Signature Biometrics

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Funding Acknowledgements

Public

SIXTH FRAMEWORK PROGRAMME

SEVENTH FRAMEWORK PROGRAMME

TABULA RASA

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cost 2101 BIOMETRICS FOR IDENTITY DOCUMENTS AND SMART CARDS

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Introduction

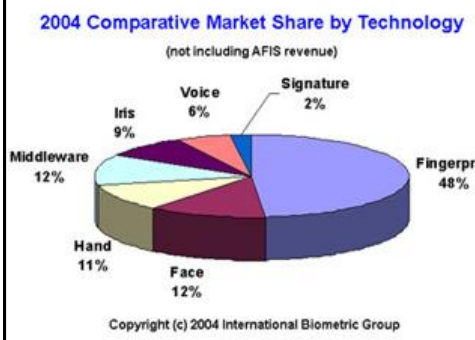
- Signature is one of the most **socially accepted** biometric traits, it has been used for centuries to validate legal and commercial documents and transactions
- Automatic signature recognition has some general **challenges**:
  - **Large intra-user variability** (**behavioral biometric**, **inter-session**)
    → *Difficult to model, large amount of training data (usually scarce)*
  - Small inter-user variability (in case of forgeries)
    →*The skill level of actual forgeries is unpredictable*

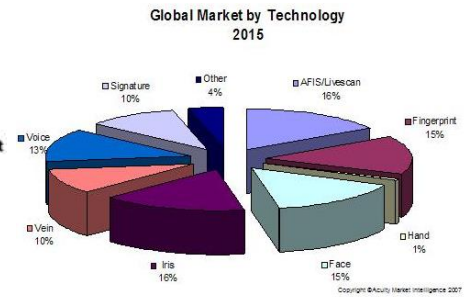
Introduction

- **High deployment** of multiple electronic devices
- Signatures can be **easily captured** by means of multiple devices
- **High deployment in banking and commercial sectors**




Biometric Market by Modality



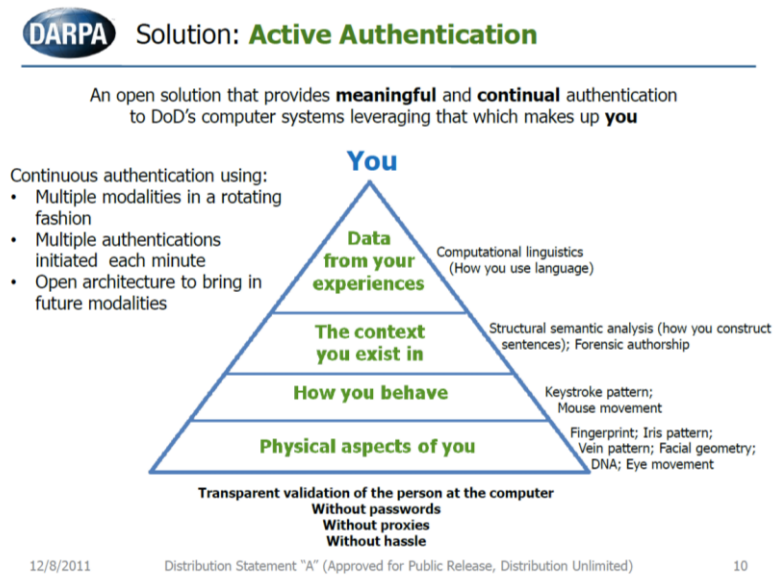


- Decreasing (in *Relative Importance*): **Fingerprint**, from 48% to 15% (31% w AFIS)
- Growing: **Iris** from 9% to 16% and **Face** from 12% to 15%
- Huge grow: **Speech** from 6% to 13% and **Signature**, from 2% to 10%

Behavioral Biometrics

- Human activity patterns are clearly stablished from childhood
- As patterns, they are stable and reproducible, though subject to variability
- Neuromotor coordination of gestures and movements
- Continuous identity monitoring possible
- User is an active part of the play
- Multilevel strategy: from dynamic trajectories to expressions, context, habits, stylometry, experiences
- Not fixed patterns but changing and adapting ones

Active Authentication by DARPA

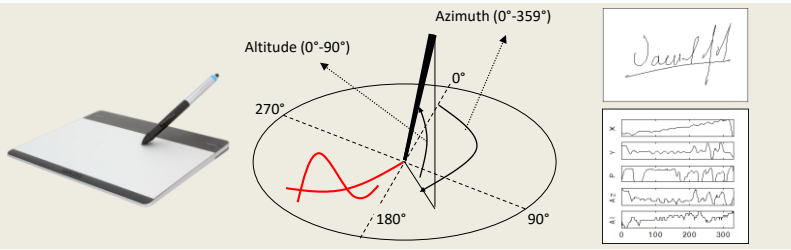


Signature as Behavioral Pattern

- Human interaction permits transparent authentication
- Make use of existing input channels, no added specific sensors:
  - Handwritting (tablets and pads)
  - Mouse dynamics
- Other sources of variability (sensor, session) included into behavior pattern modelling / compensation
- Fully revocable patterns
- Incorporates soft biometrics (gender, handedness, language, …)
- Easy of use, high user acceptance

Signature Recognition

On-line / Dynamic



Off-line / Static

J. Fierrez, J. Ortega-Garcia, et al., "HMM-based on-line signature verification: feature extraction and signature modeling", *Pattern Recognition Letters*, Vol. 28, n. 16, Dec. 2007.

J. Fierrez, and J. Ortega-Garcia, "On-Line Signature Verification", Chapter 10 in *Handbook of Biometrics*, A.K. Jain, A. Ross and P. Flynn (eds.), Springer, pp. 189-209, 2008.

On-line Signature Verification: Overview

Dynamic signature matching

Feature-based (Global Features)

Distance-based classifiers
- Mahalanobis
- Euclidean [Nelson et al., 1994]

Statistical/other classifiers
- Gaussian Mixture Models (GMM)
- Parzen Windows

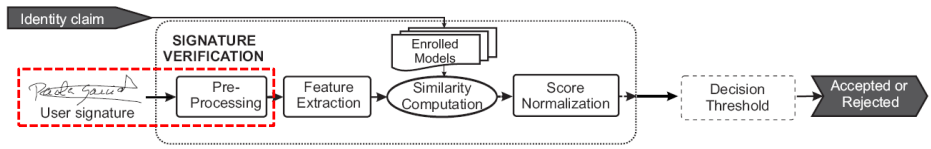
Function-based (Local Features)

Time-Sequence matching techniques
- Hidden Markov Models (HMM) [Dolfing et al., 1998]
- Gaussian Mixture Models (GMM) [Richiardi et al., 2005]
- Dynamic Time Warping (DTW) [Sato and Kogure, 1982]

J. Fierrez and J. Ortega-Garcia, "On-line signature verification", A.K. Jain et al. (Eds), *Handbook of Biometrics*, 2008.

M. Martinez-Diaz and J. Fierrez, "Signature Databases and Evaluation", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1367-1375, 2015.

On-line Signature Verification: System Model



1. **Data Acquisition & Pre-Processing**
2. Feature Extraction
3. Similarity Computation (Matching)

J. Fierrez and J. Ortega-Garcia, "On-line signature verification", A.K. Jain et al. (Eds), *Handbook of Biometrics*, 2008.

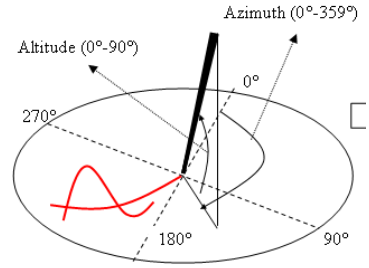
Signature Acquisition: Input Data

Time resolution: 100-200 samples/sec

Space resolution: 1000 pixels/inch resolution

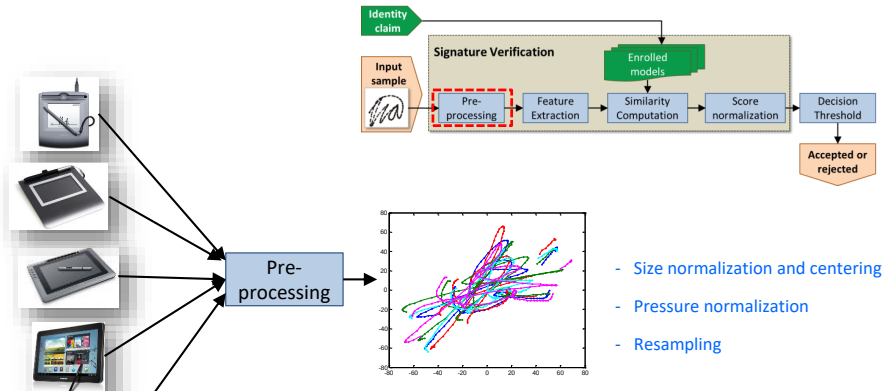
Measured:

- x,y coordinates of the signature trajectory
  - on pen down
- time stamp at each sample point
- pressure at each point
- pen inclination angles at each point
  - altitude (0-90)
  - azimuth (0-359)
- …



Signature Pre-Processing

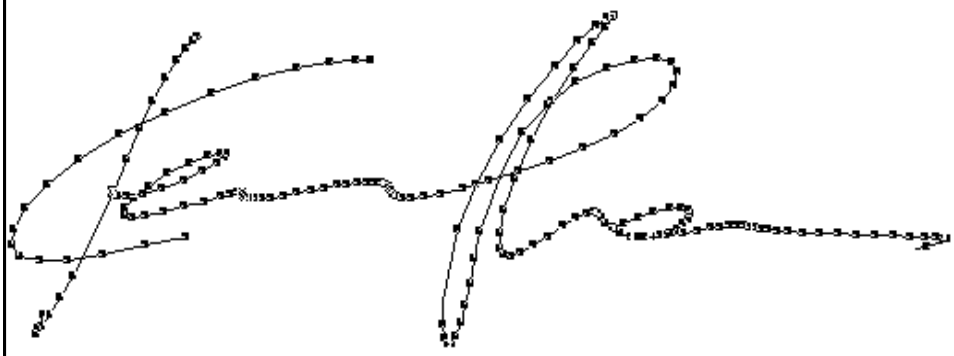
Reduce sensor interoperability issues due to diverse devices and writing tools (stylus/finger)



- Size normalization and centering
- Pressure normalization
- Resampling

M. Martinez-Diaz, J. Fierrez and S. Hangai, "Signature Features", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1375-1382, 2015.

Pre-Processing: Re-Sampling



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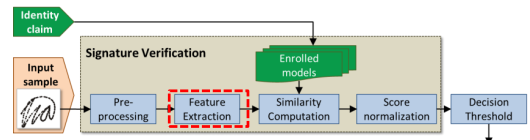
Feature Extraction

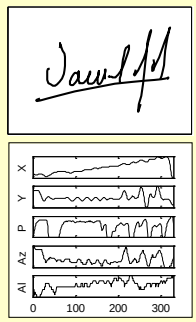
#	Feature Description	#	Feature Description
1	signature total duration T_s	2	(pen-down duration T_w)/T_s
3	(1st $t(v_{max})$)/T_w	4	$T(v_y > 0)/T_w$
5	$T(v_x < 0)/T_w$	6	$T(v_y > 0)/T_w$
7	$T(v_y < 0)/T_w$	8	$T(v_x > 0$[pen-up$)/T_w$
9	$T(v_x < 0$[pen-up$)/T_w$	10	$T(v_y > 0$[pen-up$)/T_w$
11	$T(v_x < y$[pen-up$)/T_w$	12	T(1st pen-up)/T_w
13	T(2nd pen-up)/T_w	14	T(2nd pen-down)/T_s
15	T(3rd pen-down)/T_s	16	(1st $t(v_{y,max})$)/T_w
17	(1st $t(v_{x,min})$)/T_w	18	(1st $t(v_{x,max})$)/T_w
19	(1st $t(v_{x,min})$)/T_w	20	$\frac{T((dy/dt)/(dx/dt)>2)}{T((dy/dt)/(dx/dt)<2)}$
21	T(curvature > threshold$_{curv}$)/T_w	22	(1st $t(r_{max})$)/T_w
23	(2nd $t(r_{max})$)/T_w	24	(3rd $t(r_{max})$)/T_w
25	(2nd $t(y_{max})$)/T_w	26	(3rd $t(y_{max})$)/T_w
27	(average velocity v)/v_{max}	28	$N(v_y = 0)$
29	$N(v_y = 0)$	30	$v/v_{x,max}$
31	$v/v_{y,max}$	32	(velocity rms v)/v_{max}
33	(centripetal acceleration rms a_c)/a_{max}	34	(tangential acceleration rms a_t)/a_{max}
35	(acceleration rms a)/a_{max}	36	(integrated abs. centr. acc. a_{ic})/a_{max}
37	(velocity correlation $v_{x,y}$)/v^2_{max}	38	standard deviation of v_x
39	standard deviation of v_y	40	standard deviation of a_x
41	standard deviation of a_y	42	average jerk j
43	j_x	44	j_y
45	j_{max}	46	$j_{x,max}$
47	$j_{y,max}$	48	j_{max}
49	$t(j_{max})/T_w$	50	$t(j_{x,max})/T_w$
51	$t(j_{y,max})/T_w$	52	N(pen-ups)
53	N(sign changes of dx/dt and dy/dt)	54	$\frac{T((dx/dt)/(dy/dt)>2)}{T((dx/dt)/(dy/dt)<2)}$
55	θ(initial direction)	56	θ(1st to 2nd pen-down)
57	θ(1st pen-down to 1st pen-up)	58	θ(1st pen-down to 2nd pen-up)
59	θ(2nd pen-down to 2nd pen-up)	60	θ(before last pen-up)
61	θ(1st pen-down to last pen-up)	62	direction histogram s_1
63	direction histogram s_2	64	direction histogram s_3
65	direction histogram s_4	66	direction histogram s_5
67	direction histogram s_6	68	direction histogram s_7
69	direction histogram s_8	70	direction change histogram c_2
71	direction change histogram c_3	72	direction change histogram c_4
73	$\frac{A_{min}-(y_{max}-y_{min})(x_{max}-x_{min})}{(\Delta x-\sum_{i=1}^{n_{pen-down}}(x_{max}-x_{min}))\Delta y}$	74	(max distance between points)/A_{min}
75	$(x_{1st\ pen\text{-}down} - x_{min})/\Delta_x$	76	$(x_{1st\ pen\text{-}down} - x_{min})/\Delta_x$
77	$(x_{last\ pen\text{-}up} - x_{min})/\Delta_x$	78	$(x_{last\ pen\text{-}up} - x_{min})/\Delta_x$
79	$(y_{1st\ pen\text{-}down} - y_{min})/\Delta_y$	80	$(y_{1st\ pen\text{-}down} - y_{min})/\Delta_y$
81	$(y_{last\ pen\text{-}up} - y_{min})/\Delta_y$	82	$(y_{last\ pen\text{-}up} - y_{min})/\Delta_y$
83	$\frac{x_{max}-x_{min}}{y_{max}-y_{min}}\Delta_x$	84	(standard deviation of x)/Δ_x
85	(standard deviation of y)/Δ_y	86	$(T_w\theta)/(y_{max} - y_{min})$
87	$(T_w\theta)/(y_{max} - y_{min})$	88	$(x_{max} - x_{min})$/acquisition range
89	$(y_{max} - y_{min})$/$y_{acquisition\ range}$	90	$(\bar{x} - x_{min})/\bar{x}$
91	spatial histogram t_1	92	spatial histogram t_2
93	spatial histogram t_3	94	spatial histogram t_4
95	N(local maxima in x)	96	$(x_{2nd\ local\ max} - x_{1st\ pen\text{-}down})/\Delta_x$
97	$(x_{3rd\ local\ max} - x_{1st\ pen\text{-}down})/\Delta_x$	98	N(local maxima in y)
99	$(y_{2nd\ local\ max} - y_{1st\ pen\text{-}down})/\Delta_y$	100	$(y_{3rd\ local\ max} - y_{1st\ pen\text{-}down})/\Delta_y$



#	Feature	Description
1	x-coordinate	x_n
2	y-coordinate	y_n
3	Pen-pressure	z_n
4	Path-tangent angle	$\theta_n = \arctan(y_n/x_n)$
5	Path velocity magnitude	$v_n = \sqrt{y_n + x_n}$
6	Log curvature radius	$\rho_n = \log(1/\kappa_n) = \log(v_n/\theta_n)$, where κ_n is the curvature of the position trajectory
7	Total acceleration magnitude	$a_n = \sqrt{a_t^2 + a_c^2} = \sqrt{v_n^2 + v_n^4 \kappa_n^2}$, where a_t and a_c are respectively the tangential and centripetal acceleration components of the pen motion.
8-14	First-order derivative of features 1-7	$\dot{x}_n, \dot{y}_n, \dot{z}_n, \dot{\theta}_n, \dot{v}_n, \dot{\rho}_n, \dot{a}_n$
15	Pen azimuth	γ_n
16	Pen altitude	ϕ_n
17-18	First-order derivative of features 15-16	$\dot{\gamma}_n, \dot{\phi}_n$
19-20	Second-order derivative of features 1-2	$\ddot{x}_n, \ddot{y}_n$
21	Ratio of the minimum over the maximum speed over a window of 5 samples	$v_n^* = \min\{v_{n-4}, ..., v_n\}/\max\{v_{n-4}, ..., v_n\}$
22-23	Angle of consecutive samples and first order difference	$\alpha_n = \arctan(y_n - y_{n-1}/x_n - x_{n-1})$ $\dot{\alpha}_n$
24	Sine	$s_n = \sin(\alpha_n)$
25	Cosine	$c_n = \cos(\alpha_n)$
26	Stroke length to width ratio over a window of 5 samples	$r_n^5 = \frac{\sum_{k=n-4}^{n} \sqrt{(x_k - x_{k-1})^2 + (y_k - y_{k-1})^2}}{\max\{x_{n-4}, ..., x_n\} - \min\{x_{n-4}, ..., x_n\}}$
27	Stroke length to width ratio over a window of 7 samples	$r_n^7 = \frac{\sum_{k=n-6}^{n} \sqrt{(x_k - x_{k-1})^2 + (y_k - y_{k-1})^2}}{\max\{x_{n-6}, ..., x_n\} - \min\{x_{n-6}, ..., x_n\}}$

M. Martinez-Diaz, J. Fierrez, et al., "Mobile Signature Verification: Feature Robustness and Performance Comparison", *IET Biometrics*, Dec 2014.

Feature Extraction: Global Features



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)/Δ_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 $\bar{v}$)/$v_{x,\max}$
15	$\frac{A_{\min}=(y_{\max}-y_{\min})(x_{\max}-x_{\min})}{(\Delta_x=\sum_{i=1}^{\text{pen-downs}}(x_{\max\,\vert i}-x_{\min\,\vert i}))\Delta_y}$	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	$(T_w\bar{v})/(y_{\max}-y_{\min})$
21	$(T_w\bar{v})/(x_{\max}-x_{\min})$	22	(pen-down duration T_w)/T_s
23	$\bar{v}/v_{y,\max}$	24	$(y_{\text{last pen-up}}-y_{\max})/\Delta_y$
25	$\frac{T((dy/dt)/(dx/dt)>0)}{T((dy/dt)/(dx/dt)<0)}$	26	$\bar{v}/v_{\max}$
27	$(y_{\text{1st pen-down}}-y_{\max})/\Delta_y$	28	$(x_{\text{last pen-up}}-x_{\min})/\Delta_x$
29	(velocity rms v)/$v_{\max}$	30	$\frac{(x_{\max}-x_{\min})\Delta_y}{(y_{\max}-y_{\min})\Delta_x}$
31	(velocity correlation $v_{x,y}$)/$v_{\max}^2$	32	$T(v_y>0$|pen-up)/T_w
33	$N(v_x=0)$	34	direction histogram s_1
35	$(y_{\text{2nd local max}}-y_{\text{1st pen-down}})/\Delta_y$	36	$(x_{\max}-x_{\min})/x_{\text{acquisition range}}$
37	$(x_{\text{1st pen-down}}-x_{\max})/\Delta_x$	38	$T(\text{curvature}>\text{Threshold}_{\text{curv}})/T_w$
39	(integrated abs. centr. acc. a_{Ic})/$a_{\max}$	40	$T(v_x>0)/T_w$

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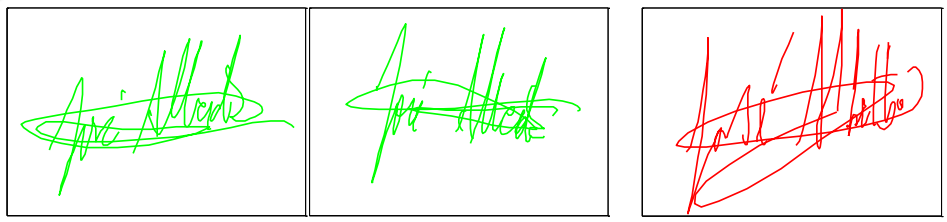
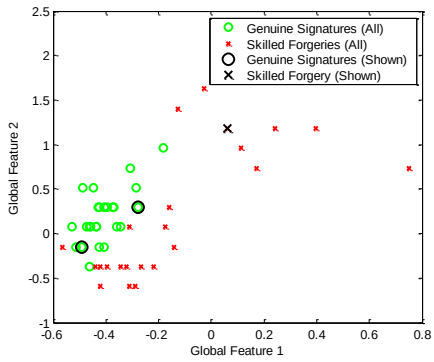
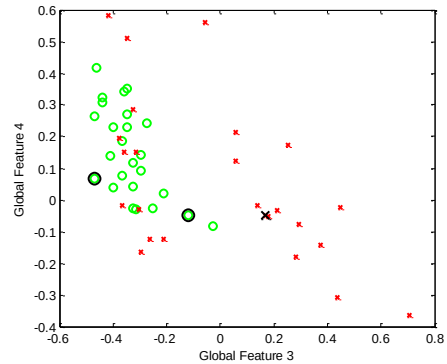
Feature Extraction: Global Features Example







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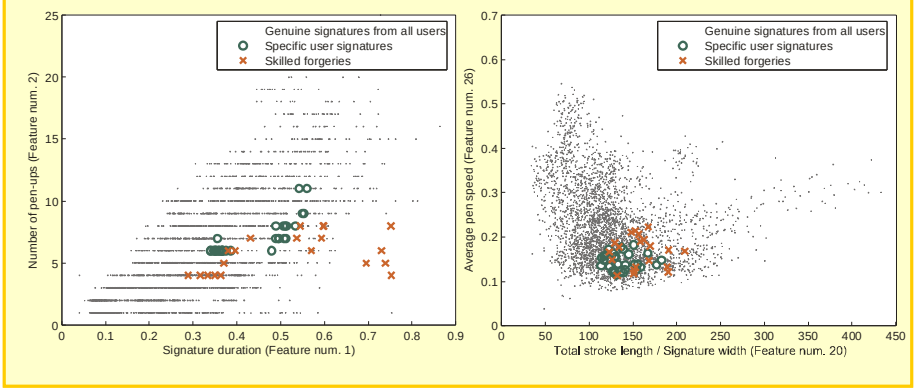

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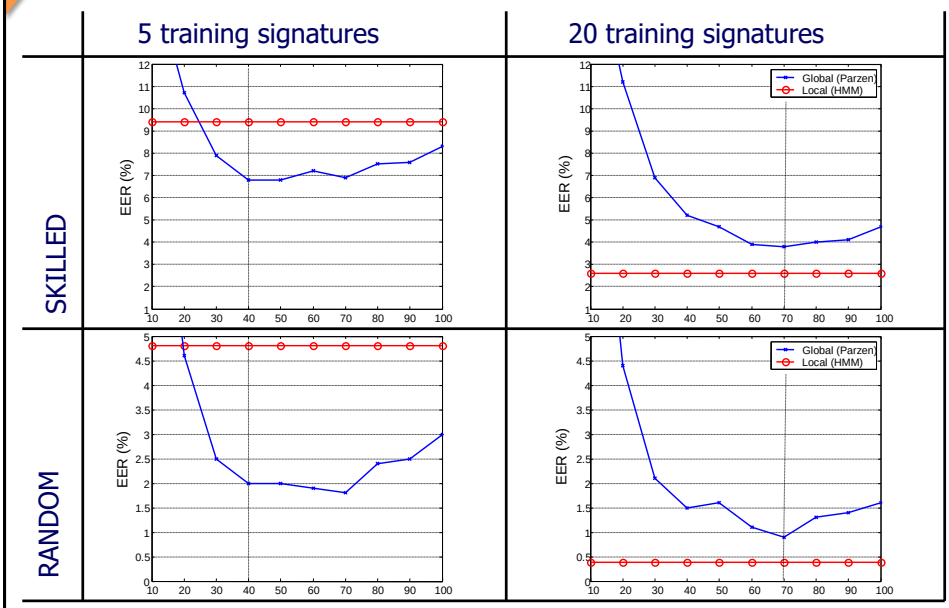
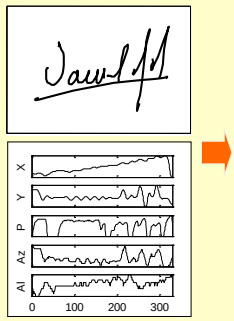
Global Features: Performance (on MCYT DB)



Feature Extraction: Time Sequences



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7	Total acceleration magnitude	$a_n = \sqrt{t_n^2 + c_n^2} = \sqrt{\dot{v}_n^2 + v_n^2\dot{\theta}_n^2}$, where t_n and c_n are respectively the tangential and centripetal acceleration components of the pen motion.
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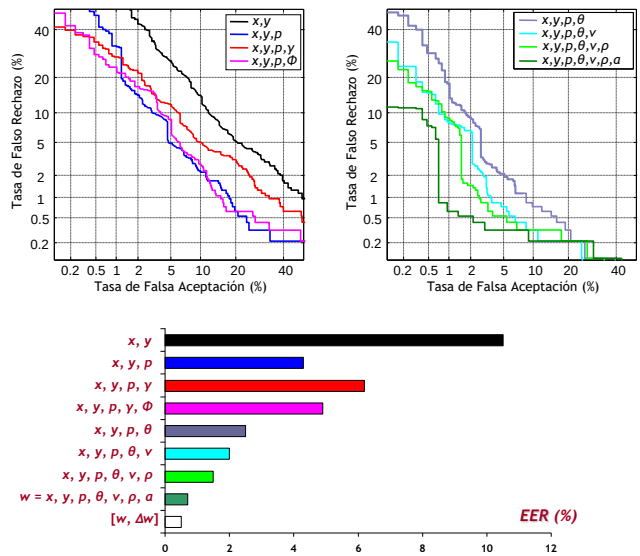
Feature Extraction: Time Sequences



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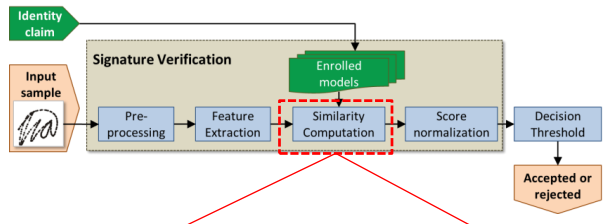
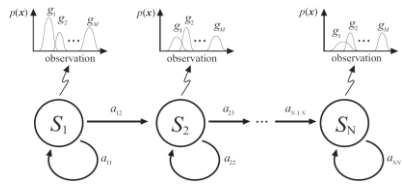
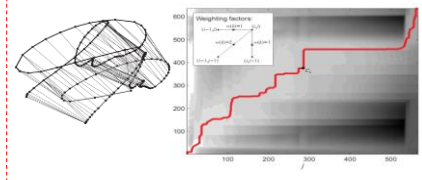
Similarity Computation





Hidden Markov Models (HMM)



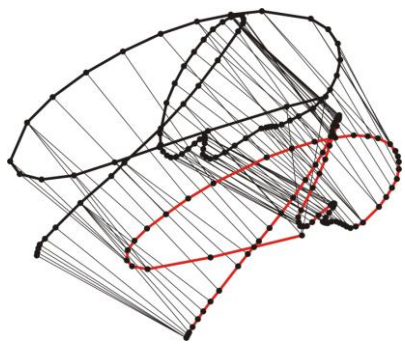
Dynamic Time Warping (DTW)

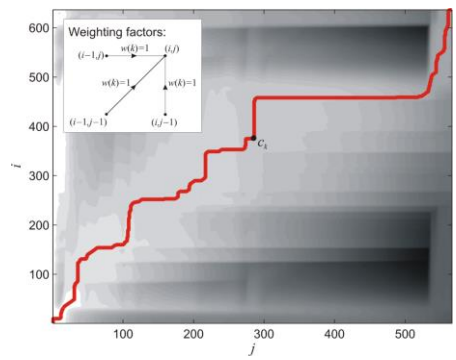
Statistical modeling of signature regions

Point-to-point correspondence

M. Martinez-Diaz, J. Fierrez and S. Hangai, "Signature Matching", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1382-1387, 2015.

Dynamic Time Warping

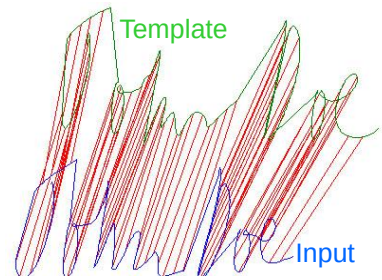




M. Martinez-Diaz, J. Fierrez and S. Hangai, "Signature Matching", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1375-1382, 2015.

Dynamic Time Warping

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



Correspondences found by the DTW algorithm

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**.

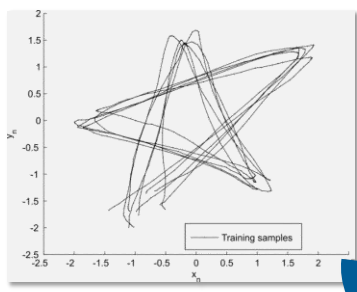
A constant factor *c* multiplied by the Euclidean distance between the two feature vectors is used instead of constant penalties.

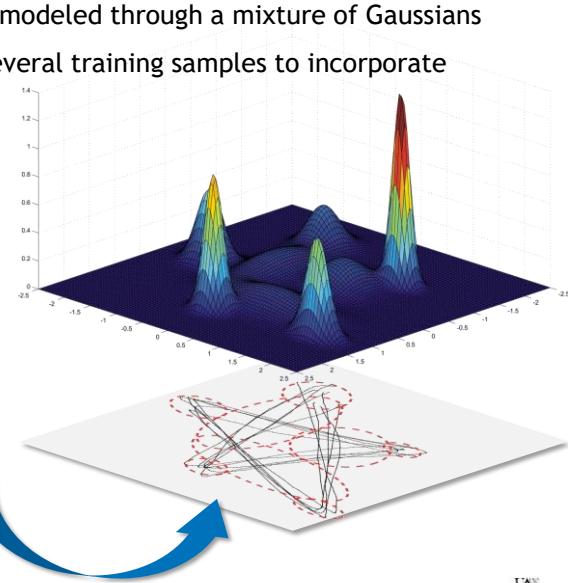
No penalty if the Euclidean distance is small.

M. Martinez-Diaz, J. Fierrez and S. Hangai, "Signature Matching", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1375-1382, 2015.

Stochastic Approach: Gaussian Mixture Models

- Probability of occurrence modeled through a mixture of Gaussians
- Model constructed with several training samples to incorporate sample variability
- Compact representation





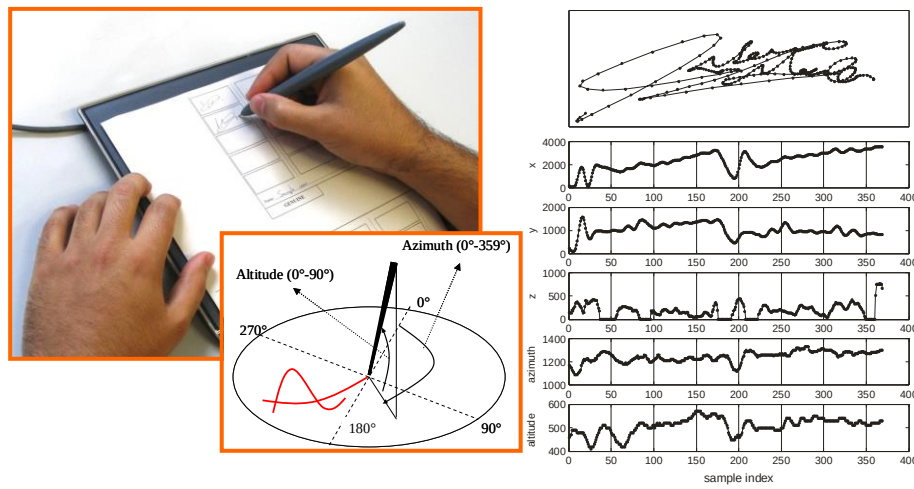
J. Fierrez, J. Ortega-Garcia, et al., "HMM-based on-line signature verification: feature extraction and signature modeling", *Pattern Recognition Letters*, Dec 2007.

Performance Evaluation: Signature Databases

- Databases allow **systematic evaluation** of algorithms
- **Large** publicly available databases are **scarce**, mainly due to
  - **Legal and privacy** issues
  - **Huge resources** needed to capture and process the data
- **MCYT database** has been the most widely used dataset since 2003, reaching performances on 330 subjects below 1% ERR
- **Other existing databases** include SVC, Biomet, MyIdea, Susig
- Recently, new databases containing **additional features** have been captured (e.g, BioSecure Multimodal Database, e-BioSign)

J. Ortega-Garcia, J. Fierrez *et al.*, "MCYT Baseline Corpus: A Multimodal Biometric Database", IEE Proceedings - Vision, Image and Signal Processing, Vol. 150, No. 6, pp. 395-401, December 2003.

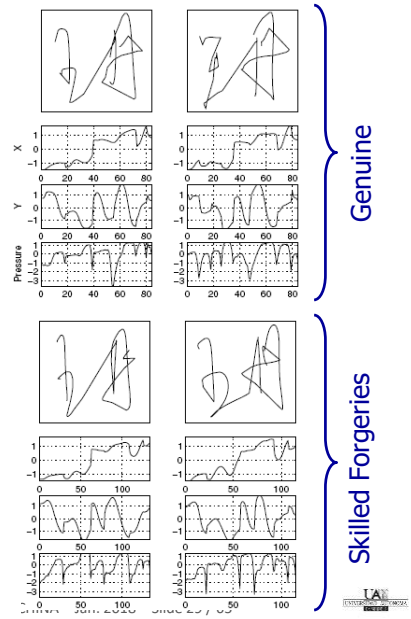
Traditional Acquisition Scenario (2000-2015)



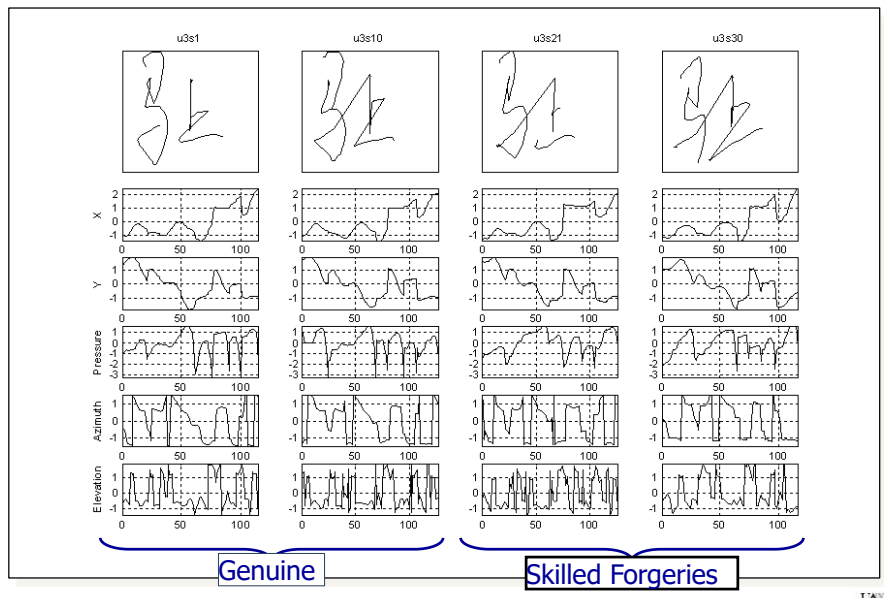
M. Martinez-Diaz and J. Fierrez, "Signature Databases and Evaluation", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1367-1375, 2015.

Benchmarks: SVC 2004

- Challenging data:
  - WACOM Intuos pen tablet with inkless pen (i.e., without visual feedback).
  - Invented signatures different to the ones used in daily life.
  - English and Chinese signatures.
  - Impostors know the dynamics of the signatures being forged.
- Acquisition protocol:
  - 40 subjects.
  - 20 genuine signatures (2 sessions) + 20 skilled forgeries (from five impostors)
- Publicly available: **http://www.cs.ust.hk/svc2004/**

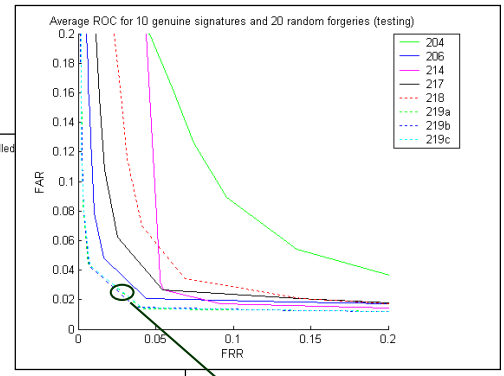


Benchmarks: SVC 2004

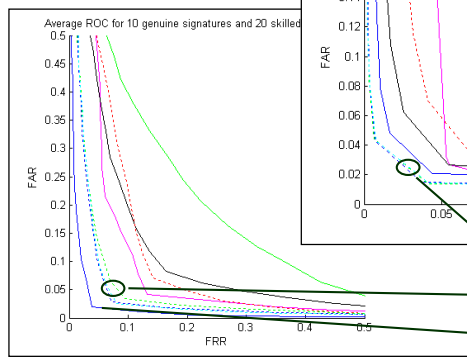


Benchmarks: SVC 2004

SVC-04 random impostors



SVC-04 skilled forgeries



Our HMM system

DTW from Turkey

http://www.cs.ust.hk/svc2004/

Resources: Multimodal Databases w Signature

- **MCYT Database** (Spanish Project 2000-2003)
  - Fingerprint (with human-labeled quality) and on-line **Signature of 330 donors**
- **BiosecurID Database** (Spanish Project 2003-2006)
  - 8 Modalities: speech, iris, face, **Signature** and handwriting (on-line and off-line), fingerprints, hand and keystroking of **400 donors** in 4 acquisition sessions
- **Biosecure Database** (EU Project 2004-2007)
  - 3 Datasets: Web scenario, Office scenario, Mobile scenario
  - **667 donors**

See: https://atvs.ii.uam.es/atvs/databases.jsp

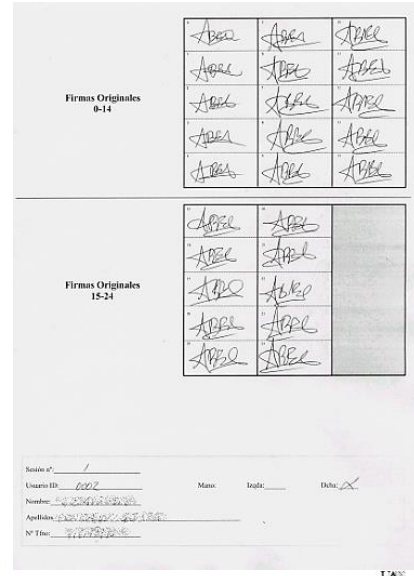
J. Ortega-Garcia, J. Fierrez-Aguilar, et al., "MCYT baseline corpus: A bimodal biometric database", *IEE Proceedings Vision, Image and Signal Processing*, December 2003.

J. Fierrez, J. Galbally, et al., "BiosecurID: A Multimodal Biometric Database", *Pattern Analysis and Applications*, Vol. 13, n. 2, pp. 235-246, May 2010.

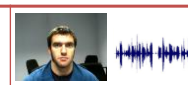
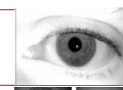
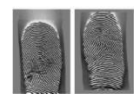
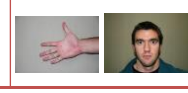
J. Ortega, J. Fierrez, et al., "The BioSecure Multimodal Database", *IEEE Trans. PAMI*, June 2010.

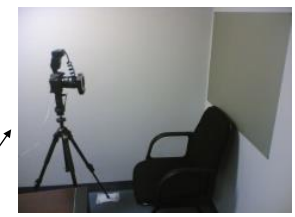
Acquisition Example: MCYT Signature

- Acquisition procedure:
  - WACOM Intuos pen tablet.
  - Ink pen over paper → both on-line and off-line corpus.
  - Restricted size grid guidelines.
- Acquisition protocol:
  - 330 subjects.
  - 25 genuine signatures (five sessions) + 25 skilled forgeries (from five impostors)



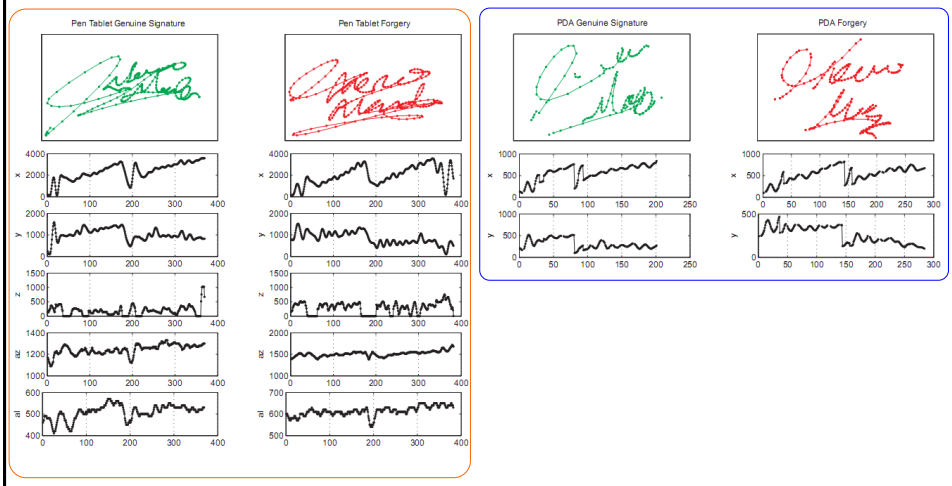
Acquisition Example: Biosecure Multimodal DB

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

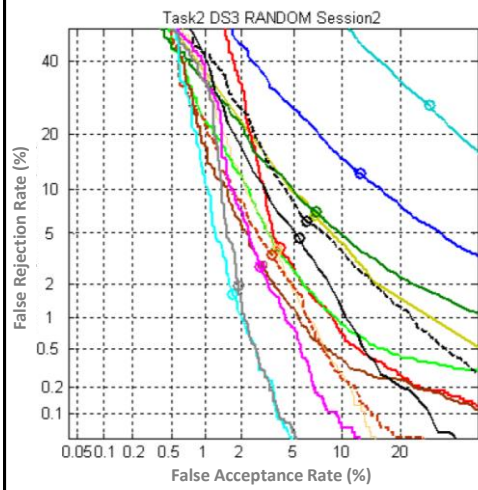


Examples from Biosecure MDB

Tablet **Mobile**



Benchmarks: BSEC 2009

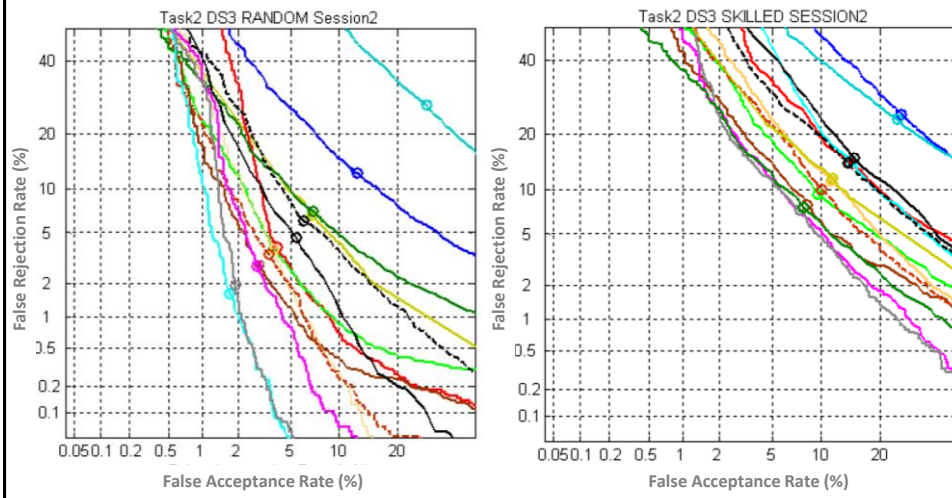


- DTW, HMM and Global Systems
- Score normalization
- Fusion of systems

N. Houmani, et al., "BioSecure signature evaluation campaign (BSEC2009): Evaluating online signature algorithms depending on the quality of signatures", *Pattern Recognition*, March 2012.

Benchmarks: BSEC 2009 - Forgeries

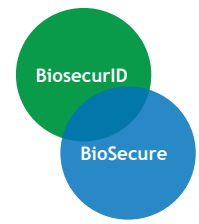
- *Shoulder surfing* (visual access to drawing process)

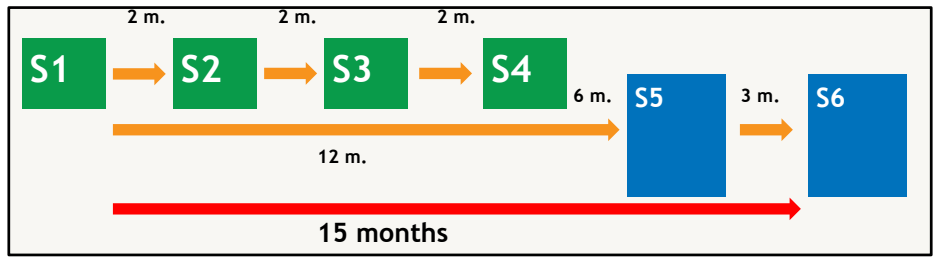


N. Houmani, et al., "BioSecure signature evaluation campaign (BSEC2009): Evaluating online signature algorithms depending on the quality of signatures", *Pattern Recognition*, March 2012.

Template Aging in Signature

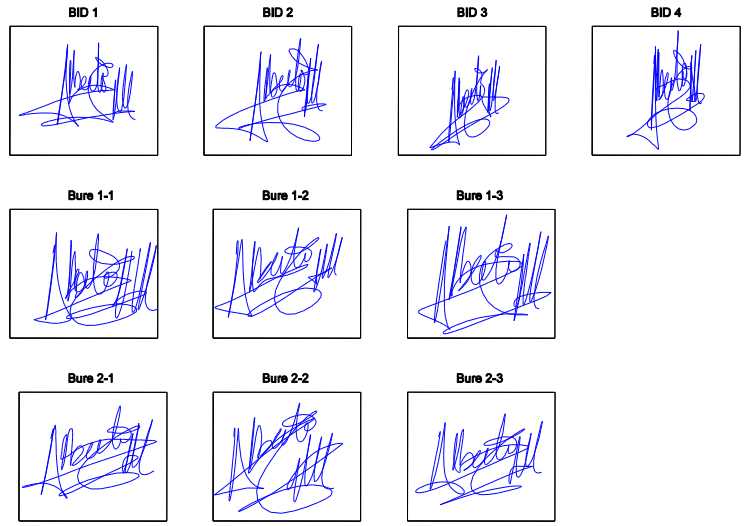
- 29 common users from BiosecureID and Biosecure.
- **6 sessions with a 15-month time span (inter-session).**
- 46 genuine signatures: 4 + 4 + 4 + 4 + 15 + 15
- 10 skilled forgeries per user



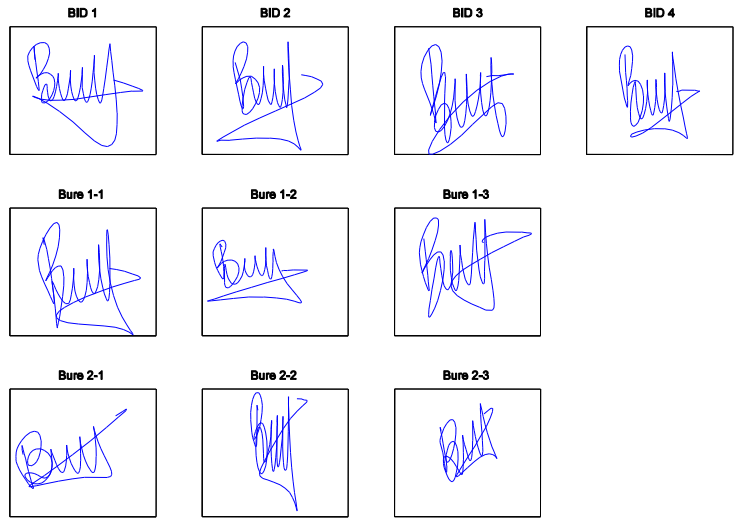


J. Galbally, M. Martinez-Diaz and J. Fierrez, "Aging in Biometrics: An Experimental Analysis on On-line Signature", *PLOS ONE*, July 2013.

Examples of the multi-session DB

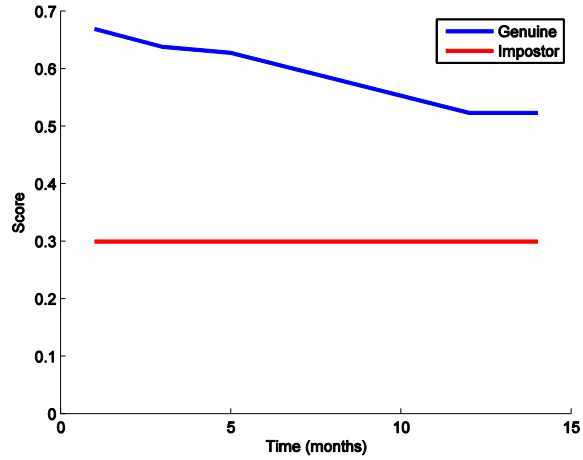


Examples of the multi-session DB



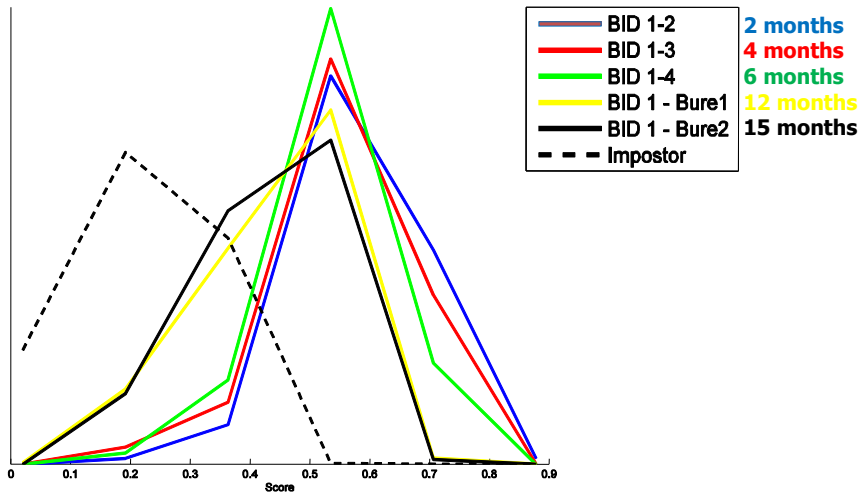
Fixed template, varying test

- Mean genuine score evolution: significant template drift (>6 months)

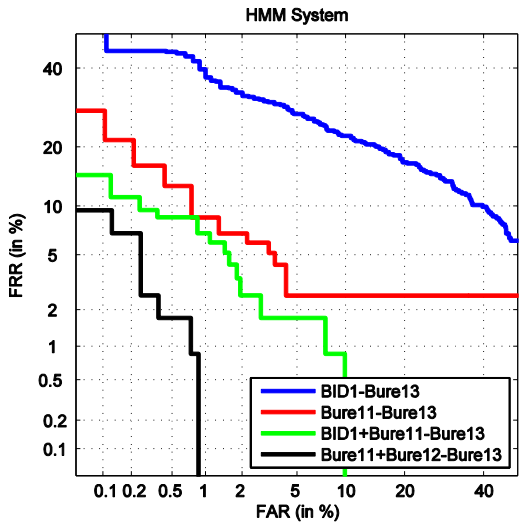


Fixed template, varying test

- Mean genuine score evolution: significant template drift (>6 months)



Template Update: Fixed test, varying enrollment



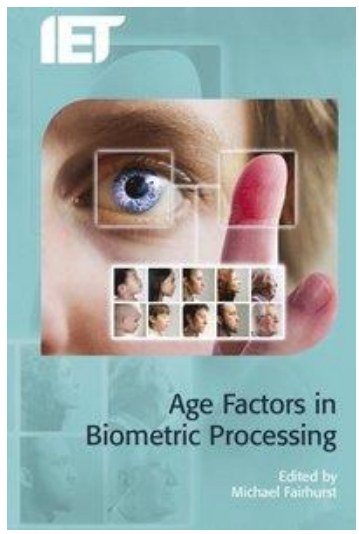
Reference: 12 months (4 sign.)
Complete update (4 sign.)
Mixed update (4 + 4 sign.)
Complete update (8 sign.)

Compared to the reference scenario (12 months train-test):

- Significant improvement by forgetting and retraining using a small set of new training data.
- This can be further improved by not forgetting but adapting using the new data.
- Enough new train data available → better than using old data.

DATA-DEPENDENT PROBLEM, STRONGLY DEPENDENT ON THE AMOUNT OF TRAINING DATA

More on Biometric Aging and Template Update



J. Galbally, M. Martinez-Diaz and J. Fierrez, "Aging in Biometrics: An Experimental Analysis on On-line Signature", *PLOS ONE*, July 2013.

Performance in 2015 → BIOTRACE100

- Accuracy (Signature Long-Term - SLT Database):

	4 training signatures	16 signatures	31 signatures	41 signatures
Random Forg.	97.2 %	99.3 %	99.9 %	99.9 %
Skilled Forg.	88.3 %	93.1 %	95.9 %	99.3 %

- State of the art performance
- Template and system configuration update strategies in order to minimize the aging effect

R. Tolosana, R. Vera-Rodriguez, J. Ortega-Garcia and J. Fierrez, "Preprocessing and Feature Selection for Improved Sensor Interoperability in Online Biometric Signature Verification", *IEEE Access*, Vol. 3, pp. 478 - 489, May 2015.

Banking Industry - Tech Transfer to cecabank

SERVICIOS FINANCIEROS

- Stylus and finger-drawn signature recognition
- Off-line fraud detection and on-line verification
- Semi-automatic tools to aid experts in signature comparison (lawsuits)

Dynamic signature acquisition and management solution already in operation
(> 46k sensors, > 500M operations/year)

e-BioSign DB (2016-2017)

WACOM STU-500

WACOM STU-530

WACOM DTU-1031

SAMSUNG ATIV 7 (WIN8)

SAMSUNG GALAXY NOTE 10.1 (ANDROID)

- 70 users, 2 capturing sessions. 5 devices (4 Wacom, 4 Samsung)
- 8 genuine signatures and 6 skilled forgeries per user and device
- Stylus and finger as writing tools (Samsung)

R. Tolosana, R. Vera-Rodriguez, J. Fierrez, A. Morales, J. Ortega-Garcia, "Benchmarking Desktop and Mobile Handwriting across COTS Devices: the e-BioSign Biometric Database" *PLOS ONE*, 2017.

2017 Performance on e-BioSign (Modern Devices)

	W1	W2	W3	W4	W5
W1	10.7 0.7	7.9 0.8	15.7 5.0	10.7 0.7	10.7 2.1
W2	11.4 1.1	10.0 0.7	16.4 5.7	14.3 0.7	11.4 1.6
W3	9.3 0.3	8.6 0.7	13.6 2.1	11.2 0.0	11.4 1.4
W4	10.0 0.7	9.3 0.9	17.1 5.0	10.7 0.7	11.4 1.4
W5	12.7 1.4	10.0 1.1	16.9 5.0	12.1 0.7	11.2 1.4

$EER_{skilled}$
EER_{random}

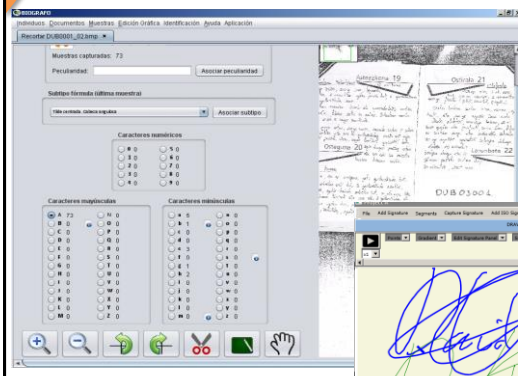
Pen Stylus Input

	W4	W5
W4	19.3 0.7	23.5 0.2
W5	24.2 0.7	22.9 0.3

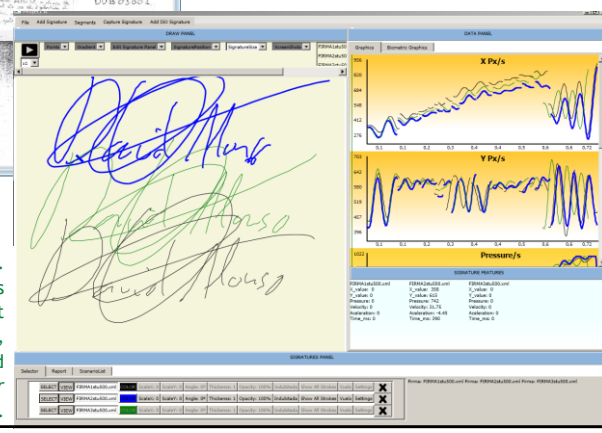
Finger Input

R. Tolosana, R. Vera-Rodriguez, J. Fierrez, A. Morales, J. Ortega-Garcia, "Benchmarking Desktop and Mobile Handwriting across COTS Devices: the e-BioSign Biometric Database", *PLOS ONE*, 2017.

Handwriting/Sign Tech Transfers to Forensic Labs



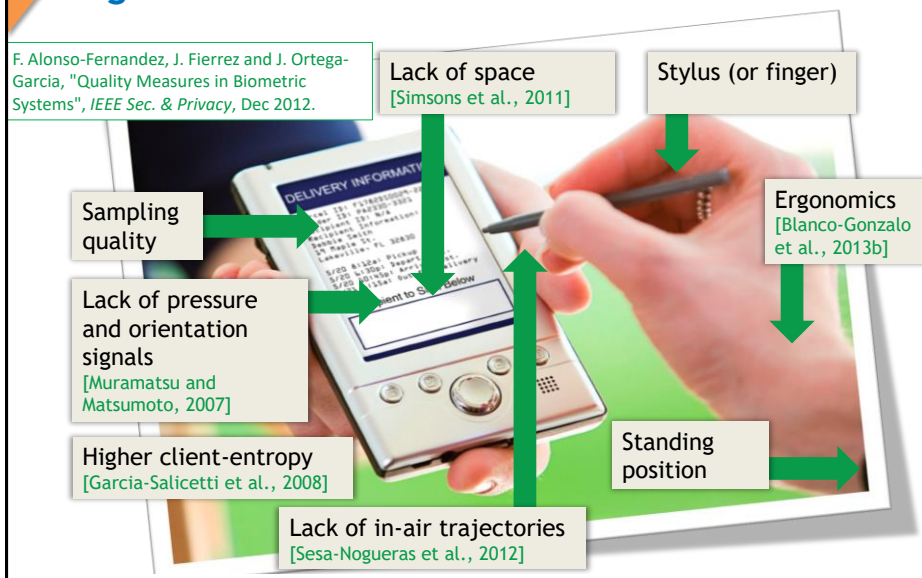
J. Galbally, S. Gonzalez-Dominguez, J. Fierrez and J. Ortega-Garcia, "Biografo: An integrated tool for forensic writer identification", in *Proc. Intl. Workshop on Computational Forensics*, Springer LNCS-8915, November 2015.



R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Dynamic Signatures as Forensic Evidence: A New Expert Tool Including Population Statistics", M. Tistarelli and C.Champod (Eds.), *Handbook of Biometrics for Forensic Science*, Springer, 2017.

Signature in Mobile Devices

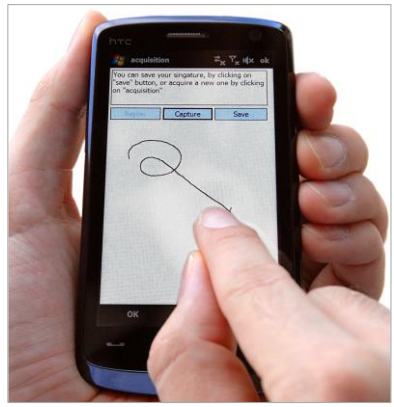
F. Alonso-Fernandez, J. Fierrez and J. Ortega-Garcia, "Quality Measures in Biometric Systems", *IEEE Sec. & Privacy*, Dec 2012.

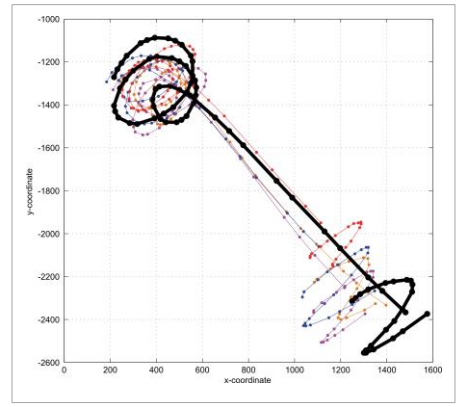


M. Martinez-Diaz, J. Fierrez, R. P. Krish and J. Galbally, "Mobile Signature Verification: Feature Robustness and Performance Comparison", *IET Biometrics*, Dec. 2014.

From Signature to Touch Gestures

- **Graphical Password-based User Authentication with Free-form Doodles**



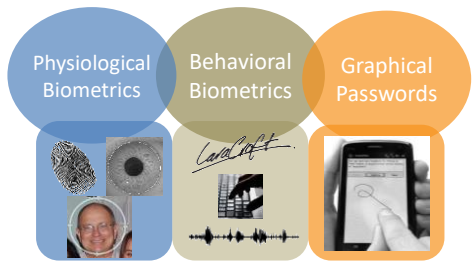


M. Martinez-Diaz, J. Fierrez and J. Galbally, "Graphical Password-based User Authentication with Free-Form Doodles", *IEEE Trans. on Human-Machine Systems*, August 2016.

M. Martinez-Diaz, J. Fierrez, and J. Galbally. "The DooDB graphical password database: Data analysis and benchmark results". *IEEE Access*, September 2013.

Graphical Passwords

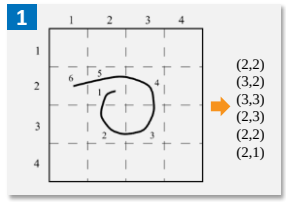
- Gesture-based authentication on touch-screens
- Slow typing in touchscreens
- Biometric-rich gestures
- Revocability



M. Martinez-Diaz, J. Fierrez and J. Galbally, "The DooDB Graphical Password Database: Data Analysis and Benchmark Results", *IEEE Access*, Sept. 2013.

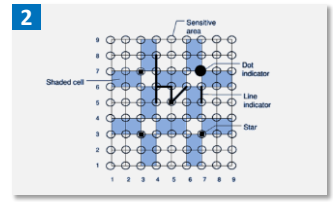
Graphical Passwords: Related Works

1



Draw a Secret [Jermyn *et al.*, 1999]
US Patent 8024775 B2

2



Pass-Go [Tao *et al.*, 2008]

3

Pattern Lock [*Google*]
US Patent 20130047252 A1

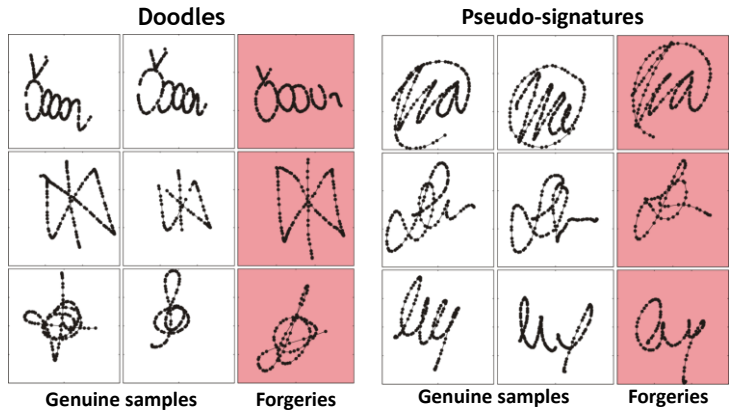
4

Picture Gesture Authentication [*Microsoft*]
US Patent 20130047252 A1

5

Multi-touch gestures [Sae-Bae *et al.*, 2012]
US Patent 20130219490 A1

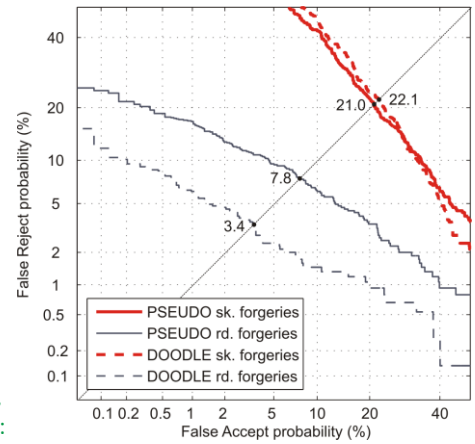
Graphical Examples



M. Martinez-Diaz, J. Fierrez and J. Galbally, "The DooDB Graphical Password Database: Data Analysis and Benchmark Results", *IEEE Access*, Sept. 2013.

Some Initial Results

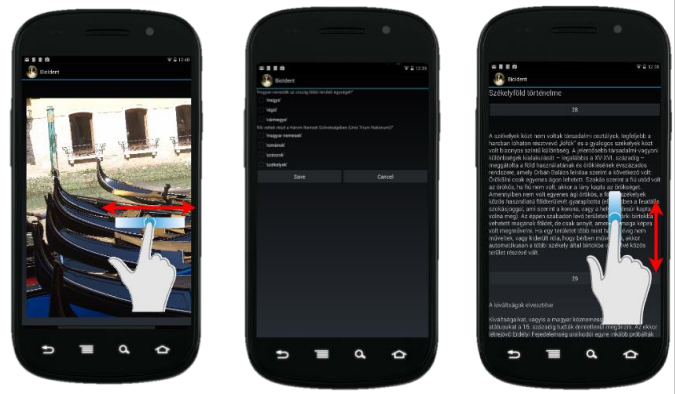
- Verification performance on the validation set
- Just *x*, *y* features
- Score fusion of GMM and DTW



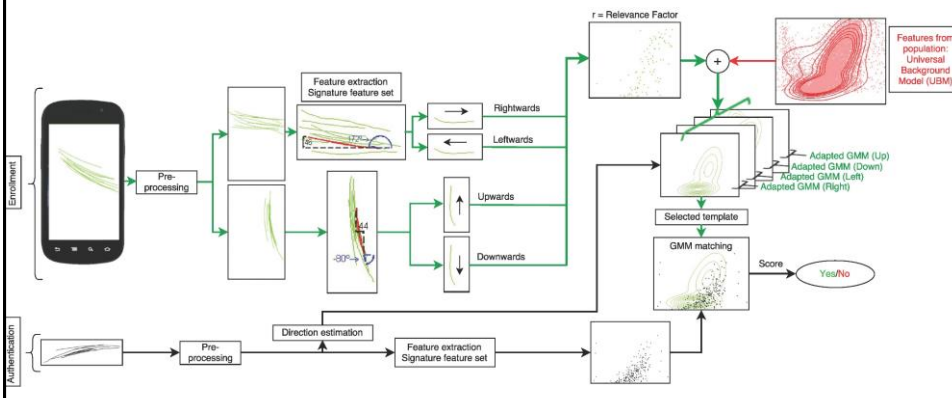
M. Martinez-Diaz, J. Fierrez and J. Galbally, "The DooDB Graphical Password Database: Data Analysis and Benchmark Results", *IEEE Access*, Sept. 2013.

Current Work: Swipe Biometrics

- Continuous user authentication through touch biometrics:
  - Security beyond the entry-point
- Situation:
  - Freely interacting with the touchscreen while reading or viewing images



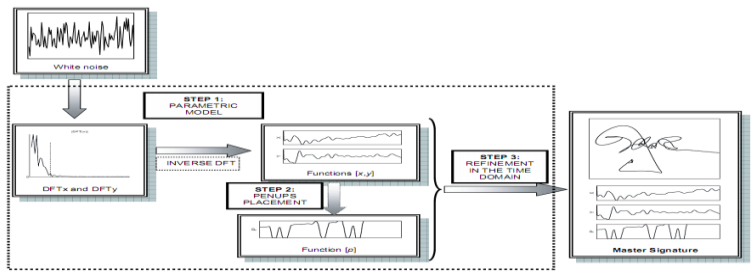
Current Work: Swipe Biometrics



A. Pozo, J. Fierrez, M. Martinez-Diaz, J. Galbally and A. Morales, "Exploring a Statistical Method for Touchscreen Swipe Biometrics", in *Proc. Intl. Carnahan Conference on Security Technology, ICCST 2017*, October 2017.

Other Recent Advances: Synthetic Signature Generation

- Novel signature generation schemes using **data-driven spectral features, or human neuromotor properties**, which generate realistic yet random full *X*, *Y*, and *Pressure* signature signals.
- Useful for improving the training with limited data.



J.Galbally, J. Fierrez, J. Ortega-Garcia and R. Plamondon, "Synthetic on-line signature generation. Part II: Experimental validation", *Pattern Recognition*, Vol. 45, pp. 2622-2632, July 2012.

J. Galbally, et al., "On-Line Signature Recognition Through the Combination of Real Dynamic Data and Synthetically Generated Static Data", *Pattern Recognition*, Sept. 2015.

Other Recent Advances: Template Protection

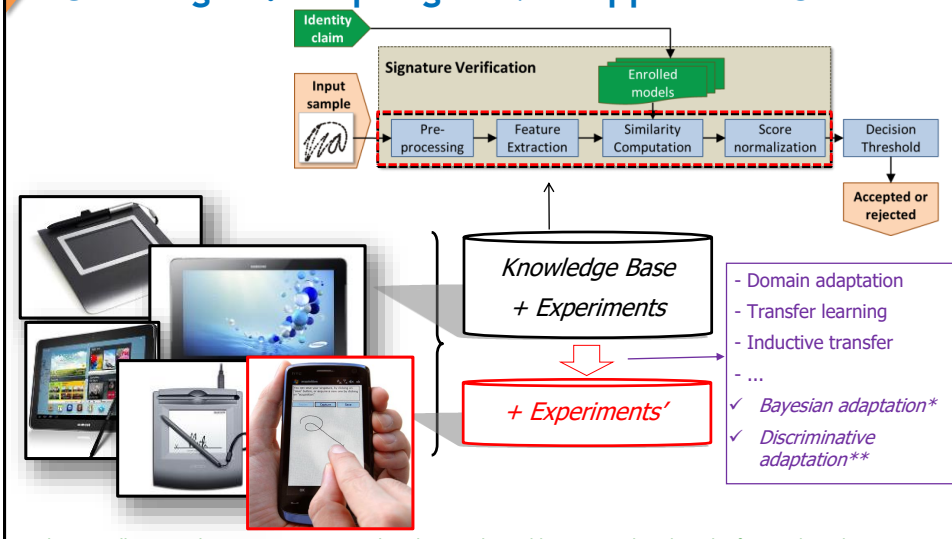
- Biometric data can be compromised if raw signals are stored
- **Template protection schemes** needed to secure user privacy
  - **Biometric cryptosystems:** combination of cryptographic keys and biometric data (e.g., fuzzy vault, fuzzy commitment)
  - **Transform-based schemes**: application of non-invertible functions to the biometric data (e.g., cancelable biometrics)
- **Dealing with variability** is the main challenge in this field

P. Campisi, E. Maiorana, J. Fierrez, J. Ortega-Garcia and A. Neri, "Cancelable Templates for Sequence Based Biometrics with Application to On-Line Signature Recognition", *IEEE Trans. on SMC-A*, May 2010.

M. Gomez-Barrero, J. Galbally, A. Morales and J. Fierrez, "Privacy-Preserving Comparison of Variable-Length Data with Application to Biometric Template Protection", *IEEE Access*, June 2017.

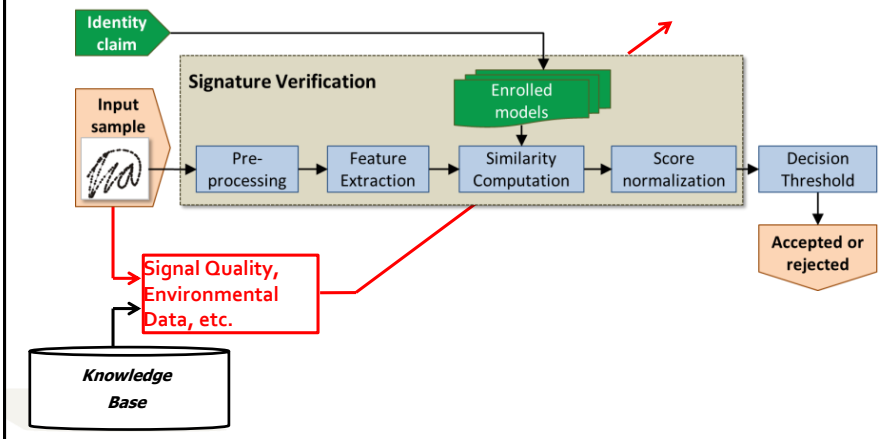
M. Gomez-Barrero, E. Maiorana, J. Galbally, P. Campisi and J. Fierrez, "Multi-Biometric Template Protection Based on Homomorphic Encryption", *Pattern Recognition*, July 2017.

The Future of Behavioral Biometrics Challenge 1: Adapting to New Application Scenarios



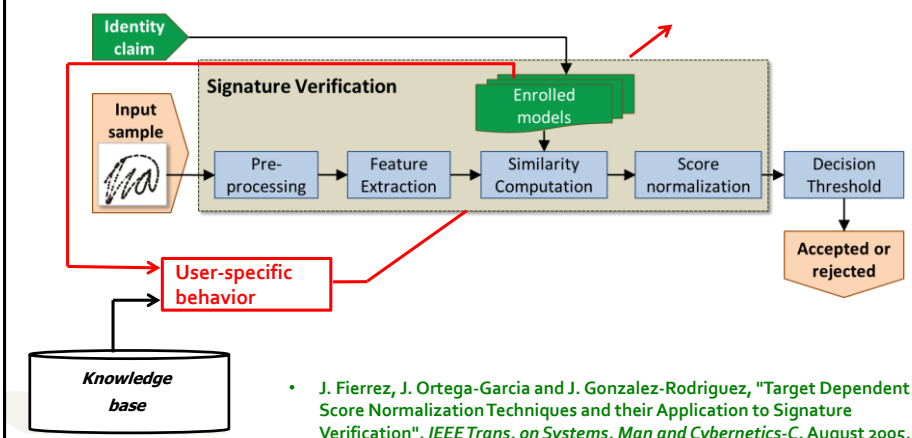
* J. Fierrez-Aguilar, D. Garcia-Romero, J. Ortega-Garcia and J. Gonzalez-Rodriguez, "Bayesian adaptation for user-dependent multimodal biometric authentication", *Pattern Recognition*, August 2005.
**J. Fierrez-Aguilar, D. Garcia-Romero, J. Ortega-Garcia and J. Gonzalez-Rodriguez, "Adapted user-dependent multimodal biometric authentication exploiting general information", *Pattern Recognition Letters*, December 2005.

The Future of Behavioral Biometrics
Challenge 2: Incorporating Contextual Information



- P. Aleksic, M. Ghodsi, et al. "Bringing Contextual Information to Google Speech Recognition", *Interspeech*, 2015.
- F. Alonso-Fernandez, J. Fierrez, et al, "Quality Measures in Biometric Systems", *IEEE Sec. & Privacy*, Dec. 2012.
- F. Alonso-Fernandez, J. Fierrez, *et al.*, "Quality-Based Conditional Processing in Multi-Biometrics: application to Sensor Interoperability", *IEEE Trans. on Systems, Man and Cybernetics A*, Vol. 40, n. 6, pp. 1168-1179, 2010.
- J. Fierrez, et al., "Multiple Classifiers in Biometrics. Part 2: Trends and Challenges", *Information Fusion*, Nov. 2018.

The Future of Behavioral Biometrics
Challenge 3: Adapting to the User (e.g., Aging)

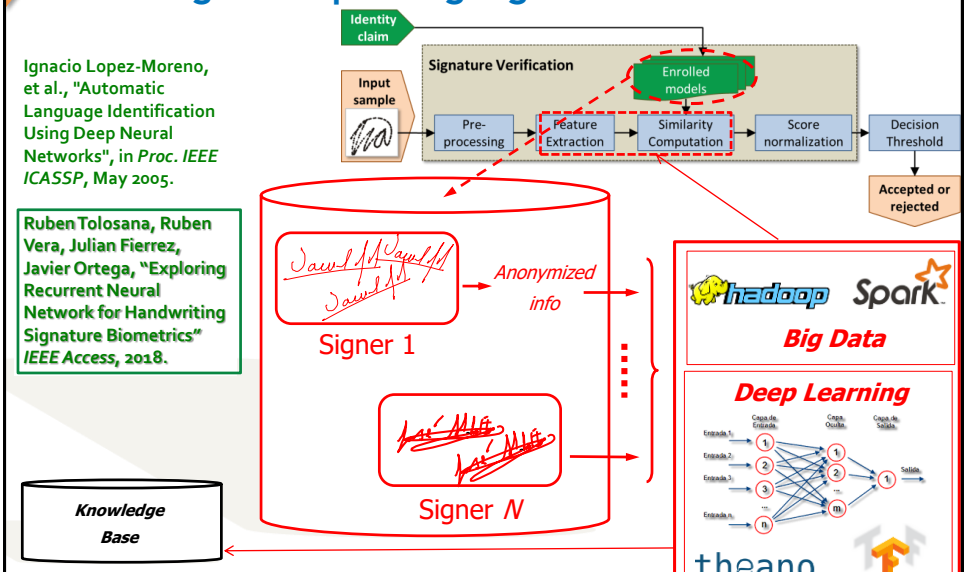


- J. Fierrez, J. Ortega-Garcia and J. Gonzalez-Rodriguez, "Target Dependent Score Normalization Techniques and their Application to Signature Verification", *IEEE Trans. on Systems, Man and Cybernetics-C*, August 2005.
- J. Galbally, M. Martinez-Diaz and J. Fierrez, "Aging in Biometrics: An Experimental Analysis on On-Line Signature", *PLOS ONE*, July 2013.
- J. Fierrez, A. Morales, R. Vera-Rodriguez and D. Camacho, "Multiple Classifiers in Biometrics. Part 2: Trends and Challenges", *Information Fusion*, Nov. 2018.

The Future of Behavioral Biometrics
Challenge 4: Exploiting Big Data

Ignacio Lopez-Moreno, et al., "Automatic Language Identification Using Deep Neural Networks", in *Proc. IEEE ICASSP*, May 2005.

Ruben Tolosana, Ruben Vera, Julian Fierrez, Javier Ortega, "Exploring Recurrent Neural Network for Handwriting Signature Biometrics" *IEEE Access*, 2018.



Signature Biometrics: Conclusions

Revocability	User intra-variability
Easy of use, user acceptance	Multi-sample training
Less sensor-interoperability issues	Model updating
Easy to integrate at low-cost	Multilevel strategies
Continuous ID	Data scarcity

- Mature technology
- Major role in on-line, mobile, and legacy applications
- User convenience to drive application development
- Room for substantial industry-applicable research

Signature Biometrics

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