Adapted Fusion Schemes for Multimodal Biometric Authentication

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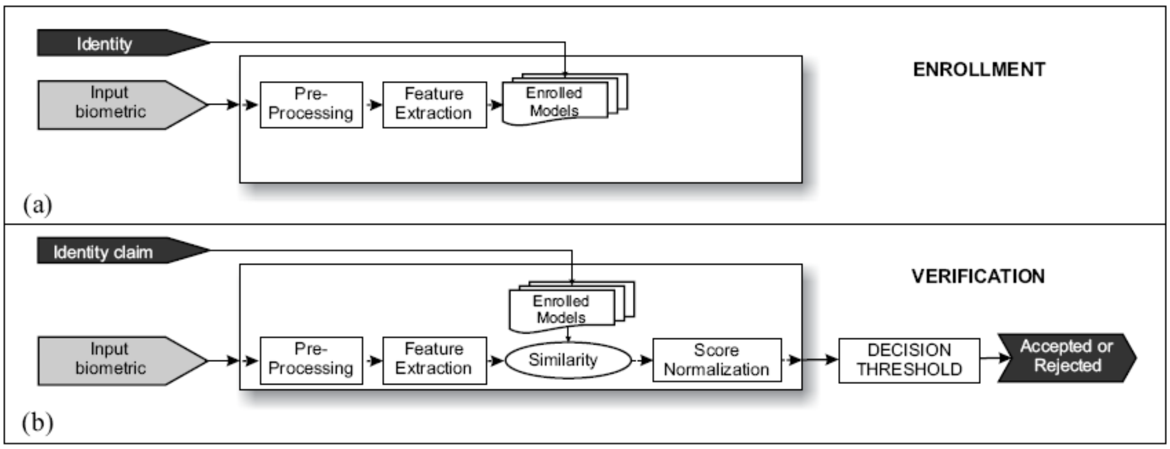
Outline

1. Introduction to Biometrics
2. The Thesis and Related Contributions
3. Adapted Fusion Schemes (User-Dependent and Q-Based)
   - Formulae of the Proposed Algorithms
4. MCYT Bimodal Biometric Database
5. Multi-Algorithm Signature Verification
   - Multi-Algorithm Speaker Verification (UD Fusion)
6. Multi-Algorithm Fingerprint Verification (Q-Based Fusion)
7. Multimodal Authentication Sign + Finger (UD Fusion)
8. Conclusions and Future Work

Introduction to Biometrics

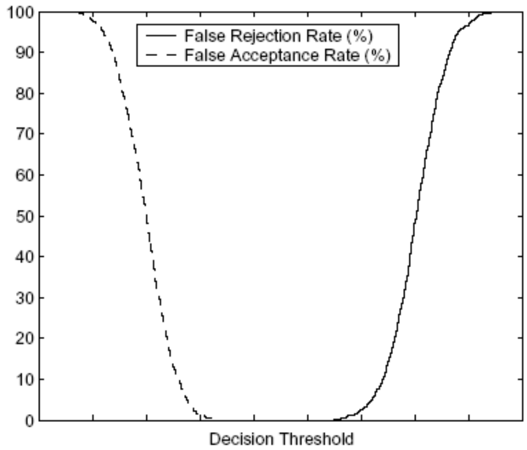
Biometric systems

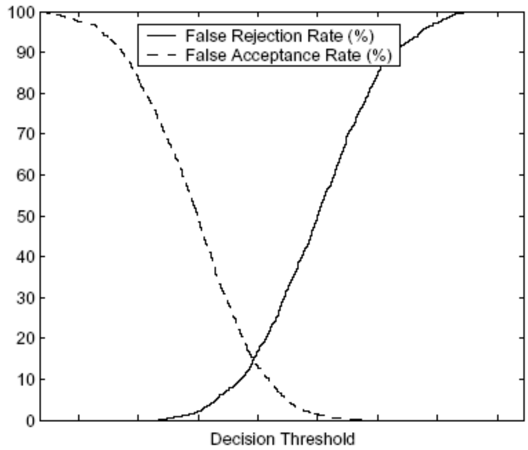
- Biometric system: Automatic pattern recognition system that makes use of personal biometric traits to recognize individuals
  - Enrollment
  - Verification (Authentication): 1-to-1 matching
  - Identification: 1-to-N matchings



Verification errors

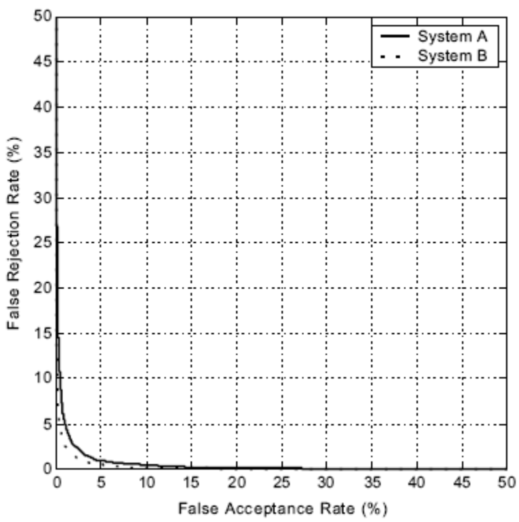
- Biometric verification is a detection task:
  - Type I Error, False Rejection (FR): a genuine user is rejected
  - Type II Error, False Acceptance (FA): an impostor is accepted
    - Casual impostors (no imitations, random forgeries)
    - Real impostors (imitations, skilled forgeries)
- Equal Error Rate (EER): error rate for the decision threshold where FA=FR

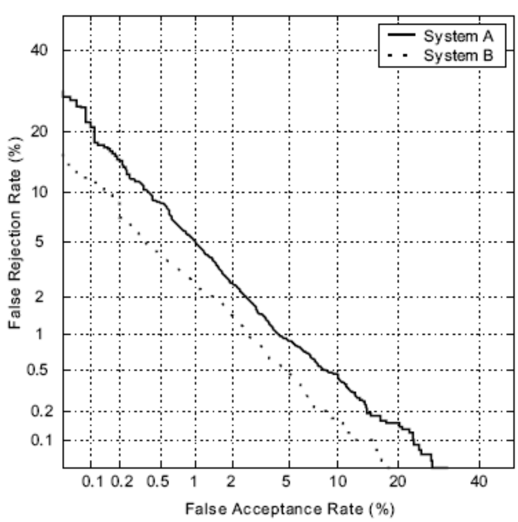




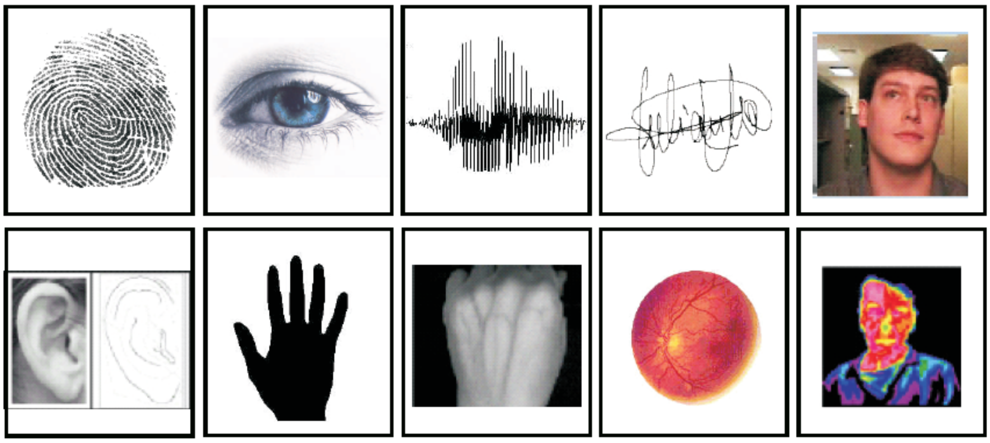
Verification errors

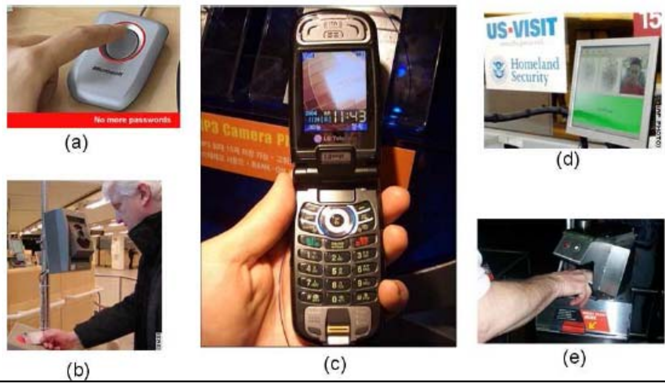
- Comparison of verification systems: ROC (left) and DET (right) curves





Biometric modalities

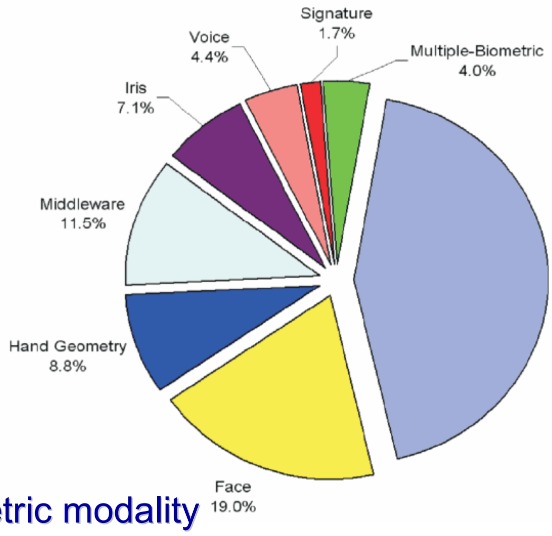




Biometric modalities

- Any human characteristic that satify these requirements:

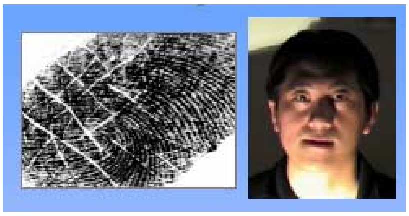
Biometric	Universality	Distinctiveness	Permanence	Collectability	Performance	Acceptability	Circumvention
Gait	M	L	L	H	L	H	M
Face	H	L	M	H	L	H	H
Hand Geometry	M	M	M	H	M	M	M
Iris	H	H	H	M	H	L	L
Speaker	*M*	*L*	*L*	*M*	*L*	*H*	*H*
Signature	*L*	*L*	*L*	*H*	*L*	*H*	*H*
Fingerprint	*M*	*H*	*H*	*M*	*H*	*M*	*M*

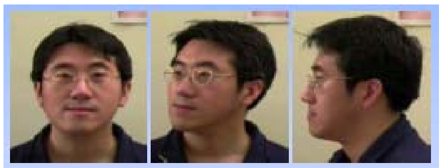


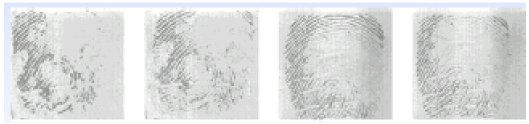
- Comparative market share by biometric modality

Limitations of single biometric modalities

- **Noise in the acquisition**: due to the sensors or to the acquisition conditions
- **Intra-user variability**: due to the interaction with the sensor, due to the variability of the biometric
- **Limited distinctiveness** of the biometric
- **Limited universality**: some users may not be enrolled in the system
- **Limited resilence to attacks**: use of artificial biometrics (gummy fingers)







Limitations in fingerprint verification: FVC (1/6)

- Recent fingerprint technology evaluations:
  - Fingerprint Vendor Technology Evaluation (FpVTE2003)
    - Organized by NIST
  - Fingerprint Verification Competitions (FVC2000, 2002, 2004)
    - Organized by BioLab (University of Bologna), National Biometric Test Center (San Jose State Univ.) and PRIP Lab. (Michigan State Univ.)

*We focus on **Fingerprint Verification Competition 2004***

FVC2004 FINGERPRINT VERIFICATION COMPETITION

BIOLAB University of Bologna

National Biometric Test Center San Jose State University

PRIP MICHIGAN STATE UNIVERSITY

Limitations in fingerprint verification: FVC (2/6)

- Development data: 10 fingers x 8 impressions x 4 sensors
- Sequestered data: 100 fingers x 8 impressions x 4 sensors
- Image quality is low to medium due to exaggerated plastic distortions, artificial dryness, wet fingers, …

DB1
Optical
CrossMatch V300

DB2
Optical
DP UareU4000

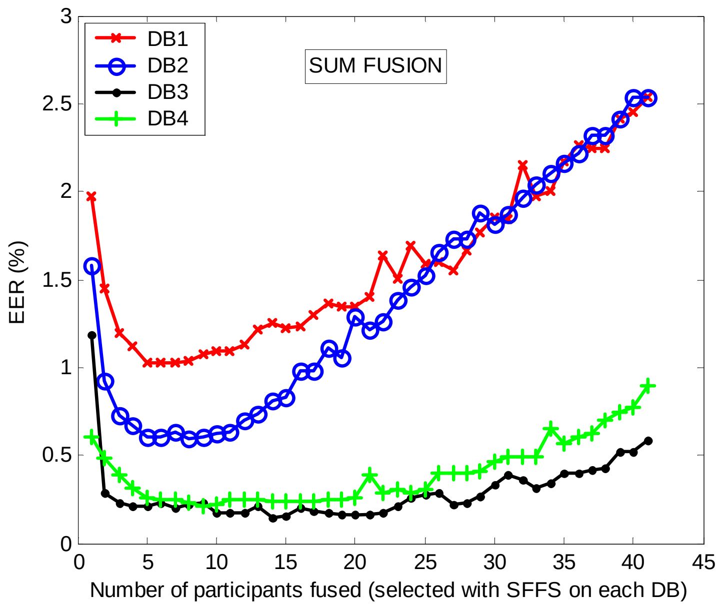
DB3
Thermal
Atmel FingerChip

DB4
Synthetic
SFinGe v3.0

Limitations in fingerprint verification: FVC (3/6)

- FVC2000 (natural acquisition, 11 algorithms):
  - Winner 1.73% EER, average of first 5 systems 4.52% EER
- FVC2002 (natural acquisition, 31 algorithms):
  - Winner 0.19% EER, average of first 5 systems 0.52% EER
- FVC2004 (exaggerated distortion, 41 algorithms):
  - Winner 2.07% EER, average of first 5 systems 2.36% EER

Limitations in fingerprint verification: FVC (4/6)



- Performance improves with the fusion of up to 7 systems.
- Performance deteriorates when combining more than 10 systems.
- The largest improvement is obtained for the fusion of 2-3 systems.

Limitations in fingerprint verification: FVC (5/6)

- Some interesting examples:

DB1				DB2				DB3				DB4			
Participant	Ranking on DB1 (EER)	EER on DB1	EER on DB1 (Sum)	*Participant*	Ranking on DB2 (EER)	EER on DB2	EER on DB2 (Sum)	*Participant*	Ranking on DB3 (EER)	EER on DB3	EER on DB3 (Sum)	*Participant*	Ranking on DB4 (EER)	EER on DB4	EER on DB4 (Sum)
047	1st	1.97		*039*	1st	1.58		*047*	1st	1.18		*071*	1st	0.61	
047	1st	1.97	1.45			1.58	0.92			1.20	0.28	*071*	1st	0.61	0.48
101	2nd	2.72				3.56				1.85		*101*	2nd	0.80	
047	1st	1.97	1.20			1.58	0.73			1.20	0.23	*071*	1st	0.61	0.39
101	2nd	2.72				3.56				1.85		*101*	2nd	0.80	
004	6th	4.10				4.99				7.56		*113*	12th	1.98	
047	1st	1.97	1.17	*039*	1st	1.58	0.67	*101*	2nd	1.20	0.21	*071*	1st	0.61	0.31
101	2nd	2.72		*004*	3rd	2.79		*075*	5th	1.85		*101*	2nd	0.80	
004	6th	4.10		*101*	7th	3.56		*004*	6th	1.89		*039*	4th	1.07	
052	19th	8.41		*103*	14th	4.99		*002*	13th	3.82		*075*	31st	5.99	

Matching Strategy Based on:

- Ridge correlation
- Minutiae Local
- Minutiae Global

Limitations in fingerprint verification: FVC (6/6)

FVC 2006 Fingerprint Verification Competition

- Some changes with respect to previous editions:
  - DATA: Larger DBs, 150 fingers, 12 impressions per finger
  - DATA: Most difficult fingers from a larger pool of fingers (NFIQ) extracted from BIOSEC DB
  - PLANNED STUDIES: Interoperability, Quality

IMPORTANT DATES:

Participant registration deadline:	June 30, 2006
Development databases available online:	July 1, 2006
Algorithm submission deadline:	October 31, 2006
Expected publication of the results:	January, 2007

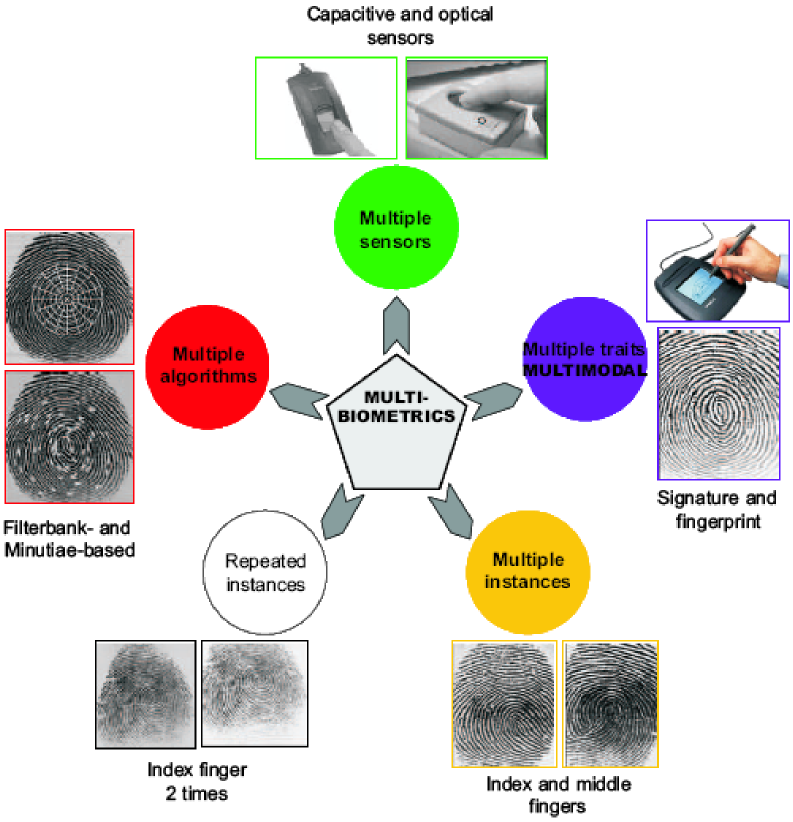
For further information, please visit: **http://bias.csr.unibo.it/fvc2006**
or send an e-mail to: **fvc2006@csr.unibo.it**

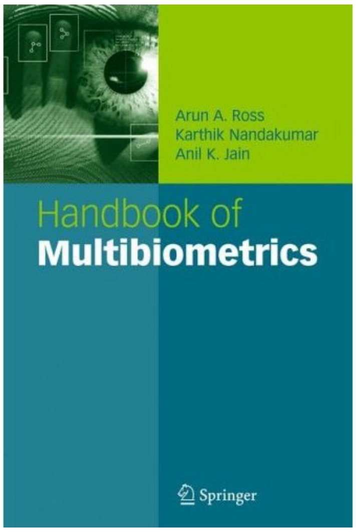
Multibiometric systems

- **Various biometric evidences are combined in order to improve the performance** (or other requirements) **of the system**
- When combining different biometric modalities (multimodal biometrics), the **population coverage improves significantly**
- **The security improves significantly** due to the difficulty to fool several evidences

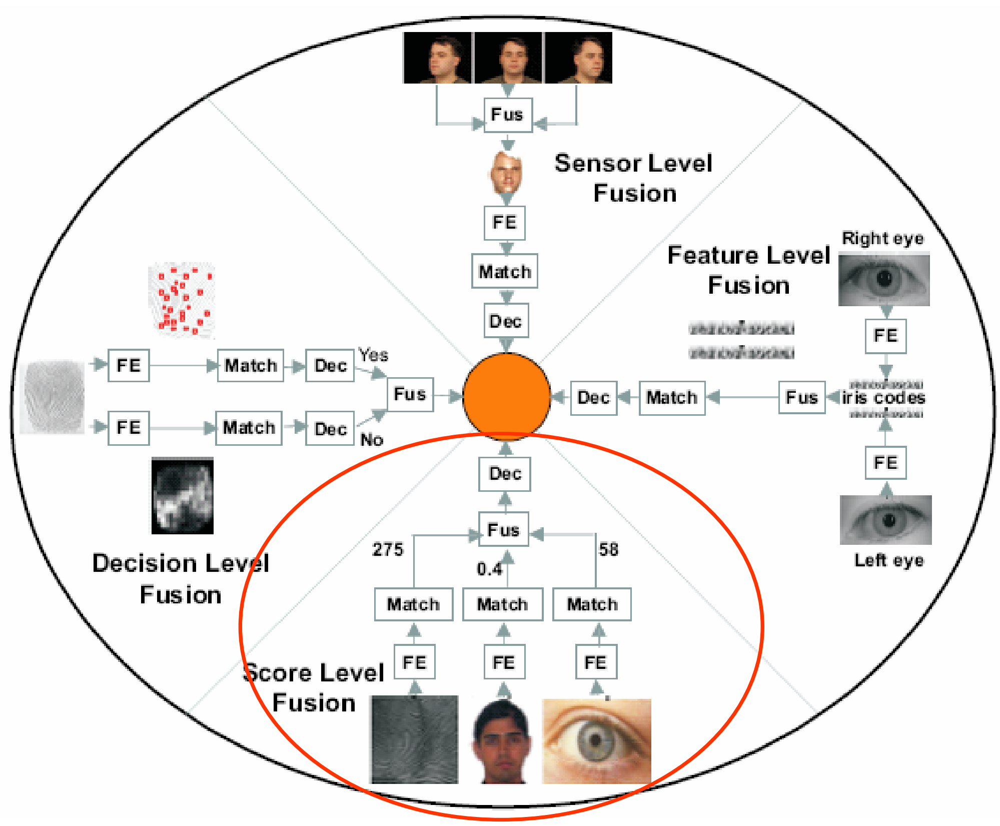
…but the complexity and acceptability of the system may deteriorate

Fusion scenarios

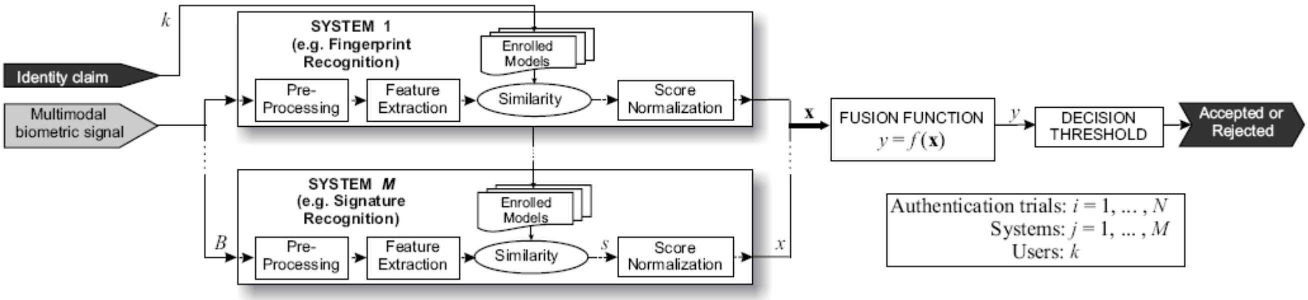




Fusion levels



System model and previous works



Work	Modalities	M	Arch.	Level	Gain
Brunelli and Falavigna [1995]	Speaker, face	5	P	C	ID:17→2 (TE)
Duc *et al.* [1997]	Speaker, face	2	P	C	VER:6.7→0.5 (TE)
Kittler *et al.* [1998]	Speaker, face	3	P	C	VER:1.4→0.7 (EER)
Hong and Jain [1998]	Face, fingerprint	2	S	R/C	ID:6.9→4.5 (FR@0.1%FA)
Jain *et al.* [1999b]	Speaker, face, finger	3	P	C	VER:15→3 (FR@0.1%FA)
Ben-Yacoub *et al.* [1999]	Speaker, face	3	P	C	VER:4→0.5 (EER)
Choudhury *et al.* [1999]	Speaker, face	3	P	C	ID:16.5→6.5 (TE)
Chatzis *et al.* [1999]	Speaker, face	4	P	C	ID:6.7→1.07 (TE)
Verlinde *et al.* [2000]	Speaker, face	3	P	C	VER:3.7→0.1 (TE)
Ross and Jain [2003]	Face, finger, hand	3	P	C	VER:16→2 (FR@0.1%FA)
Kumar and Zhang [2003]	Face, palmprint	2	P	C	VER:3.6→0.8 (EER)
Wang *et al.* [2004]	Speaker, finger	2	P	C	VER:2→0.7 (EER)
Poh and Bengio [2006]	Speaker, face	8	P	C	VER:2.2→0.7 (TE)

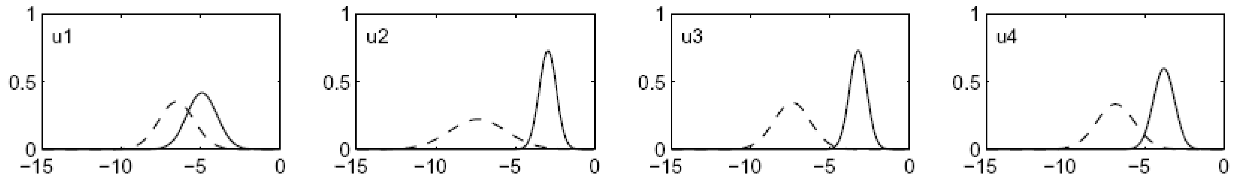
The Thesis and Related Contributions

Motivations and main related works

- Performance drop of single biometrics under degraded Q (FVC campaigns [Cappelli et al., 2006]), which may affect the different modules of a multibiometric system in a different way [Jain and Ross, 2004]

  → Incorporating biometric Q in multibiometrics **[Bigun et al., 1997; Chatzis et al., 1999]**

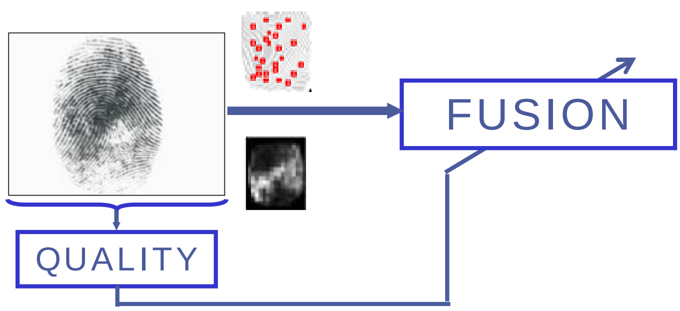
- Strong user-dependencies in the score distributions of some biometric traits, such as voice (NIST SRE campaigns [Doddington et al., 1998]), or signature (SVC evaluation [Yeung et al., 2004]).



→ User-dependent fusion in multibiometrics **[Jain and Ross, 2002; Toh et al., 2004]**

The Thesis

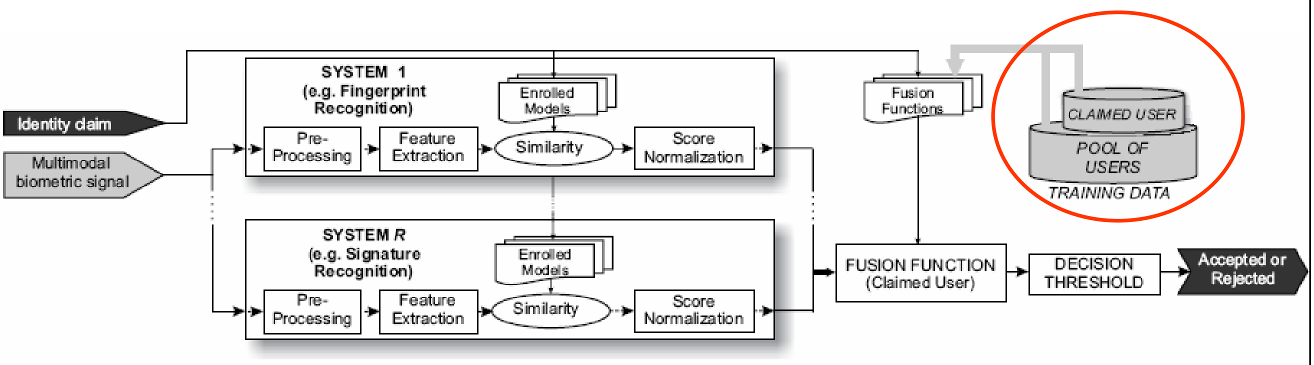
The adaptation of the fusion functions at the score level in multimodal biometric authentication can report significant verification performance improvements. Examples of input information for this adaptation include a reduced number of scores from individual users and signal quality measures of the input biometrics. This statement also applies to other problems in multibiometrics such as multi-algorithm fusion.



Research contributions

- **Literature reviews:** score fusion strategies; score normalization
- **Theoretical frameworks:** score normalization
- **Novel methods:** user-dependent score normalization; user-dependent score fusion (Bayesian and SVM); quality-based score fusion (Bayesian and SVM)
- **Biometric systems:** improvement of the ATVS function-based signature system; new feature-based signature system (with J. Lopez); new ridge-based fingerprint matcher (with L.M. Muñoz)
- **Biometric data:** contribution to the acquisition and management of the MCYT bimodal database
- **Experimental studies:** score normalization in signature; multi-algorithm signature, speaker and fingerprint; multimodal signature and fingerprint

Adapted fusion schemes: user-dependent fusion



- **Contribution:** combined used of global and local information for training the user-dependent fusion functions. This is commonly done in speaker verification [Reynolds et al., 2000] but it is applied for the first time to multibiometric fusion. Existing user-dependent fusion approaches only consider local information [Jain and Ross, 2002; Toh et al., 2004]

GLOBAL: Set of training scores from a pool of users (genuine and impostor)
LOCAL: Set of training scores from the user at hand (genuine and impostor)

→ **Bayesian** and **SVM** user-dependent fusion algorithms

Bayesian adaptation of the fusion functions

Multilevel score:

$$\mathbf{x} = [x_1, \ldots, x_R]'$$

Fused score:

$$s_T = f(\mathbf{x}_T) = \log p(\mathbf{x}_T|\omega_1) - \log p(\mathbf{x}_T|\omega_0)$$

Fusion training set:

$$X = (\mathbf{x}_i, y_i)_{i=1}^{N}$$

$$y_i \in \{\omega_0, \omega_1\} = \{\text{Impostor}, \text{Client}\}$$

$$p(\mathbf{x}|\omega_0) = N(\mathbf{x}|\mu_0, \sigma_0^2)$$

$$p(\mathbf{x}|\omega_1) = N(\mathbf{x}|\mu_1, \sigma_1^2)$$

Global training set:

$$X_{\mathrm{G}} \xrightarrow{\mathrm{ML}} \{\mu_{\mathrm{G},0}, \sigma^2_{\mathrm{G},0}\} \ \{\mu_{\mathrm{G},1}, \sigma^2_{\mathrm{G},1}\}$$

Local training set:

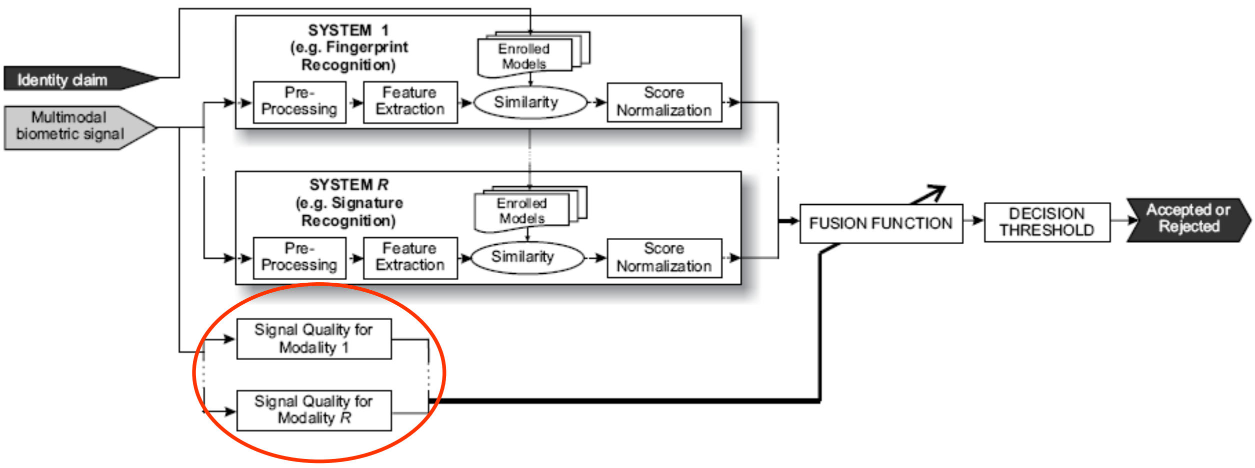
$$X_{j,\mathrm{L}} \xrightarrow{\mathrm{ML}} \{\mu_{j,\mathrm{L},0}, \sigma^2_{j,\mathrm{L},0}\} \ \{\mu_{j,\mathrm{L},1}, \sigma^2_{j,\mathrm{L},1}\}$$

MAP adaptation

$$\mu_{j,\mathrm{A},k} = \alpha_k \mu_{j,\mathrm{L},k} + (1-\alpha_k)\mu_{\mathrm{G},k}$$

$$\sigma^2_{j,\mathrm{A},k} = \alpha_k(\sigma^2_{j,\mathrm{L},k} + \mu^2_{j,\mathrm{L},k}) + (1-\alpha_k)(\sigma^2_{\mathrm{G},k} + \mu^2_{\mathrm{G},k}) - \mu^2_{j,\mathrm{A},k}$$

Adapted fusion schemes: quality-based fusion



- **Contribution:** Although some existing theoretical frameworks for multibiometric fusion describe confidence measures [Bigun et al., 1997; Bengio et al., 2002], they were not related to the input biometric quality. This is the first experimental work on quality-based fusion

→ **Combination**, **Bayesian** and **SVM** quality-based fusion algorithms

Quality-based adaptation of the fusion functions

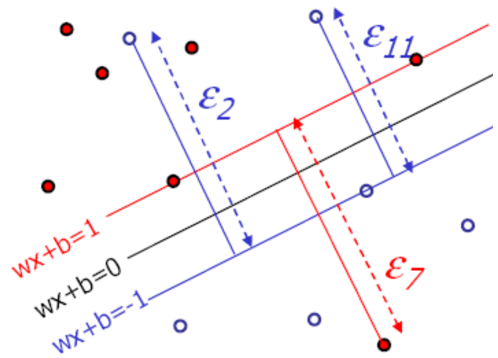
SVM learning:

$$\min_{\mathbf{w}, w_0, \xi_1, \ldots, \xi_N} \left(\frac{1}{2} \|\mathbf{w}\|^2 + \sum_{i=1}^{N} C \xi_i \right)$$

$$y_i(\langle \mathbf{w}, \Phi(\mathbf{x}_i) \rangle_{\mathbb{H}} + w_0) \geq 1 - \xi_i, \quad i = 1, \ldots, N$$

$$\xi_i \geq 0, \quad i = 1, \ldots, N$$

$$C_i = C \left(\frac{\prod_{r=1}^{R} q_{i,r}}{Q_{max}^{R}} \right)^{\alpha_1}$$



SVM-based score fusion:

$$s_T = f(\mathbf{x}_T) = \langle w, \Phi(\mathbf{x}_T) \rangle_{\mathbb{H}} + w_0$$

$$f_{\mathrm{SVM}_Q}(x_T) = \beta_1 \sum_{r=1}^{R-1} \frac{\beta_r}{\sum_{j=1}^{R-1} \beta_j} f_{\mathrm{SVM}_r}(x_T^{(r)}) + (1 - \beta_1) f_{\mathrm{SVM}}(x_T),$$

MCYT Bimodal Biometric Database

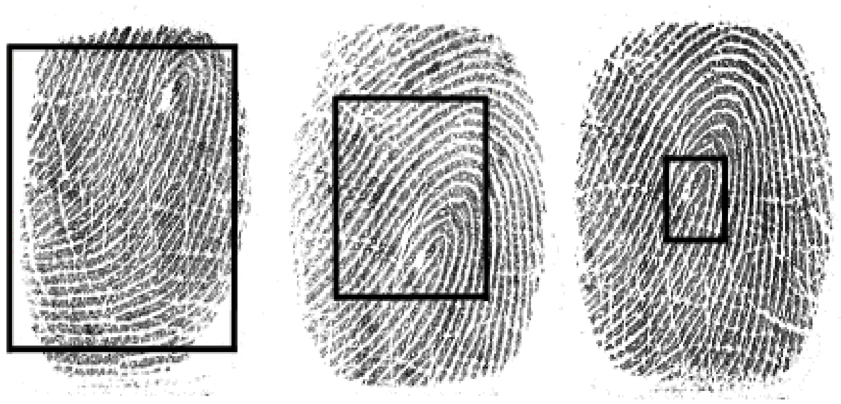
MCYT bimodal biometric database

- **Acquired within the Spanish MCYT TIC00-1669 project**
- **Fingerprints and handwritten signatures**

  FINGERPRINTS:

  - 330 donors x 10 fingers x 12 samples x 2 sensors (optical and capacitive) = 79200 fingerprint images

  - 3 levels of control



MCYT bimodal biometric database: QMCYT

QMCYT fingerprint subcorpus:

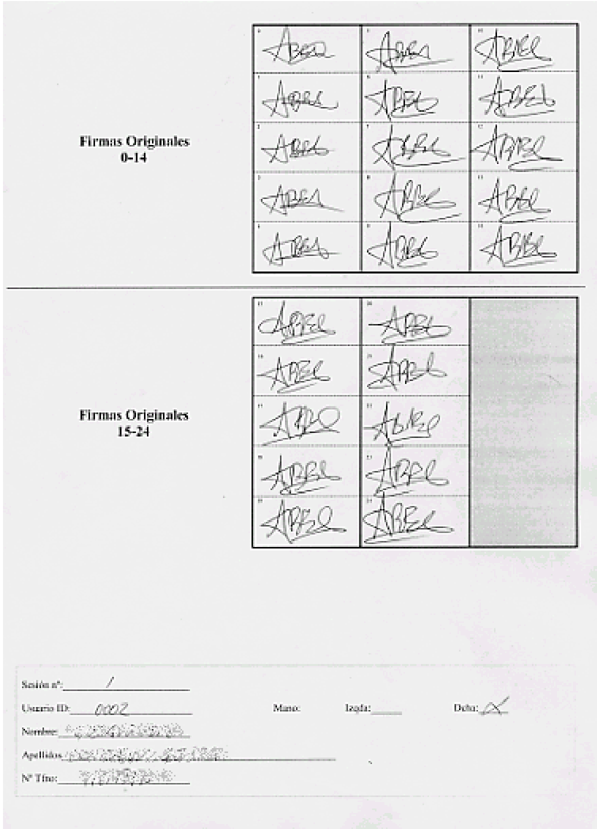
- 75 donors x 10 fingers x 12 impressions (optical sensor) = 9,000 images
- All images labeled manually according to the image quality [0,9]

Q=0 Q=3 Q=6 Q=9

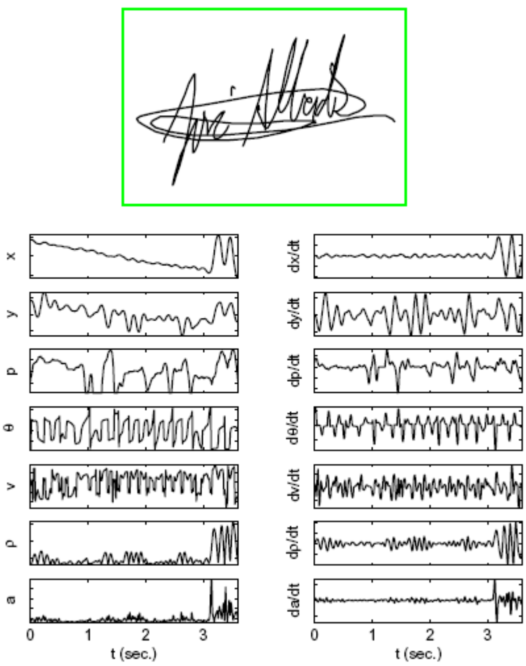
MCYT bimodal biometric database: Signature

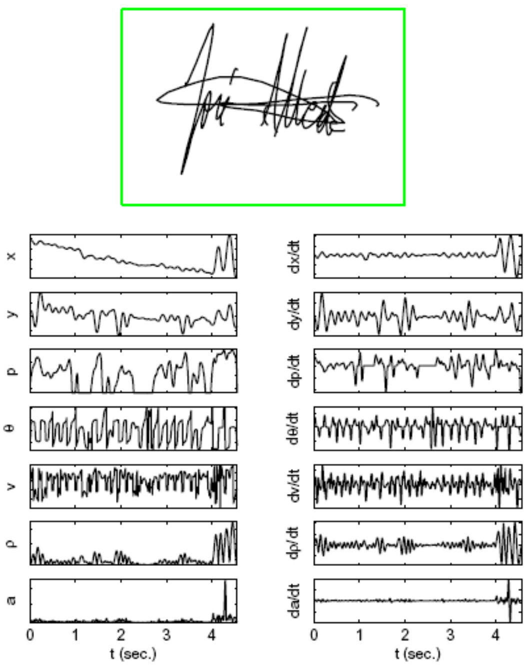
SIGNATURE:

- Acquisition procedure:
  - WACOM Intuos pen tablet
  - Ink pen over paper templates → on-line and off-line corpora
  - Restricted size guidelines
- Acquisition protocol:
  - 330 subjects
  - 25 genuine signatures (in groups of five) + 25 skilled forgeries (from five impostors) → 16,500 signatures

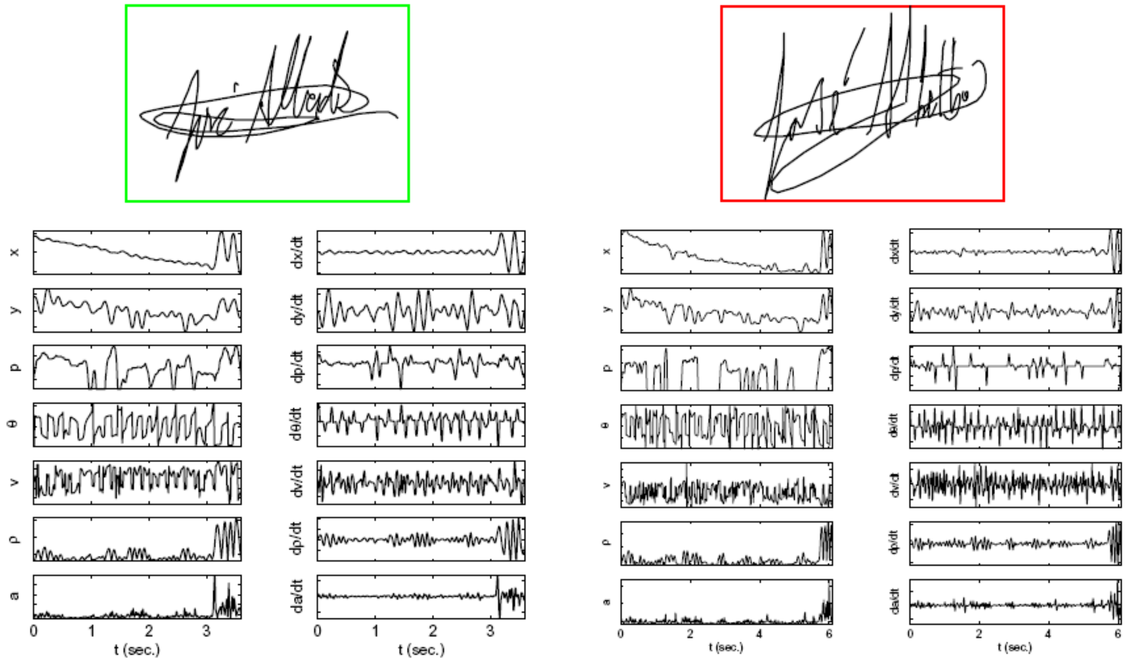


MCYT bimodal biometric database: signature



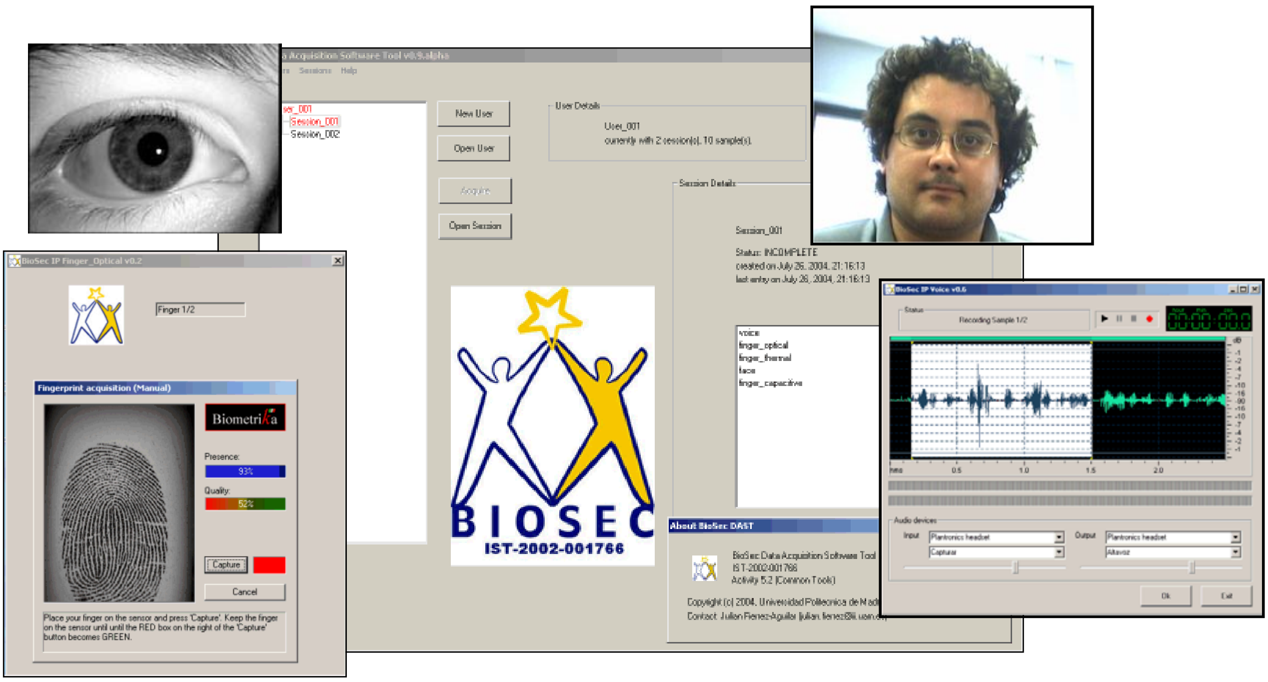


MCYT bimodal biometric database: signature



Multimodal biometric databases: ongoing work

BioSec (FP6 IP), **Biosecur-ID** (CICYT TIC2003), **Biosecure** (FP6 NoE):
Face, Voice, Iris, Fingerprint, Hand, …



BIOSEC DB

Acquisition sites:

- **UAM, UPC, TID, MIFIN**

Collaborators:

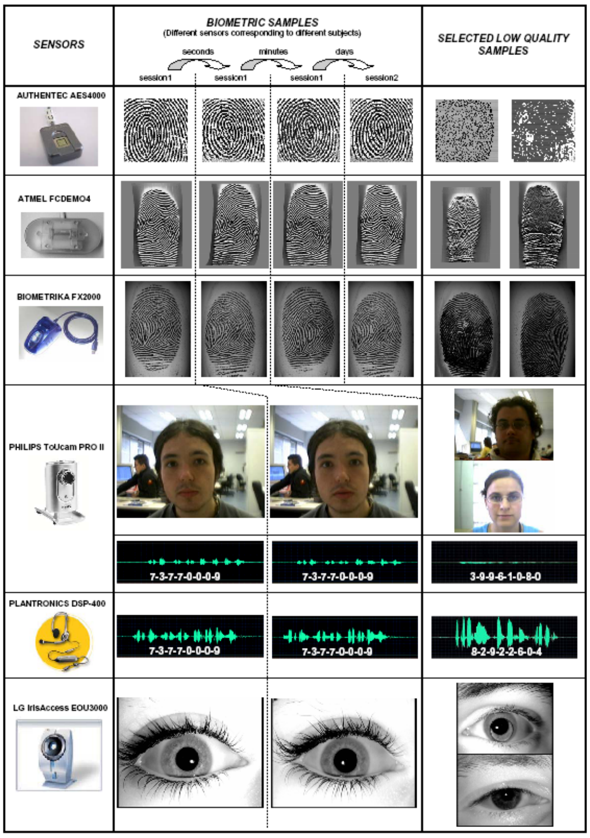
- **UCOL, UTA (usability and acceptance study)**
- **KULRD (legal issues)**

Acquisition protocol (in each session):

- **4 frontal face images (neutral pose)**
- **4 utterances of a PIN (8 digits) + 3 repetitions of other users' PINs**
  (x 2 microphones x 2 languages)
- **4 iris images (x 2 eyes)**
- **4 fingerprint images (x 4 fingers x 3 sensors)**

Two releases:

- **Baseline (available from mid-2005):**
  - **200 subjects, 2 acquisition sessions (1 to 2 weeks between them)**
- **Extended (available from late-2006):**
  - **250 subjects, 4 acquisition sessions (1 week to 1 month)**



BIOSECURE DB: Call for Participation

Llévate 30 € por la cara

Participa en un proyecto de investigación europeo dando de forma anónima tus rasgos biométricos

2 sesiones de 40 minutos entre noviembre de 2006 y marzo de 2007

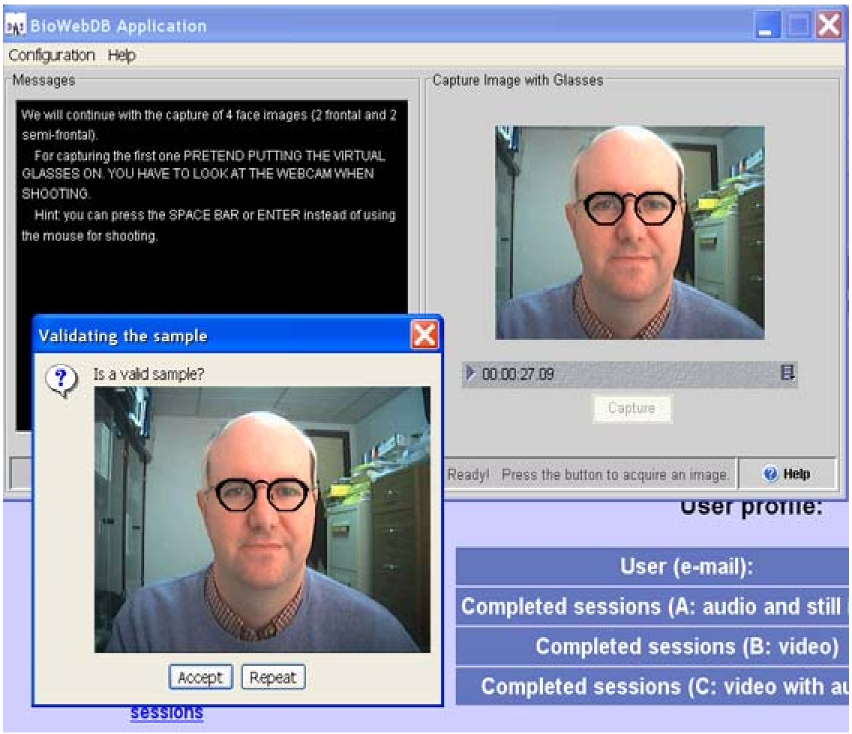
Abierto a todos: alumnos, personal, familiares y amigos

UAM

Más información en el laboratorio **B203,** Escuela Politécnica Superior, UAM

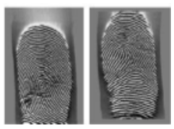
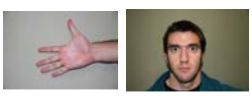
Escuela Politécnica Superior

BIOSECURE DB: Dataset 1

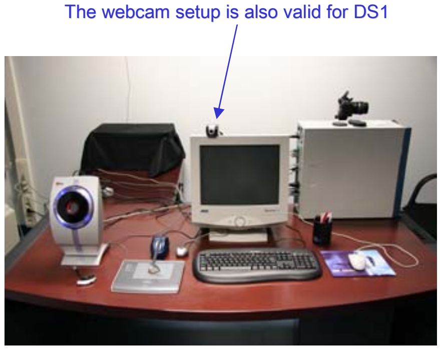


- EQUIPMENT: low-cost webcam, e.g., Philips SPC 900NC

BIOSECURE DB: Dataset 2

PHILIPS SPC 900NC + PLANTRONICS Voyager 510		
LG IrisAccess EOU3000		
BIOMETRIKA FX2000		
YUBEE (Atmel FingerChip)		
WACOM Intuos A6 + Inking Pen		
CANON EOS 30D + Ring Flash		

The webcam setup is also valid for DS1



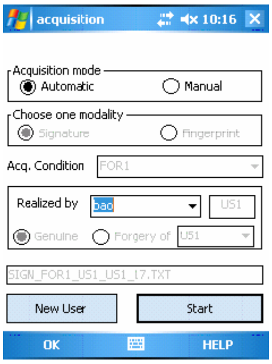
BIOSECURE DB: Dataset 3

HP iPAQ hx2790

Fingerprint and Signature

SAMSUNG Q1 + WebCam

Face and Voice

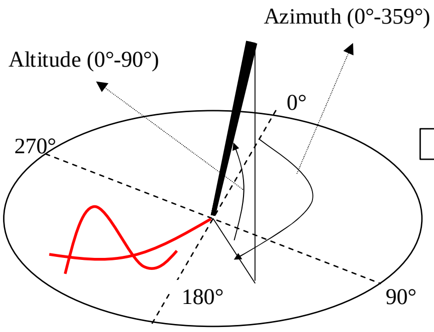


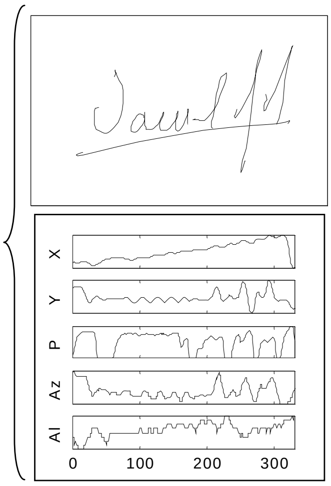
- SETUP:
(Indoor/Outdoor Acquisition)

Multi-Algorithm Signature Verification

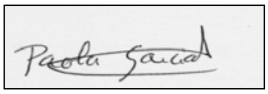
On-line signature

- On-line signature verification → dynamic information: *x, y, pressure, …*





- Off-line signature verification:

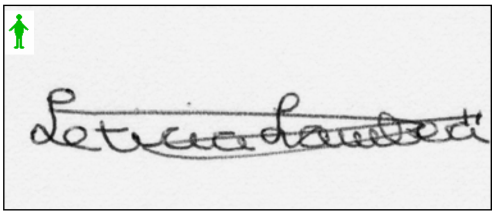
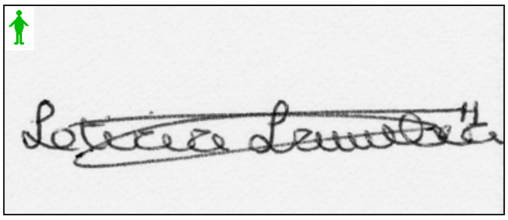
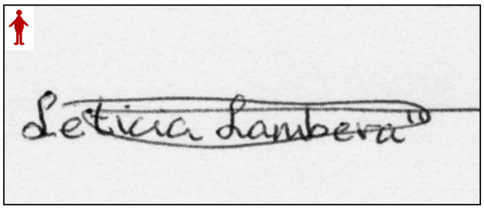


Advantages of on-line signature

- User-friendly
- Well accepted socially and legally
- Non invasive
- Already used in a number of applications (e.g., points of sales)
- Acquisition hardware already integrated in some devices (Tablet PC, PDA, …)

Challenges of on-line signature

- Intra-class variability
- Temporal (inter-session) variability
- Impostors may produce (skilled) forgeries
- Not appropriate for previously acquired off-line signature images

On-line signature methods

Global:

- Representation: global feature vector
- Similarity: distance computation between vectors (e.g., Mahalanobis, Euclidean, Neural Networks, …)

Local:

- Representation: sequence of vectors (e.g., strokes, segments, spatial windows, …)
- Similarity: matching of vectors considering the spatio-temporal structure of the sequence (e.g., DTW, HMM, …)

Milestones related to our work

1989: State-of-the-art, by Leclerc and Plamondon (*PR*)

1994: Feature-based system, by Nelson et al. (*IJPRAI*)

1995: Stroke-based HMM system, by Prasad *et al.* (*PR*)

1996: Feature-based system, by Lee *et al.* (*T-PAMI*)

2000: State-of-the-art, by Plamondon (*T-PAMI*)

2005: Function-based HMM system, Fierrez-Aguilar *et al.* (*T-SMC-C*)

2005: Feature-based system, by Fierrez-Aguilar *et al.* (*AVBPA*)

SVC 2004: Organized by Yeung et al. (ICBA)

→ ATVS ranked 2nd (1st for random forgeries)

Research significance

- A combined set of **novel**, **adapted** and **existing** global features
- Sorting of features according to discriminative capability
- Novel machine expert based on global information
- Fusion of the global system with a competitive local system based on HMMs
- Usage of MCYT DB (330 subjects: 8,250 genuine signatures and 8,250 skilled forgeries)
- 6,600 genuine matches; 8,250 skilled forger matches; 108,570 random impostor matches

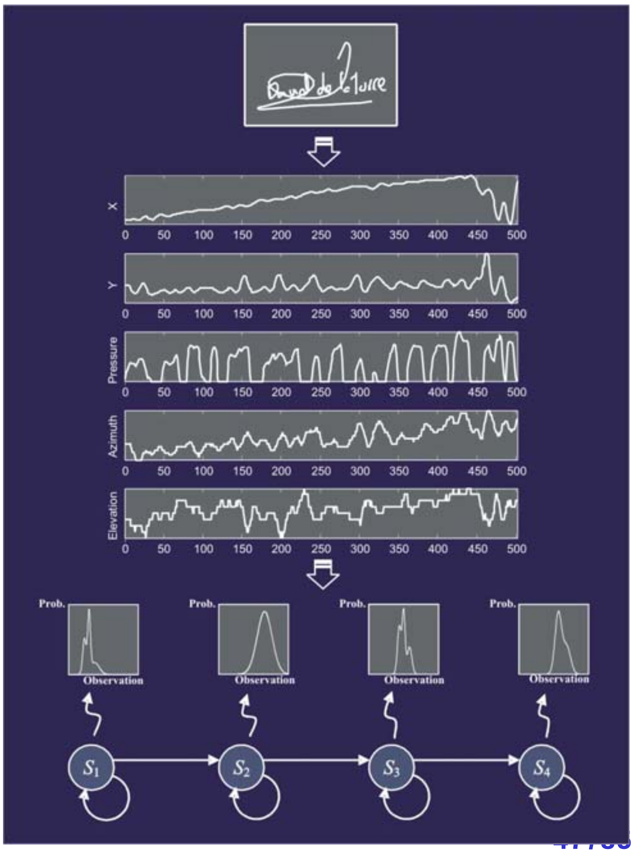
Local system: feature extraction and matching

FEATURE EXTRACTION:

- 3 basic functions (100 Hz):
  - *x, y, p*
- Geometric normalization:
  - *position, rotation*
- 4 extended functions:
  - *path-tangent angle*
  - *path velocity magnitude*
  - *log curvature radius*
  - *total acceleration magnitude*
- First-order time derivative functions → 14 time-functions.

MODELING AND MATCHING:

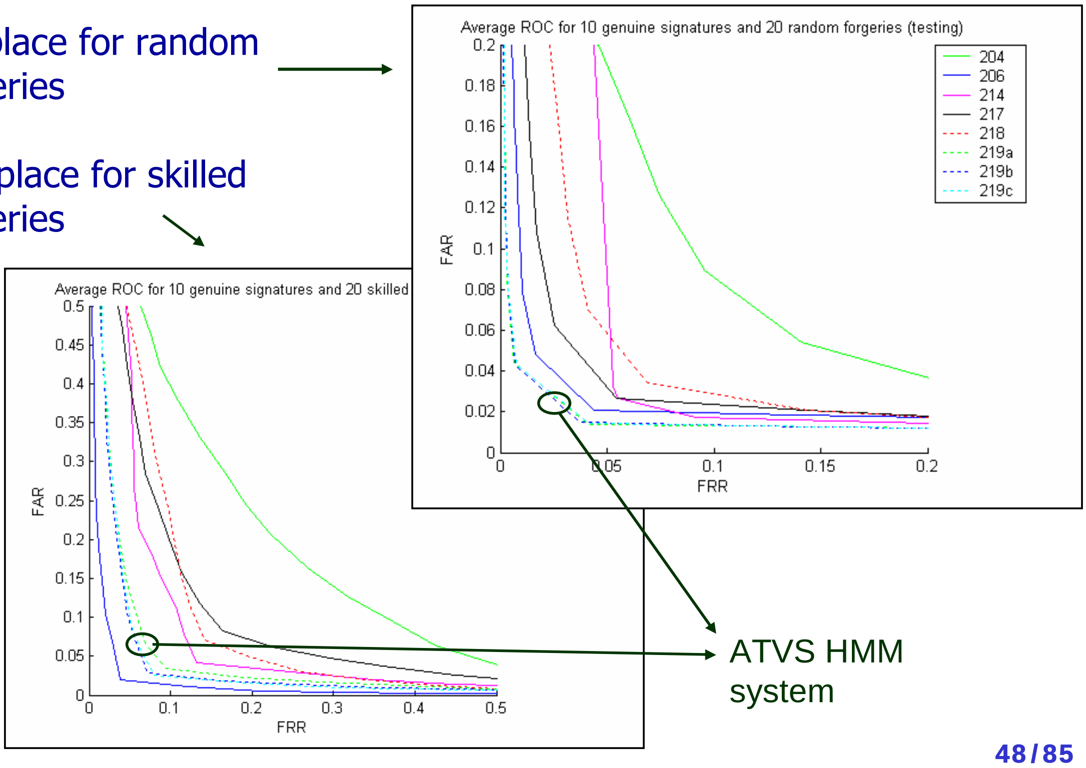
- HMM (2 states, 32 mixtures).



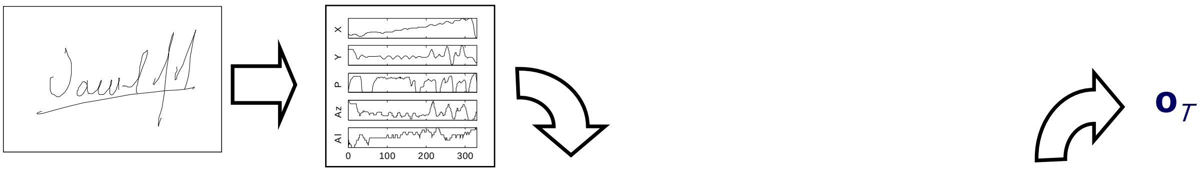
Local system: comparison with the state-of-the-art

SVC2004, TASK 2 (*x, y, p*)

- 1st place for random forgeries
- 2nd place for skilled forgeries



Global system: feature extraction

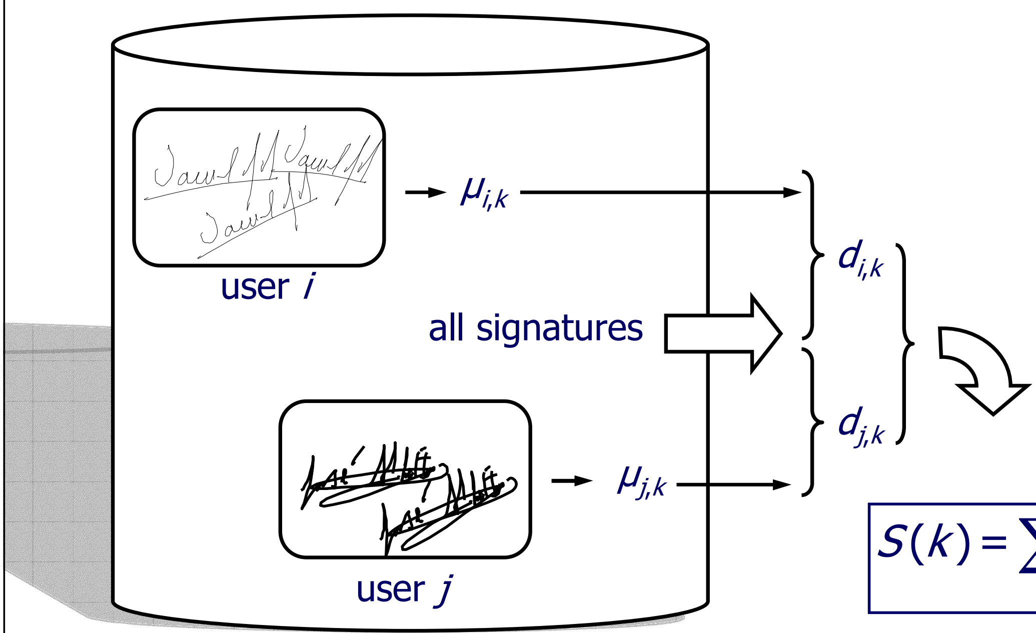


Ranking	Feature Description	Ranking	Feature Description
1	signature total duration T_s	2	N(pen-ups)
3	N(sign changes of dx/dt and dy/dt)	4	average jerk $\bar{j}$
5	standard deviation of a_y	6	standard deviation of v_y
7	(standard deviation of y)$/\Delta_y$	8	N(local maxima in x)
9	standard deviation of a_x	10	standard deviation of v_x
11	j_{rms}	12	N(local maxima in y)
13	t(2nd pen-down)$/T_s$	14	(average velocity $\bar{v}$)$/v_{x,\mathrm{max}}$
15	$\frac{A_{\min}=(y_{\max}-y_{\min})(x_{\max}-x_{\min})}{(\Delta_x=\sum_{i=1}^{\text{pen-downs}}(x_{\max}\|_i-x_{\min}\|_i))\Delta_y}$	16	$(x_{\text{last pen-up}}-x_{\max})/\Delta_x$
17	$(x_{\text{1st pen-down}}-x_{\min})/\Delta_x$	18	$(y_{\text{last pen-up}}-y_{\min})/\Delta_y$
19	$(y_{\text{1st pen-down}}-y_{\min})/\Delta_y$	20	$(T_w\bar{v})/(y_{\max}-y_{\min})$
⋮	⋮	⋮	⋮
99	θ(before last pen-up)	100	(2nd $t(y_{\max})$)$/T_w$

Features ranked according to individual inter-user class separability

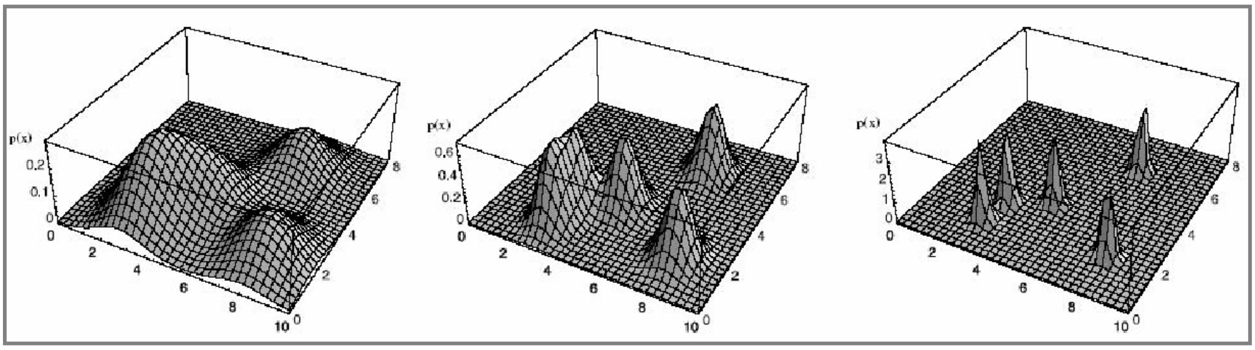
Global system: feature selection

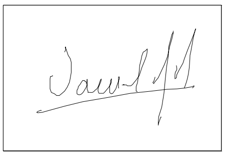
For each feature k with $k = 1, \ldots, 100$



$$S(k)=\sum_i \sum_j \left| d_{i,k} - d_{j,k} \right|$$

Global system: matching



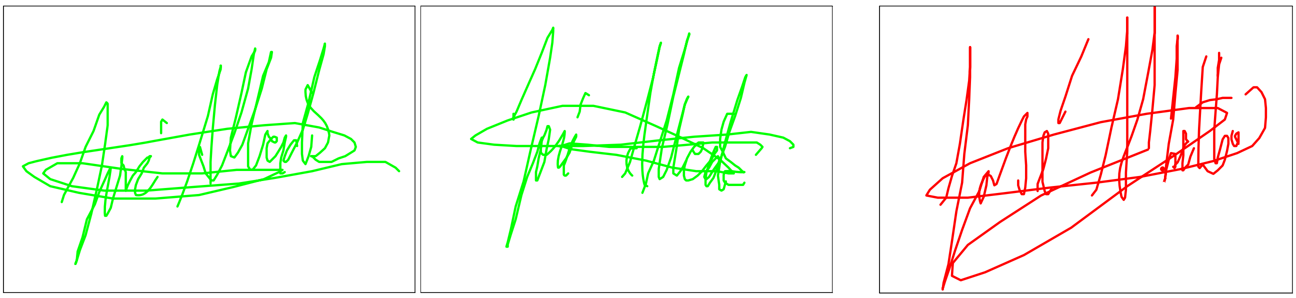


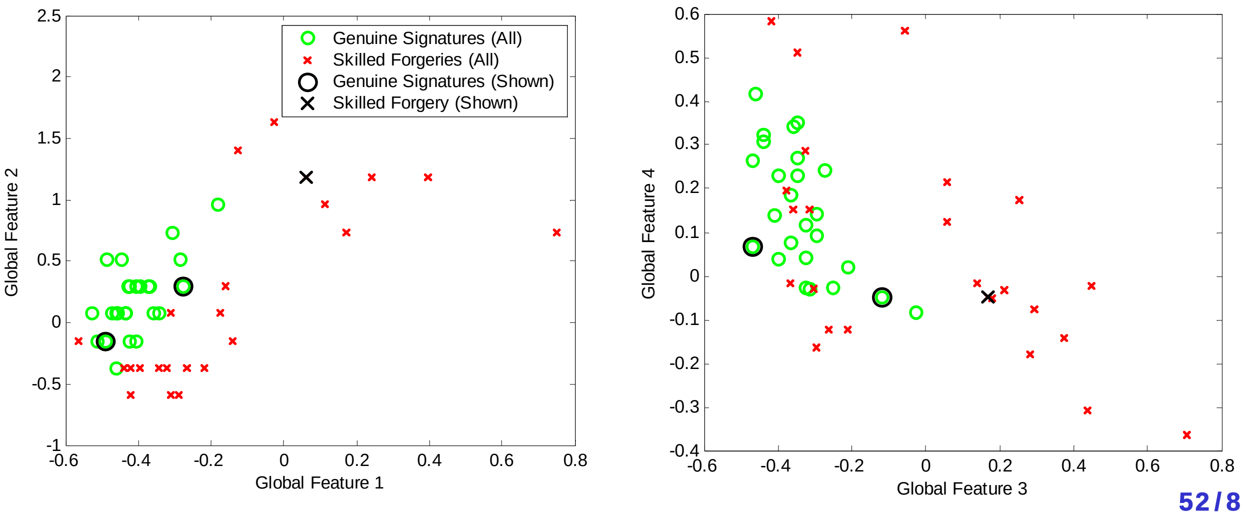
λ^{parzen}

$\mathbf{o}_T$

$$p(\mathbf{o}_T \mid \lambda^{\text{parzen}})$$

Global system: feature extraction example

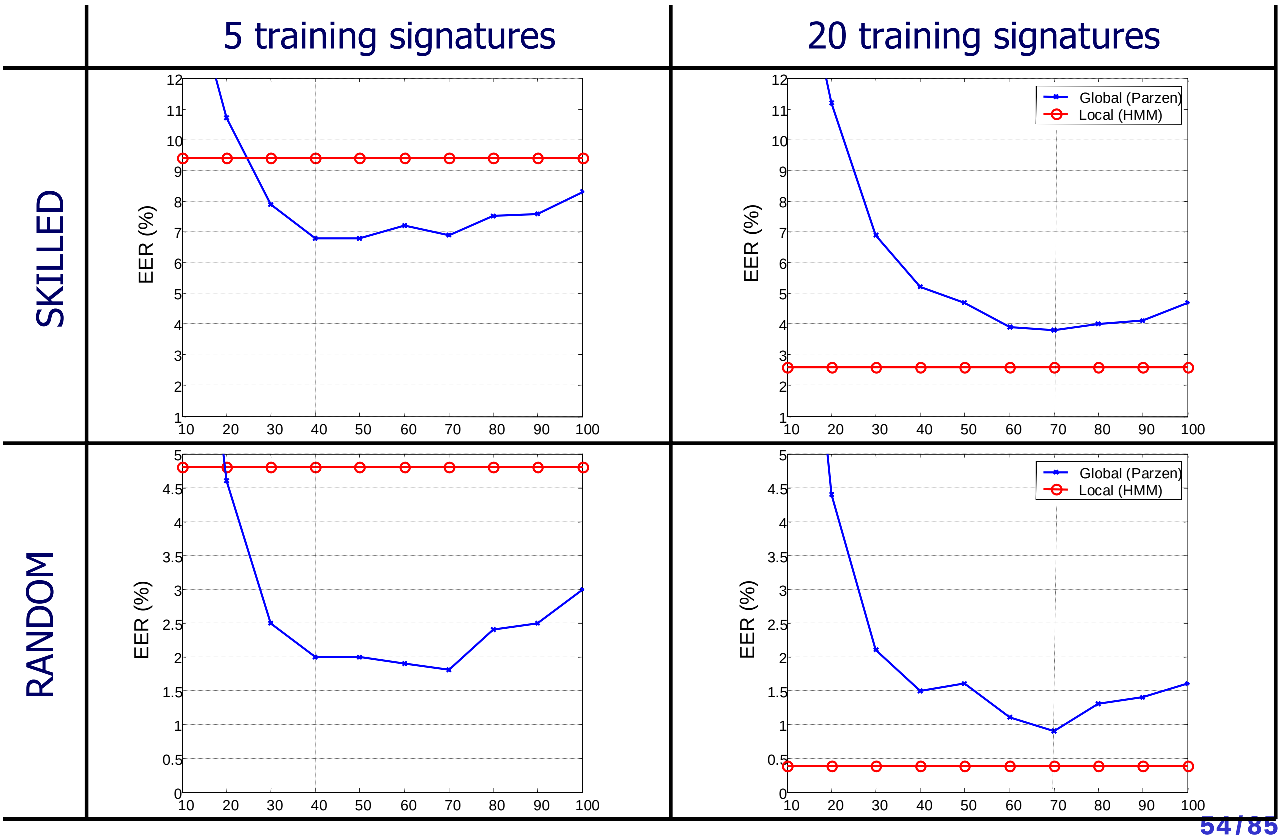




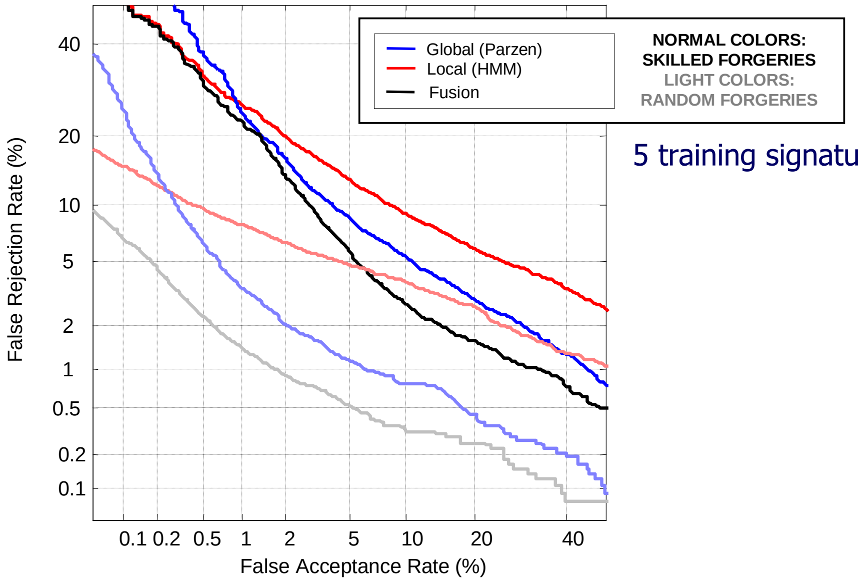
Experimental protocol

- MCYT Signature DB
- Number of signers: 330
- Training:
  - GENUINE: either 5 or 20 signatures
- Testing:
  - GENUINE: the remaining 20 or 5 signatures
  - RANDOM FORGERIES: first signature of the remaining users
  - SKILLED FORGERIES: the 25 forgeries available

Results: feature selection



Results: fusion



5 training signatures

	skilled forgeries		random forgeries	
	user-indep.	user-dep.	user-indep.	user-dep.
Local (HMM)	9.39	2.51	4.86	0.59
Global (40 Feat. + PWC)	6.89	5.61	2.02	1.27
Combined (MAX)	5.29	2.39	1.23	0.41

Conclusions

- Novel set of ranked global features for signature verification
- New system based on global information
- Fusion of the *global* system with a competitive *local* system based on HMMs
- Experiments on a large dataset (330 subjects; 16,500 signatures) both on random and skilled forgeries
- Experimental findings:
  - *Global* better than *local* for small training set size
  - *Local* improves faster than *global* for increasing training set size
  - User-dependent thresholds significantly improve the performance, specially for *local*
  - *Local* and *global* provide complementary information
  - Best EERs:
    - 5 training signatures: **2.39**% (skilled) and **0.41**% (random)
    - 20 training signatures: **0.55**% (skilled) and **0.0**% (random)

Ongoing work in signature verification: DTW

FUNCTIONAL FEATURE EXTRACTION:

- 3 Functions (100 Hz): δx, δy, p
- Geometric Normalization: *position, size*

MATCHING:

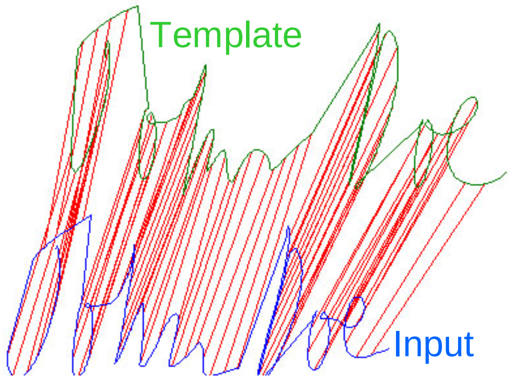
- DTW:

$$D(i,j) = \min \begin{cases} D(i-1, j-1) + d_E(i,j) \\ D(i-1, j) + d_E(i,j) * c \\ D(i, j-1) + d_E(i,j) * c \\ d_E(i,j) < thresh \rightarrow 0 \end{cases}$$

D serves to define the optimal alignment between point *i* in the input signature and point *j* in the template, which is computed via **dynamic programming**.

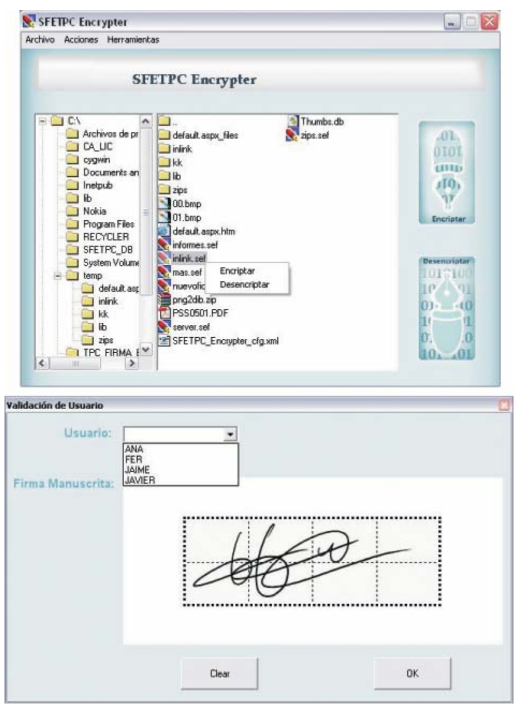
A constant factor *c* multiplied by the Euclidean distance between the two feature vectors is used instead of constant penalties.

No penalty if the Euclidean distance is small.

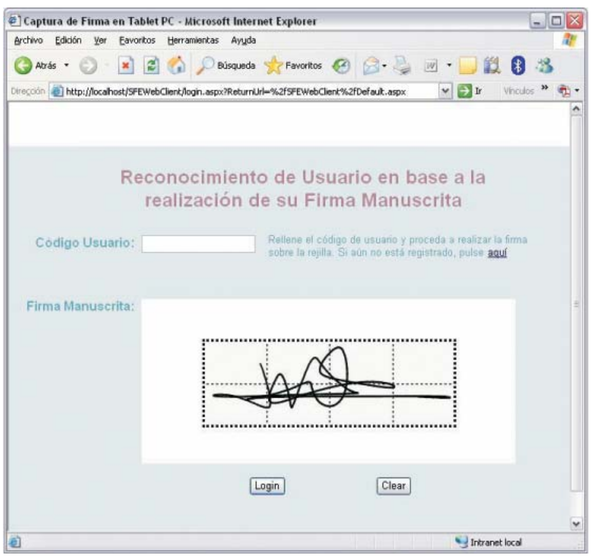


Correspondences found by the DTW algorithm

Applications of signature verification: BBVA

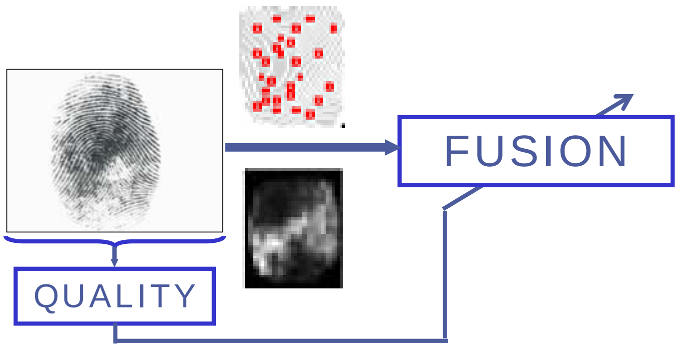


SECURE ENCRYPTION



WEB-BASED ACCESS

Q-Based Multi-Algorithm Fingerprint Verification



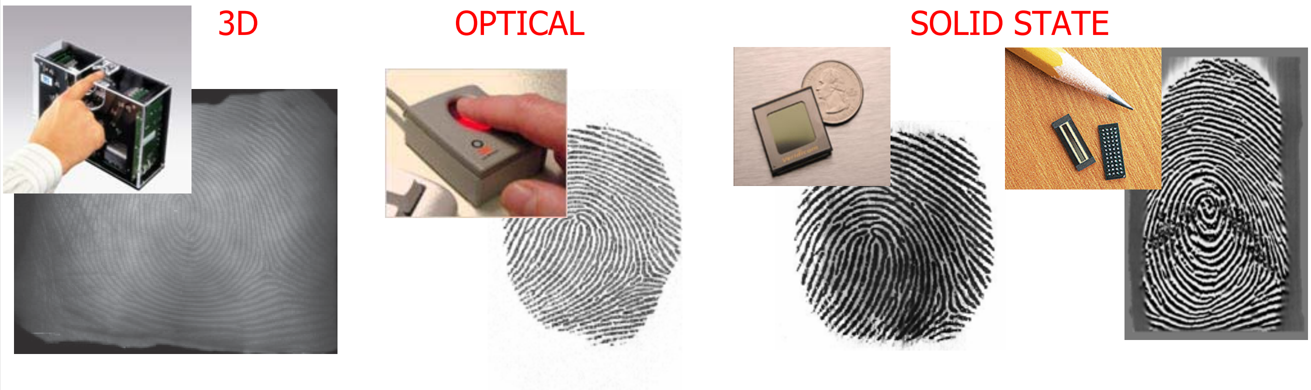
Introduction: fingerprint verification

- Advantages:
  - Permanence, uniqueness and distinctiveness
  - Large experience in the forensic environment
  - Small and cheap sensors that can be easily embedded
  - Growing demand for civilian applications

Introduction: fingerprint verification

- Challenges:
  - Universality (subjects unable to use fingerprints)
  - Intra-class variability (skin or weather conditions, technology of the sensor, user cooperation, …) → image quality

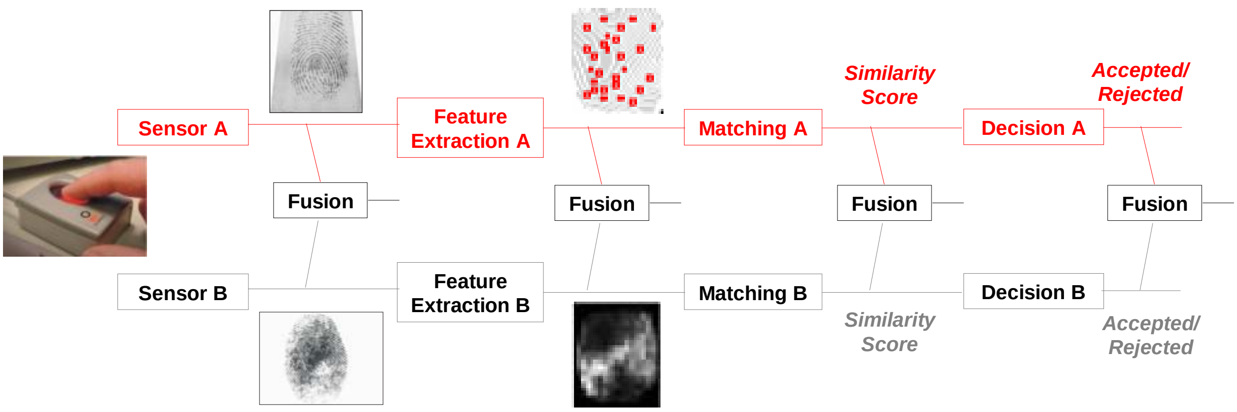
Higher ← **Cost and size of the sensor** → Lower



Higher ← **Image quality** → Lower

Introduction: fingerprint verification

- Multi-algorithm fingerprint recognition:
  - A number of works have shown the benefits of combining multiple approaches for fingerprint recognition
  - Different levels of combination: sensor-level, feature-level, score-level, decision-level



*We focus on **score-level fusion***

Milestones related to our work

1997: Bayesian Expert Conciliation by Bigun *et al.* (*AVBPA*)

1997: Minutiae-Based Fingerprint Matcher by Jain *et al.* (*T-PAMI*, *P-IEEE*)

2000: Ridge-Based Fingerprint Matcher by Jain et al. (*T-IP*)

2003: State-of-the-Art by Maltoni *et al.* (*Handbook*)

2003: Q-Based Mulimodal Fusion by Bigun *et al.* (*ICIAP, MMUA*)

2005: Q-Based Multimodal Fusion by Fierrez-Aguilar *et al.* (*PR*)

2005: Global Quality Measure, by Chen *et al.* (*AVBPA*)

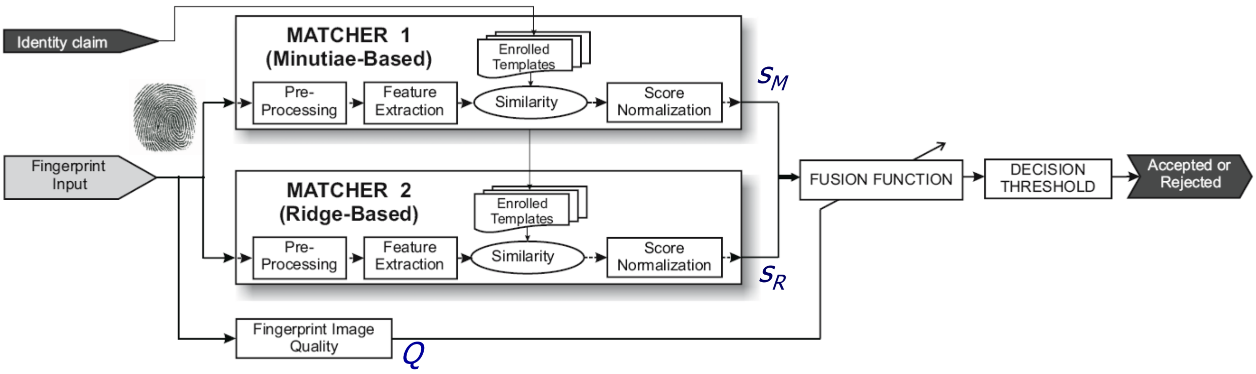
ICB 2006: Q-Based Fusion for Multi-Level Fingerprint Verification

Motorola Best Student Paper Award

Research significance

- First published work on quality-based fusion for biometrics using real multi-level data and automatic quality measures
- Comparison of minutiae- and ridge-based matching performance for different image quality groups
- Usage of a large DB (QMCYT) including 7,500 images from 750 fingers (6,750 genuine and 561,750 impostor matchings, respectively)

System architecture



Assumptions:

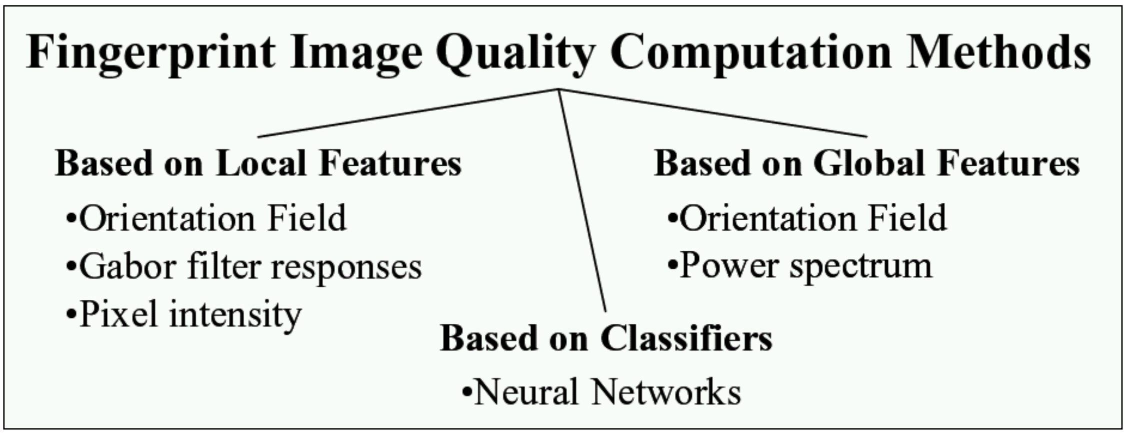
- Matching scores s_M and s_R are already normalized to the range [0,1]
- Performance of one matcher (minutiae) drops significantly as compared to the other under image quality degradation

$$\rightarrow \quad s_Q = \frac{Q}{2} s_M + \left(1 - \frac{Q}{2}\right) s_R$$

NOTE: More general formulations (*n* matchers) using Bayesian theory and SVMs are developed in Chapter 3 of the Thesis

Fingerprint image quality

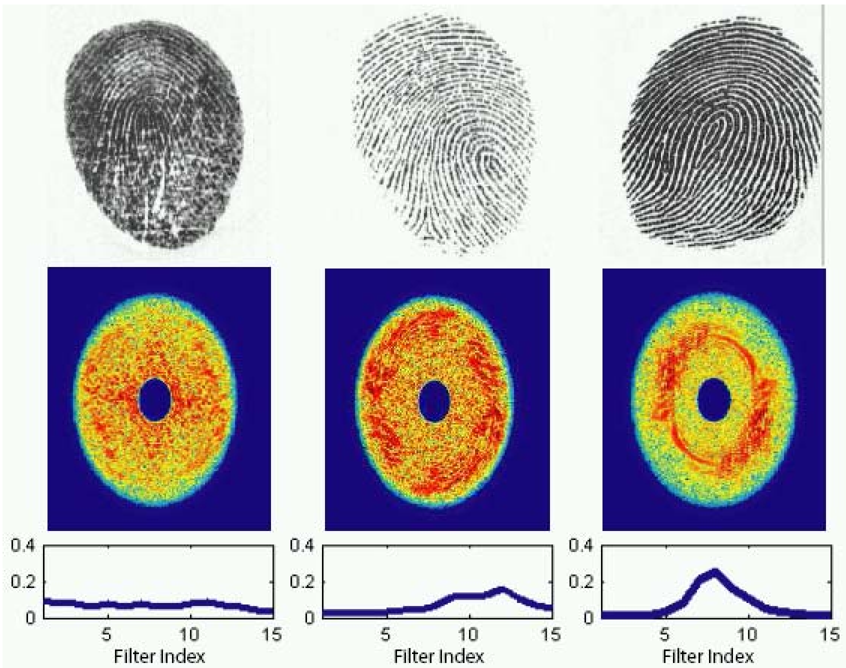
- Measure of separability of ridges and valleys
- Extractability of fingerprint features (minutiae, core points…)



*We use a **Global Image Quality** based on the **Power Spectrum***

Automatic fingerprint quality assessment

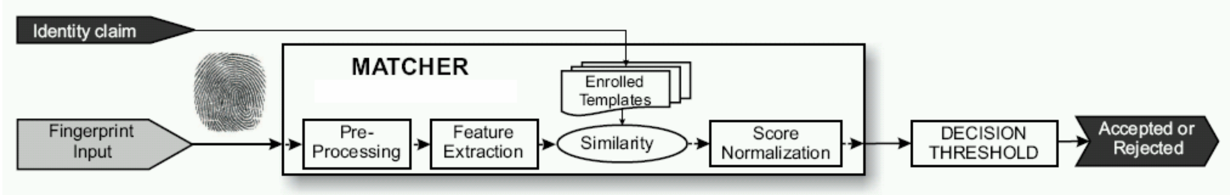
- Based on global features:
  - A global measure of quality is computed for each image
  - The quality is related to the energy concentration in ring-shaped regions of the power spectrum



Q=0.05 Q=0.36 Q=0.92

NOTE: Method developed by Yi Chen *et al.* (AVBPA 2005)

Minutiae-based matcher



PREPROCESSING

- Normalization
- Orientation field
- ROI
- Ridge extraction & profiling

SIMILARITY

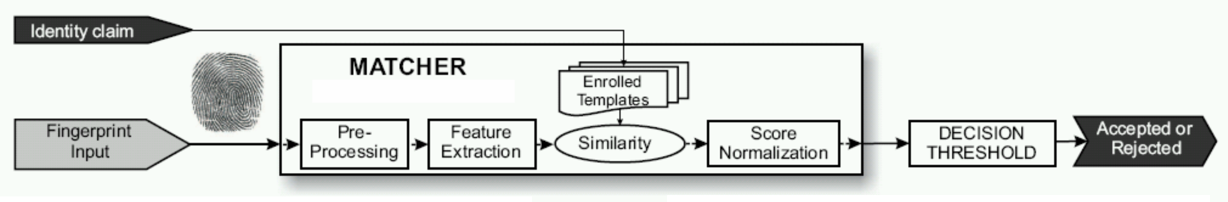
- Minutiae alignment
- Pattern matching (edit distance)

FEATURE EXTRACTION

- Thinning
- Imperfection removal
- Minutiae extraction

D. Simon-Zorita, J. Ortega-Garcia, J. Fierrez-Aguilar, J. Gonzalez-Rodriguez, "Image quality and position variability assessment in minutiae-based fingerprint verification", *IEE Proc. VISP*, vol. 150, no. 6, pp. 402-408, 2003.

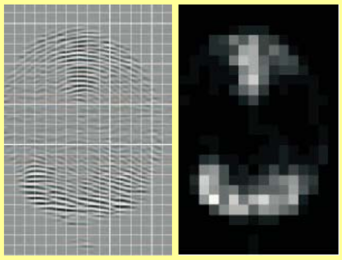
Ridge-based matcher



PREPROCESSING

<NONE>

SIMILARITY



- Correlation-based alignment
- Matching based on Euclidean Distance

FEATURE EXTRACTION

- Energy responses of Gabor filters in different directions
- FingerCode

A. Ross, J. Reisman, A.K. Jain, ”Fingerprint matching using feature space correlation”, Proc. BioAW, *Springer LNCS*, vol. 2359, pp. 48-57, 2002.

Database: QMCYT

- Scanner: UareU from Digital Persona
- Fingerprint image: 500dpi, 400 x 256 pixels
- Fingerprint corpus: 750 fingers (75 subjects) x 10 impressions

Experimental protocol

- Enrollment: one impression of each finger
- Genuine matchings: remaining 9 impressions (9 x 750 trials)
- Impostor matchings: 1 impression from all the remaining fingers (750 x 749 trials)

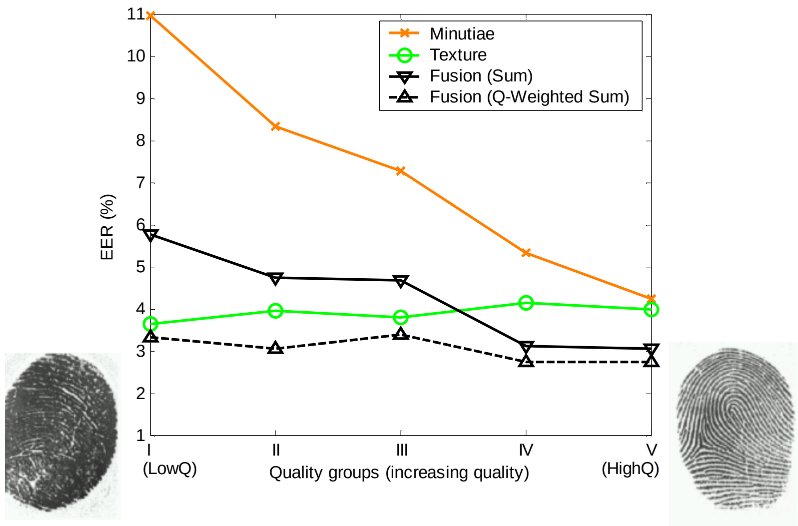
- All fingers are classified into 5 equal-sized disjoint quality groups, based on a quality ranking

- The quality ranking is based on the average quality of the genuine matchings corresponding to each finger:

$$Q_{matching} = \sqrt{Q_{enrolled} \cdot Q_{test}}$$

where $Q_{enrolled}$ and Q_{test} are global image quality measures

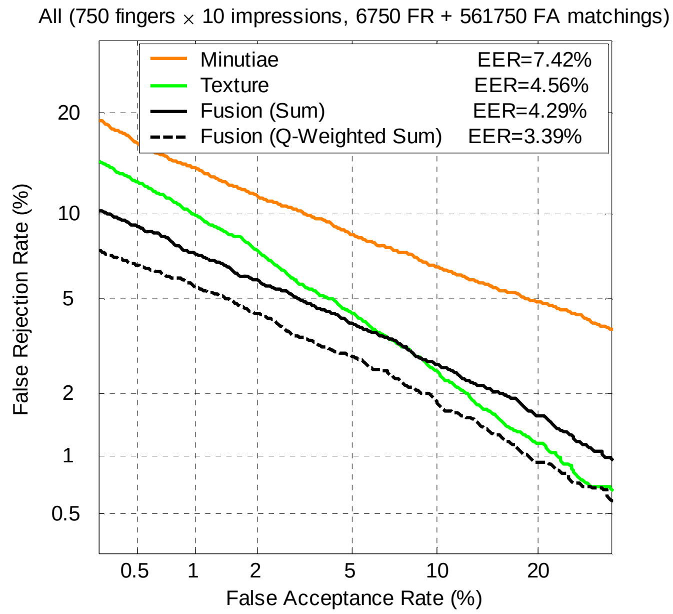
Performance comparison for quality groups



Observations:

- The performance of the minutiae-based matcher drops significantly under degraded image quality
- The performance of the ridge-based matcher is robust to the global image quality measure considered
- Sum fusion outperforms the best system only for good quality images
- *Quality-based fusion* outperforms the best system in all cases

Fusion results



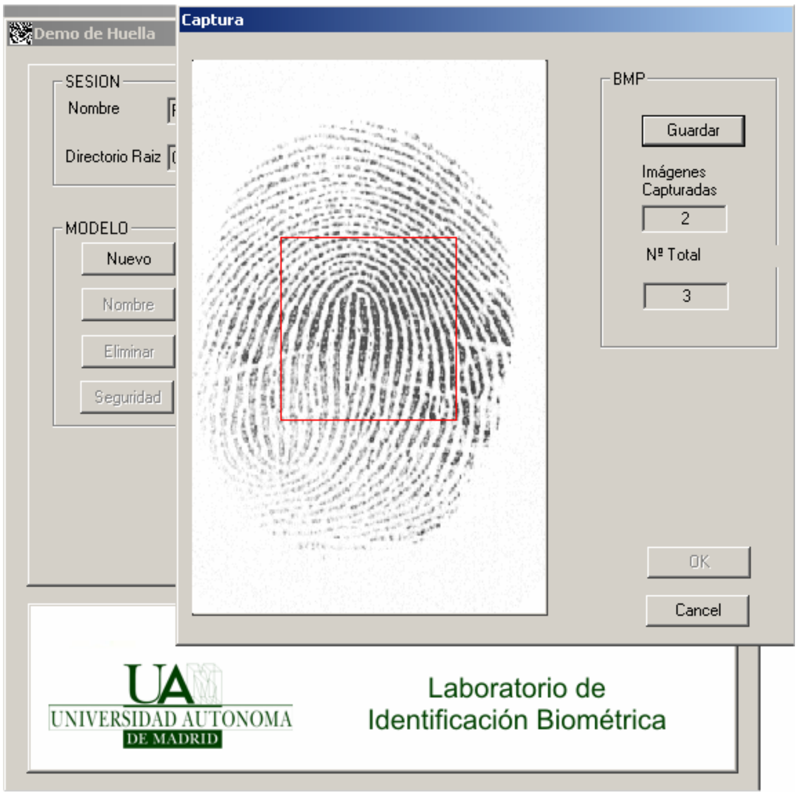
Observations:

- Due to large differences in performance between the two systems, sum fusion improves the performance only in a region of the DET curve
- Incorporating the image quality in the sum fusion leads to improved performance in all cases

Conclusions

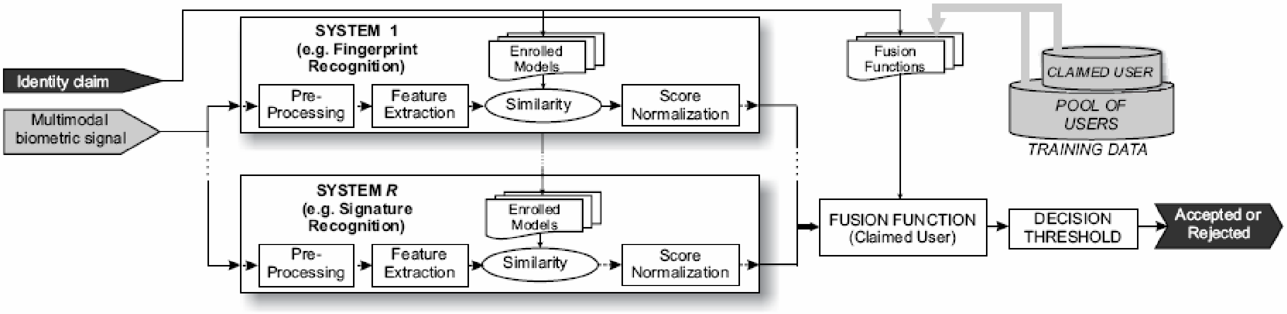
- Quality-based fusion of ridge- and minutiae-based matchers
- Usage of a global quality measure based on power spectrum, and a large corpus comprising 7500 images from 750 fingers
- Experimental findings:
  - The ridge-based approach outperforms the minutiae-based approach in low quality image conditions
  - Both approaches obtain similar performance for good image quality
  - The ridge-based approach is more robust to quality image degradation (almost independent of image quality) while the minutiae-based approach experiments a large performance drop
  - Quality-based fusion overcomes the problem of performance drop of one component in multi-algorithm fingerprint verification

Applications of fingerprint verification: TID



User-Dependent Multimodal Authentication

User-dependent multimodal fusion: experiments



- Function-Based Signature System + Minutiae-Based Fingerprint System
- GLOBAL, LOCAL, and ADAPTED fusion (and decision) are compared
- Bayesian and SVM-based (RBF kernel) fusion algorithms

User-dependent multimodal fusion: experimental protocol

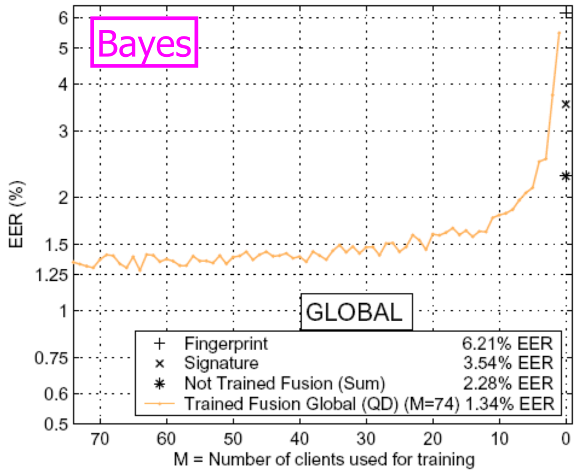
- Database used in the experiments:
  - 75 subjects from QMCYT
  - 10 impressions of one finger (lowest Q finger for 10% of the subjects, and highest Q finger for the remaining subjects)
  - 17 genuine signatures per user
- Experimental setup based on **worst-case scenario**:
  - 3 fingerprints for enrollment
    - → 7 genuine matchings
    - → 10 impostor matchings (with the best 10 impostor fingerprints from a pool of 750 different fingers)
  - 10 signatures for enrollment
    - → 7 genuine matchings
    - → 10 impostor matchings (skilled forgeries from 5 skilled imitators)

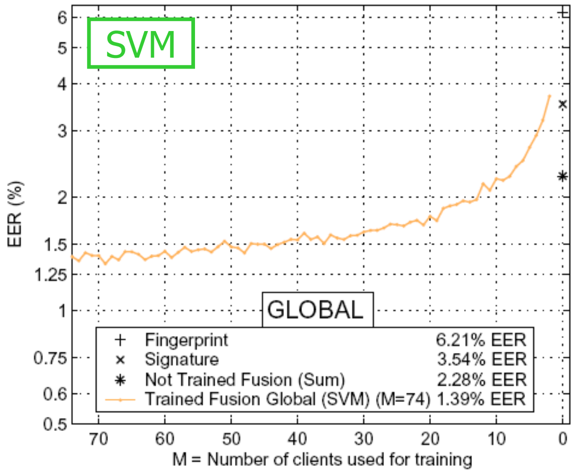
75x7 genuine
75x10 impostor

Real bimodal test trials in a worst-case scenario

User-dependent multimodal fusion: results

GLOBAL FUSION: *M* users are randomly selected with replacement 200 times. Each time, the selected matching scores are used to train a user-independent fusion function, which is tested on the remaining users. Errors are finally averaged after the 200 iterations

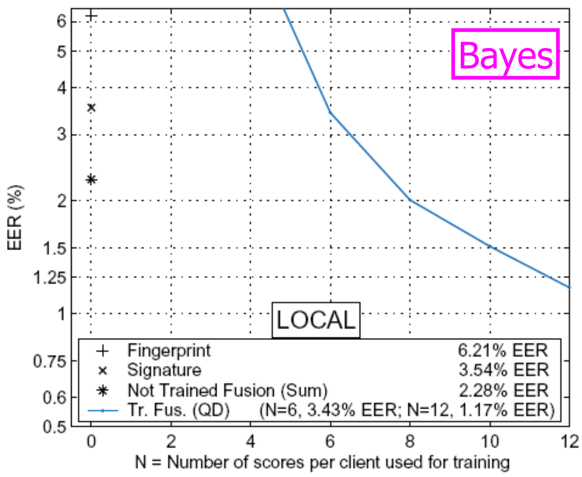


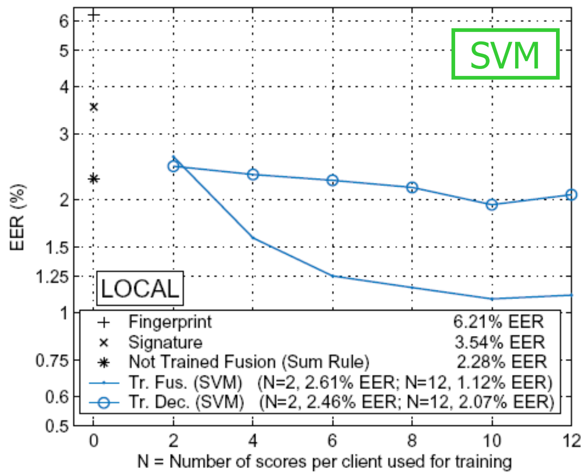


- Large performance improvement for *M* < 10, stable results for *M* > 20
- SVM more robust to small training set sizes

User-dependent multimodal fusion: results

LOCAL FUSION: For each user, *N* scores are randomly selected without replacement and forcing half of them in each class client/impostor, 50 times. Each time, a user-dependent fusion function is trained, which is tested on the remaining scores of the given user

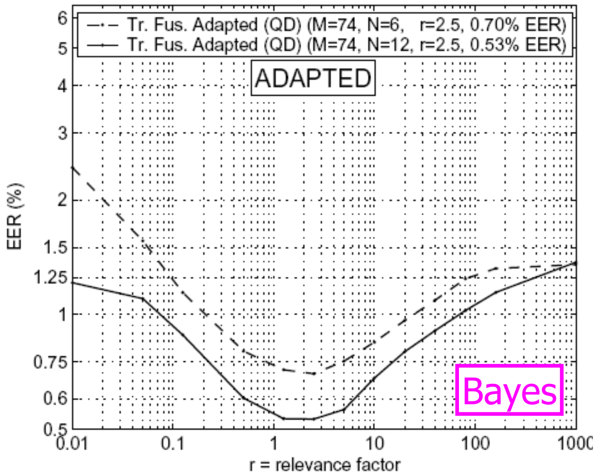


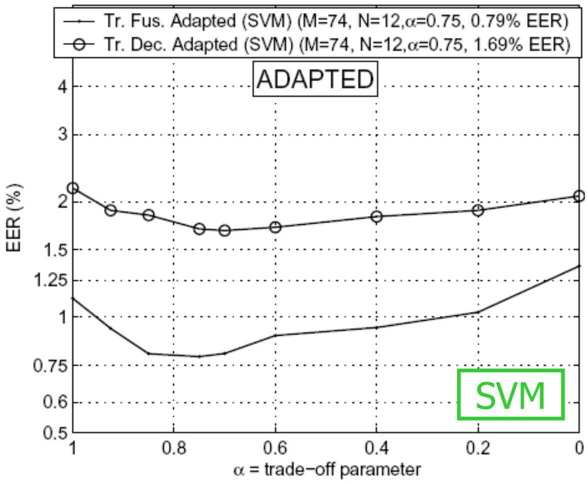


- Trained fusion is better than trained decision on summed scores
- SVM much more robust to small training set sizes

User-dependent multimodal fusion: results

ADAPTED FUSION: Users are sampled as in the GLOBAL case. Each time, all the remaining users are sampled and tested as in the LOCAL case but using the background information provided by users in the GLOBAL dataset from which the given user was left out





- Incorporating global information in user-dependent fusion is specially helpful for small user-dependent training set sizes
- Bayes (0.53%) outperforms SVM (0.79%) in the best operating point

Conclusions and Future Work

Conclusions

SIGNATURE:

- Fusion of a new feature- with an enhanced function-based approach
- Outstanding EERs, one of the largest DB in the literature (16,500 signs.)
- User-dependent decision thresholds significantly improve the performance

FINGERPRINT:

- Comparison and fusion of ridge- and minutiae-based matchers based on Q
- Q-based fusion outperforms the standard sum rule approach

MULTIMODAL FUSION:

- User-dependent fusion: SVM, Bayes
  - The incorporation of background information in user-dependent fusion schemes is demonstrated to enhance the verification performance
  - SVM more robust to small training set sizes, best results for Bayes with large training set sizes
- Quality-based fusion: Combination, SVM, Bayes

Ongoing and Future Work

SIGNATURE:

- Development and fusion of DTW approach [M. Martinez]
- Application to different scenarios: Tablet PC, PDAs, …
- Cryptobiometrics using written signatures [M. Freire]
- Study of vulnerabilities: skilled forgeries, hill-climbing attacks, … [J. Galbally]

FINGERPRINT:

- Development and fusion of image correlation approach [F. Alonso]
- Match-on-card
- Cryptobiometrics using fingerprints [M. Freire]
- Study of vulnerabilities: gummy fingers, hill-climbing attacks, … [J. Galbally]

MULTIMODAL FUSION:

- Application of adaptive kernel methods
- User-dependent and Q-based fusion
- Exploitation of the new MM DBs to study time lapse effects, image Q effects, …
- Quality measures for common biometrics (signature Q?) [F. Alonso]
- Application-independent evaluation [D. Ramos]
- Evaluation methodologies (CC, ISO/IEC JCT1/SC27/SC37)

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