


# Signature and Touchscreen Biometrics


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<http://biometrics.eps.uam.es>



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## Funding Acknowledgements


### Public



### Private



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- Introduction to Behavioral and Signature Biometrics
- System Model: Pre-processing, Features, Matching
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- Biometric Aging and Template Update
- A Note on Tech Transfers to Industry
- Handwriting, Touchscreen and Multimodal Mobile Biometrics
- Handwriting Generation, Privacy, e-Health Applications
- The Future of Behavioral Biometrics

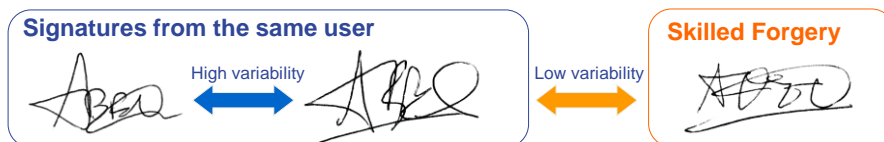
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## Introduction

- 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



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## Introduction

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



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## Behavioral Biometrics

- Human activity patterns are clearly established 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

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## Active Authentication by DARPA

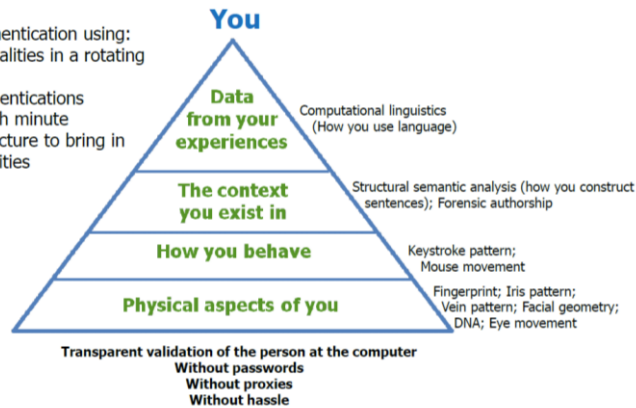


Solution: **Active Authentication**

An open solution that provides **meaningful** and **continual** authentication to DoD's computer systems leveraging that which makes up **you**

Continuous authentication using:

- Multiple modalities in a rotating fashion
- Multiple authentications initiated each minute
- Open architecture to bring in future modalities



12/8/2011

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## Signature as Behavioral Pattern

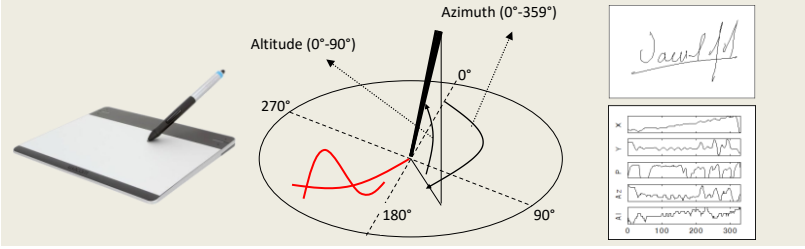
- Human interaction permits transparent authentication
- Make use of existing input channels, no added specific sensors:
  - Handwriting (tablets and pads)
  - Mouse dynamics
- Other sources of variability (sensor, session) included into behavior pattern modelling / compensation
- Fully revocable patterns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

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On-line / Dynamic



Off-line / Static

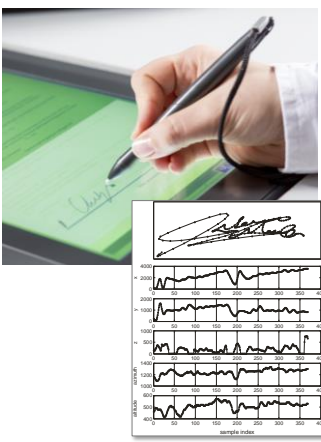


J. Fierrez, J. Ortega-Garcia, et al., "HMM-based on-line signature verification: feature extraction and signature modeling", *Pattern Recognition Letters*, Vol. 28, n. 16, Dec. 2007.

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.

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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.

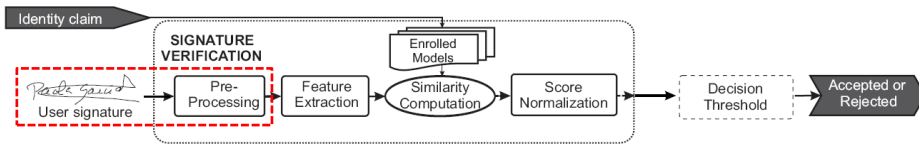
M. Martinez-Diaz and J. Fierrez, "Signature Databases and Evaluation", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1367-1375, 2015.

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## 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.

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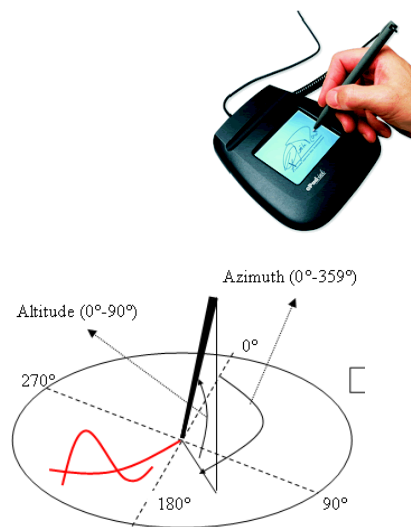
## Signature Acquisition: Input Data

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)
- ...



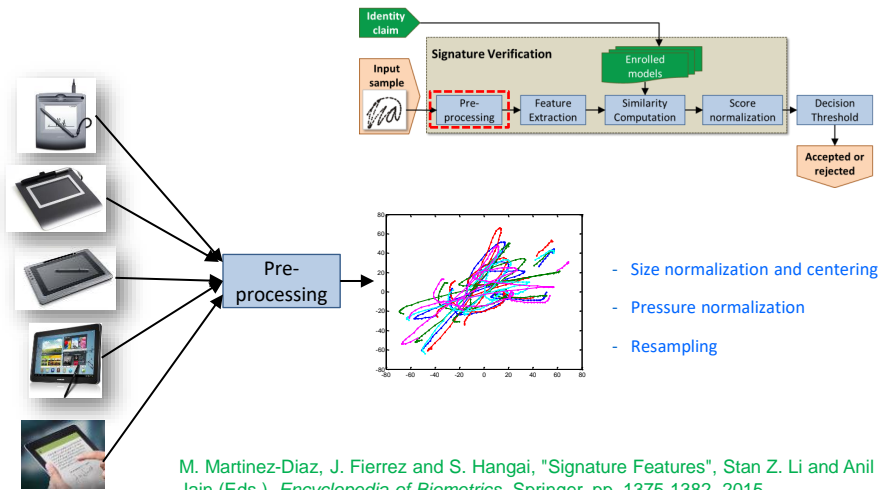
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## Signature Pre-Processing

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

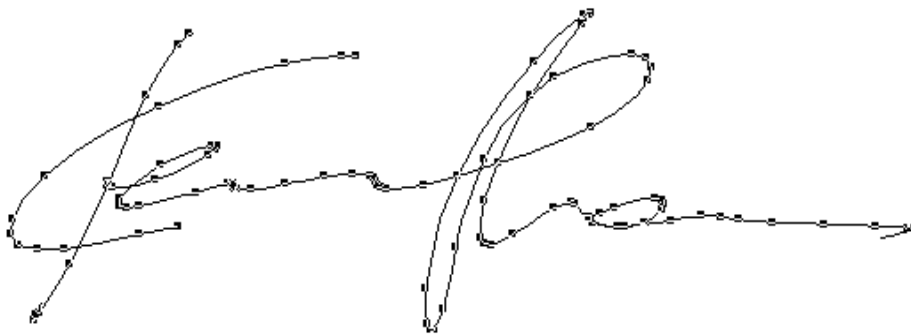


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## Pre-Processing: Re-Sampling



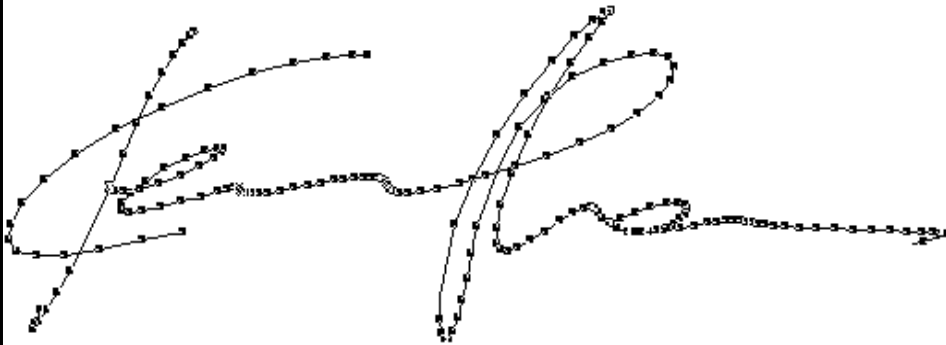
M. Martinez-Diaz, J. Fierrez and S. Hangai, "Signature Features", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1375-1382, 2015.

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## Pre-Processing: Re-Sampling



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.

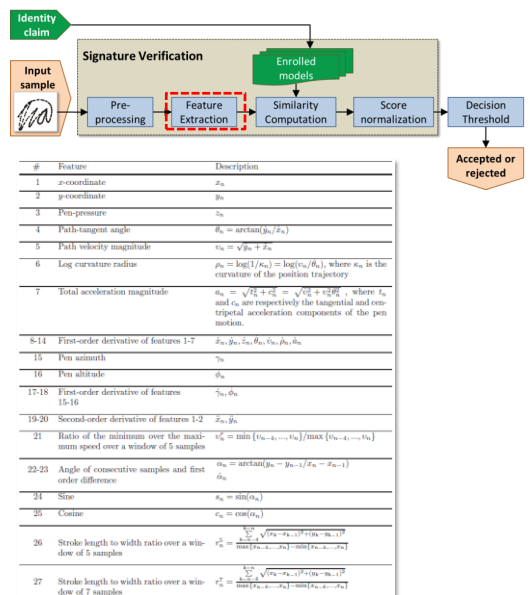
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## Feature Extraction

#	Feature Description	#	Feature Description
1	signature total duration $T_s$	2	(pen-down duration $T_{pd}$ )/ $T_s$
3	(lat $t_{(pen-up)}$ )/ $T_s$	4	$T_{(p_2 > 0)}/T_s$
5	$T_{(p_2 < 0)}/T_s$	6	$T_{(p_2 > 0)}/T_s$
7	$T_{(p_2 < 0)}/T_s$	8	$T_{(p_2 > 0)}/T_s$
9	$T_{(p_2 < 0)}/T_s$	10	$T_{(p_2 > 0)}/T_s$
11	$T_{(p_2 < 0)}/T_s$	12	$T_{(p_2 > 0)}/T_s$
13	$T_{(p_2 < 0)}/T_s$	14	$T_{(p_2 > 0)}/T_s$
15	$T_{(p_2 < 0)}/T_s$	16	(lat $t_{(pen-up)}$ )/ $T_s$
17	(lat $t_{(pen-up)}$ )/ $T_s$	18	(lat $t_{(pen-up)}$ )/ $T_s$
19	(lat $t_{(pen-up)}$ )/ $T_s$	20	(lat $t_{(pen-up)}$ )/ $T_s$
21	$T_{(curvature > threshold_{cur})}/T_s$	22	(lat $t_{(pen-up)}$ )/ $T_s$
23	(2nd $t_{(curvature)}$ )/ $T_s$	24	(2nd $t_{(curvature)}$ )/ $T_s$
25	(2nd $t_{(curvature)}$ )/ $T_s$	26	(2nd $t_{(curvature)}$ )/ $T_s$
27	(average velocity $v$ )/ $v_{max}$	28	$N(v_2 = 0)$
29	$N(v_2 = 0)$	30	$N(v_{2max})$
31	$N(v_{2max})$	32	(velocity max $v$ )/ $v_{max}$
33	(centripetal acceleration run $a_c$ )/ $a_{cmax}$	34	(centripetal acceleration run $a_c$ )/ $a_{cmax}$
35	(centripetal acceleration run $a_c$ )/ $a_{cmax}$	36	(centripetal acceleration run $a_c$ )/ $a_{cmax}$
37	(velocity correlation $v_{xy}$ )/ $v_{xmax}$	38	(standard deviation of $v_x$ )
39	(standard deviation of $v_y$ )	40	(standard deviation of $v_x$ )
41	(standard deviation of $v_y$ )	42	(standard deviation of $v_x$ )
43	$J_x$	44	$J_y$
45	$J_{xmax}$	46	$J_{ymax}$
47	$J_{xmax}$	48	$J_{ymax}$
49	$t_{(x,max)}/T_s$	50	$t_{(x,max)}/T_s$
51	$t_{(y,max)}/T_s$	52	$t_{(y,max)}/T_s$
53	$N(\text{sign changes of } dx/dt \text{ and } dy/dt)$	54	$N(\text{sign changes of } dx/dt \text{ and } dy/dt)$
55	$\theta(\text{initial direction})$	56	$\theta(\text{initial direction})$
57	$\theta(\text{lat pen-down to lat pen-up})$	58	$\theta(\text{lat pen-down to lat pen-up})$
59	$\theta(\text{2nd pen-down to 2nd pen-up})$	60	$\theta(\text{2nd pen-down to 2nd pen-up})$
61	$\theta(\text{lat pen-down to lat pen-up})$	62	$\theta(\text{lat pen-down to lat pen-up})$
63	direction histogram $a_1$	64	direction histogram $a_1$
65	direction histogram $a_2$	66	direction histogram $a_2$
67	direction histogram $a_3$	68	direction histogram $a_3$
69	direction histogram $a_4$	70	direction histogram $a_4$
71	direction change histogram $a_1$	72	direction change histogram $a_1$
73	(max distance between points)/ $A_{min}$	74	(max distance between points)/ $A_{min}$
75	( $r_{min} - r_{max}$ )/ $\Delta r$	76	( $r_{min} - r_{max}$ )/ $\Delta r$
77	( $r_{min} - r_{max}$ )/ $\Delta r$	78	( $r_{min} - r_{max}$ )/ $\Delta r$
79	( $r_{min} - r_{max}$ )/ $\Delta r$	80	( $r_{min} - r_{max}$ )/ $\Delta r$
81	( $r_{min} - r_{max}$ )/ $\Delta r$	82	( $r_{min} - r_{max}$ )/ $\Delta r$
83	( $r_{min} - r_{max}$ )/ $\Delta r$	84	( $r_{min} - r_{max}$ )/ $\Delta r$
85	( $r_{min} - r_{max}$ )/ $\Delta r$	86	( $r_{min} - r_{max}$ )/ $\Delta r$
87	( $r_{min} - r_{max}$ )/ $\Delta r$	88	( $r_{min} - r_{max}$ )/ $\Delta r$
89	( $r_{min} - r_{max}$ )/ $\Delta r$	90	( $r_{min} - r_{max}$ )/ $\Delta r$
91	( $r_{min} - r_{max}$ )/ $\Delta r$	92	( $r_{min} - r_{max}$ )/ $\Delta r$
93	( $r_{min} - r_{max}$ )/ $\Delta r$	94	( $r_{min} - r_{max}$ )/ $\Delta r$
95	( $r_{min} - r_{max}$ )/ $\Delta r$	96	( $r_{min} - r_{max}$ )/ $\Delta r$
97	( $r_{min} - r_{max}$ )/ $\Delta r$	98	( $r_{min} - r_{max}$ )/ $\Delta r$
99	( $r_{min} - r_{max}$ )/ $\Delta r$	100	( $r_{min} - r_{max}$ )/ $\Delta r$

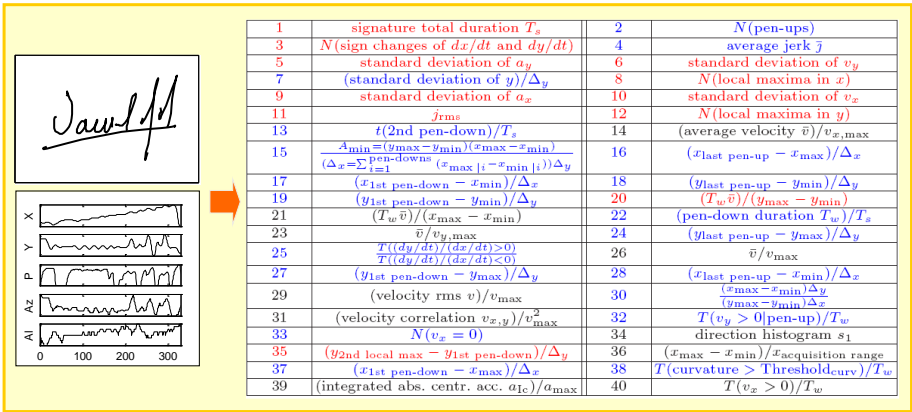


M. Martinez-Diaz, J. Fierrez, et al., "Mobile Signature Verification: Feature Robustness and Performance Comparison", *IET Biometrics*, Dec 2014.

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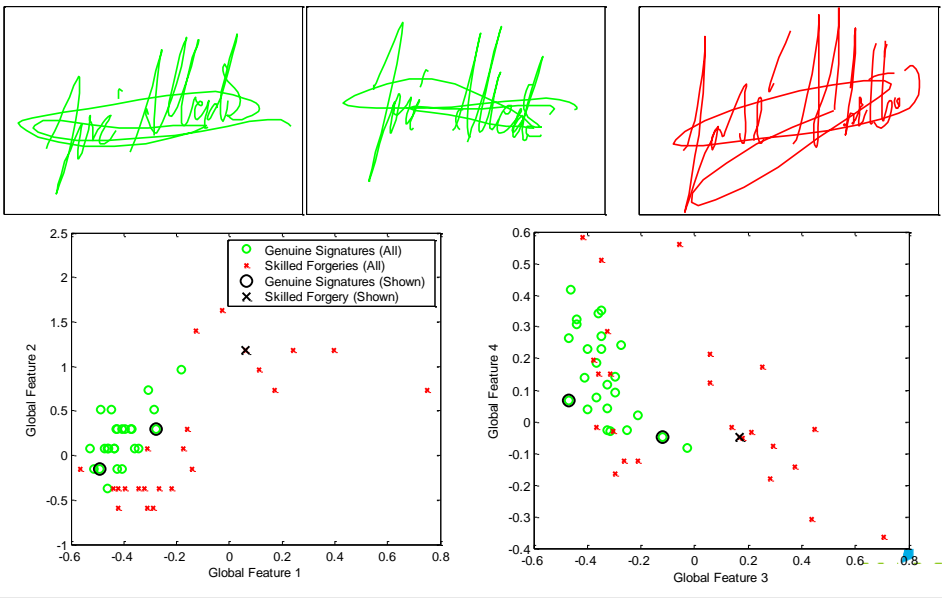
Feature Extraction: Global Features



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

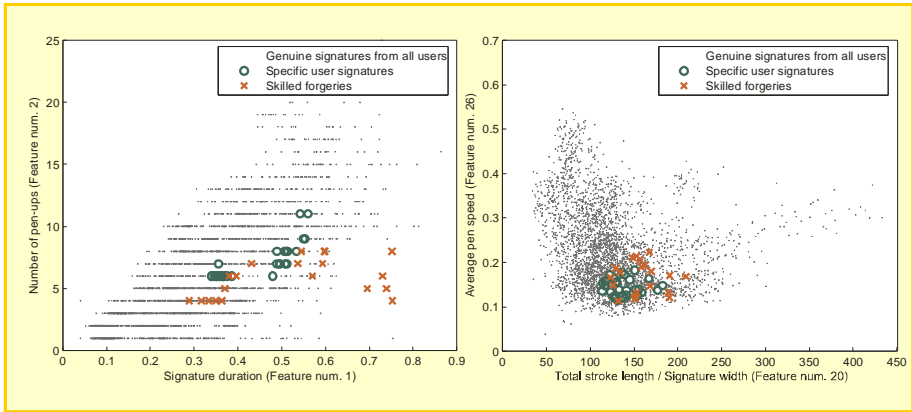
17

Feature Extraction: Global Features Example



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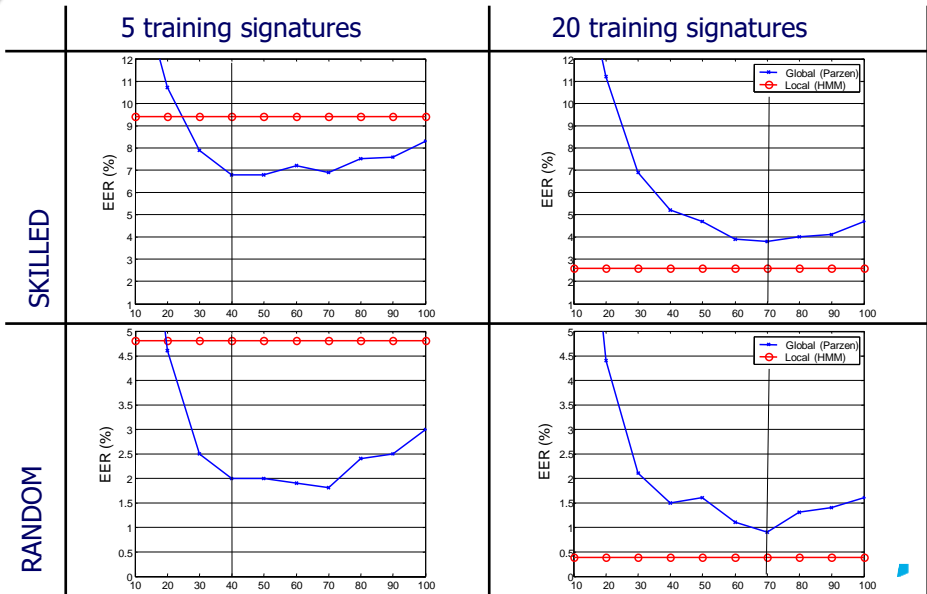
Feature Extraction: Global Features Example



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

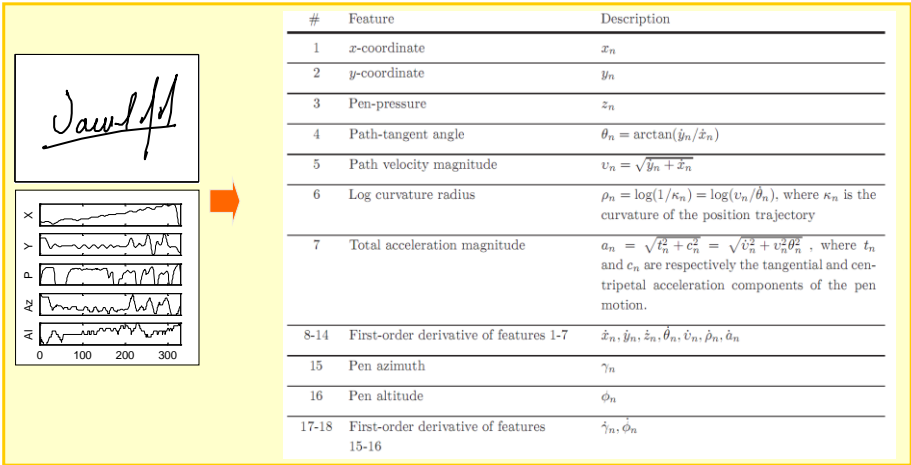
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Global Features: Performance (on MCYT DB)



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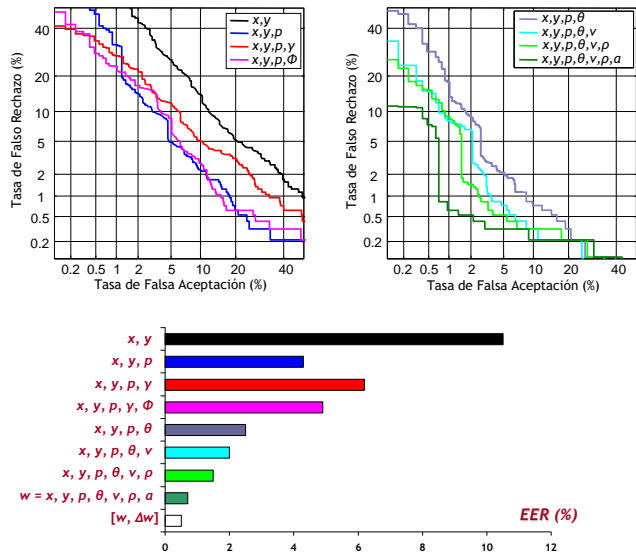
Feature Extraction: Time Sequences



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.

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Feature Extraction: Time Sequences



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.

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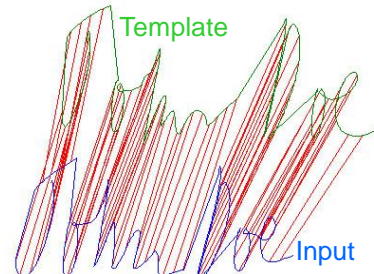
## Dynamic Time Warping

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

$D$  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

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.

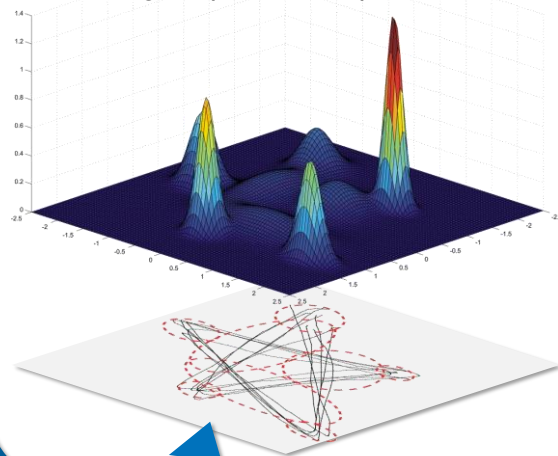
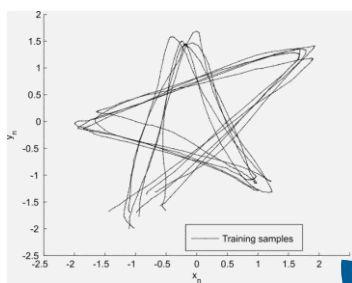
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## Stochastic Approach: Gaussian Mixture Models

- 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.

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## 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, Myldea, Susig
- Recently, new databases containing **additional features** have been captured (e.g, BioSecure Multimodal Database, e-BioSign)

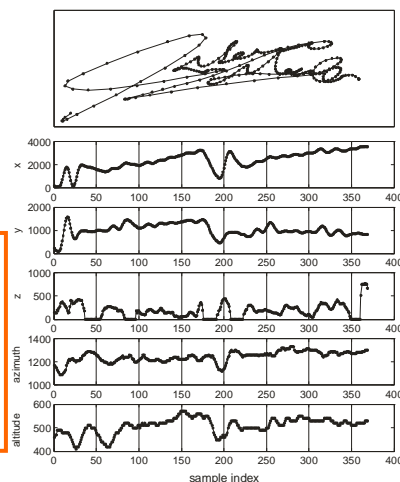
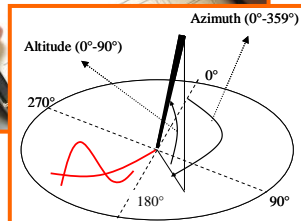
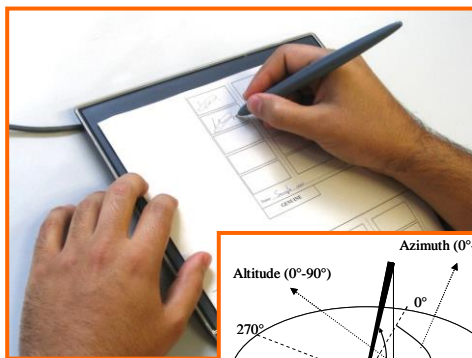
J. Ortega-Garcia, J. Fierrez *et al.*, "MCYT Baseline Corpus: A Multimodal Biometric Database", IEE Proceedings - Vision, Image and Signal Processing, Vol. 150, No. 6, pp. 395-401, December 2003.

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## 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.

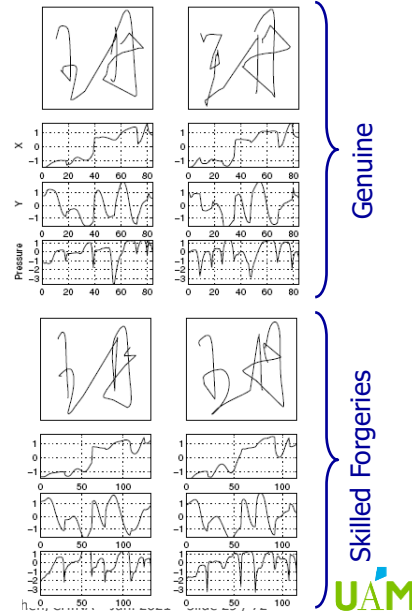
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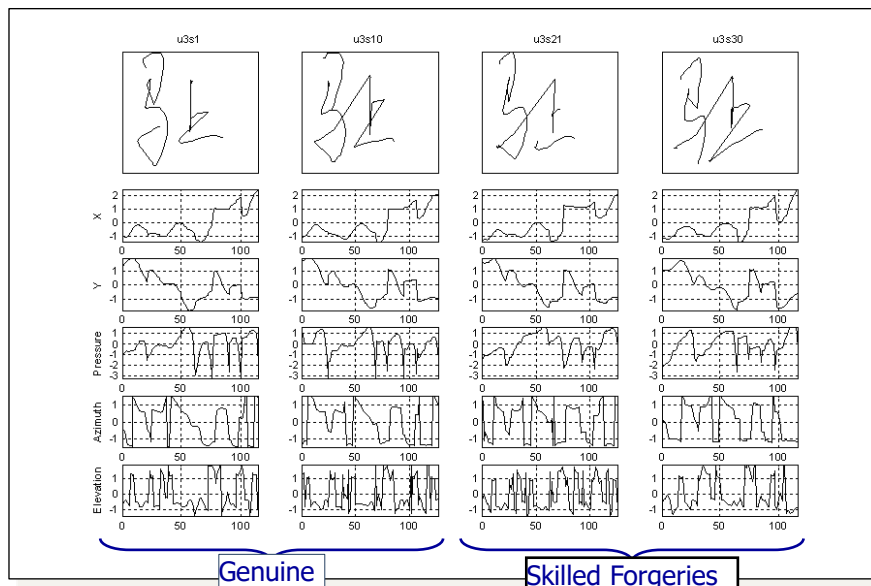
## Benchmarks: SVC 2004

- 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/>



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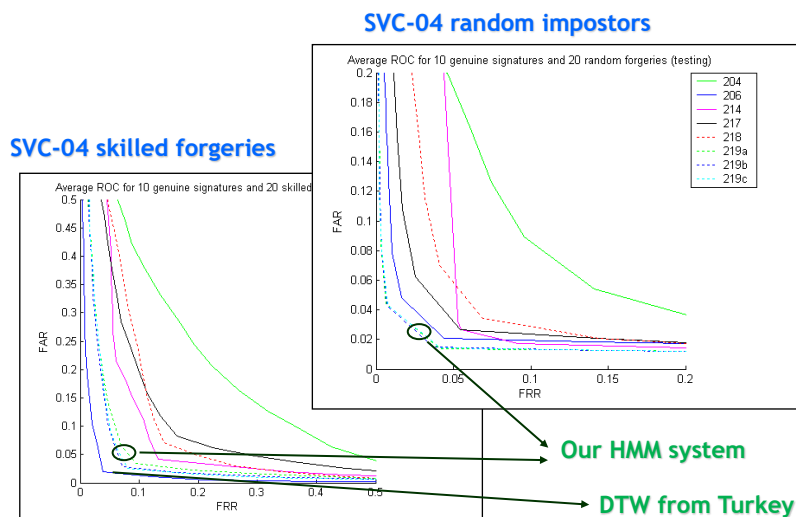
## Benchmarks: SVC 2004



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## Benchmarks: SVC 2004



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

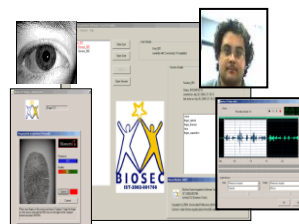
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## Resources: Multimodal Databases w Signature

- **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", *IEEE 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.

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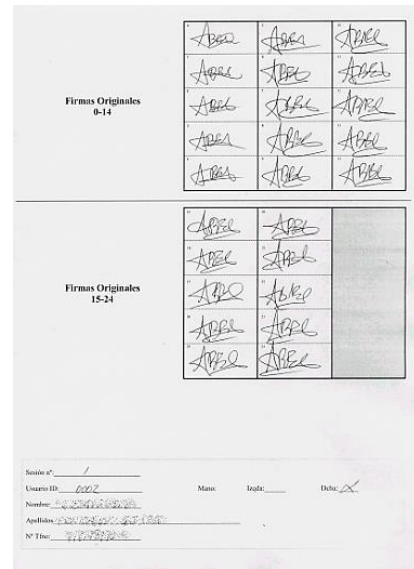


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## Acquisition Example: MCYT Signature

- 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)



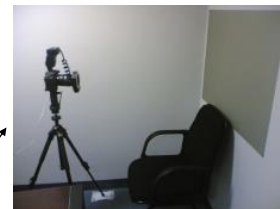
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## Acquisition Example: Biosecure Multimodal DB

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



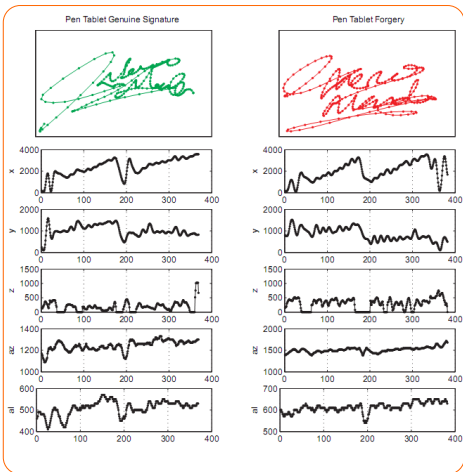
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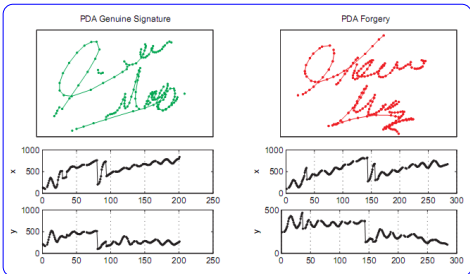
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## Examples from Biosecure MDB

### Tablet



### Mobile

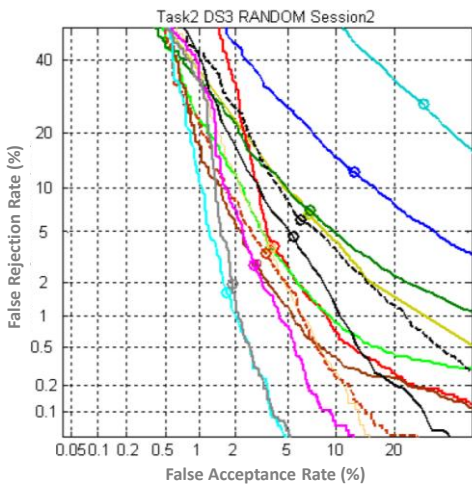


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## Benchmarks: BSEC 2009



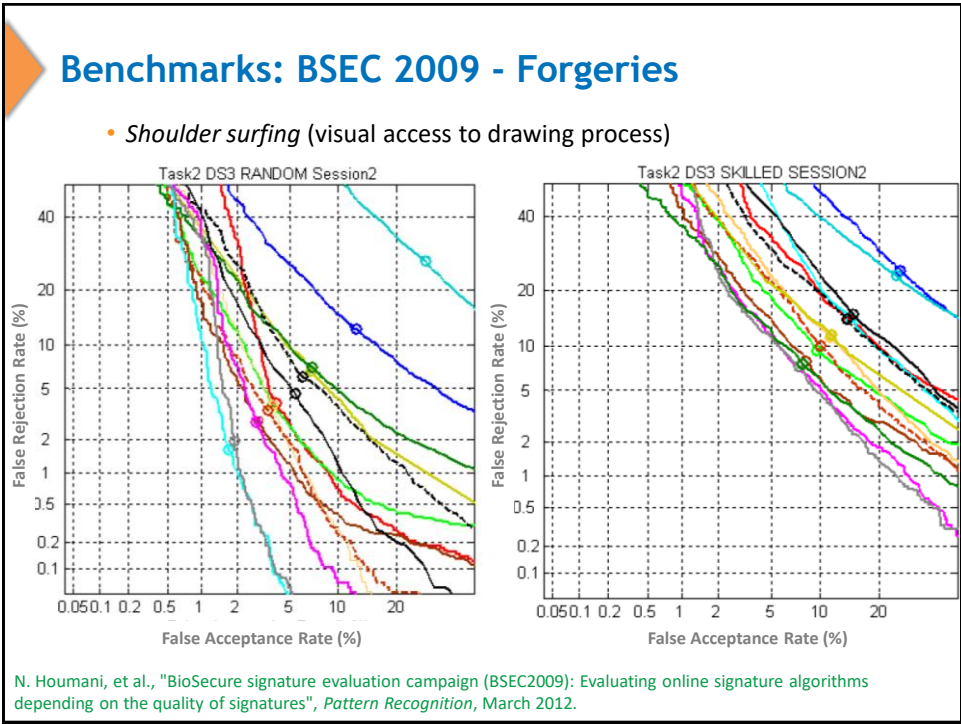
- DTW, HMM and Global Systems
- Score normalization
- Fusion of systems

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

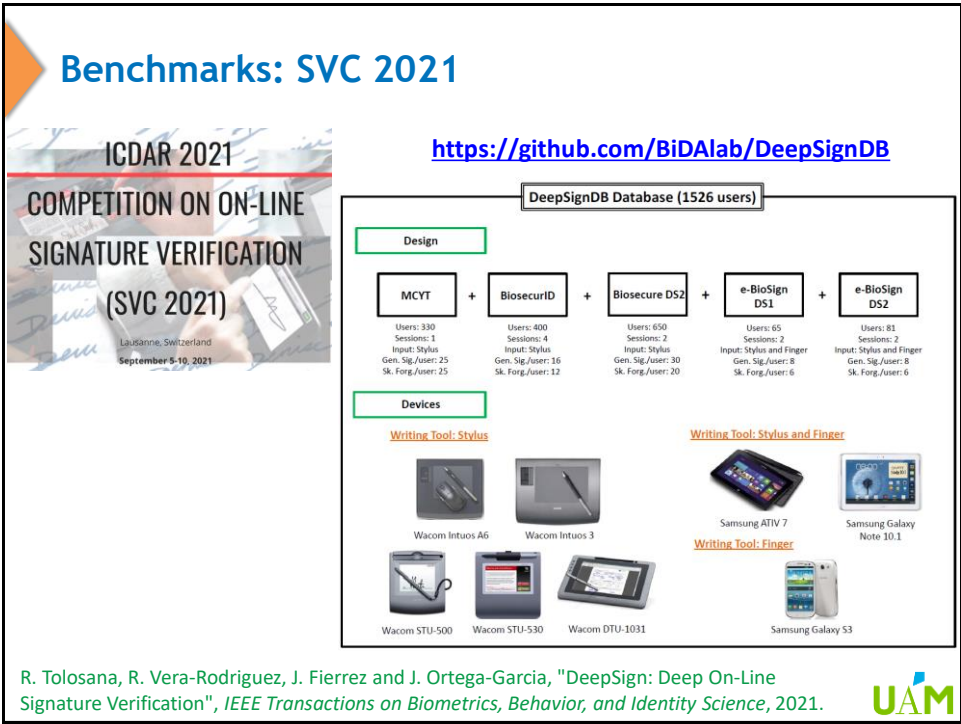
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Template Aging in Signature

- 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

BiosecureID

BioSecure

S1

S2

S3

S4

S5

S6

2 m.

2 m.

2 m.

6 m.

3 m.

12 m.

15 months

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

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Examples of the multi-session DB

BID 1

BID 2

BID 3

BID 4

Bure 1-1

Bure 1-2

Bure 1-3

Bure 2-1

Bure 2-2

Bure 2-3

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

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### Examples of the multi-session DB

BID 1

BID 2

BID 3

BID 4

Bure 1-1

Bure 1-2

Bure 1-3

Bure 2-1

Bure 2-2

Bure 2-3

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

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### Fixed template, varying test

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

Score

0.7

0.6

0.5

0.4

0.3

0.2

0.1

0

0

5

10

15

Time (months)

Genuine

Impostor

Time (months)	Genuine Score	Impostor Score
0	0.67	0.30
5	0.63	0.30
10	0.55	0.30
15	0.52	0.30

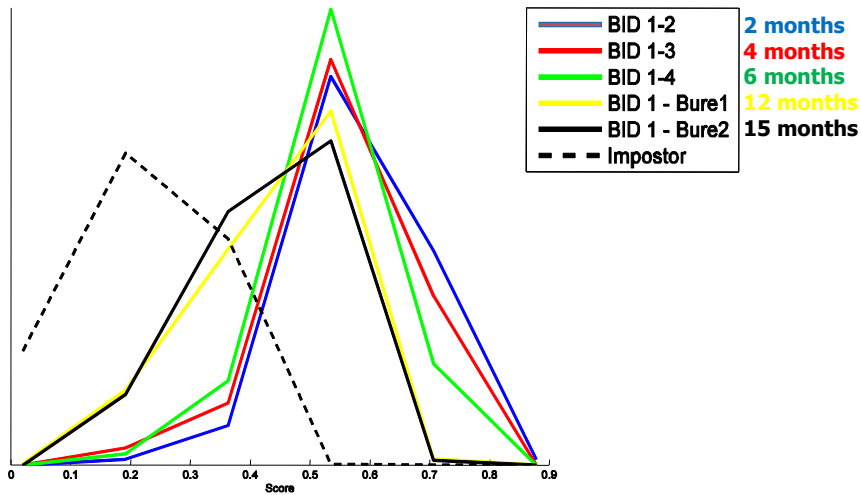
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## Fixed template, varying test

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

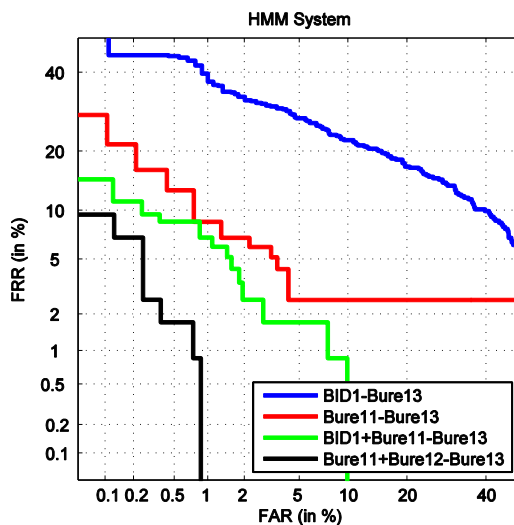


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## Template Update: Fixed test, varying enrollment



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.

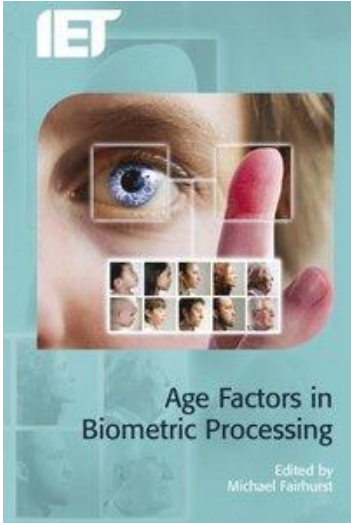
DATA-DEPENDENT PROBLEM,  
 STRONGLY DEPENDENT ON THE  
 AMOUNT OF TRAINING DATA

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More on Biometric Aging and Template Update



Age Factors in Biometric Processing  
Edited by Michael Fairhurst

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

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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.

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## 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)



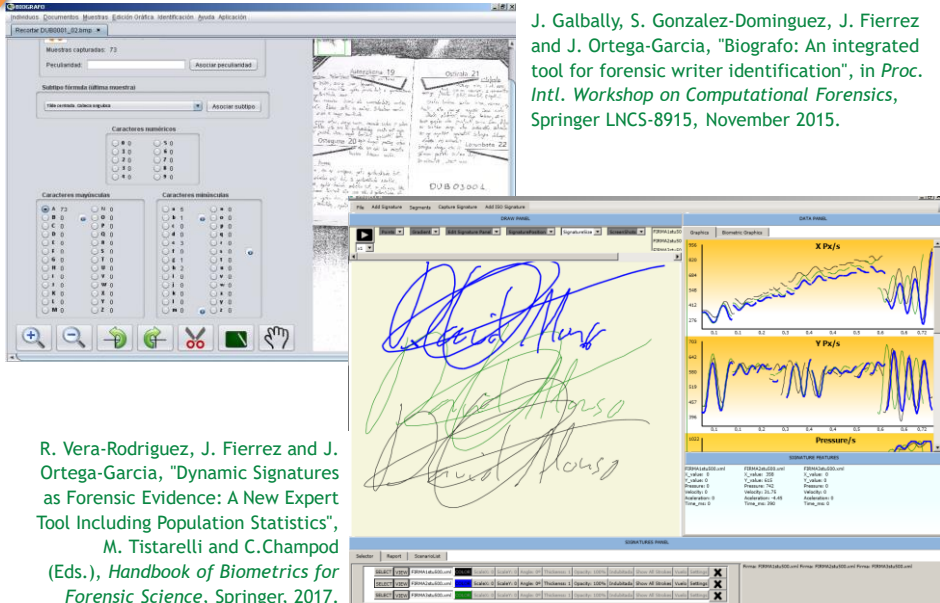
Dynamic signature acquisition and management solution already in operation  
(> 46k sensors, > 500M operations/year)

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## 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.

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### Signature in Mobile Devices

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

Lack of space [Simmons et al., 2011]

Stylus (or finger)

Ergonomics [Blanco-Gonzalo et al., 2013b]

Sampling quality

Lack of pressure and orientation signals [Muramatsu and Matsumoto, 2007]

Higher client-entropy [Garcia-Salicetti et al., 2008]

Standing position

Lack of in-air trajectories [Sesa-Nogueras et al., 2012]

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

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### e-BioSign DB (2016-2017)



- 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.

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Performance on e-BioSign (2017)

	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	EER <sub>skilled</sub> EER <sub>random</sub>
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	

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

Pen Stylus Input

Finger Input

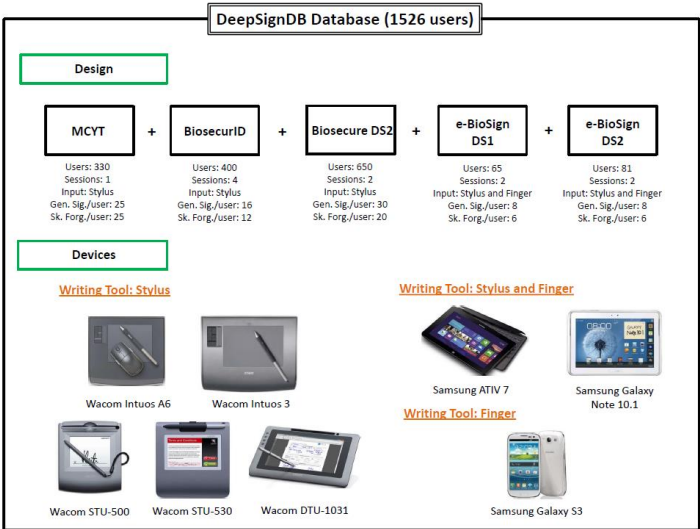
R. Tolosana, R. Vera-Rodriguez, J. Fierrez, A. Morales, J. Ortega-Garcia, "Benchmarking Desktop and Mobile Handwriting across COTS Devices: the e-BioSign Biometric Database", PLOS ONE, 2017.

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DeepSignDB (2018-2020)



R. Tolosana, R. Vera-Rodriguez, J. Fierrez, A. Morales and J. Ortega-Garcia, "Do You Need More Data? The DeepSignDB On-Line Handwritten Signature Biometric Database", in Proc. ICDAR, September 2019.

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## Deep Learning applied to Signature Biometrics

TABLE I: Comparison of different deep learning approaches for on-line signature verification.

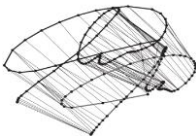
Study	Classifiers	Database Name	# Users	# Train Users	Experimental Protocol Input	# Train Sig.	Performance (EER)
Otte <i>et al.</i> (2014) [20]	LSTM	SigComp2011	20	20	Stylus	12	Skilled = 23.8%
Tolosana <i>et al.</i> (2018) [21]	BLSTM/BGRU	BiosecurID	400	300	Stylus	1	Skilled = 6.8% Random = 5.4%
						4	Skilled = 5.5% Random. = 2.9%
Lai and Jin (2018) [22]	GARU	MCYT	100	80	Stylus	5	Skilled = 1.8% Random = 0.2%
		Mobisig	83	70	Finger	5	Skilled = 10.9% Random = 0.6%
		e-BioSign	65	30	Stylus	4	Skilled = 6.9% Random = 0.4%
Ahrabian and Babaali (2018) [23]	LSTM Autoencoder	SigWiComp2013	31	11	Stylus	5	Skilled = 8.7% Random = Unknown
Wu <i>et al.</i> (2019) [24]	CNNs + DTW	MCYT	100	50	Stylus	5	Skilled = 2.4% Random = Unknown
Li <i>et al.</i> (2019) [25]	LSTM	BiosecurID	132	110	Stylus	1	Skilled = 3.7% Random = 1.9%
		MCYT	100	Unknown	Stylus	1	Skilled = 10.5% Random = Unknown
		SCUT-MMSIG	50	Unknown	Stylus	1	Skilled = 13.9% Random = Unknown
		Mobisig	83	Unknown	Stylus	1	Skilled = 16.1% Random = Unknown
Sekhar <i>et al.</i> (2019) [26]	CNNs	MCYT	100	95	Stylus	1	Skilled = 93.9% Acc.
		SVC	40	35	Stylus	1	Skilled = 77.0% Acc.
Proposed	TA-RNNs	DeepSignDB	1526	1084	Stylus	1	Skilled = 4.2% Random = 1.5%
						4	Skilled = 3.3% Random = 0.6%
					Finger	1	Skilled = 13.8% Random = 1.8%
						4	Skilled = 11.3% Random = 1.0%

R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "DeepSign: Deep On-Line Signature Verification", *IEEE Transactions on Biometrics, Behavior, and Identity Science*, 2021.



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## DeepSign: Results (2019)



DTW

EER (%)

1vs1

4vs1

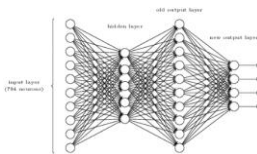
Skilled Forgeries

10.17

7.75

Development: BiosecurID (300 users)

Evaluation: BiosecurID (100 users)



DeepSign

EER (%)

1vs1

4vs1

Skilled Forgeries

3.90

3.40

Development: DeepSign (1084 users)

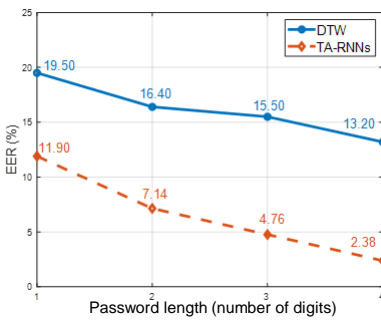
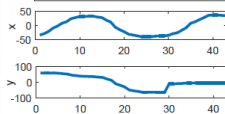

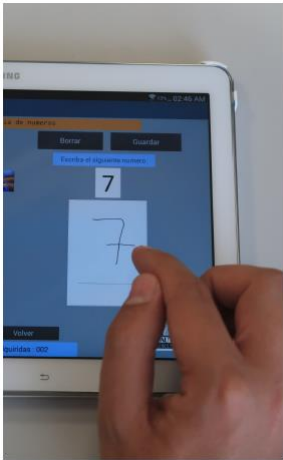
Evaluation: BiosecurID (100 users)

R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "DeepSign: Deep On-Line Signature Verification", *IEEE Transactions on Biometrics, Behavior, and Identity Science*, 2021.



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## From Signature to Handwritten Passwords




Password length (number of digits)	DTW EER (%)	TA-RNNs EER (%)
1	19.50	11.90
2	16.40	7.14
3	15.50	4.76
4	13.20	2.38

R. Tolosana, R. Vera-Rodriguez and J. Fierrez, "BioTouchPass: Handwritten Passwords for Touchscreen Biometrics", *IEEE Transactions on Mobile Computing*, 2020.

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Unsupervised Scenario



94 different smartphone models

# MobileTouchDB Database


217 users

6 different acquisition sessions


S1 ..... S6

Acquisition Time >= 3 weeks


Sensor Information



72 different characters



Different acquisition conditions

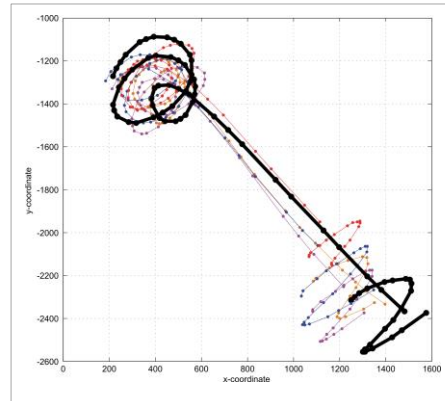
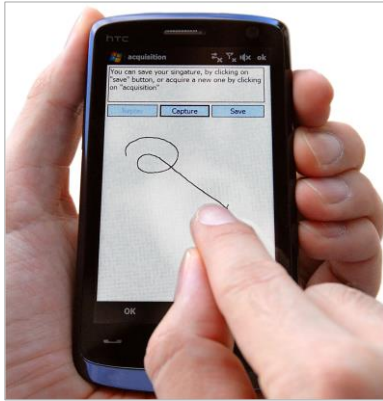


[Tolosana et al., "MobileTouchDB: Mobile Touch Character Database in the Wild and Biometric Benchmark", *Proc. CVPRw*, 2019]

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## From Signature to Touch Gestures

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



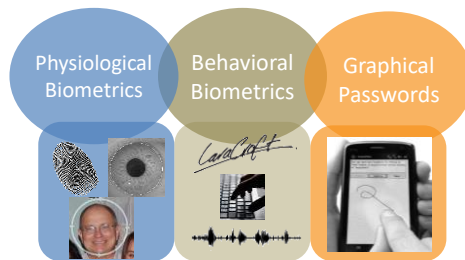
M. Martinez-Diaz, J. Fierrez and J. Galbally, "Graphical Password-based User Authentication with Free-Form Doodles", *IEEE Trans. on Human-Machine Systems*, August 2016.

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

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## Graphical Passwords

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



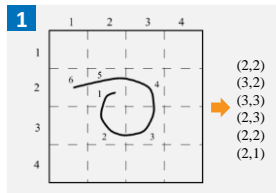
M. Martinez-Diaz, J. Fierrez and J. Galbally, "The DooDB Graphical Password Database: Data Analysis and Benchmark Results", *IEEE Access*, Sept. 2013.

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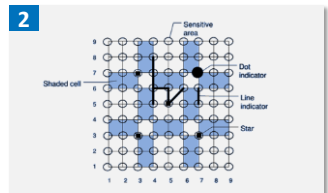
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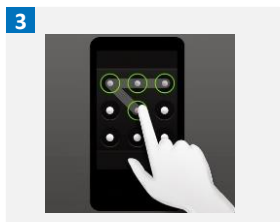
## Graphical Passwords: Related Works



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



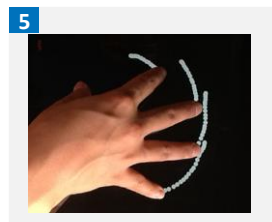
**Pass-Go** [Tao et al., 2008]



**Pattern Lock** [Google]  
US Patent 20130047252 A1



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



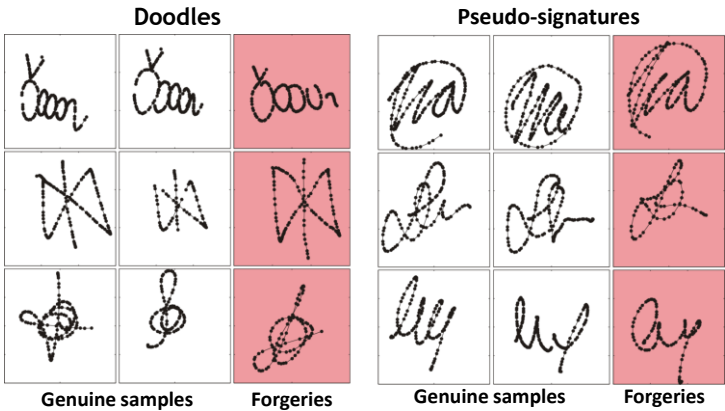
**Multi-touch gestures** [Sae-Bae et al., 2012]  
US Patent 20130219490 A1

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## Graphical Examples



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

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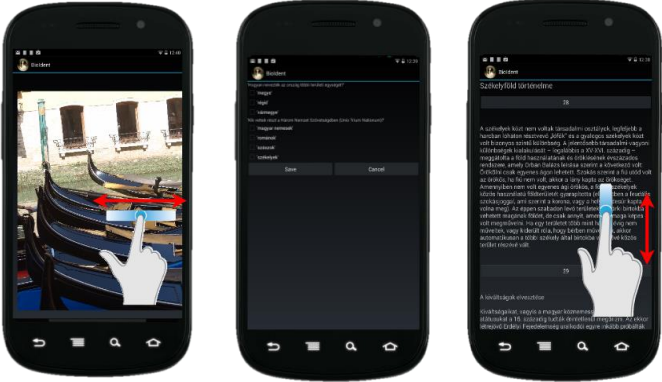


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# Swipe Biometrics

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



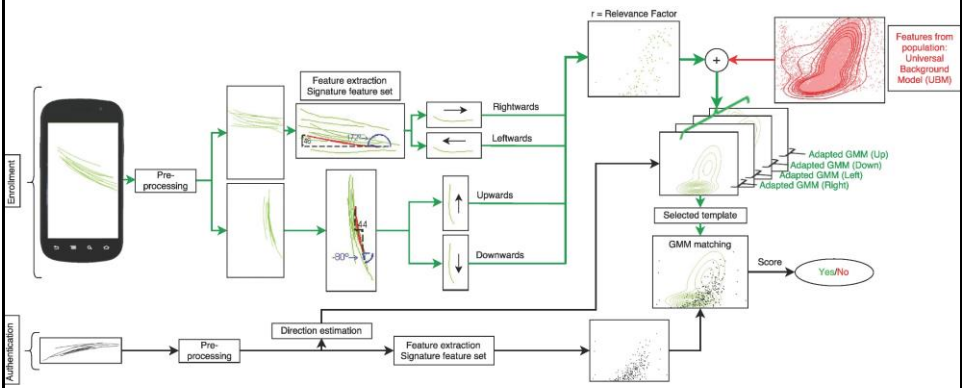
J. Fierrez, A. Pozo, M. Martinez-Diaz, J. Galbally and A. Morales, "Benchmarking Touchscreen Biometrics for Mobile Authentication", *IEEE Trans. on Information Forensics and Security*, November 2018.

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# Swipe Biometrics



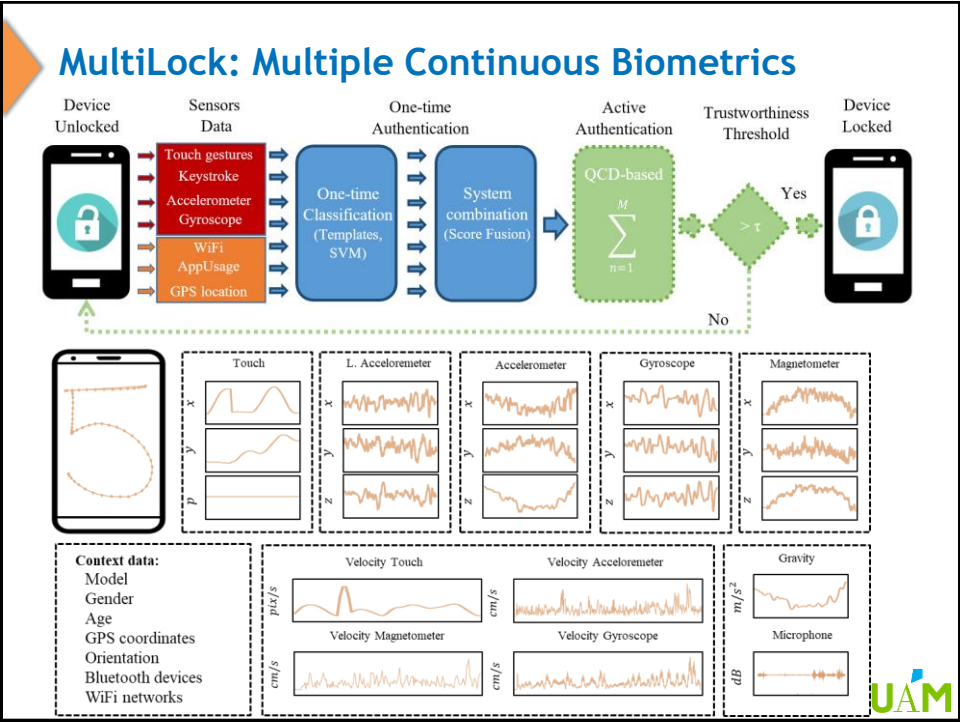
J. Fierrez, A. Pozo, M. Martinez-Diaz, J. Galbally and A. Morales, "Benchmarking Touchscreen Biometrics for Mobile Authentication", *IEEE Trans. on Information Forensics and Security*, November 2018.

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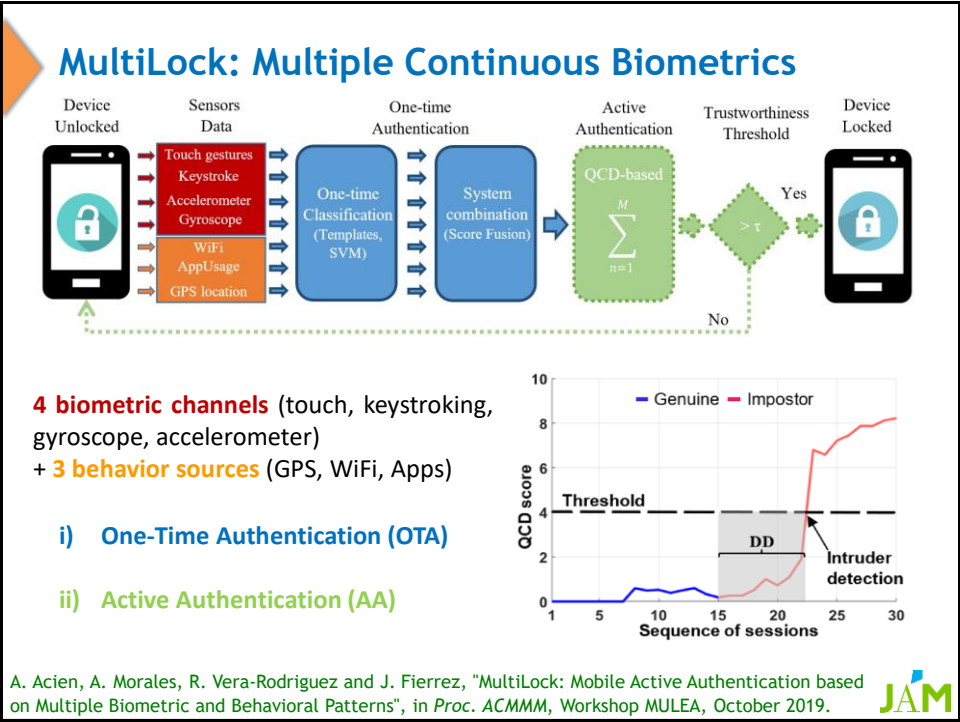
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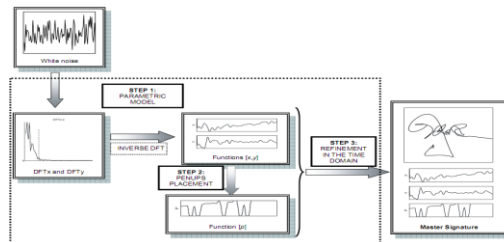


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## Other Research Topics in Signature Biometrics: Synthetic Signature Generation

- **Data-driven spectral features, human neuromotor properties, or GAN-based approaches** > generate realistic  $X$ ,  $Y$ , and  $P$  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.

R. Tolosana, P. Delgado-Santos, et al., "DeepWriteSYN: On-Line Handwriting Synthesis via Deep Short-Term Representations", in *AAAI Conf. on Artificial Intelligence (AAAI)*, February 2021.

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## Other Research Topics in Signature Biometrics: 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)
  - **Blockchain technologies**
- **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.

O. Delgado-Mohatar, J. Fierrez, R. Tolosana and R. Vera-Rodriguez, "Biometric Template Storage with Blockchain: A First Look into Cost and Performance Tradeoffs", in *Proc. CVPRW*, June 2019.

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### Other Research Topics in Signature Biometrics: e-Health - Neurodegenerative Monitoring




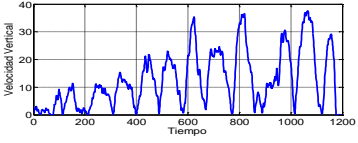
Sensor

Signal Processing

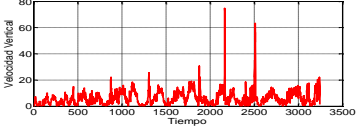
Feature Extraction

Pattern Recognition






**Control Subject:**  
Test time: 6.1 seconds  
Strokes: 12  
Muscle activation velocity (average): 300 ms (SD=31)  
Muscle de-activation velocity (average): 275 ms (SD=27)




**Parkinson (grade 19):**  
Test time: 16.6 seconds  
Strokes: 26  
Muscle activation velocity (average): 150 ms (SD=61)  
Muscle de-activation velocity (average): 163 ms (SD=68)

Other biometrics:  
face video, touch  
HCI, wearables, etc.




imi


innovative medicines initiative




+20M€  
+20M€



efpia



+40 other EU partners



IDEA FAST

R. Castrillon, A. Acien, J. Orozco-Arroyave, A. Morales, J. Vargas, R. Vera-Rodriguez, J. Fierrez, J. Ortega-Garcia and A. Villegas, "Characterization of the Handwriting Skills as a Biomarker for Parkinson Disease", in *IEEE FG*, April 2019.

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### The Future of Behavioral Biometrics

#### Challenge 1: Adapting to New Application Scenarios

Identity claim

Input sample

Signature Verification

Enrolled models

Pre-processing

Feature Extraction

Similarity Computation

Score normalization


Decision Threshold

Accepted or rejected

Knowledge Base + Experiments

+ Experiments'

- Domain adaptation
- Transfer learning
- Inductive transfer
- ...
- ✓ Bayesian adaptation\*
- ✓ Discriminative adaptation\*\*



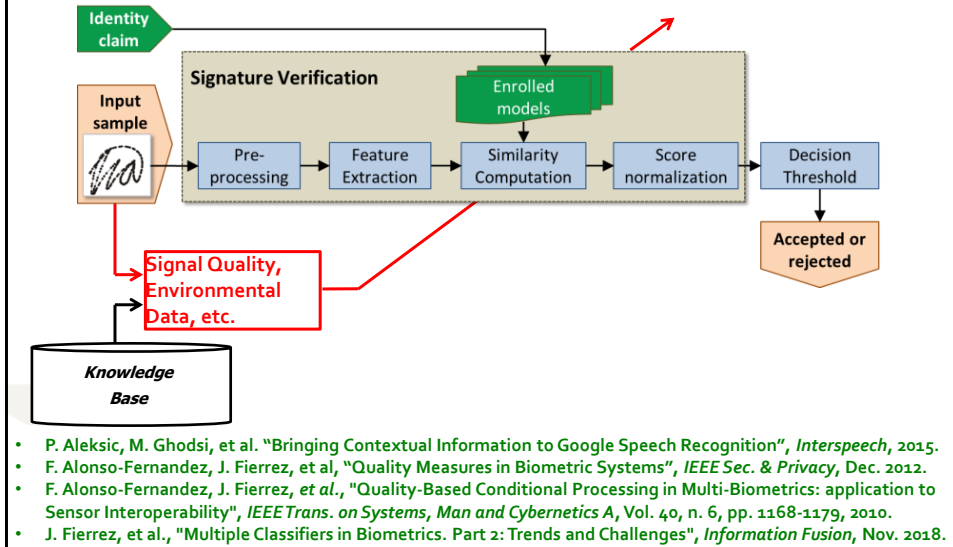
\* J. Fierrez-Aguilar, D. Garcia-Romero, J. Ortega-Garcia and J. Gonzalez-Rodriguez, "Bayesian adaptation for user-dependent multimodal biometric authentication", *Pattern Recognition*, August 2005.  
\*\*J. Fierrez-Aguilar, D. Garcia-Romero, J. Ortega-Garcia and J. Gonzalez-Rodriguez, "Adapted user-dependent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

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## The Future of Behavioral Biometrics

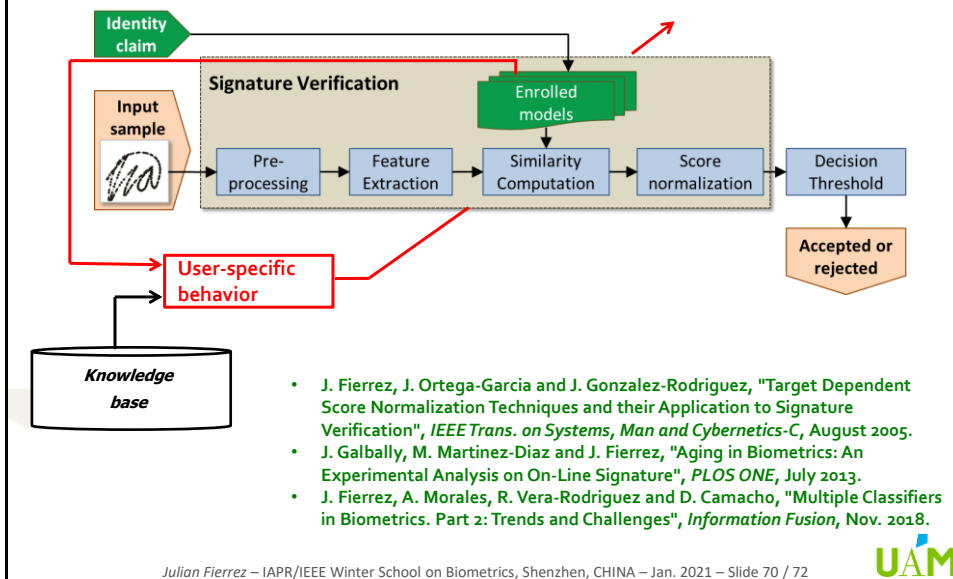
### Challenge 2: Incorporating Contextual Information



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## The Future of Behavioral Biometrics

### Challenge 3: Adapting to the User (e.g., Aging)



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## Signature and Touchscreen Biometrics: Conclusions

- |   |   |
|---|---|
| <ul style="list-style-type: none"> <li>- Revocability</li> <li>- Easy of use, user acceptance</li> <li>- Easy to integrate at low-cost</li> <li>- Mobile and touch devices</li> <li>- Fusion with other biometrics and user data channels</li> <li>- Continuous ID</li> </ul> | <ul style="list-style-type: none"> <li>- User intra-variability</li> <li>- Multi-sample training</li> <li>- Model updating</li> <li>- Multilevel strategies</li> <li>- Data scarcity for deep-learning</li> </ul> |
|---|---|

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

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# Signature and Touchscreen Biometrics

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