Cognitive Inspired Model to Generate Duplicated Static Signature Images

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Outline

Current Section

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Target

Verifier a Cognitive Inspired Approach for the Artificially Realistic Signature Generation Through Off-line Automatic Signature Verifier.

We **do not model** the motor equivalence theory

We have **approached**, **taken the idea**, **inspired** on the motor equivalence theory

Introduction

Handwritten signatures occupy a very special place in the wide set of biometric traits because of Industry, Forensic and Scientific interest.
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 biometric samples (iris, fingerprint, face, etc.)

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 found to generate Synthetic Handwritten Signatures:

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

Current Section

Theory

Signing process involves a high complex fine motor control to generate trajectory with over-learned movements. The motor equivalence theory define the personal ability to perform the “same” movement pattern by different muscles.

Effector independent: Spatial position of each trajectory points for each individual stroke and the relative position among them

Effector dependent

Theory

Effector independent

Effector dependent: Sequence of motor commands directed to obtain particular muscular contraction and articulatory movements

Although both effects are quite stables, there is certain grade of variability between both effects: We do not sign equally under pressure, when we are happy, sad, busy or with a neurodegenerative disorder, etc.

Inspired Approach

Effector independent

"Spatial position of each trajectory points for each individual stroke and the relative position among them"

- *Intra-stroke variability:* Spatial deformation like a sinusoidal transformation deforming the most relevant points of the signature.
- *Inter-stroke variability:* Local perturbation of each individual stroke position.

Effector dependent

Inspired Approach

Effector independent

Effector dependent

"Sequence of motor commands directed to obtain particular muscular contraction and articulatory movements"

We reconstructed the ballistic trajectory of the signature filtering each stroke according to its inertial.

Current Section

Towards signature variability model

Input: x, y, p

1. A stroke segmentation
2. Perceptual points selection
3. Intra-stroke variability
4. Inter-stroke variability
5. Ballistic trajectory reconstruction
6. A virtual Ink Deposition Model

Output: An artificially signature image

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A stroke segmentation

- Pen-downs and Pen-ups Segmentation
- Scale: $\kappa = \frac{RScan}{RTab}$
- Interpolation: Bresenham's line drawing algorithm

Stroke Classification

- *"low"* if $v_{avg_i} \leq 0.6 v_{avg}$
- *"high"* if $v_{avg_i} \geq 1.35 v_{avg}$
- *"medium"* Otherwise

This classification defines the grid density of perceptual relevant points in order to approach the cognitive map and design the inertial of the filter which approximates the motor apparatus.

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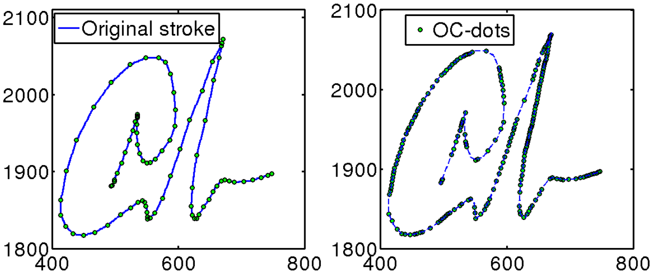
Perceptual points selection

- Stroke corners are the most relevant points, but not the only ones
- Corner points selection using the curvature of each pixel. It is approached by the radius of its osculating curves. The minimum of the curvature radius are selected as relevant perceptual point.
- Extra points selection according to stroke classification



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Intra-stroke variability

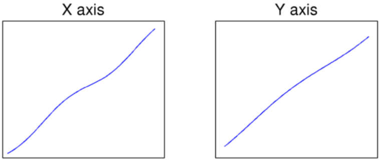
The variability due to *the cognitive map* is approximated through a sinusoidal transformation applied to the perceptual points of the signature.

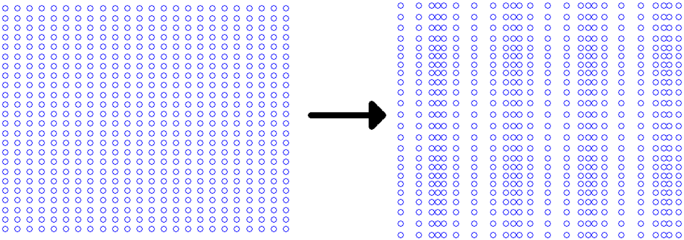
$$
\begin{aligned}
x'[n] &= x_p[n] + A_x \sin\left[\frac{2\pi(x_p[n] - \min(x_p[n]))N_x}{h_x}\right] \\
y'[n] &= y_p[n] + A_y \sin\left[\frac{2\pi(y_p[n] - \min(y_p[n]))N_y}{h_y}\right]
\end{aligned}
\quad (1)
$$

- Interpolation of the new trajectory using Bresenham's line.

Intra-stroke variability

Sinusoidal transformation allows to approach slight variations in the signer's cognitive map





Original Grid $\rightsquigarrow$ Distorted Grid

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Inter-stroke variability

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

$$(D_x, D_y) = \begin{cases} (\mathcal{N}(1,\,4), \mathcal{N}(1,\,1)) & \text{if } v_{avg_i} \text{ is } \textit{low} \\ (\mathcal{N}(1,\,8), \mathcal{N}(5,\,2)) & \text{if } v_{avg_i} \text{ is } \textit{medium} \\ (\mathcal{N}(1,\,12), \mathcal{N}(5,\,4)) & \text{if } v_{avg_i} \text{ is } \textit{high} \end{cases}$$

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Ballistic trajectory reconstruction

- A filter emulates the motor system
- Handwriting trajectories approached as polynomial curves
- A Savitsky-Golay filter is used to produce human-like trajectory
  - A frame size *f* and the degree *k* of the polynomial regression on a values
  - Hand rapid movements are usually less precise than slower ones: low velocity implies more details and a higher polynomial.

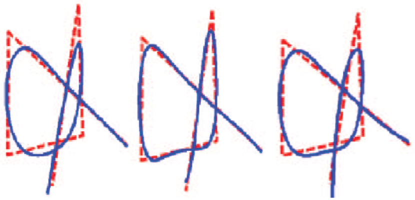
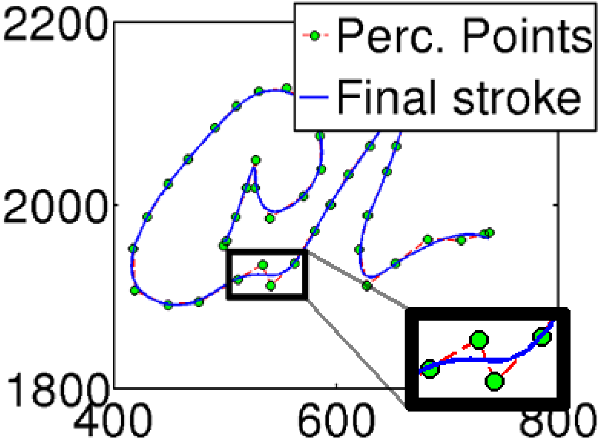


Figure 2. Signature path example (dashed line) and handwriting styles (solid line) according to different k and f values. From left to right $k = 3, 4, 4$ and $f = 70, 70, 90$ respectively

Ballistic trajectory reconstruction



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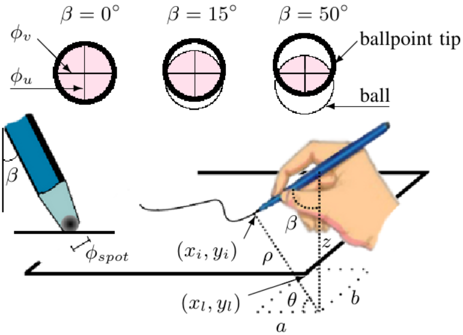
Ballpoint pen model

The most of the handwriting, which include off-line signatures, are usually written by using a ballpoint pen.
To produce realistic signature images, a ballpoint model has been designed.
The ballpoint generate a sequence of ink spots

Ink Deposition Model

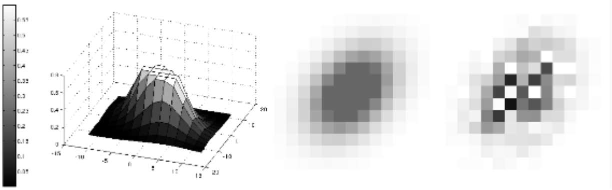
The pen model proposed relies on the spot produced by the ballpoint pen. The spot depends on:

- The pen inclination
- Ballpoint diameter
- Ellipse



Ink Deposition Model

The spot intensity is not uniform: In the center is darker than on the sides.
In our case, the intensity profile is approximate by a cropped Gaussian. The Gaussian height corresponds to the pressure previously calculated



Visual Results

Above: Real. Bellow: Synthetic

Visual Results

Miguel A. Ferrer, Moises Diaz-Cabrera, Aythami Morales. “Static Signature Synthesis: A Neuromotor Inspired Approach for Biometrics”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2014

Miguel A. Ferrer, Moises Díaz-Cabrera, Aythami Morales. "Synthetic Off-Line Signature Image Generation", *Proc. 6th IAPR International Conference on Biometrics*, Madrid, 2013.

Miguel A. Ferrer, Moises Diaz-Cabrera, Aythami Morales, Javier Galbally, Marta Gomez-Barrero. "Realistic Synthetic Off-Line Signature Generation Based on Synthetic On-Line Data", *Proc. 47th IEEE International Carnahan Conference on Security Technology*, 2013, pp. 116-121.

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Duplicated Vs Realistic

Realistic

Duplicated

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Current Section

On-line Database and Off-line Automatic Signature Verifier

MCYT corpus

- 330 signers
- 25 genuine and 25 skilled (deliberated) forgeries
- Multi-session scenario

Texture features + LSSVM

- LBP and LDP images and divided into 12 overlapped sectors.
- The classifier is based on a least square support vector machine (LSSVM).

J. Ortega-Garcia, J. Fierrez-Aguilar, D. Simon, J. Gonzalez, M. Faundez, V. Espinosa, A. Satue, I. Hernaez, J. J. Igarza, C. Vivaracho, D. Escudero and Q. I. Moro, "MCYT baseline corpus: A bimodal biometric database", *IEE Proceedings Vision, Image and Signal Processing, Special Issue on Biometrics on the Internet*, Vol. 150, n. 6, pp. 395-401, December 2003.

Miguel A. Ferrer, Jesus F. Vargas, Aythami Morales and Aaron D. Ordonez. "Robustness of Off-line Signature Verification based on Gray Level Feratures". *IEEE Trans. Information Forensics & Security 2012*, Vol. 7, No. 3, pp. 966 - 977.

Evaluating the variability of the duplicated signatures

Training		Validation 1	
Real	**Synt.**	**Random Forgeries**	**Deliberated Forgeries**
5	-	1.88 %	19.17 %
10	-	1.07 %	13.13 %
5	5	1.97 %	16.52 %
5	20	1.63 %	16.37 %
5	100	1.43 %	16.19 %

Training		Validation 2	
Real	**Synt.**	**Random Forgeries**	**Deliberated Forgeries**
2	-	3.70 %	23.73 %
4	-	2.43 %	18.53 %
2	2	3.33 %	19.86 %
2	8	3.13 %	19.73 %
2	40	2.89 %	19.12 %

Current Section

Conclusions

- A new method inspired by the cognitive neuromotor perspective to generate static duplicated signatures is proposed
- Non-linear deformations in on-line signatures emulating the human variability
- Validation: improving the performance of a recent state-of-the-art ASV.
- Best results found in the critical case: with a few samples in the training set

Improvements

- Stroke Stability Control vs Stroke Velocity Control
- Duplicated Signature Generation On-line to On-line: Spatial and Temporal Challenge
- Duplicated Signature Generation Off-line to Off-line: Image Processing Challenge
- Opportunity to mimic behavioral disorders, neurodegenerative diseases and other cognitive impairment related to muscular path variability

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