Handwritten Signature Recognition

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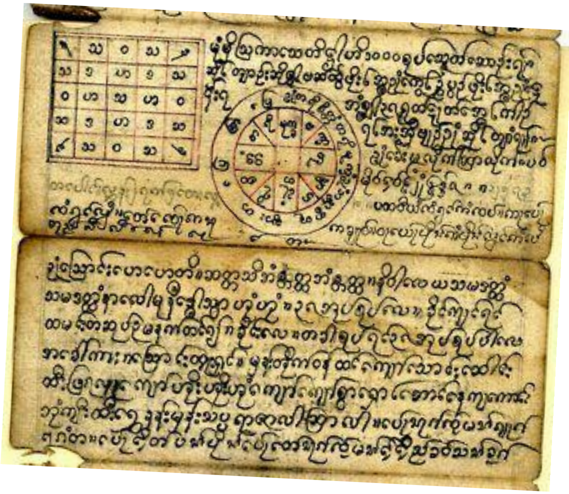
In the News…

The certificate presented by Madrid exregional leader as proof of her master’s degree has two forged signatures.

What is it?

Handwritten signature is one of the most socially accepted biometrics traits. It has been used for centuries to validate legal, commercial documents, and transactions.



- M. Diaz, M. A. Ferrer, D. Impedovo, M. I. Malik, G. Pirlo and R. Plamondon, “A Perspective Analysis of Handwritten Signature Technology,” *ACM Computing Surveys* 51(6): 1–39, 2019.

Applications

User login / activation:

- Access control.
- Local or remote system activation.

Payments in commercial environments:

- Remotely or at the Point of Sale
- Access to commercial transactions, e-banking, etc.

- M. Faundez-Zanuy, J. Fierrez, M. A. Ferrer, M. Diaz, R. Tolosana and R. Plamondon, "Handwriting Biometrics: Applications and Future Trends in e-Security and e-Health", *Cognitive Computation*, 2020.

Applications

e-Government

Legal transactions:

- Legal documents or certificates.
- E-government applications.

Client validation:

- Parcel delivery.

Secure Access:

- Medical Records, encryption of data.

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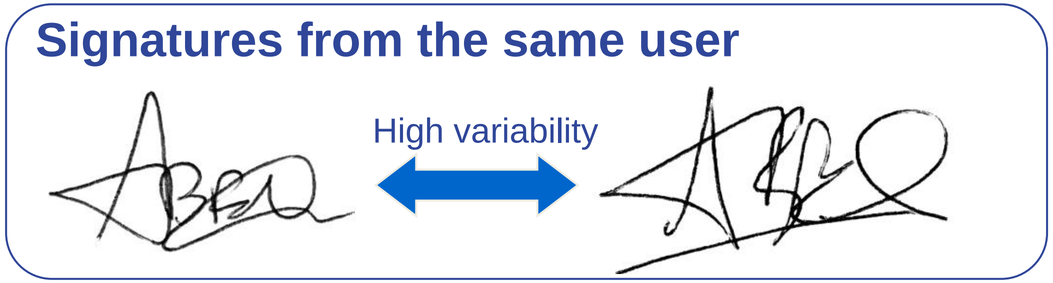
Automatic Signature Recognition

Automatic signature recognition has some challenges:

- Large intra-user variability (behavioral biometrics, inter-session):
  - Difficult to model, large amount of training data (usually scarce).



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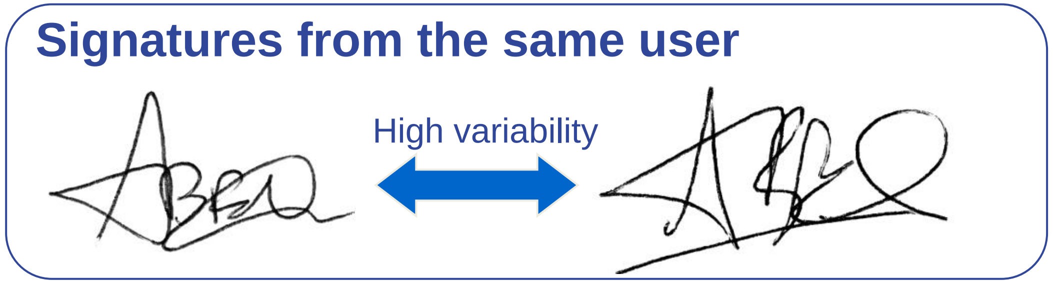
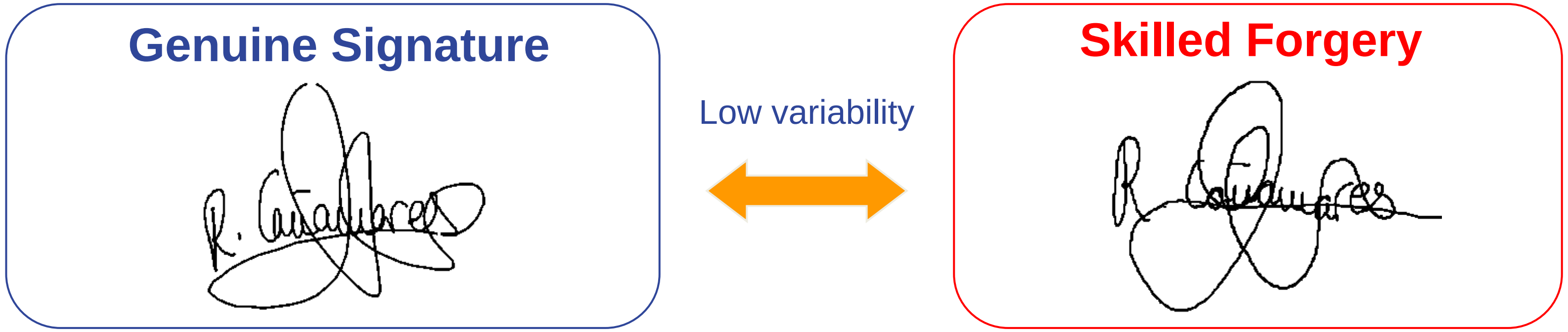


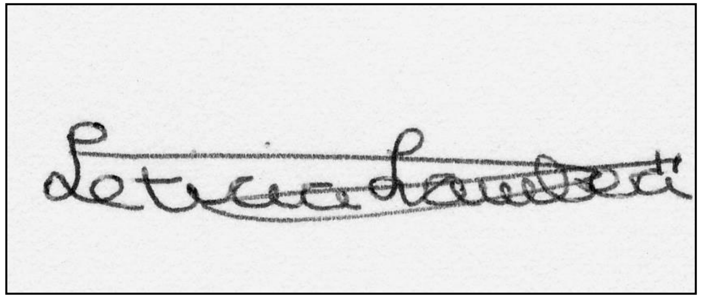
- Small inter-user variability (in case of forgeries).
  - The skill level of actual forgeries is unpredictable.



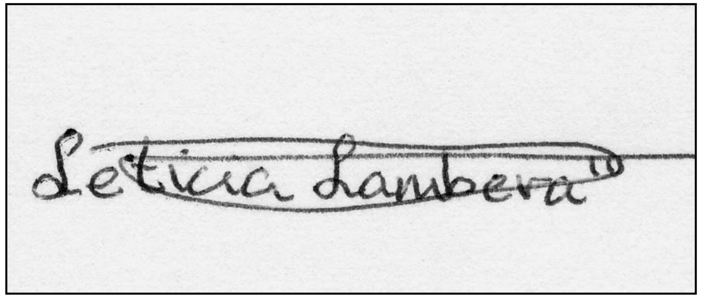
- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Presentation Attacks in Signature Biometrics: Types and Introduction to Attack Detection", *Handbook of Biometric Anti-Spoofing (2nd Edition),* Springer, 2018.

Real or Forgery?

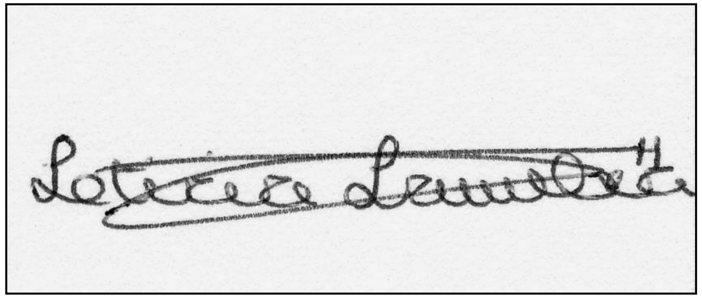
Genuine



1 ?



2 ?



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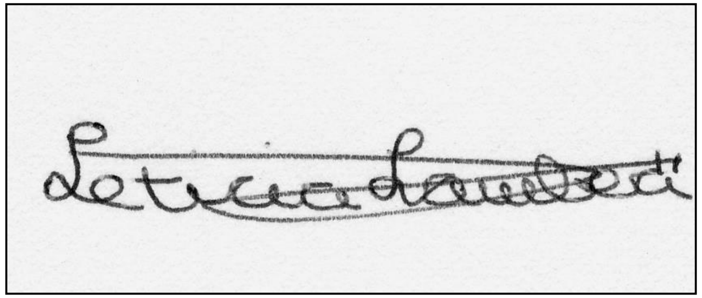
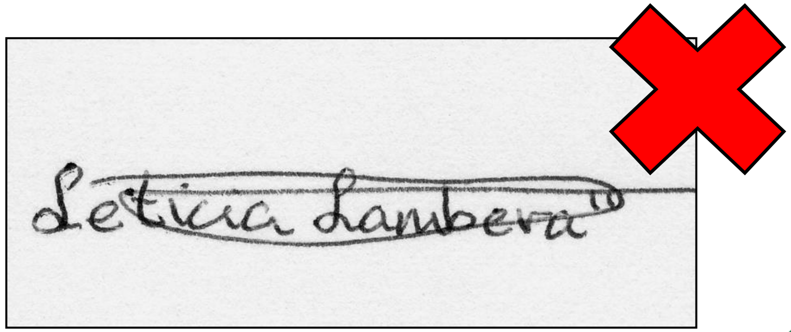
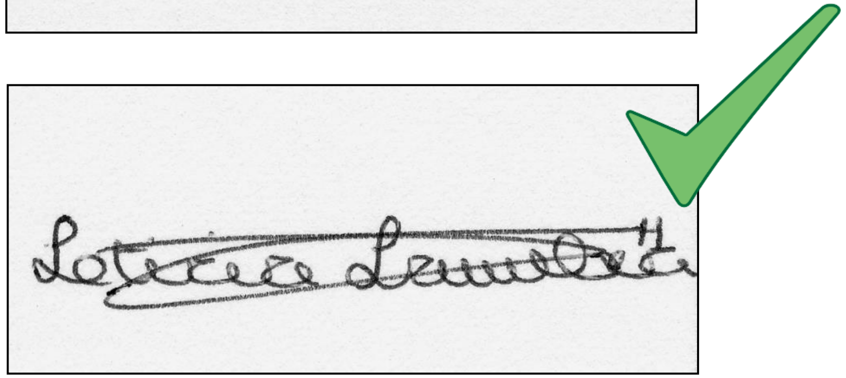


1 Forgery



2 Genuine

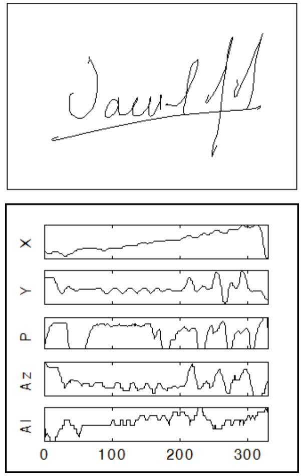


Signature Recognition Approaches

There are two different approaches:

- Off-line (or 'static'): Once signature is produced, only the remaining static image information is available.

- On-line (or 'dynamic'): While being produced, signature time sequences ($x(t)$, $y(t)$, $p(t)$, etc.) are acquired.

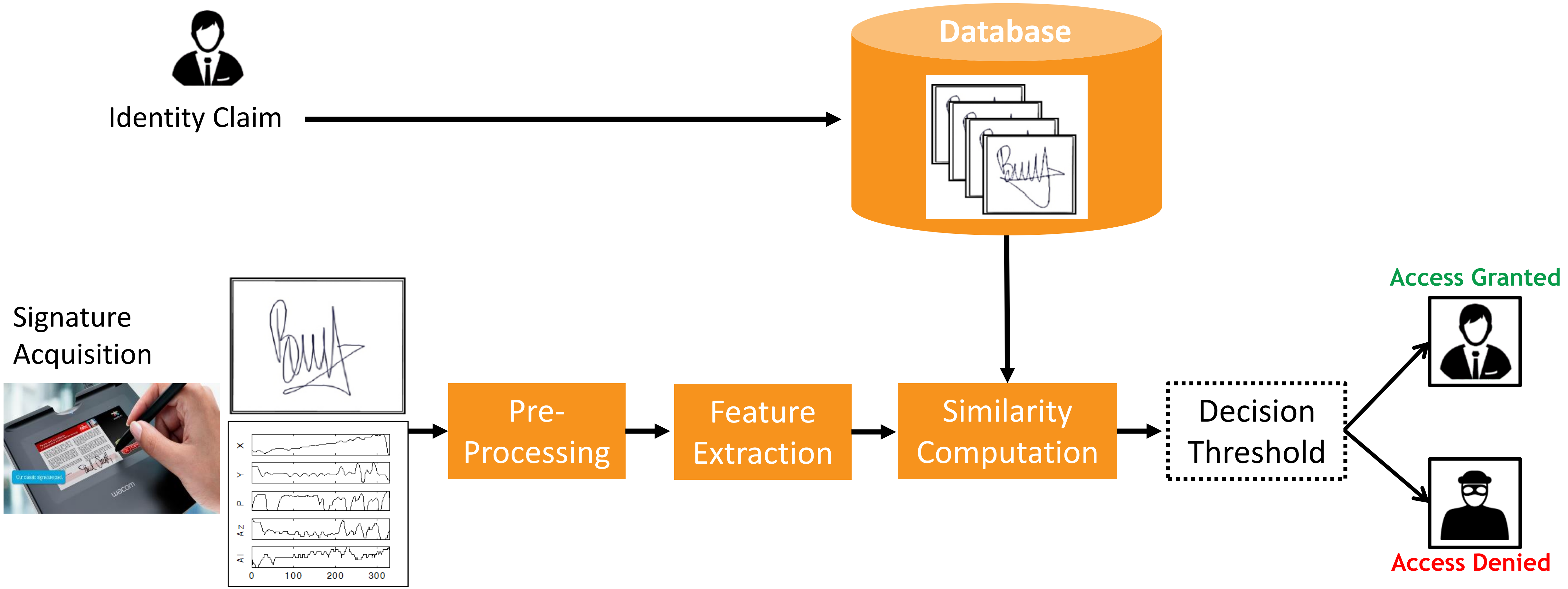


Signature Recognition Approaches

The on-line approach usually outperforms the off-line (more information about the signing process is acquired, not only the image), BUT it needs an electronic device for the acquisition.

Here we focus on on-line or dynamic signature biometric verification.

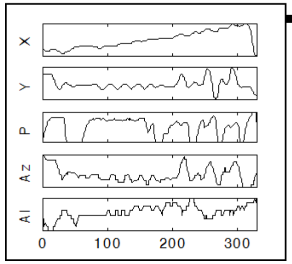
On-Line Signature Verification: Architecture



On-Line Signature Verification: Architecture

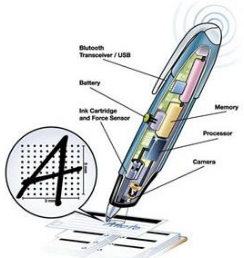
Identity Claim

Signature Acquisition



Signature Acquisition

On-line signatures can be captured using:



Specific handwriting devices such as Wacom, Signotec, Anoto, etc.

Signature Acquisition

On-line signatures can be captured using:

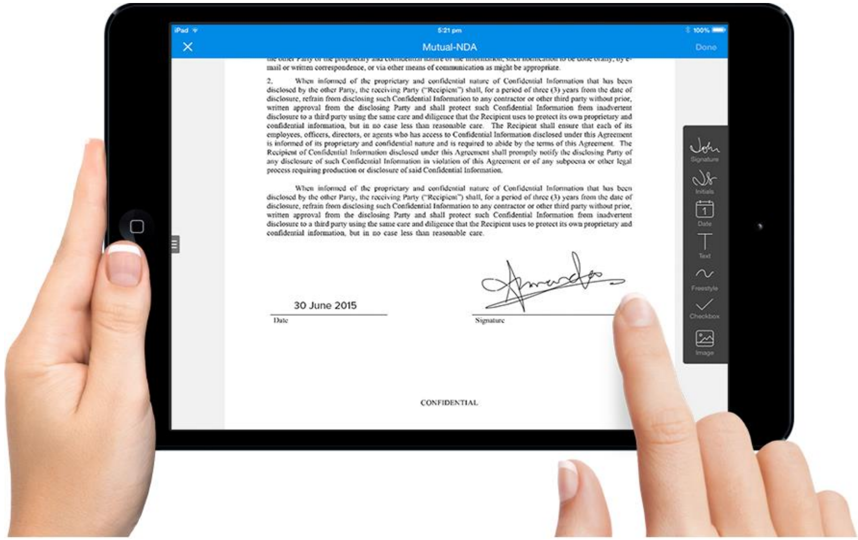
Specific handwriting devices such as Wacom, Signotec, Anoto, etc.

General purpose devices

Signature Acquisition

On-line signatures can be captured using:

Stylus (Pen)



Finger (Touch)

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez, A. Morales and J. Ortega-Garcia, "Benchmarking Desktop and Mobile Handwriting across COTS Devices: the e-BioSign Biometric Database", *PLOS ONE*, Vol. 5, n. 12, 2017.

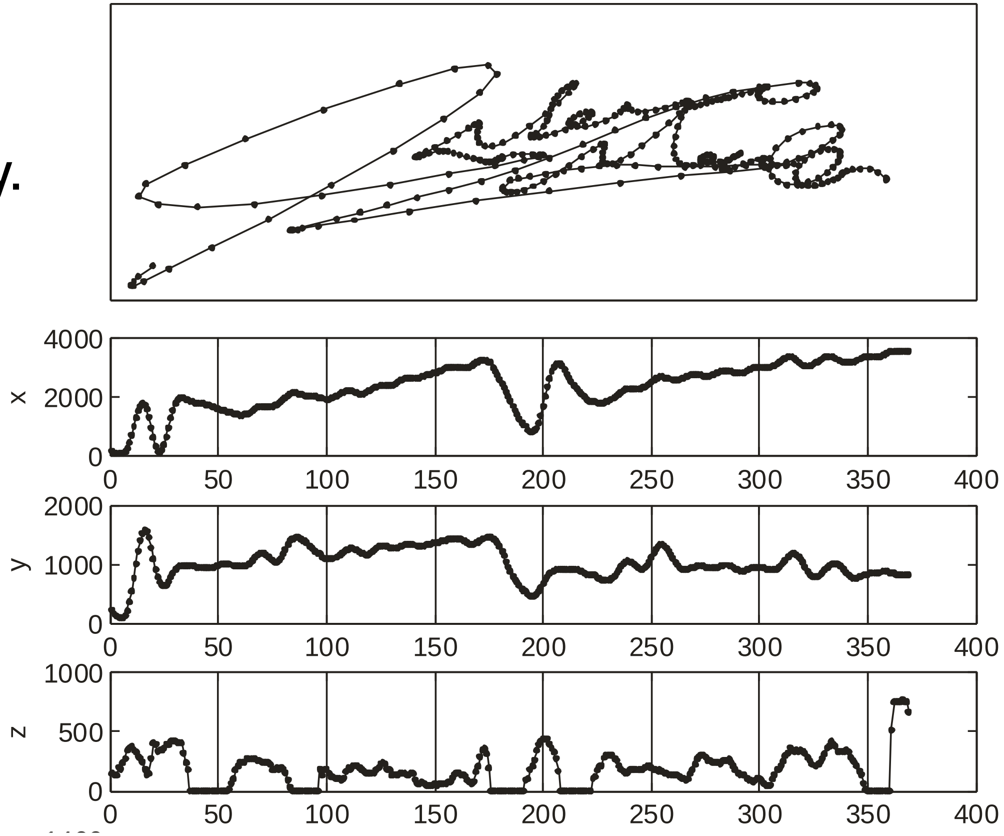
Signature Acquisition

Device Properties:

- Time resolution: 100-200 samples/sec (100-200Hz).
- Spatial Resolution: higher than 1000 pixels/inch.

Dynamic Signature Signals:

- X and Y spatial coordinates of the signature trajectory.
- Pressure.
- Time stamp at each sample point.
- Azimuth and altitude of the pen (optional).



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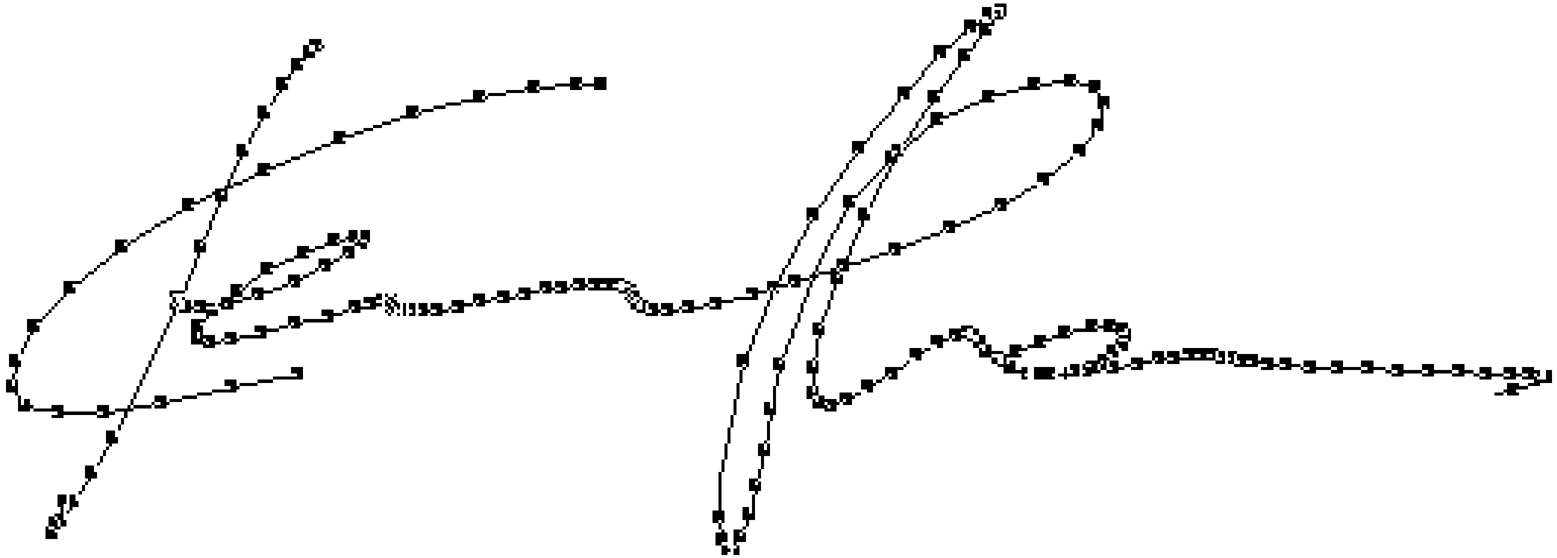
Signature Acquisition

The tablet device samples the pen position along the signature trajectory.

Points are equally-distant in time, not in space.



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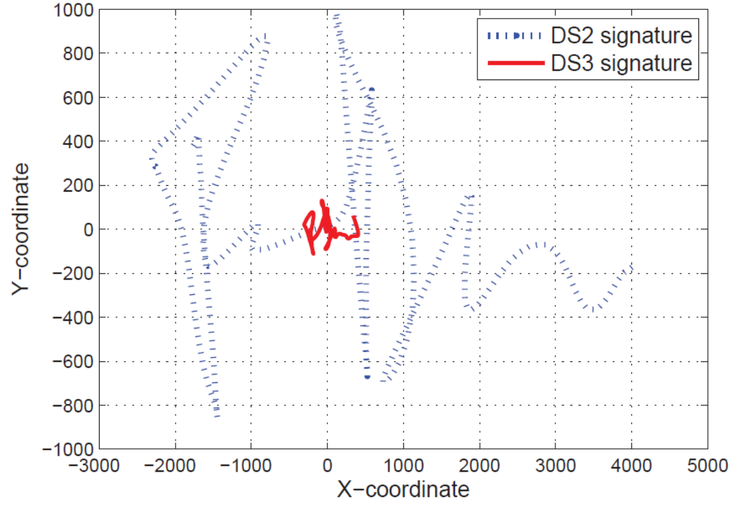
Signature Acquisition

Challenges:

- Different spatial position between devices.



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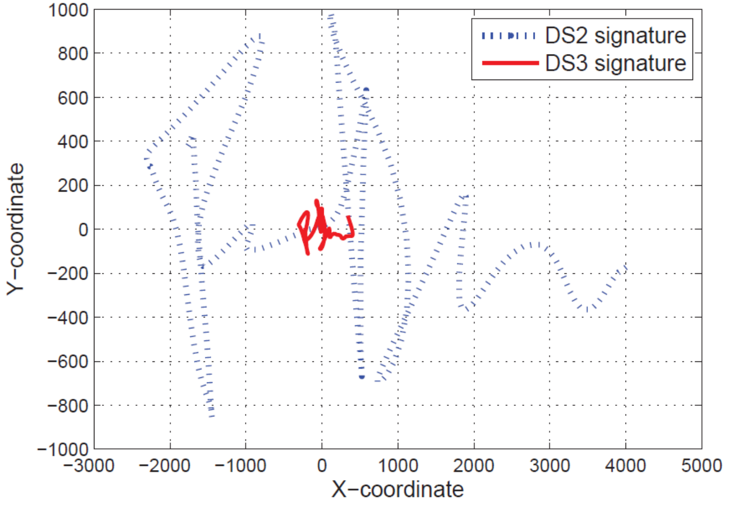
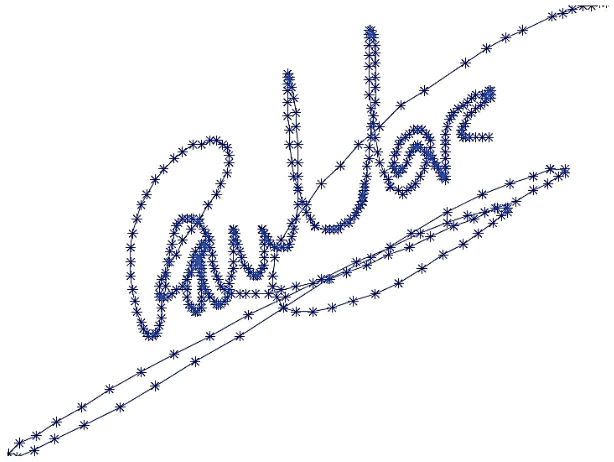


Challenges:

- Different spatial position and resolution between devices.
- Different time resolution between devices (and writing input).



Stylus (Pen)

Finger (Touch)

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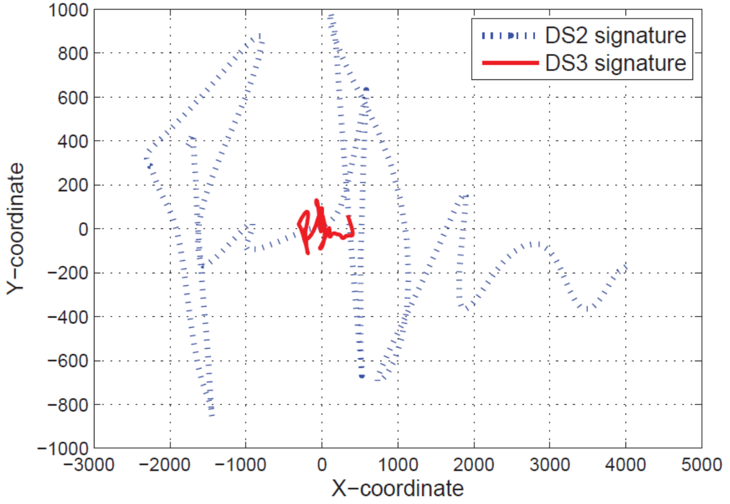
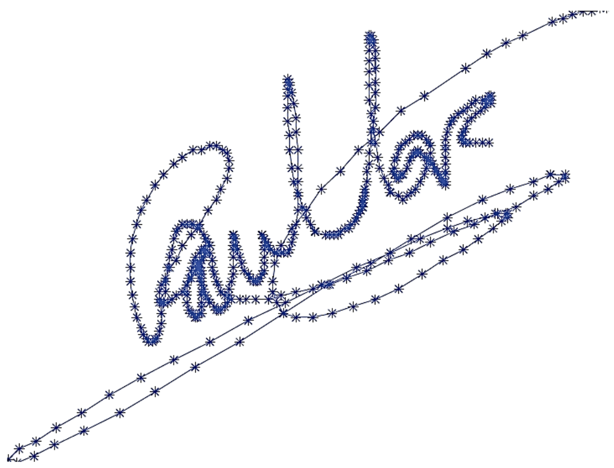


Challenges:

- Different spatial position and resolution between devices.
- Different time resolution between devices (and writing input).
- Lack of pressure and pen-up trajectories.



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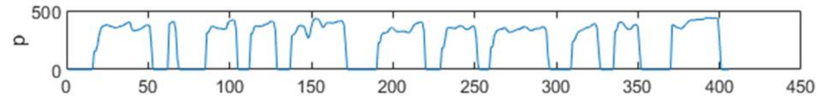

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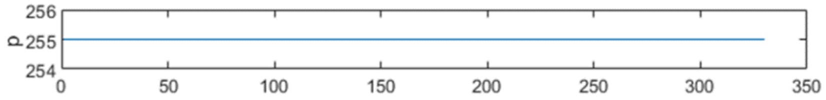

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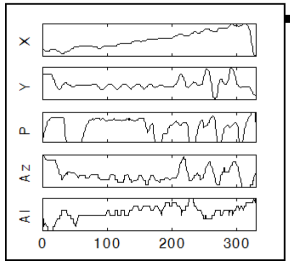
On-Line Signature Verification: Architecture

Identity Claim

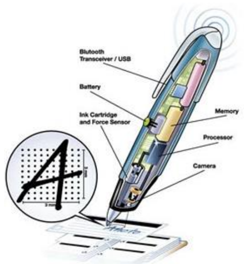
Signature Acquisition

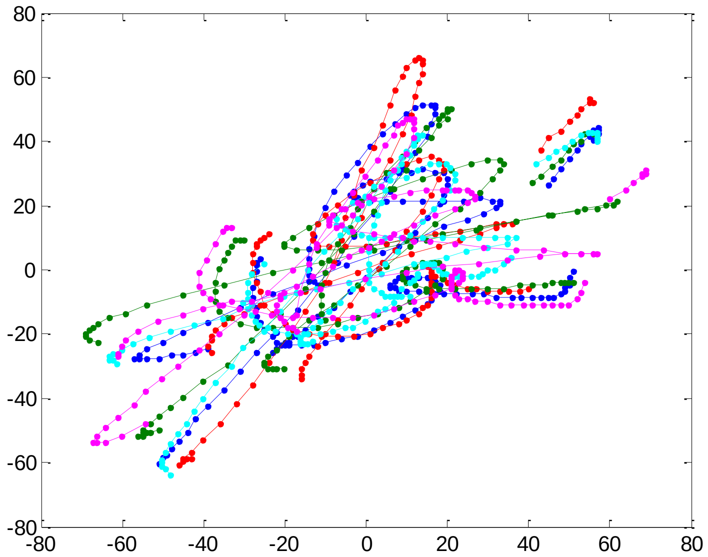


Pre-Processing

Preprocessing

Goal: Obtain signatures with the same type of information (pressure, pen-up trajectories, etc.) and time and spatial position standard formats (universal scenario).





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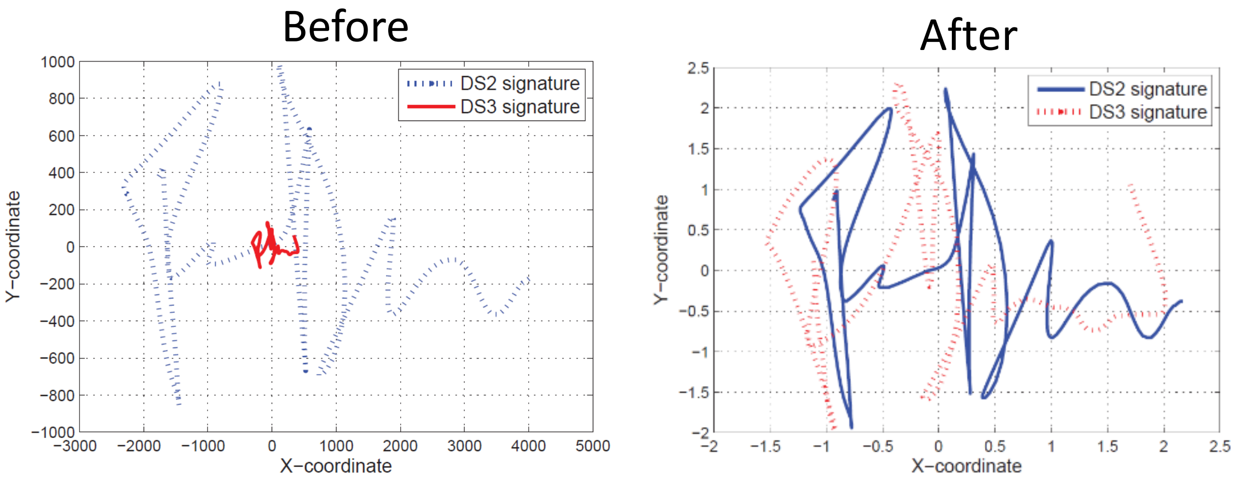
Spatial Normalization:

- Size (keeping the X and Y proportions).
- Position (centre of mass).
- Rotation.



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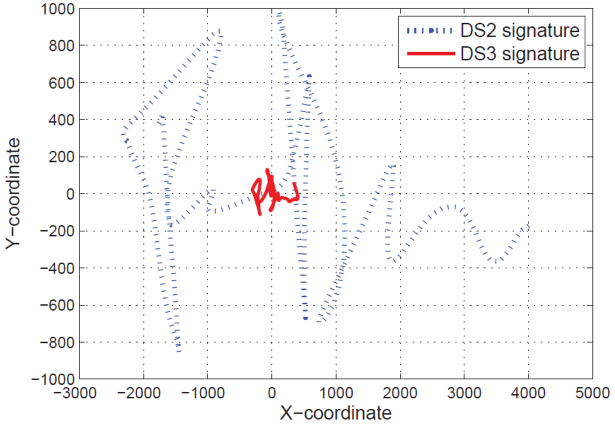
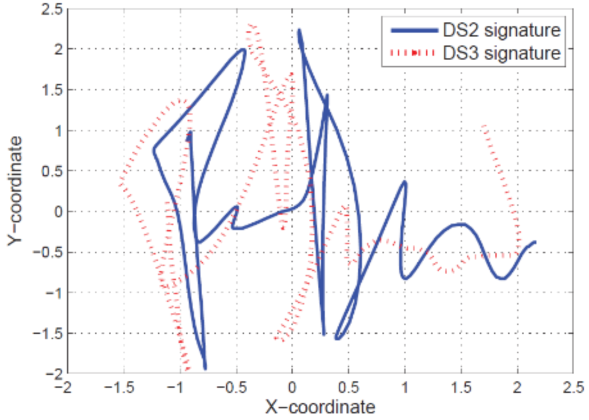
Time Normalization:

- Sampling frequency (interpolation)

Before



After



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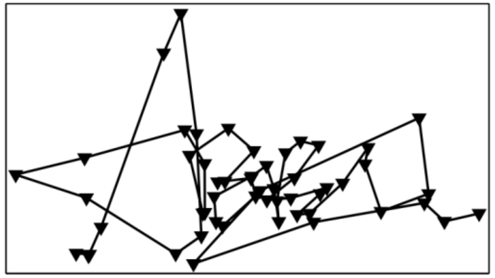

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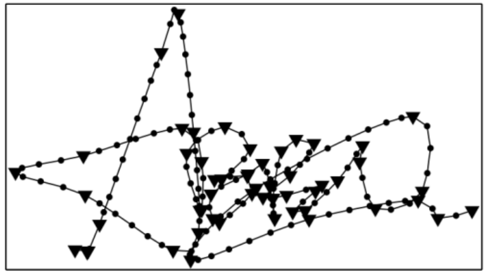

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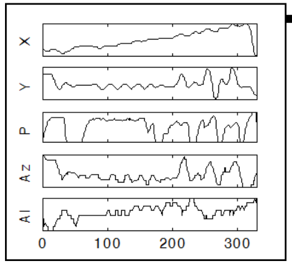
- M. Martinez-Diaz, J. Fierrez, M. R. Freire and J. Ortega-Garcia, "On the effects of sampling rate and interpolation in HMM-based dynamic signature verification", in *Proc. Intl. Conf. on Document Analysis and Recognition, ICDAR*, Vol. 2, pp. 1113-1117, Curitiba, Brazil, September 2007.

On-Line Signature Verification: Architecture

Identity Claim

Signature Acquisition

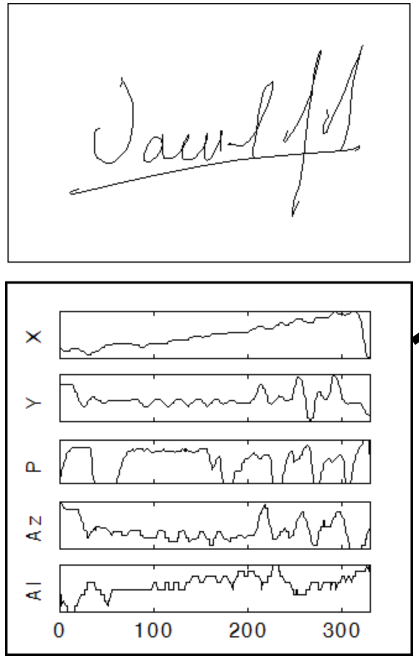


Pre-Processing

Feature Extraction

Feature Extraction

Main approaches to signature representation.



Global Features

Signatures are described as **multi-dimensional holistic vectors.**

E.g., signature duration, average velocity, number of pen-ups, initial orientation, etc.

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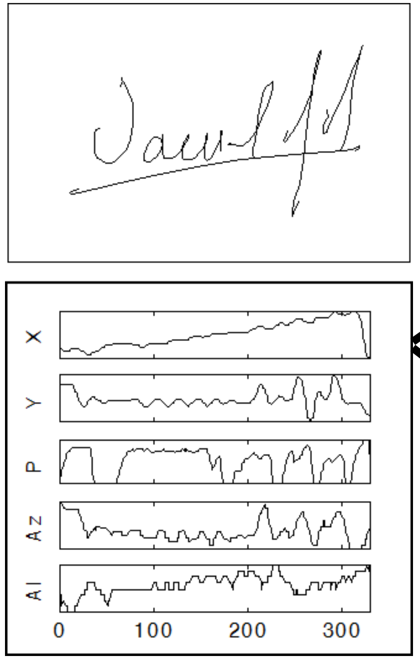

Global Features

Signatures are described as **multi-dimensional holistic vectors.**

E.g., signature duration, average velocity, number of pen-ups, initial orientation, etc.

Local Features

Signatures are described as a set of **time sequences.**

E.g., x-coordinate, pen-pressure, speed, acceleration, etc.

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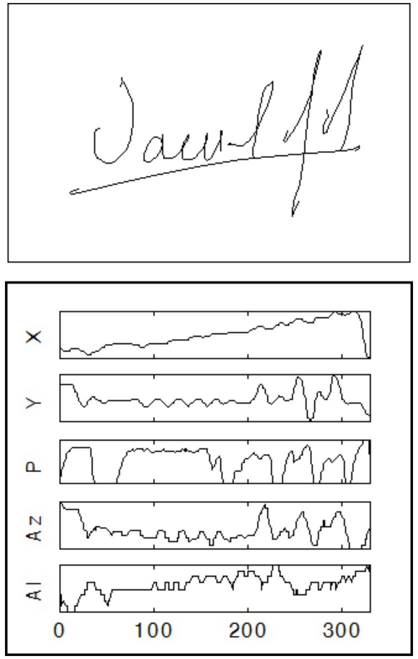
Feature Extraction

Example of global features:



Global Features

#	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	$T(v_x > 0)/T_w$
5	$T(v_x < 0)/T_w$	6	$T(v_y > 0)/T_w$
7	$T(v_y < 0)/T_w$	8	$T(v_x > 0 \mid \text{pen-up})/T_w$
9	$T(v_x < 0 \mid \text{pen-up})/T_w$	10	$T(v_y > 0 \mid \text{pen-up})/T_w$
11	$T(v_x < y \mid \text{pen-up})/T_w$	12	$T(\text{1st pen-up})/T_w$
13	$T(\text{2nd pen-up})/T_w$	14	$T(\text{2nd pen-down})/T_s$
15	$T(\text{3rd pen-down})/T_s$	16	(1st $t(v_{y,\max})$)/T_w
17	(1st $t(v_{y,\min})$)/T_w	18	(1st $t(v_{x,\max})$)/T_w
19	(1st $t(v_{x,\min})$)/T_w	20	$\frac{T((dy/dt)/(dx/dt)>0)}{T((dy/dt)/(dx/dt)<0)}$
21	$T(\text{curvature} > \text{threshold}_{\text{curv}})/T_w$	22	(1st $t(x_{\max})$)/T_w
23	(2nd $t(x_{\max})$)/T_w	24	(3rd $t(x_{\max})$)/T_w
25	(2nd $t(y_{\max})$)/T_w	26	(3rd $t(y_{\max})$)/T_w
27	(average velocity $\bar{v}$)/$v_{\max}$	28	$N(v_x = 0)$
29	$N(v_y = 0)$	30	$\bar{v}/v_{x,\max}$
31	$\bar{v}/v_{y,\max}$	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

...

117 global features

#	Feature Description	#	Feature Description
101	average pressure $\bar{z}$	102	median pressure
103	N(Pen Downs samples)	104	N(Pen Ups samples)
105	median N(Pen Ups samples) individually	106	average N(Pen Ups samples) individually
107	median N(Pen Downs samples) individually	108	average N(Pen Downs samples) individually
109	$\bar{z}$ / p_{max}	110	($\bar{z}$ - z_{min}) / $\bar{z}$
111	median pressure last pen-down	112	average pressure last pen-down
113	median pressure first pen-down	114	average pressure first pen-down
115	(z_{max} - z_{min}) / $\bar{z}$	116	average velocity $\bar{v}$
117	average acceleration $\bar{a}$		

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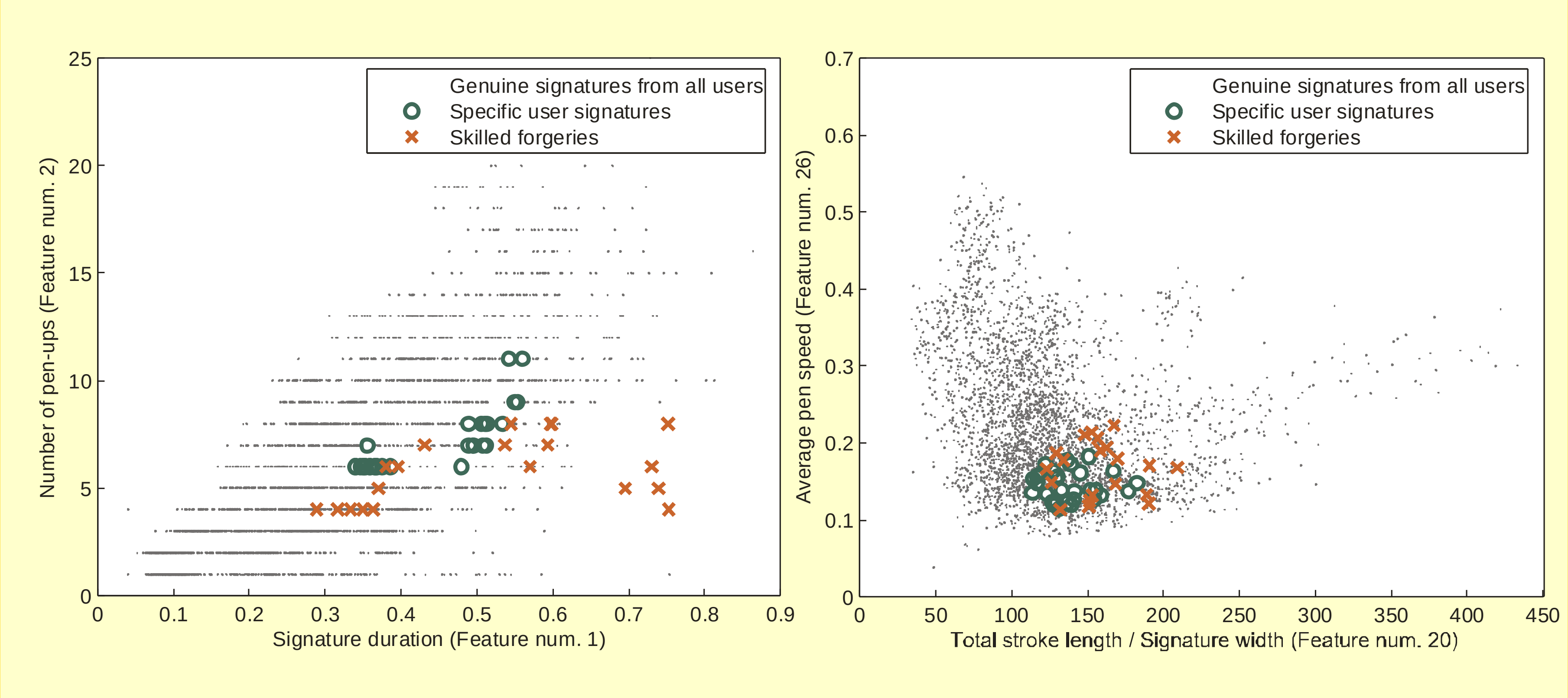
Feature Extraction

BiDA Lab
Biometrics & Data Pattern Analytics Lab

Example of global features:



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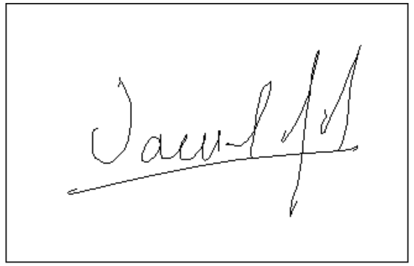
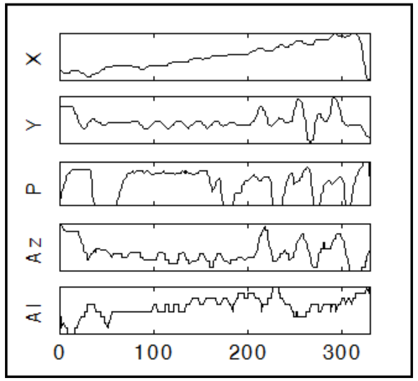
Feature Extraction

Example of local features:





Local Features

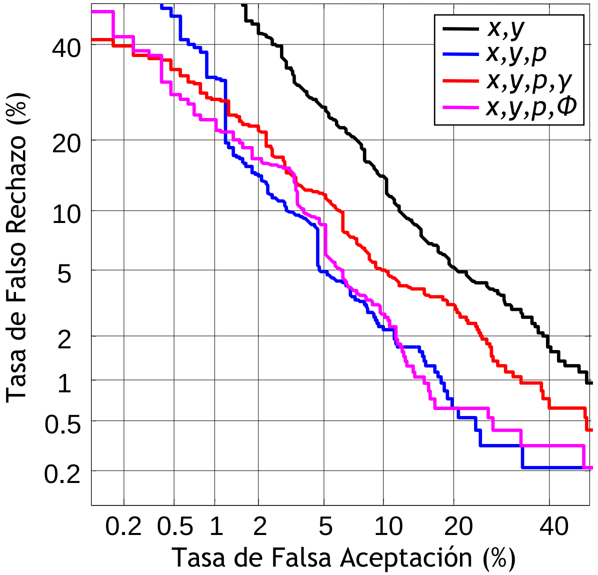
23 local features

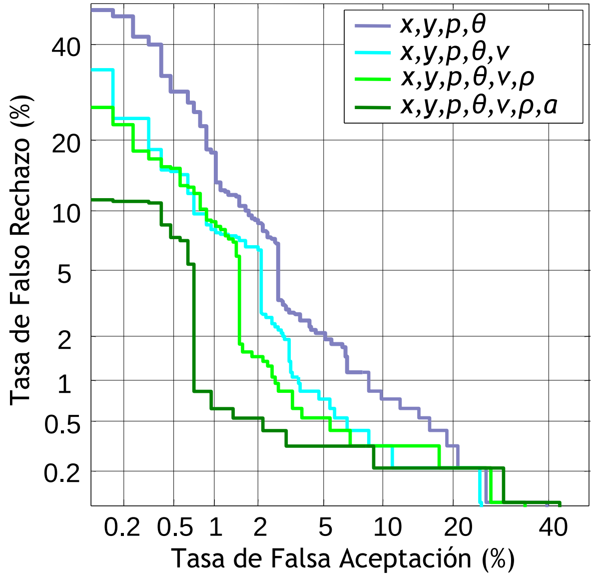
#	Feature	Description
1	x-coordinate	x_n
2	y-coordinate	y_n
3	Pen-pressure	z_n
4	Path-tangent angle	$\theta_n = \arctan(\dot{y}_n/\dot{x}_n)$
5	Path velocity magnitude	$v_n = \sqrt{\dot{y}_n + \dot{x}_n}$
6	Log curvature radius	$\rho_n = \log(1/\kappa_n) = \log(v_n/\dot{\theta}_n)$, where κ_n is the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

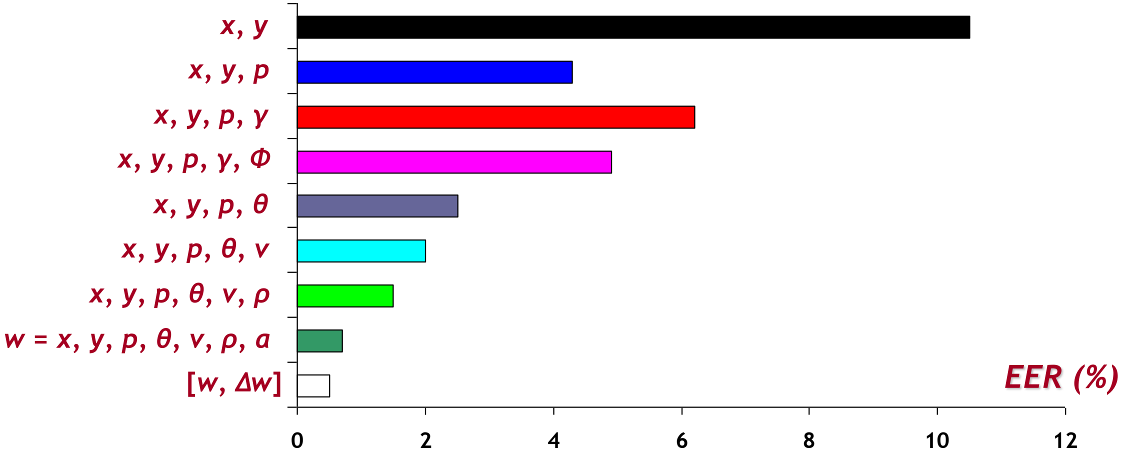
- M. Martinez-Diaz, J. Fierrez and S. Hangai, "Signature Features", Stan Z. Li and Anil K. Jain (Eds.), *Encyclopedia of Biometrics*, Springer, pp. 1375-1382, 2015.

Feature Extraction

Example of local features:

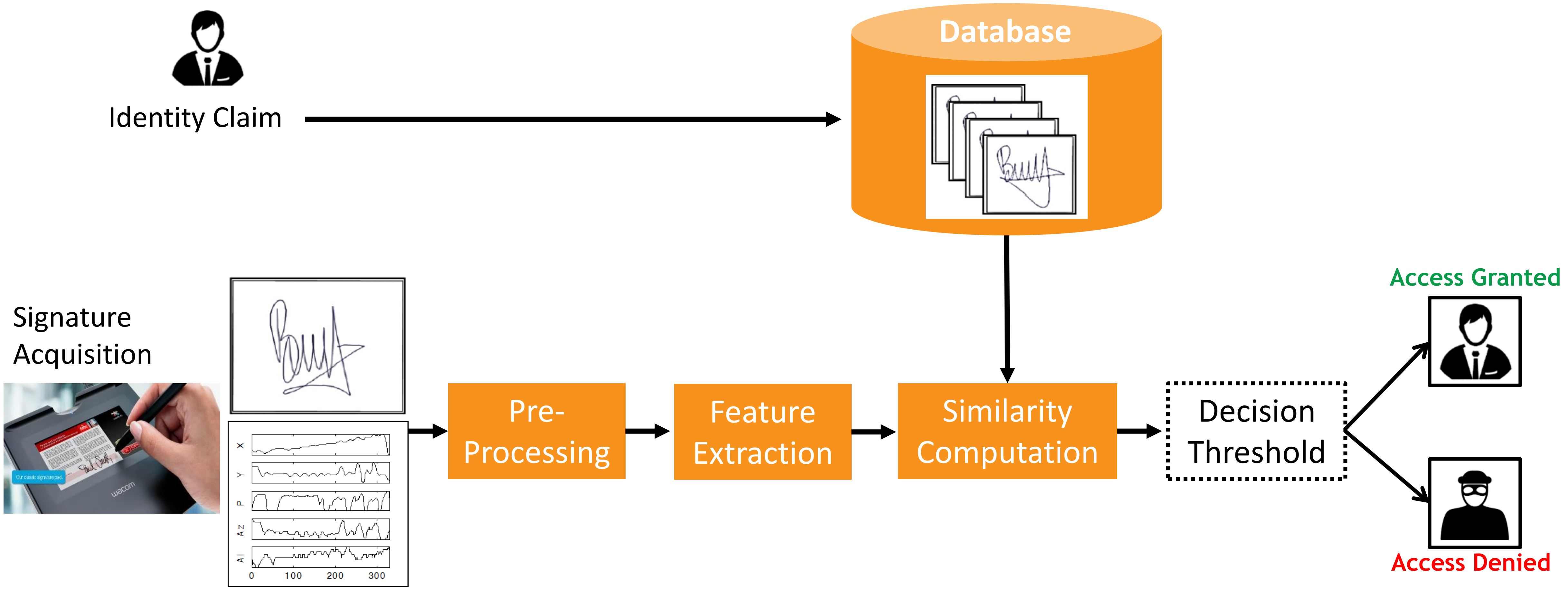






S. Garcia-Salicetti, *et al*., "Biosecure Reference Systems for On-Line Signature Verification; A Study of Complementarity", *Annals of Telecommunications Journal*, Vol. 62, Nos.: 1&2, Jan.-Feb. 2007

On-Line Signature Verification: Architecture



Similarity Computation

Global Features

Distance-based Classifiers

- Mahalanobis
- Euclidean

Statistical/Other Classifiers

- Support Vector Machines
- Neural Networks

- 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

Similarity Computation

Global Features

- Distance-based Classifiers
  - Mahalanobis
  - Euclidean
- Statistical/Other Classifiers
  - Support Vector Machines
  - Neural Networks

Local Features

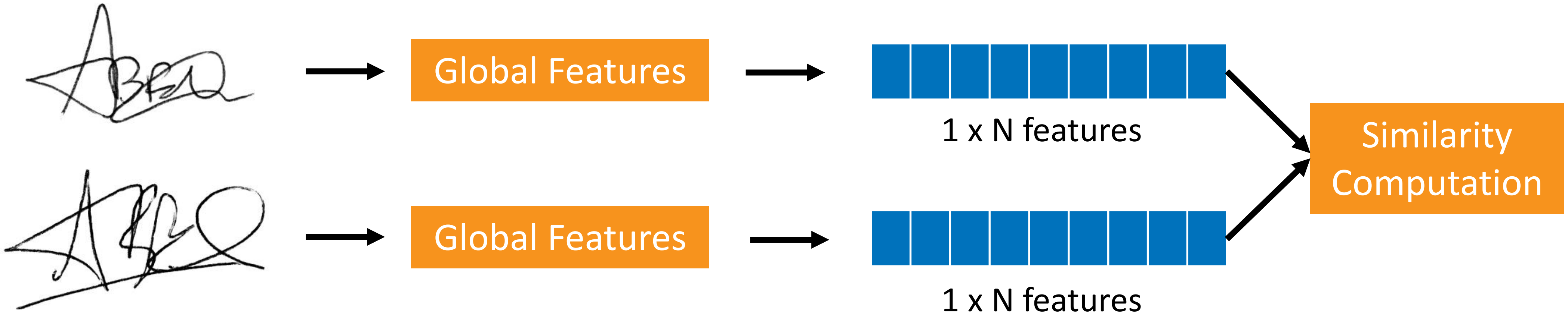
- Regional (segment-to-segment)
- Local (point-to-point)

→ Dynamic Time Warping, Hidden Markov Models, Deep Learning

• 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

Similarity Computation for Global Features

Each signature is described by an equal number of global features, i.e., feature vectors are of the same length.



• M. Martinez-Diaz, J. Fierrez and S. Hangai, "Signature Matching", Stan Z. Li (Eds.), Encyclopedia of Biometrics (ISBN 978-0-387-73003-5), Springer Verlag, 2009.

Similarity Computation for Global Features

Distance-based classifiers: simple approach. It does not require training.

- Euclidean distance between signature x and y:

$$d(\mathbf{x},\mathbf{y}) = \sqrt{\sum_{i=1}^{N} (\mathbf{x}_i - \mathbf{y}_i)^2}$$

Problem: Scale and importance of individual feature dimensions are not taken into account.

- Mahalanobis distance between signature x and a reference set with mean m, and covariance matrix Σ.

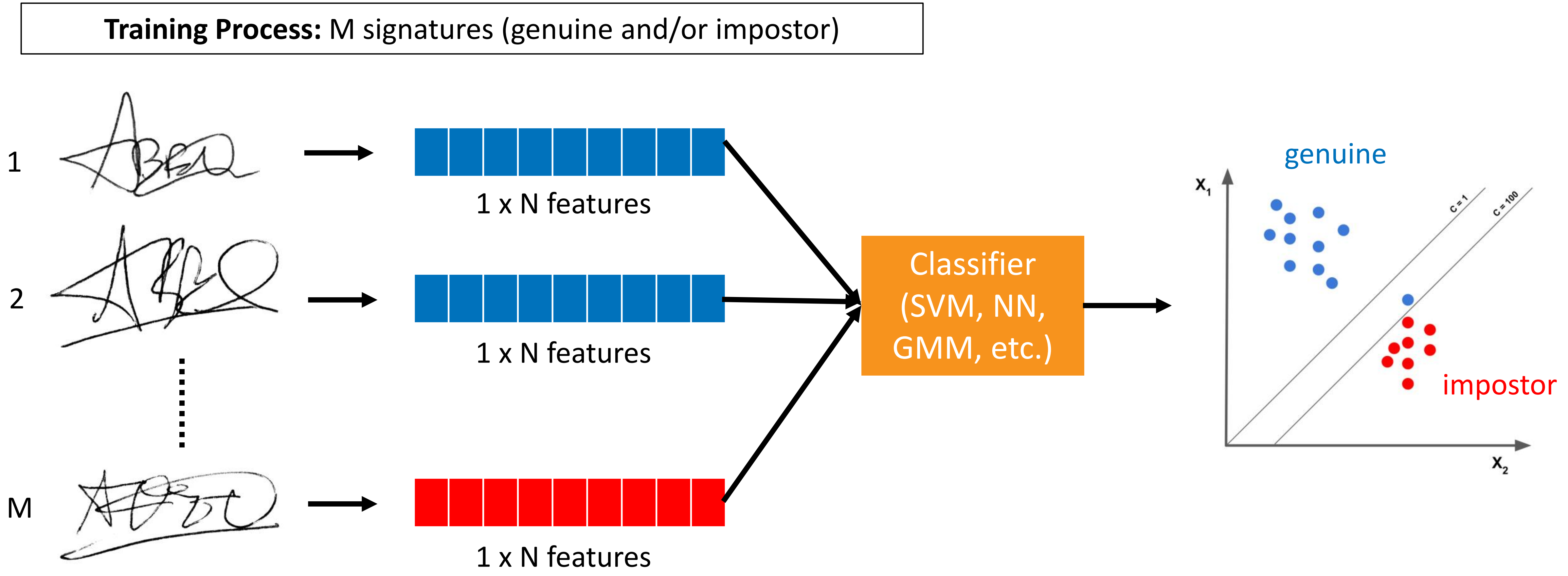
$$d(\mathbf{x},\mathbf{m}) = (\mathbf{x}-\mathbf{m})^T \Sigma^{-1} (\mathbf{x}-\mathbf{m})$$

Problem: Having enough genuine signatures of the user to estimate the covariance matrix.

- M. Martinez-Diaz, J. Fierrez and S. Hangai, "Signature Matching", Stan Z. Li (Eds.), Encyclopedia of Biometrics (ISBN 978-0-387-73003-5), Springer Verlag, 2009.

Similarity Computation for Global Features

Statistical/Other classifiers: more complex approach. It does require training (forgeries might not be available).

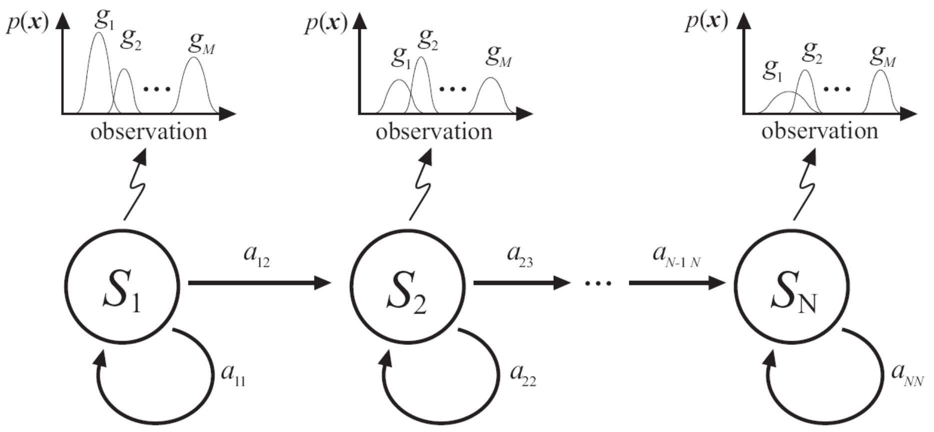


- M. Diaz, M. A. Ferrer, D. Impedovo, M. I. Malik, G. Pirlo and R. Plamondon, "A Perspective Analysis of Handwritten Signature Technology," *ACM Computing Surveys* 51(6): 1–39, 2019.

Similarity Computation for Local Features

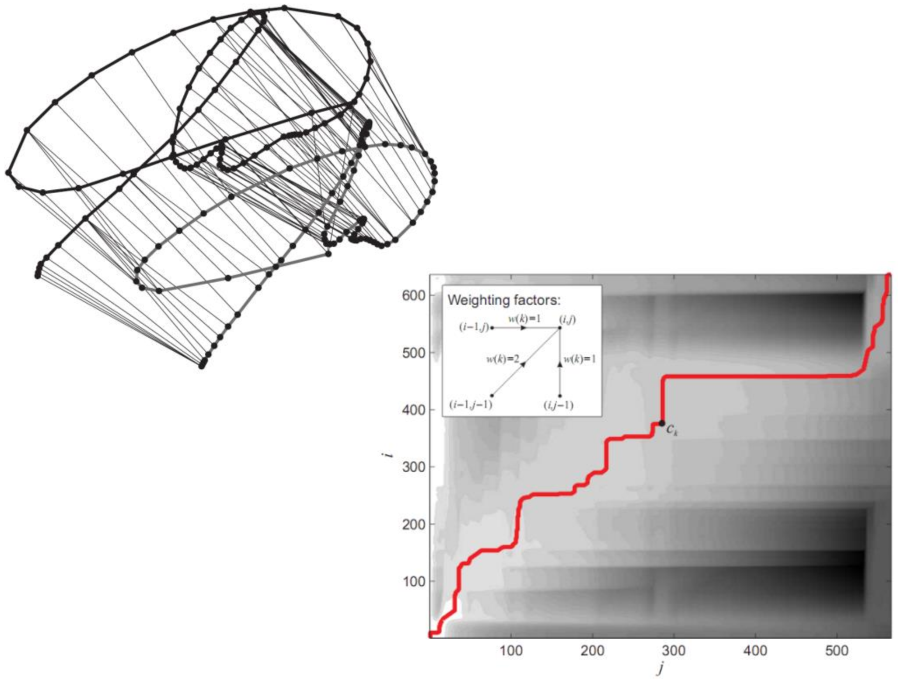
Traditional approaches:

Hidden Markov Models (HMM)



Statistical modeling of signature regions

Dynamic Time Warping (DTW)



Point-to-point correspondence

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Reducing the Template Aging Effect in On-Line Signature Biometrics", *IET Biometrics*, Vol. 8, n. 6, pp. 422-430, June 2019.

Similarity Computation for Local Features

BiDA Lab
Biometrics & Data Pattern Analytics Lab

Experimental Results: Long-Term Database (ATVS-SLT DB), 41 signatures/user in 15 months.

Multi-algorithm fusion.

		DTW	HMM	FUSION
Skilled	Exp. A (4 firmas)	11.7	17.9	11.7
	Exp. B (16 firmas)	9.0	8.9	6.9
	Exp. C (31 firmas)	7.6	4.8	4.1
	Exp. D (41 firmas)	4.8	1.4	0.7
Random	Exp. A (4 firmas)	2.8	11.0	2.8
	Exp. B (16 firmas)	1.4	2.0	0.7
	Exp. C (31 firmas)	0.2	0.7	0.1
	Exp. D (41 firmas)	0.2	0.1	0.1

Performance in EER (%)

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Reducing the Template Aging Effect in On-Line Signature Biometrics", *IET Biometrics*, Vol. 8, n. 6, pp. 422-430, June 2019.

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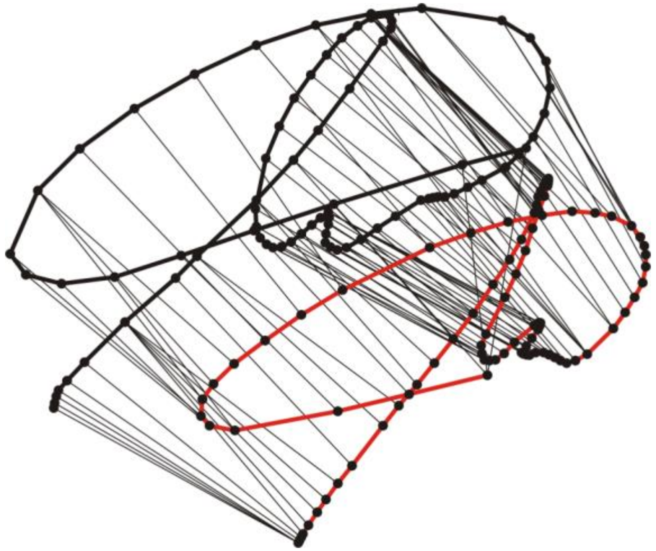
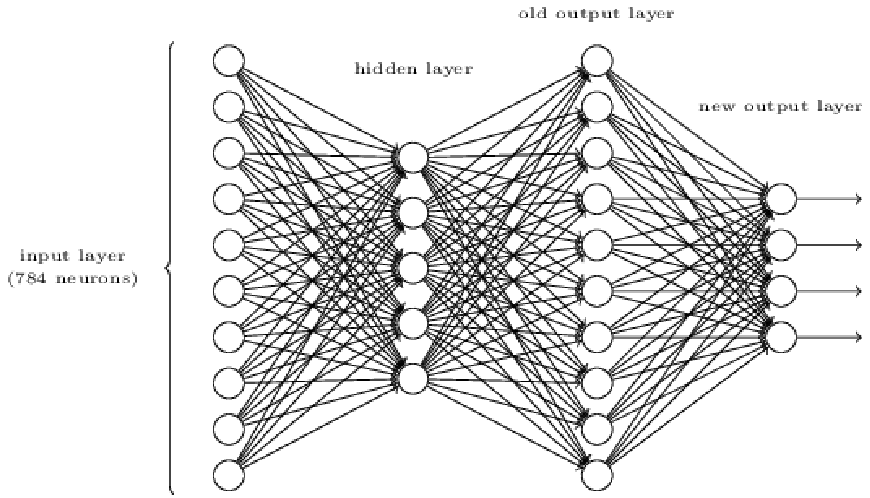
Traditional vs Deep Learning



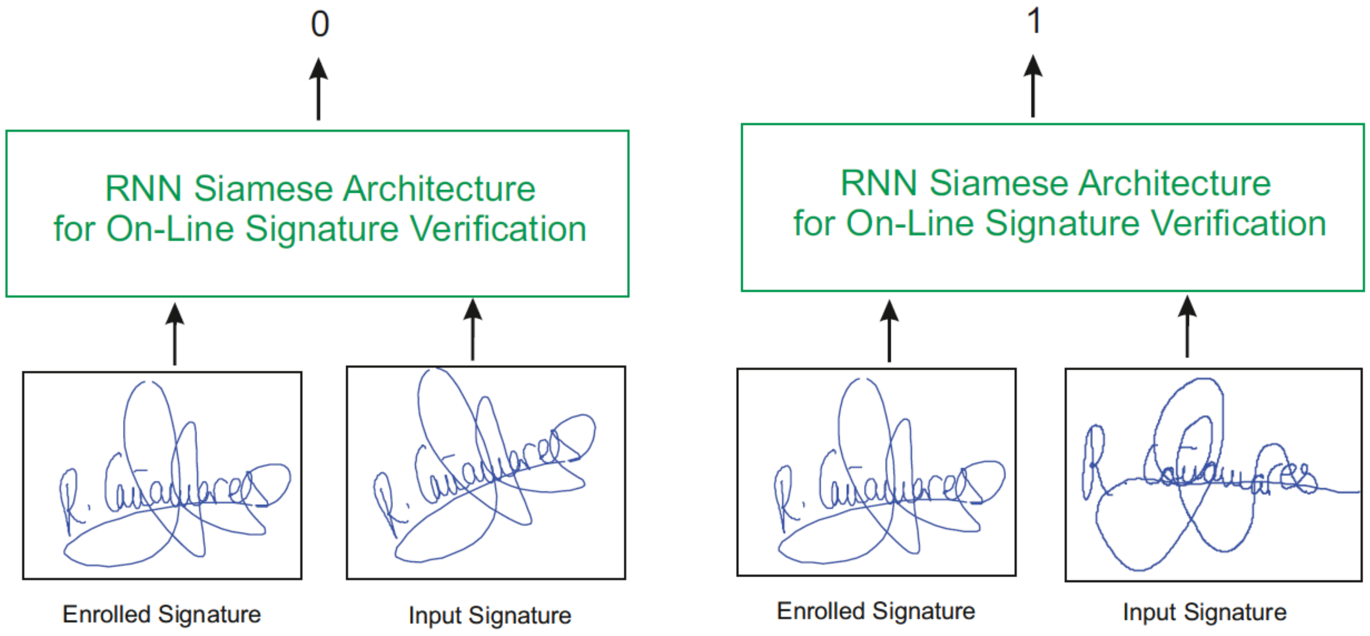


Deep Learning using Local Features

1st Deep Learning Approach:

- Writer-independent on-line signature verification system based on Siamese Architecture.

Goal: learn a dissimilarity metric from data to be small for pairs of genuine signatures from the same user, and longer for pairs of signatures coming from different users.

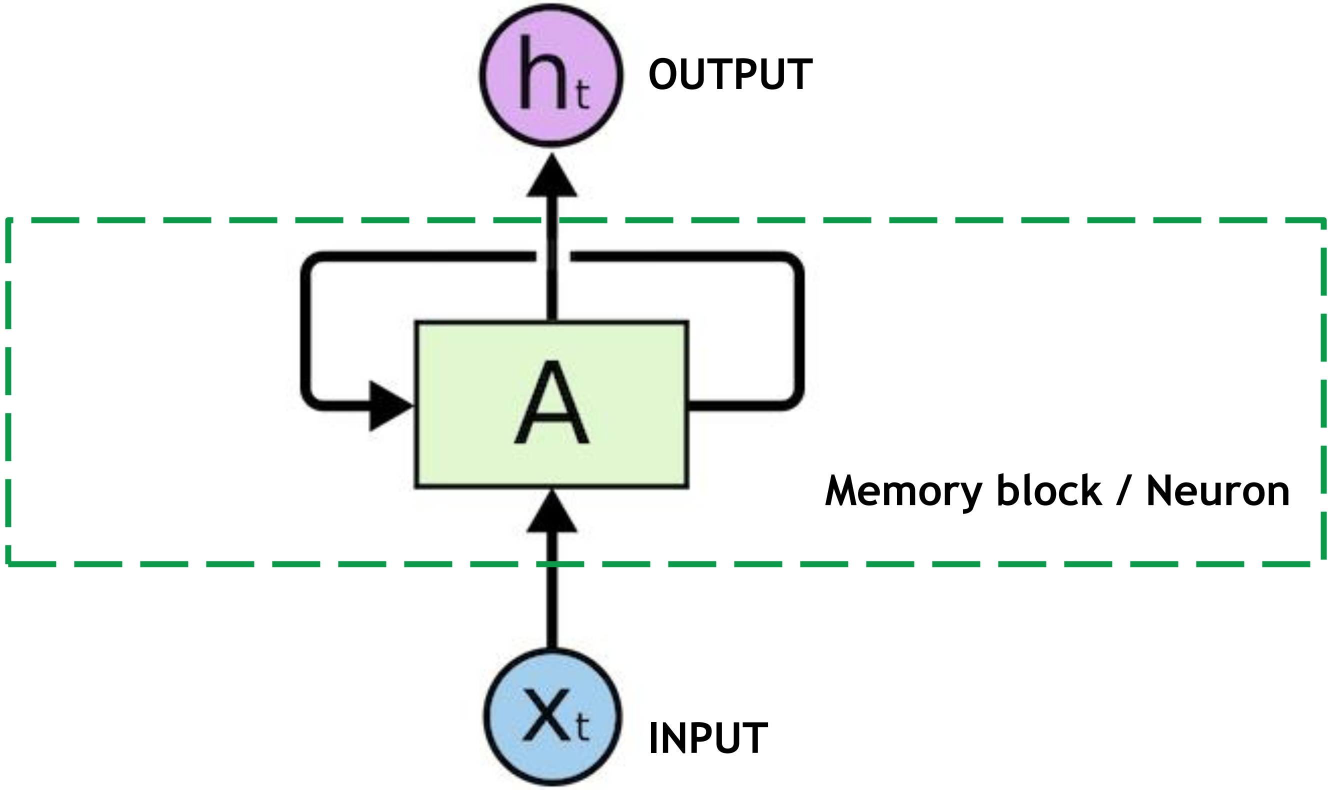


Genuine Case Impostor Case

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Exploring Recurrent Neural Networks for On-Line Handwritten Signature Biometrics", *IEEE Access*, vol. 6, pp. 5128 - 5138, 2018.

Recurrent Neural Networks (RNNs):

- They are defined as a connectionist model containing a self-connected hidden layer. One benefit of the recurrent connection is that a memory of previous inputs remains in the network internal state, allowing it to make use of past context. Most common types of RNNs are LSTM and GRU.



- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Exploring Recurrent Neural Networks for On-Line Handwritten Signature Biometrics", *IEEE Access*, vol. 6, pp. 5128 - 5138, 2018.

Deep Learning using Local Features

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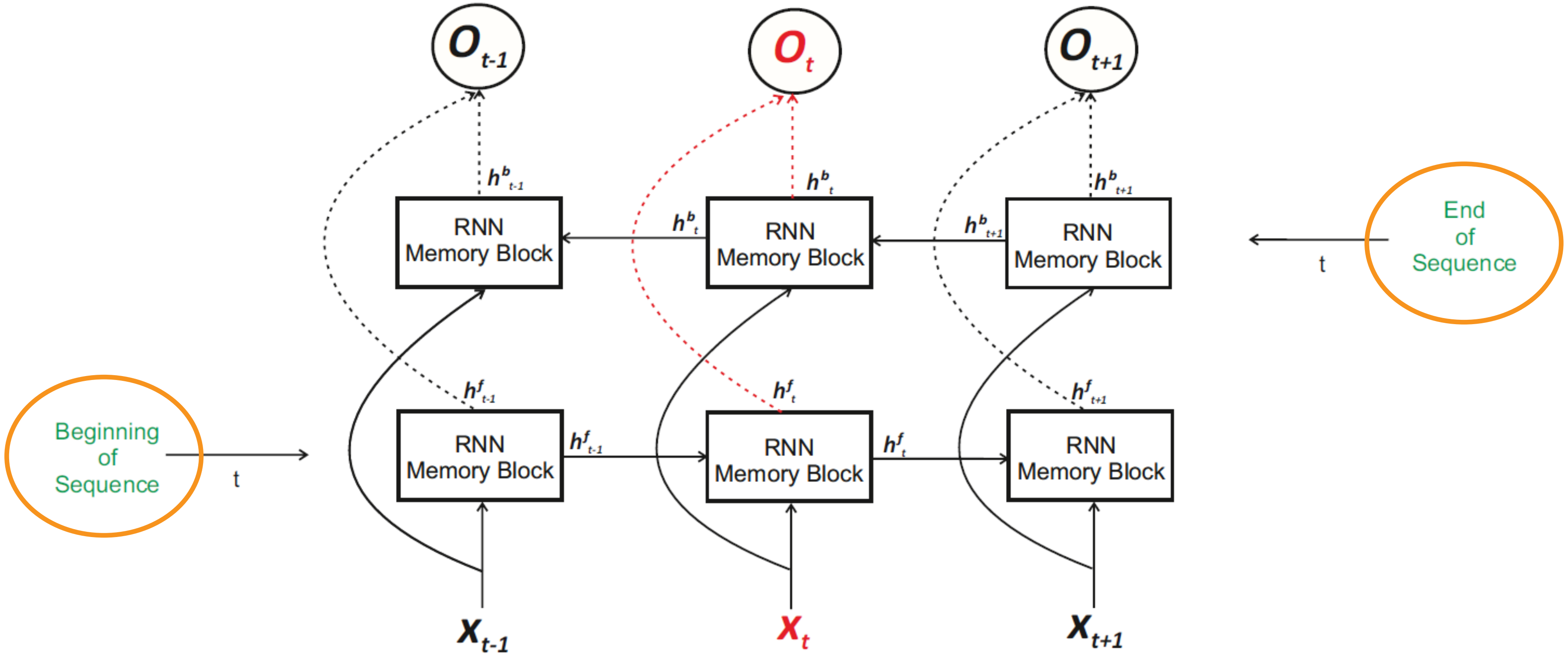
LSTM and GRU memory blocks have access only to the past and present context.
Bidirectional schemes provide access to also future context (BLSTM and BGRU).



Top: propagates the information backward in time (towards the left)

Bottom: propagates the information forward in time (towards the right)

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Exploring Recurrent Neural Networks for On-Line Handwritten Signature Biometrics", *IEEE Access*, vol. 6, pp. 5128 - 5138, 2018.

Deep Learning using Local Features

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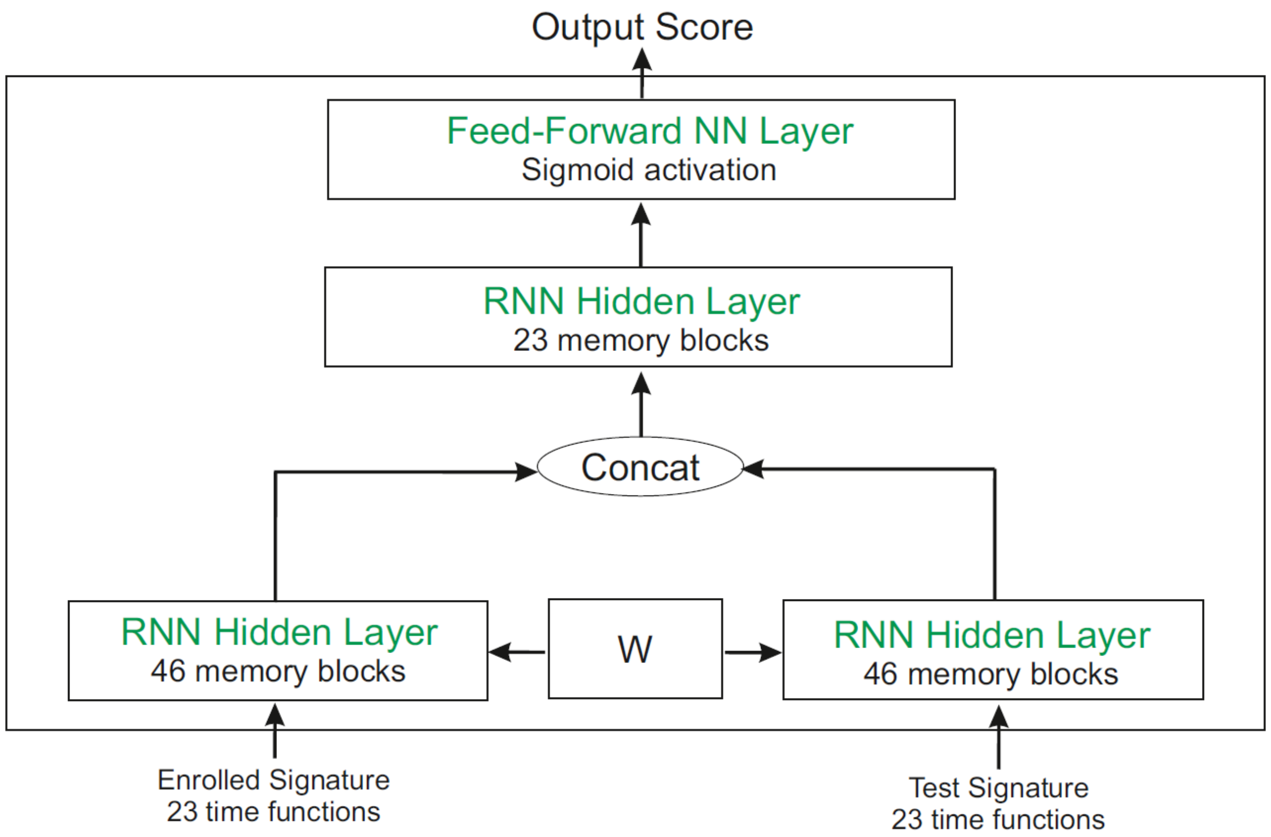
End-to-end writer-independent signature verification system.



- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Exploring Recurrent Neural Networks for On-Line Handwritten Signature Biometrics", *IEEE Access*, vol. 6, pp. 5128 - 5138, 2018.

DeepSign Database

DeepSign Database (1526 users)

Design

MCYT	+	BiosecurID	+	Biosecure DS2	+	e-BioSign	+	e-BioSign 2
Users: 330 Sessions: 1 Input: Stylus Gen. Sig./user: 25 Sk. Forg./user: 25		Users: 400 Sessions: 4 Input: Stylus Gen. Sig./user: 16 Sk. Forg./user: 12		Users: 650 Sessions: 2 Input: Stylus Gen. Sig./user: 30 Sk. Forg./user: 20		Users: 65 Sessions: 2 Input: Stylus and Finger Gen. Sig./user: 8 Sk. Forg./user: 6		Users: 81 Sessions: 2 Input: Stylus and Finger Gen. Sig./user: 8 Sk. Forg./user: 6

Devices

Writing Tool: Stylus

Wacom Intuos A6

Wacom Intuos 3

Wacom STU-500

Wacom STU-530

Wacom DTU-1031

Writing Tool: Stylus and Finger

Samsung ATIV 7

Samsung Galaxy Note 10.1

Writing Tool: Finger

Samsung Galaxy S3

- 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. 15th International Conference on Document Analysis and Recognition, ICDAR*, Sydney, Australia, September 2019.

Deep Learning using Local Features

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Biometrics & Data Pattern Analytics Lab

Dynamic Time Warping

EER (%)	1vs1	4vs1
Skilled Forgeries	10.17	7.75

Deep Learning (RNNs)

EER (%)	1vs1	4vs1
Skilled Forgeries	3.90	3.40

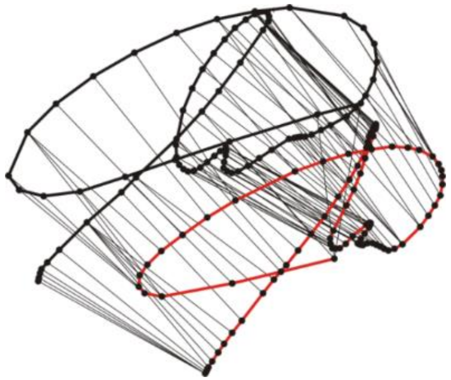
Results using the final evaluation dataset of BiosecurID.

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Exploring Recurrent Neural Networks for On-Line Handwritten Signature Biometrics", *IEEE Access*, vol. 6, pp. 5128 - 5138, 2018.

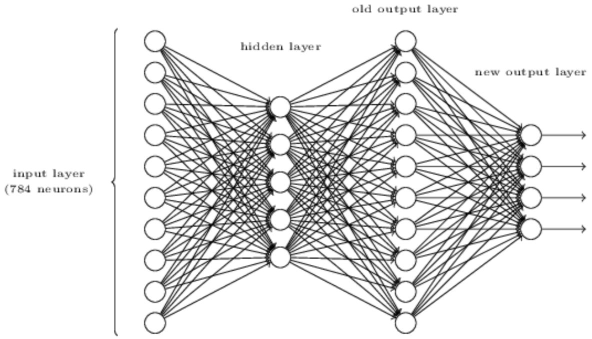
Deep Learning using Local Features

Time-Aligned Recurrent Neural Networks (TA-RNNs)

Dynamic Time Warping

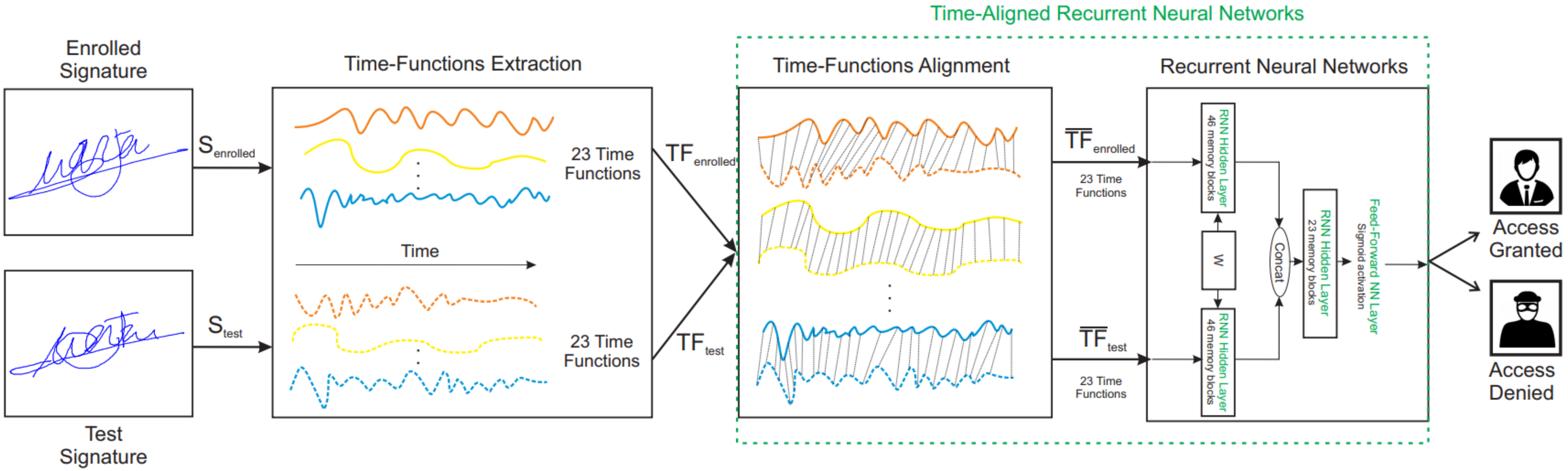


Deep Learning



- 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.

Deep Learning using Local Features



Spanish Patent Application (P202030060), Expandable to International Protection

- 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.

Deep Learning using Local Features

Dynamic Time Warping

EER (%)	1vs1	4vs1
Skilled Forgeries	10.17	7.75

Deep Learning (RNNs)

EER (%)	1vs1	4vs1
Skilled Forgeries	3.90	3.40

Deep Learning (TA-RNNs)

EER (%)	1vs1	4vs1
Skilled Forgeries	1.90	1.30

Results using the final evaluation dataset of BiosecurID.

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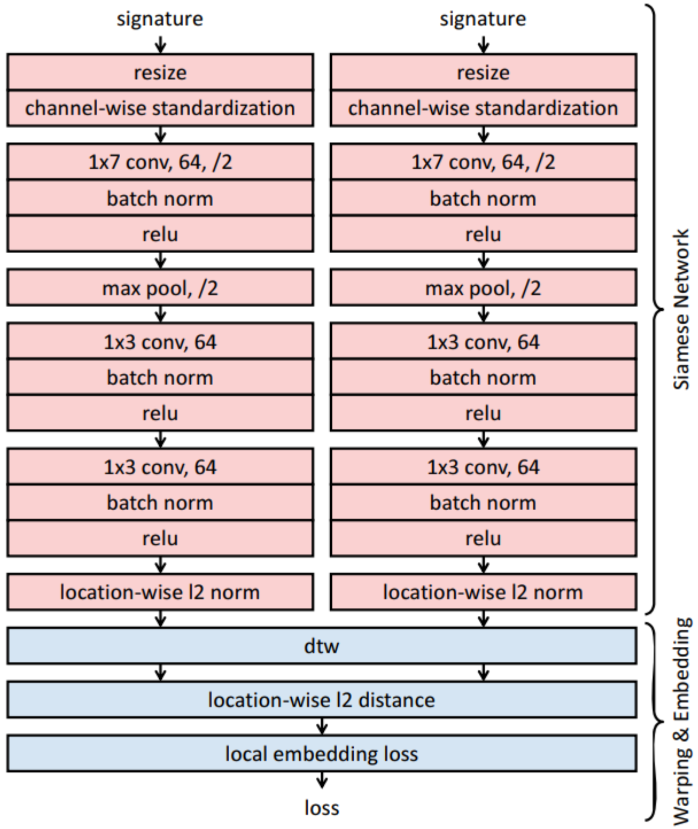
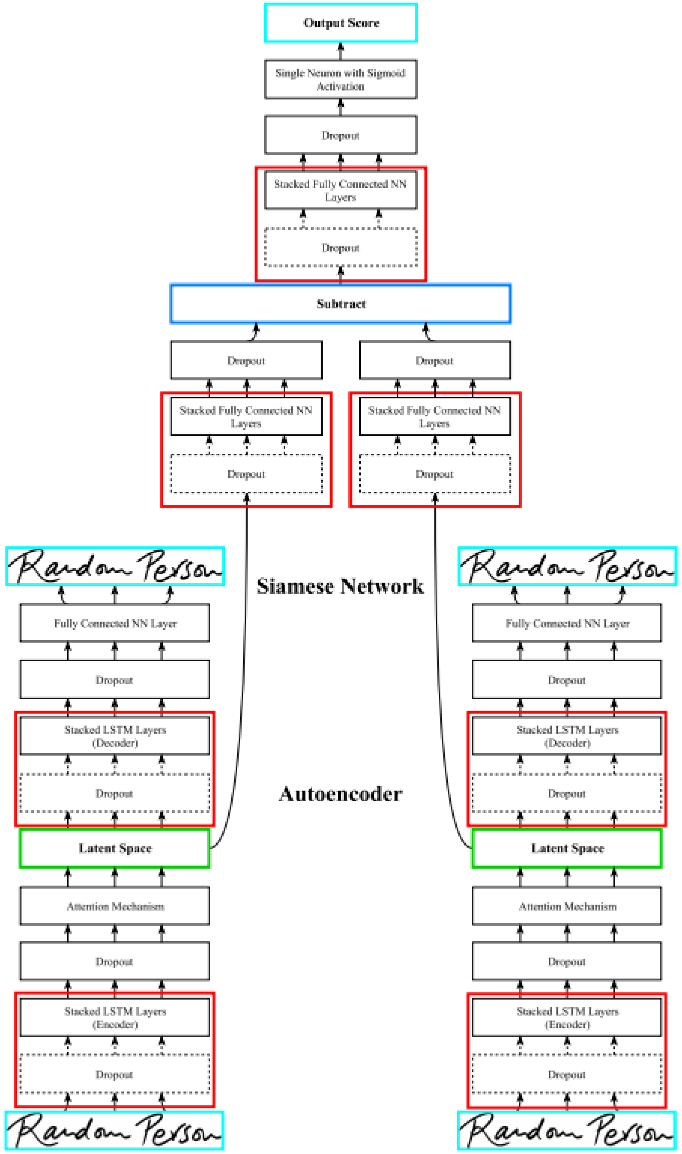
Deep Learning using Local Features



Convolutional Neural Networks



Autoencoders

- K. Ahrabian and B. BabaAli, "Usage of autoencoders and Siamese networks for online handwritten signature verification" *Neural Computing and Applications*, 2019
- S. Lai and L. Jin, "Recurrent adaptation networks for online signature verification," *IEEE Transactions on Information Forensics and Security*, 14(6), 1624-1637, 2018
- X. Wu, A. Kimura, B. K. Iwana, S. Uchida and K. Kashino, "Deep Dynamic Time Warping: End-to-End Local Representation Learning for Online Signature Verification*", in Proc. International Conference on Document Analysis and Recognition (ICDAR)*, 2019.

ICDAR 2021 On-Line Signature Verification Competición (SVC 2021)

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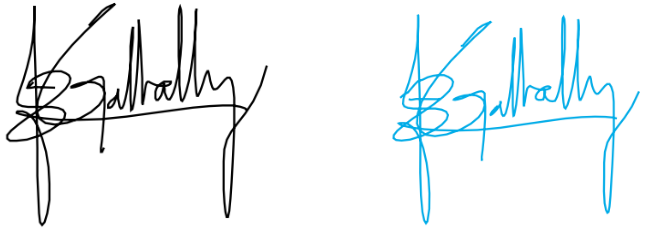
https://sites.google.com/view/SVC2021/home

OTHER RESEARCH LINES

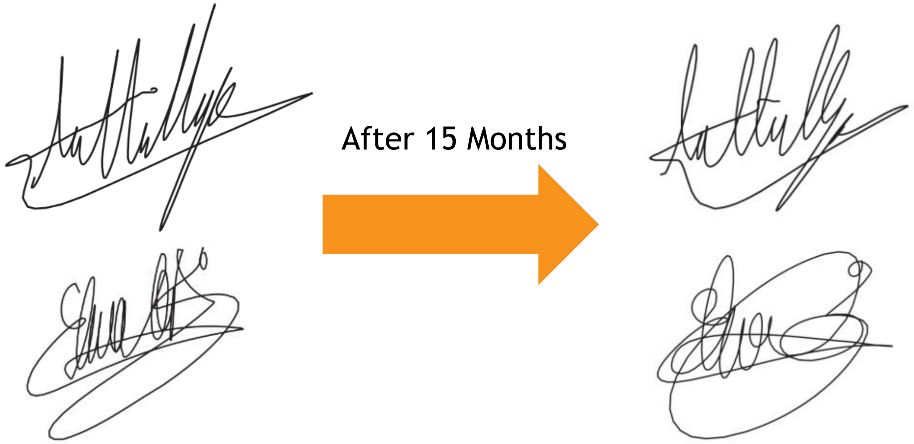
Signature Synthesis



Real | Synthetic

Signature Complexity

Signature Aging

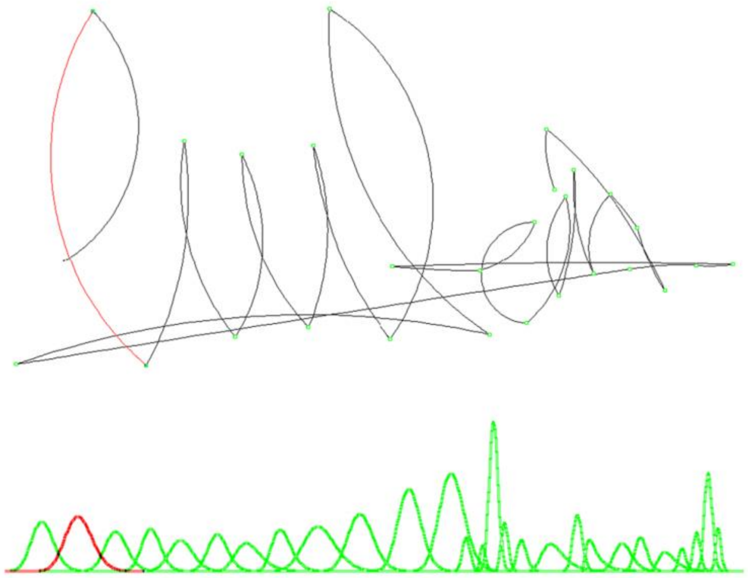


Handwritten Passwords

OTP System
(e.g. 934)

Signature Synthesis

Sigma lognormal writer generation model: It emulates the physiological human movement production for the generation of signatures. The idea is based on the fact that one signature can be decomposed into strokes in which each stroke i follows a lognormal velocity distribution $vi(t)$:



$$|\vec{v}_i(t)| = \frac{D_i}{\sigma_i(t - t_{0i})\sqrt{2\pi}} \exp\left(\frac{(\ln(t - t_{0i}) - \mu_i)^2}{-2\sigma_i^2}\right)$$

It depends of Neuromuscular parameters

The complete signature can be modelled as the sum of the different individual stroke velocity profiles as:

$$\vec{v}(t) = \sum_{i=1}^{N} \vec{v}_i(t)$$

- O. C. Reilly and R. Plamondon, “Development of a Sigma-Lognormal Representation for On-Line Signatures,” *Pattern Recognition* 42(12): 3324–3337, 2009.
- M. A. Ferrer, M. Diaz, C. Carmona-Duarte and R. Plamondon, “iDeLog: Iterative Dual Spatial and Kinematic Extraction of Sigma-Lognormal Parameters,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 42(1): 114–125, 2020

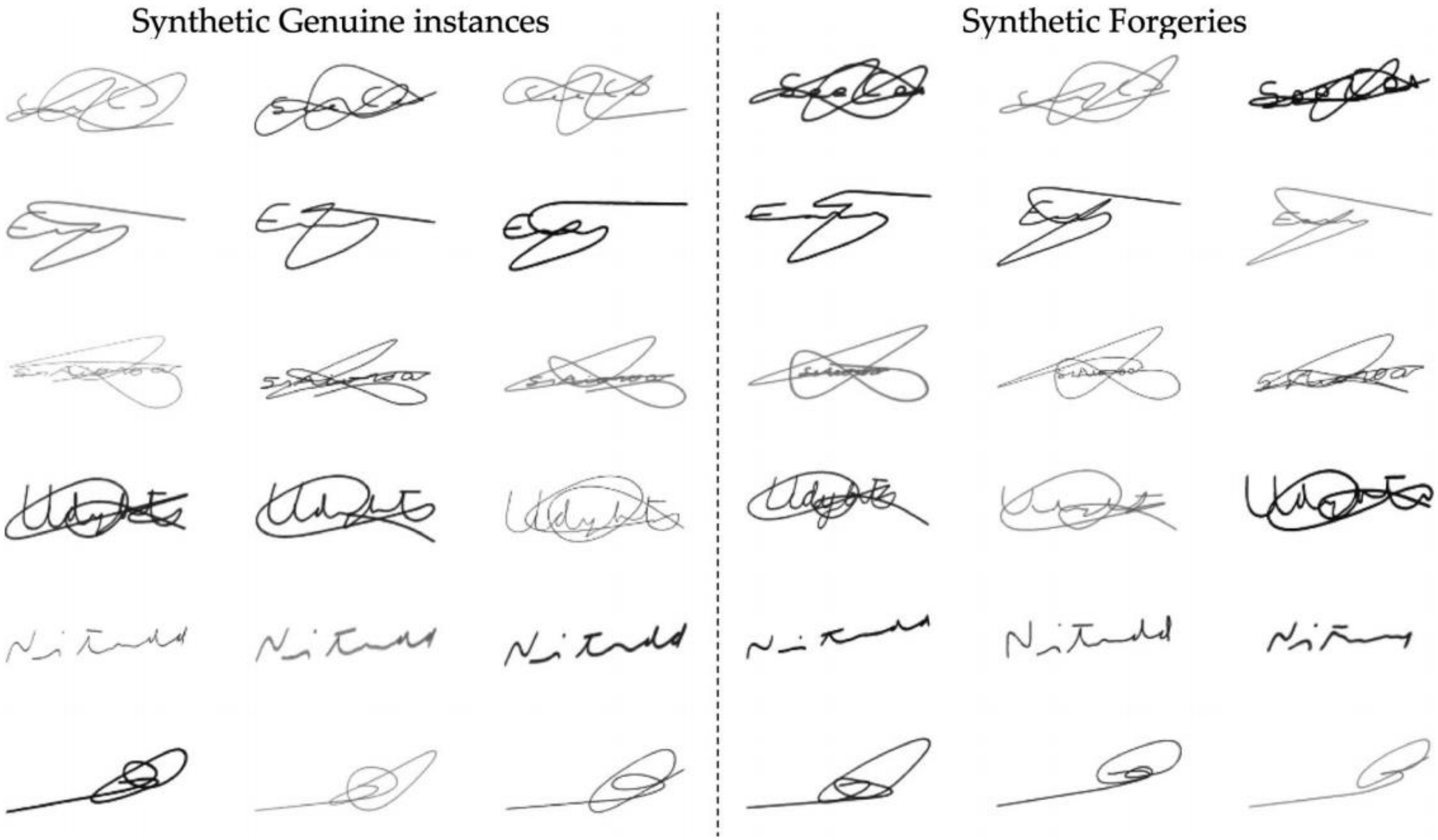
Guess Which One is Synthetic

J Galbally, R Plamondon, J Fierrez, J Ortega-Garcia, “Synthetic On-Line Signature Generaton. Part I: Methodology and Algorithms”, Pattern Recognition, 2012

Guess Which One is Synthetic

J Galbally, R Plamondon, J Fierrez, J Ortega-Garcia, "Synthetic On-Line Signature Generaton. Part I: Methodology and Algorithms", Pattern Recognition, 2012

Signature Synthesis



- M. A. Ferrer, M. Diaz-Cabrera, and A. Morales, “Static signature synthesis: A neuromotor inspired approach for biometrics,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 37(3), 667-680, 2014.

Signature Synthesis

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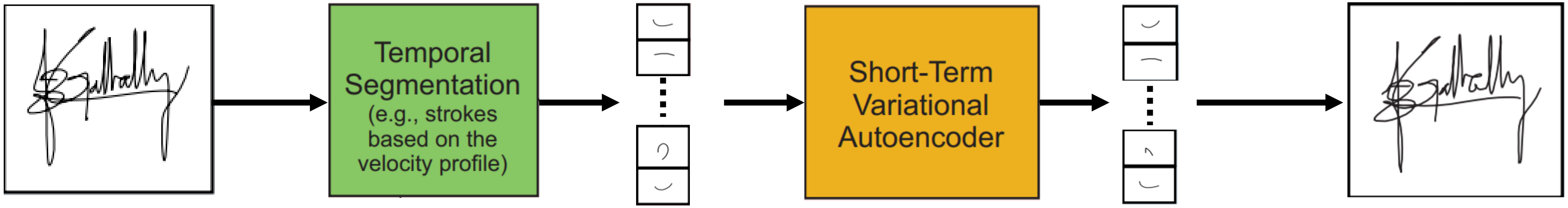
Biometrics & Data Pattern Analytics Lab

DeepWriteSYN: On-line handwriting synthesis using deep learning technology.



- R. Tolosana, P. Delgado-Santos, A. Perez-Uribe, R. Vera-Rodriguez, J. Fierrez and A. Morales, "DeepWriteSYN: On-Line Handwriting Synthesis via Deep Short-Term Representations", in *Proc. 35th AAAI Conference on Artificial Intelligence*, 2021.

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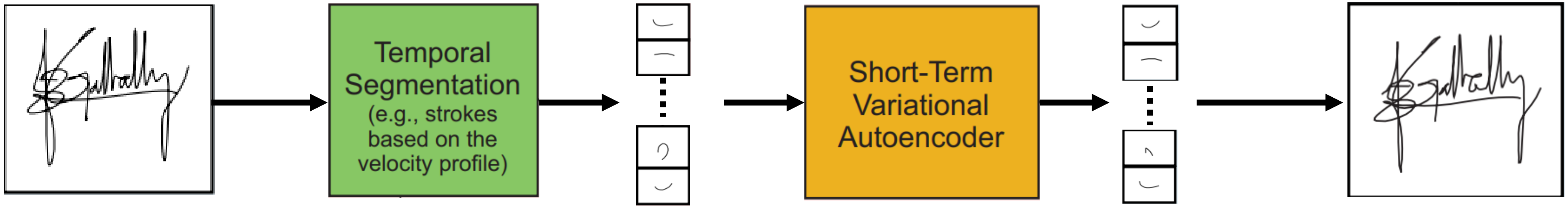

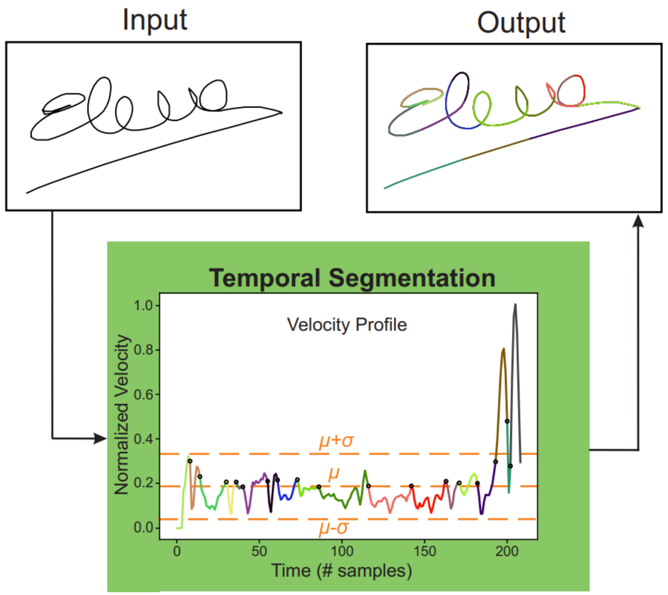

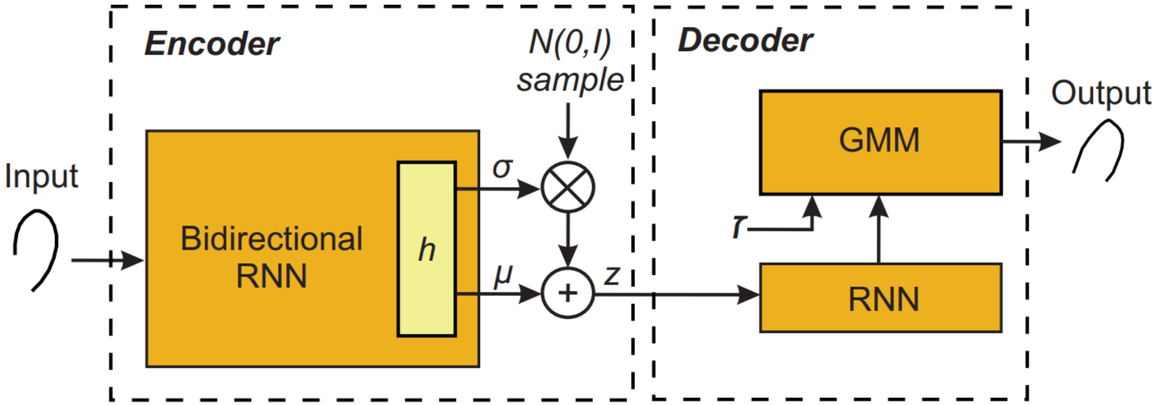

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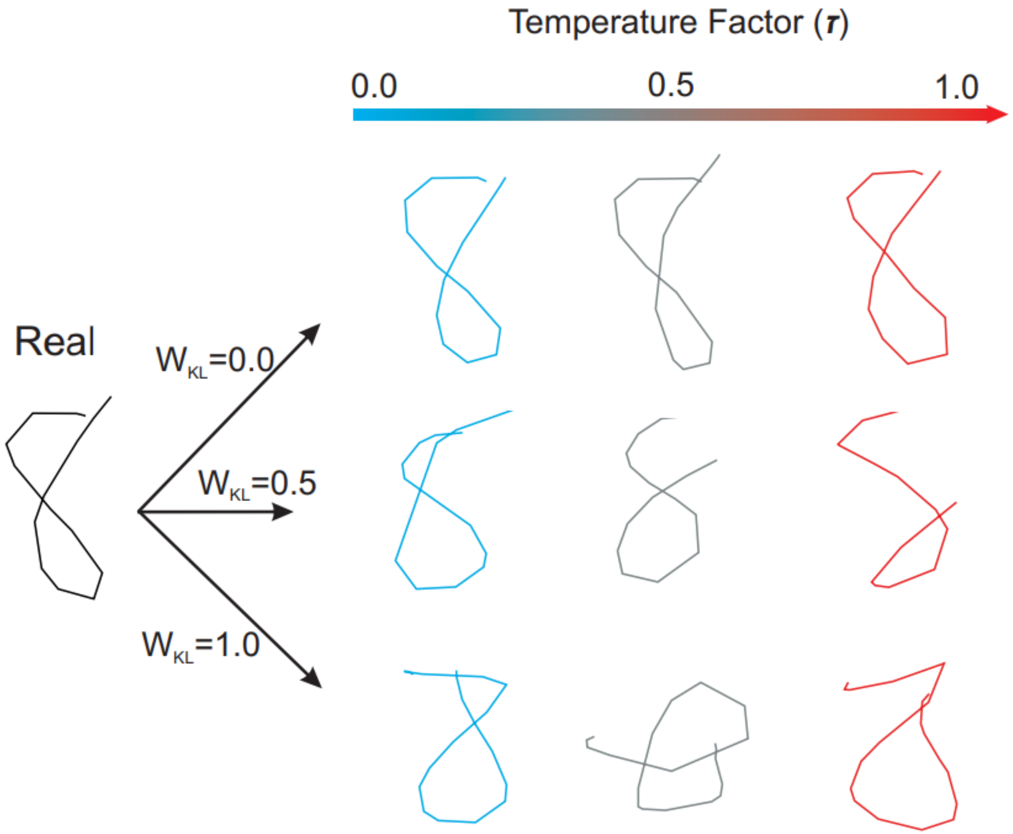

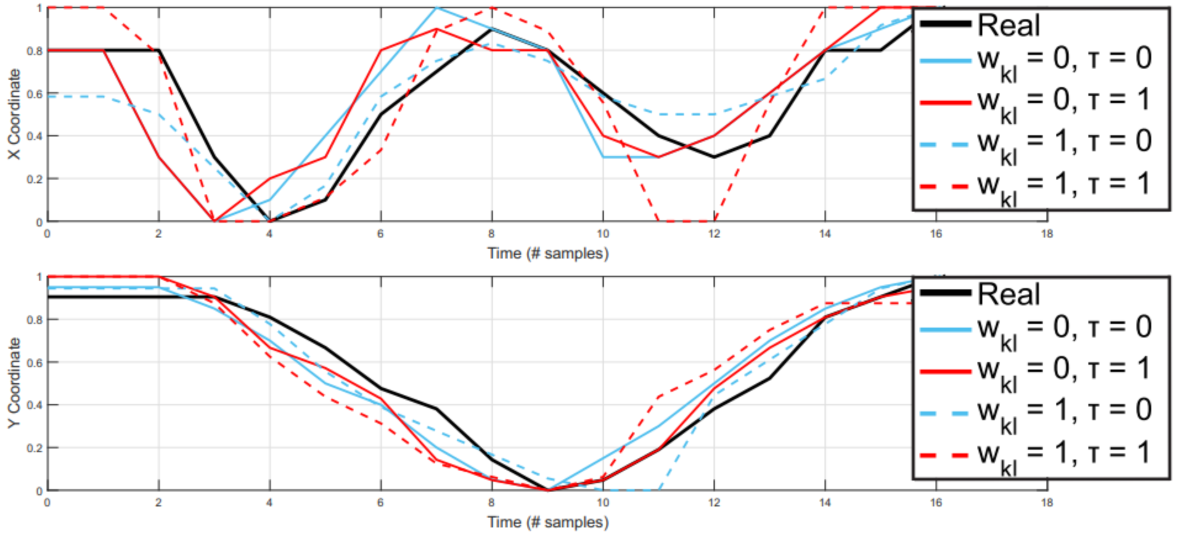

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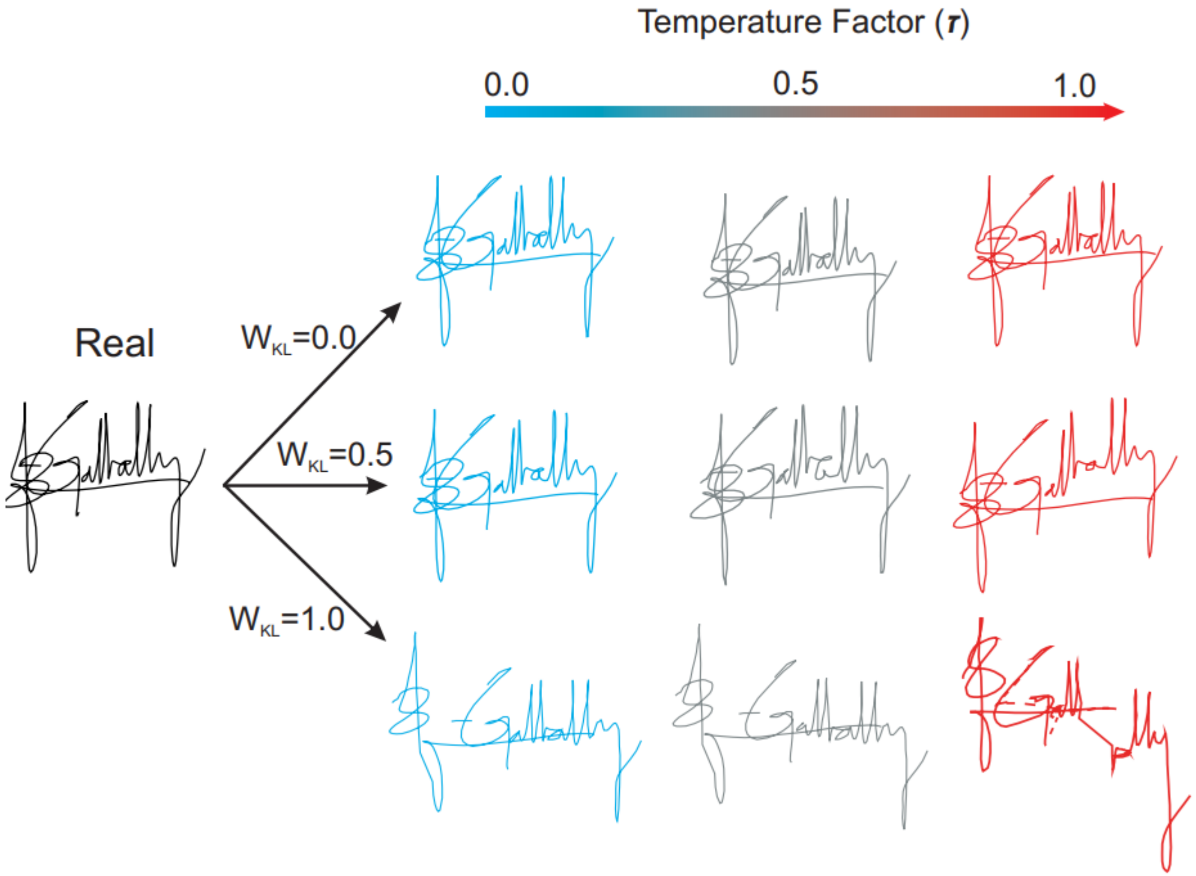
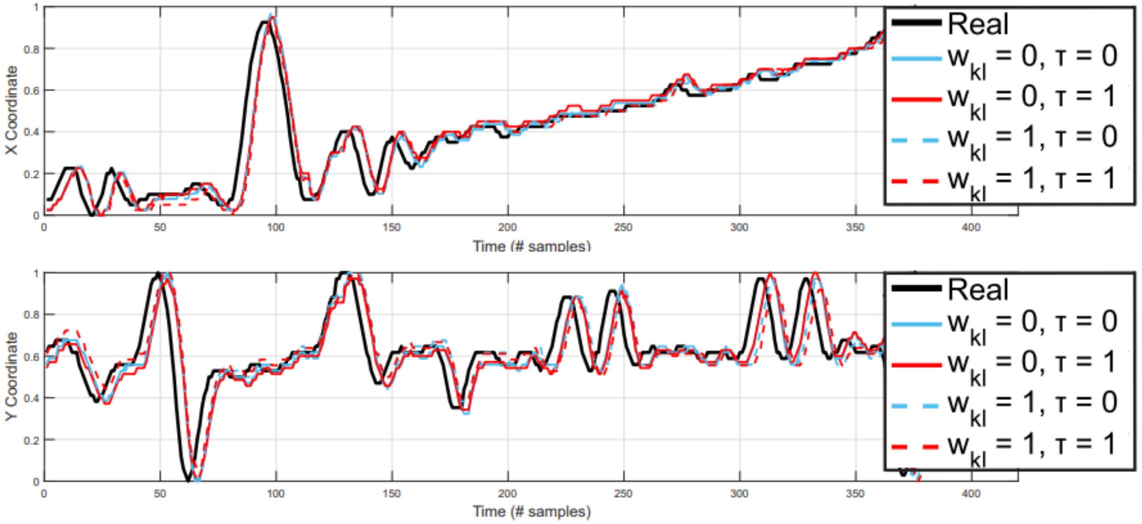
Signature Synthesis

DeepWriteSYN: On-line handwriting synthesis using deep learning technology.

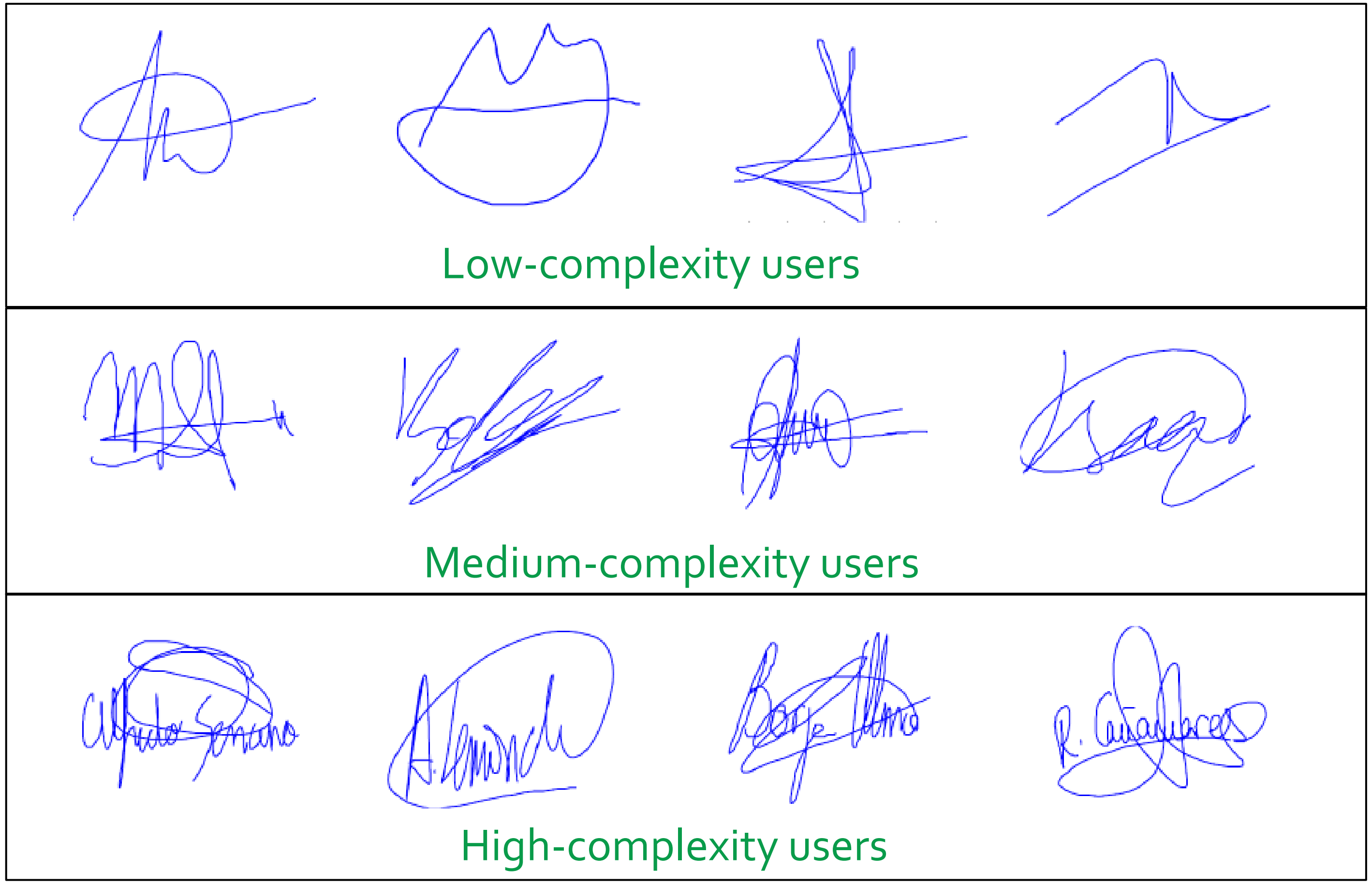




- R. Tolosana, P. Delgado-Santos, A. Perez-Uribe, R. Vera-Rodriguez, J. Fierrez and A. Morales, "DeepWriteSYN: On-Line Handwriting Synthesis via Deep Short-Term Representations", in *Proc. 35th AAAI Conference on Artificial Intelligence*, 2021.

Signature Complexity

Exploiting the signature complexity to develop more robust on-line signature verification systems.



- R. Tolosana, R. Vera-Rodriguez, R. Guest, J. Fierrez and J. Ortega-Garcia, "Exploiting Complexity in Pen-and Touch-based Signature Biometrics", *International Journal on Document Analysis and Recognition*, n. 23, pp. 129–141, 2020.
- R. Vera-Rodriguez, R. Tolosana, M. Caruana, G. Manzano, C. Gonzalez-Garcia, J. Fierrez and J. Ortega-Garcia, "DeepSignCX: Signature Complexity Detection using Recurrent Neural Networks", in *Proc. 15th International Conference on Document Analysis and Recognition, ICDAR*, Sydney, Australia, September 2019.

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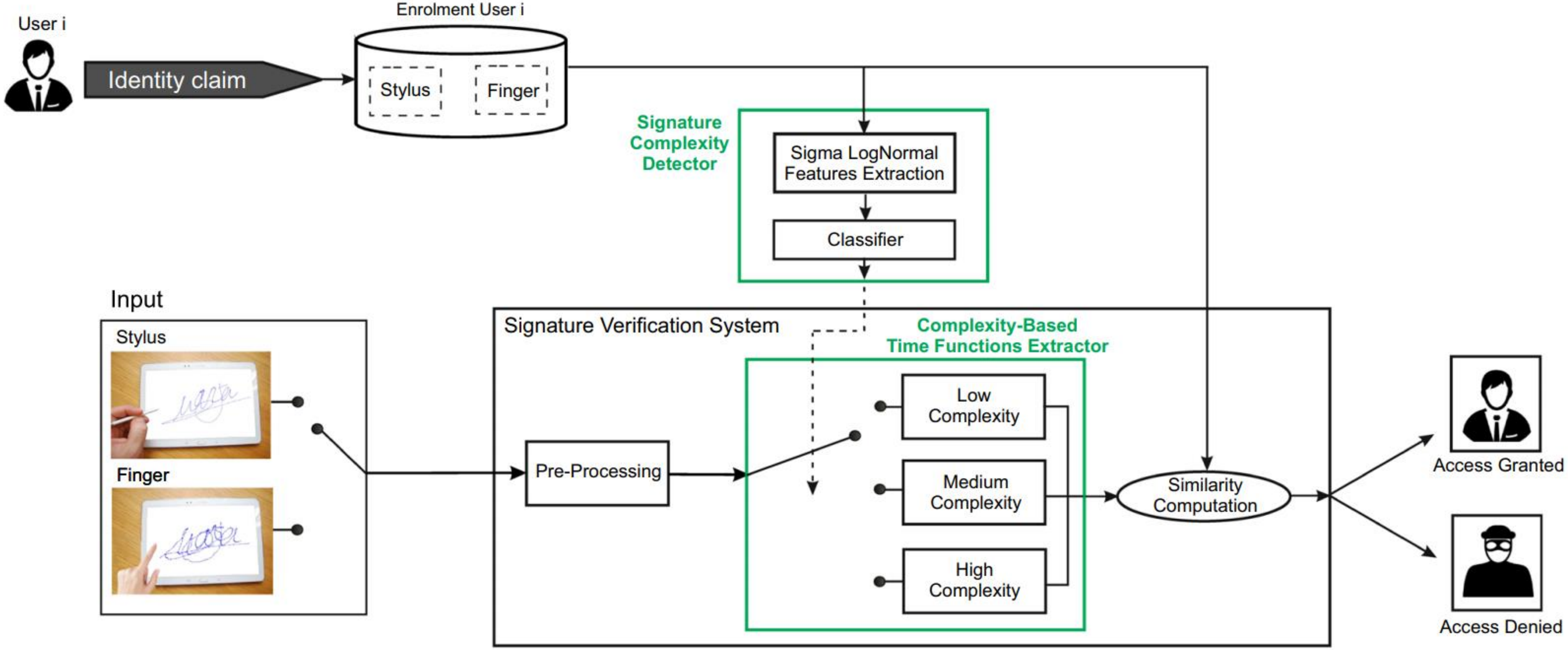

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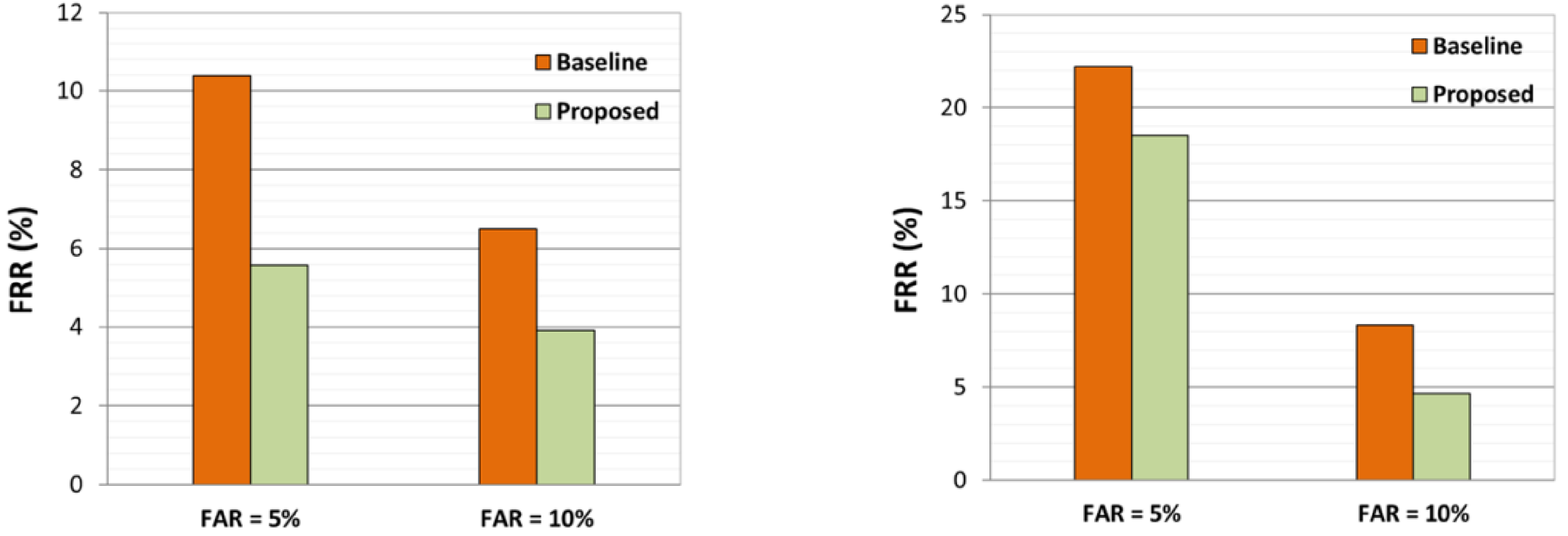

(a) BiosecurID (b) e-BioSign

Baseline: on-line signature verification system trained regardless of the signature complexity.
Proposed: on-line signature verification system trained considering the signature complexity.

- R. Tolosana, R. Vera-Rodriguez, R. Guest, J. Fierrez and J. Ortega-Garcia, "Exploiting Complexity in Pen-and Touch-based Signature Biometrics", *International Journal on Document Analysis and Recognition*, n. 23, pp. 129–141, 2020.

Signature Aging

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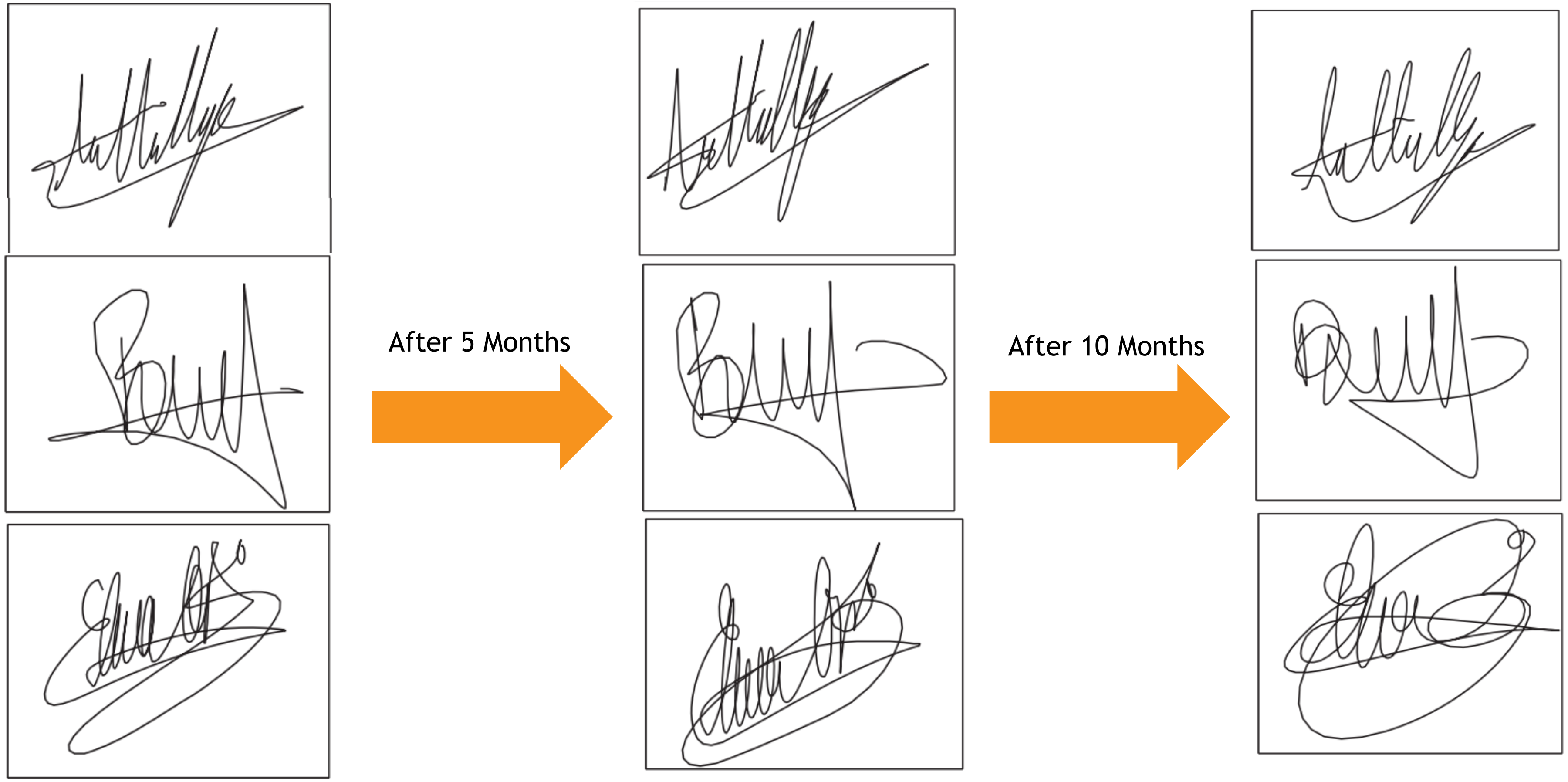
Aging: the gradual degradation of the system performance due to the changes suffered by the user's trait along the time.



- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Reducing the Template Aging Effect in On-Line Signature Biometrics", *IET Biometrics*, Vol. 8, n. 6, pp. 422-430, June 2019.
- J. Galbally, M. Martinez-Diaz and J. Fierrez, "Aging in Biometrics: An Experimental Analysis on On-Line Signature", *PLOS ONE*, Vol. 8, n. 7, pp. e69897, July 2013.

Signature Aging

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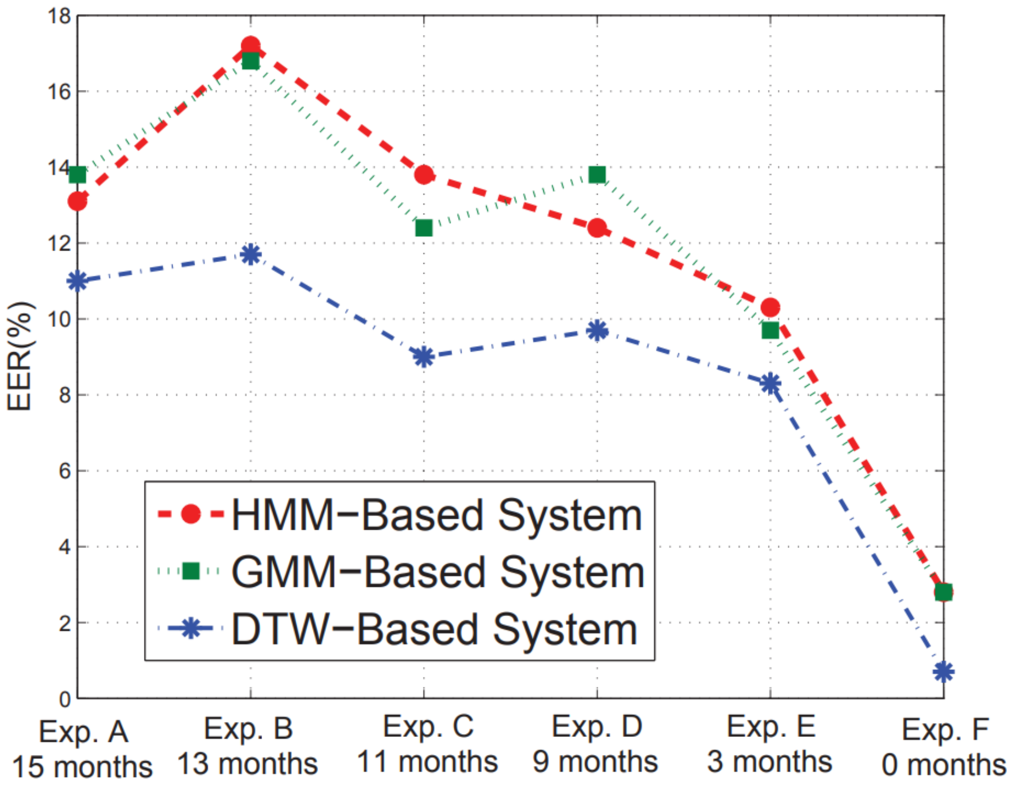

(a) Skilled forgery cases

Increasing the time between test and enrolment samples

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Reducing the Template Aging Effect in On-Line Signature Biometrics", *IET Biometrics*, Vol. 8, n. 6, pp. 422-430, June 2019.

Signature Aging

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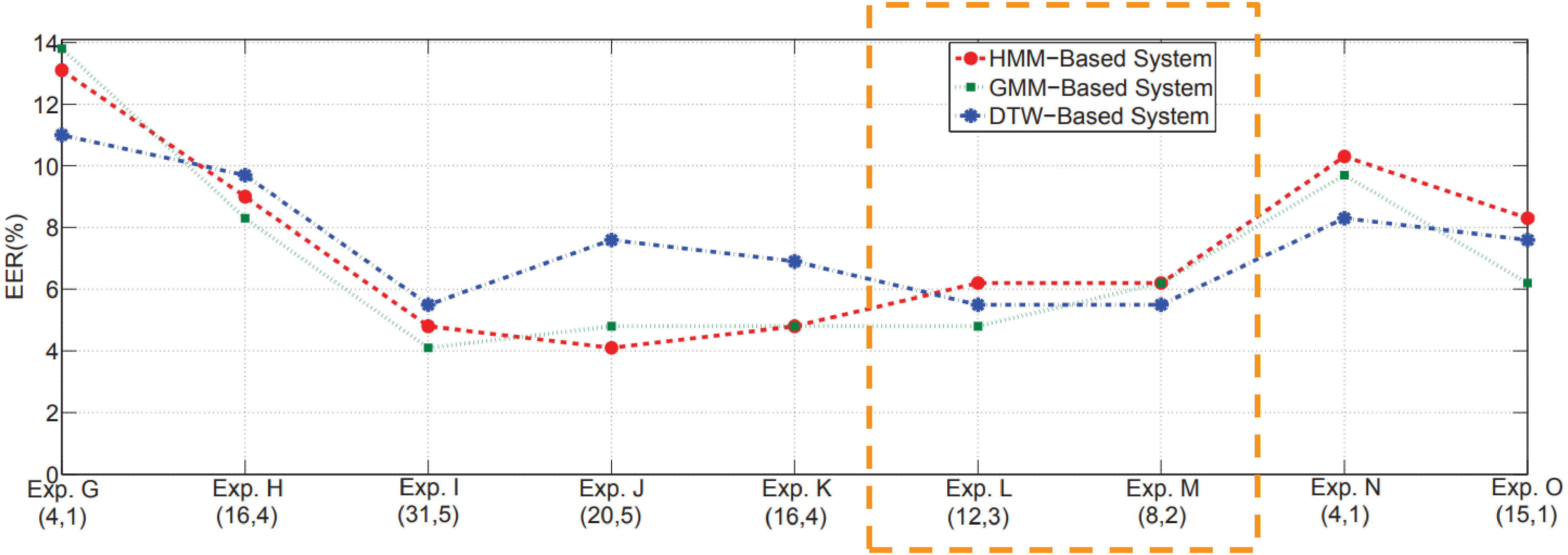
Template update strategies: reduce the aging effect.

Optimum template update: good performance, fewer training signatures



Newer signatures included for training

Older signatures removed for training

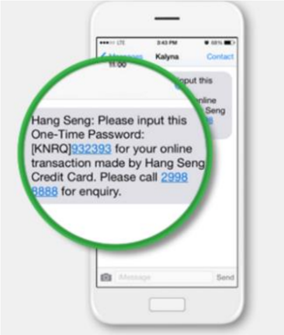
- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "Reducing the Template Aging Effect in On-Line Signature Biometrics", *IET Biometrics*, Vol. 8, n. 6, pp. 422-430, June 2019.

Handwritten Passwords

Traditional authentication approach.

amazon
ebay
Alibaba.com
Booking.com
airbnb
skyscanner
tripadvisor

Password
57618



- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "BioTouchPass2: Touchscreen Password Biometrics Using Time-Aligned Recurrent Neural Networks", *IEEE Transactions on Information Forensics and Security*, Vol. 5, pp. 2616-2628, 2020.
- R. Tolosana, R. Vera-Rodriguez and J. Fierrez, "BioTouchPass: Handwritten Passwords for Touchscreen Biometrics", *IEEE Transactions on Mobile Computing*, Vol. 19, n. 7, pp. 1532-1543, 2020.

Handwritten Passwords

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BioTouchPass: TouchScreen Password Biometrics.

amazon
ebay
Alibaba.com
Booking.com
airbnb
skyscanner
tripadvisor

OTP System
(e.g. 934)

Advantages:

- Users **do not memorize** passwords
- **User-friendly** interface (mobile scenarios)
- **Security level** easily configurable
  - # enrolment samples
  - Length password

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "BioTouchPass2: Touchscreen Password Biometrics Using Time-Aligned Recurrent Neural Networks", *IEEE Transactions on Information Forensics and Security*, Vol. 5, pp. 2616-2628, 2020.
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Handwritten Passwords

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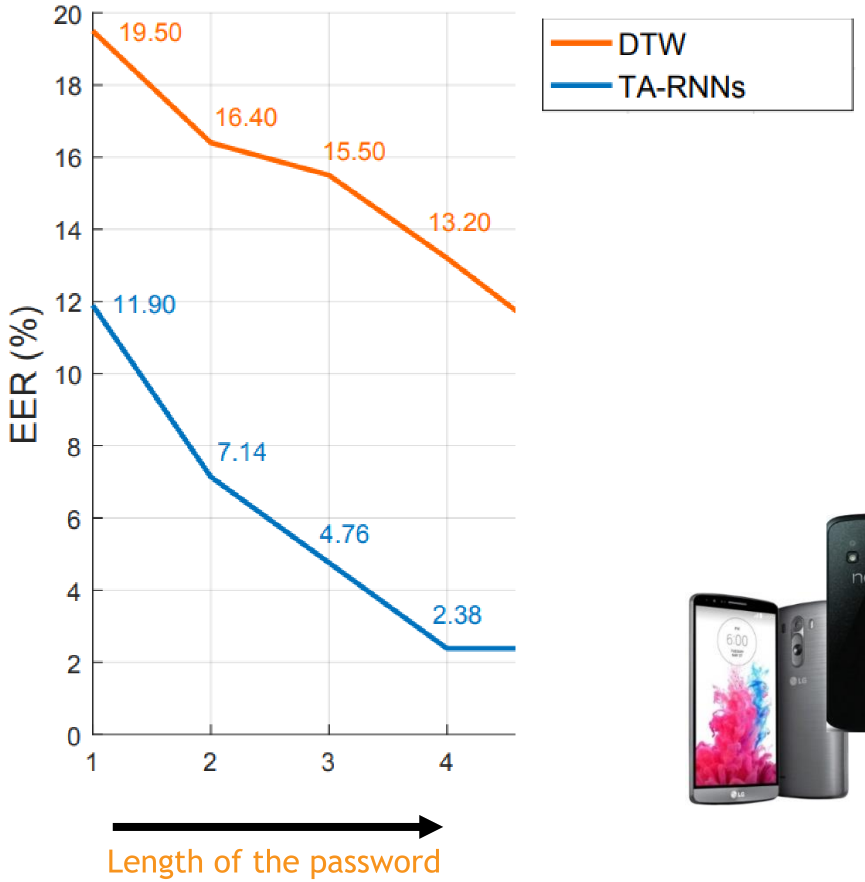
BioTouchPass: TouchScreen Password Biometrics.



Unsupervised Scenario

94 different smartphone models

- R. Tolosana, R. Vera-Rodriguez, J. Fierrez and J. Ortega-Garcia, "BioTouchPass2: Touchscreen Password Biometrics Using Time-Aligned Recurrent Neural Networks", *IEEE Transactions on Information Forensics and Security*, Vol. 5, pp. 2616-2628, 2020.
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e-health: Neuromotor Ability Monitoring

Sensor

Digitization

Dynamic sequences

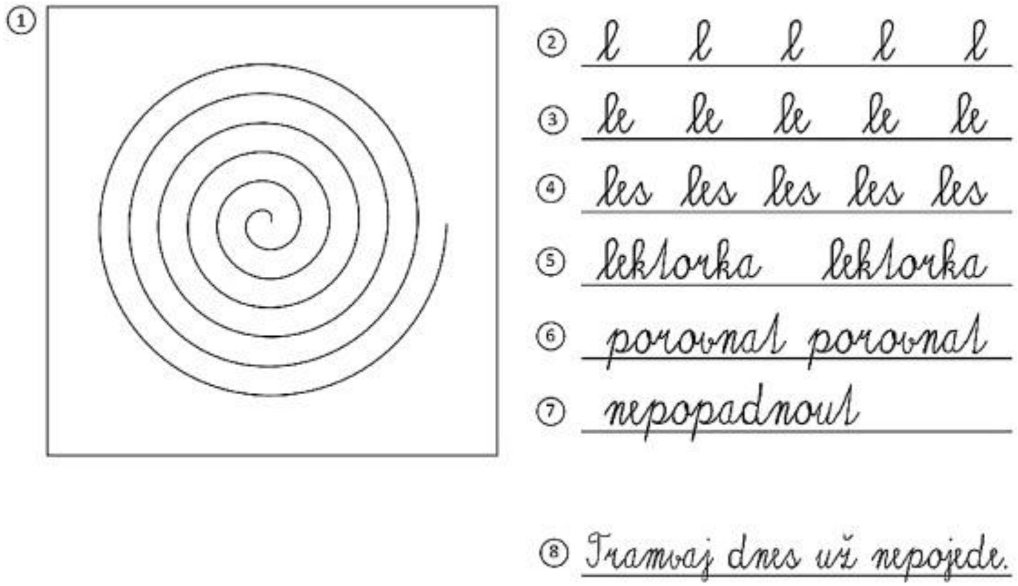
Feature Extraction

Local and Global

Modeling

Supervised Learning

Medical Report (mobile app)



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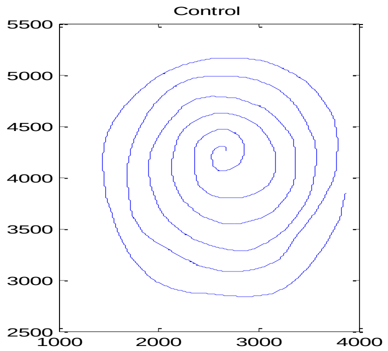
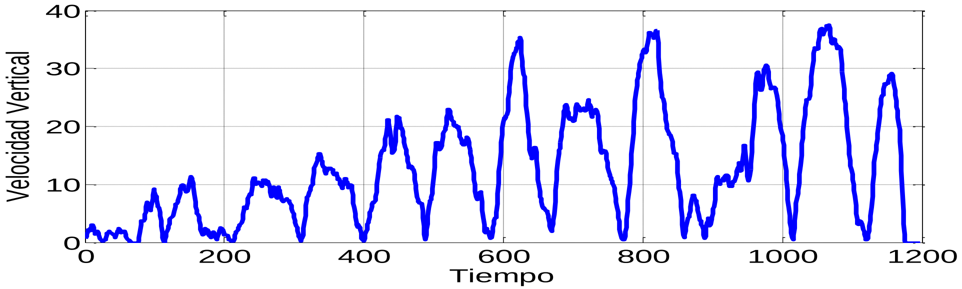
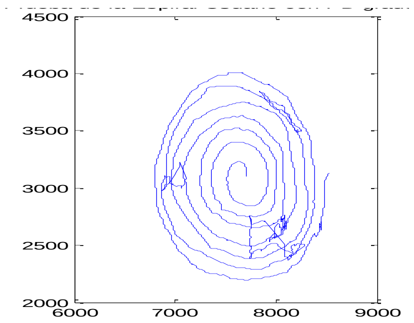
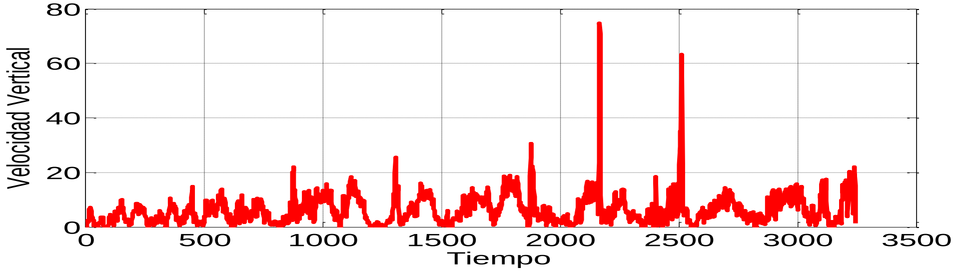


Control User





Parkinson's Pacient



Parkinson's affects writer neuromotor ability

R. Castrillon, A. Acien, J. Orozco-Arroyave, A. Morales, J. Vargas, R.Vera-Rodrıguez, J. Fierrez, J. Ortega-Garcia and A. Villegas, "Characterization of the Handwriting Skills as a Biomarker for Parkinson Disease", Proc. of IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019) – Human Health Monitoring Based on Computer Vision, Lille, France, April 2019.

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Handwritten Signature Recognition

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