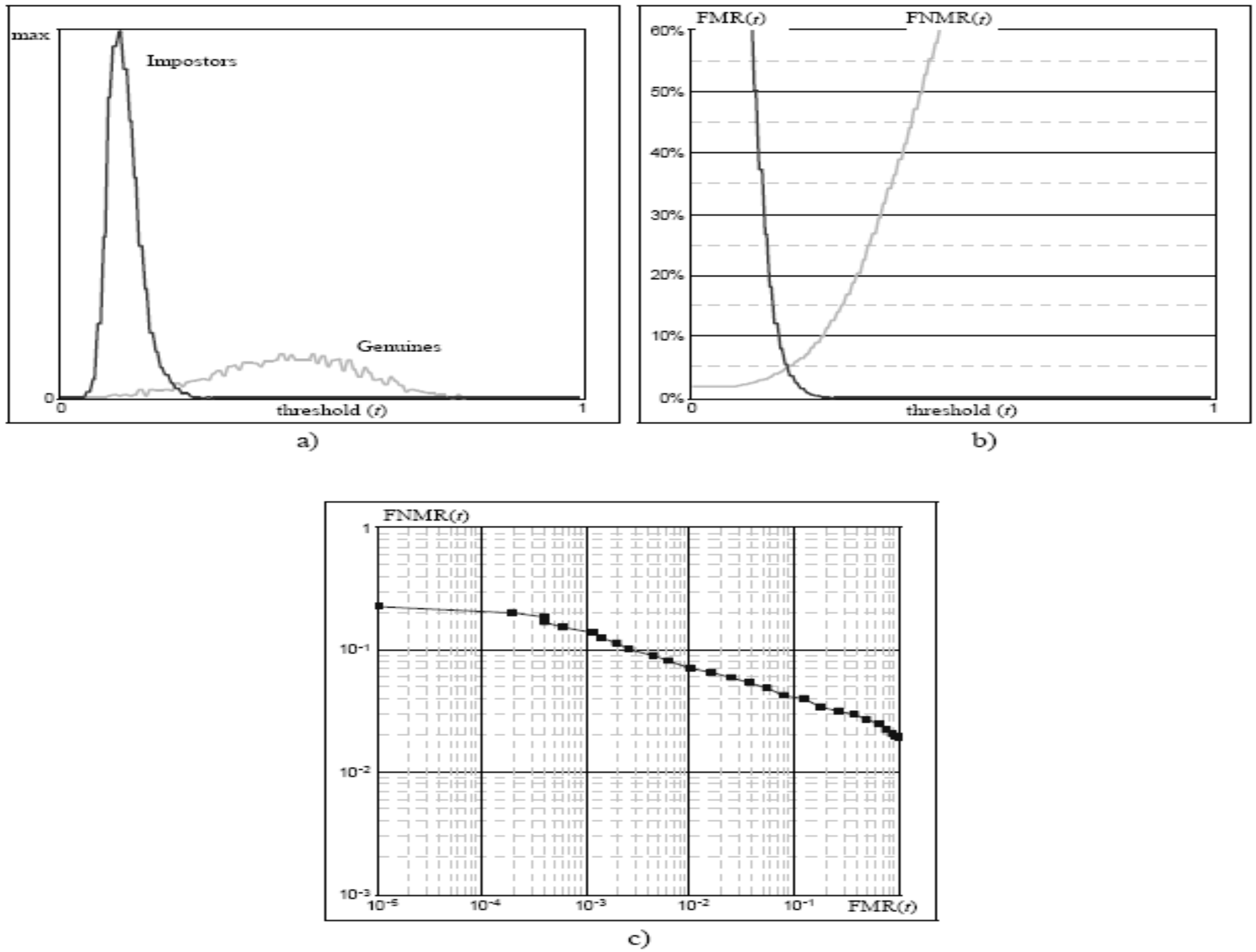


Figure 1.5. Evaluation of a fingerprint verification algorithm over FVC2002 database DB1 (Maio et al., 2002b): a) genuine and impostor distributions were computed from 2800 genuine pairs and 4950 impostor pairs, respectively; b) FMR(t) and FNMR(t) are derived from the score distributions in a); c) DET curve is derived from the FMR(t) and FNMR(t) curves in b).

FVC 2004 results

- http://bias.csr.unibo.it/fvc2004/
- http://www.nist.gov/srd/biomet.htm

Algorithm	EER(%)	Avg Enroll Time (sec)	Avg Match Time (sec)	Avg Model Size (KB)
Bioscrypt Inc.	2.07	0.08	1.48	24
Sonda Ltd	2.10	2.07	2.07	1.3
Chinese Academy of Sciences	2.30	0.35	0.67	16.4
Gevarius	2.45	0.69	0.71	2.0
Jan Lunter	2.90	1.01	1.19	3.1

- Database:
  - DB1: optical sensor "V300" by CrossMatch
  - DB2: optical sensor "U.are.U 4000" by Digital Persona
  - DB3: thermal sweeping sensor "FingerChip FCD4B14CB" by Atmel
  - DB4: synthetic fingerprints

FVC COMPARISION

NIST Fingerprint Vendor Technology Evaluation

- http://fpvte.nist.gov/

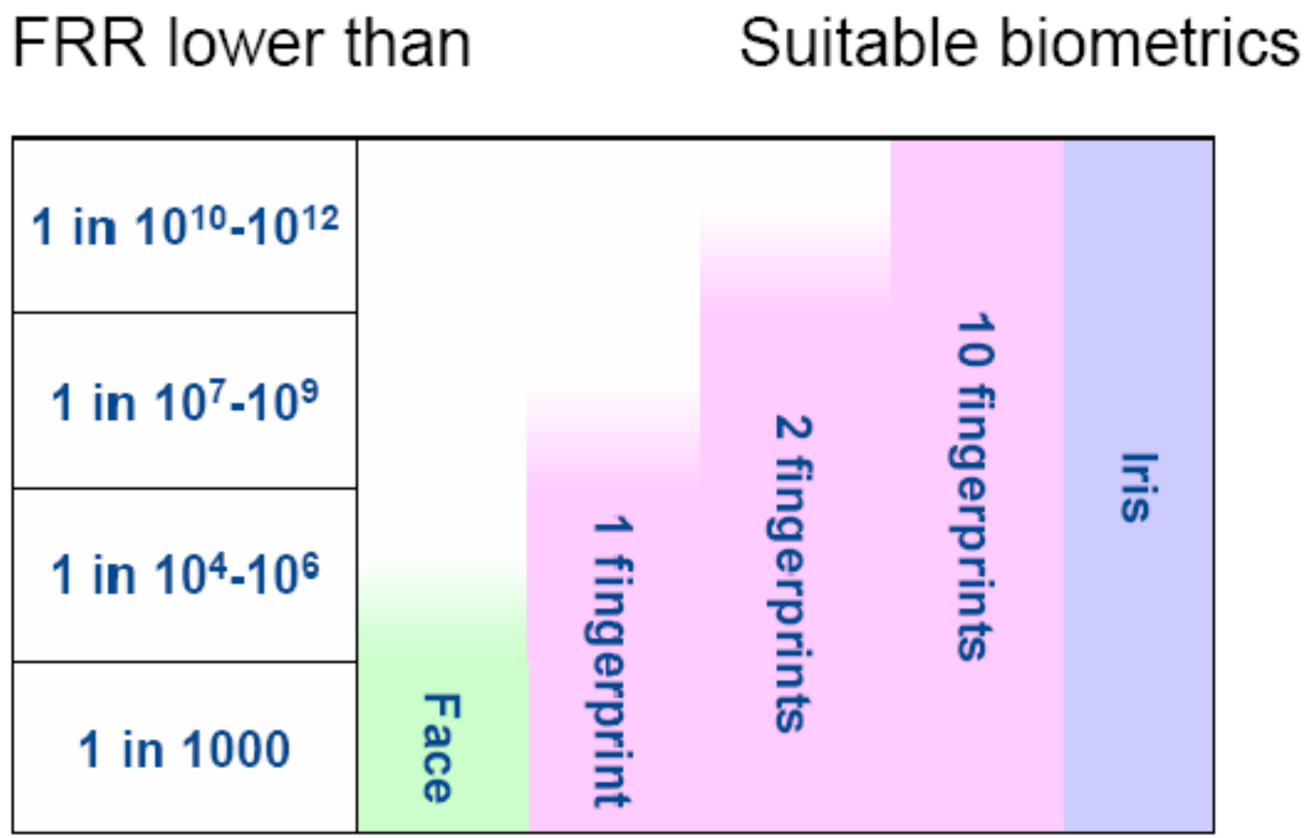
–NIST Proprietary Fingerprint Template (PFT) Testing

- http://fingerprint.nist.gov/SDK/

	DB1	DB2	DB3	DB4
FVC2000	2.30%	1.39%	4.34%	3.38%
FVC2002	0.20%	0.17%	0.63%	0.16%
FVC2004	1.61%	2.32%	1.34%	0.81%
FVC2006	5.88%	0.05%	1.59%	0.39%

Table 4.3. Average accuracy (EER) of the three best performing algorithms over the different FVC databases. A direct comparison across the different competitions is not possible due to the use of databases of unequal difficulty.

Accuracy and scalability



Mansfield 2004

Convenience vs Security

- The higher the FRR, the less convenient an application is because more subjects are incorrectly recognized and therefore subject to denial of service or the exception handling process

$$\boxed{Convenience = 1 - FRR}$$

- Similarly, the FAR is often used as some measure of security of a verification system

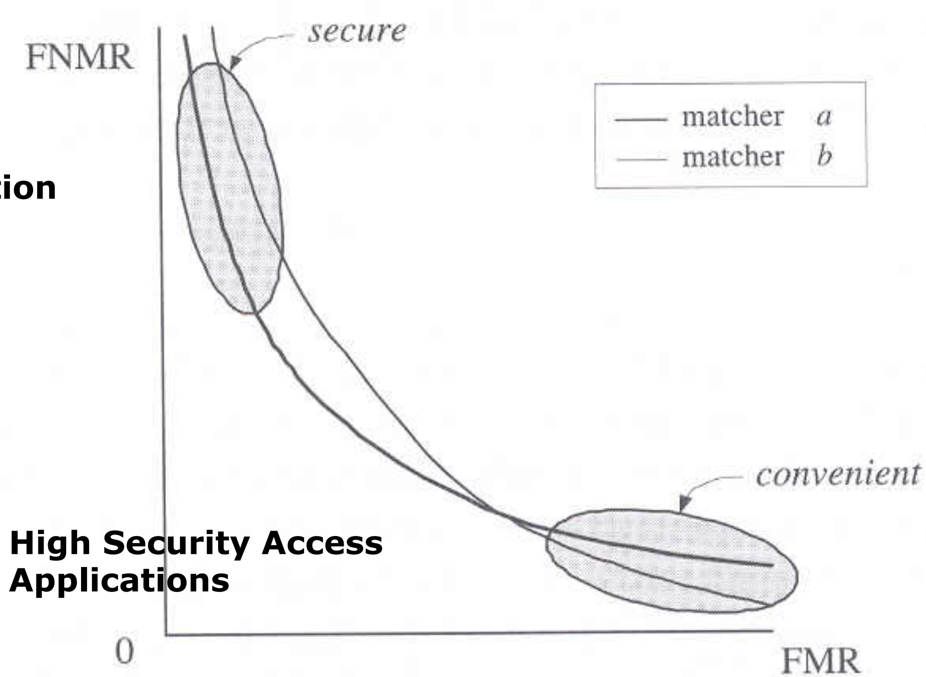
$$\boxed{Security = 1 - FAR}$$

Convenience vs Security

- Convenience of a Biometric
- Convenience of Implementation

$$Convenience = 1 - \mathrm{FRR}$$

$$Security = 1 - \mathrm{FAR}$$



Errors specific to biometrics

- The **Failure to Acquire (FTA)** rate is the percentage of the target population that does not possess a particular biometric, i.e. does not deliver a usable biometric sample (e.g. the fingerprint of a brick layer (the ridges have been worn away)
- The **Failure to Enroll (FTE)** rate is the proportion of the population that somehow cannot be enrolled because of limitations of the technology or procedural problems.

Synthetic fingerprint generation

Daniel Novák

6.12, 2011, Prague

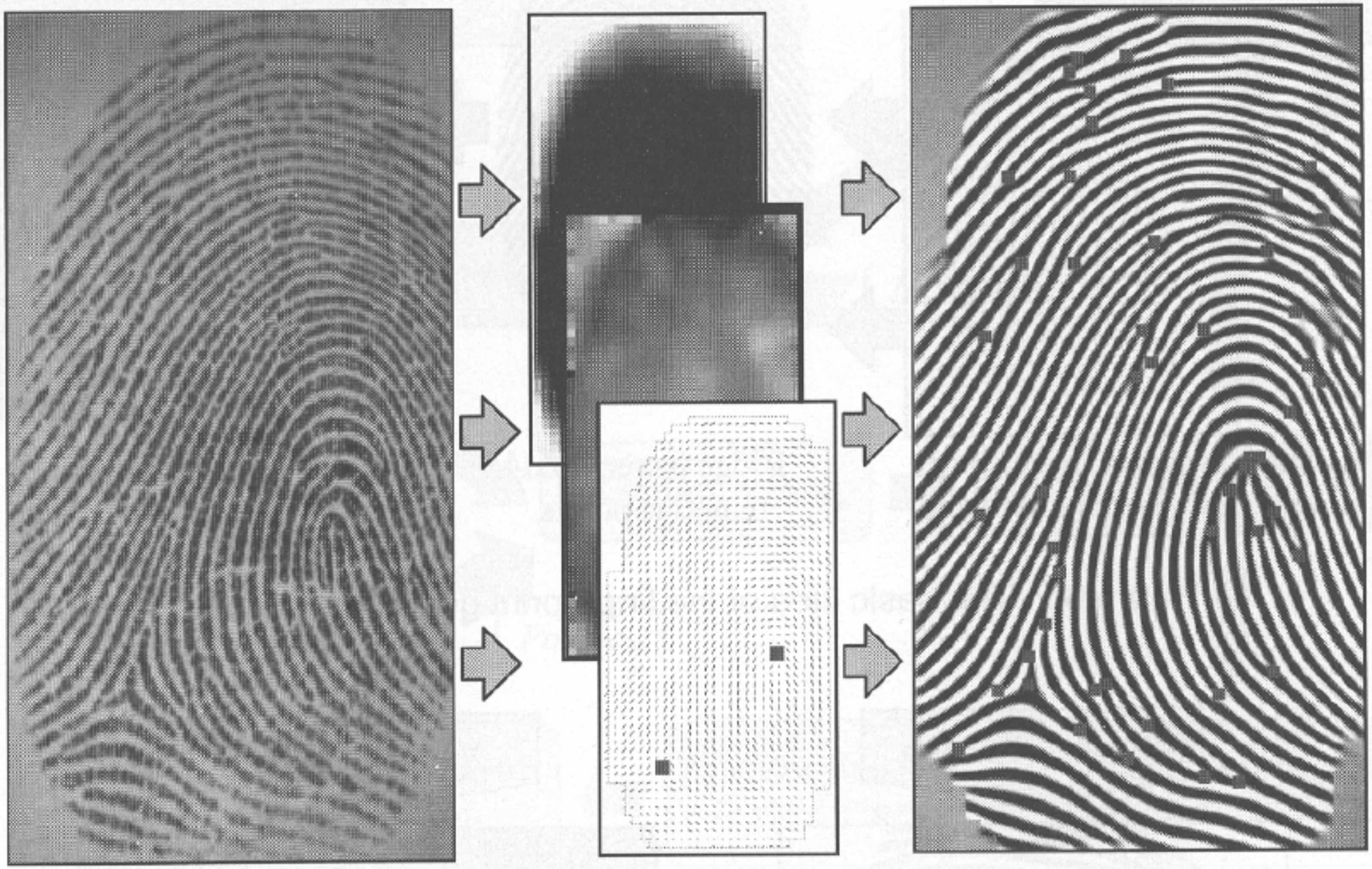
Acknowledgments: Xavier Palathingal, Andrzej Drygajlo,
Handbook of Fingerprint Recognition

Department of Cybernetics, Czech Technical University

Synthetic fingerprint generation

- Motivation
  - Accuracy of each algorithm is usually evaluated on relatively small proprietary databases
  - Evaluation on small databases makes the accuracy estimates highly data dependent
  - When the databases are proprietary, the accuracy of various fingerprint matching algorithms cannot be compared directly
- Synthetic fingerprint generation can be used to automatically create large databases of fingerprints, thus allowing fingerprint recognition algorithms to be effectively trained, tested, optimized, and compared

Feature extraction process

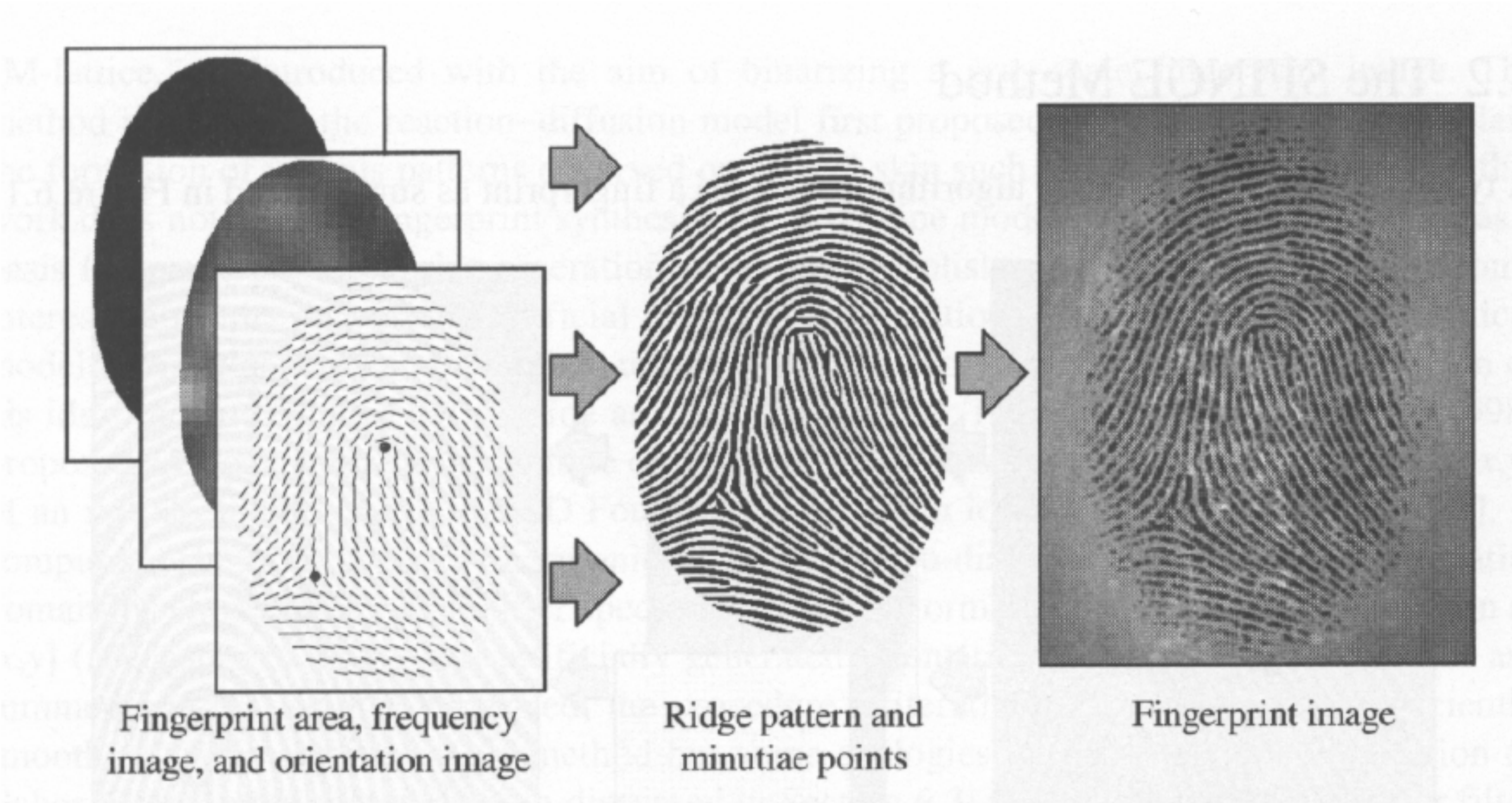


Fingerprint image

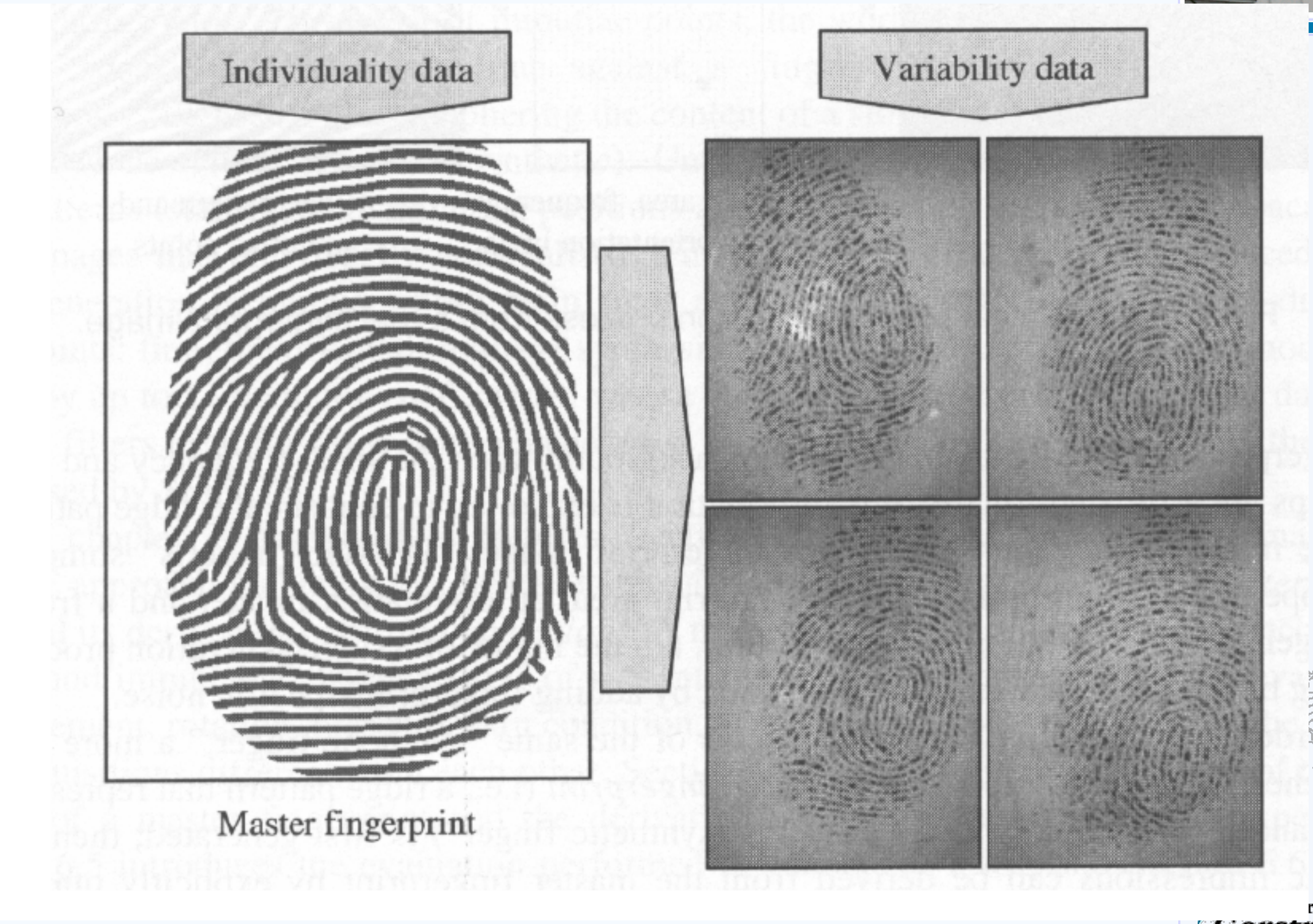
Fingerprint area, frequency image, and orientation image

Ridge pattern and minutiae points

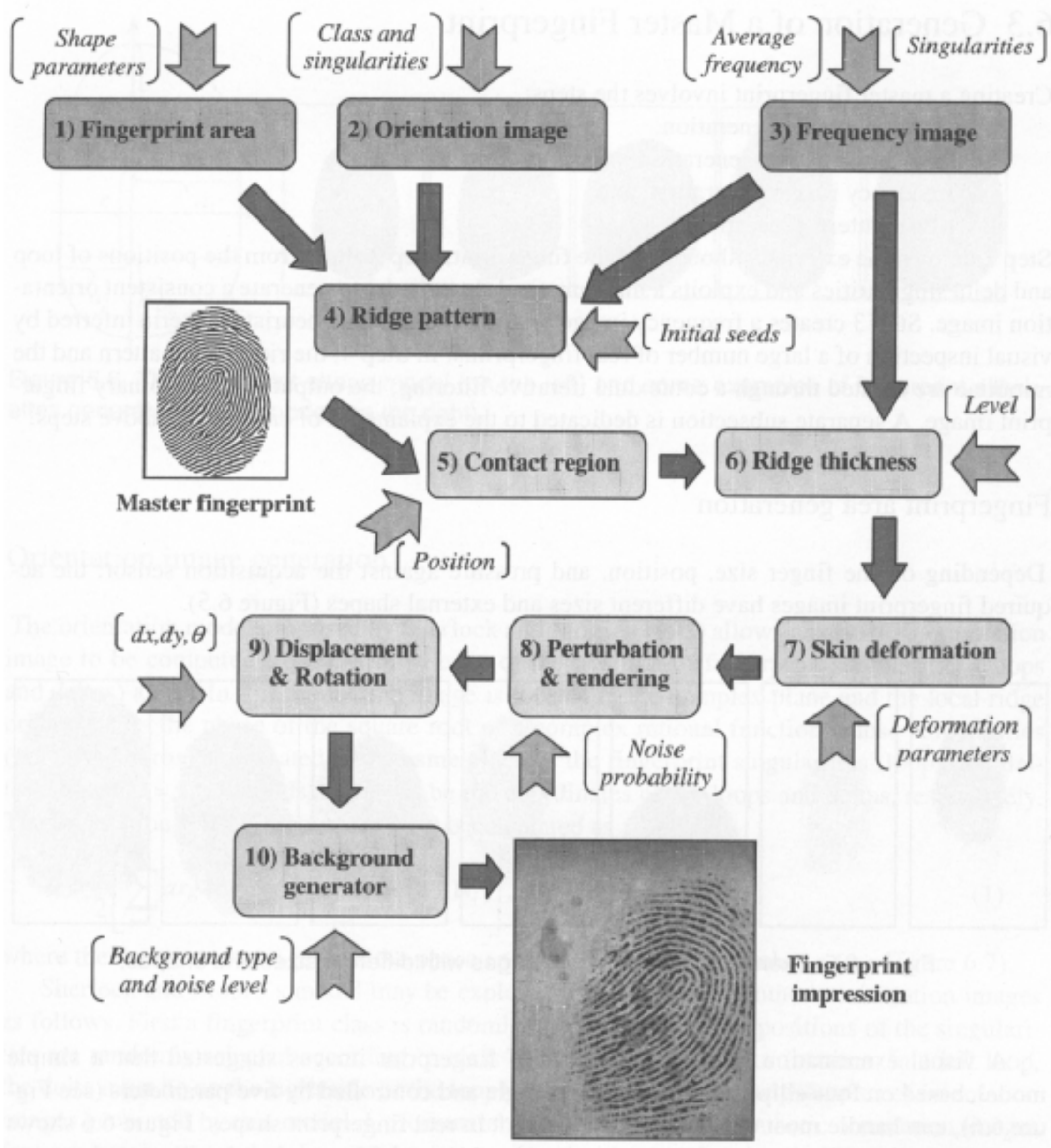
Basic idea


Fingerprint area, frequency image, and orientation image
Ridge pattern and minutiae points
Fingerprint image

From master to final impression

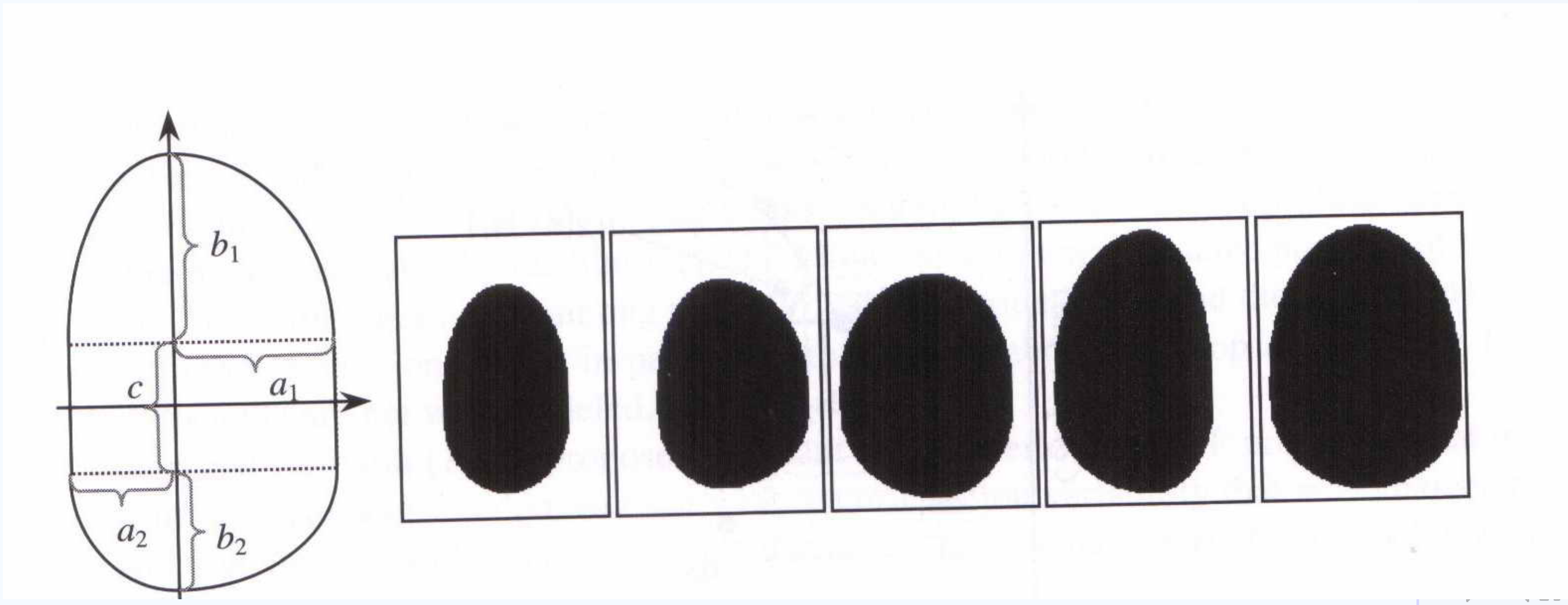


SFINGE

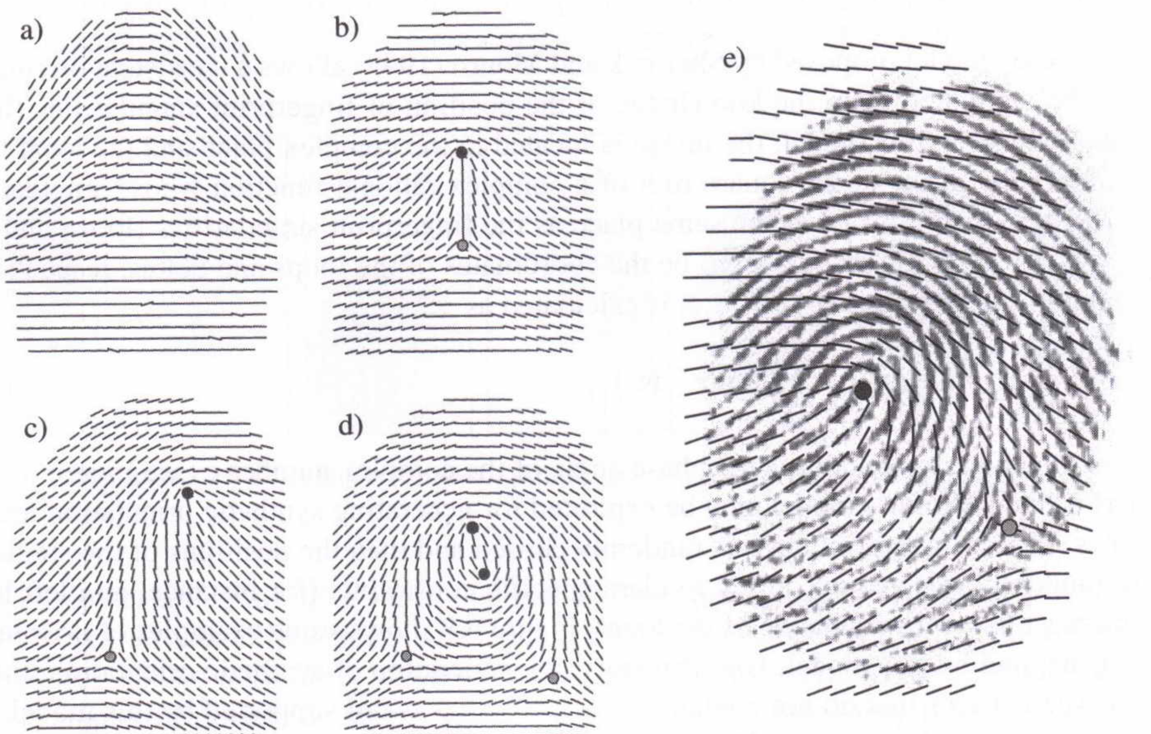


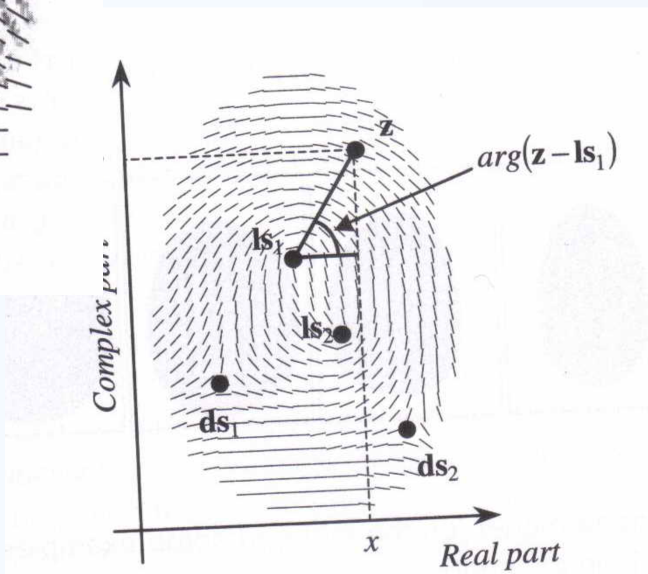
Shape parameters
Class and singularities
Average frequency
Singularities
1) Fingerprint area
2) Orientation image
3) Frequency image
4) Ridge pattern
Initial seeds
Master fingerprint
Level
5) Contact region
6) Ridge thickness
Position
dx,dy,θ
9) Displacement & Rotation
8) Perturbation & rendering
7) Skin deformation
Deformation parameters
Noise probability
10) Background generator
Background type and noise level
Fingerprint impression

FP area generation

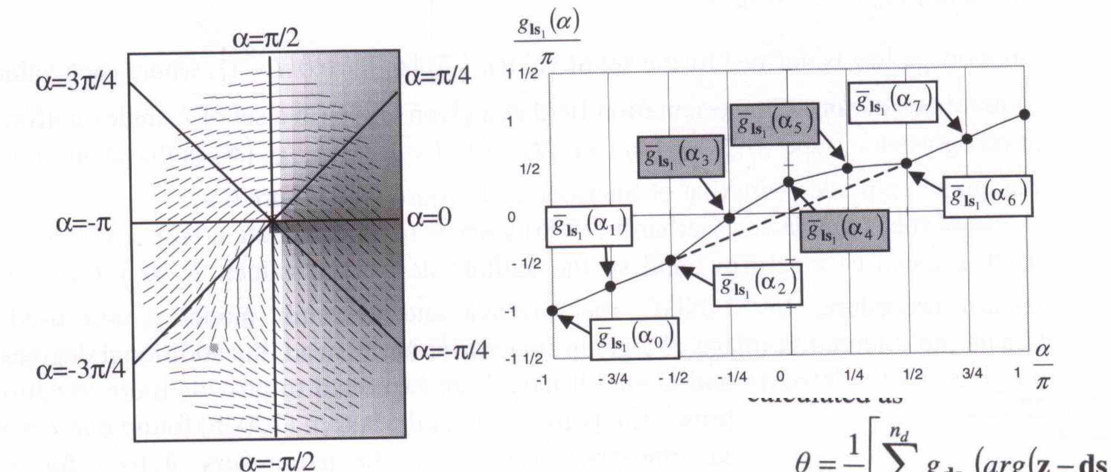


Orientation





Orientation



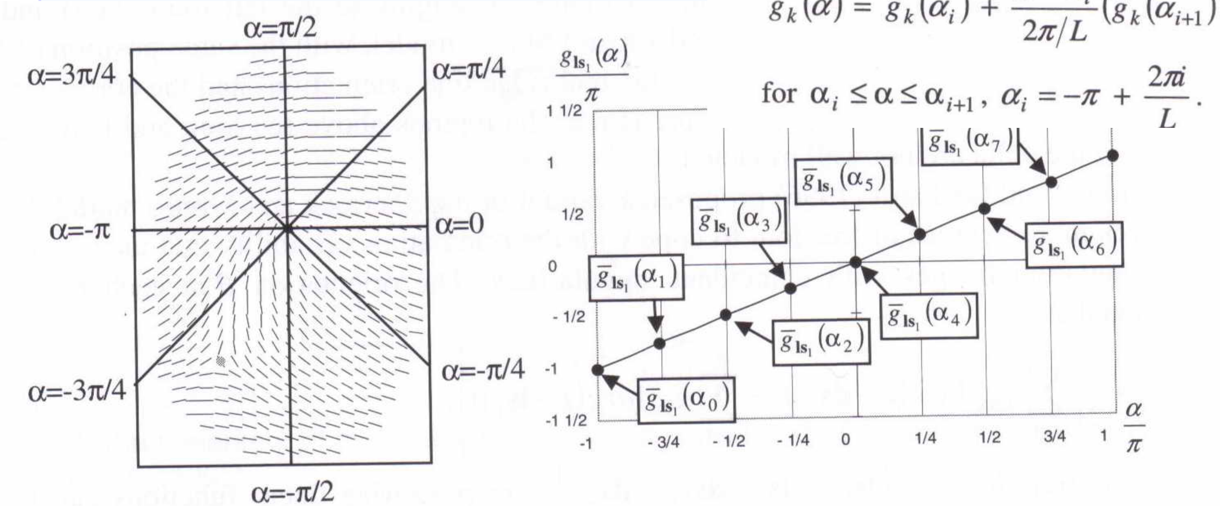
calculated as

$$\theta = \frac{1}{2}\left[\sum_{i=1}^{n_d} g_{\mathbf{ds}_i}\left(arg\left(\mathbf{z}-\mathbf{ds}_i\right)\right) - \sum_{i=1}^{n_c} g_{\mathbf{ls}_i}\left(arg\left(\mathbf{z}-\mathbf{ls}_i\right)\right)\right], \quad (2)$$

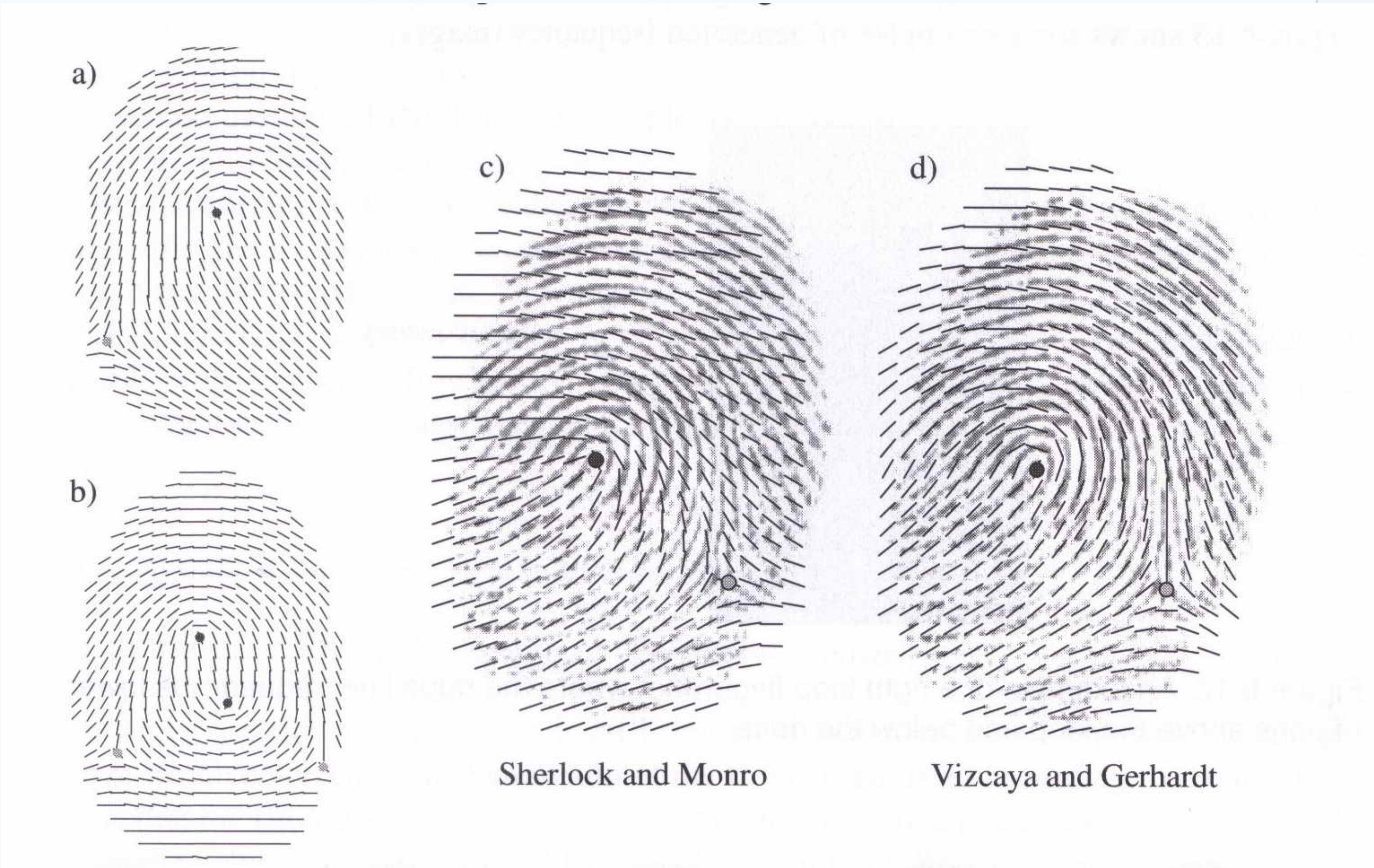
where $g_k(\alpha)$, for $k \in \{\mathbf{ls}_1, ..., \mathbf{ls}_{n_c}, \mathbf{ds}_1, ..., \mathbf{ds}_{n_d}\}$, are piecewise linear functions capable of locally correcting the orientation field with respect to the value given by the Sherlock and Monroe model:

$$g_k(\alpha) = \bar{g}_k(\alpha_i) + \frac{\alpha - \alpha_i}{2\pi/L}\left(\bar{g}_k(\alpha_{i+1}) - \bar{g}_k(\alpha_i)\right), \quad (3)$$

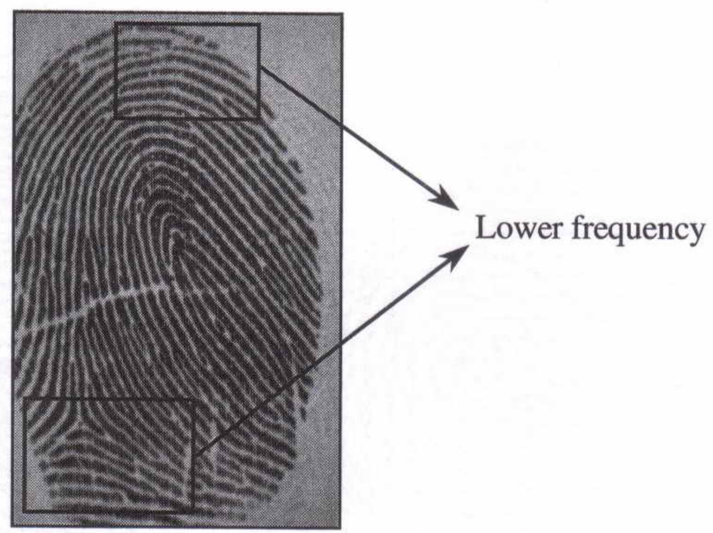
for $\alpha_i \leq \alpha \leq \alpha_{i+1}$, $\alpha_i = -\pi + \frac{2\pi i}{L}$.

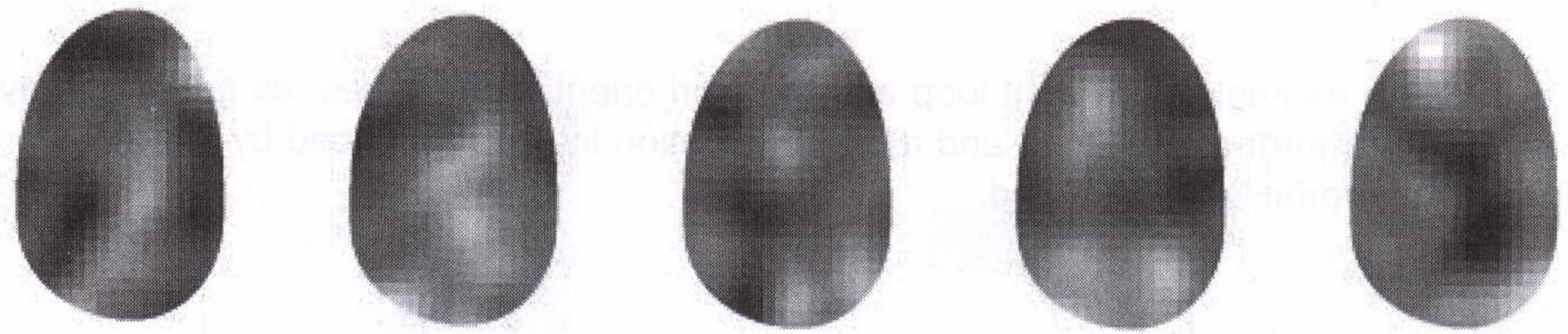


Orientation



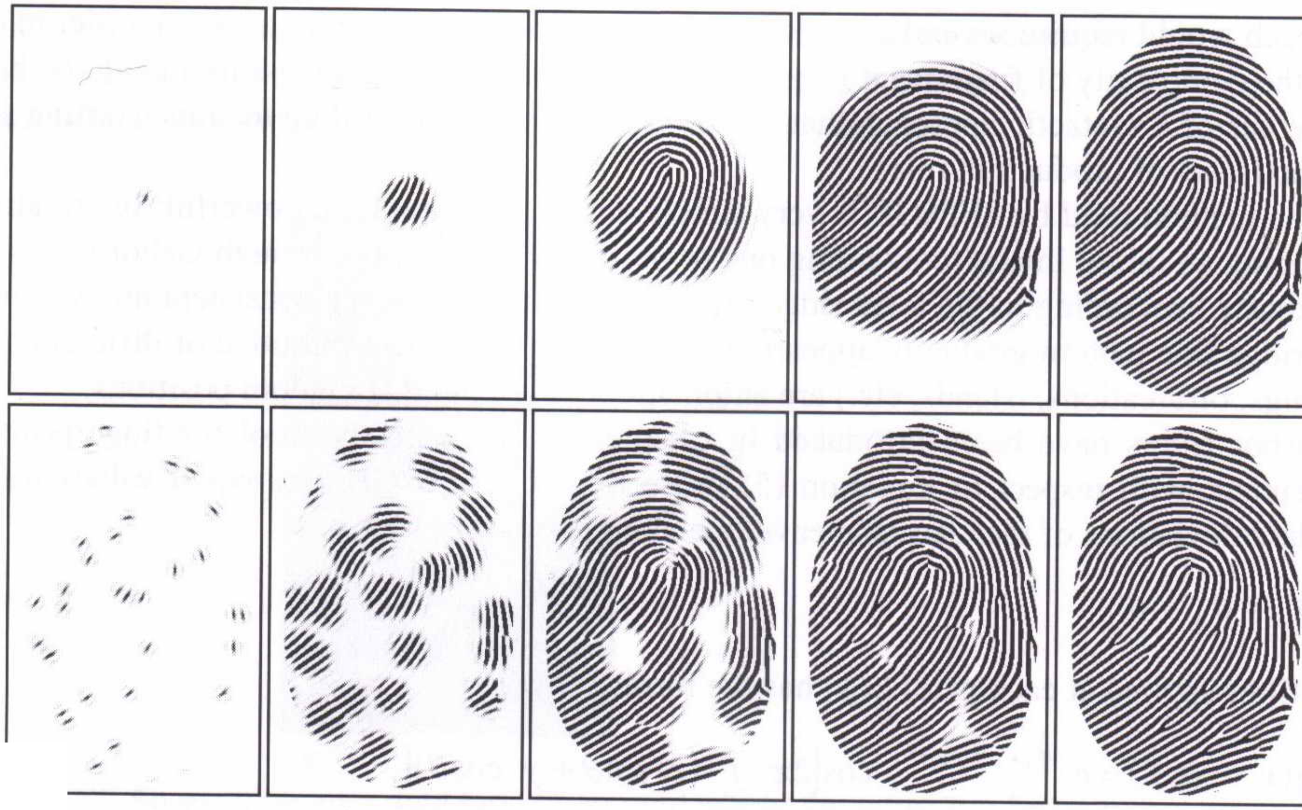
Frequency





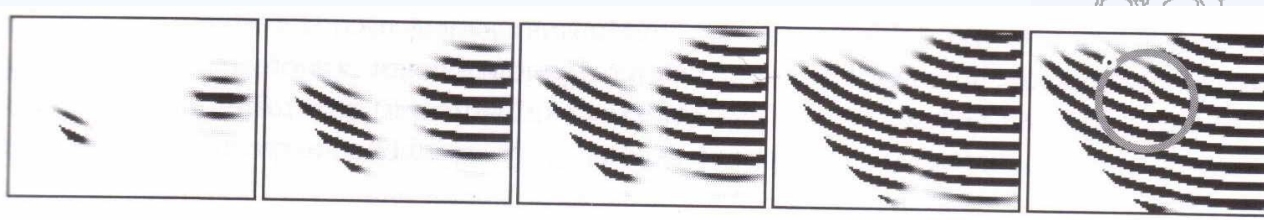
Ridge line

- Gabor filter
- Seeds



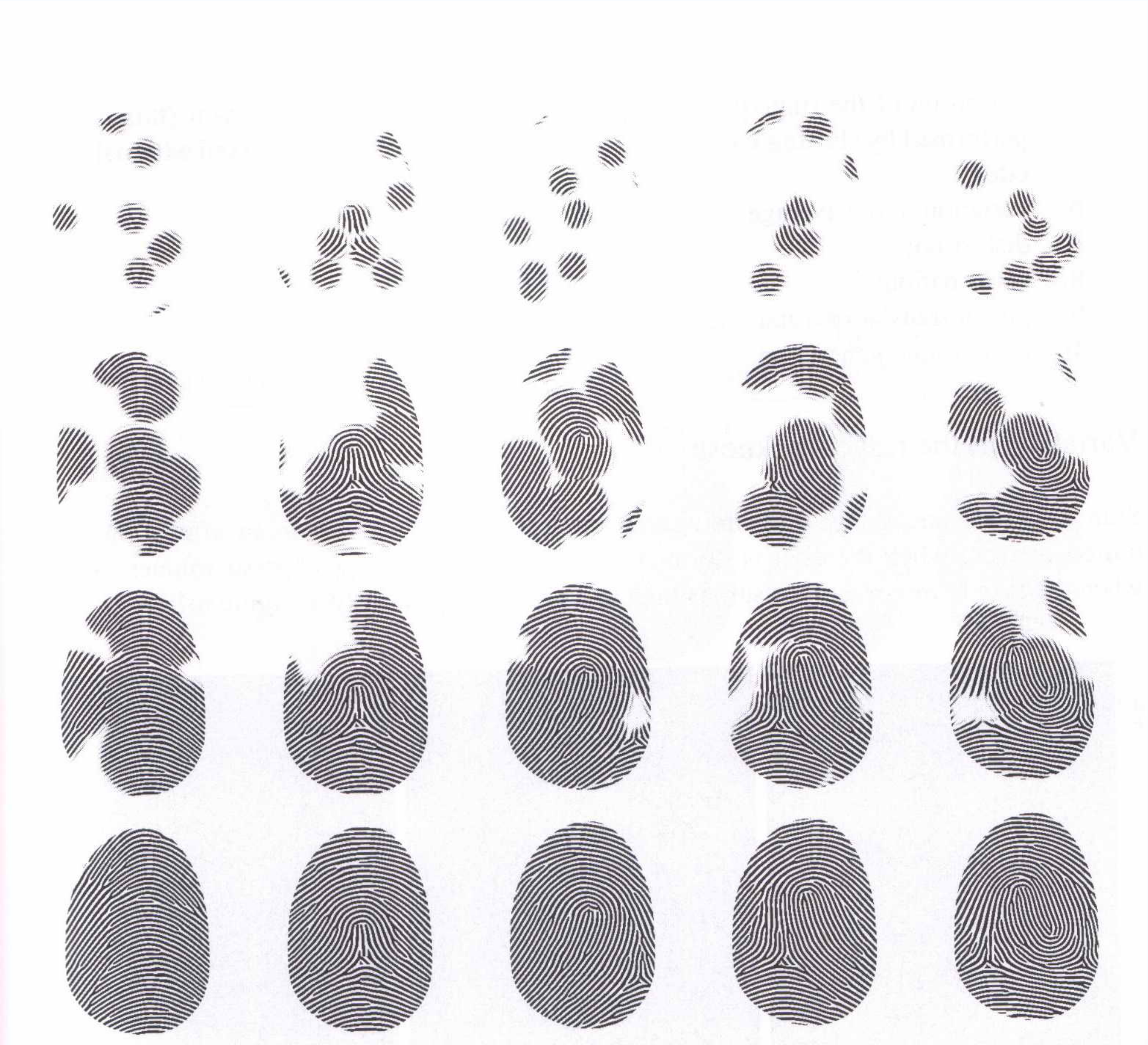
$$\sigma_x = \sigma_y = \sigma$$

$$e^{-\left(\left(\frac{3}{2f}\right)^2 / 2\sigma^2\right)} = 10^{-3}.$$

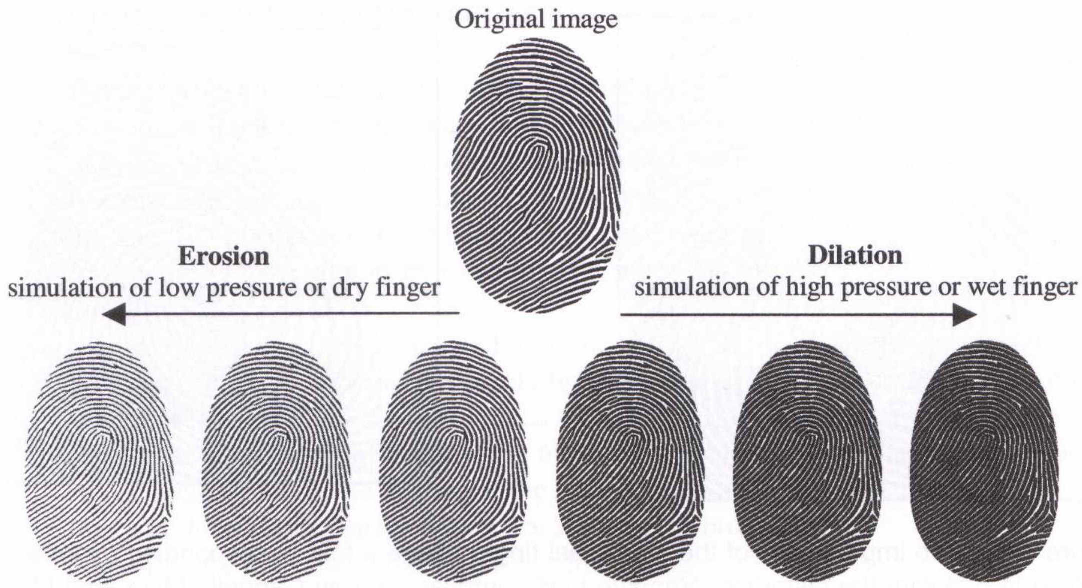


$$g(x, y : \theta, f) = e^{-\left((x^2+y^2)/2\sigma^2\right)} \cdot cos\left[2\pi \cdot f \cdot (x \cdot sin\,\theta + y \cdot cos\,\theta)\right],$$

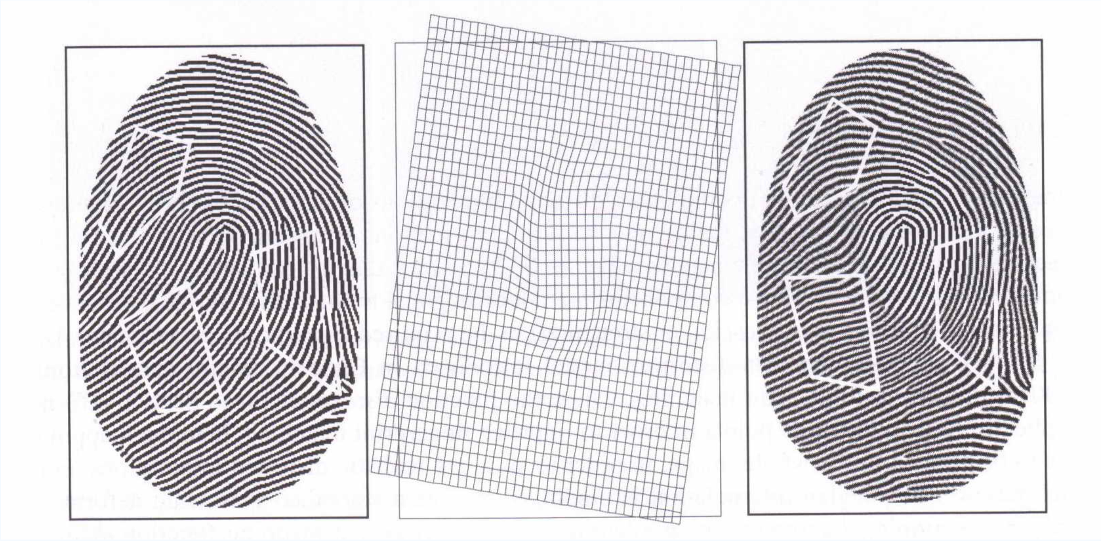
Ridge line



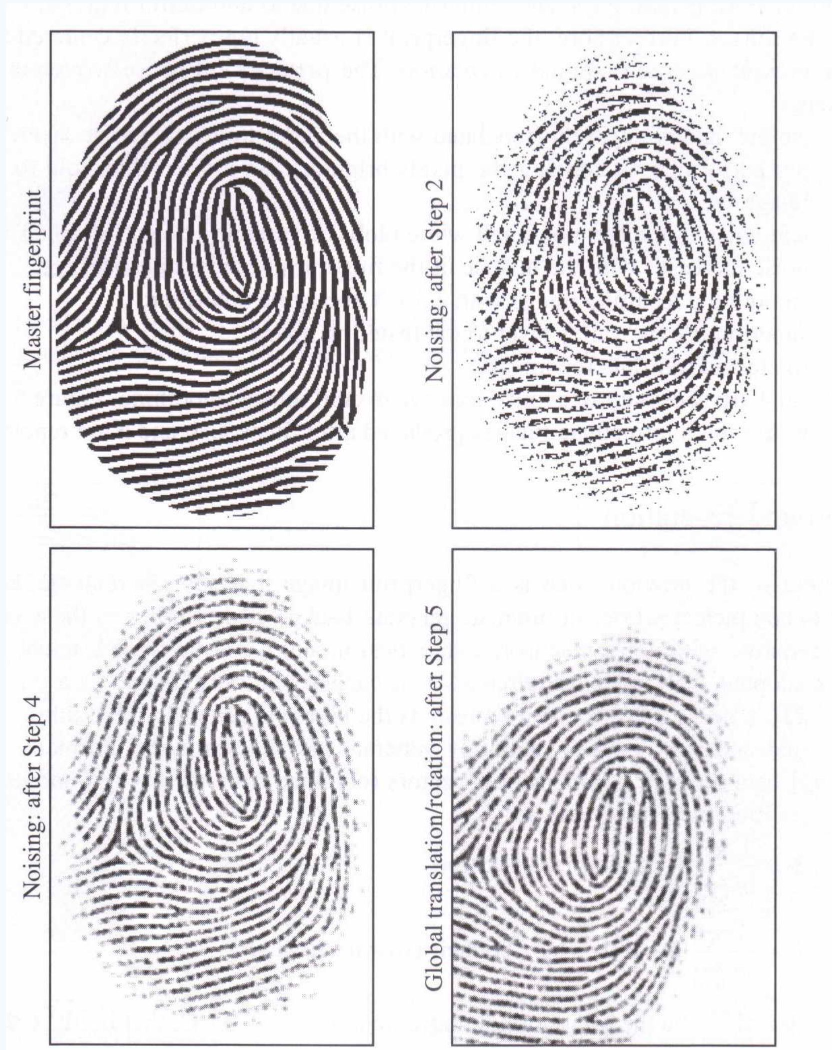
Ridge thickness



Distortion



Perturbation & Translation



Background

- $\overline{\mathbf{b}} = \frac{1}{m}\sum_{\mathbf{b}\in \mathrm{B}} \mathbf{b}$ be their mean vector;
- $\mathbf{C} = \frac{1}{m}\sum_{\mathbf{b}\in \mathrm{B}} (\mathbf{b}-\overline{\mathbf{b}})(\mathbf{b}-\overline{\mathbf{b}})^T$ be their covariance matrix;
- $\mathbf{\Phi} \in \Re^{n\times n}$ be the orthonormal matrix that diagonalizes $\mathbf{C}$; that is, $\mathbf{\Phi}^T\mathbf{C}\mathbf{\Phi} = \mathbf{\Lambda}$,

  $\mathbf{\Lambda} = Diag(\lambda_1, \lambda_2, \ldots, \lambda_n)$, $\mathbf{\Phi} = [\boldsymbol{\varphi}_1, \boldsymbol{\varphi}_2, \ldots, \boldsymbol{\varphi}_n]$,

where λ_i and $\boldsymbol{\varphi}_i$, $i = 1..n$ are the eigenvalues and the eigenvectors of $\mathbf{C}$, respectively.

1. a k-dimensional vector $\mathbf{y} = [y_1, y_2, \ldots, y_k]$ is randomly generated according to k normal distributions: $y_j = N\left(0, \lambda_{i_j}^{1/2}\right)$, $j = 1..k$;
2. the corresponding n-dimensional vector $\mathbf{b}$ is obtained as: $\mathbf{b} = \mathbf{\Phi}_k \mathbf{y} + \overline{\mathbf{b}}$.

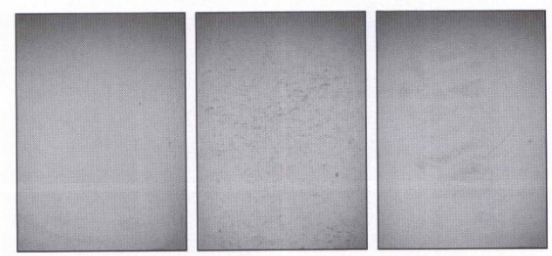
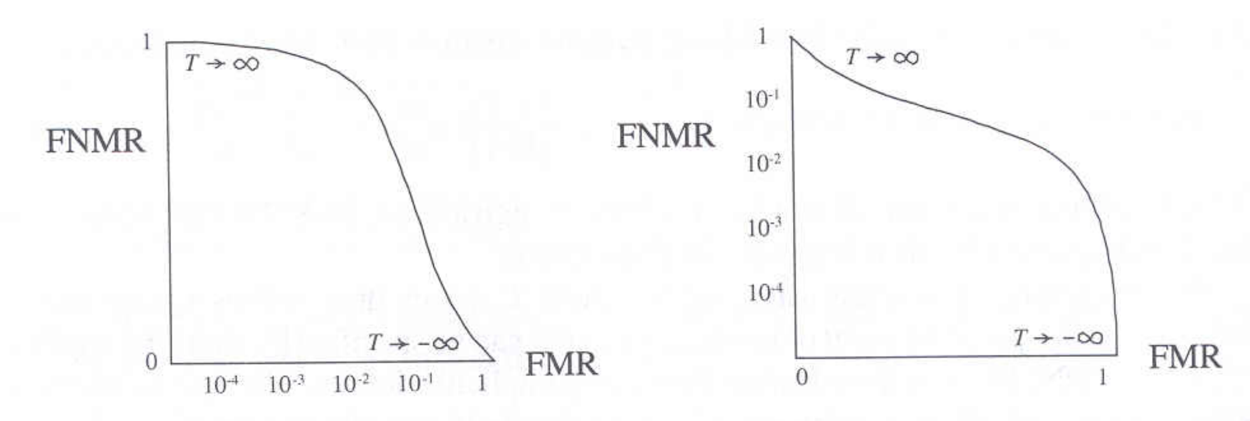


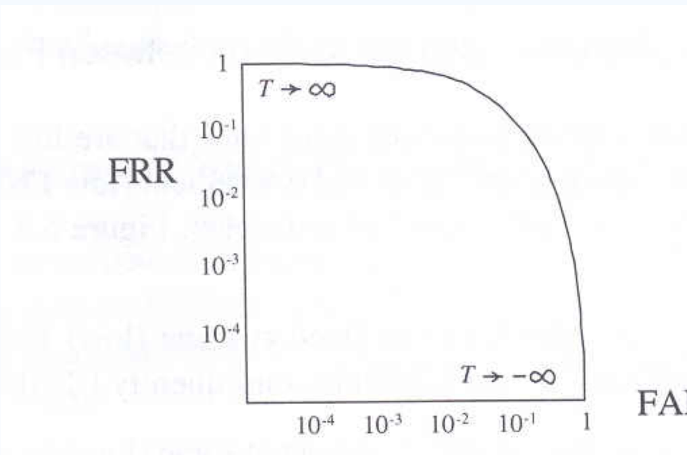
Figure 6.22. Examples of background-only images (acquired from an optical scanner) used for training the background generator.

Figure 6.23. Three synthetic images with backgrounds generated according to the model (the parameters used for training are m = 65 and k = 8).

Variations of ROCs



Semi-log plots



Log-log plot