Personal Digital Bodyguards for e-Security, e-Health and e-Learning: an International Journey

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Personal Digital Bodyguards for e-Security, e-Health and e-Learning: an International Journey

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A Vision

In the forthcoming years, the ubiquity of hand-held tablets and cell phones, along with their increased computing power and ergonomic data capture performances, will make it possible to convert these devices into

Personal Digital Bodyguards (**PDB**s).

A Vision

PDBs will protect people's sensitive data with signature verification, provide equipment use security with writer authentication, handwritten CAPTCHAs **(e-security**). PDBs will perform word spotting and gesture recognition to monitor user fine motor control, which can detect stress, aging and health problems **(e-health)**. In the hands of children, these tools will turn into toys helping them to learn and master their fine motricity and become better writers and students **(e-learning)**.

The hardware is almost there: Samsung Galaxy Note Pro 12.2

The hardware is almost there: Microsoft Surface Pro 4

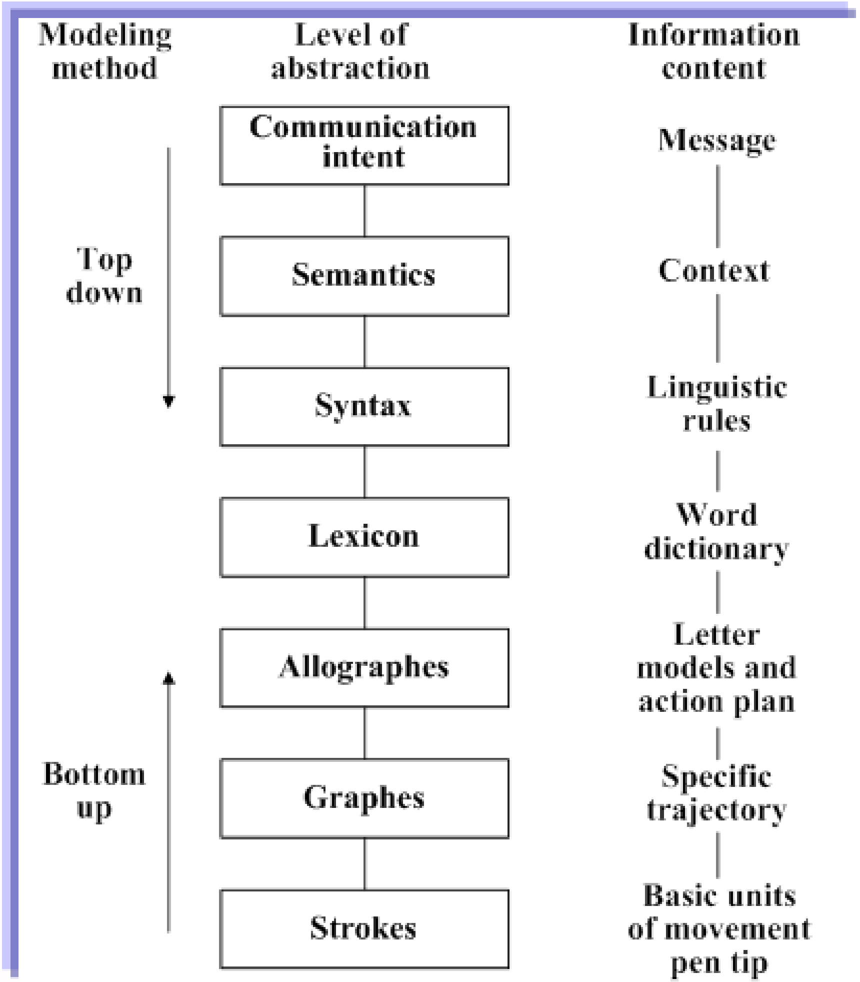
The hardware is almost there: other Samsung Products

Introduction

From a broader perspective.

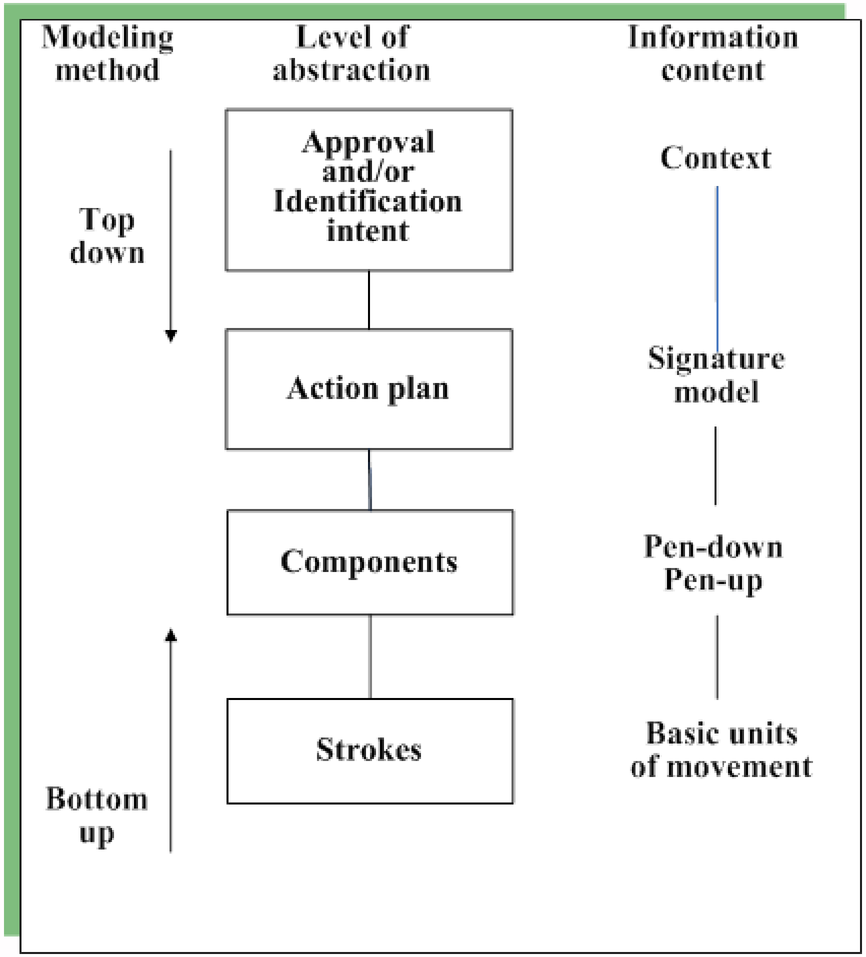
at Scribens laboratory, we have been working on some of these potential e-applications for many years, directly or indirectly guided by the **Lognormality Principle.**

Handwriting Generation



PLAMONDON, R., LOPRESTI, D., SCHOMAKER, L.R.B., SRIHARI, R., “On-Line Handwriting Recognition”, Encyclopedia of Electrical and Electronics Engineering, J.G. Webster (Ed.), John Wiley & Sons, N.Y., vol. 15, 1999, p. 123-146.

Signature Generation



PLAMONDON, R., PIRLO, G., IMPEDOVO, D.," On-line Signature Verification" in Handbook of Document Image Processing and Recognition, D.Doermann , K.Tombre Eds, In Press, Springer, 2012.

1 - What is a Handwriting Stroke?

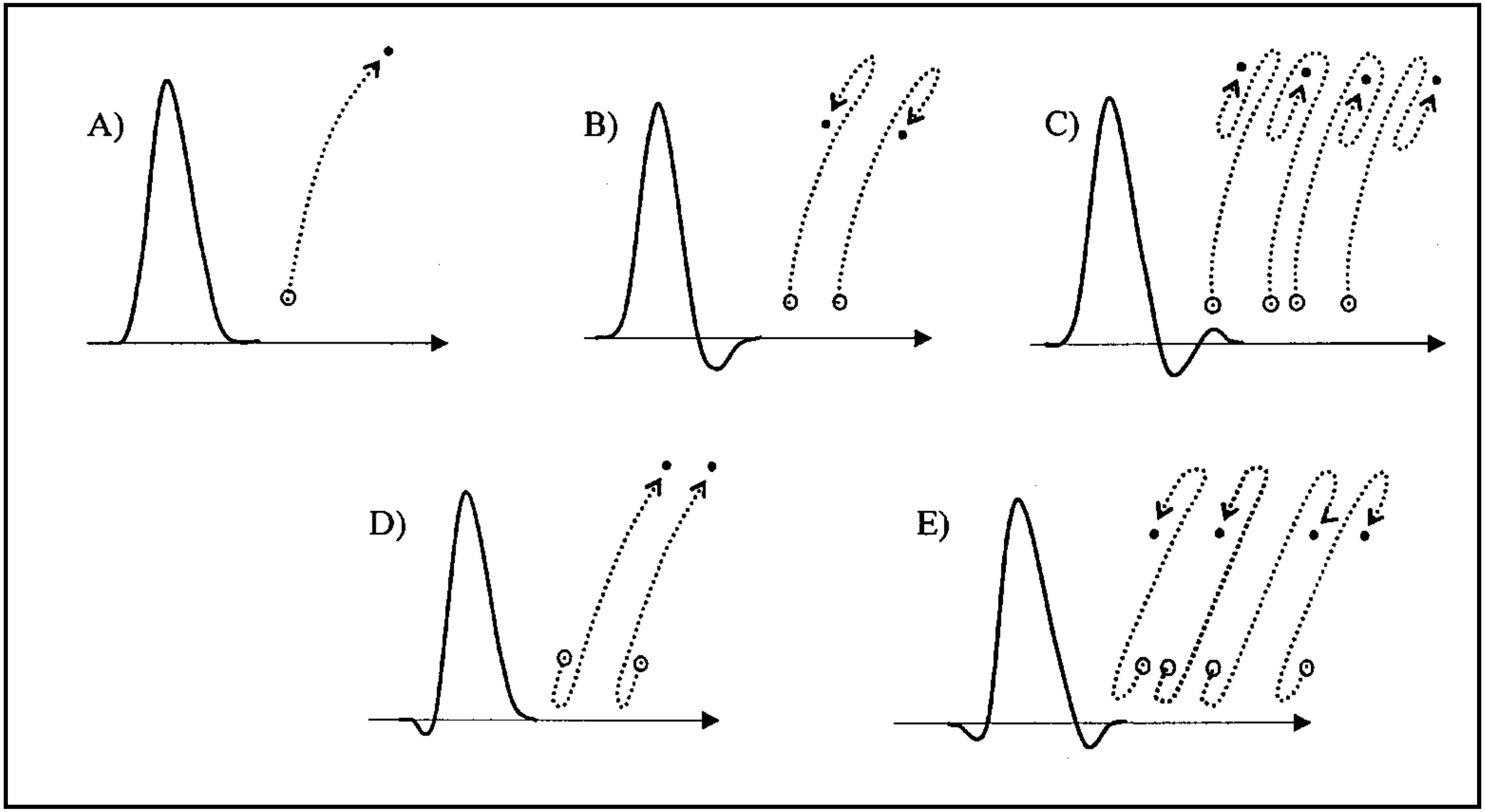
1 - What is a Handwriting Stroke?

Searching for the fundamental unit of Handwriting

Do not mix up…

- Stroke: the fundamental unit of Handwriting.
- Component: The trace between a pen down and a pen up.

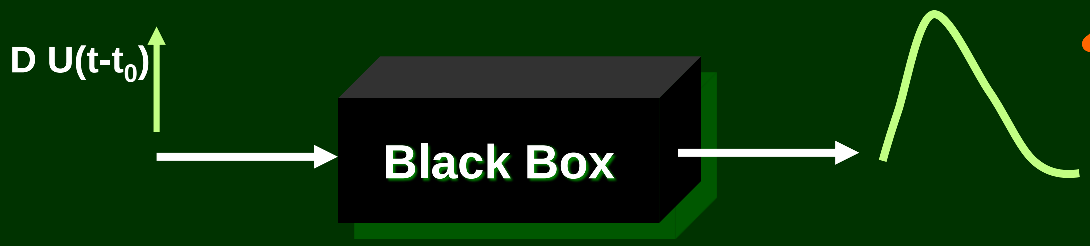
Typical Velocity Profiles and Trajectories



WOCH, A., PLAMONDON, R., «Using the Framework of the Kinematic Theory for the Definition of a Movement Primitive», Motor Control, Special Issue, vol. 8, No 4, pp. 547-557, 2004.

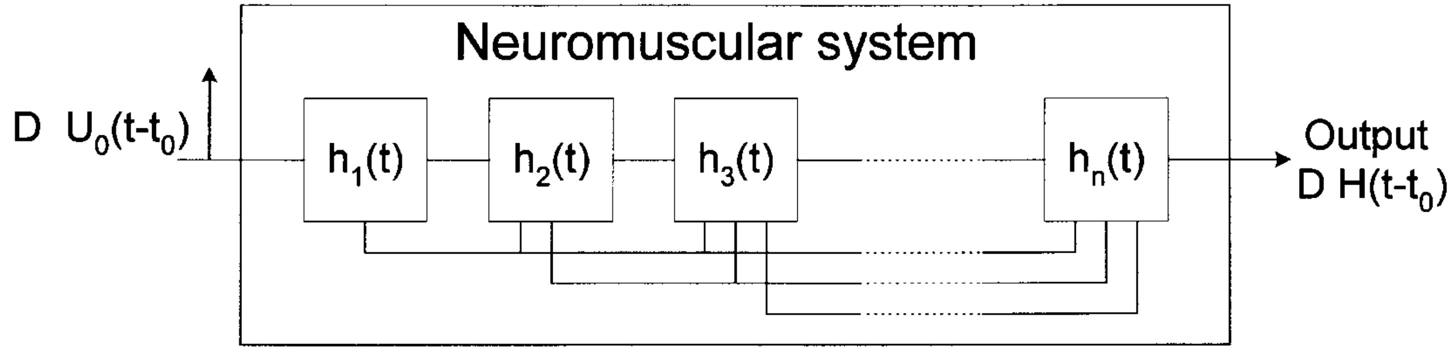
Modeling a Stroke

Stimulus



Command	NMS	Response
Impulse wheighted by a distance	*Convolution of an infinite number of coupled subsystems*	*Velocity profile*

- Mathematical proof based on the Central Limit Theorem
- Convergence of the NMS impulse response towards a lognormal profile



- Hypothesis

$$T_n = (1+\varepsilon_n)T_{n-1}$$

$$n \to \infty$$

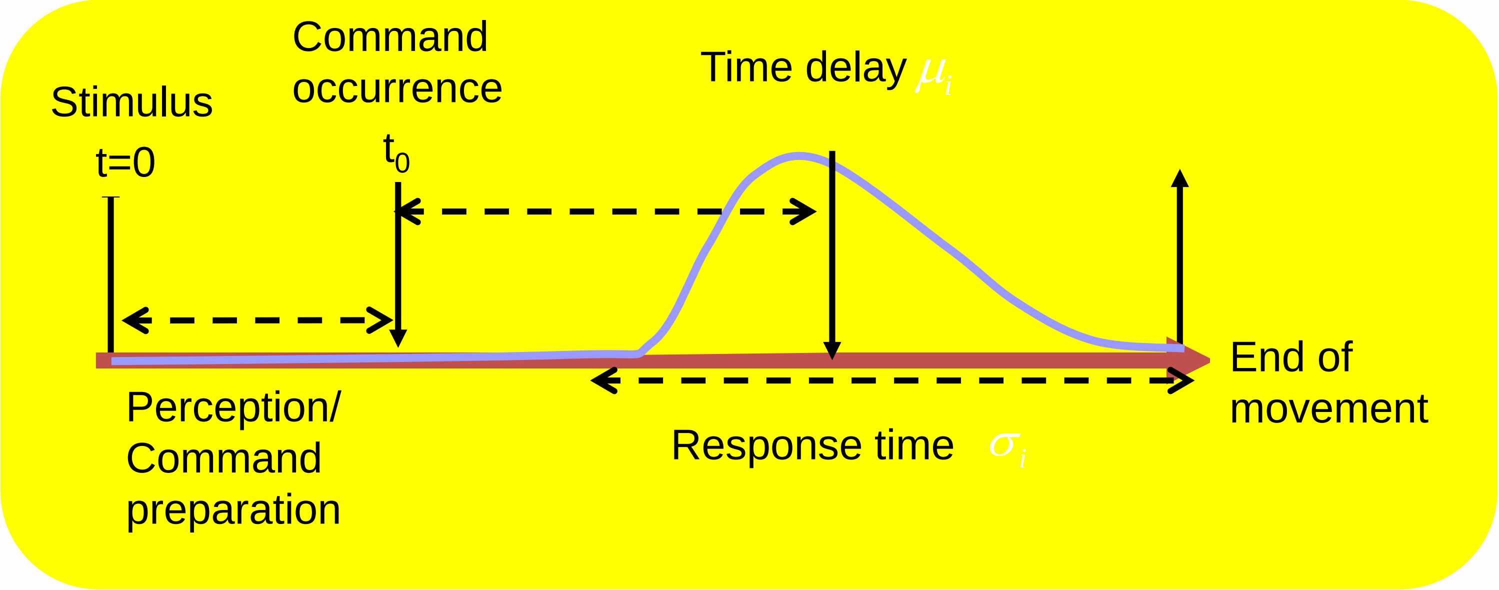
$$H(t-t_0) \Rightarrow \Lambda(t;t_0,\mu,\sigma^2)$$

Lognormal Velocity

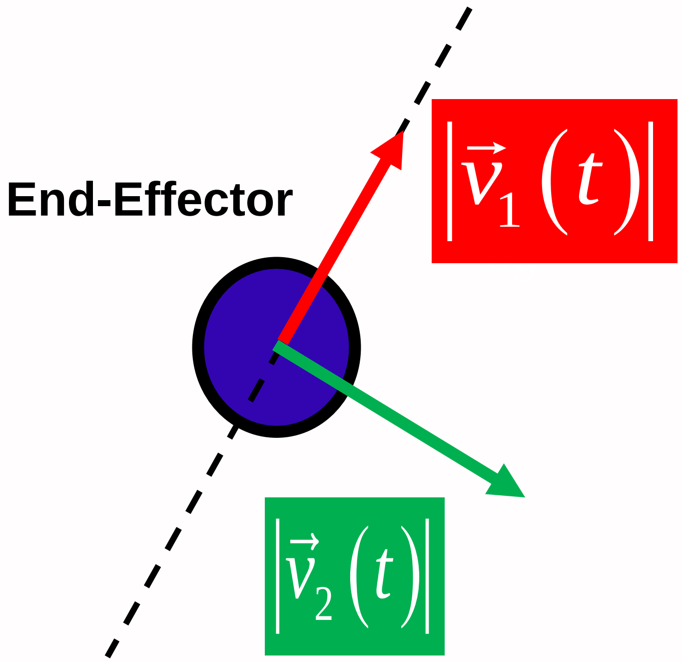
$$\left|\vec{v}(t,P)\right| = D\Lambda(t;t_o,\mu,\sigma)$$

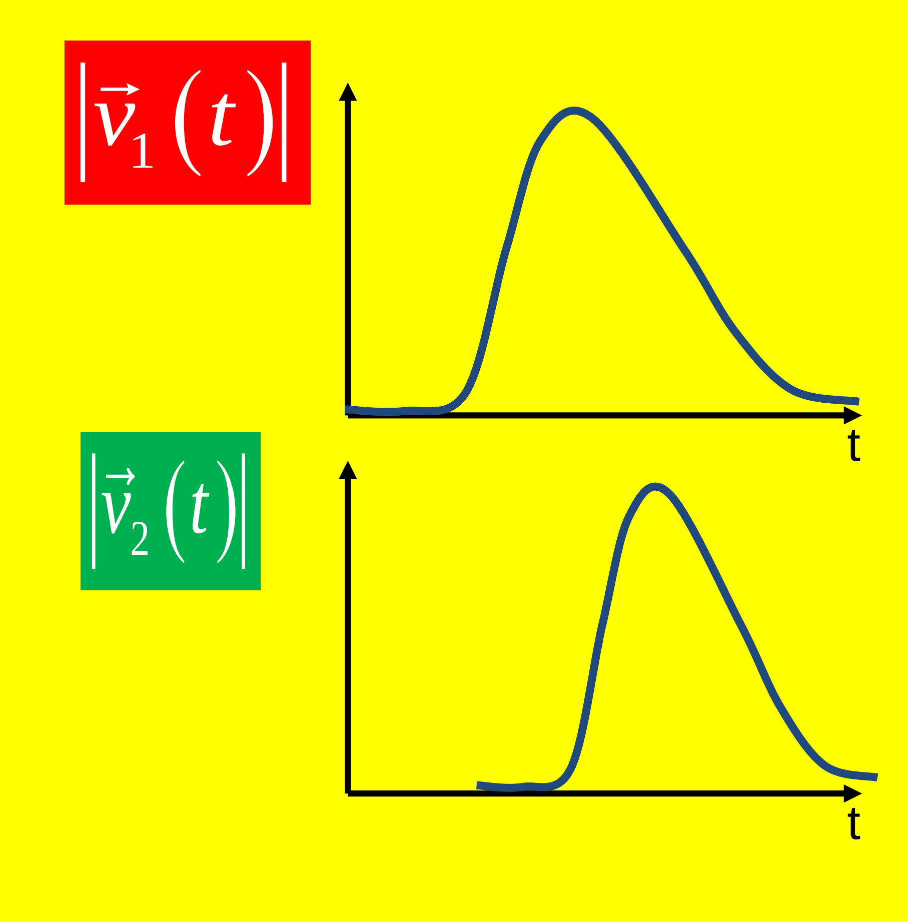
$$= \frac{D}{\sigma\sqrt{2\pi}(t-t_0)}\exp-\left[\frac{[\ln(t-t_0)-\mu]^2}{2\sigma^2}\right]$$

Temporal analysis of a movement component (agonist or antagonist)



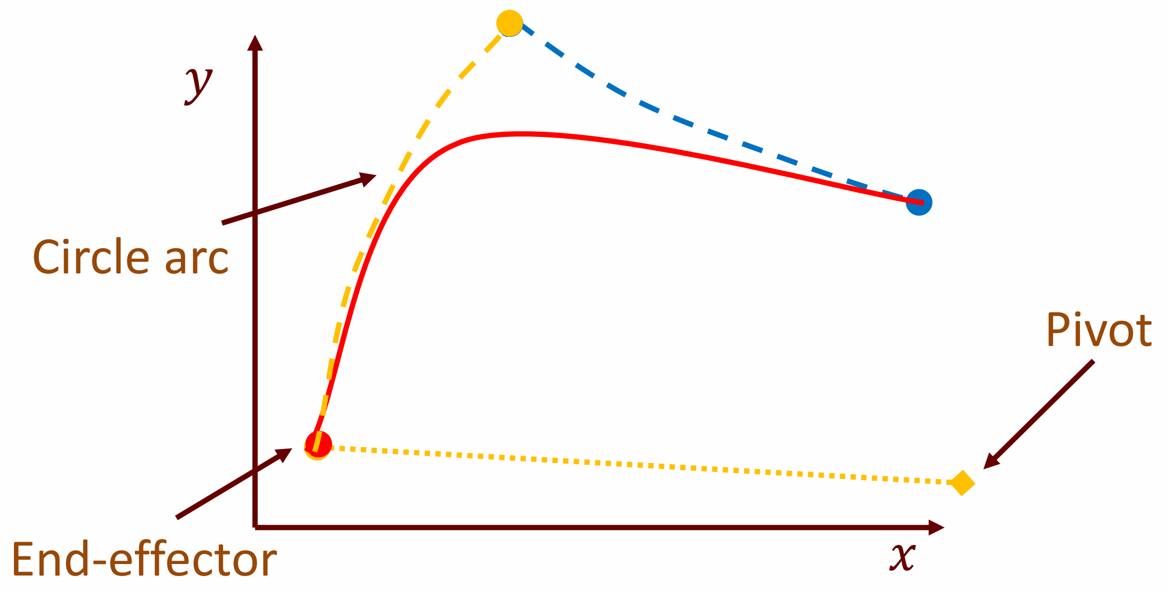
Vectorial summation





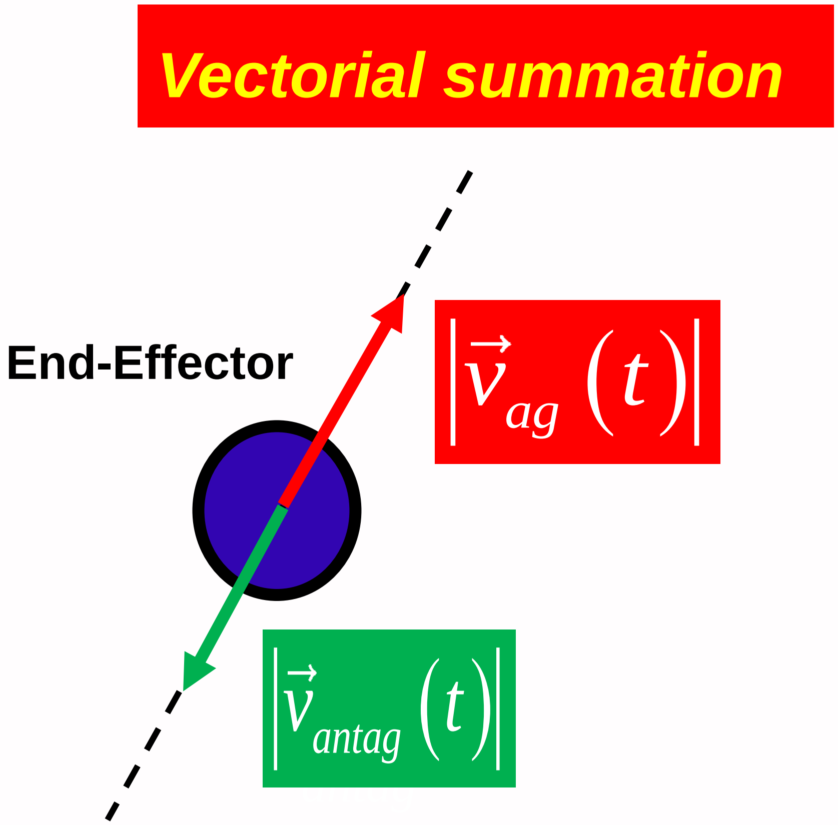
Component representation and synergy

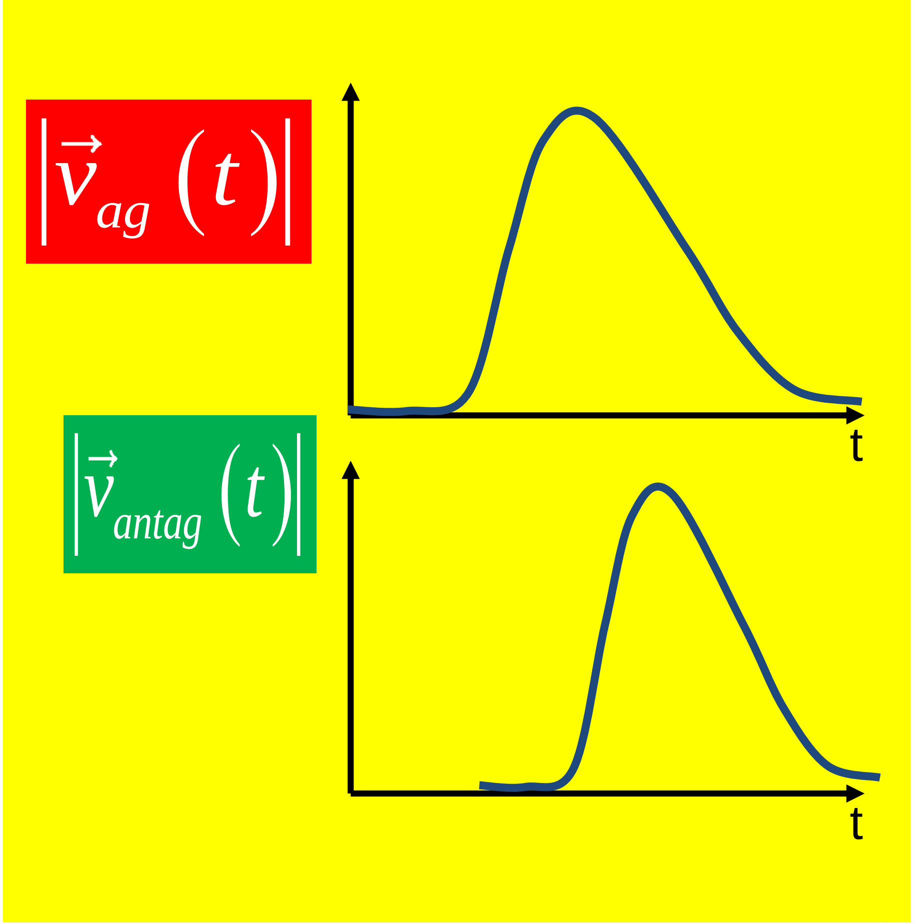
- A neuromotor component is acting around a pivot point.



Velocity profile of a single stroke: Sigma-Lognormal Model

$$\vec{v}(t) = \vec{v}_1(t) + \vec{v}_2(t)$$


Vectorial summation
End-Effector
$\left|\vec{v}_{ag}(t)\right|$
$\left|\vec{v}_{antag}(t)\right|$


$\left|\vec{v}_{ag}(t)\right|$
t
$\left|\vec{v}_{antag}(t)\right|$
t

Velocity profile of a single stroke: **Sigma-Lognormal Model**

$$\vec{v}(t) = \vec{v}_1(t) + \vec{v}_2(t)$$

Special case: perfect opposition of the agonist and the antagonist components

$$v(t) = v_{ag}(t) - v_{antag}(t)$$

Delta-Lognormal Model

Sigma-Lognormal model

- Discontinuous action plan
- Virtual targets
- Vectorial summation of curved strokes
- Time overlap
- Individual strokes hidden in the signal
  - Velocity profiles : Lognormal functions
  - Direction angle profiles: Error functions (Erf)

Component representation and synergy

- A neuromotor component is acting around a pivot point.

- Direction of the i^th component trajectory :

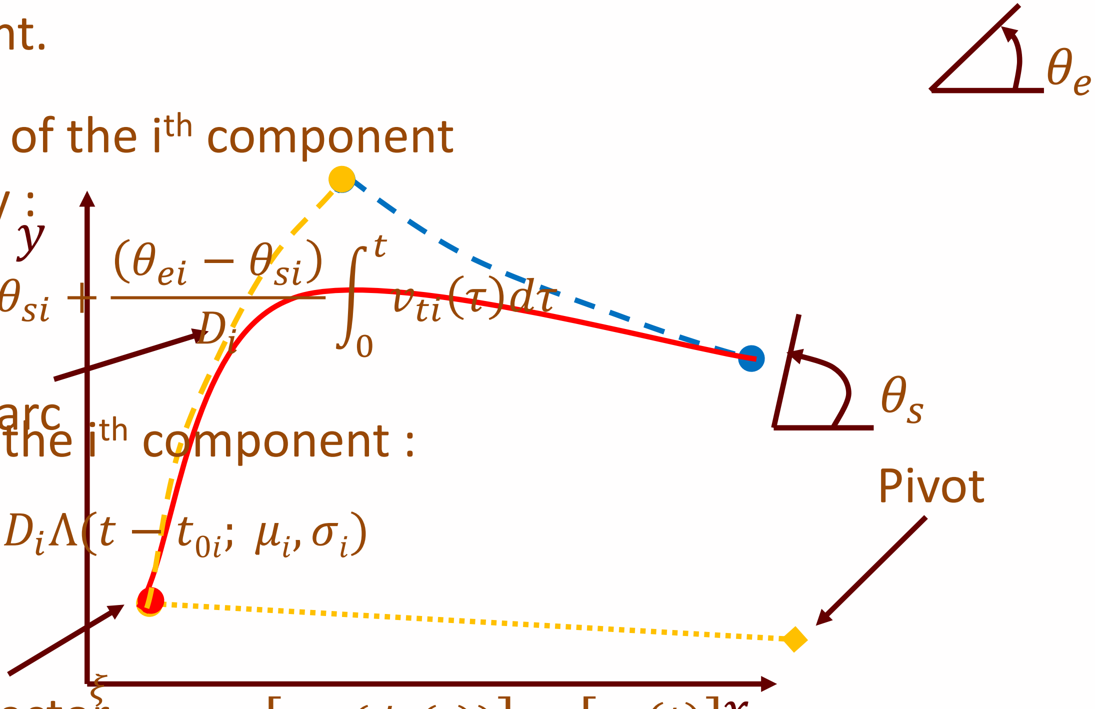
$$\varphi_i(t) = \theta_{si} + \frac{(\theta_{ei} - \theta_{si})}{D_i}\int_0^t v_{ti}(\tau)d\tau$$

- Speed of the i^th component :

$$v_{ti}(t) = D_i \Lambda(t - t_{0i};\ \mu_i, \sigma_i)$$

- Synergy :

$$v(t) = \sum_{i=1}^{\xi} v_{ti}(t) \begin{bmatrix} \cos(\phi_i(t)) \\ \sin(\phi_i(t)) \end{bmatrix} = \begin{bmatrix} v_x(t) \\ v_y(t) \end{bmatrix}$$



2 - Can we recover the action plans ?

A reverse engineering problem: Lognormal parameter extraction

Fitting — Four parameter extractors

1 INFLEX-INITRI-XZERO (IIX)

- ΔΛ representation (locally optimal)
- Fast reaching motion

M. Djioua and R. Plamondon, "A new algorithm and system for the characterization of handwriting strokes with delta-lognormal parameters," *IEEE Trans Pattern Anal Mach Intell*, vol. 31, pp. 2060-72, Nov 2009.

2 Branch and bound (B&B)

- ΔΛ representation (globally optimal)
- Fast reaching motion

C. O'Reilly and R. Plamondon, "A globally optimal estimator for the Delta-Lognormal modeling of fast reaching movements " *IEEE Trans. on System, Man and Cybernetics. Part B. Cybernetics,* in press.

3 Robust X_0

- ΣΔ representation
- Complex and arbitrary movements

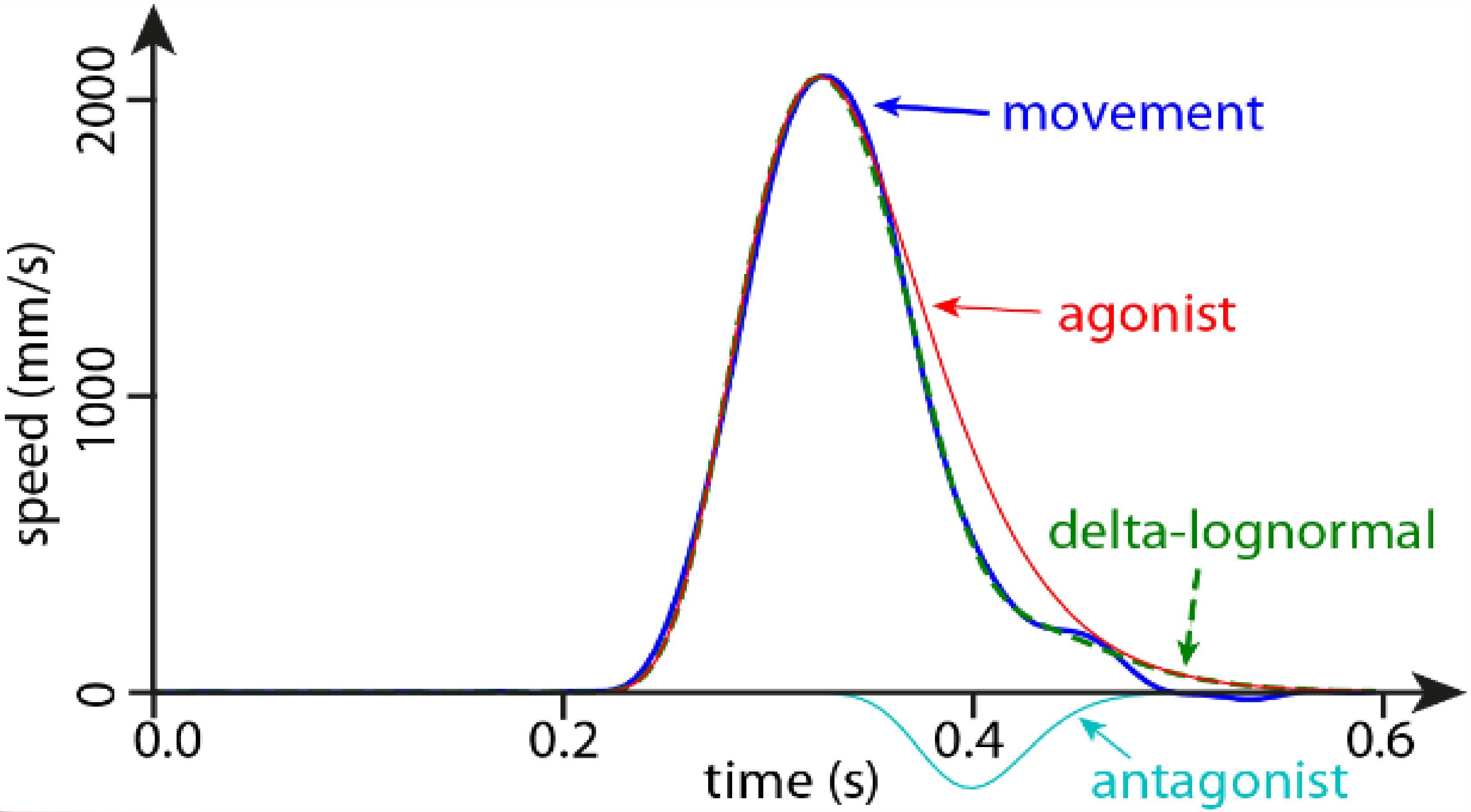
C. O'Reilly and R. Plamondon, "Development of a Sigma-Lognormal representation for on-line signatures," *Pattern Recognition,* vol. 42, pp. 3324-3337, 2009.

4 Prototype based

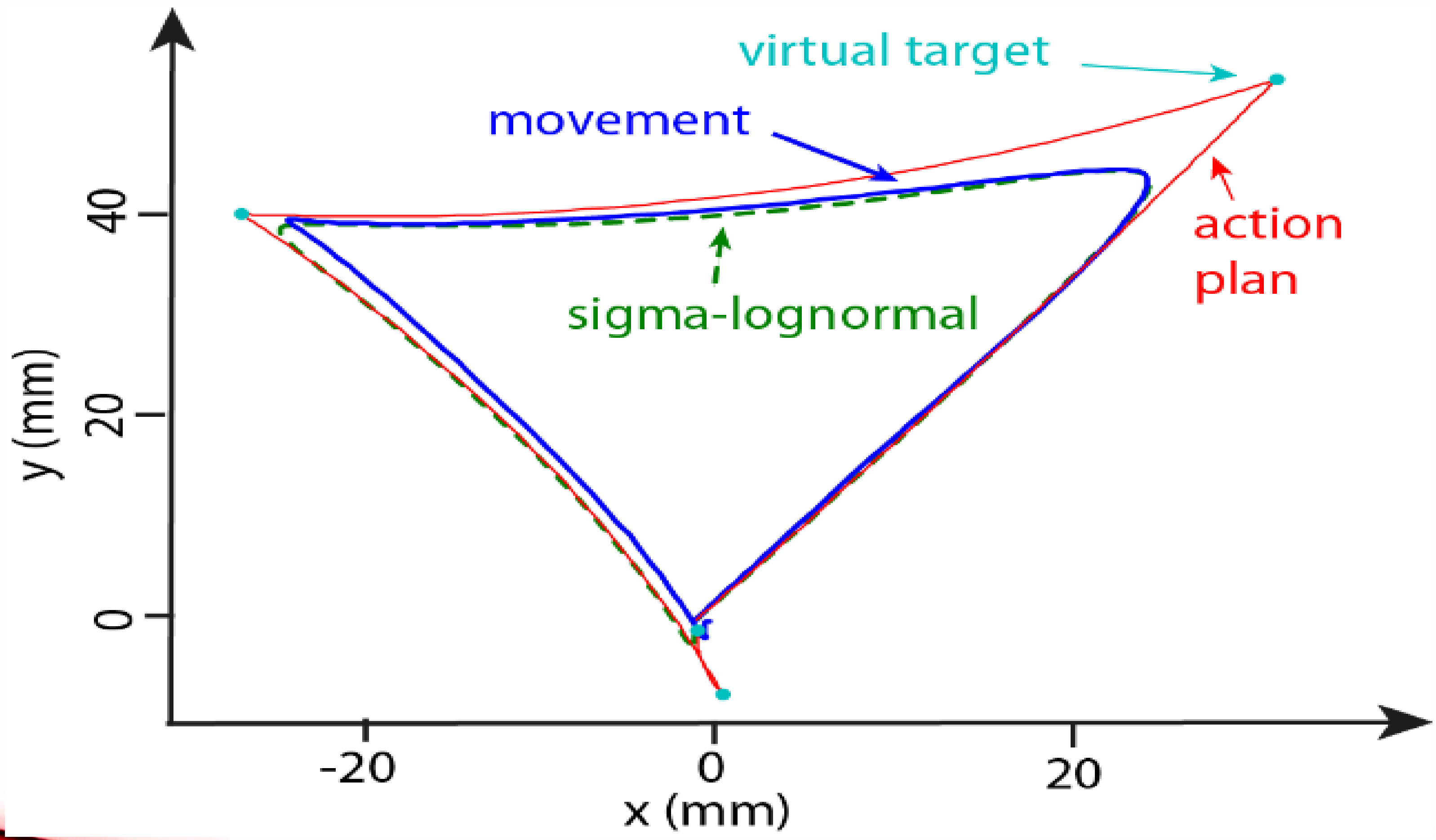
- ΣΔ representation
- Complex and stereotypical movements
- Allow performing ANOVA of the ΣΔ parameters

O'Reilly and R. Plamondon, "Prototype-based methodology for the statistical analysis of local features in stereotypical handwriting tasks," proceedings of 20^{th} Int. Conference on Pattern Recognition , Istanbul, Turkey, pp. 1864-1867, 2010.

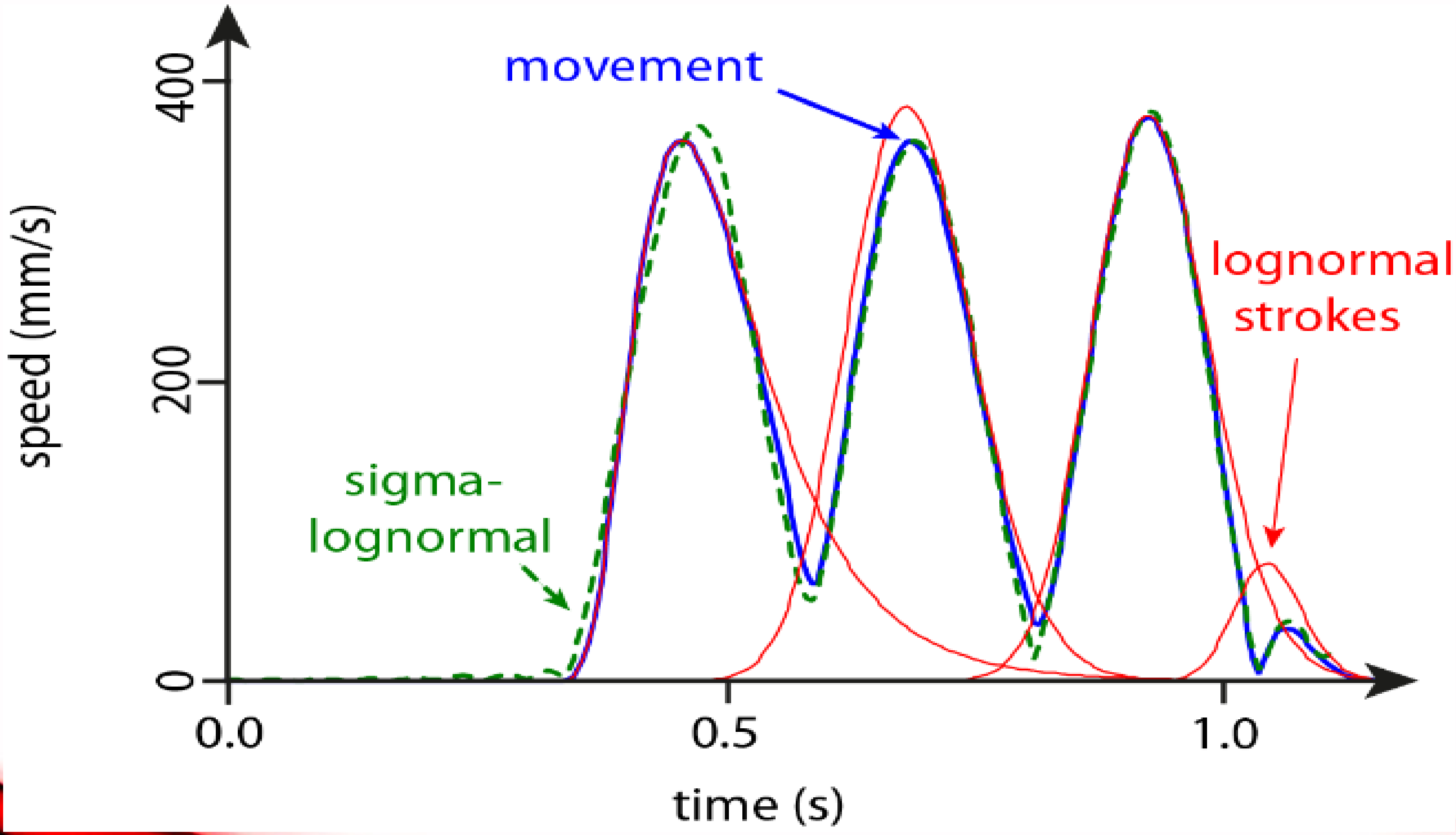
Delta-lognormal model



Sigma-lognormal model



Sigma-lognormal model



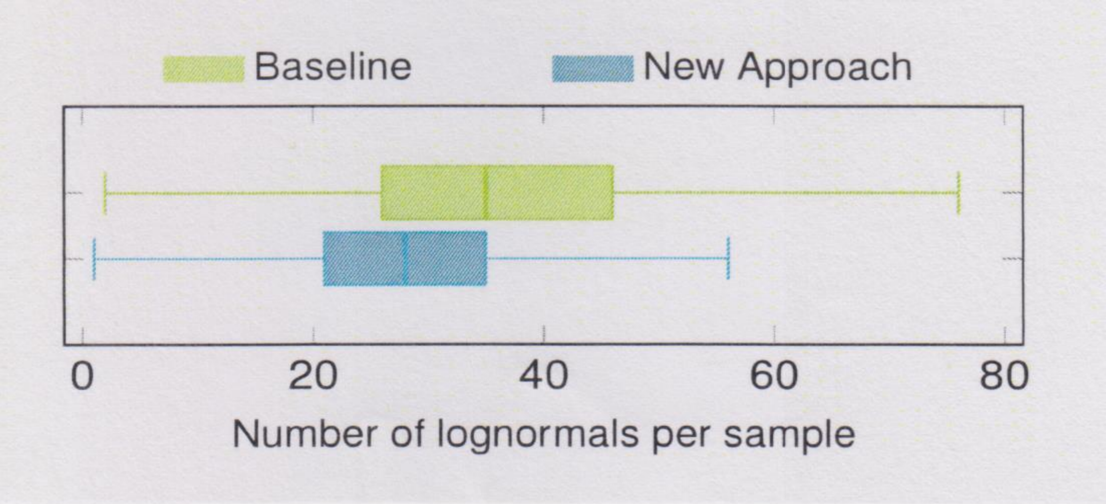
Work still in progress

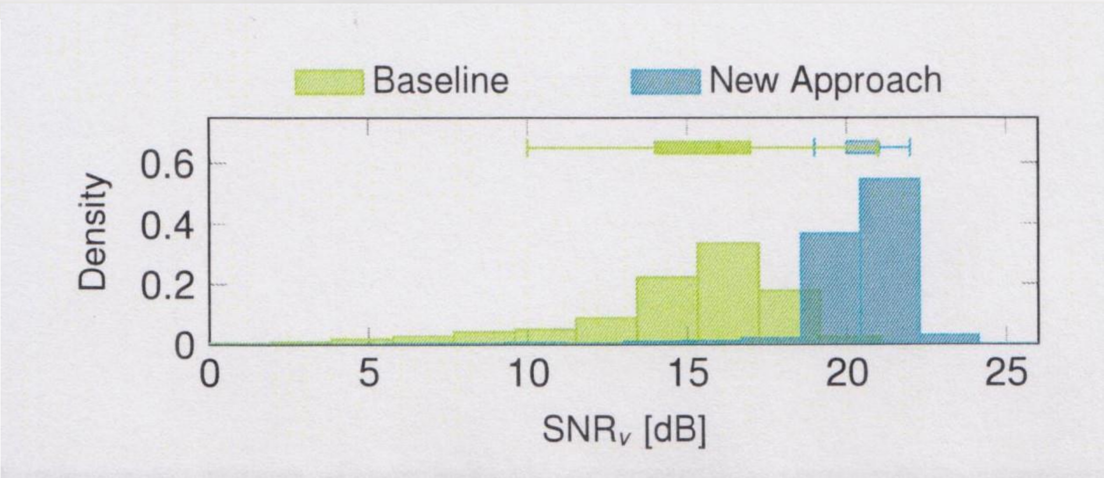
The actual algorithms have been developed mostly for biomedical, educational and psychophysical applications.

Optimization for signature verification and handwriting recognition is under way. Here is an example:

Improving Sigma-Lognormal Parameter Extraction

Daniel Martín-Albo, Réjean Plamondon and Enrique Vidal,
ICDAR 2015





3 - Is the theory Physiologically meaningfull ?

Testing the basic underlying hypotheses

Theoretical Problem No 1

Experimental investigation of t_0

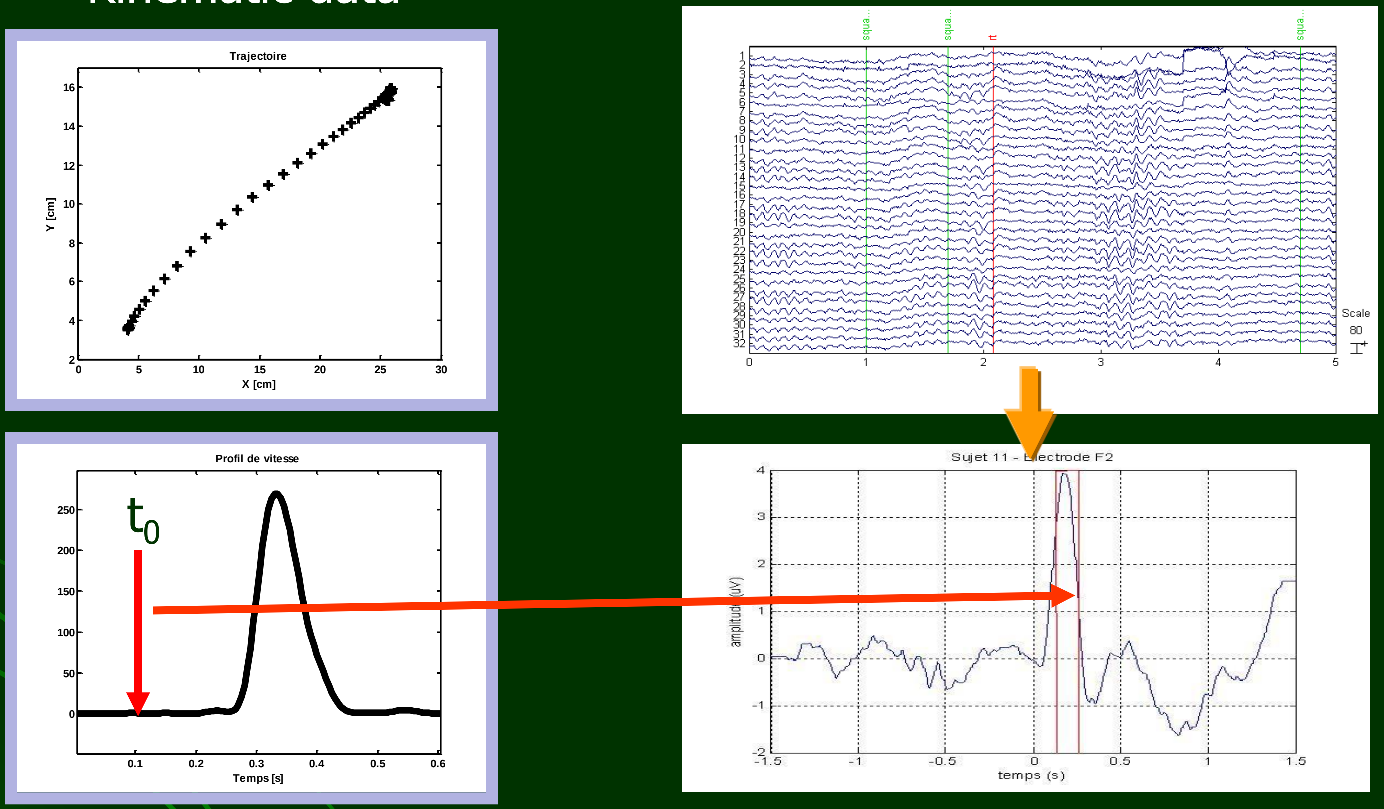
O'REILLY, C., PLAMONDON, R., LANDOU M. K., STEMMERS B.,. Prediction of the Time Occurrence a Motor ERP based on the Kinematic Analysis of Movement with the Delta-Lognormal Model. European Journal of Neuroscience, Vol. 37, pp. 173–180, 2013.

Typical trial

Typical Correlation

Kinematic data

EEG signals



- **A visually evoked response potential emerges at t_0**

Theoretical Problem No 2

Experimental Observation of the Proportional Effect Hypothesis

$$T_j = (1 + \varepsilon_j) T_{j-1}$$

PLAMONDON, R. DJIOUA, M., MATHIEU, P.-A., The Kinematic Theory of Rapid Human Movements: Experimental Observation of the Proportional Effect Hypothesis ,Human Movement Science, available online at http://dx.doi.org/10.1016/j.humov.2012.07.006, July 2012.

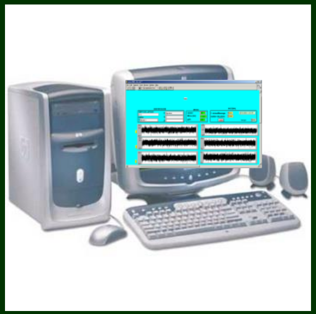
Apparatus

EMG Signal
Acquisition System
(GRASS)

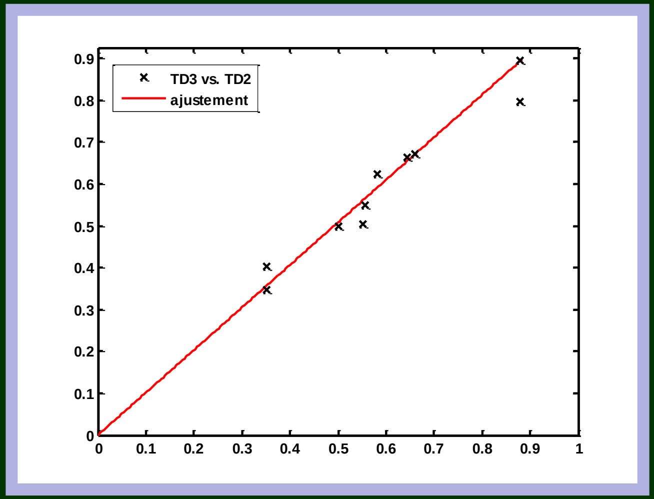
Amplifier

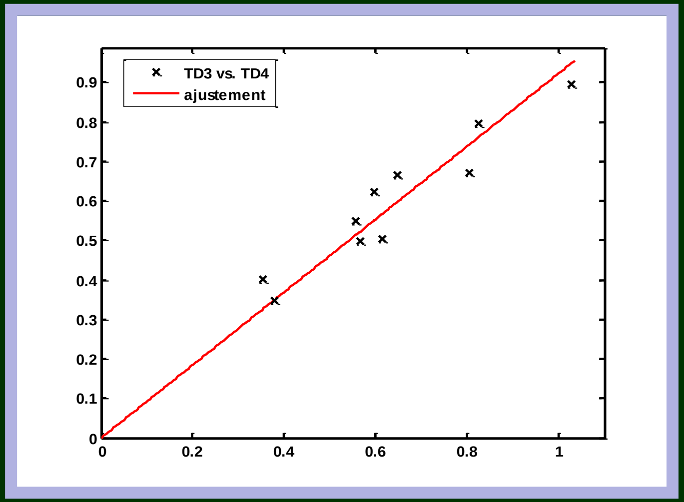
Data Acquisition System

SYNC
signal



Typical proportional regressions



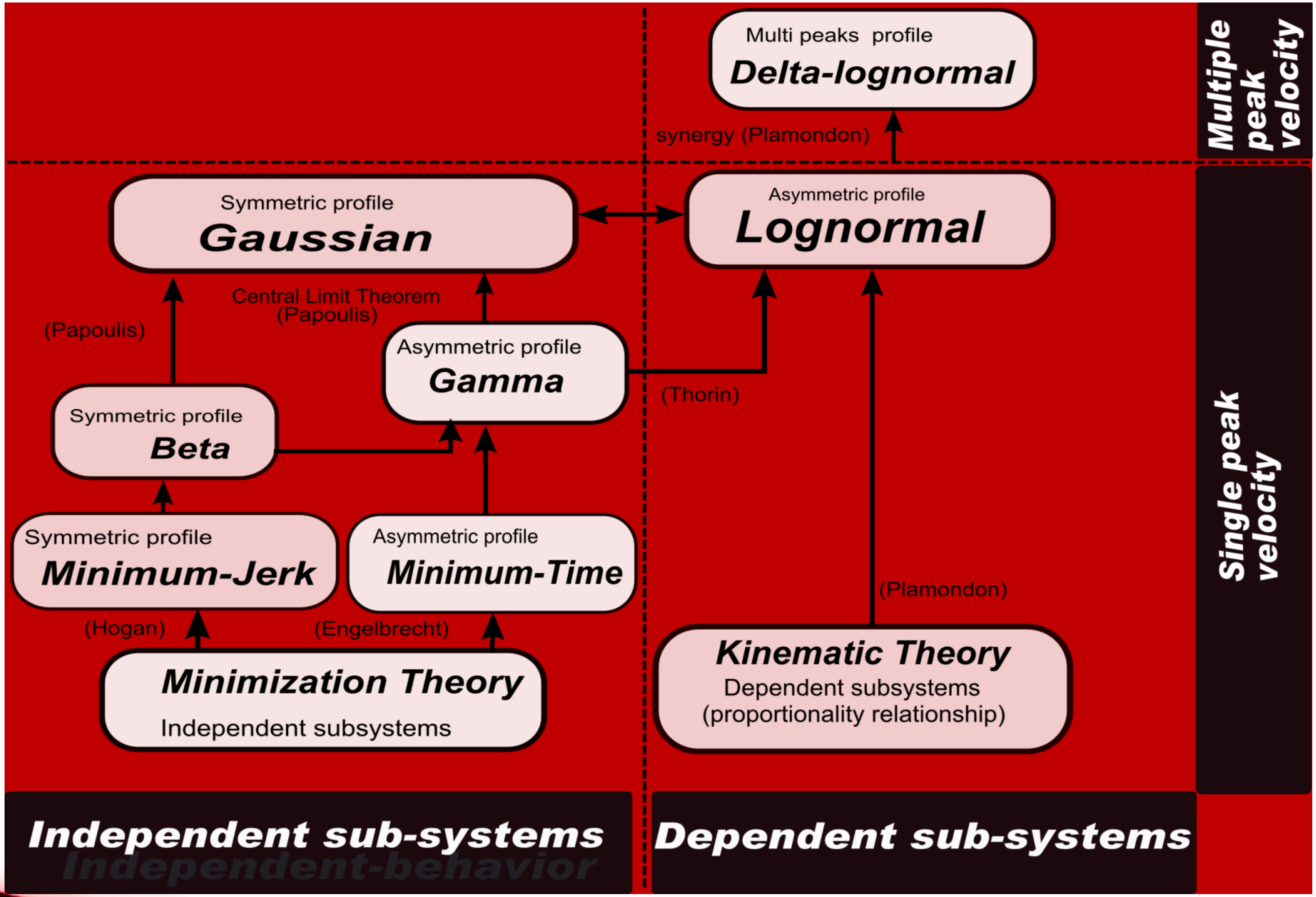


Correlation Coefficient r^2

Y(X) X	TD1	TD2	TD3	TD4	TD5	TD6
TD1	1.0	0.92	0.95	0.89	0.92	0.89
TD2	0.93	1.0	0.94	0.90	0.84	0.86
TD3	0.96	0.95	1.0	0.95	0.94	0.90
TD4	0.89	0.89	0.88	1.0	0.93	0.88
TD5	0.93	0.85	0.93	0.94	1.0	0.92
TD6	0.87	0.82	0.85	0.86	0.89	1.0

$r^2 > 0.82$

THEORETICAL COMPARISON



DJIOUA, M., PLAMONDON, R., “The Limit Profile of a Rapid Movement Velocity”
Human Movement Science, vol. 29, (2010), pp.48-61.

4 – Lognormality Principle

Lognormality Principle

The lognormal velocity patterns, which are the results of an asymptotic convergence, can be interpreted as reflecting the behavior of subjects who are in perfect control of their movements.

Corollary

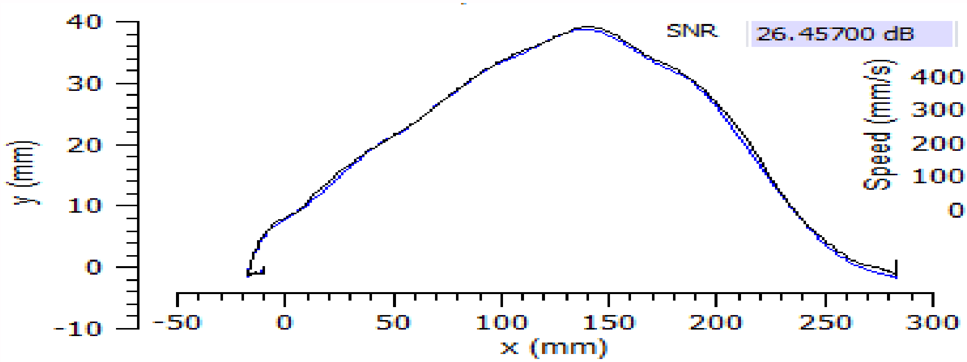
If we specifically focus on the basic mathematical convergence toward lognormality, handwriting learning, on the one hand, can be interpreted as a migration toward an ideal representation of perfectly mastered movements. On the other hand, aging and health problems should reveal a progressive departure from lognormality. In between, writers are taking advantage of lognormality.

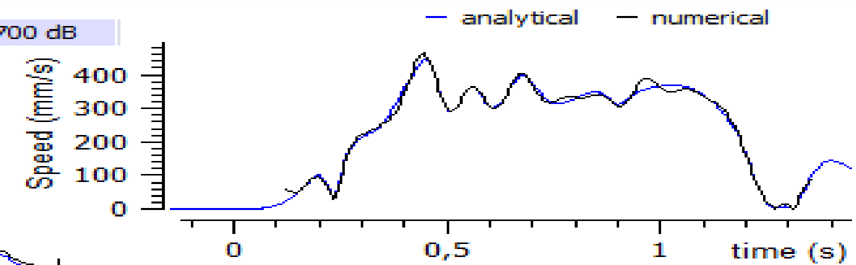
4.1 - Learning:

Moving toward Lognormality

- Cooperation with Céline Rémi and Thérésa Duval, Université des Antilles et de la Guyanne.
- DUVAL, T., RÉMI, C., PLAMONDON, R., O'REILLY, C.,, On the Use of the Sigma-Lognormal Model to Study Children Handwriting, , Proc.16th Biennial Conf. of the Graphonomics Society, Nara, Japan, June 10-14 2013, pp26-29.

Fitness of the reconstruction: SNR

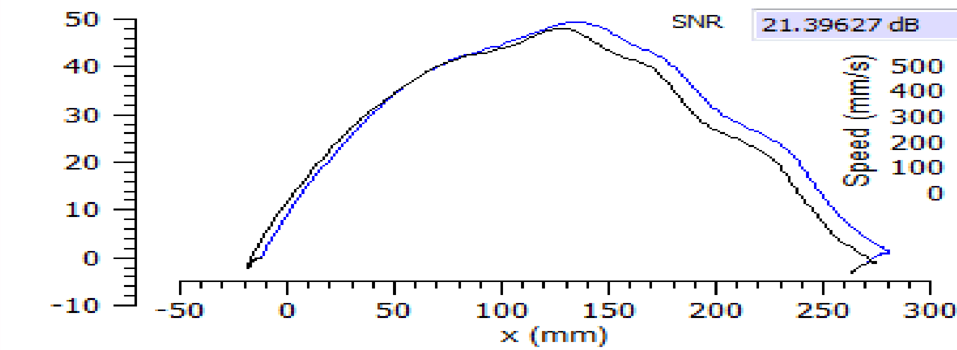


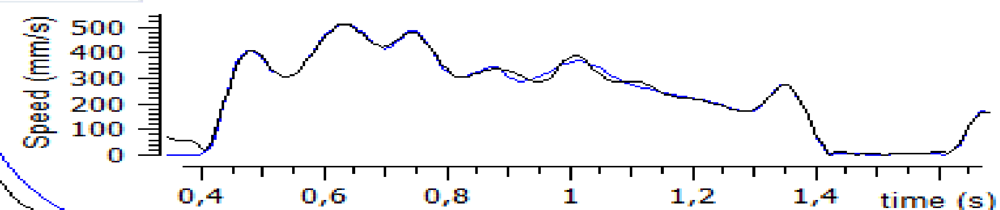


SNR ≥25

***Excellent Quality**

***Master level**

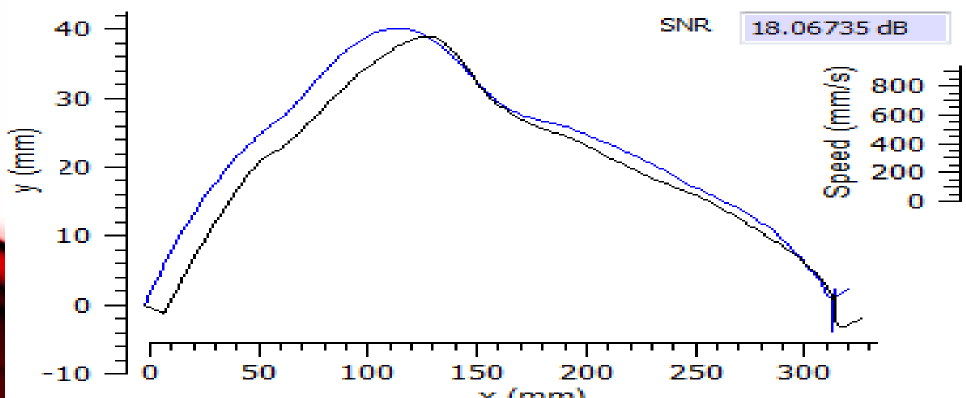


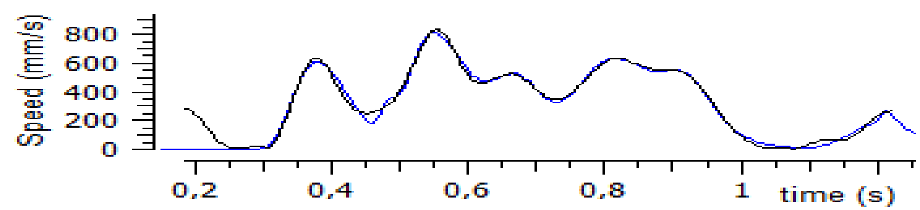


20≤ SNR<25

***Correct quality**

***Intermediate level**



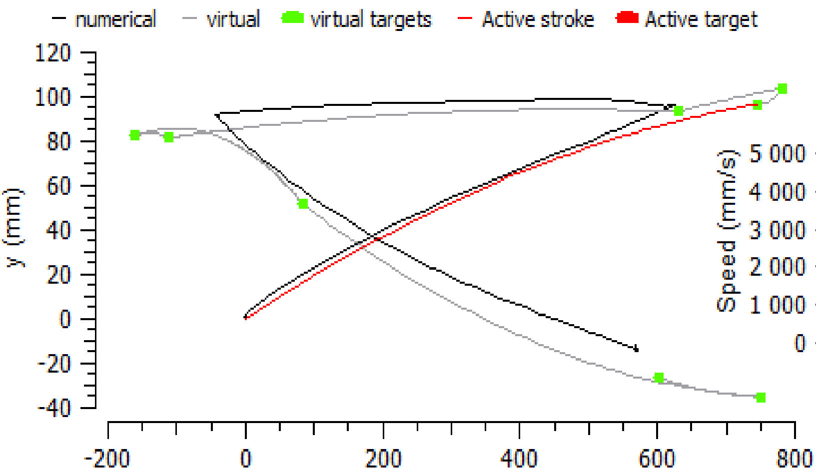


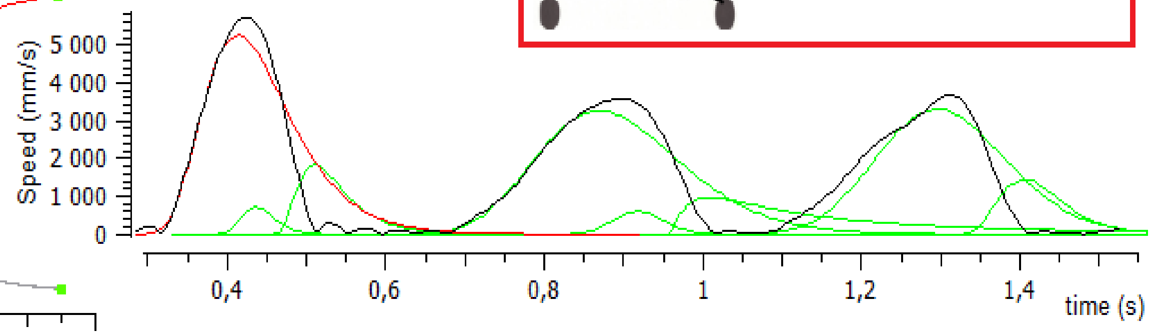
SNR<20

***Weak Quality**

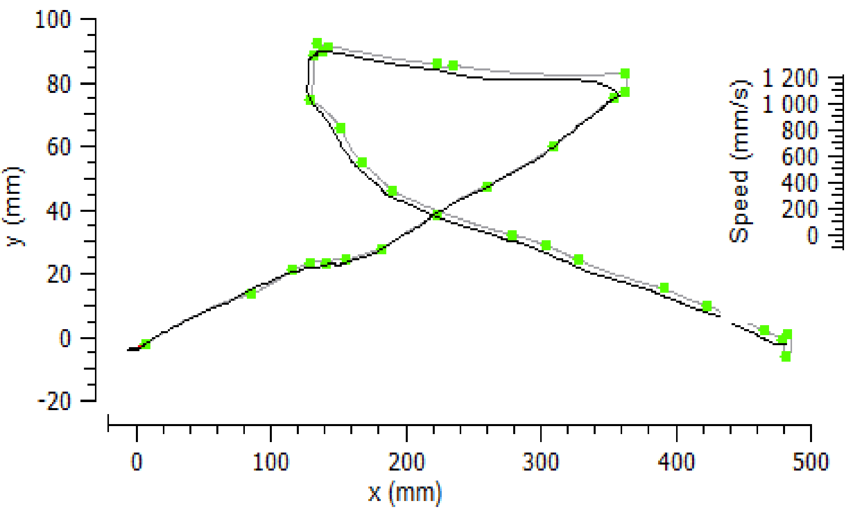
***Beginner level**

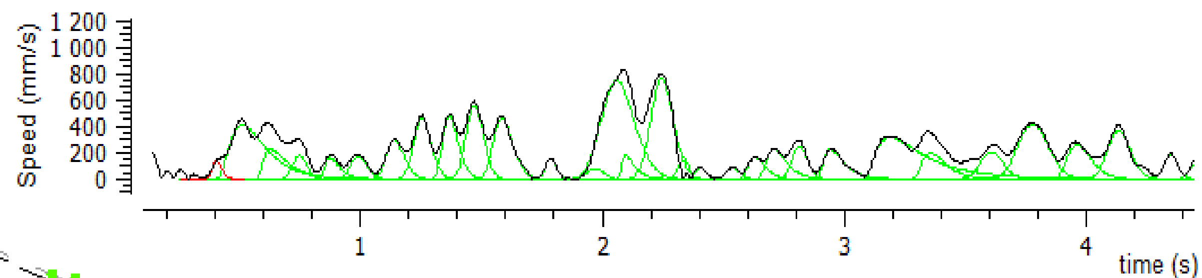
Fluidity of the movements: Nblog





nblog = 8





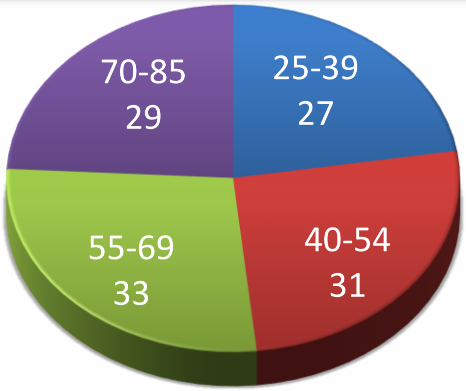
nblog = 32

4.2 – Aging:
Moving away from Lognormality

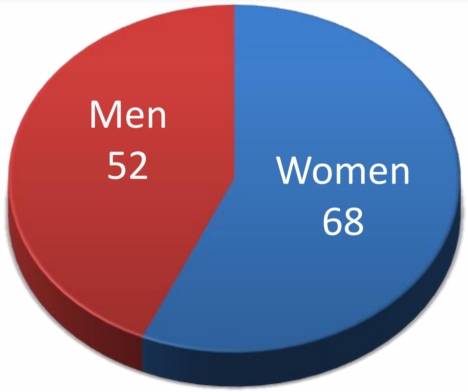
Back to a Previous Study on
Brain Stroke Risk Factors Assessment

5 Data — Sample (120 subjects)

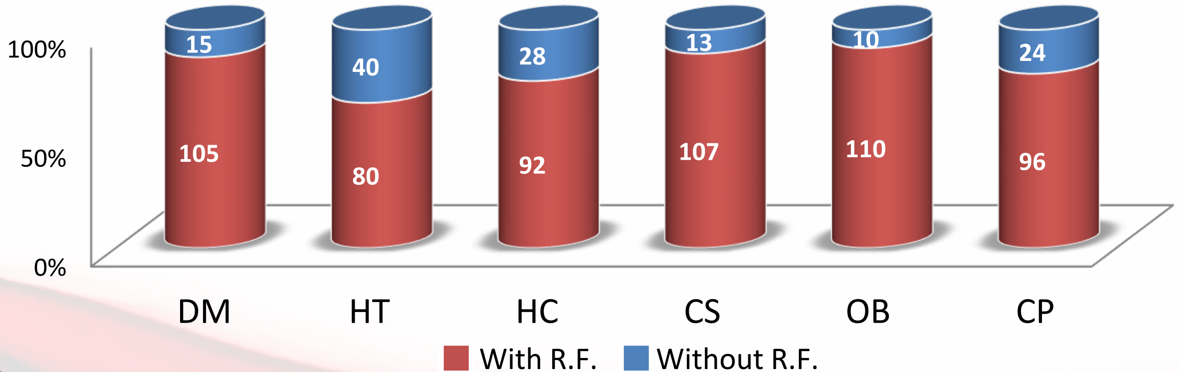
Age



Gender



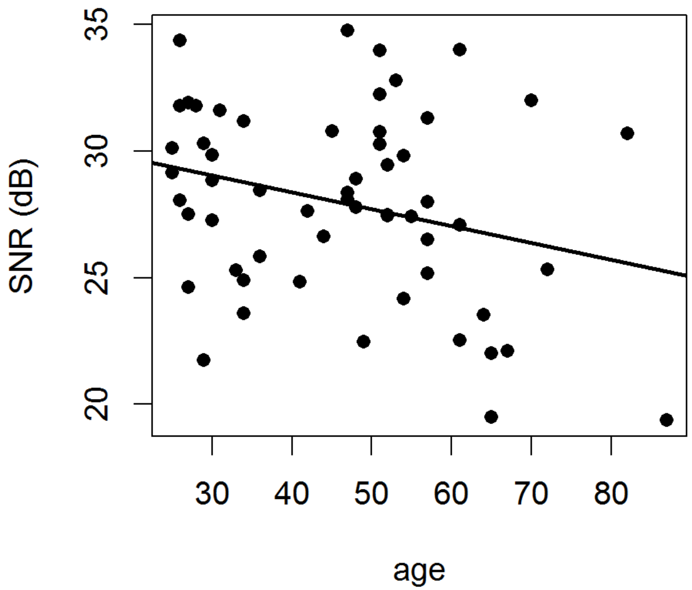
Brain stroke risk factors (R.F.)



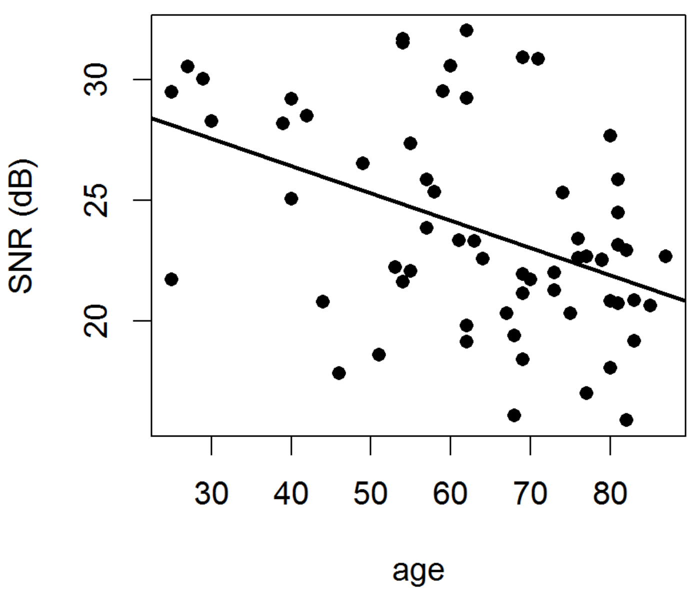
DM: Diabetes mellitus
HT : Hypertension
HC : Hypercholesterolemia
CS : Cigarette smoking
OB : Obesity
CP : Cardiac problems

Reaching Movements

Delta-Lognormal Analysis



No risk factor



With risk factors

For Further Information

Plamondon, R., O'Reilly, C., Rémi, C., Duval, T.,
"The lognormal hand writer:
learning, performing and declining."
Frontiers in Psychology, (2013)
Special Issue on Writing Words: from Brain to Hand(s),
S. Kandel and M. Longcamp, Eds.
A Nature Publishing Group Journal.

5 – BACK to the VISION:

Personnal Digital Bodyguards

Overview of Some On-site Projects
and Collaborative Quests
in the context of the current state of the art

E-Security Vision

"PDBs will protect people's sensitive data with signature verification, provide equipment use security with writer authentication, handwritten CAPTCHAs "

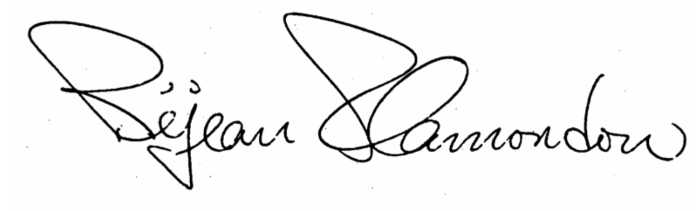
Where do we stand now?

A Working Prototype

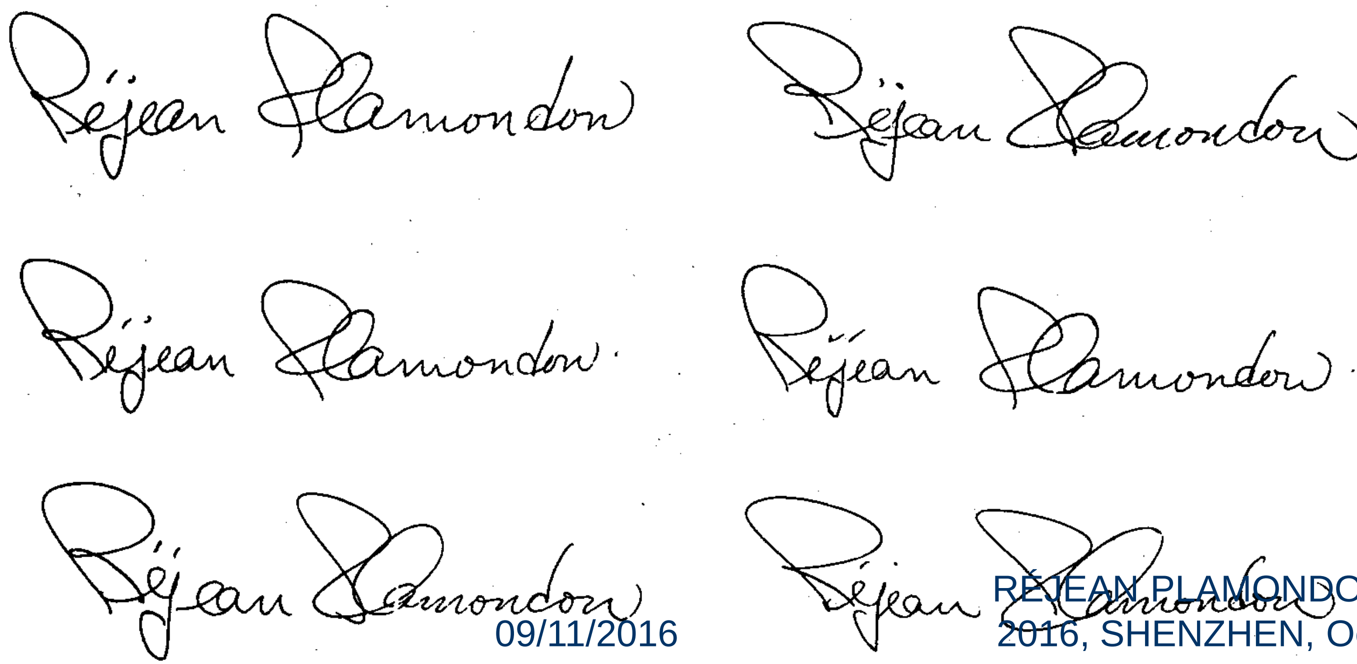
System Characteristics

- Enrolment with only 3 signatures
- Model-based analysis
- Configurable to any desired level of security
- Runs under any OS

Skill Game
Which Ones are Forgeries?



A B C D E F



Current DSV DATABASES

- MCYT [1](2003)
- SVC [2] (2004)
- MyIDEA [3] (2005)
- Biosecure [4](2007)
- BiosecureID [5] (2007)
- e-BioSign [6] (20xx)
- ...+++

TABLE 1. System Performances

Full Database (FD) , Signature (S), Genuine Signatures (G) , Forgeries (F), Random Forgeries (RF), Simple Forgeries (SF), Skilled Forgeries (SK), Number of Authors (A)

Matching Technique	Main features	Database	Results	Reference
HMM	Position	FD) 1000(G) (20(G) x 50(A)) , 1000(SK) (20(SK) x 50(A)) , Training) 250(G) (5(G) x 50(A)) Test) 750(G) (15(G)x50(A)) , 2450 (RF) (50(RF) x 49(A)) , 1000 (SK) (20(SK) x 50(A)) ,	EER: 5.2% (with RF) ; EER: 15.8% (with SF)	M. Martinez-Diaz et al. [36]
HMM	Global features Local features	FD) 120(A) (of the 120 'common DS2/DS3' signature dataset) Training) 350 (G) (5(G) x 70(A)) Test) 1050 (G) (15(G) x 70(A)), 1400 (SF) (20(SF) x 70(A)), 1380 (RF) (20(RF) x 69(A))	SFFS Optimization scenario: skilled forgeries Global features: EER: 7.2% (with RF) ; EER: 16.3% (with SF) Local features: EER: 6.0% (with RF) ; EER: 17.5% (with SF) SFFS Optimization scenario: random forgeries Global features: EER: 5.4% (with RF) ; EER: 17.7% (with SF) Local features: EER: 5.8% (with RF) ; EER: 22.2% (with SF)	M. Martinez-Diaz et al. [48]
SVM	Position, pressure	FD) 100(A) Training) 1000(G) (10(G) x 100(A)), 1000(SF) (10(SF) x 100(A))	Feature Set reduction based on the Fisher's Ratio Analysis - Emulated device: capacitive screen-based (no pressure signal) - EER: 10% - Emulated device: resistive screen-based - EER: 8.5%	A. Mendaza-Ormaza et al.[46]
DTW	Position, pressure	FD) 6860 (S) (3920 (G) + 2940 (F))	Best performances (Samsung ATIV 7). Stylus: EER: 0.05% (with RF) ; EER: 6.35% (with SF) Finger (no pressure information): EER: 0.36% (with RF) ; EER: 13.23% (with SF)	R. Vera-Robdriguez [41]
DTW SVM	Position, pressure	FD) each one of the five database (one for each device) consists of: 1400 (S)= (28 (G) + 28 (SF)) x 25 (A)	- First experiment (Portable Device Model vs Portable Device Database): - Best performance with capacitive screen EER: 1.58% (DTW) ; EER: 4.03% (SVM) - Best performance with resistive screen EER: 2.23% (DTW) ; EER: 4.25% (SVM) - Second experiment:(Digital Pen Tablet Model vs Portable Device Database): - Best performance with capacitive screen EER: 12.08% (DTW) ; EER: 14.51% (SVM) - Best performance with resistive screen EER: 8.16% (DTW) ; EER: 14.05% (SVM)	A. Mendaza-Ormaza et al. [47]
DTW LCS	3-D Acceleration (in air)	FD) 350 (G) (7(G) x 50(A) 2100 (F)	(Best performance when no normalization is made) EER: 3.34% (LCS-based) ; EER: 2.80% (DTW-based)	J. Guerra-Casanova [49]
DTW	Position, path-tangent angle, total acceleration magnitude, etc.	FD) 120(A) (of the 120 'common DS2/DS3' signature dataset)	Feature Set reduction based on the Sequential Forward Feature Selection (SFFS) Training vs testing: DS2 – DS3 EER: 4.3% (RF) ; EER: 18.3% (SF) Training vs testing: DS3 – DS3 EER: 1.9% (RF) ; EER: 12.7% (SF)	R. Tolosana et al. [44]

Curent issues

1-The problem of interoperability

The availability in daily operative condition of a wide set of mobile devices as well as of hundreds traditional pen tablets for signature acquisition make device interoperability a very challenging problem for signature verification systems.

Currrent issues

2- Acquisition ergonomy

Verifying the extent to which specific factors related to technology of the input system of the handheld device (i.e. type of writing surface, small input area, visual feedback, etc.) and to writing conditions (posture of the user, writing with a stylus or finger, user in movement, etc.) can modify the verification performance.

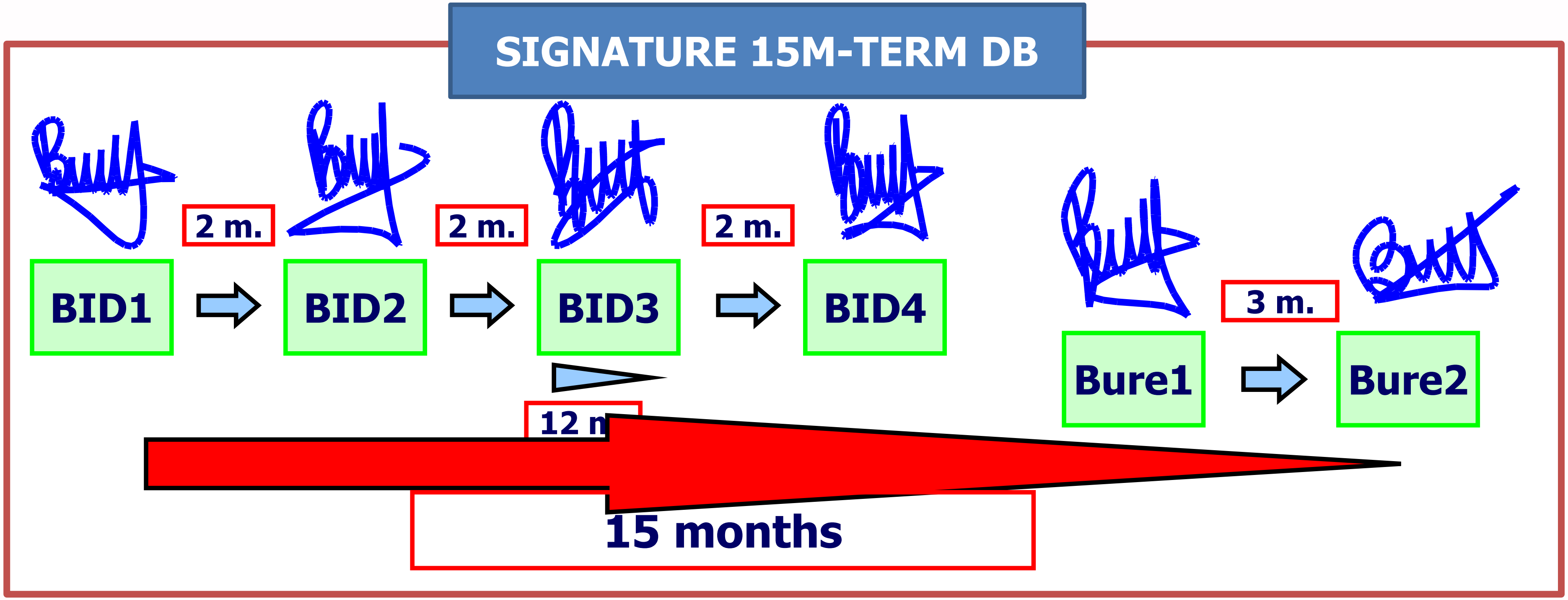
On going projects: e-security

- Aging effects
- Stability analysis
- Synthetic signatures
- Performance enhancement
- Model-based system
- Reference minimization
- …+++

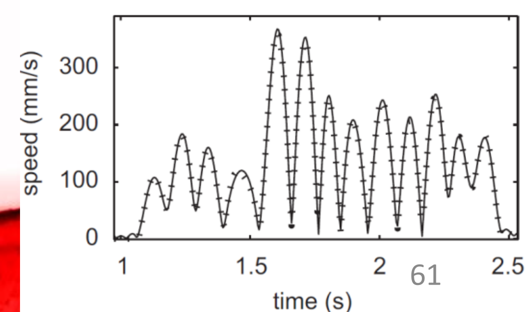
Signature vs Time

- A Cooperation with Javier Ortega-Garcia, Julian Fierrez, Javier Galbally and Marta Gomez-Romero, Biometric Recognition Group, ATVS,Universitad Autonoma de Madrid.
- GOMEZ-BARRERO, M., Galbally, J., Fierrez, J., Ortega-Garcia, M., Variations of Handwritten Signatures with Time: a Sigma-lognormal Analysis, Proceedings of the 6th IAPR International Conference on Biometrics, Madrid, Spain, June 4-7, 2013, PS3.1-PS3.6.

Variations of Handwritten Signatures with Time: A Sigma-Lognormal Analysis



Sigma Log-Normal Representation
(N, t_0, D, θ_d, θ_f, μ, σ)



Statistical Measures

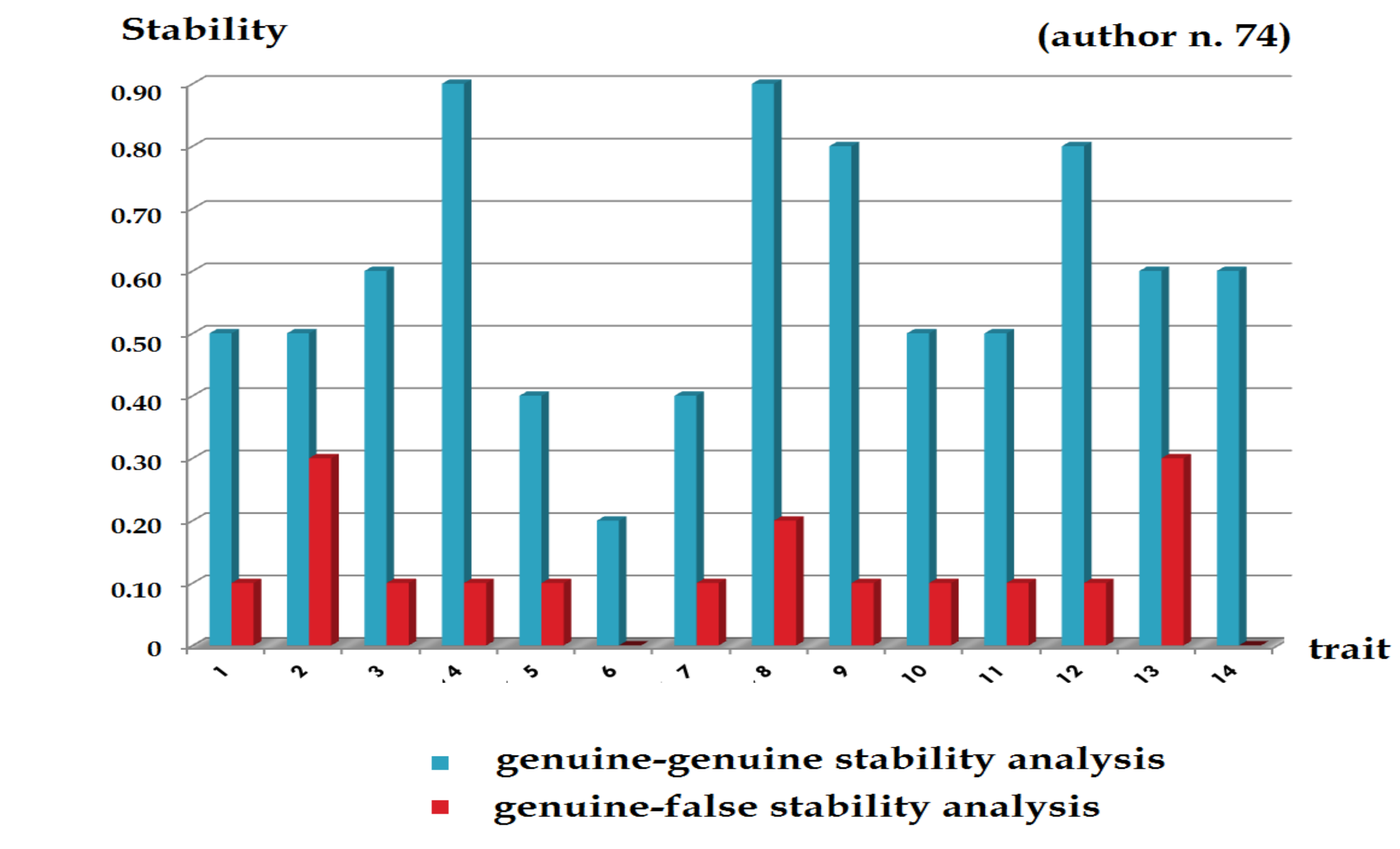
Exp 1: Variation of the same signer with time

Exp 2: Variations between signers of different age groups

Signature Stability

- A cooperation with Guiseppe Pirlo, Donato Impedovo, Annamaria Cozzolongo, Roberta Gravinese, Andrea Rollo, Department of Computer Science, University di Bari, Italy.
- PIRLO, G., IMPEDOVO, D., PLAMONDON, R., O'REILLY, C., "Stability Analysis of Online Signatures in the Generation Domain"in G. Pirlo, D. Impedovo, M. Fairhurst (Eds). Advances in Digital Handwritten Signature Processing, A Human Artefact for e-Society Selected papers from the Workshop on "Emerging Aspects in Handwritten Signature Processing" World Scientific ISBN: 978-981-4579-62-9, pages: 1-12, 2014

EXPERIMENTAL RESULTS
(trait-oriented stability analysis)

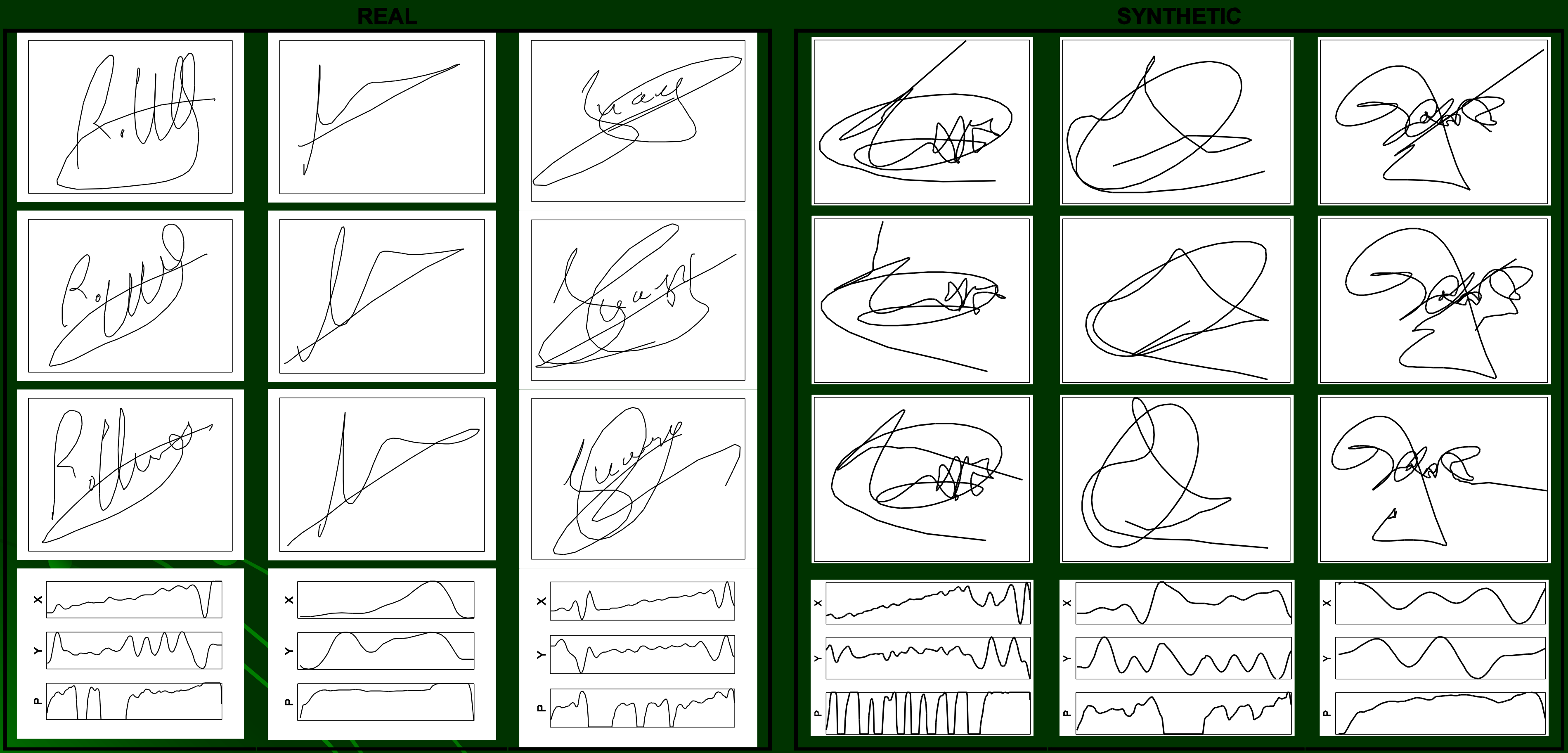


Synthetic Signature Generation

- A cooperation with Javier Galbally, Julian Fierrez and Javier Ortega-Garcia, Biometric Recognition Group, ATVS, Universitad Autonoma de Madrid.

- GALBALLY, J., PLAMONDON R., FIERREZ, J. ORTEGA-GARCIA, J., "Synthetic On-Line Signature Generation Part I: Methodology and Algorithms, Pattern Recognition, Vol 45, No.7, pp. *2610-2621* 2012.
- GALBALLY, J., FIERREZ, J. ORTEGA-GARCIA, J., PLAMONDON R., " Synthetic On-Line Signature Generation Part II: Experimental Validation, Pattern Recognition, Vol.45, No.7, pp. 2622-2632, 2012.

TYPICAL RESULTS



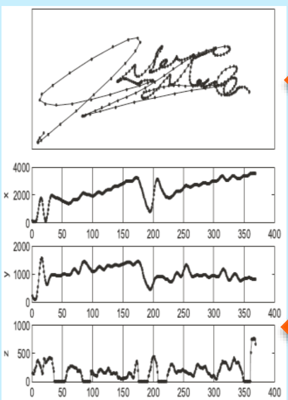
Enhanced On-line Signature Verification Based on Skilled Forgery Detection Using Sigma LogNormal Features

Marta Gomez-Barrero[1], Javier Galbally[1], Julian Fierrez[1], Javier Ortega-Garcia and Réjean Plamondon[2]

[1] **Biometric Recognition Group – ATVS**
Escuela Politécnica Superior
Universidad Autónoma de Madrid, SPAIN

[2] Laboratoire Scribens,
Département de Génie Électrique,
École Polytechnique de Montreal, CANADA

Enhanced System



Skilled Forg. Detector (Sigma LogNormal Feats)

$C = \{Gen, Sk\}$

$$S = \begin{cases} S_{DTW}\,(1 + W_{fg}) & \text{if } \textit{Skilled} \\ S_{DTW}\,(1 - W_{gen}) & \text{if } \textit{Genuine} \\ S_{DTW}\,(1 + W_{fg}) & \text{if } \textit{Impostor} \end{cases}$$

Verification System (Dynamic Functions)

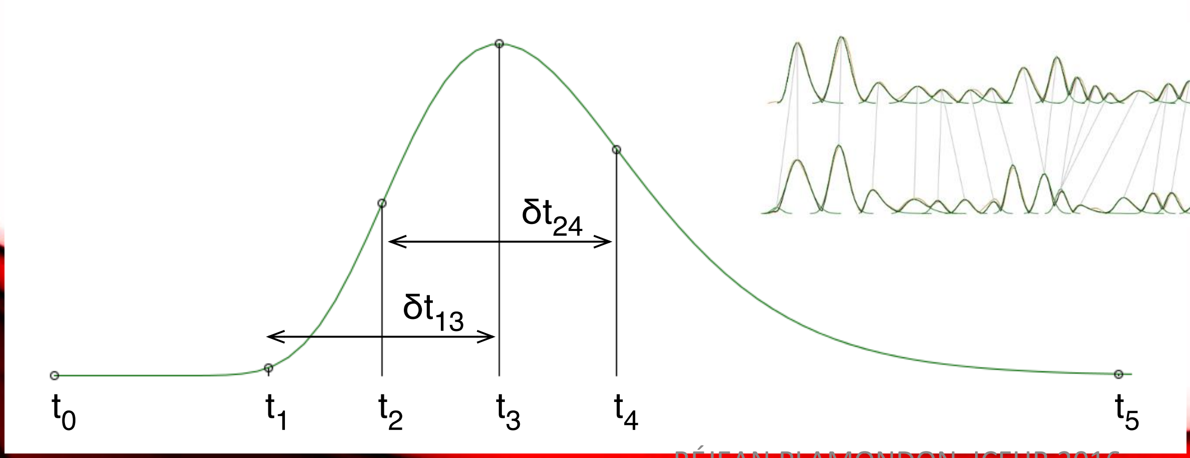
S_{DTW}

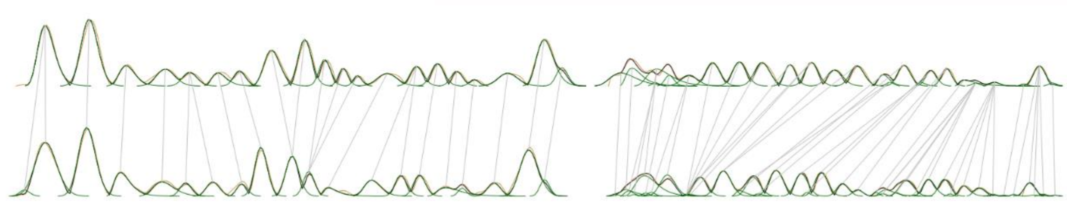
S

Model-Based Signature Verification

[A. Fischer, R. Plamondon – IGS'15]

- Use model directly for signature verification
  - cognitive psychomotor characteristics of the signer
- 18 neuromuscular features of the ΣΛ model
  - dissimilarity based on dynamic time warping





Towards an Automatic On-Line Signature Verifier Using Only One Reference Per Signer

Moises Diaz[1], Andreas Fischer[234],
Réjean Plamondon[4] and Miguel A. Ferrer[1]

[1]IDeTIC Institute, Universidad de Las Palmas de Gran Canaria, Spain
[2]DIUF Department, University of Fribourg, Switzerland
[3] iCoSys Institute, University of Applied Sciences and Arts Western Switzerland
[4] École Polytechnique de Montréal. Laboratoire Scribens, Canada

To appear in IEEE Trans. Cybernetics 2016

Target

- The Problem:

What can be done with only one enrolled real handwritten signature in Automatic Signature Verification (ASV)?

- Our Solution:

Standard features, DTW and **duplicate** the enrolled signature by **fine-tunning** the Sigma-Lognormal parameters.

Captcha Generation

- A Cooperation with Venu Govindaraju and Chetan Ramaiah, Deparment of Computer Science and Engineering, Center for Unified Biometric and Sensors, SUNY at Buffalo, USA.

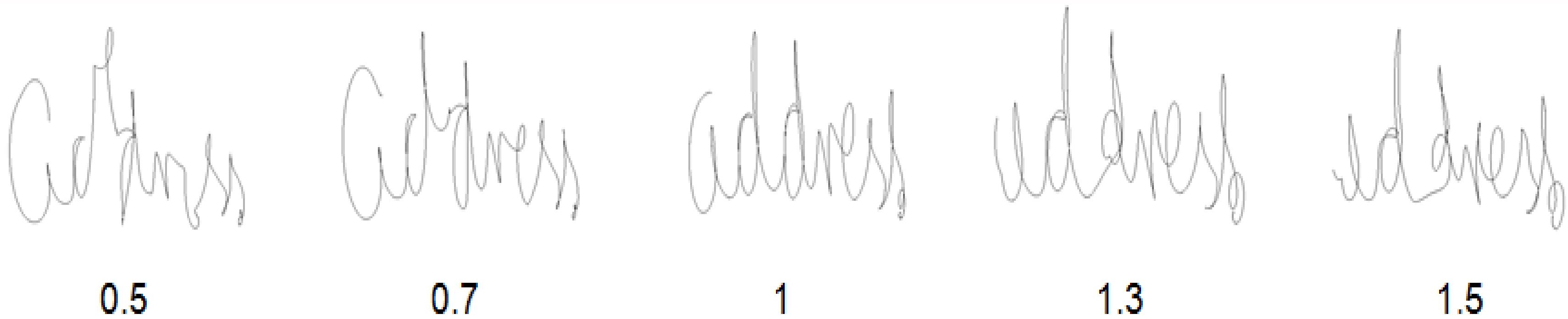
- RAMAIAH, C., PLAMONDON, R., GOVINDARAJU, V., Handwritten CAPTCHA generation based on the Sigma-Lognormal model, Proc.16th Biennial Conf. of the Graphonomics Society, Nara, Japan, June 10-14, 2013, pp. 105-108.

Sigma-Lognormal model for handwritten CAPTCHAs

- Randomly pick out a word from a online handwriting database.
- Determine the parameters of the Sigma-Lognormal model for the chosen word.
- Modify the parameters of the model within an acceptable range of values.
- Render the modified word as the handwritten CAPTCHA.

Experiments

- Experiment 2A results:



A sample where the parameters were modified by the same quantity. The numbers below the images indicate the ratio between the original values and the modified values.

Experiments

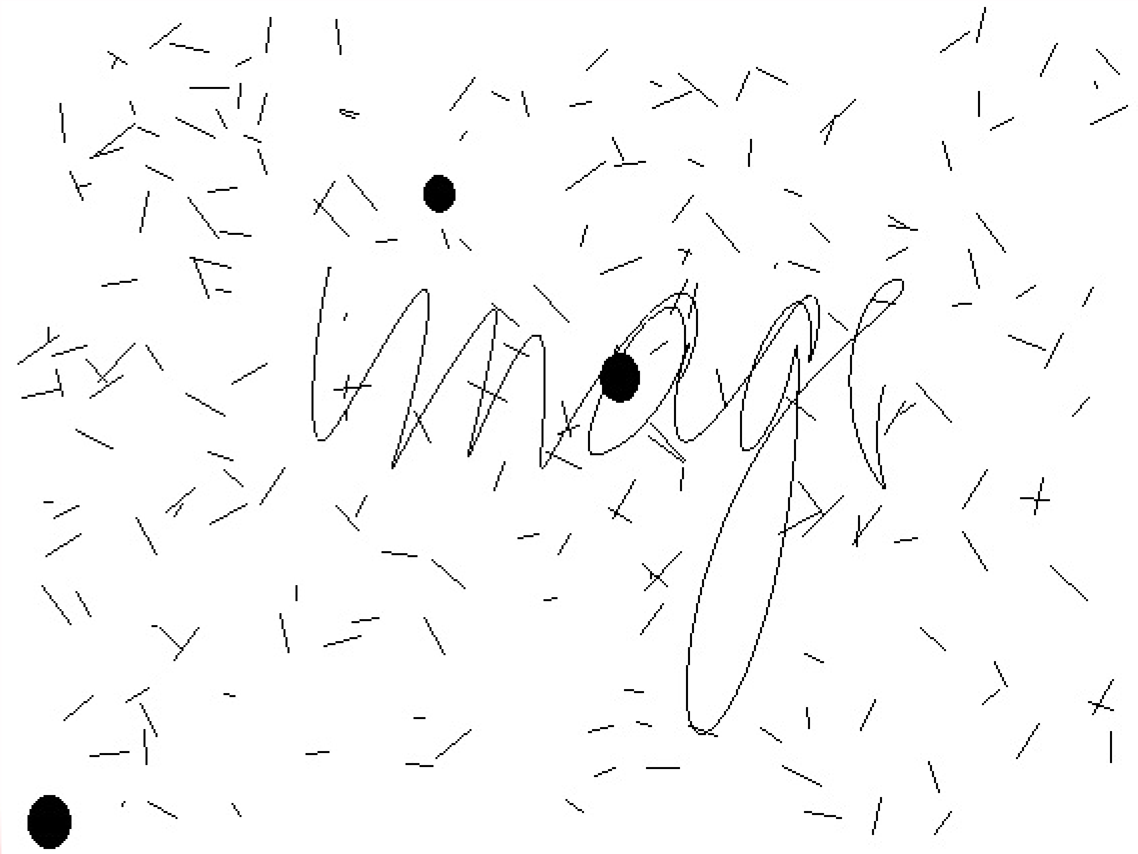
- Experiment 2A results

Ratio	0.5	0.6	0.7	0.8	0.9	1.1	1.2	1.3	1.4	1.5
WMR accuracy	5.52	13.77	18.92	17.89	33.36	29.23	16.86	20.98	5.52	3.72
Human Evaluation	48.45	70.1	87.62	96.9	100	100	97.93	87.62	64.94	50.51

- The ratio indicates how much each parameter was changed with respect to its original value.
- A range of 0.7-1.3 might be appropriate for our purposes.

Follow up at ICPR 2014

We have made an extensive experimental analysis of different noise models.



e-Health

"PDBs will perform word spotting and recognition to monitor user fine motor control, which can detect stress, aging and health problems"

Where do we stand now?

A broad field

Several studies were dealing with Parkinson's disease, Alzheimer's disease, Huntington's disease, schizophrenia, hemispheric lesions, agraphia, dysgraphia, micrographia, macrographia, tardive dyskinesia , dystonia and writer's cramp, visuospatial neglect, hyperactivity, attention problems, ADHD, depression, psychosis, alcohol consumption, nicotine, cannabis and other illicit drugs.

Typical on-line handwriting analysis systems

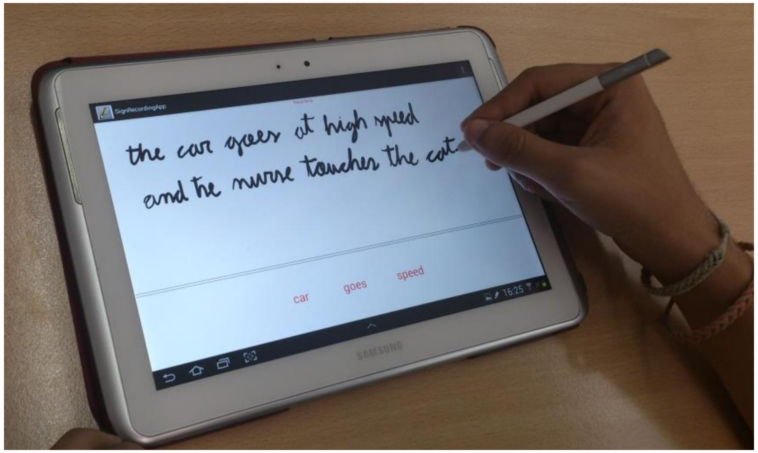
- MoValyZeR (H-L. Teulings)(Neuroscript)
- *Com*Pet (Computerized Handwriting Evaluation and Remediation tool (S.Rosenblum)
- …+++

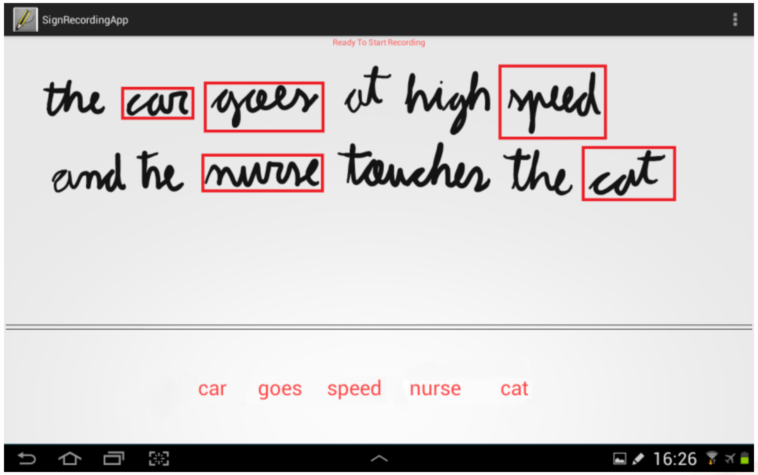
A Pen Based Interface

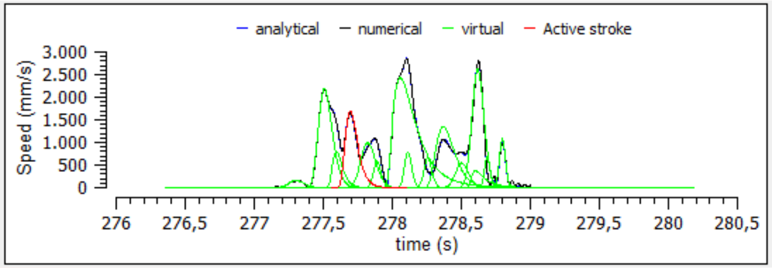
- An on-going Cooperation with Josep Llados and Alicia Fornes, Computer Vision Center, Universitad Autonomous de Barcelona, Spain.
- Pen-based user-centred tool for on-line word spotting and fine motricity monitoring to evaluate diseases in clinical research, to design rehabilitation task, to implement learning interfaces.

Proposed System: A Pen-based Interface for On-line Word Spotting and Fine Motricity Monitoring

1. **On-line word spotting**
   - The user defines his key-words
   - The system recognizes the key-words in the sentences written on the tablet
2. **Kinematic Analysis**
   - For each detected key-word, it computes the kinematic parameters and compares with the ones from stored instances of the same key-word: **Motricity monitoring** (evolution of HW)







A First Prototype

Monitoring Neuromotricity On-line:

a Cloud Computing Approach

Olivier LEFEBVRE [a], Pau RIBA [b], Jules GAGNON-MARCHAND [a], Charles FOURNIER [a], Alicia FORNES [b], Josep LLADOS [b] and Réjean PLAMONDON [a]

IGS 2015

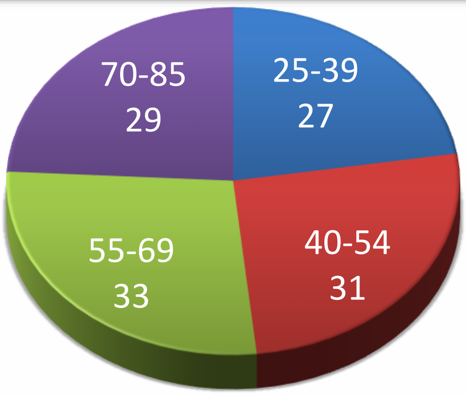
On-going Studies: e-Health

- Brain stroke risk factors
- Parkinson disease
- Alzheimer's disease
- ADHD
- Concussion
- …+++

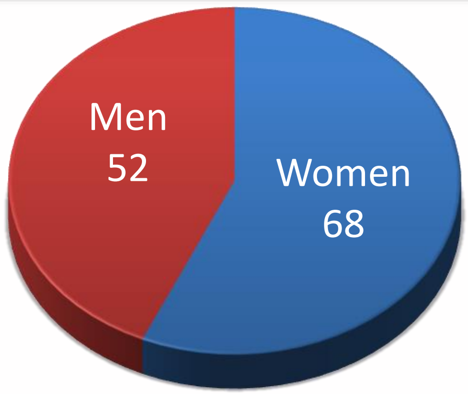
5 Data

Sample (120 subjects)

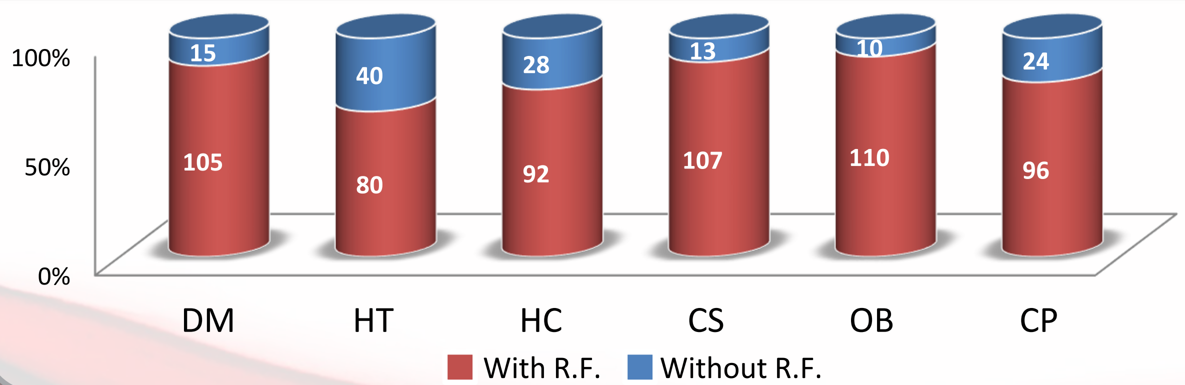
Age



Gender



Brain stroke risk factors (R.F.)

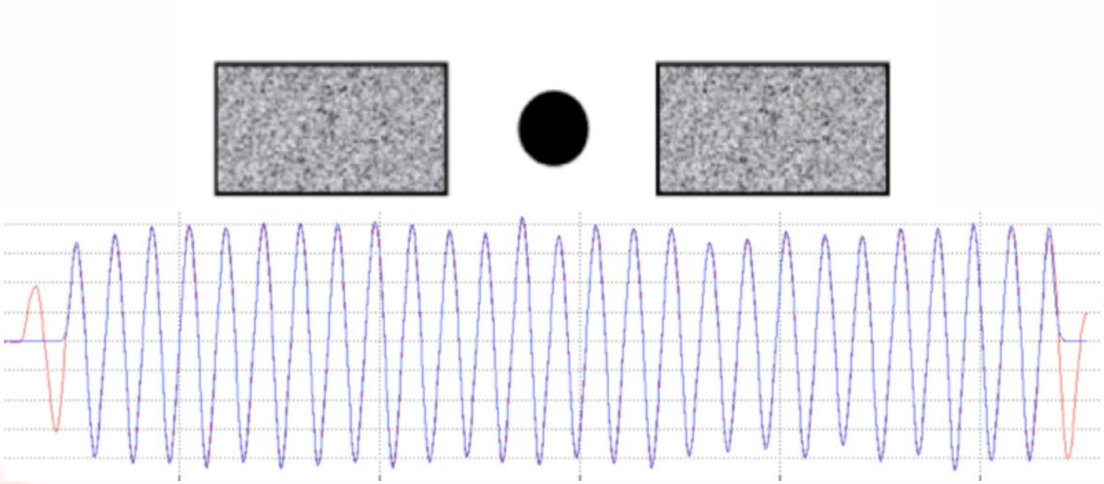


DM: Diabetes mellitus
HT : Hypertension
HC : Hypercholesterolemia
CS : Cigarette smoking
OB : Obesity
CP : Cardiac problems

Handwriting Strokes & Brain Strokes

[A. Bou, A. Fischer, R. Plamondon – IGS'15]

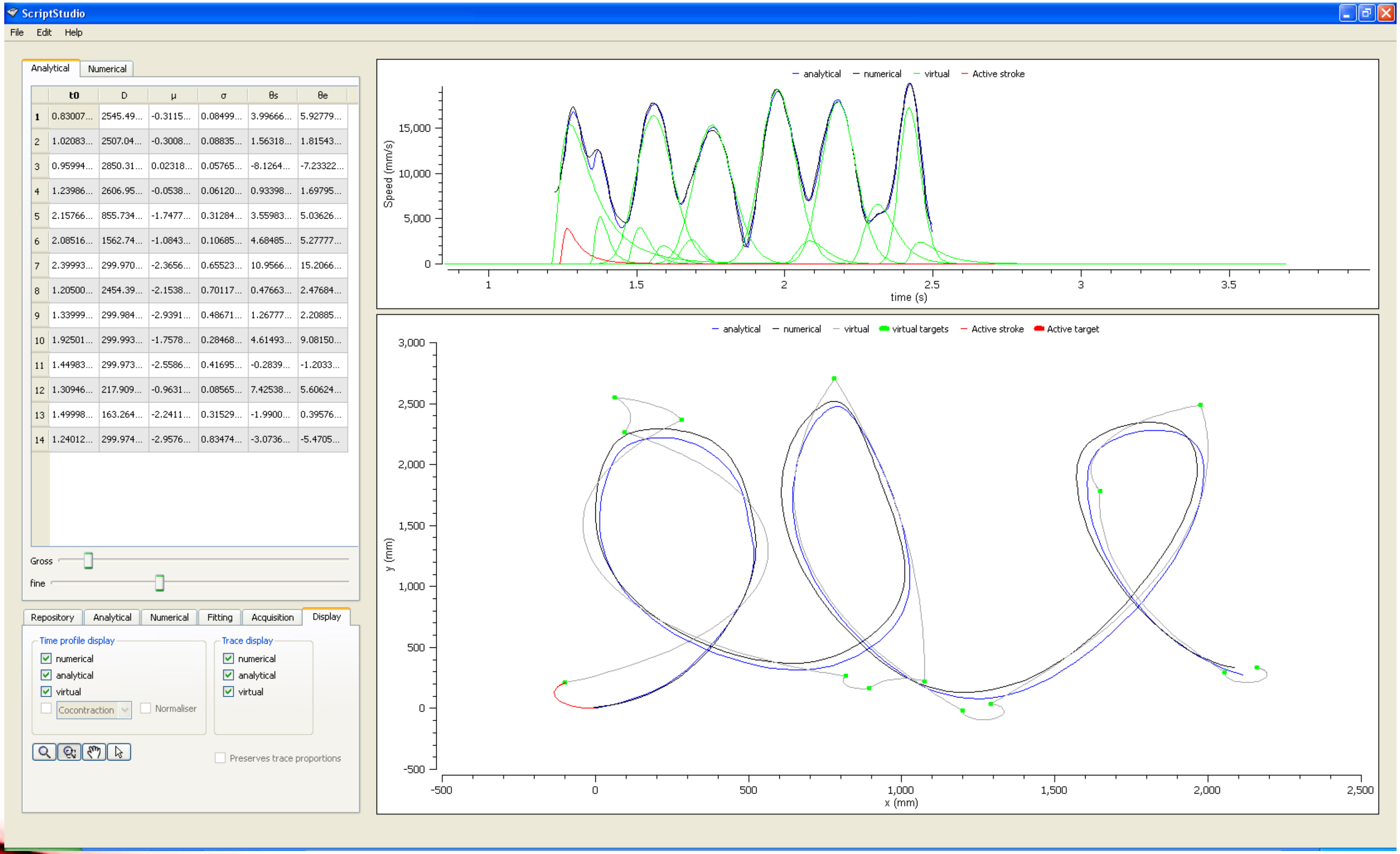
- Analysis of oscillatory movements
  - linking fine motor control with brain stroke risk factors
- 7 neuromuscular features of the ΩΛ model
  - differ between subjects with and without risk factors



Parkinson Disease

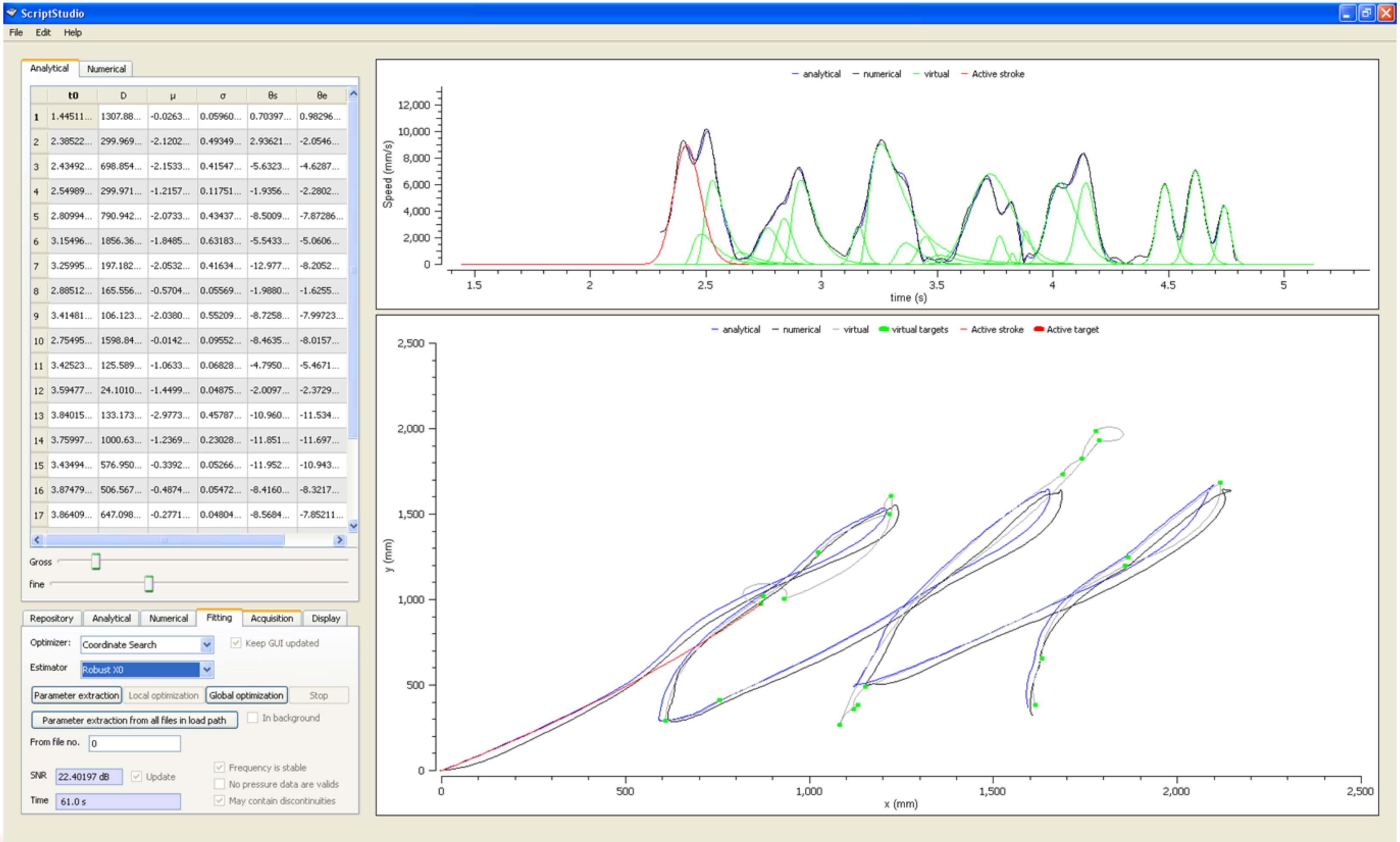
- A cooperation with Aren van Gemmert, Zhujun Pan and Christopher Aiken, Department of Kinesiology, Louisiana State University.
- VAN GEMMERT, A, PLAMONDON, R. O'REILLY,C, Using the Sigma-lognormal model to investigate handwriting of individuals with Parkinson's disease, Proc.16th Biennial Conf. of the Graphonomics Society,Nara, Japan, June 10-14, 2013,pp. 119-122.

Results (Older control)



	t0	D	μ	σ	θs	θe
1	0.83007...	2545.49...	-0.3115...	0.08499...	3.99666...	5.92779...
2	1.02083...	2507.04...	-0.3008...	0.08835...	1.56318...	1.81543...
3	0.95994...	2850.31...	0.02318...	0.05765...	-8.1264...	-7.23322...
4	1.23986...	2606.95...	-0.0538...	0.06120...	0.93398...	1.69795...
5	2.15766...	855.734...	-1.7477...	0.31284...	3.55983...	5.03626...
6	2.08516...	1562.74...	-1.0843...	0.10685...	4.68485...	5.27777...
7	2.39993...	299.970...	-2.3656...	0.65523...	10.9566...	15.2066...
8	1.20500...	2454.39...	-2.1538...	0.70117...	0.47663...	2.47684...
9	1.33999...	299.984...	-2.9391...	0.48671...	1.26777...	2.20885...
10	1.92501...	299.993...	-1.7578...	0.28468...	4.61493...	9.08150...
11	1.44983...	299.973...	-2.5586...	0.41695...	-0.2839...	-1.2033...
12	1.30946...	217.909...	-0.9631...	0.08565...	7.42538...	5.60624...
13	1.49998...	163.264...	-2.2411...	0.31529...	-1.9900...	0.39576...
14	1.24012...	299.974...	-2.9576...	0.83474...	-3.0736...	-5.4705...

Results (Parkinson)



Preliminary Results (IGS 2013)

- PD patients use significant more Lognormals than controls
  - PD patients have difficulty to precisely control agonist and antagonist resulting in more co-contraction => smaller movements.
- PD patients have trouble to efficiently recruit the order of lognormals to produce smooth movements
- Sigma-Lognormal model useful to find primitives in motor movements of Parkinson Disease patients.

Newly Started Projects

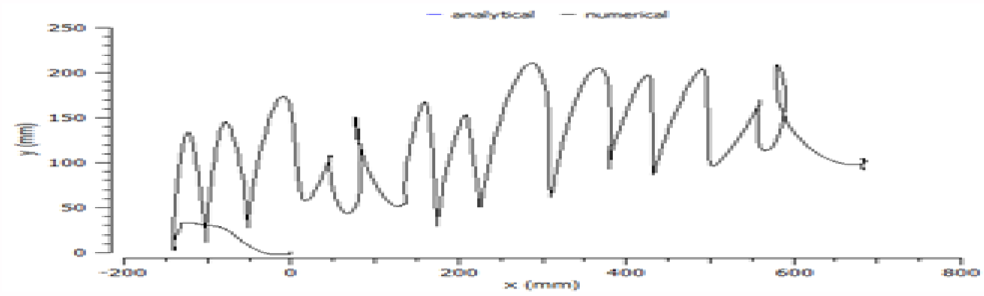
Effect of aerobic exercise training with or without music with preferred rhythms on motor skill learning in Parkinson's disease.

with Julien Doyon, Arnaud Boré
and Alexandra Nadeau
Institut de Gériatrie
Université de Montréal

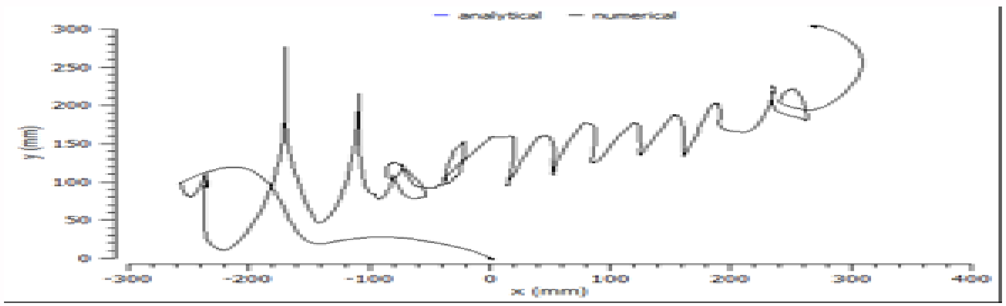
Alzheimer Handwriting Analysis

- A Cooperation with Donato Impedovo, Giuseppe Pirlo, Francesco Morizio Mangini, Donato Barbuzzi, Andrea Rollo, Allesandro Balestrucci, Sebastiano Impedovo, Lucia Sarcinella, Department of Computer Science, University di Bari, Italy.
- D. Impedovo, G. Pirlo,F. M. Mangini, D. Barbuzzi, A. Rollo, A. Balestrucci, S. Impedovo, L. Sarcinella, C. O'Reilly, R. Plamondon, Writing Generation Model for Health Care Neuromuscular System Investigation, Proceedings of the 10th International Meeting on Computational Intelligence Methods for Bioinformatics and Biostatistics, Nice, France, In Press.

WORD «mamma»



analytical
numerical
250
200
150
100
50
0
y (mm)
-200
0
200
400
600
800
x (mm)



analytical
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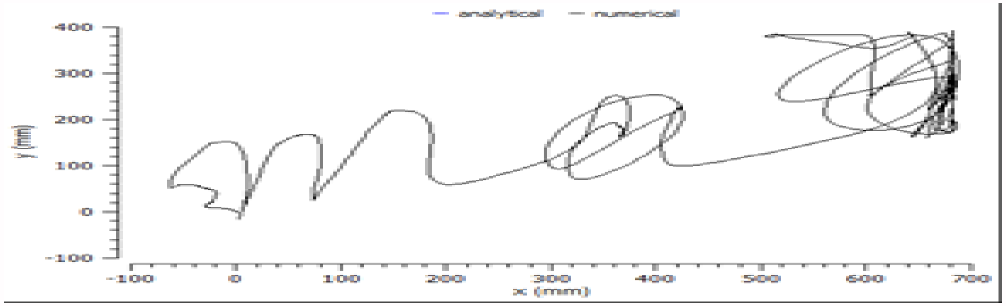

analytical
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-100
y (mm)
-100
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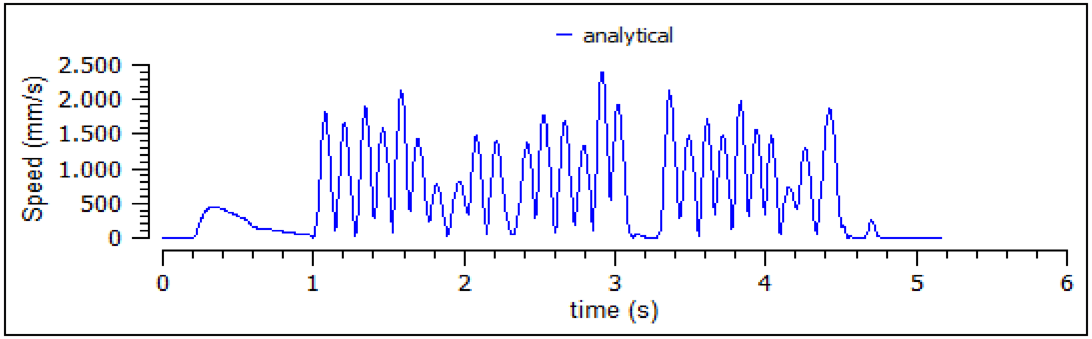
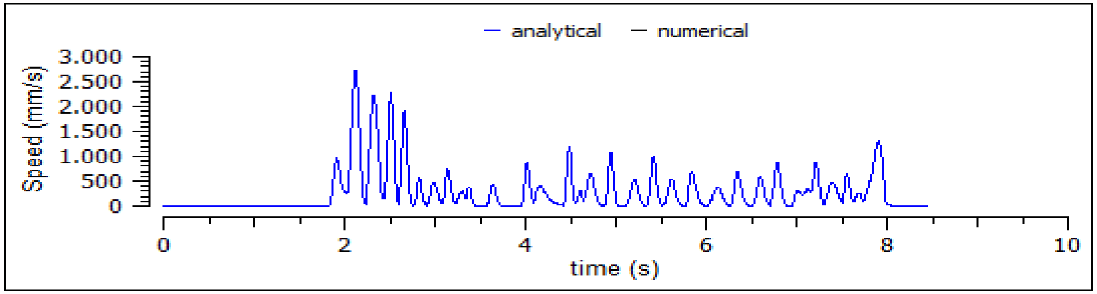
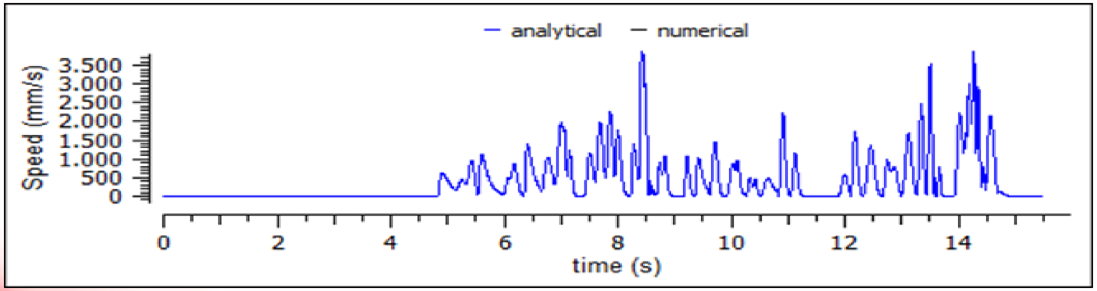
700
x (mm)

VELOCITY PROFILES







Newly starting Project

Kinematic analysis of graphomotor abilities in children with ADHD

with Bruno Gauthier and Patricia Laniel
Département de Psychologie
Université de Montréal

This study explores how fine motor skills in children with Attention Deficit/Hyperactivity Disorder (ADHD) are manifested in the kinematic graphomotor domain. More specifically, the goal is to compare graphomotor control in children with and without ADHD using the sigma-lognormal model.

Newly Starting Project

Pediatric and Youth Mild Traumatic Brain Injury Common Data Elements Study: improving the assessment of children with concussion.

with Miriam Beauchamp , Naddley Désiré,

Département Psychologie - Université de Montréal et Centre de recherche de l'hôpital Ste-Justine;

and Isabelle Gagnon,

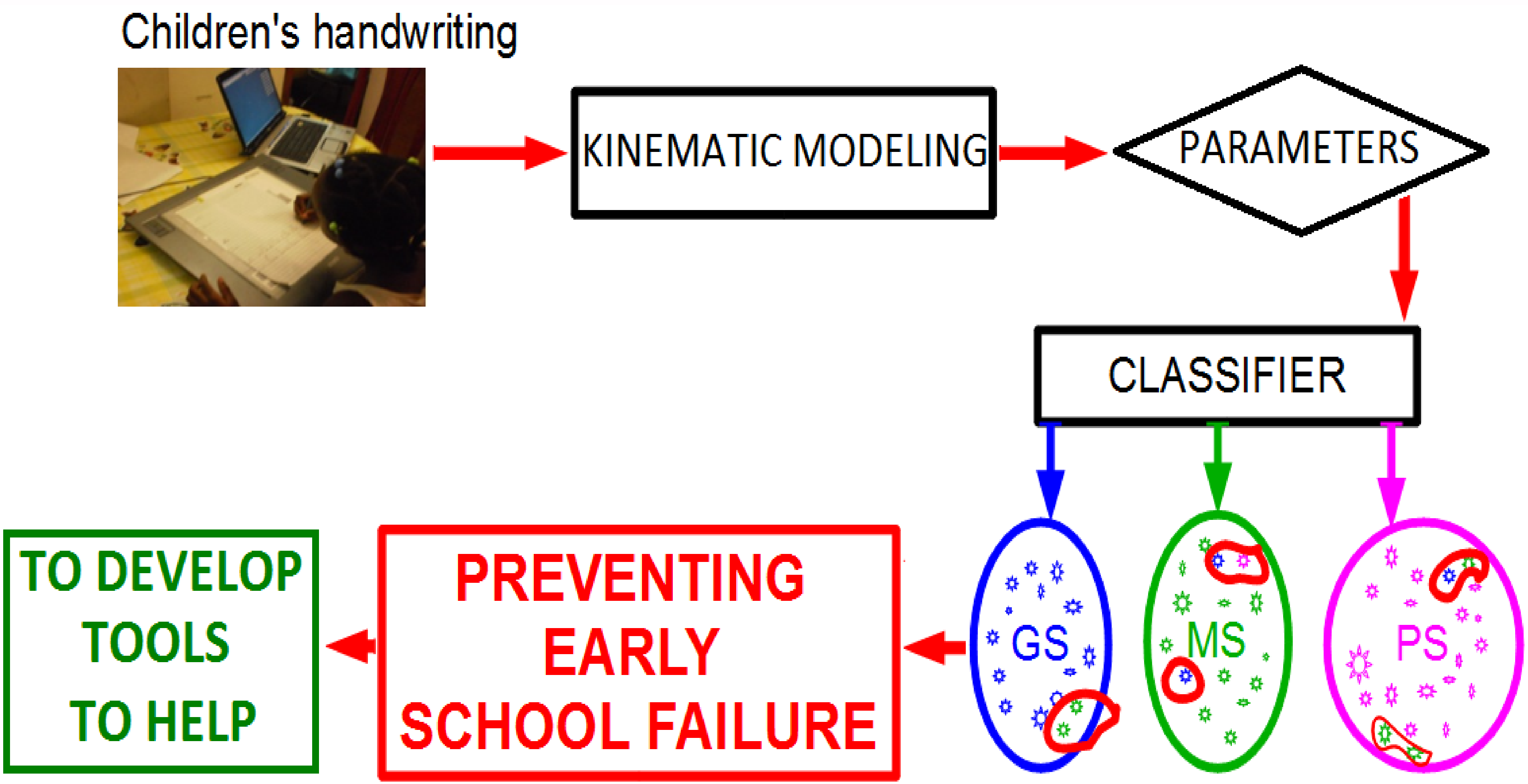
School of Physical and Occupational Therapy-McGill University and Trauma Department-Montreal Children's Hospital

e-Learning

"In the hands of children, PDBs will turn into toys helping them to learn and master their fine motricity and become better writers and students."

Where do we stand now?

Collaboration with Guadeloupe:GOAL



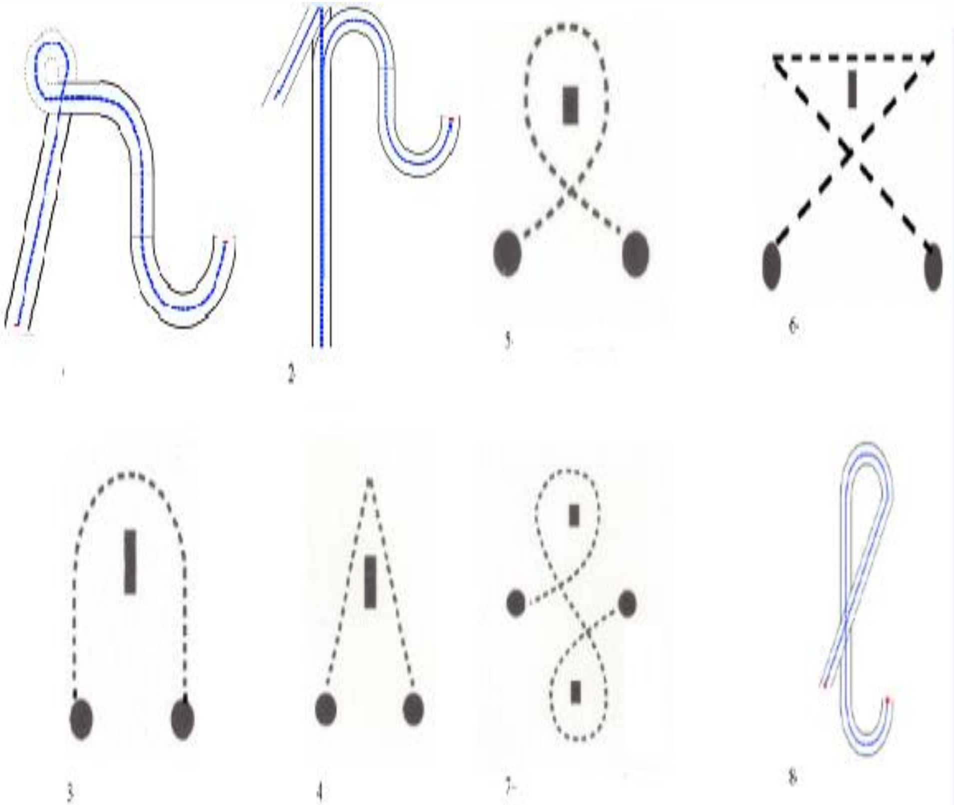
DATABASE

Number of days : 5

Section	Large (GS)	Medium (MS)	Small (PS)	Total
Children	27	17	22	66
Age (years)	5	4	3	

44 trajectories by children ⟶ 2640

TOOLS,PROTOCOL OF ACQUISITION



Number of patterns : 11

FUNDAMENTAL ANSWERS

Context ⟶ preliminary study to test the relevance of the Sigma-lognormal model on young writers

1. ***The Sigma lognormal model is efficient to synthesize children's handwriting with a good quality.***

2. ***The Signal to Noise Ratio (SNR) is efficient to classify young writers.***

3. ***The number of lognormals (nblog) is efficient to classify young writers.***

Most recent results

Combining sigma-lognormal modeling and classical features for analyzing gaphomotor performances in kindergarten children.

Thérésa Duval, Céline Rémi, Réjean Plamondon, Jean Vaillant, Christian O'Reilly.

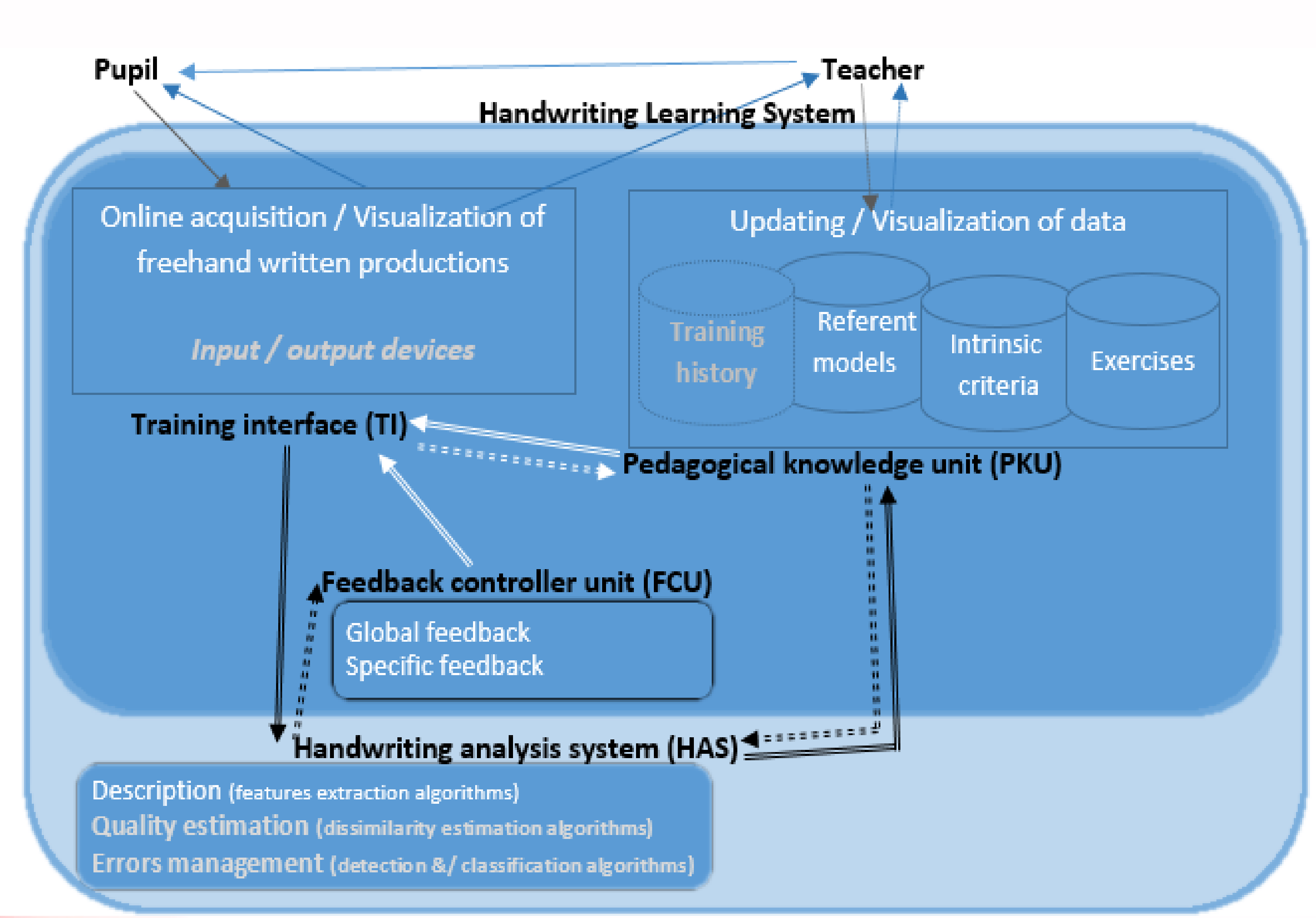
Human Movement Science, in Press (2015)

Exploring the Kinematic Dimension of Kindergarten Children's Scribbles.

Céline Rémi, Jean Vaillant, Thérésa Duval, Réjean Plamondon

IGS 2015

Generic architecture of e-learning tools



Basic modules

- The training interface can be associated with one, two or three of the following background functional units :
- The pedagogical knowledge unit (PKU) achieves the management of the data that are acquired on-line and displayed through the training interface.
- A handwriting analysis system (HAS) can be integrated as fourth complementary unit.
- A feedback controller unit (FCU) determines the feedbacks that have to be provided to the pupil and his teacher by the training interface.

Typical tools

- Toutaki
- Scriptôt
- TRAZO
- Telemaque
- Easysketcch
- SwissHood
- Intuiscript
- ...+++

Context of use

- **AGE RANGE**
- **DEVICE**
  - Digitizer
  - E-ink tablet
  - E-pen
  - Interactive whiteboard
- **MODALITIES**
  - Individual use
  - Classroom group use
  - Collaborative use
- **EXPRESSIONS**
  - Isolated letter
  - words
  - Colouring
  - Free sketch
  - Graphical patterns
  - Sentences
  - Geometrical symbols
  - Digits

FUNCTIONS

Replay execution

Auto-correction

History of activities

Follow-up of progress

Encouragement

Shape analysis

Stroke analysis

Direction analysis

Interline analysis

Visuo-spatial guide

Procedural guide Kinematics guide

Haptic guide

Models

- **REFERENCE MODEL**
  - **Visuo-spatial**
  - **Procedural (sense & order)**
  - **Kinematics**
- **ORIGIN OF THE REFERENT MODELS**
  - **Provided by teacher**
  - **Learned from pupil**
  - **Learned from pupil’s class**

ANALYSIS

INTRINSIC CRITERIA

Shape analysis

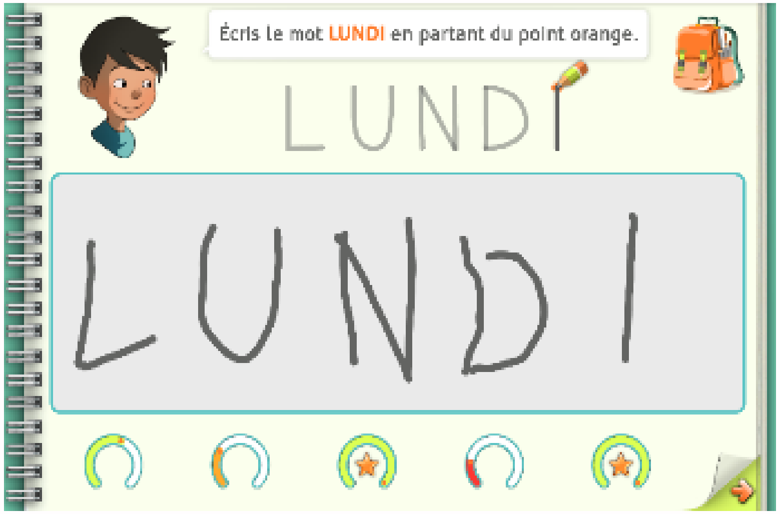
Stroke analysis

Direction analysis

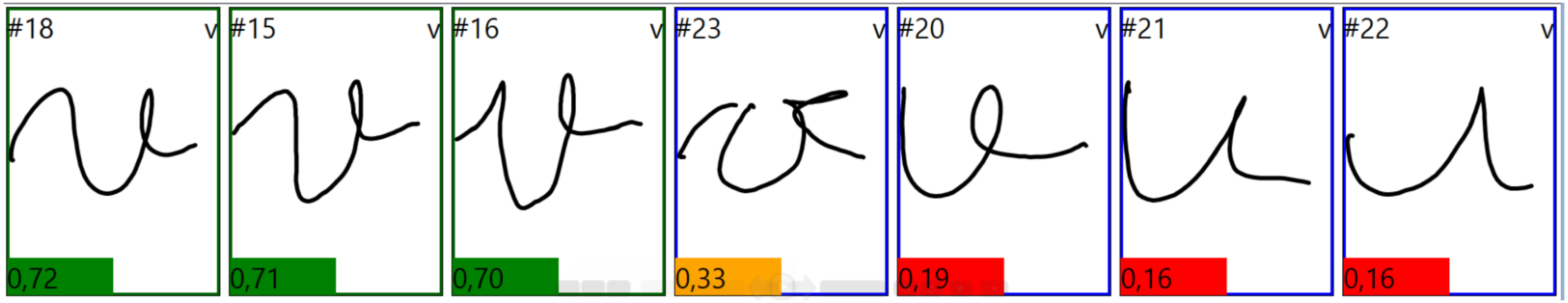
Interline analysis

Intuiscript (Éric Anquetil)

Figure 5: Example of a child using the Intuiscrpit handwriting e-learning tool



Snapshots of Intuiscript Application



Results of an automated evaluation of the quality of cursive isolated letters provided by Intuiscript

5 – The Personal Digital Bodyguard Challenge

Overview of Some Inherent Open problems

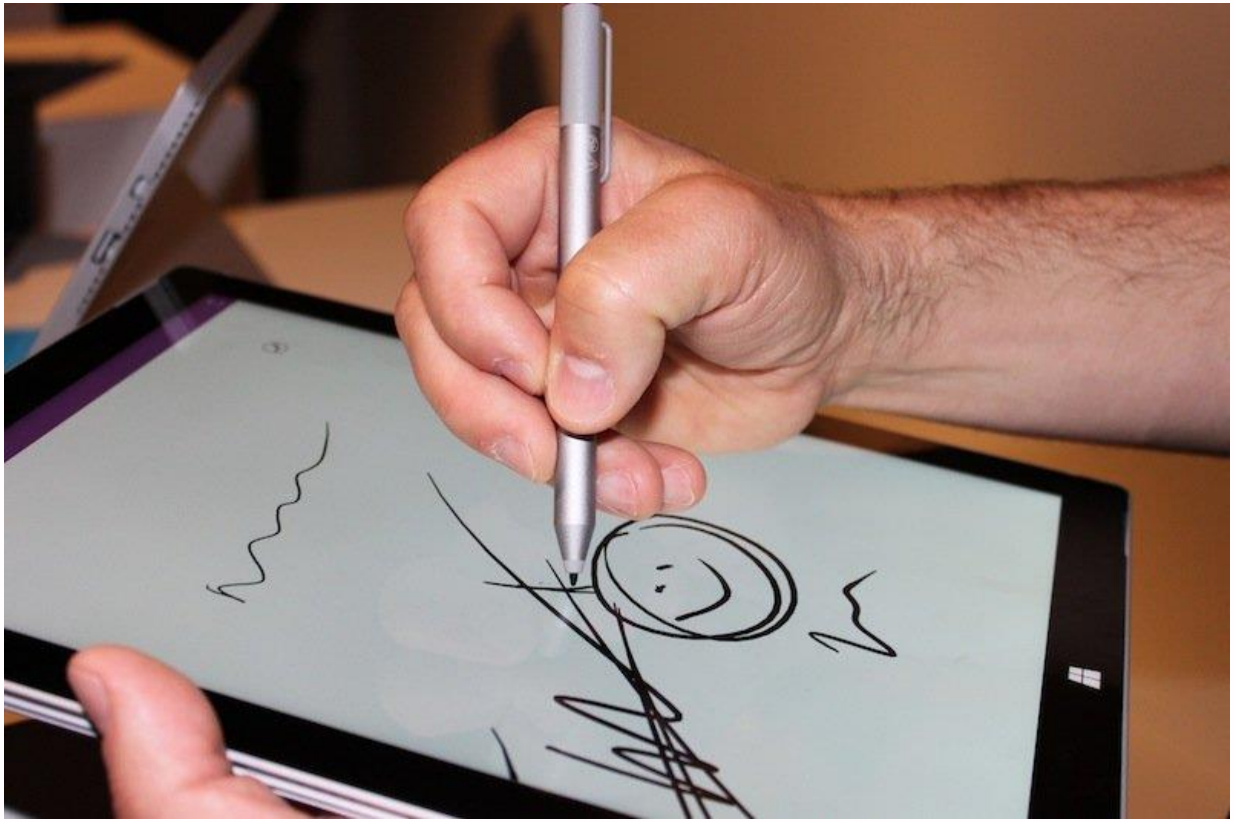
Technical Issues: traditional scenario

- Almost all the previous studies have been conducted with standard digitizers (1000dpi spatial resolution, 200Hz sampling frequency).
- Paper and writing pen or protected writing surface and non writing stylus.
- Comfortable writing environment and training periods before data collection.
- Minimizing experimental variability.

Technical issues: mobile scenario

- Small and glossy writing surface, lower resolution and sampling frequency (often not stable).
- Holding the device in the hand while writing.
- Almost no training.
- Using unfamiliar stylus or simply finger tip.
- Touchscreen: lost of non-contact information.
- Unconstrained ergonomic experimental environment.

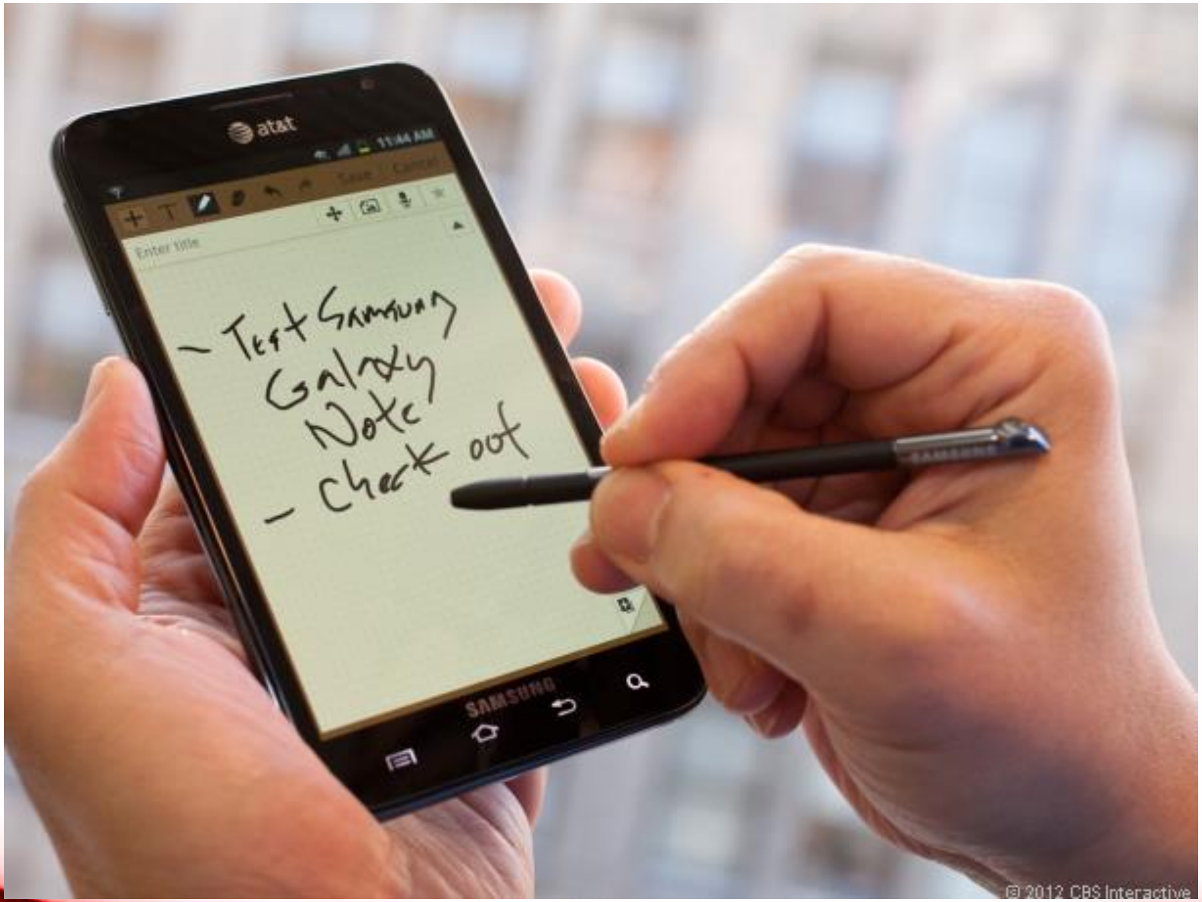
The Mobility Challenge
Microsoft Surface Pro 3



The Mobility Challenge
Microsoft Surface Pro 3

Typical equipment in action: Microsoft Surface Pro 3

Typical equipment in action: Samsung Galaxy Note



The integration challenge

How do we select, implement and integrate the proper e-security, e-Health and e-learning applications?

How to separate the wheat from the chaff?

The Diffusion Challenge?

Who cares?

Who is willing to pay for a PDB?

Meanwhile…

We have fun in the Lab! Keep on dreaming!

6 – The tip of an iceberg

There Is Much More to Do with LOGNORMALITY!!!

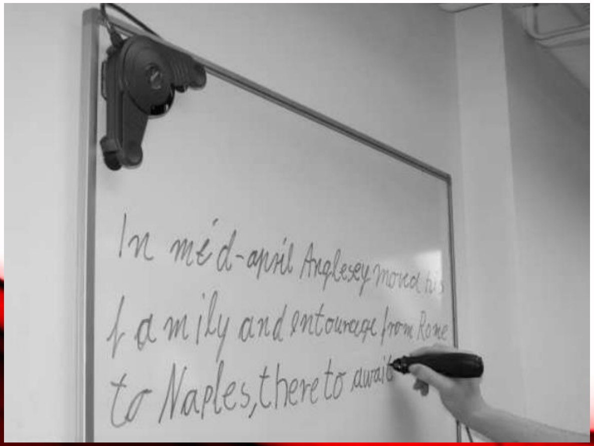
Potential Applications

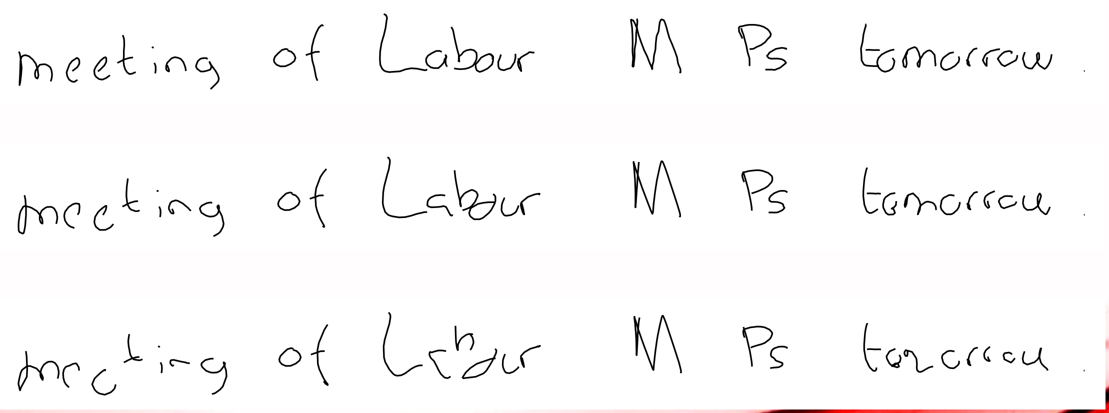
- On-line handwriting recognition / Signature Verification:
- a new representation space, automatic segmentation…
- writer style characterization, automatic data base generation
- new on-line recognizers and verifiers
- interactive tools to help children to learn handwriting...
- Biomedical signal processing:
- a new set of parameters to characterize the human motor control system…
- design of psychomotor evaluation tests
- detection of fine motor control problems (Parkinson, Alzheimer, CVA)
- prevention and rehabilitation tests and tools
- effects of medication, alcohol, drugs, weight loss…
- New open fields:
- a new set of functions for 2D and 3D smoothest curve modeling
- anthropomorphic arm design
- exoskeletons and prosthetics
- humanoid movements modeling of virtual reality objects.

Beyond Tablets: Whiteboard Notes

[A. Fischer, R. Plamondon, C. O'Reilly, Y. Savaria – ICFHR'14]

- New modality for lognormal analysis
  - writer standing, complete text lines, natural language
- Improve recognition with synthetic learning samples
  - add Gaussian noise to ΣΛ model parameters μ and σ





Project AutoGraff

Collaboration with Daniel Berio and Frederic Fol Leymarie
Project website: http://www.doc.gold.ac.uk/autograff/

Goldsmiths
UNIVERSITY OF LONDON

- **Goal:** Computational analysis and synthesis of graffiti art

Graffiti on a wall

Synthetic graffiti tag (AUTOGRAFF) generated with the AutoGraff system and Kinematic Theory models.

KINEMATIC MODELLING OF DIPTHONG ARTICULATION

Cristina Carmona-Duarte[1], Jesús B. Alonso[1], Moises Diaz[1], Miguel A. Ferrer[1], Pedro Gómez-Vilda[2], Réjean Plamondon[3].

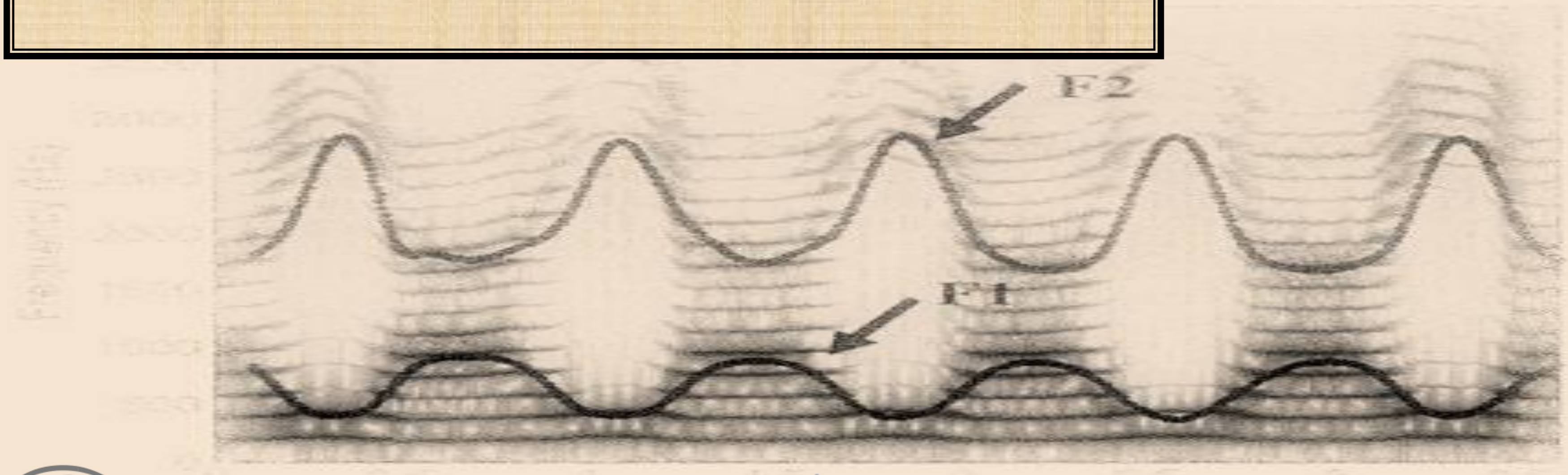
[1]Instituto Universitario para el Desarrollo Tecnológico y la Innovación en Comunicaciones, Universidad de Las Palmas de Gran Canaria, Las Palmas de Gran Canaria, Spain

[2]Facultad de Informática, Universidad Politécnica de Madrid, Campus de Montegancedo, s/n, 28660 Boadilla del Monte, Madrid, Spain

[3]Laboratoire Scribens, Département de Génie Électrique, École Polytechnique de Montréal, Canada

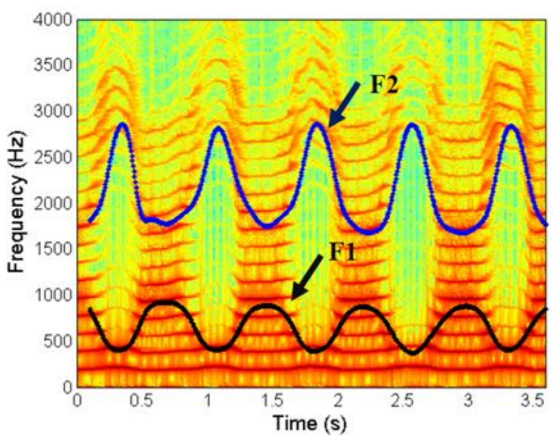
Speaker: Cristina Carmona Duarte, Ph.D.

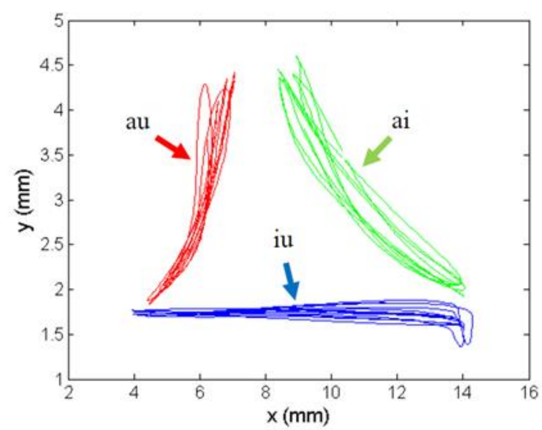
NOLISP 2015

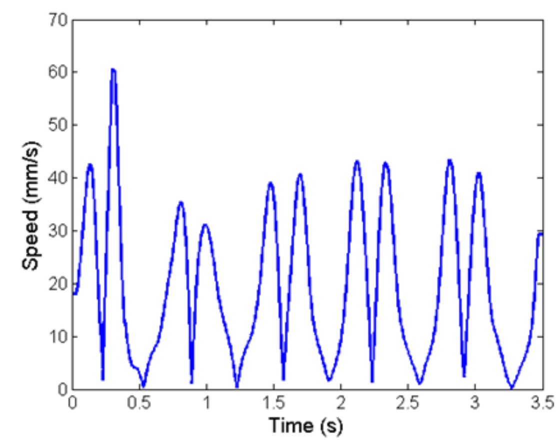


METHOD

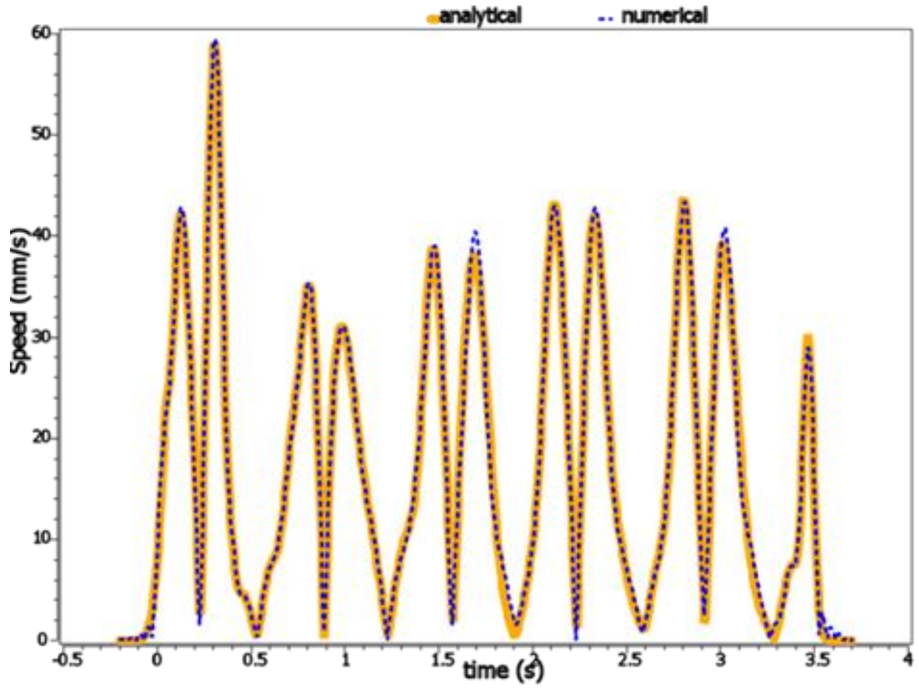
- Subjects:
  - 20 middle aged healthy subjects.
  - three different diphthong phonations pronounced by Spanish speakers (/au/, /iu/, and /ai/).
  - recorded at 22,050 Hz and 16 bits resolution
- Formant estimation.





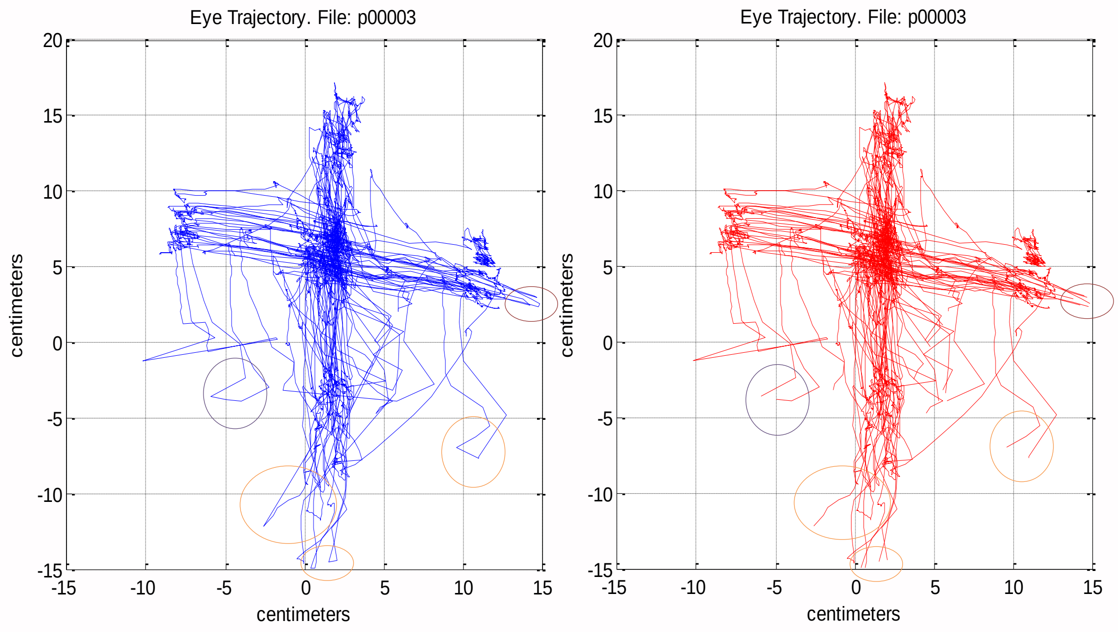


- How close is the original profile to the reconstructed lognormal speed profile?



Alzheimer Eye Movement Analysis

- A Cooperation with Nicole Vincent and Zoi Kapulla Université Paris-Descartes, France.
- Joan Carbo, Polytecnica Barcelona



These are the results
of national and international
collaborations built around software
licence agreements.

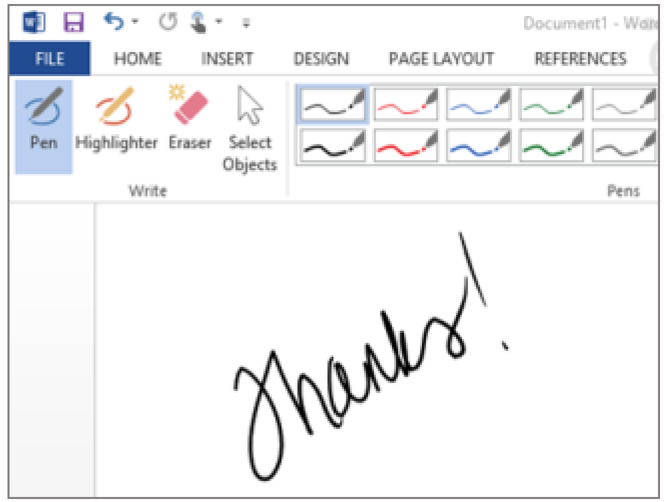
Any group interested ?

TWO TYPES OF AGREEMENTS

Share our knowledge and software with research partners

$hare our knowledge and software with commercial partners

Personal Digital Bodyguards for e-Security, e-Health and e-Learning



QUESTIONS ?