Synthetic Signature Generation for Automatic Signature Verification

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Doctoral Dissertation

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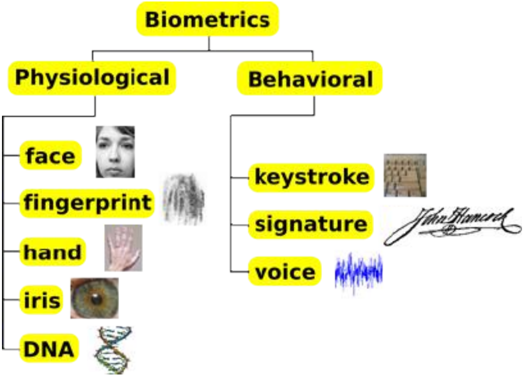
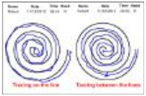
biometric systems



† A. Jain et al. (2016), "50 years of biometric research: Accomplishments, challenges, and opportunities". *Pattern recognition letters*, 79:80 - 105

High Acceptability



ULPGC IDeTIC

Random and Skilled forgeries.

How many forgeries could you detect? *Solutions in page 3 of the Thesis*

Figure extracted from Morocho et al, 2016

† D. Morocho, A. Morales, et al. (2016), "Signature recognition: establishing human baseline performance via crowdsourcing". *In 4th Int. Conf. on Biometrics and Forensics (IWBF)*, pp. 1-6

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On-line and Off-line Signatures

(a) Real on-line signature signals

(b) Real off-line signature image

Figure extracted from Galbally et al, 2015

† J. Galbally, **M. Diaz-Cabrera**, M. A. Ferrer, M. Gomez-Barrero, A. Morales and J. Fierrez (2015), "On-Line Signature Recognition Through the Combination of Real Dynamic Data and Synthetically Generated Static Data", *Pattern Recognition*, Vol. 48, pp. 2921-2934

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Use of Signatures in biometric

Reliable evaluation of the signature verifiers requires:

- Availability of large databases
- Common benchmarks

Drawbacks

- Slow, boring, costly, complex process and require a high degree of cooperation of the donors
- Legal issues according to data protection

Alternative -> Synthesis of signatures

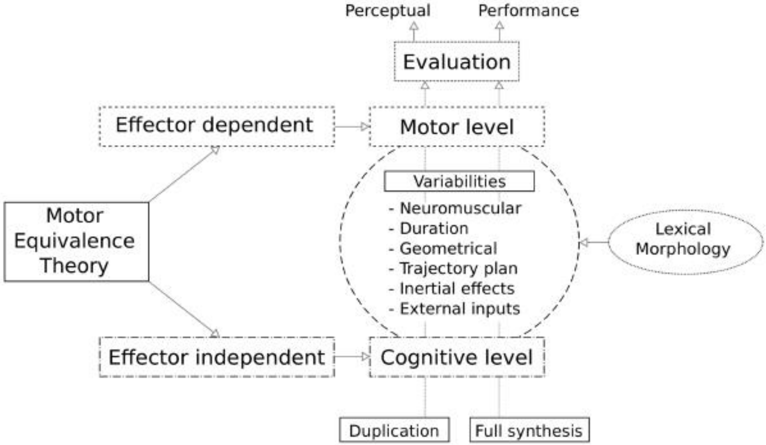
Advantage to use synthetic signatures

- Easy to generate through developed algorithm.
- There are nor size restriction neither limitation (genuine and forged signatures)
- They are not subject to legal procedures.

Two Proposals to generate synthetic signatures:

- Generation of duplicated samples. No new users.
- Generation of new synthetic identities. New users

The Thesis


Perceptual
Performance
Evaluation
Effector dependent
Motor level
Variabilities
- Neuromuscular
- Duration
- Geometrical
- Trajectory plan
- Inertial effects
- External inputs
Motor Equivalence Theory
Lexical Morphology
Effector independent
Cognitive level
Duplication
Full synthesis

What does “Motor Equivalence Theory” mean?

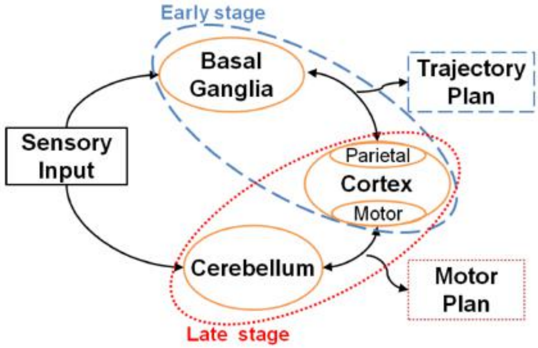


Figure extracted from Marcelli et al, 2013

† A. Marcelli al. (2013), “Some Observations on Handwriting from a Motor Learning Perspective”, *2nd Workshop on Automated Forensic Handwriting Analysis*
† A. M. Wing (2000), “Motor control: mechanisms of motor equivalence in handwriting”, *Current Biology*, vol. 10, pp. 245 - 248

What/How is a signature?

1 Two non-connected flourish signature

2 Complex two line signature: text plus flourish

3 Ascendant skew and initial letter with dot

4 Isolated capital letter at the end of the signature

5 Flourish merged with the letter

6 Simple signature with three legible letters

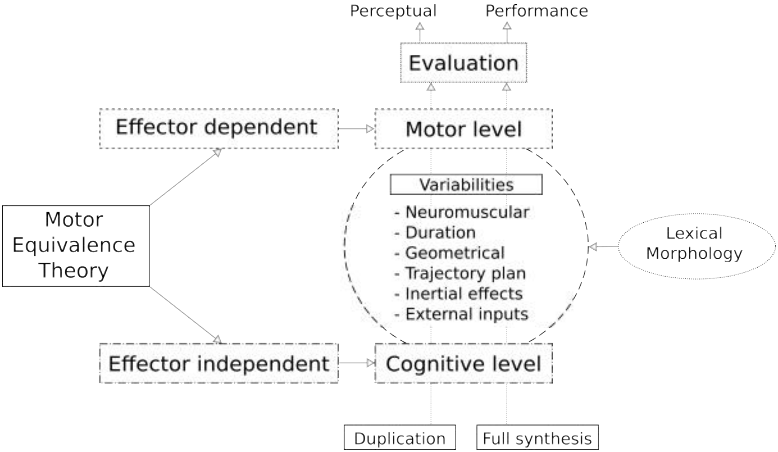
7 Corners to characterize the flourish

8 Slant

Figure extracted from Diaz-Cabrera et al, 2015

M. Diaz-Cabrera, M. A. Ferrer, A. Morales, (2015), “Modeling the Lexical Morphology of Western Handwritten Signatures”, *PLoS ONE* 10(4): e0123254

The Thesis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Cognitive level
Duplication
Full synthesis

Outline

1. **On-2-On**
   - Generation of duplicated signatures
   - Model Evaluation
2. **Off-2-Off**
   - Generation of duplicated signatures
   - Model Evaluation
3. **Full Synthesis**
   - Off-Line and On-Line signature generation
   - Model Evaluation
4. **Conclusions**

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FROM a real signature TO a synthetic signature

Intra-class variability

Proposals on signature duplication

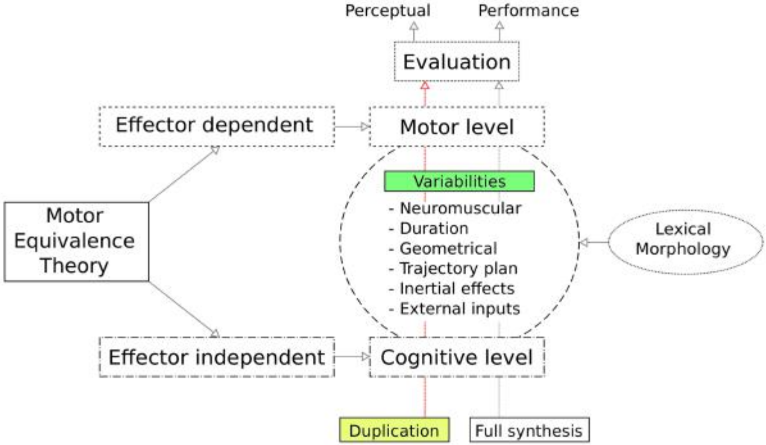
Conversion	Authors	Methods	Seed[1]	Target
On-2-On	Munich et al., 2003 (Munich and Perona, 2003)	Affine-scale/geometrical transformations	>1 Sign.	Statistically meaningful evaluation
On-2-On	Rabasse et al., 2007 (Rabasse et al., 2007)	Affine-scale/geometrical transformations	2 Sign.	Approaching the baseline performance
On-2-On	Galbally et al., 2009 (Galbally et al., 2009)	Affine-scale/geometrical transformations	1 Sign.	Improve the performance
On-2-On	Song et al., 2014 (Song and Sun, 2014)	Clonal Selection Algorithm	>1 Sign.	Improve the performance
On-2-Off	Rabasse et al., 2008 (Rabasse et al., 2008)	Affine-scale/geometrical transformations	2 Sign.	Approaching the baseline performance
On-2-Off	Guest et al., 2014 (Guest et al., 2014)	Interpolation methods	1 Sign.	Approaching the baseline performance
On-2-Off	Galbally et al., 2015 (Galbally et al., 2015)	Ink Deposition Model	1 Sign.	Approaching the baseline performance
Off-2-Off	Oliveira et al., 1997 (de Oliveira et al., 1997)	Convolution produces from polynomials and signals representation	1 Sign.	Enlarge database
Off-2-Off	Huang et al., 1997 (Huang and Yan, 1997)	Affine-scale/geometrical transformations	1 Sign.	Improve the performance
Off-2-Off	Fang et al., 2002 (Fang et al., 2002)	Elastic matching method	2 Sign.	Improve the performance
Off-2-Off	Frias et al., 2006 (Frias-Martinez et al., 2006)	Affine-scale/geometrical transformations	1 Sign.	Enlarge database
Off-2-On	*Open Issue*	-	-	-

[1] *Seed* refers to the number of necessary signatures to carry out each conversion

TODO

- Generation with reference to the signing process ✓
- Useful duplicates for multiple signature databases ✓
- Useful duplicates in several state-of-the-art ASVs ✓
- Duplication from off-2-on *In process*

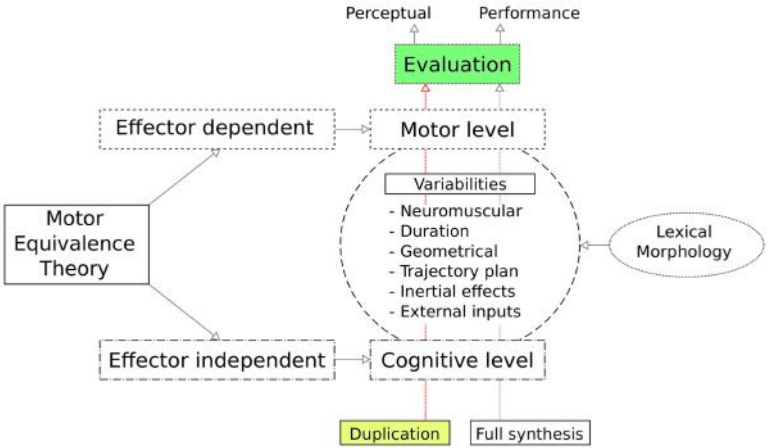
The Thesis



Go to generation

Go to evaluation

The Thesis



Go to generation Go to evaluation

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4. **Conclusions**

Input: $\{x, y, t\}_o$

1. Signature reconstruction
2. Method 1: stroke-wise
3. Method 2: target-wise

Output: $\{x, y, t\}_d$

M. Diaz, Andreas Fischer, R. Plamondon and M. A. Ferrer (2015). “Towards an automatic on-line signature verifier using only one reference per signer”, *Proc. 14th IAPR Conf. on Document Anal. and Recognition.*, pp. 631-635. *Best Student Paper Award*

M. Diaz, Andreas Fischer, M. A. Ferrer, and R. Plamondon (2016), “Dynamic Signature Verification System Based on One Real Signature”, *IEEE Transactions on Cybernetics*, *Accept under minor revision*

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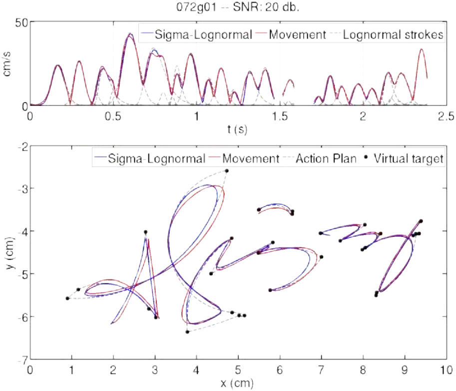
Reconstructed Signature - ΣΛ model



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

$$\phi_i(t) = \theta_{s_i} + \frac{\theta_{e_i}-\theta_{s_i}}{D_i} \int_0^t |\vec{v}_i(\tau)|d\tau$$

$$s_i = (D_i, t_{0_i}, \mu_i, \sigma_i, \theta_{s_i}, \theta_{e_i})$$

C O'Reilly, R Plamondon (2009), "Development of a Sigma - Lognormal representation for on-line signatures", *Pattern Recognition* 42 (12), 3324-3337

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ULPGC IDeTIC

Method 1: stroke-wise

$$s_i \rightarrow \widehat{s}_i = (\widehat{D}_i, \widehat{t}_{0_i}, \widehat{\mu}_i, \widehat{\sigma}_i, \widehat{\theta}_{s_i}, \widehat{\theta}_{se})$$

- neuromuscular execution of the stroke

$$\begin{cases} \widehat{\mu}_i = \mathcal{N}(\mu_i; (\mu_i \cdot d_\mu)^2) \\ \widehat{\sigma}_i = \mathcal{N}(\sigma_i; (\sigma_i \cdot d_\sigma)^2) \end{cases}$$

- motor command time occurrence

$$\begin{cases} \widehat{t}_{0_i} = t_{0_i} + \mathcal{N}(0; (d_{t_0})^2) \end{cases}$$

- geometrical stroke distortion

$$\begin{cases} \widehat{D}_i = \mathcal{N}(D_i; (D_i \cdot d_D)^2) \\ \widehat{\theta}_{s_i} = \theta_{s_i} + \mathcal{N}(0; (d_{\theta_s})^2) \\ \widehat{\theta}_{e_i} = \theta_{e_i} + \mathcal{N}(0; (d_{\theta_e})^2) \end{cases}$$

Input: $\{x, y, t\}_o$

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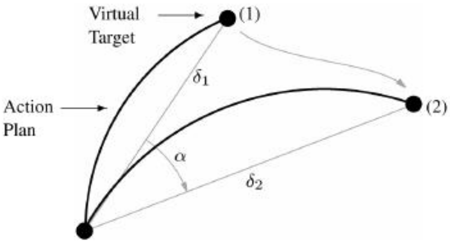
Method 2: target-wise

Sinusoidal Transformation

$$\widehat{x}_{VT} = x_{VT} + A_x \sin(\omega_x x_{VT} + \phi_x); \qquad \widehat{y}_{VT} = y_{VT} + A_y \sin(\omega_y y_{VT} + \phi_y)$$



$$\widehat{D}_i = D_i \cdot \delta_2/\delta_1; \qquad \widehat{\theta}_{s_i} = \theta_{s_i} + \alpha; \qquad \widehat{\theta}_{e_i} = \theta_{e_i} + \alpha$$

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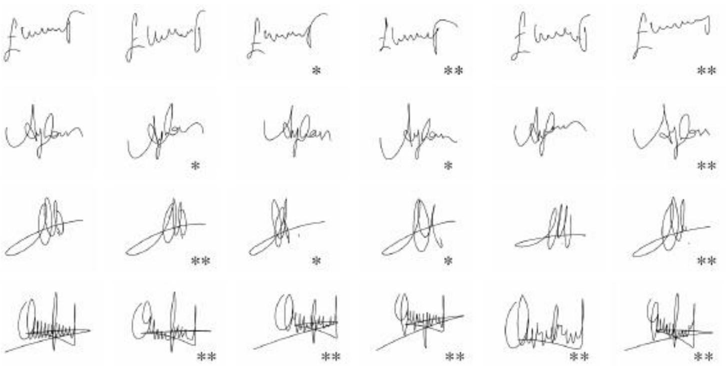
Visual Turing Test

scheme

Average confusion: 51.57 %



**Stroke-wise, **Target-wise*

Database and Automatic Signature Verifier

1. On-Line SUSIG-Visual: *(94 signers)*
2. On-Line SUSIG-Blind: *(88 signers)*
3. On-Line MCYT100: *(100 signers)*
4. On-Line SVC-Task1: *(40 signers)*
5. On-Line SVC-Task2: *(40 signers)*
6. On-Line SGNOTE: *(25 signers)*

---

1. function-based + DTW

   A. Fischer, **M. Diaz**, R. Plamondon, and M. A. Ferrer, (2015) "Robust score normalization for DTW-based on-line signature verification," in *Int. Conf. on Document Anal. and Recognition*, pp. 241-245.
2. function-based + Manhatan
3. function-based + HMM

Evaluating the variability of the duplicated signatures

Database	System A: DTW-based [7][24]					
	Random Forgery			Skilled Forgery		
	BL	SW	TW	BL	SW	TW
SUSIG-Visual	8.09	2.13	1.62	15.53	7.45	6.60

BL: baseline
SW: stroke-wise method
TW: target-wise method

Evaluating the variability of the duplicated signatures

Database	System A: DTW-based [7][24]					
	Random Forgery			Skilled Forgery		
	BL	SW	TW	BL	SW	TW
SUSIG-Visual	8.09	2.13	1.62	15.53	7.45	6.60
SUSIG-Blind	9.45	1.91	1.54	13.75	5.68	5.22
SVC-Task1	10.50	4.00	1.50	29.13	17.25	17.88
SVC-Task2	8.10	1.90	0.50	23.66	18.25	18.63
MCYT100	12.48	5.04	4.04	23.20	13.72	13.56
Mobile	12.80	2.06	1.03	-	-	-

BL: baseline
SW: stroke-wise method
TW: target-wise method

Evaluating the variability of the duplicated signatures

Database	System A: DTW-based [7][24]						System B: Manhattan-based [33]					
	Random Forgery			Skilled Forgery			Random Forgery			Skilled Forgery		
	BL	SW	TW	BL	SW	TW	BL	SW	TW	BL	SW	TW
SUSIG-Visual	8.09	2.13	1.62	15.53	7.45	6.60	46.85	11.36	12.64	8.51	5.53	5.85
SUSIG-Blind	9.45	1.91	1.54	13.75	5.68	5.22	52.14	8.05	8.86	13.64	8.52	8.64
SVC-Task1	10.50	4.00	1.50	29.13	17.25	17.88	44.00	13.60	15.20	29.50	27.88	28.25
SVC-Task2	8.10	1.90	0.50	23.66	18.25	18.63	42.50	10.40	12.80	28.00	25.00	27.88
MCYT100	12.48	5.04	4.04	23.20	13.72	13.56	56.32	10.20	10.96	33.88	20.36	21.36
Mobile	12.80	2.06	1.03	-	-	-	47.20	10.72	11.04	-	-	-

Database	System C: HMM-based [28]					
	Random Forgery			Skilled Forgery		
	BL	SW	TW	BL	SW	TW
SUSIG-Visual	11.98	4.76	4.32	40.96	30.64	31.60
SUSIG-Blind	7.19	2.86	2.76	31.25	18.07	18.52
SVC-Task1	10.79	8.16	5.53	33.25	27.00	24.12
SVC-Task2	7.50	3.81	3.68	31.88	22.38	23.88
MCYT100	14.62	5.79	5.66	31.96	16.32	16.24
Mobile	9.05	2.35	2.73	-	-	-

BL: baseline
SW: stroke-wise method
TW: target-wise method

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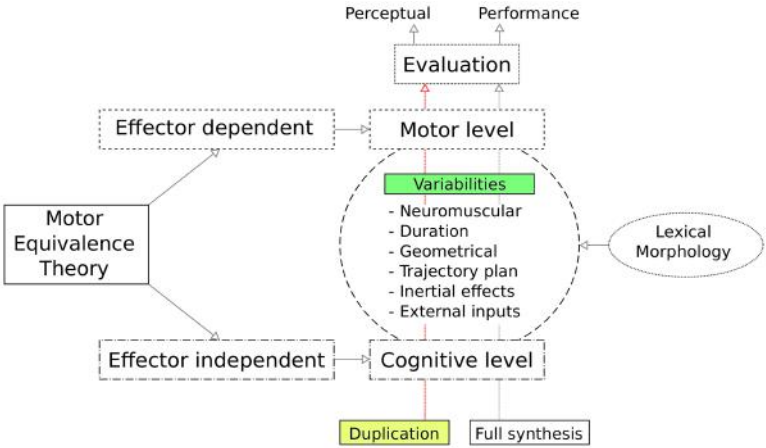
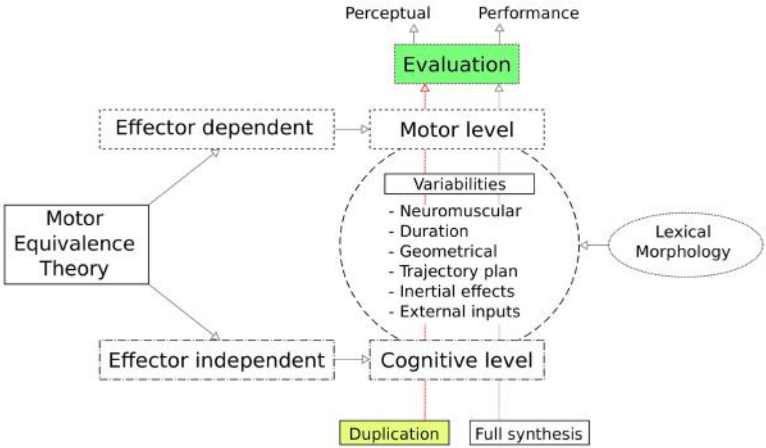


Go to generation
Go to evaluation

The Thesis



Go to generation
Go to evaluation

ULPGC IDeTIC

Input: I_{in} *gray scale image*

1. Intra-component variability
2. Component labeling
3. Inter-component variability
4. Signature inclination

Output: An artificial signature image

M. Diaz, M. A. Ferrer, G. Eskander, R. Sabourin (2016), "Generation of Duplicated Off-line Signature Images for Verification Systems", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, In press.

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Intra-component variability

The cognitive level variability is approached by this kind of variability

We need a grid deformation pattern to enlarge/shorter some strokes

=> Sinusoidal Transformation to the whole image

Input: I_{in} *gray scale image*

1. Intra-component variability
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4. Signature inclination

Output: An artificial signature image

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Component labeling

(a) Western (b) Bengali (c) Devanagari

- Components (pen-downs) are detected
- We search through all 8 connected areas so as to detect the connected components in the image

Input: I_{in} *gray scale image*

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Inter-component variability

The inter-component variability originated by the spatial cognitive map variability is approached by a local component displacement.

$$\delta_x = \begin{cases} \text{gevrnd}\{\xi_x^1, \sigma_x^1, \mu_x^1\} & \text{if } \Gamma_i < \kappa_1 \\ \text{gevrnd}\{\xi_x^2, \sigma_x^2, \mu_x^2\} & \text{if } \kappa_1 \leq \Gamma_i < \kappa_2 \\ \text{gevrnd}\{\xi_x^3, \sigma_x^3, \mu_x^3\} & \text{if } \Gamma_i \geq \kappa_2 \end{cases}$$

$$\delta_y = \begin{cases} \text{gevrnd}\{\xi_y^1, \sigma_y^1, \mu_y^1\} & \text{if } \Gamma_i < \kappa_1 \\ \text{gevrnd}\{\xi_y^2, \sigma_y^2, \mu_y^2\} & \text{if } \kappa_1 \leq \Gamma_i < \kappa_2 \\ \text{gevrnd}\{\xi_y^3, \sigma_y^3, \mu_y^3\} & \text{if } \Gamma_i \geq \kappa_2 \end{cases}$$

Three sections refer to the longer the component, the bigger the displacement because the motor control is reduced and, therefore, more variability is applied

Input: I_{in} *gray scale image*

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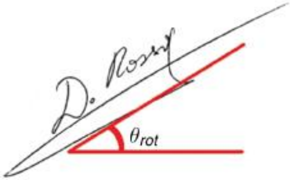
Signature inclination: Skew

According to previous studies**, the skew intra-personal variability can be modeled through a GEV distribution

$$\theta_{rot} = \text{gevrnd}\{-0.19, 3.28, -1.30\}$$



** **M. Diaz**, M. A. Ferrer, A. Morales (2015), "Modeling the lexical morphology of Western handwritten signatures", *PLoS ONE* 10(4): e0123254

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Database and Automatic Signature Verifier

▸ scheme

1. Off-Line MCYT: *(75 signers)*
2. Off-Line GPDS 300: *(+100 signers)*
3. Off-Line Bengali: *(100 signers)*
4. Off-Line Hindi: *(100 signers)*

---

1. Texture features + LSSVM

Evaluating the variability of the duplicated signatures

Training		Random Forgery			
R*	D/R**	MCYT-75			
2	0	1.98			
2	1	1.79			
2	10	1.40			
2	20	0.89			

Training		Skilled Forgery			
R*	D/R**	MCYT-75			
2	0	17.39			
2	1	18.36			
2	10	17.10			
2	20	16.59			

*R means the real enrolled signatures and

**D/R means the duplicated per real enrolled signature.

Evaluating the variability of the duplicated signatures

Training		Random Forgery			
R*	**D/R****	**MCYT-75**	**GPDS-300**		
2	0	1.98	2.84		
2	1	1.79	2.59		
2	10	1.40	1.69		
2	20	0.89	1.43		

Training		Skilled Forgery			
R*	**D/R****	**MCYT-75**	**GPDS-300**		
2	0	17.39	24.86		
2	1	18.36	25.11		
2	10	17.10	22.68		
2	20	16.59	21.63		

* **R** means the real enrolled signatures and

** **D/R** means the duplicated per real enrolled signature.

Evaluating the variability of the duplicated signatures

Training		Random Forgery		
R*	D/R**	MCYT-75	GPDS-300	Bengali-100
2	0	1.98	2.84	4.00
2	1	1.79	2.59	3.67
2	10	1.40	1.69	1.93
2	20	0.89	1.43	1.78

Training		Skilled Forgery		
R*	D/R**	MCYT-75	GPDS-300	Bengali-100
2	0	17.39	24.86	16.43
2	1	18.36	25.11	15.20
2	10	17.10	22.68	12.17
2	20	16.59	21.63	10.67

*__R__ means the real enrolled signatures and

**__D/R__ means the duplicated per real enrolled signature.

Evaluating the variability of the duplicated signatures

Training		Random Forgery			
R*	D/R**	MCYT-75	GPDS-300	Bengali-100	Devanagari-100
2	0	1.98	2.84	4.00	2.06
2	1	1.79	2.59	3.67	1.84
2	10	1.40	1.69	1.93	1.49
2	20	0.89	1.43	1.78	1.34

Training		Skilled Forgery			
R*	D/R**	MCYT-75	GPDS-300	Bengali-100	Devanagari-100
2	0	17.39	24.86	16.43	11.90
2	1	18.36	25.11	15.20	12.53
2	10	17.10	22.68	12.17	11.96
2	20	16.59	21.63	10.67	11.88

*R means the real enrolled signatures and

**D/R means the duplicated per real enrolled signature.

Outline

FROM “nothing” TO synthetic signatures

Intra- and Inter class variability

Proposals on full signature generation

Figure extracted from Popel, 2007 †

Real signatures in gray. Figure extracted from Galbally et al, 2012 ‡

† Popel, D. V. (2007). "Signature analysis, verification and synthesis in pervasive environments", vol. 67, *chapter In Synthesis and Analysis in Biometrics*, pp 31 - 64. World Scientific.

‡ J. Galbally, et al. (2012), "Synthetic on-line signature generation. Part II: Experimental validation", *Pattern Recognition*, Vol. 45, pp. 2622-2632

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TODO

- Generation of Text plus flourishes ✓
- Generation of Off-line signatures ✓
- Generation of dynamic properties ✓
- Generation of forgeries ✓
- Feasibility to approach different lexicons & morphologies ✓
- Generation of multi-script signatures *In process*
- Generation of multi-sessions, emotions, neurodegenerative diseases, ... ×

Outline

1. **On-2-On**
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   - Model Evaluation
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3. **Full Synthesis**
   - Off-Line and On-Line signature generation
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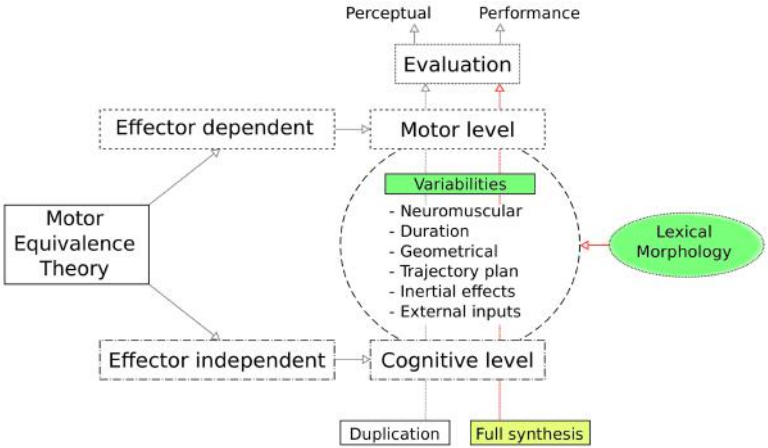
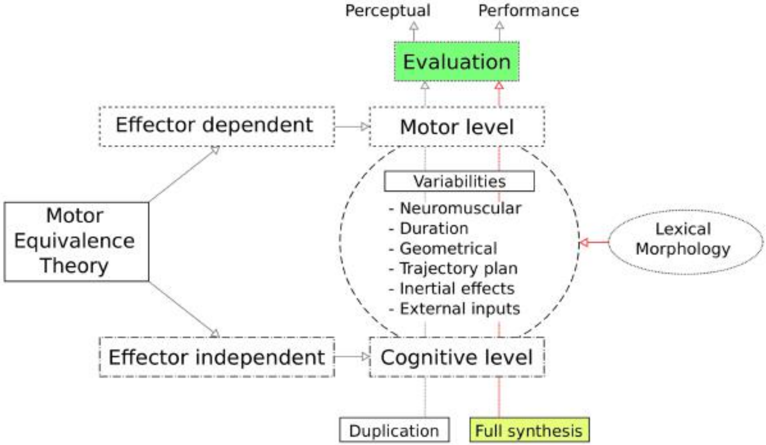
4. **Conclusions**

The Thesis



Go to generation
Go to evaluation

The Thesis



Go to generation Go to evaluation

1. Morphology and Lexicon definition
2. Cognitive Plan: pen-down/pen-up
3. Motor Control: ballistic trajectory
4. Generation of duplicated signature
5. Signature imitation
6. Output 1: On-Line signature
7. Output 2: Off-Line signature

M. A. Ferrer, **M. Diaz**, C. Carmona-Duarte, A. Morales, (2016) “A Behavioral Handwriting Model for Static and Dynamic Signature Synthesis”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, In press.

M. A. Ferrer, **M. Diaz**, A. Morales, (2015) “Static Signature Synthesis: A Neuromotor Inspired Approach for Biometrics”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.37, n.3, pp. 667-680.

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A morphology and lexicon language model is needed to model signatures with similar appearance to real ones

The performance of a signature database depends on the average number of words, letters per word, Text-Flourish dependences, etc.

Real names are avoided for privacy reason, but readable names are recommended for perceptual acceptability

M. Diaz, M. A. Ferrer, A. Morales (2015), "Modeling the lexical morphology of Western handwritten signatures", *PLoS ONE* 10(4): e0123254

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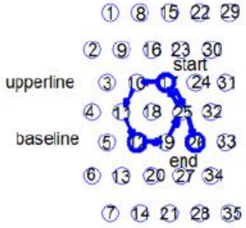
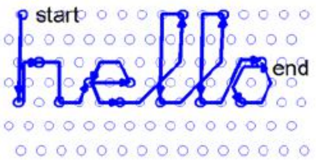
Pen-down model

The cognitive spatial map establishes the signature trajectory plan as a set of consecutive target points.

According to Moser experiments: rats/mice describe hexagonal spatial structures for orientation

Inspired by this idea: targets points located in a hexagonal grid.



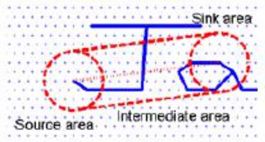


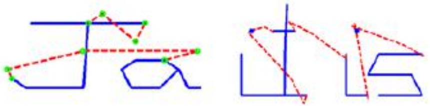
Pen-up model

Three zones: source, intermediate, sink areas

Source and Sink radius: 10% of the pen-up distance

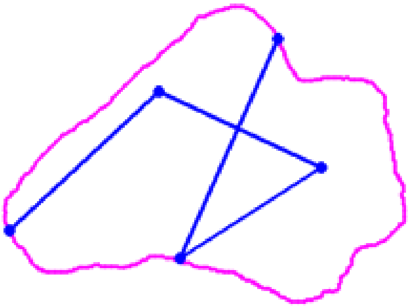
The more grids within the radius, the more hesitation





Flourish engram

ASM model of the signature enveloped from MCYT.
Synthetic envelope obtained by such ASM model
Flourish target points are randomly located inside



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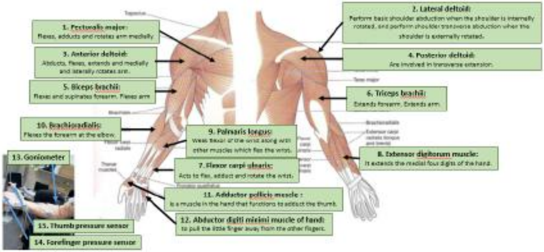
Psychophysical experiments

Experiment: Record the EMG signals on 9 arm muscles while a text or flourish is written.

=> Findings: Three clusters according to the muscle activity.



C. Carmona-Duarte, Rafael Torres-Peralta, **M. Diaz**, M. A. Ferrer, Marcos Martin-Rincon, (2016) “Myoelectronic Signal-Based Methodology for the Analysis of Handwritten Signatures”, *Human Movement Science*, *Major revision*.

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Filtering out the trajectory plan

Kaiser Filter

$$h^t[n] = \begin{cases} \frac{I_0\left(\pi\beta\sqrt{1-\left(\frac{2n}{N-1}-1\right)^2}\right)}{I_0(\pi\beta)} & 0 \leq n \leq N-1 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

β is a shape factor
$N \propto (l, v)$, (l being the distance between grid nodes and v the signing velocity)

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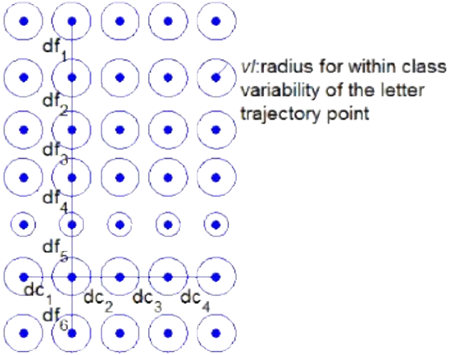
- Morphology and lexicon are constant
- Geometrical variation of pen-down and pen-up engram: each point change inside a ball
- Motor control parameters (Kaiser filter) inside a certain range



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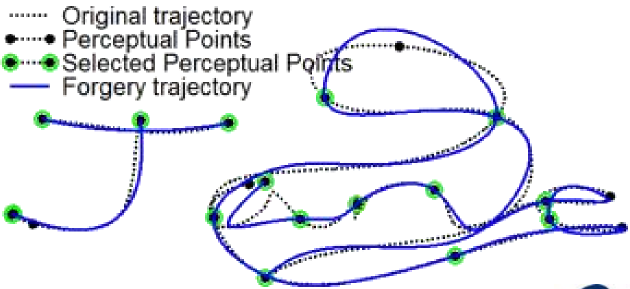
Proposal: Forgeries pay attention to the relevant perceptual points (maximum curvature)

Sinusoidal distortion to these points

Signature duration from 3.08 s to 5.29 s



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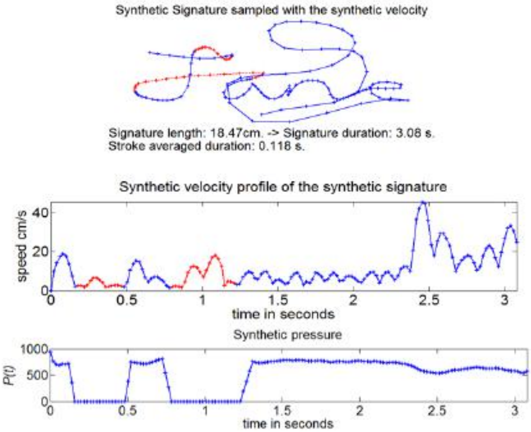
Velocity in the space domain

Lognormal sampling of 8-connected trajectory

Pressure model: inversely proportional to the velocity



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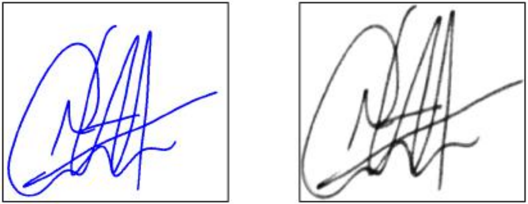
Output 2: Off-Line signature

A ballpoint model was designed to generate realistic images.

The ballpoint generates a sequence of ink spots



M. Diaz-Cabrera, M. A. Ferrer, A. Morales (2014). "Cognitive Inspired Model to Generate Duplicated Static Signature Images", *ICFHR*, pp. 62-66. *Best Student Paper Award*

M. A. Ferrer, **M. Diaz-Cabrera**, A. Morales (2013). "Synthetic Off-Line Signature Image Generation", *Proc. 6th IAPR International Conference on Biometrics*, pp. 1-6

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4. Conclusions

Visual Turing Test

▸ scheme

Average confusion: 44.06 %

^{x} *synthetic signatures*

Database and Automatic Signature Verifier

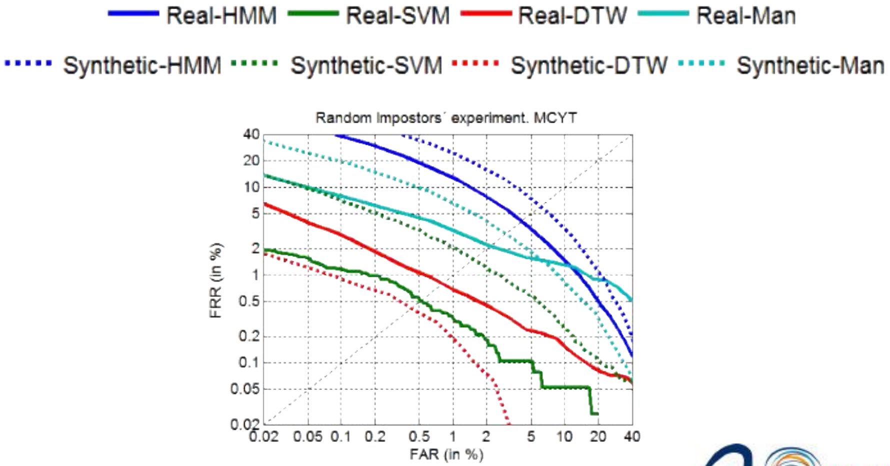
1. On-Line MCYT** *(+100 signers)*
2. On/Off-Line BiosecureID: *(+100 signers)*
3. On/Off-Line NISDCC *(100 signers)*
4. On-Line SVC 2004 Task1 & 2** *(80 signers)*
5. SUSIG Blind subcorpus** *(88 signers)*
6. SUSIG Visual subcorpus** *(94 signers)*

** *Off-Line signatures generated by the ink deposition model*

---

1. Texture features + LSSVM (Off-Line ASV)
2. Geometrical features + HMM (Off-Line ASV)
3. Function-based + Manhatan (On-Line ASV)
4. Function-based + DTW (On-Line ASV)

Closeness evaluation of real and synthetic databases



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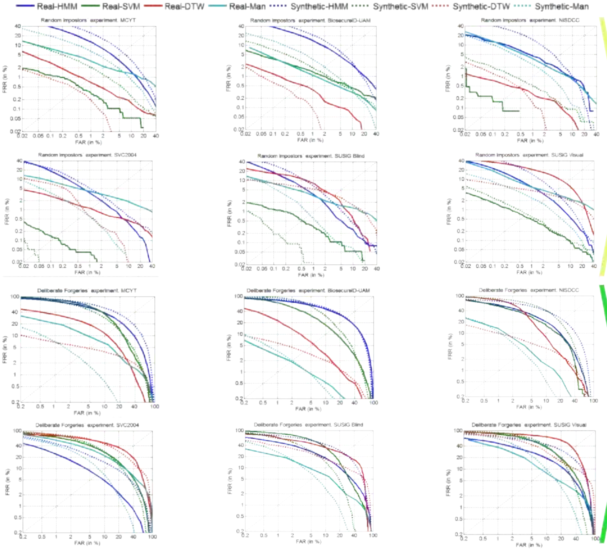
Closeness evaluation of real and synthetic databases



Random Forgery

Skilled Forgery

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Outcomes

- Motor equivalence theory to synthesis design motivation
- Contributions to duplication on-2-off, off-2-off, on-2-on and fully synthesis generation
- Ink deposition model for image-based generation
- Lognormal re-sampling for signal-based generation
- Perceptual-based evaluation: appearance confusion
- Performance-based evaluation: system improvements and coherent performances

Future works

- Script-independent methods to synthesize handwriting signatures (Bengali, Devanagari, Chinese, etc)
- Off-2-On duplication modality for improvements in static ASVs.
- From handwriting signature to signer parameters: *opportunity for a new feature space (?), new writer parameters (?)*
- Synthetic generator for additional behavioral biometrics synthesis based on motor equivalence theory: voice, keystroking, gait

Ongoing collaborations

1. Indian Statistical Institute, Kolkata (Prof. Umapada Pal)
   Redesigning of handwriting signature synthesizer
2. University of Bari (Prof. Giuseppe Pirlo)
   Stability of handwriting signatures
3. University of Salerno (Prof. Angelo Marcelli)
   Dynamics properties of static handwriting signatures
4. École Polytechnique de Montréal (Prof. Réjean Plamondon)
   Kinematic Theory of Rapid Movement for handwriting and voice
5. École technologie supérieure, Montreal (Prof. Robert Sabourin)
   Intra-class variability estimation in genuine signatures

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The practical lessons learned (so far)

- Less enrolled signatures can be used in ASVs
- Improvements in state-of-the-art systems
- International benchmarks can use synthetic signatures for large evaluations
- Perceptual evaluation is not required for a good performance

The theoretical lessons learned

- Both perceptual and performance evaluation for a better understanding of the human handwriting process
- Pattern recognition methods can be used for approaching (modeling?) the motor equivalence theory

Synthetic Signature Generation for Automatic Signature Verification

Moises Diaz

Doctoral Dissertation

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November 8th, 2016