ÉCOLE POLYTECHNIQUE

Neuromuscular Studies of Handwriting Generation and Representation

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SCRIBENS LABORATORY
École Polytechnique

Theory

Modelling of Trajectory Perception
and Human Movement Generation

Applications

Automatic Processing of Handwriting

PROJECTS

BIOMETRY	RECOGNITION	EDUCATION	BIOMEDICAL	DOCUMENTS
Automatic Signature Verification	On-line Handwriting Processing	Handwriting Learning Tools	Neuromuscular Condition Evaluation	Model-based Preprocessing

Collaborators

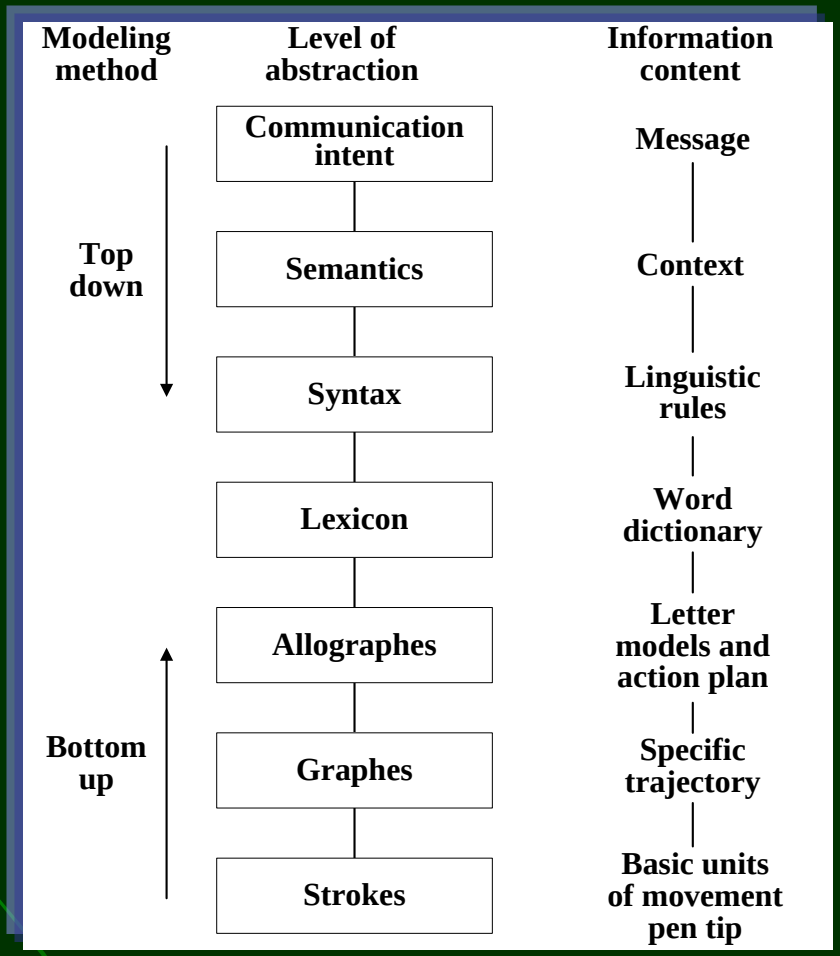
- Prof. Pierre A. Mathieu
- Prof. Brigitte Stemmer
- Prof. Bernard Clément
- Prof. Xiaolin Li
- Prof. Chunhua Feng
- Dr. Louise-Hélène Lebrun
- Dr. Moussa Djioua
- Dr. Anna Woch
- M. Christian O'Reilly
- M. Mohamed-Kefil Landou

- Prof. Angelo Marcelli
- Prof. Antonio Della Cioppa

- Prof. Javier Ortega-Garcia
- Prof. Julian Fierrez
- Dr. Javier Galbally

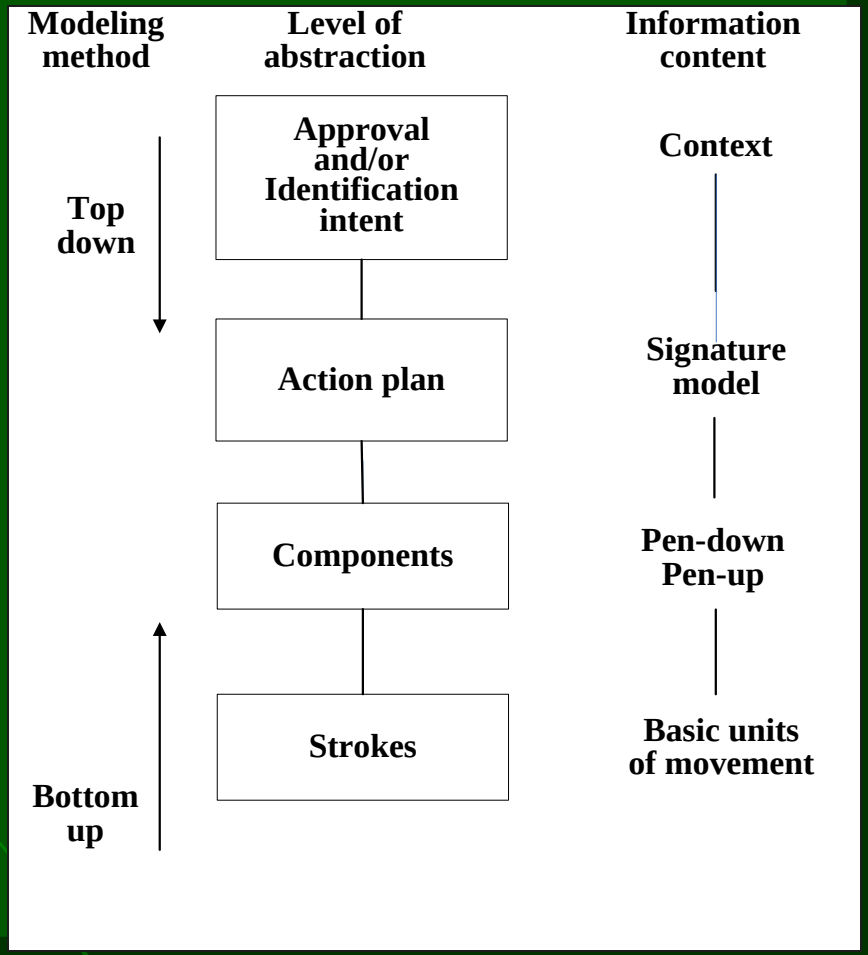
- Prof. Éric Anquetil
- M. Abdhulla Almaksour

HANDWRITING GENERATION



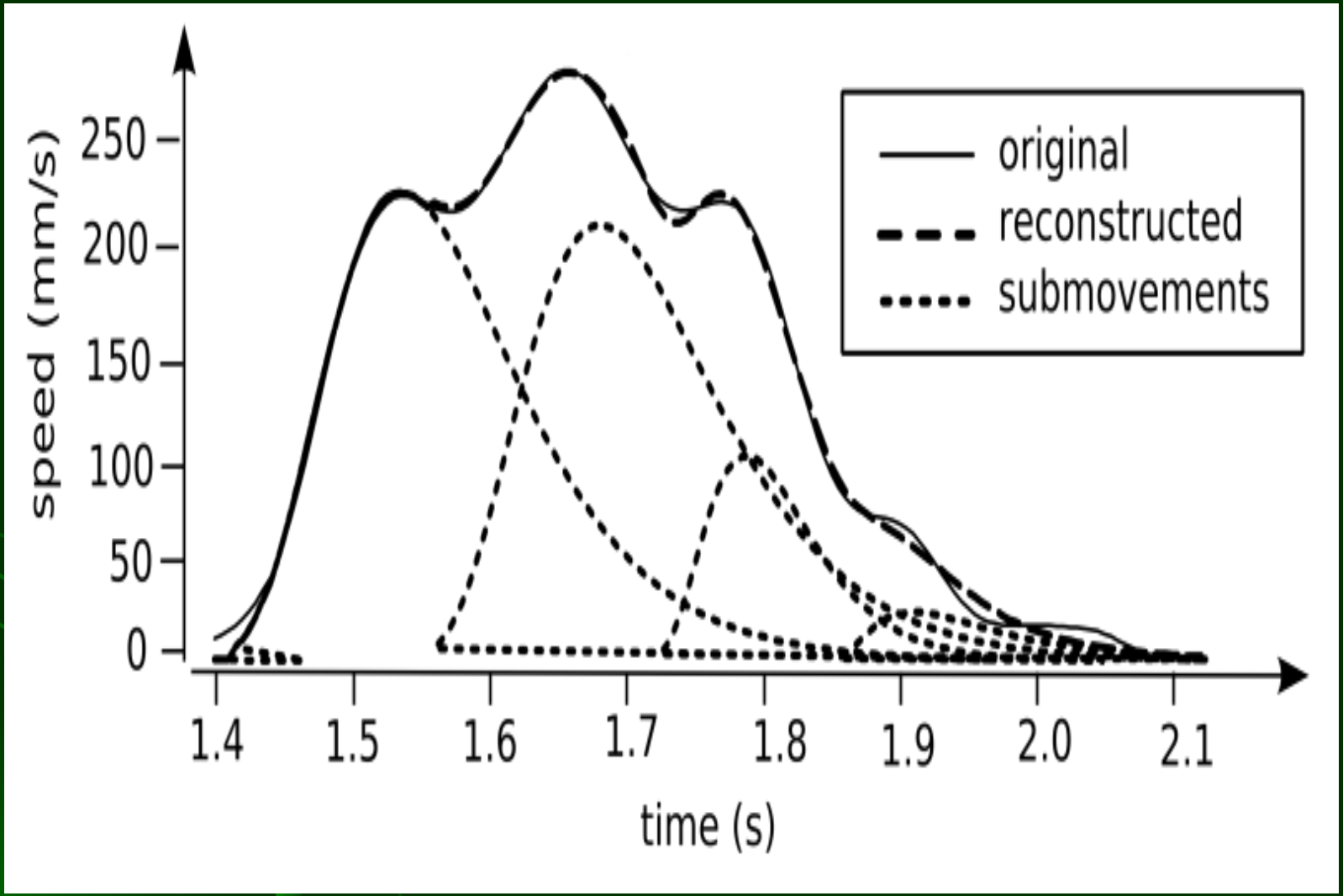
PLAMONDON, R., LOPRESTI, D., SCHOMAKER, L.R.B., SRIHARI, R., “On-Line Handwriting Recognition”, Encyclopedia of Electrical and Electronics Engineering, J.G. Webster (Ed.), John Wiley & Sons, N.Y., vol. 15, 1999, p. 123-146.

SIGNATURE GENERATION

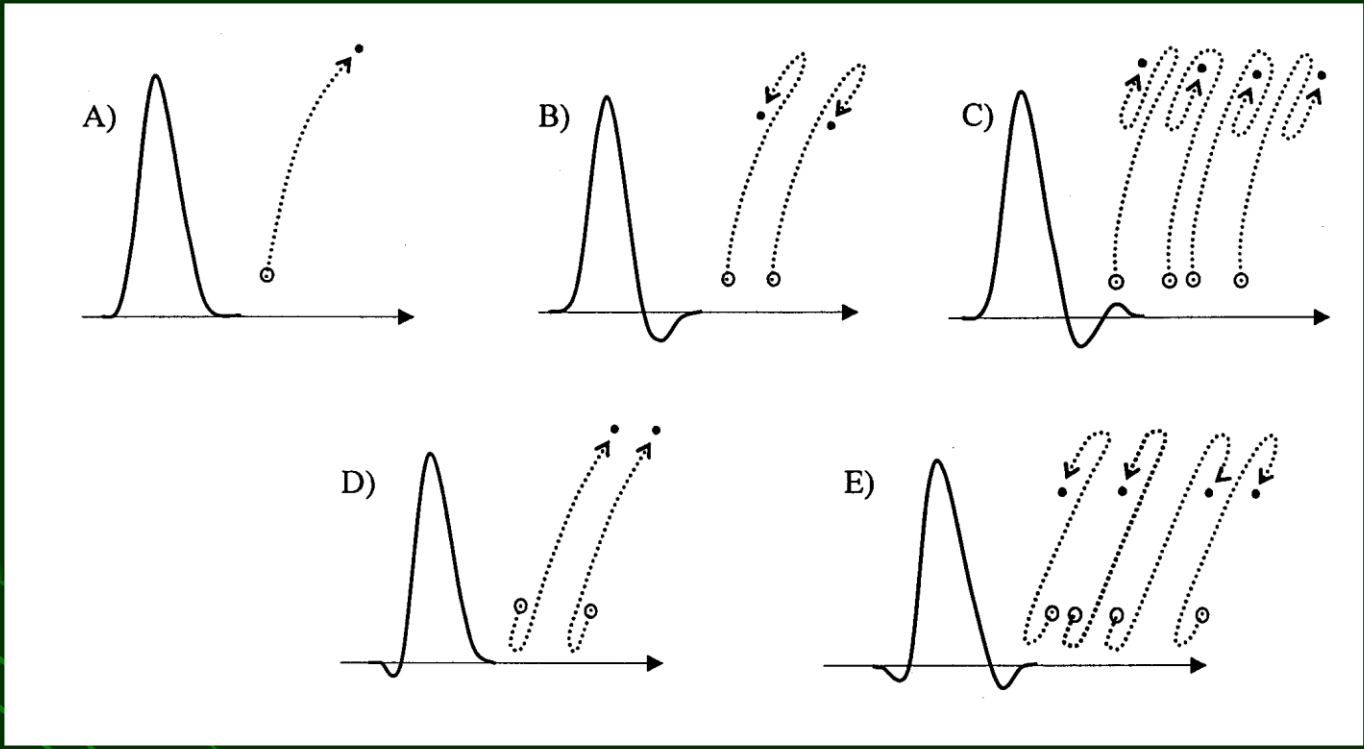


What is a Stroke?

MOVEMENT DECOMPOSITION EXAMPLE



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, vol 8, pp.547-557, 2004.

Basic Characteristics of a Single Stroke

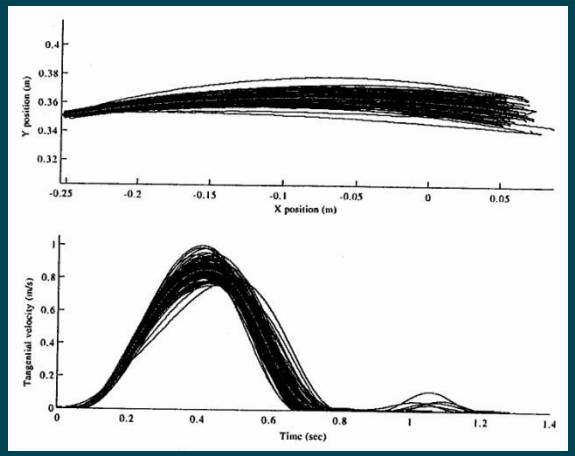


Figure : Typical trajectories and velocity profiles

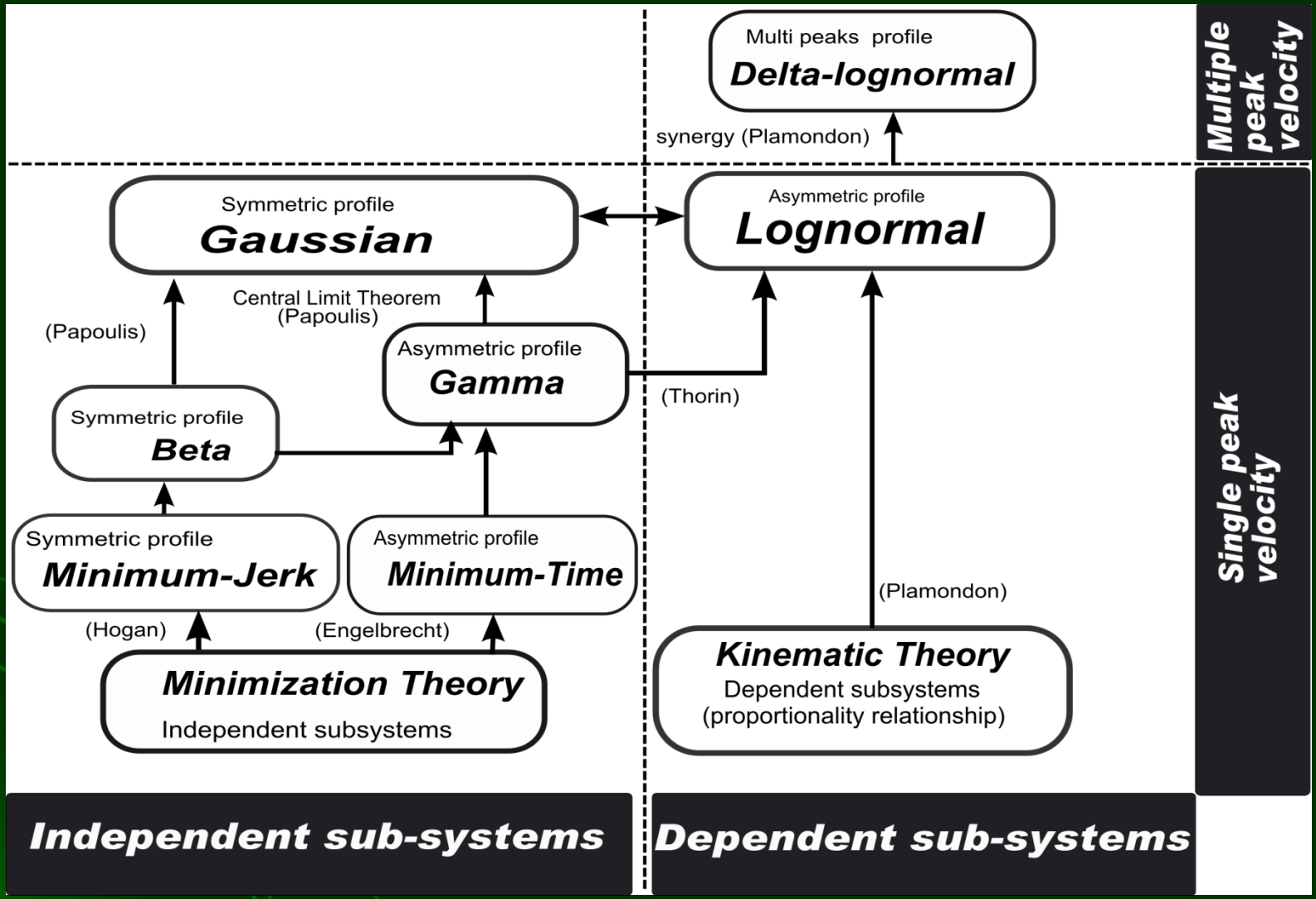
- No visual feedback
- Speed accuracy trade-offs
- Almost rectilinear trajectory of the end effector
- Asymetric bell-shaped velocity profile
- Up to two secondary velocity peaks
- Possible direction inversion at the begining and/or at the end

Miyamoto H., Wolpert D.M., Kawato M., (2002) in: Biologically Inspired Robot Behavior Engineering, Springer-Verlag.

Model Classification

- Criterion: Motor Control Basic Hypothesis
  - Equilibrium Point (Feldman ,Bizzi, Hollerbach…)
  - Neural Networks (Bullock, Schomaker, Gangadhar…)
  - Optimization Principles (Flash, Kawato, Alimi…)
  - Non-linear Dynamics (Kelso, Athenes, Zazone…)
  - Proportionality and Convergence (Plamondon)

MODEL COMPARISON



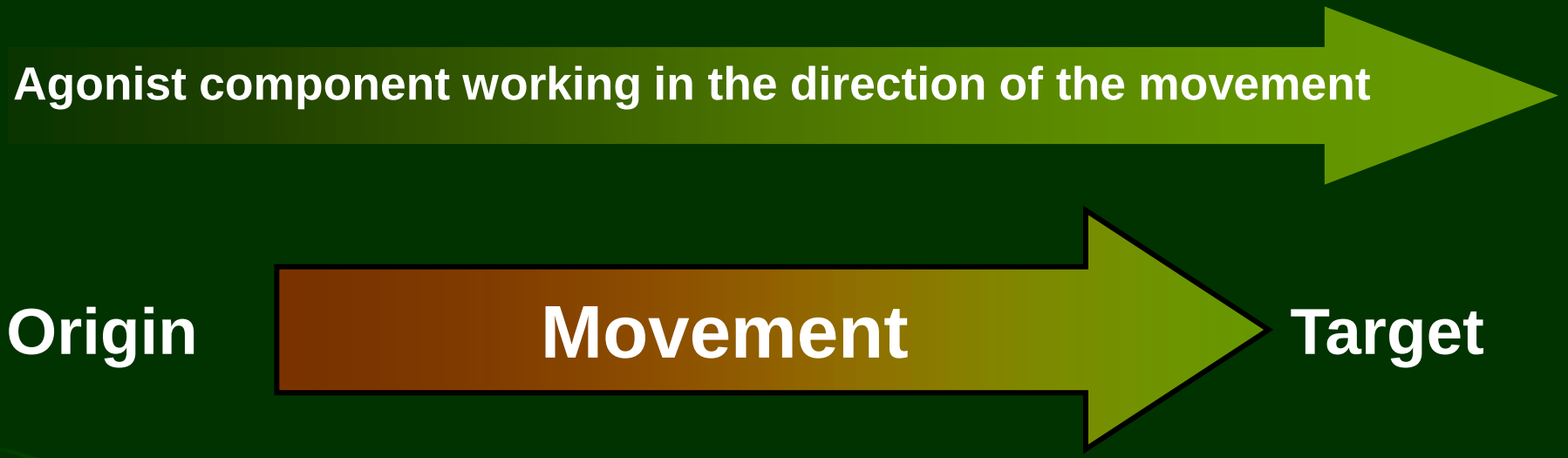
DJIOUA, M., PLAMONDON, R., "The Limit Profile of a Rapid Movement Velocity" , **Human Movement Science**, vol. 29, (2010), pp.48-61.

Introduction to the Kinematic Theory

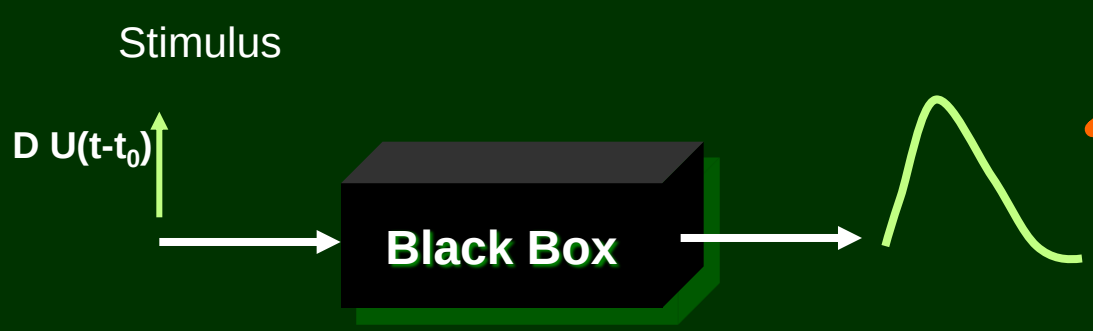
Basic Hypothesis

The invariant properties of some characteristics of rapid human movements reflect the asymptotic behavior of complex systems, made up of a large number of coupled neuromuscular networks.

Agonist – Antagonist Synergy

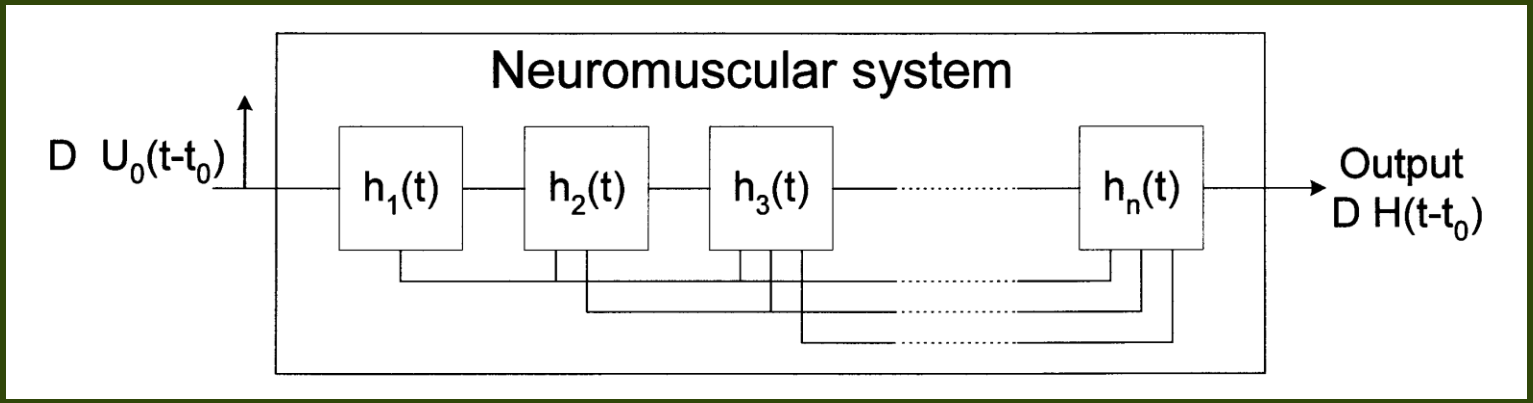


Modeling a stroke



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

- **Mathematical proof:**
- **Convergence of the NMS impulse response towards a lognormal profile**



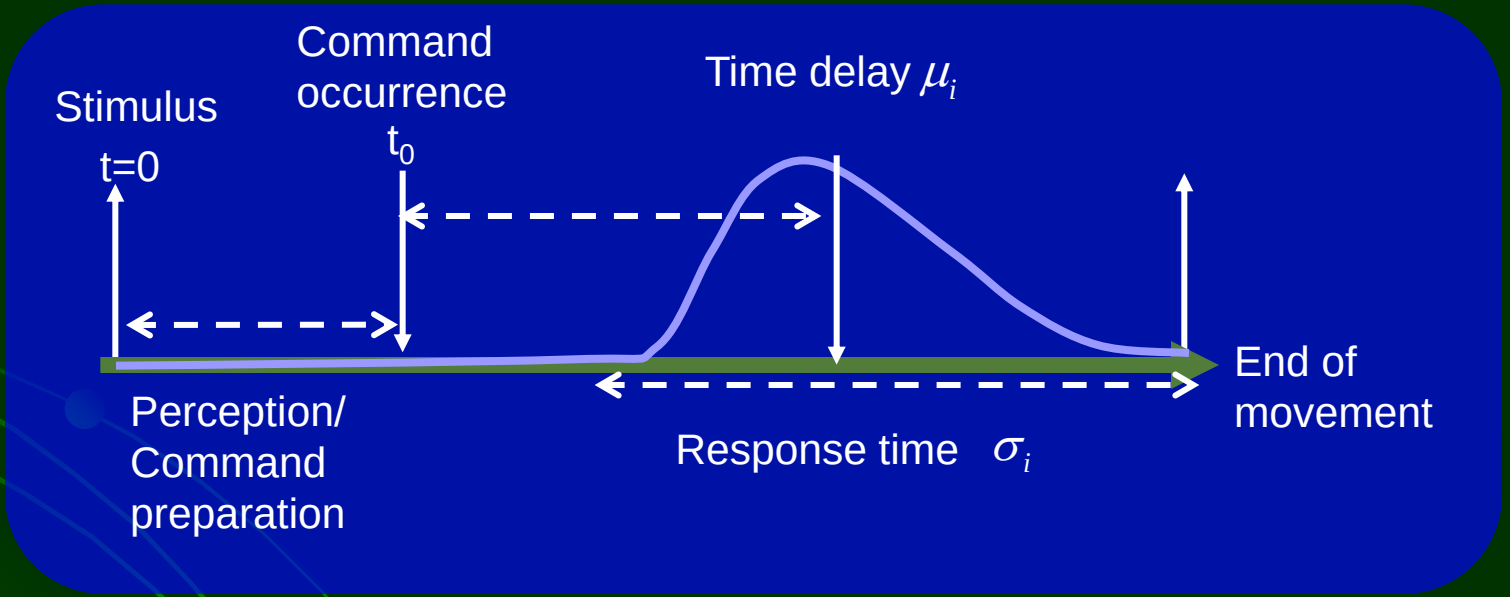
- **Hypothesis**

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

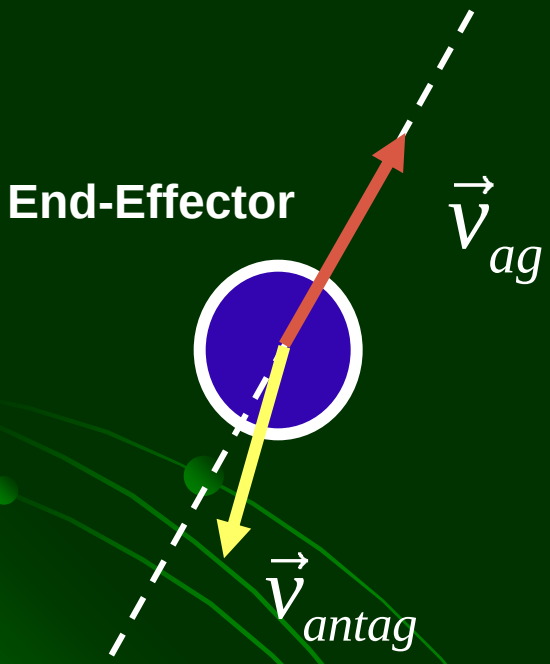
$$n \to \infty$$

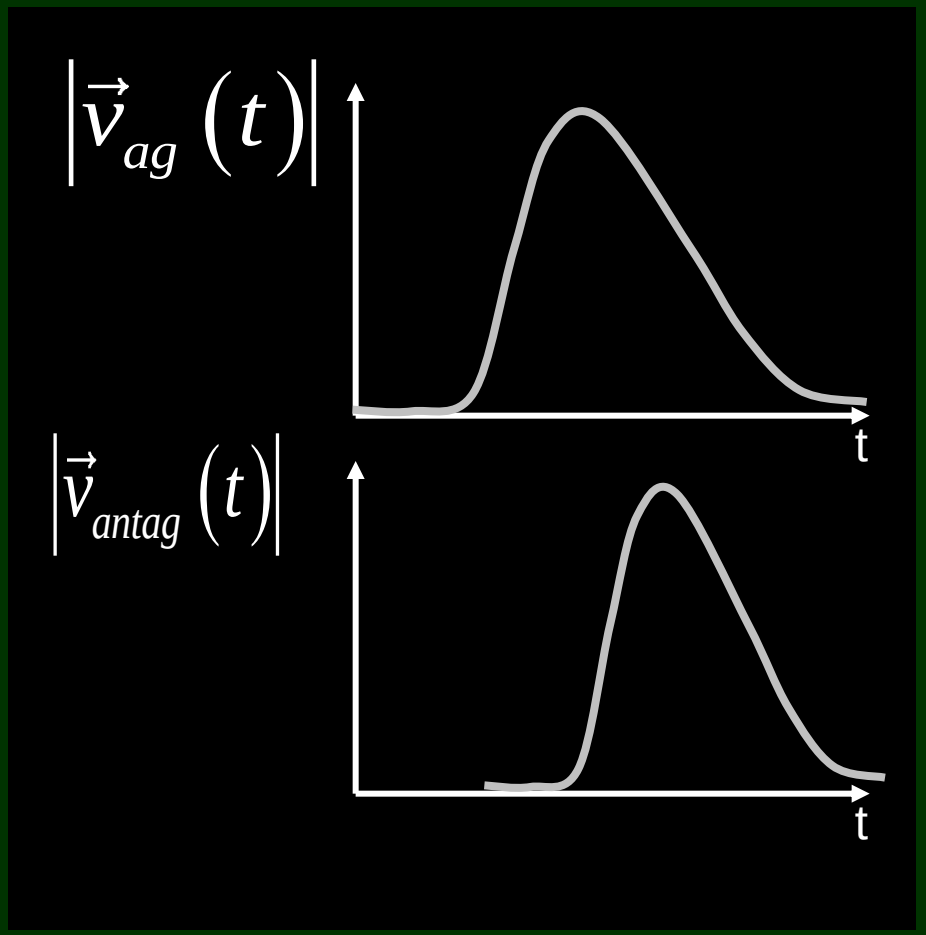
$$H(t-t_0) \Rightarrow \Lambda(t;t_0,\mu,\sigma^2)$$

•*Temporal analysis of a movement component (agonist or antagonist)*



Vectorial summation





Velocity profile of a single stroke

$$\vec{v}(t) = \vec{v}_{ag}(t) + \vec{v}_{antag}(t)$$

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

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

Delta-Lognormal Model

Delta-Lognormal equation

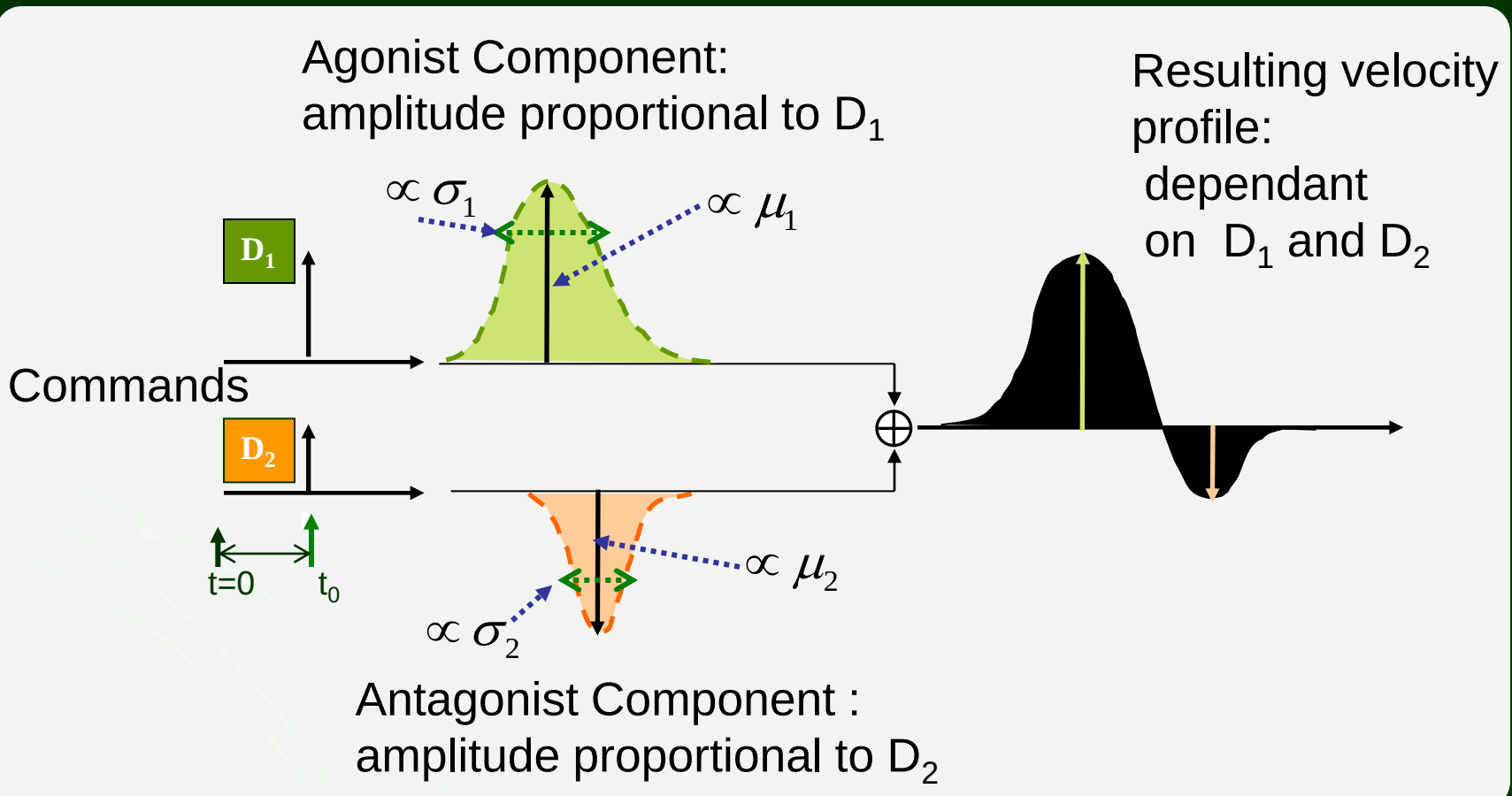
$$\left|\vec{V}(t)\right| = D_1\Lambda(t;t_0,\mu_1,\sigma_1^2) - D_2\Lambda(t;t_0,\mu_2,\sigma_2^2)$$

where

$$\Lambda(t;t_0,\mu_i,\sigma_i^2) = \frac{1}{\sigma_i\sqrt{2\pi}(t-t_0)}\exp\left(\frac{-\left[\ln(t-t_0)-\mu_i\right]^2}{2\sigma_i^2}\right)$$

PLAMONDON, R., “A Kinematic Theory of Rapid Human Movements: Part I: Movement Representation and Generation”, Biological Cybernetics, vol. 72, no 4, 1995, p. 295-307.

Schematic Summary



Some predictions for a single stroke

$$MA = \int_{t_0}^{t_1} v(t)dt \cong D_1 - D_2$$

$$a_1(\ln MT)^2 + a_2 \ln MT + a_3 = \ln \frac{D_1}{D_2}$$

$$a_1 = \frac{\sigma_2^2 - \sigma_1^2}{2\sigma_1^2\sigma_2^2}, \qquad a_2 = \frac{\mu_2\sigma_1^2 - \mu_1\sigma_2^2}{\sigma_1^2\sigma_2^2}, \quad \bar{V} = mean\ velocity$$

$$a_3 = \frac{\mu_1^2\sigma_2^2 - \mu_2^2\sigma_1^2 + 2\sigma_1^2\sigma_2^2 \ln \frac{\sigma_1}{\sigma_2}}{2\sigma_1^2\sigma_2^2}, \quad a_4 = a_3 + \ln\left(\frac{\gamma_2}{\gamma_1}\right)$$

PLAMONDON, R., ALIMI, A., “Speed/Accuracy Tradeoffs in Target Directed Movements”, Behavioral and Brain Sciences, vol. 20, no 2, 1997, p. 279-349.

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Conclusion: future trends.

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

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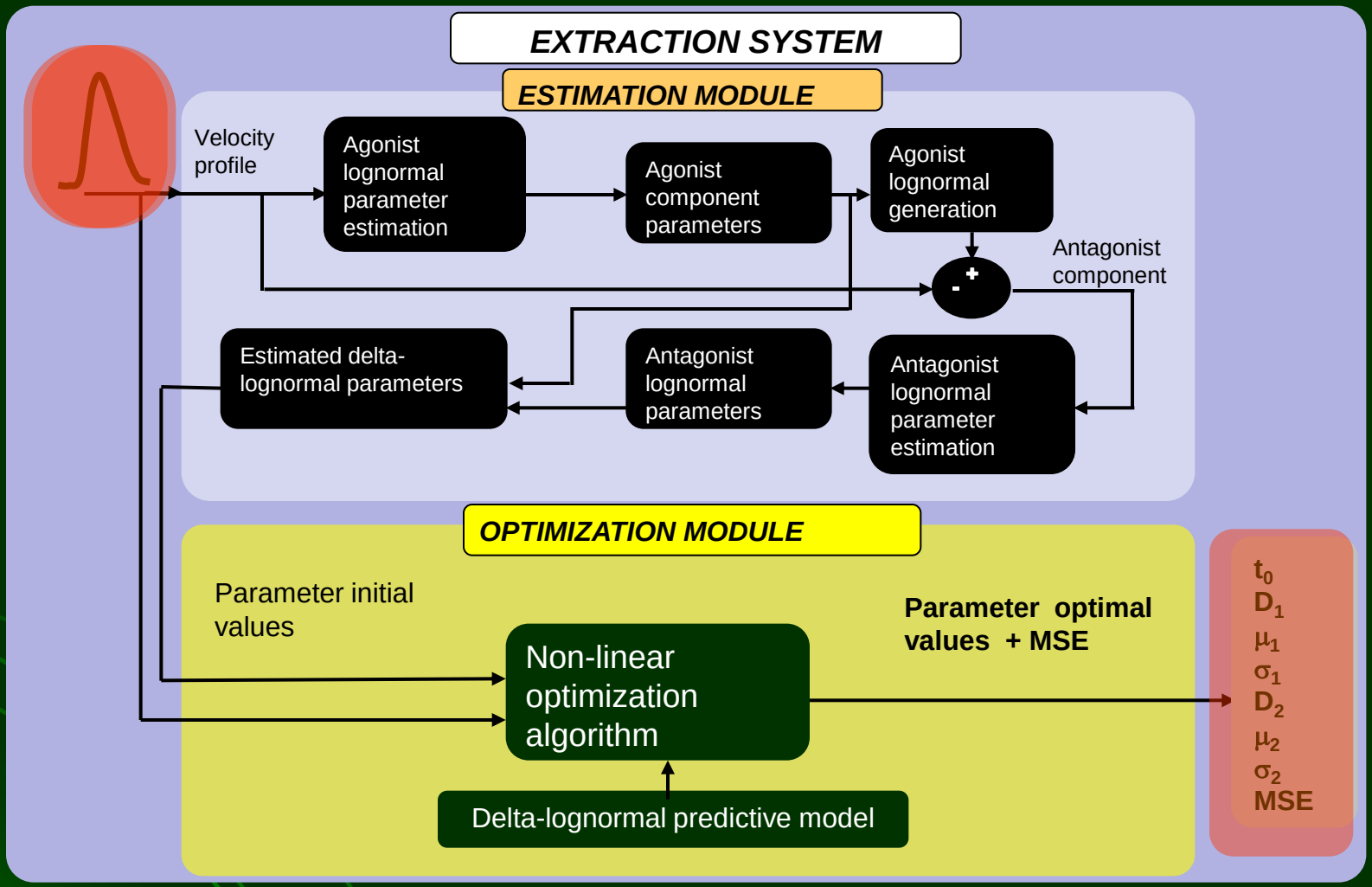
1. Conclusion: future trends.

Practical
Problem No 1

Design of a Delta-Lognormal Parameter extraction system

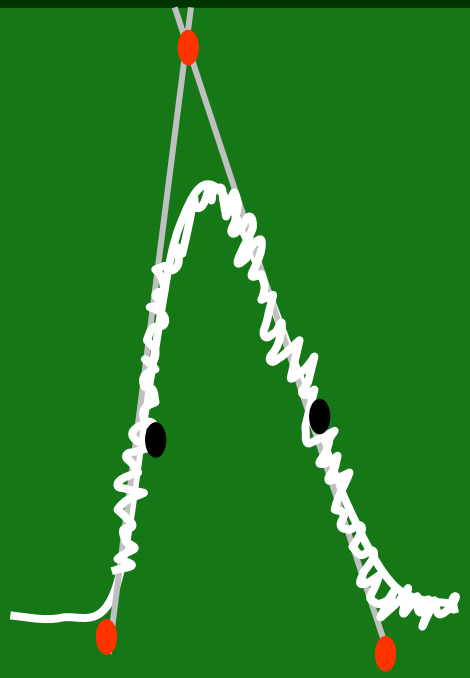

EXTRACTION SYSTEM
ESTIMATION MODULE
Velocity profile
Agonist lognormal parameter estimation
Agonist component parameters
Agonist lognormal generation
Antagonist component
Estimated delta-lognormal parameters
Antagonist lognormal parameters
Antagonist lognormal parameter estimation
OPTIMIZATION MODULE
Parameter initial values
Non-linear optimization algorithm
Parameter optimal values + MSE
Delta-lognormal predictive model
t_0
D_1
μ_1
σ_1
D_2
μ_2
σ_2
MSE

estimation algorithm #1: INFLEX

INFLEX Algorithm

(Guerfali&Plamondon,1995)

Graphical method
based on three points defined
by the intersection
of the inflexion point tangents
and a table of values
computed by Wise (1963)



Limitations

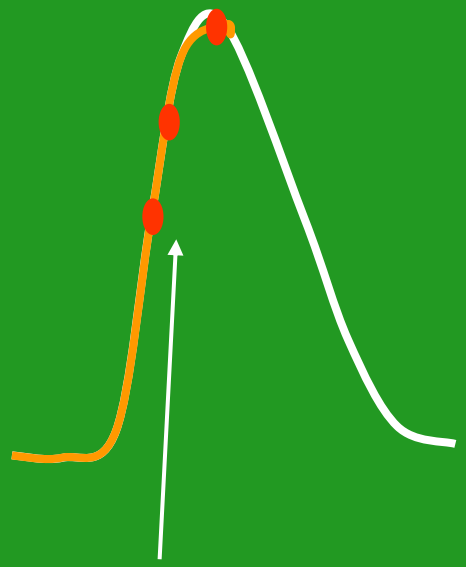
- negative t_0
- very sensitive to noise
- sensitive to the antagonist vs agonist component location

estimation algorithm #2: MINIT

MINIT Algorithm

(Plamondon et al.2007)

Use of three points :
the maximum and
two arbitrary points
taken on the rising phase
of the velocity signal



Agonist component

Advantages

Less sensitive to noise

Limitations

Sensitive to the profile asymmetry

Sensitive to the antagonist vs. agonist component location

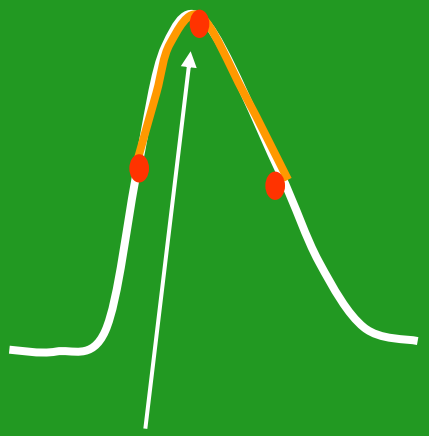
estimation algorithm #3: Xzero

XZERO Algorithm

(Djioua and Plamondon, PAMI 2008)

Use of three points :
the maximum and
the two inflexion points

Exploit the analytical relationships
between these points
and the four parameters
of a single lognormal



Agonist Component

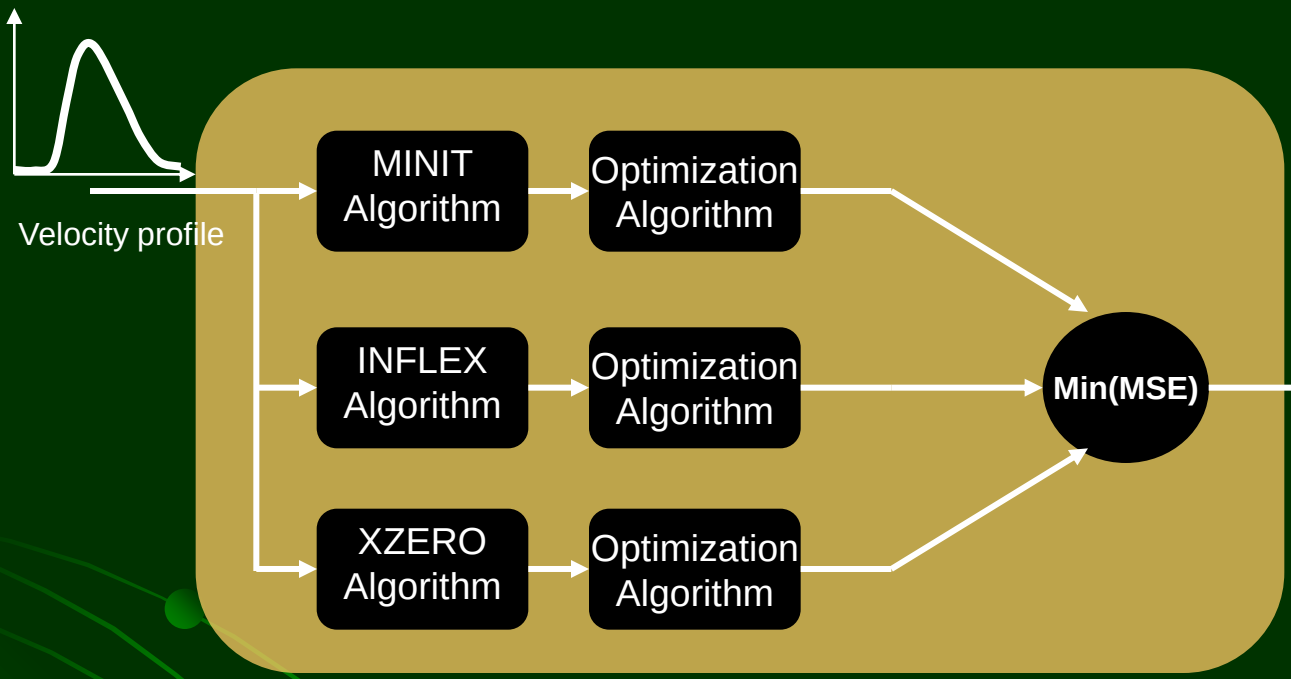
Advantages

- Less sensitive to noise
- Independent of the antagonist vs. agonist position

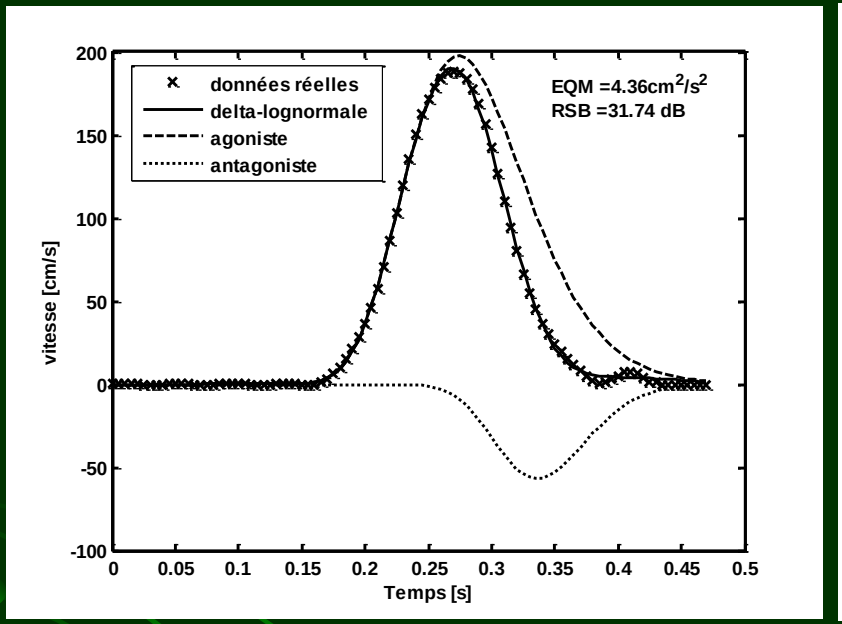
Limitations

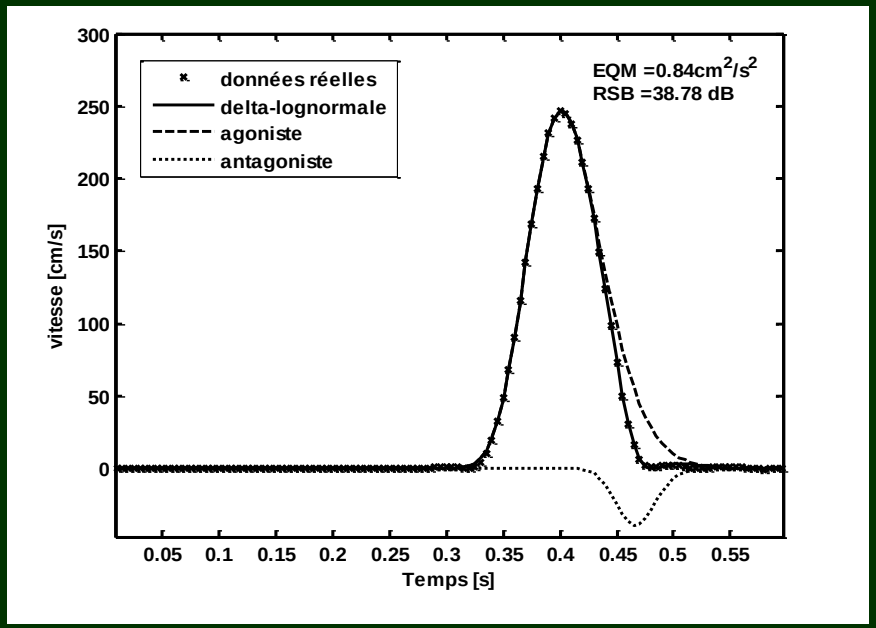
Sensitive to the number of velocity samples between the two inflexion points

Extraction system architecture



Typical examples with real data





FIRST TEST PROTOCOL

Extraction system characterization

Goals:

1. Comparative evaluation of the three estimation algorithms
2. Computation of the confidence intervals on the delta-lognormal parameters

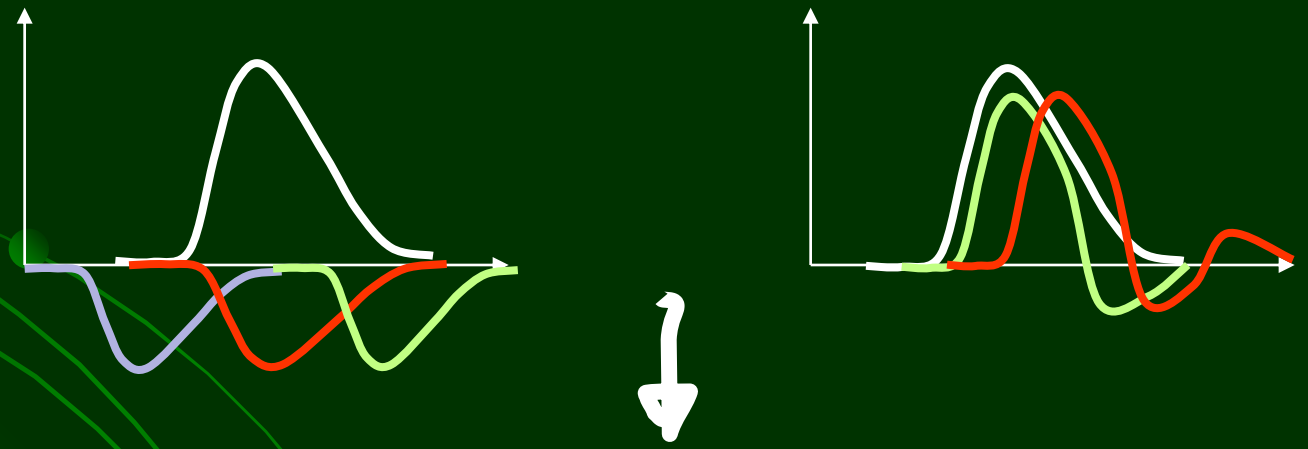
Methodology

- Generate a database of ideal profiles
- Compare the performances of each algorithm
- Add Gaussian noise to the ideal profiles
- Evaluate the precision on each parameter value

Database generation: Classification of the Delta-Lognormal profiles

Two criteria:

1. **Relative position of the antagonist vs. agonist component**
2. **Number of zero crossings**



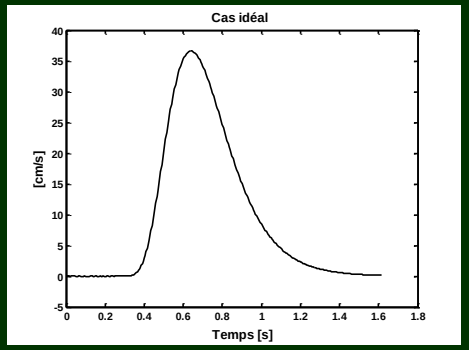
7 classes

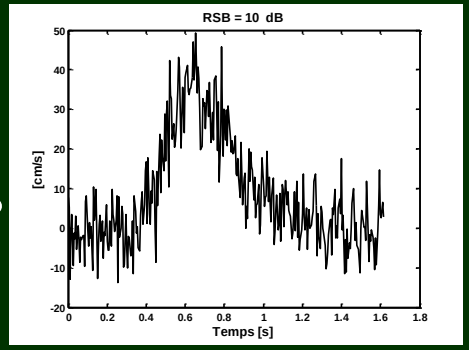
Performance : ideal case

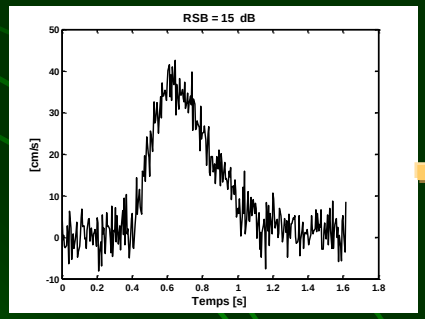
	Performance: % of successful extraction for each class							
Algorithms	C_{f0}	C_{di}	C_{fi}	C_{d1}	C_{f1}	C_{s2}	C_{f2}	Total (%)
INFLEX	77.1	0	75.1	6.9	89.4	87.9	90	**60.9**
MINIT	74.6	0.4	95.9	39.4	89.2	57.5	100	**65.2**
XZERO	95.2	98.1	100	97.9	96.6	92.0	100	**97.1**
Extraction System	**99.7**	**98.1**	**100**	**98.5**	**99.5**	**99.6**	**100**	**99.3**

Performance: noisy conditions

8 noise levels: 10,15,20,25,30,35,40,80 dB







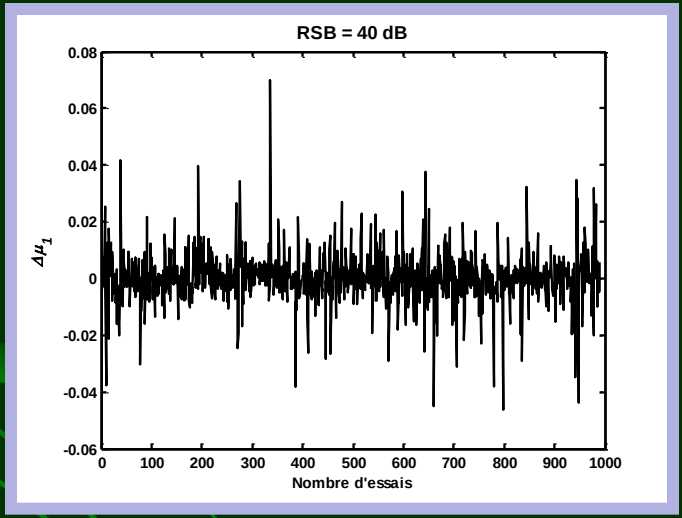
Extraction System

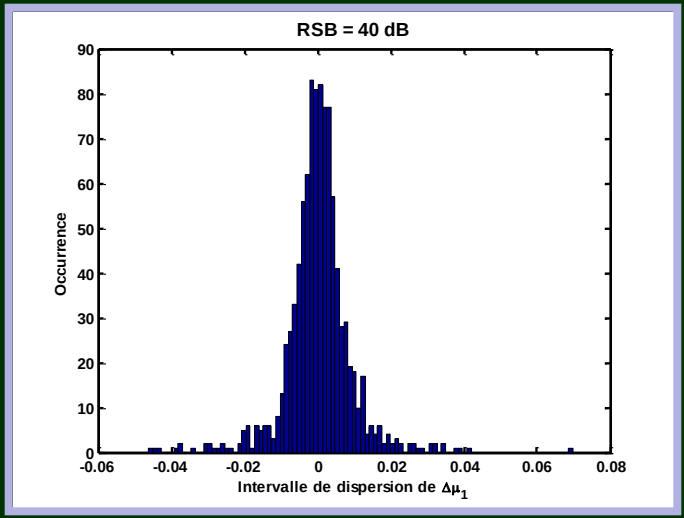
$t_0 \pm \Delta t_0$
$D_1 \pm \Delta D_1$
$\mu_1 \pm \Delta \mu_1$
$\sigma_1 \pm \Delta \sigma_1$
$D_2 \pm \Delta D_2$
$\mu_2 \pm \Delta \mu_2$
$\sigma_2 \pm \Delta \sigma_2$
MSE
SNR

Important observations

- **First result**

Distribution of the parameter errors : $\Delta\mu_1 = \mu_{1o} - \mu_{1m}$



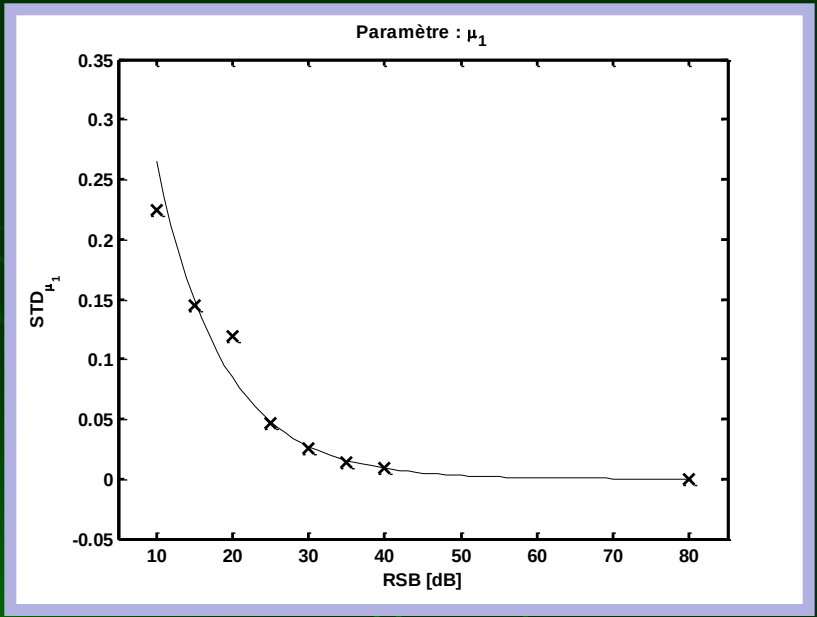


The parameter measurement error is a Gaussian noise

Important observations

- **Second result :** Relationship between the SNR and the parameter confidence interval (PIC)

$$PIC_{\mu} = \left[\mu_{1e} - 1.96 * STD_{\mu_1}, \mu_{1e} + 1.96 * STD_{\mu_1} \right]$$



$$STD_{t_0} \simeq 0.1304 e^{-0.116 * SNR}$$

$$STD_{D_1} \simeq 13.4248 e^{-0.1089 * SNR}$$

$$STD_{\mu_1} \simeq 0.827 e^{-0.1139 * SNR}$$

$$STD_{\sigma_1} \simeq 0.2818 e^{-0.1121 * SNR}$$

$$STD_{D_2} \simeq 11.953 e^{-0.1075 * SNR}$$

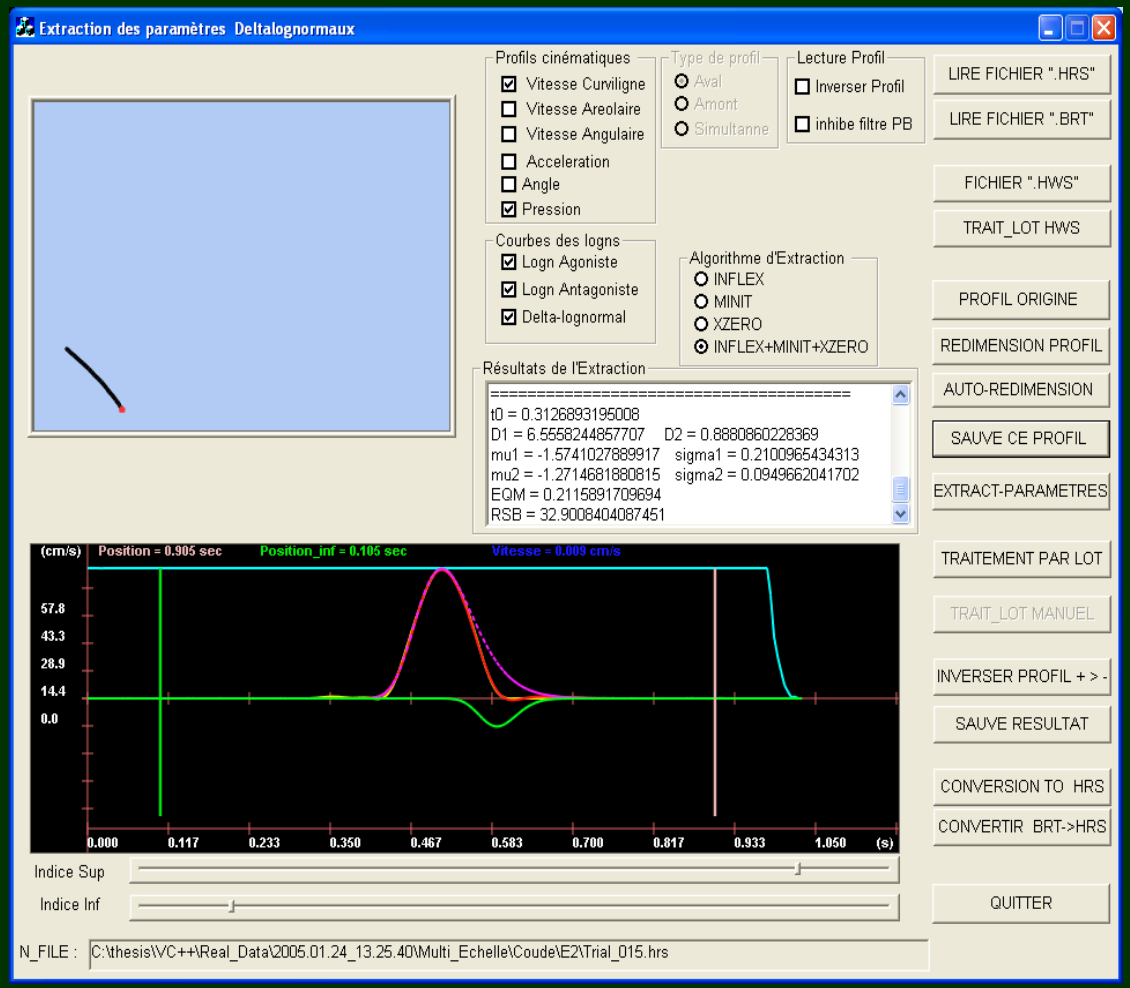
$$STD_{\mu_2} \simeq 2.1089 e^{-0.1276 * SNR}$$

$$STD_{\sigma_2} \simeq 0.4823 e^{-0.1084 * SNR}$$

Extraction System: final version

Implementation of the three extraction algorithms

Extraction system characterization



Djioua, M., Plamondon,R.
IEEE PAMI 2008 online

SECOND TEST PROTOCOL

- **Two independent teams**
  (Montréal - Salerno)
- **Two different approaches**
  (deterministic vs evolutionary)
- **No access to the real values of the parameters**
  (Truth Table)

RESULTS: DETERMINISTIC ALGORITHM

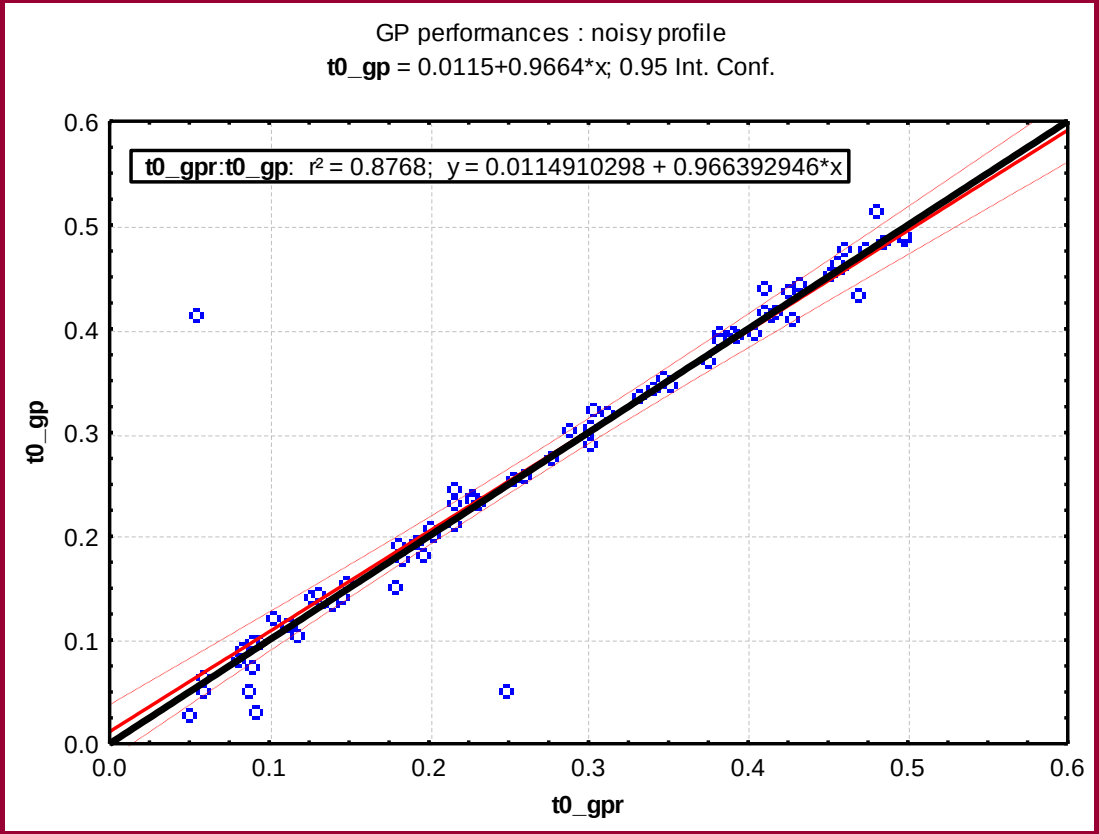


Figure 2.a. Comparison of extracted t_0 values (ordinates) vs original (abscissa) on the noisy curves.

RESULTS: DETERMINISTIC ALGORITHM

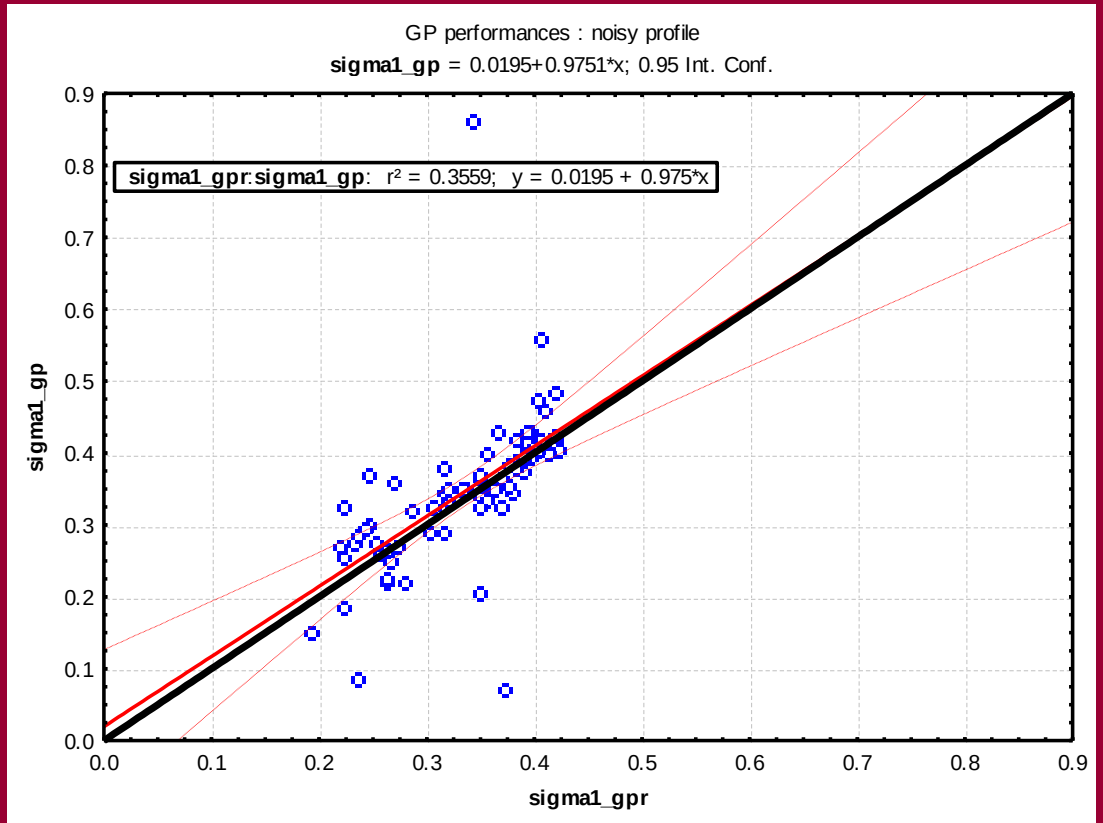


Figure 2.b. Comparison of extracted σ_1 values (ordinates) vs original (abscissa) for the GP algorithm on the noisy curves.

RESULTS: EVOLUTIONARY ALGORITHM

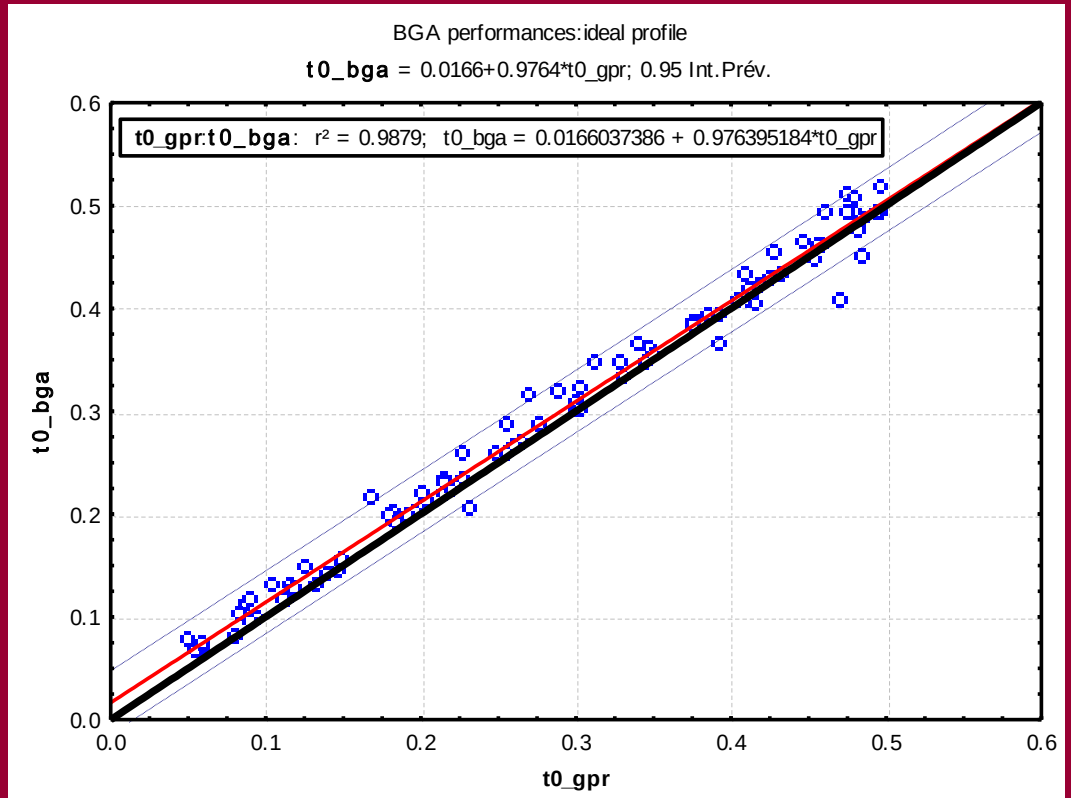


Figure 3.a. Comparison of extracted t_0 values (ordinates) vs original (abscissa), for the BGA algorithm on the ideal curves.

RESULTS: EVOLUTIONARY ALGORITHM

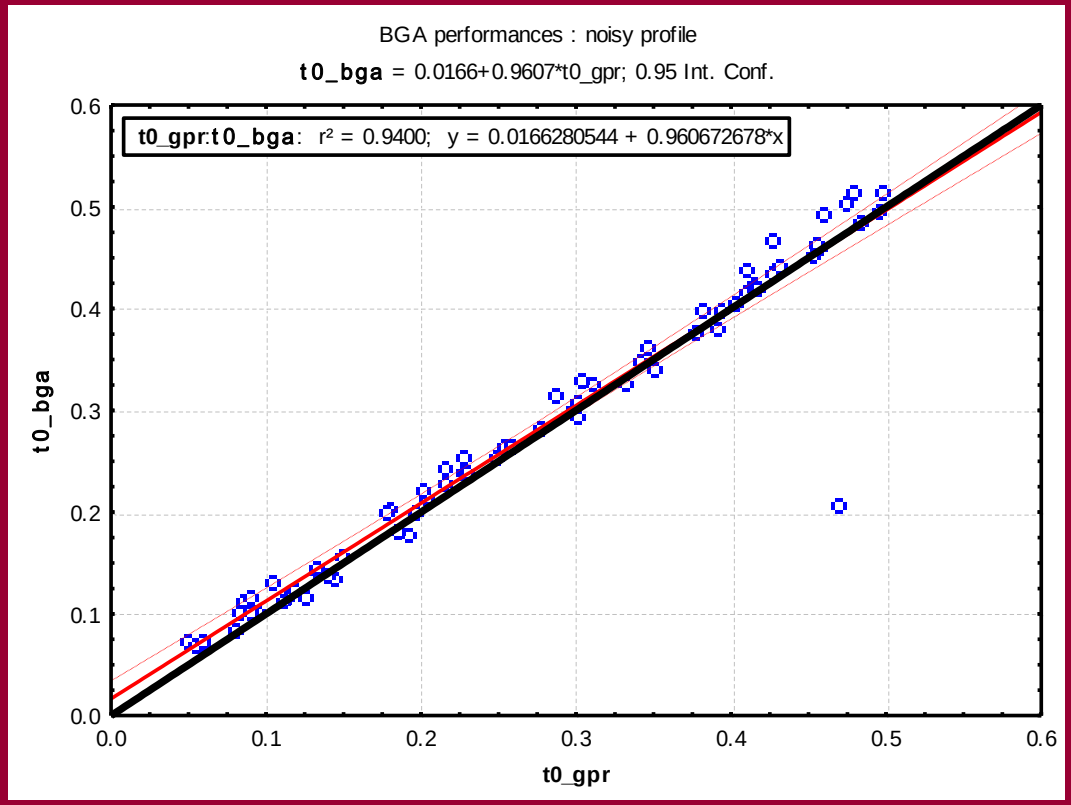


Figure 3.b. Comparison of extracted t_0 values (ordinates) vs original (abscissa), for the BGA algorithm on the noisy curves.

SUMMARY

- **Deterministic algorithm**
  - 93 % perfect extraction on ideal curves
  - 72 % on noisy curve
  - 28 % of outliers
  - Processing time: milliseconds/curve
- **Evolutionary algorithm**
  - Never found an optimal solution
  - Always converge to a non-optimal solution
  - Less sensitive to noise
  - Processing time: minutes/curve

DJIOUA, M., PLAMONDON, R., DELLA CIOPPA, A. & MARCELLI, A.,
«Deterministic and Evolutionary Extraction of Delta-lognormal Parameters: Perfomance Comparaison»,
International Journal of Pattern Recognition and Artificial Intelligence (IJPRAI), vol. 21, no. 1, pp. 21-41, 2007.

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Conclusion: future trends.

Theoretical Problem No 1

Experimental Observation of the Proportional Effect Hypothesis

Apparatus

Data Acquisition System

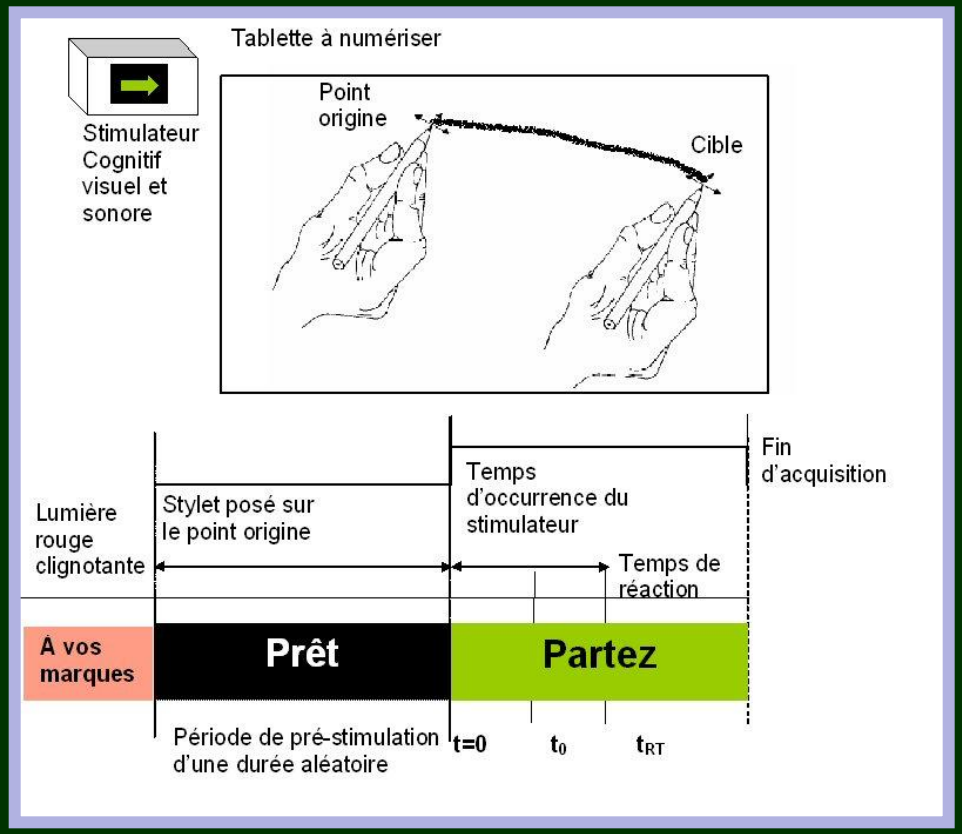
SYNC signal

Amplifier

EMG Signal Acquisition System (GRASS)

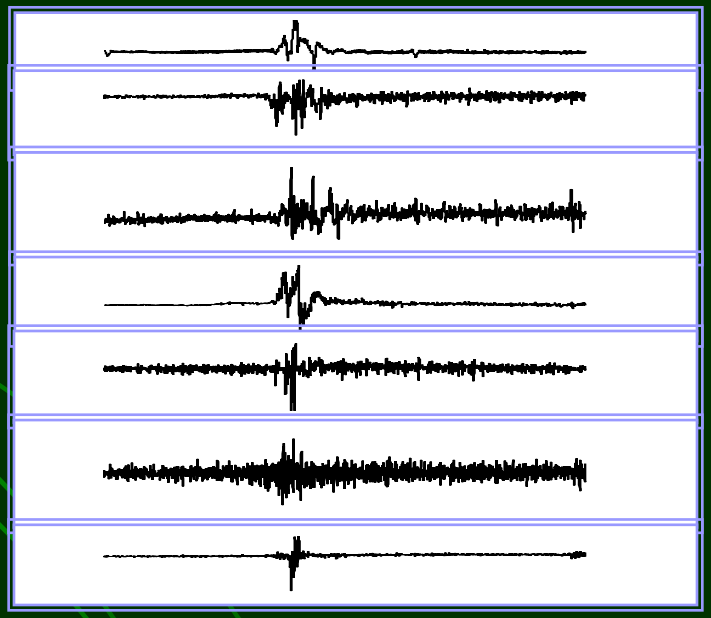
Experimental Protocol

- 10 subjects
- right handed, good health,
- between 22 and 38
- Produce large strokes between a departure point and a target zone, following a reaction time protocol
- Auditory stimulus
- 20 valid trials

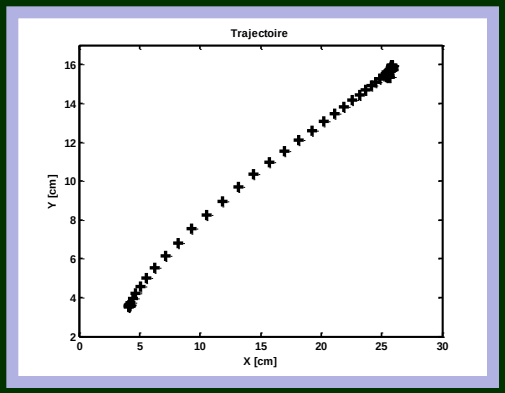


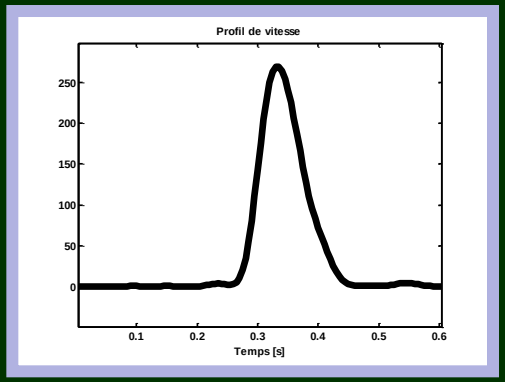
Typical raw data of biosignals

Raw EMG signals



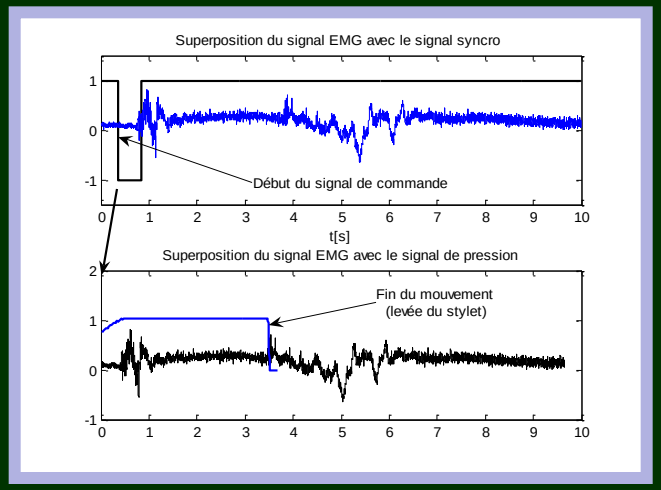
Kinematic data





Preprocessing

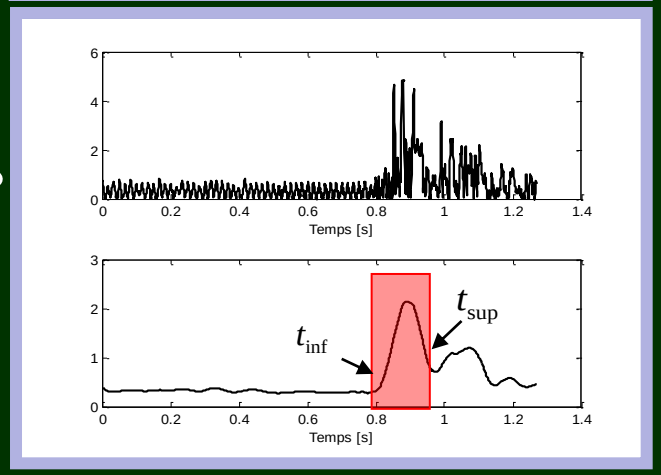
1. Time Origin Definition



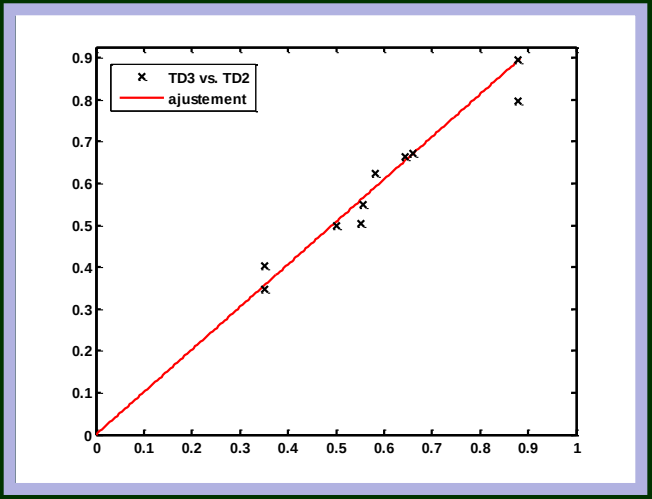
2. Computation of EMG envelopes and cumulative time delays

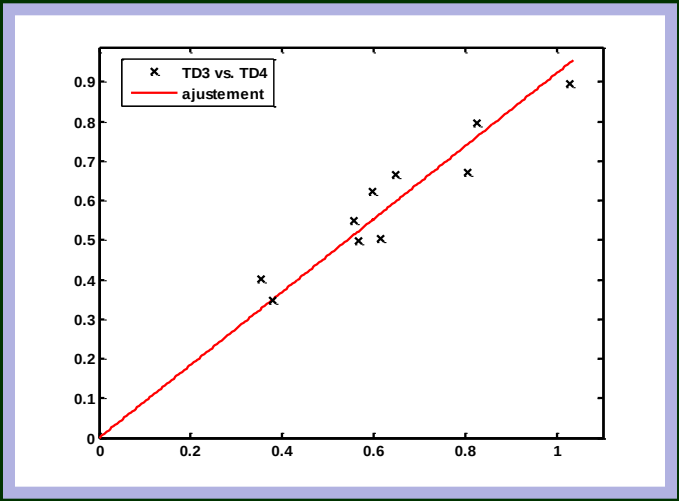
Savitzky-Golay Filter

$$T = \frac{\int_{t_{inf}}^{t_{sup}} t.Enveloppe_{EMG}(t)\,dt}{\int_{t_{inf}}^{t_{sup}} Enveloppe_{EMG}(t)\,dt}$$



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 Problem No 2

Experimental investigation of t_0

Plamondon, R., Landou, K., Stemmer, B., “Experimental observation of a new ERP signal, as predicted by the Kinematic Theory”, NeuroScience 2009, Chicago, USA, October 17 – 21, (2009).

Goal

Look for Correlations Between EEG Signals (through evoked response potentials) and the Parameter t_0 of the Delta-Lognormal Model

Experimental Protocol

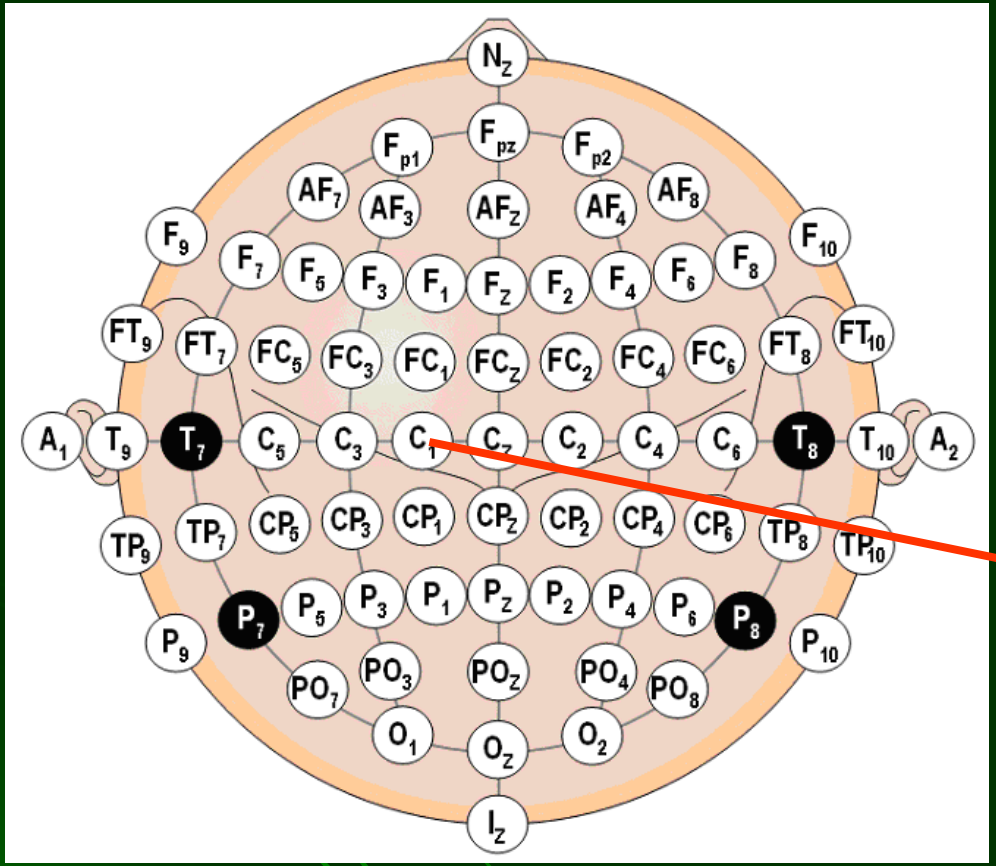
- Reaction time experiment.
- Audio or visual stimuli
- Task: to produce a handwriting stroke as fast as possible
- Twelve subjects
- Experiments performed at the laboratoire de neuropragmatique du Centre de Recherche de l'Institut Universitaire de Gériatrie de Montréal

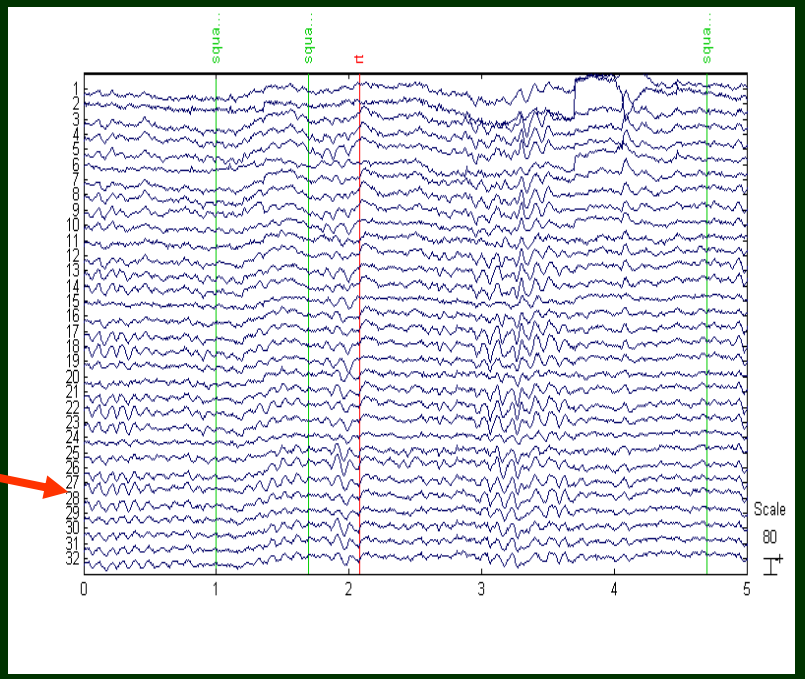
Experimental Protocol

- Recording evoked potentials with 64 electrodes

Typical trial

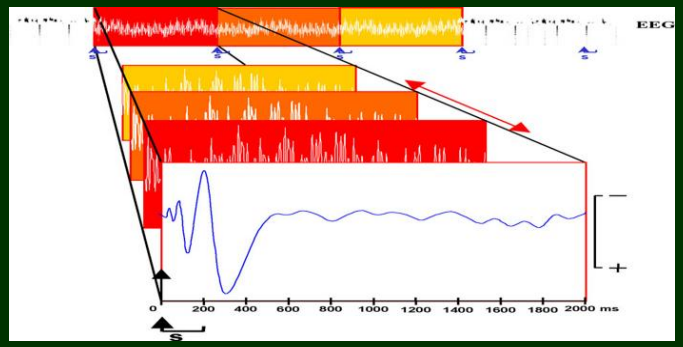
EEG recording

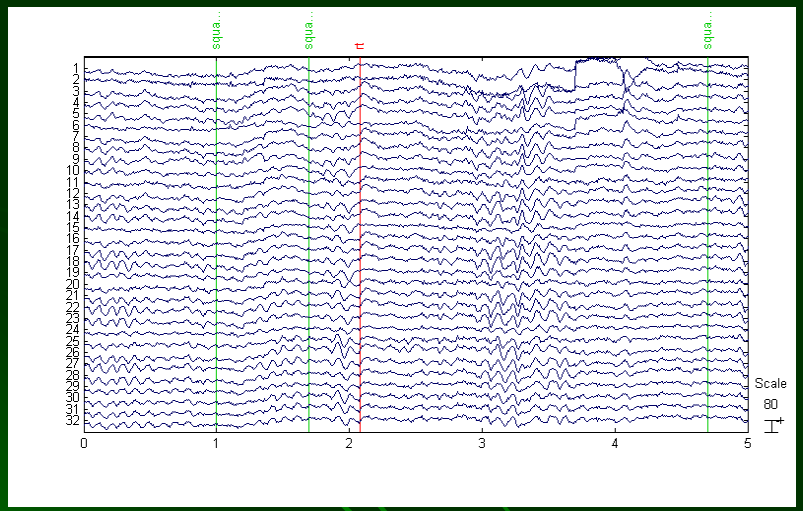


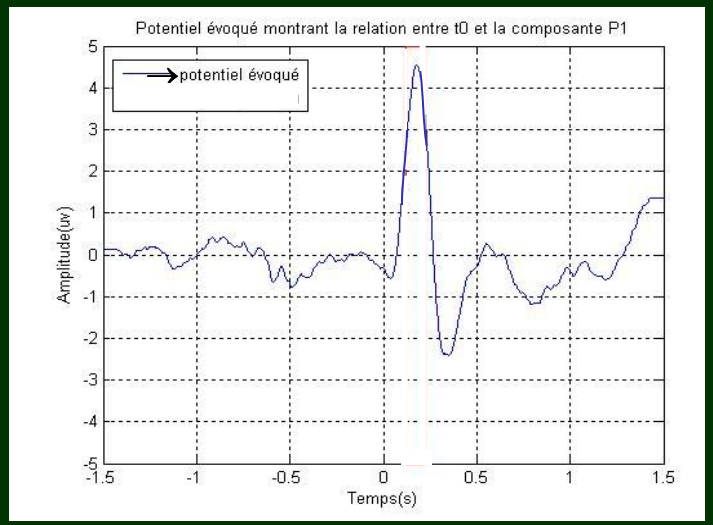


- **Position of the Electrodes**
- **32 Typical Recordings of the C1 Channel**

Computation of the Evoked Response Potentials



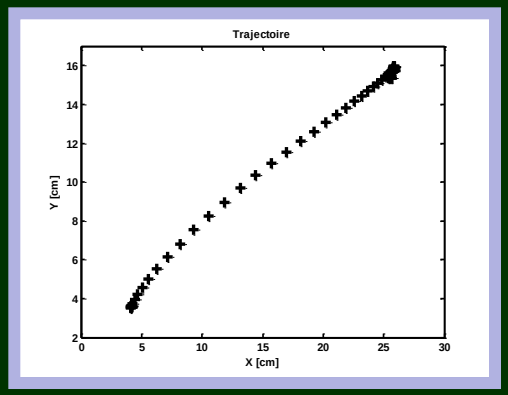


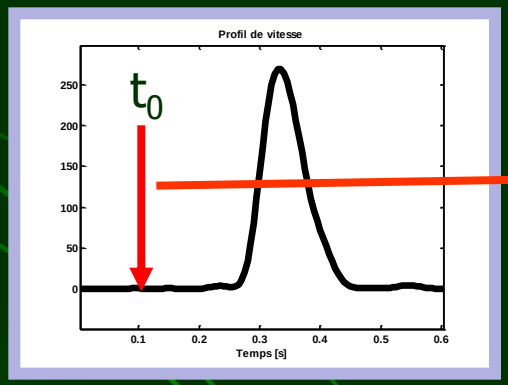


ERP can emerge through mean trace computation among trials for each electrode

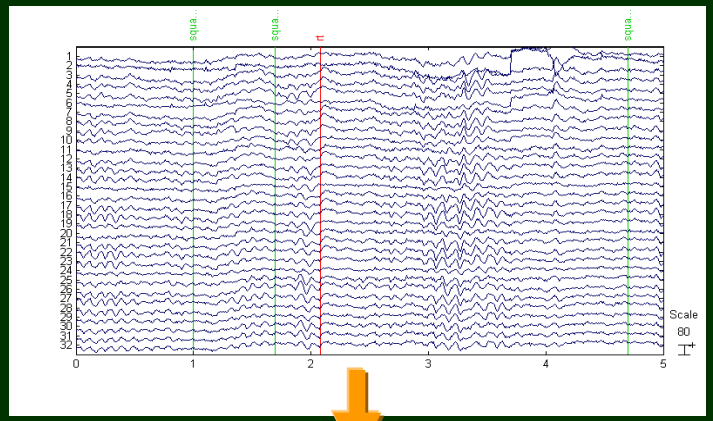
Typical Correlation

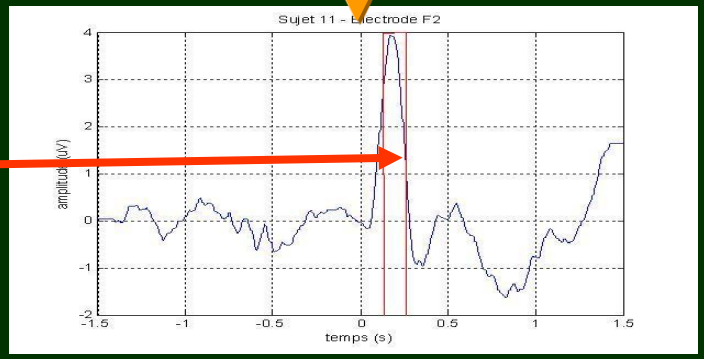
Kinematic data





EEG signals





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

Summary of the results on the visual data

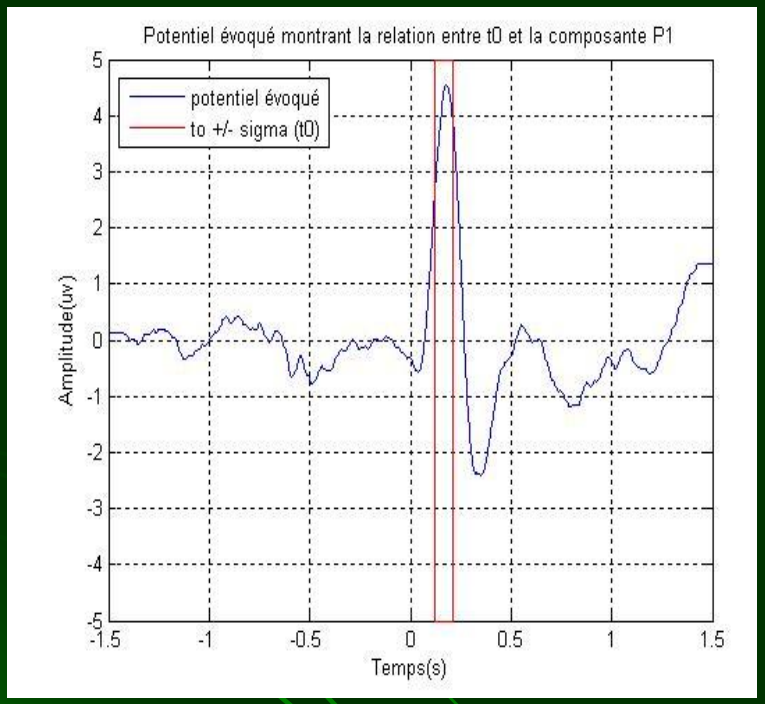
➔Visually evoked response potentials are observed in such an experiment.

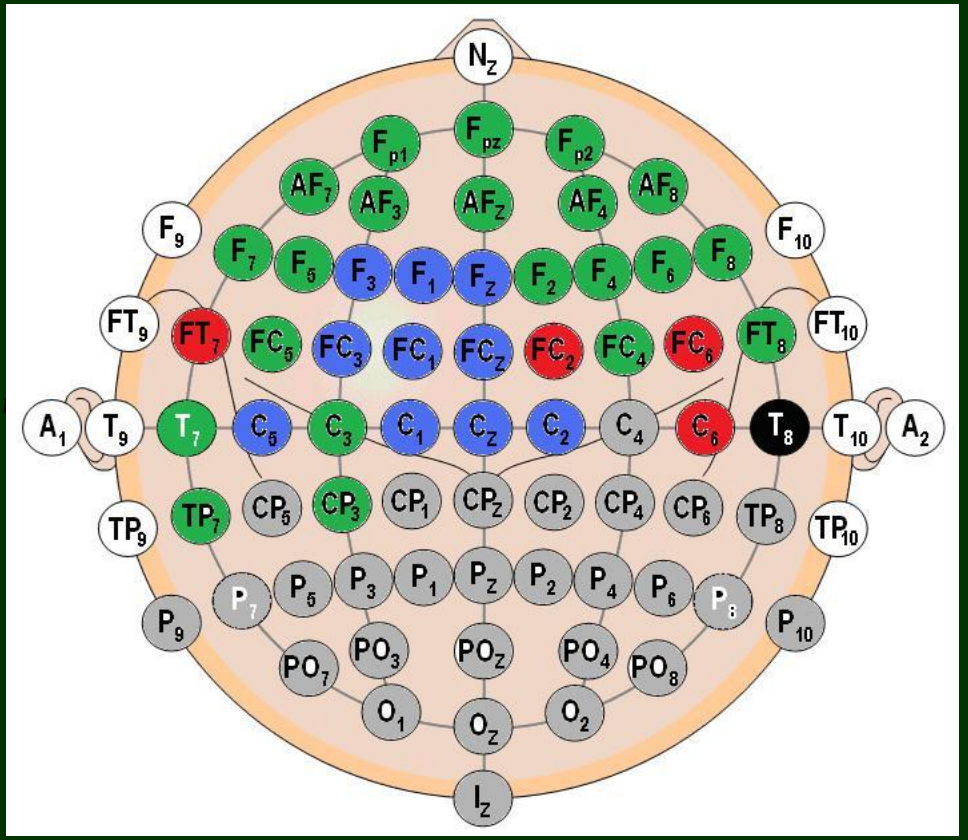
➔For any subject, there are always many electrodes for which the ERP positive peak matches the time occurrence (t_0) of the command.

➔Some of these electrodes are the same for a majority of subjects

Summary of the Results

GOOD MATCH





Blue: $t = t_0$

Red $t > t_0$

Green: $t < t_0$

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

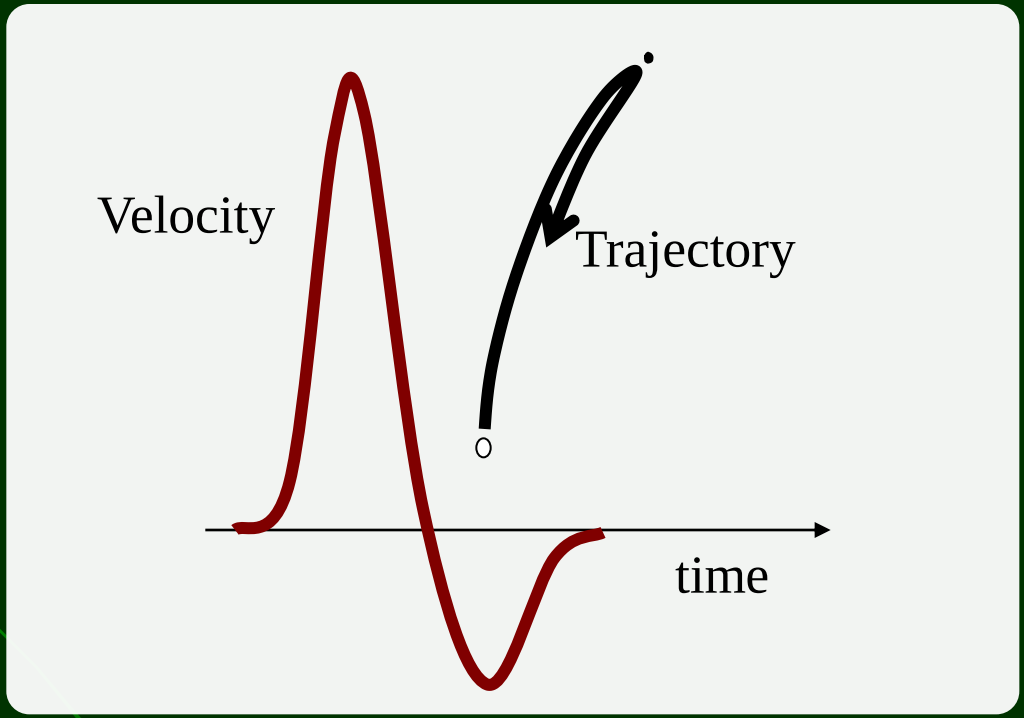
1. Conclusion: future trends.

Practical Application No 1

Studying the effect of age on the production of movement primitives

Woch A. and Plamondon R. (2007) Analysis of movement primitives with the Delta-lognormal model : insights on the age effect. *Proceedings of the 13th Conference of the International Graphonomics Society (IGS2007),* 13, pp:56-60

A specific Delta-Lognormal prediction: a stroke with a direction reversal



Goals of the experiment

- Confirm the existence of bidirectional primitives
- Compare the performances of young and aged subjects

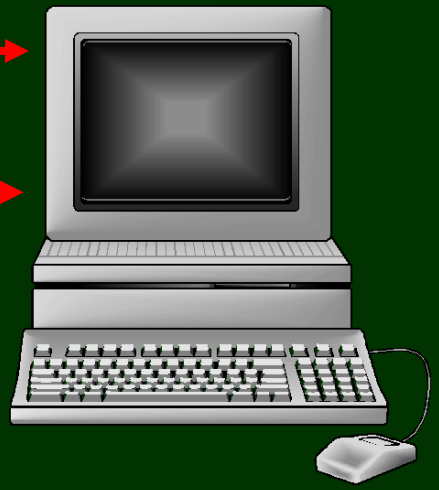
Experiment Description

- 7 aged subjects between 63 and 70
- 7 young subjects between 26 and 29
- Task: production of a rapid stroke with a direction reversal (without pause at the breaking point)
- 100 trials per subject

Experimental Protocol and Equipment

Stimulus generator

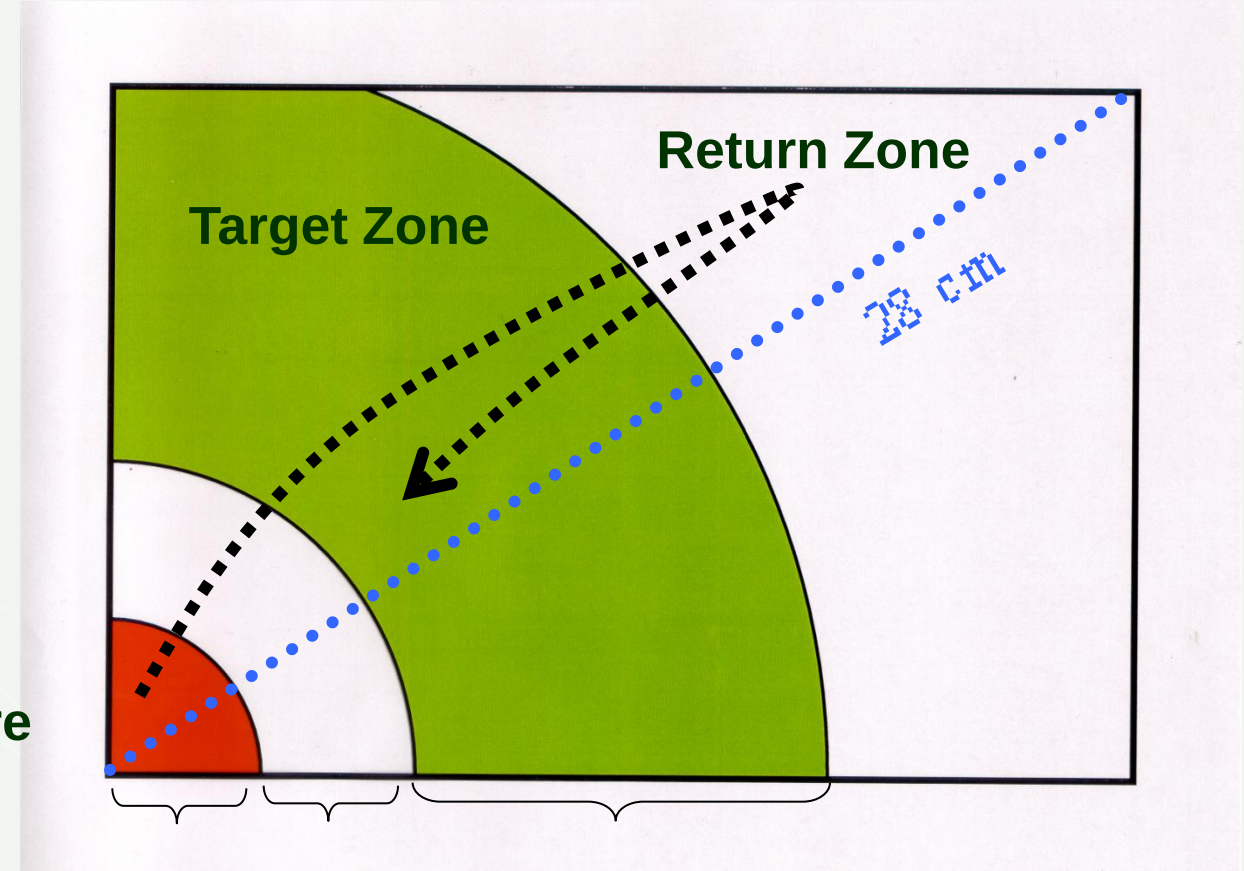
Acquisition System



Digitizer (Wacom SD-510C)

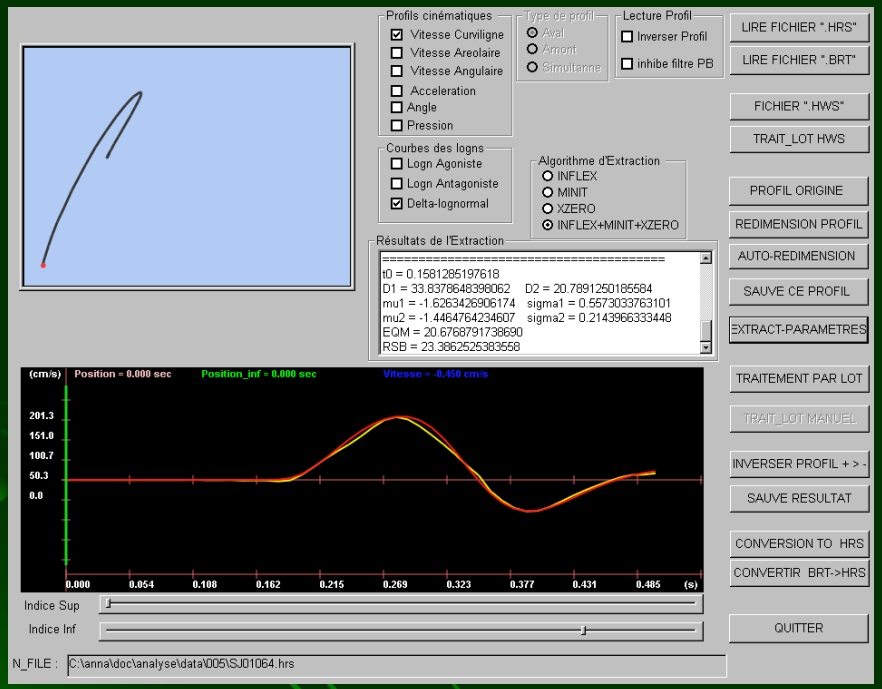
Stylus

Experimental Protocol and Equipment

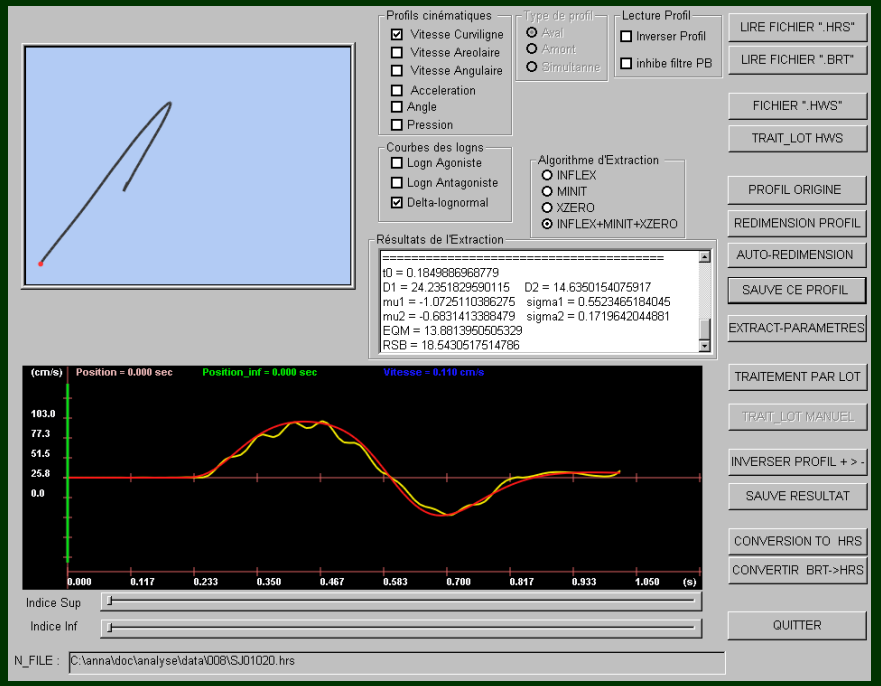


Typical Results

Young subject



Aged subject



Confirmation of the bidirectional primitive prediction

➔Number of primitives observed

Young subjects:
27 to 106 per person

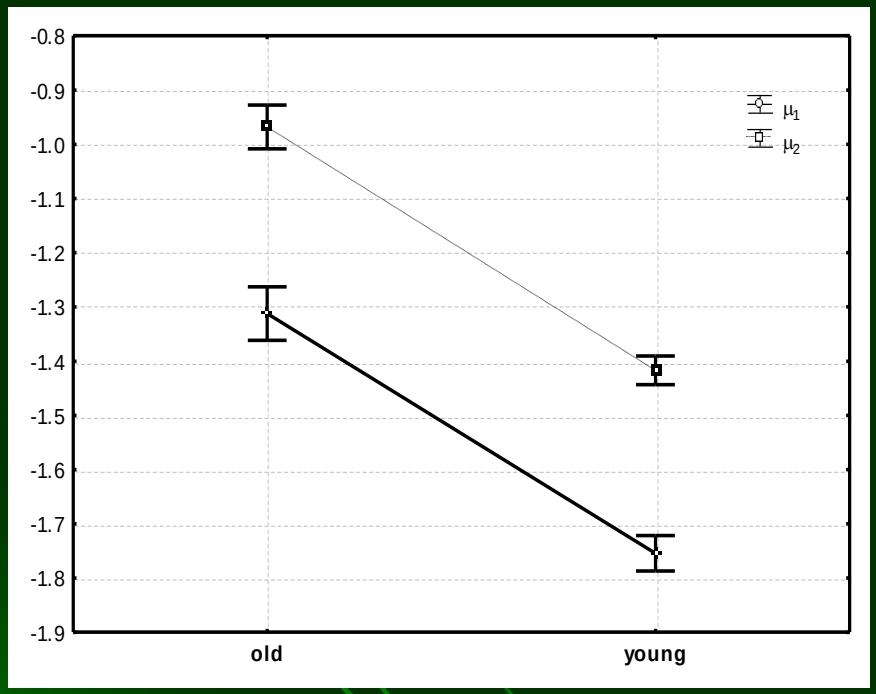
Aged subjects:
3 subjects only produced 3 to 8 primitives
the others: 28 to 73 per person

ANOVA ANALYSIS

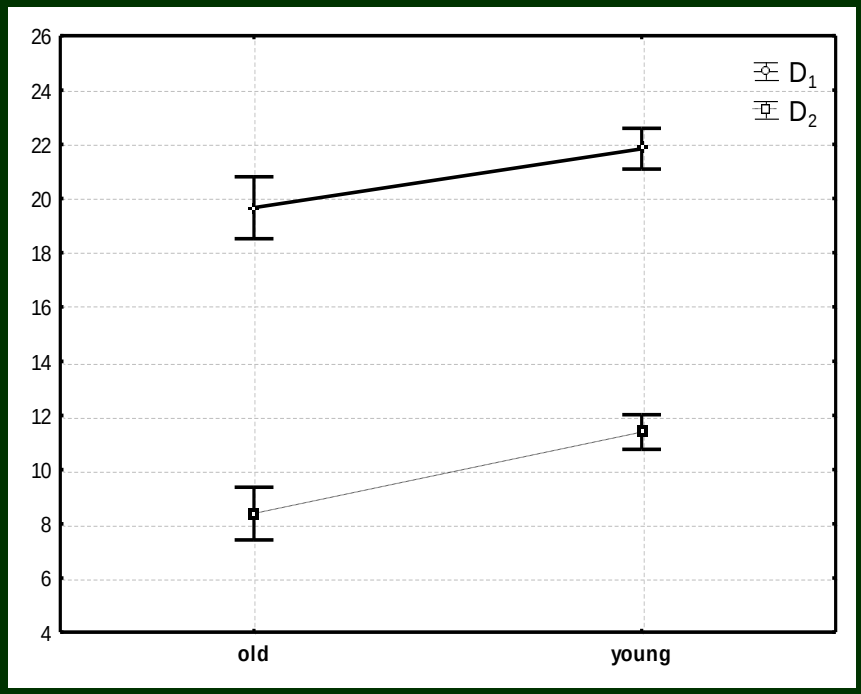
- The Delta-Lognormal parameters μ_i, D_i and t_0 differences statistically significant (p<.01, 0,95 confidence interval):
- Significant age effects on the parameters
  - μ_i increases with age
  - D_i decreases with age
  - t_0 increases with age
- Similar changes observed both on the agonist and the antagonist components

ANOVA ANALYSIS

Effect on μ_i



Effect on D_i

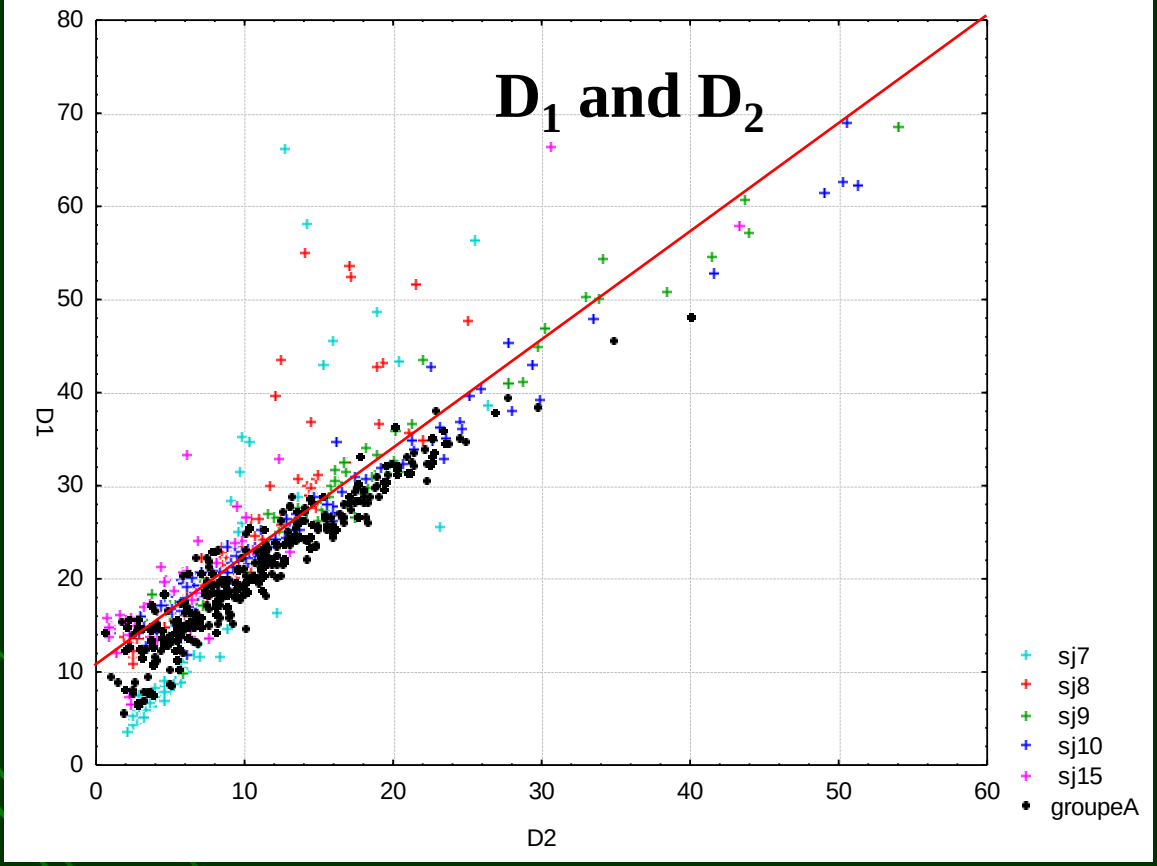


Correlation between the agonist and the antagonist components

D_1 and D_2 μ_1 and μ_2 σ_1 and σ_2

Variable	Corrélations (sujet5) femme jeune Corrélations significatives marquées à p < .01000 N=64										
	TM	Vmax	distance	TR	t0	D1	mu1	s1	D2	mu2	s2
MT	1.00	-0.86	0.20	0.21	0.27	0.21	0.40	0.38	0.14	0.34	0.04
Vmax	-0.86	1.00	0.05	-0.15	-0.26	-0.24	-0.32	-0.48	-0.21	-0.25	-0.20
distance	0.20	0.05	1.00	0.25	0.30	0.16	-0.01	0.29	0.04	-0.14	0.19
TR	0.21	-0.15	0.25	1.00	0.85	0.03	0.10	0.19	-0.02	0.10	0.03
t0	0.27	-0.26	0.30	0.85	1.00	0.13	-0.32	0.57	0.05	-0.35	0.37
D1	0.21	-0.24	0.16	0.03	0.13	1.00	0.22	0.48	0.99	-0.12	0.68
mu1	0.40	-0.32	-0.01	0.10	-0.32	0.22	1.00	-0.34	0.24	0.90	-0.34
s1	0.38	-0.48	0.29	0.19	0.57	0.48	-0.34	1.00	0.39	-0.53	0.75
D2	0.14	-0.21	0.04	-0.02	0.05	**0.99**	0.24	0.39	1.00	-0.09	0.65
mu2	0.34	-0.25	-0.14	0.10	-0.35	-0.12	**0.90**	-0.53	-0.09	1.00	-0.61
s2	0.04	-0.20	0.19	0.03	0.37	0.68	-0.34	**0.75**	0.65	-0.61	1.00

Correlation between the agonist and the antagonist components



Practical Applications No 2

Improving EMG signal processing

Movement Generation

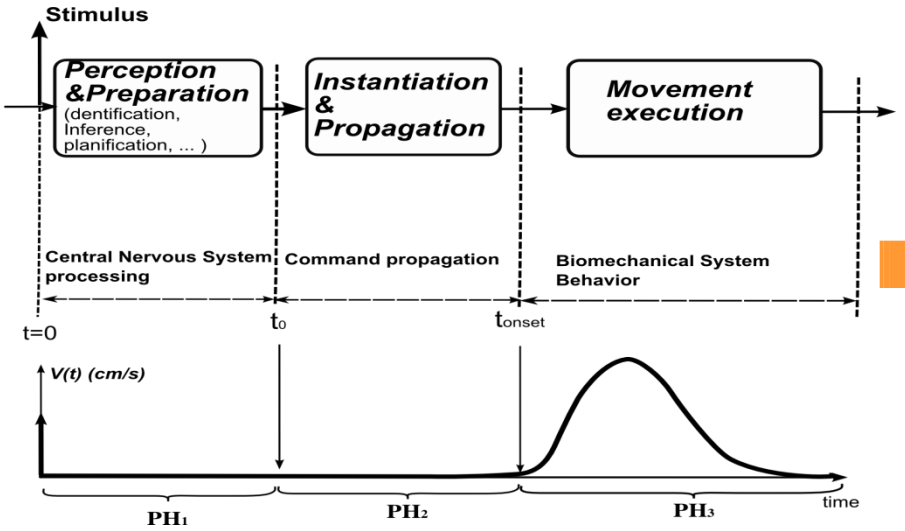


Figure 1a: Temporal analysis of a rapid movement generation

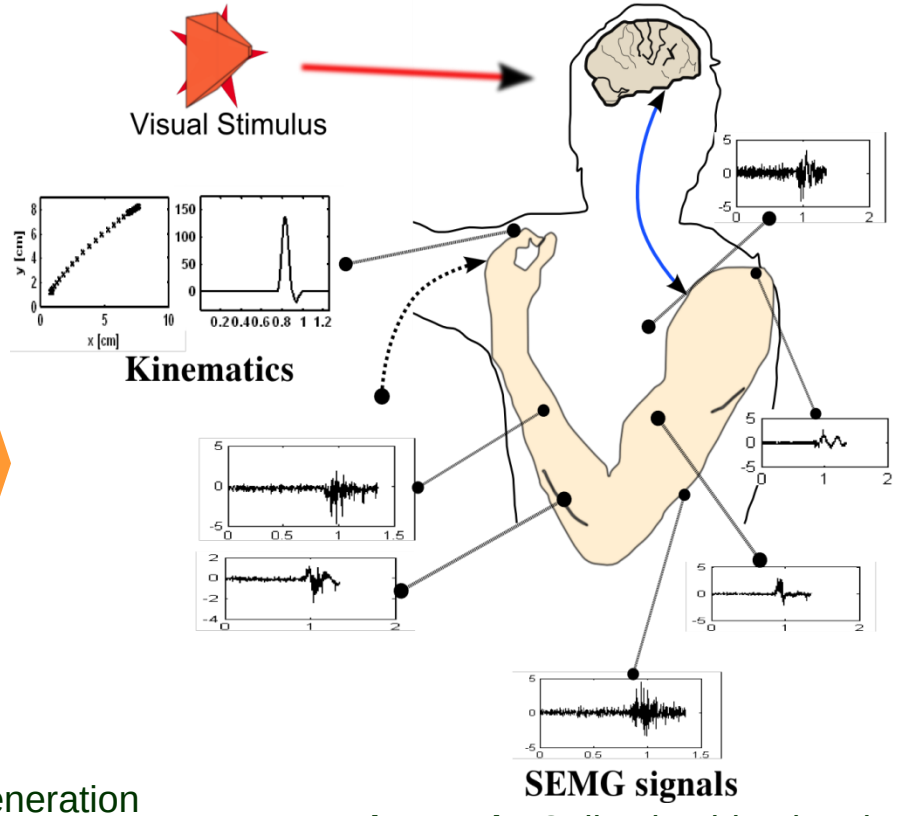
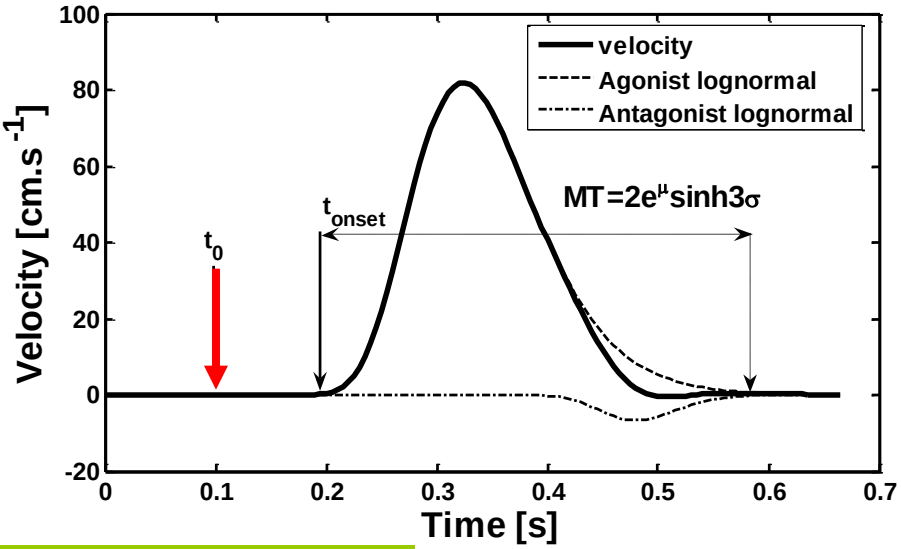


Figure 1b: Collecting bio-signals (Kinematics and SEMG)

Djioua, M. & Plamondon, R. (2008). A New methodology to improve myoelectric signal processing using Handwriting. *International Conference on Frontiers in Handwriting Recognition,ICFHR'08,*112-118.

Theoretical recalls



$$v(t) = D_1 \Lambda\left(t; t_0, \mu_1, \sigma_1^2\right) - D_2 \Lambda\left(t; t_0, \mu_2, \sigma_2^2\right)$$

$$\Lambda\left(t; t_0, \mu, \sigma^2\right) = \begin{cases} \dfrac{1}{\sigma\sqrt{2\pi}(t-t_0)} \exp\left\{-\dfrac{1}{2\sigma^2}\left[\ln(t-t_0)-\mu\right]^2\right\} & \text{si } t_0 < t \\ 0 & \text{sinon} \end{cases}$$

Movement kinematics completely described
With seven parameters
Motor control level : (t_0, D_1, D_2)
Neuromuscular level : $(\mu_1, \sigma_1, \mu_2, \sigma_2)$

Movement onset analytical expression

- $t_{onset} = t_0 + \min\left\{e^{\mu_1 - 3\sigma_1}, e^{\mu_2 - 3\sigma_2}\right\}$

Movement duration analytical expression

- $MT = \max\left\{e^{\mu_1 + 3\sigma_1}, e^{\mu_2 + 3\sigma_2}\right\} - \min\left\{e^{\mu_1 - 3\sigma_1}, e^{\mu_2 - 3\sigma_2}\right\}$

Application 2a: Temporal Index Estimation

Psychophysical Experiment

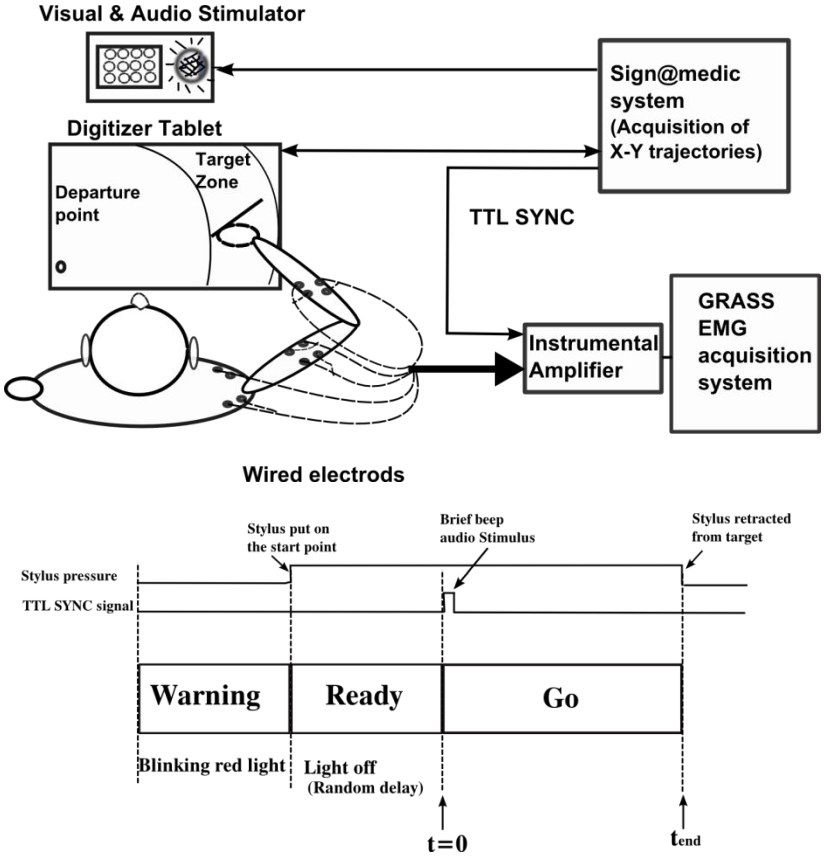


Figure 3b: Experimental protocol

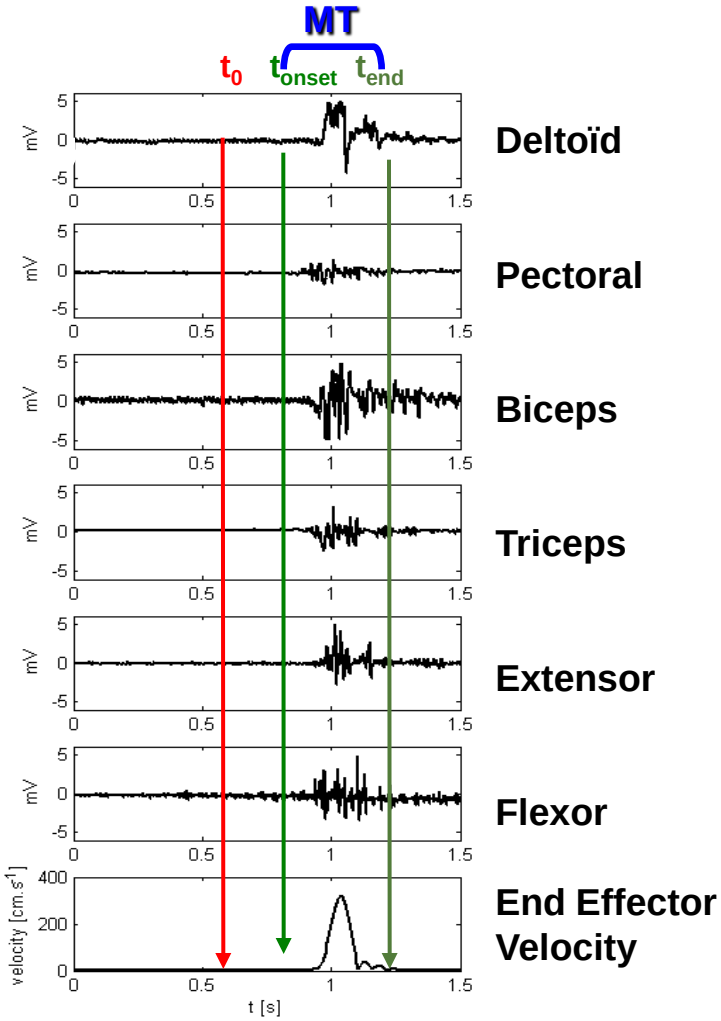
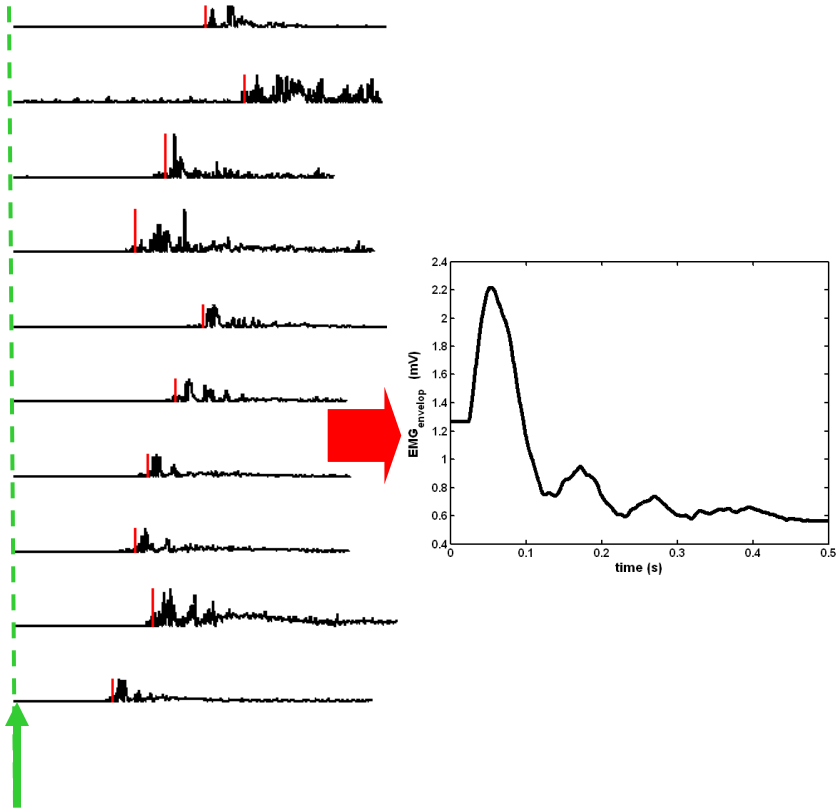


Figure 3c:Selecting EMG signals corresponding to a movement

Application 2b: SEMG Signal Synchronization

Reference time : Movement onset (Hodges and Bui, 1996)

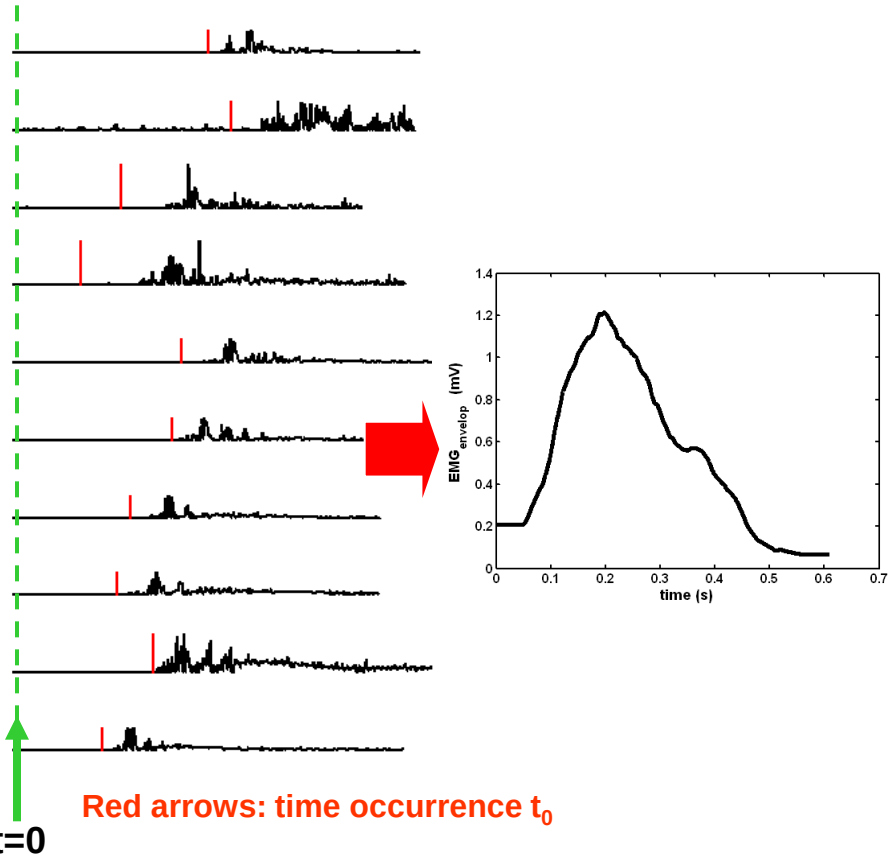


t=0

Red arrows: Movement onset (Hodges and Bui,1996)

Figure 4c: Typical SEMG signals recorded on a flexor muscle and its envelope as computed from the movement onset (tonset)

Reference time:Time occurrence t0 (Djioua & Plamondon, 2008)



t=0

Red arrows: time occurrence t_0

Figure 4b: Same SEMG signals recorded on a flexor muscle and its envelope as computed from t_0

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

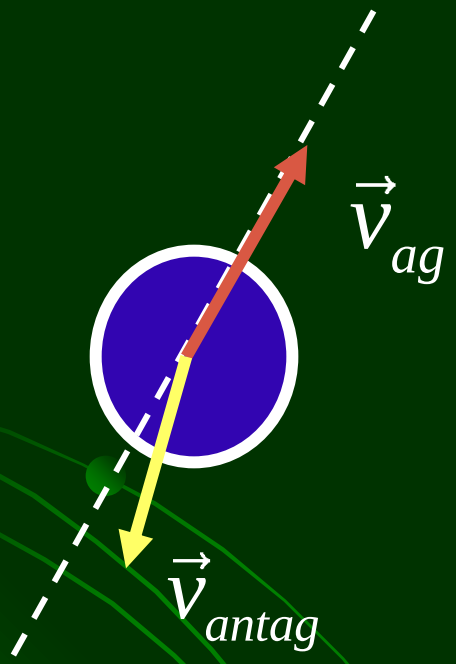
c) Practical applications

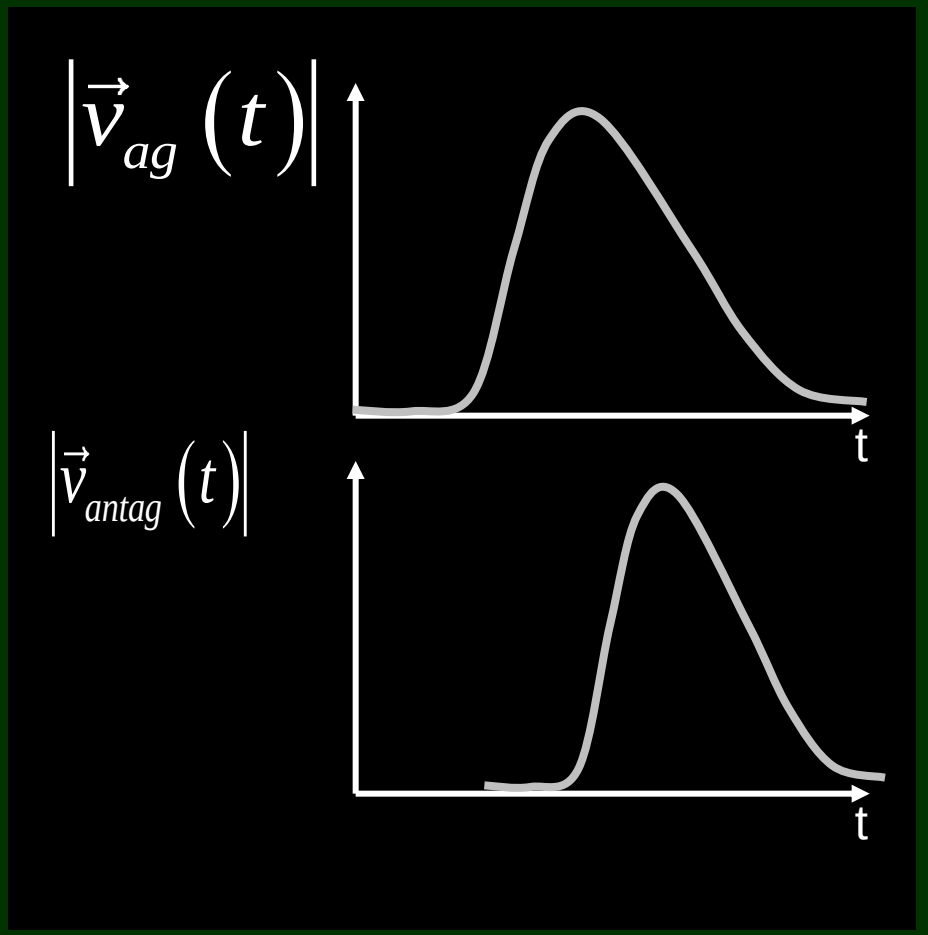
1. Conclusion: future trends.

Generalizing the Kinematic Theory: The Sigma-lognormal model

PLAMONDON, R. DJIOUA, M., «A Multi-Level Representation Paradigm for Handwriting Stroke Generation», **Human Movement Science**, vol. 25, pp. 586-607, 2006

Vectorial summation





Velocity profile of a single Delta-Lognormal stroke

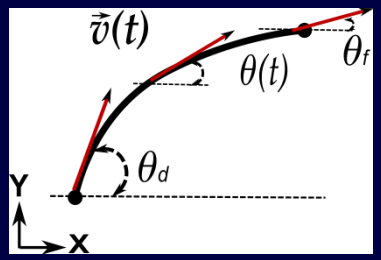
$$v(t) = v_{ag}(t) - v_{antag}(t)$$

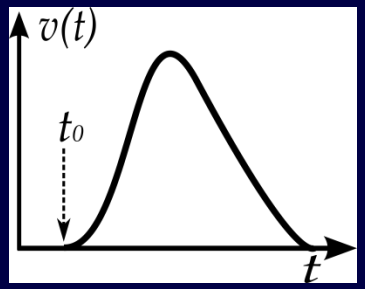
General case: non perfect opposition of the agonist and the antagonist components

$$\vec{v}(t) = \vec{v}_{ag}(t) + \vec{v}_{antag}(t)$$

Sigma-Lognormal Model

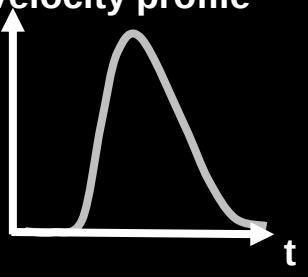
Sigma-Lognormal vectorial model



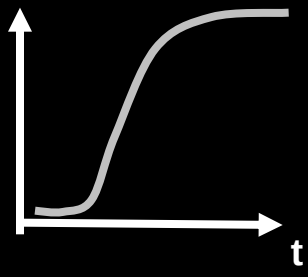


Movement primitive

Lognormal Velocity profile



Erf angular direction profile



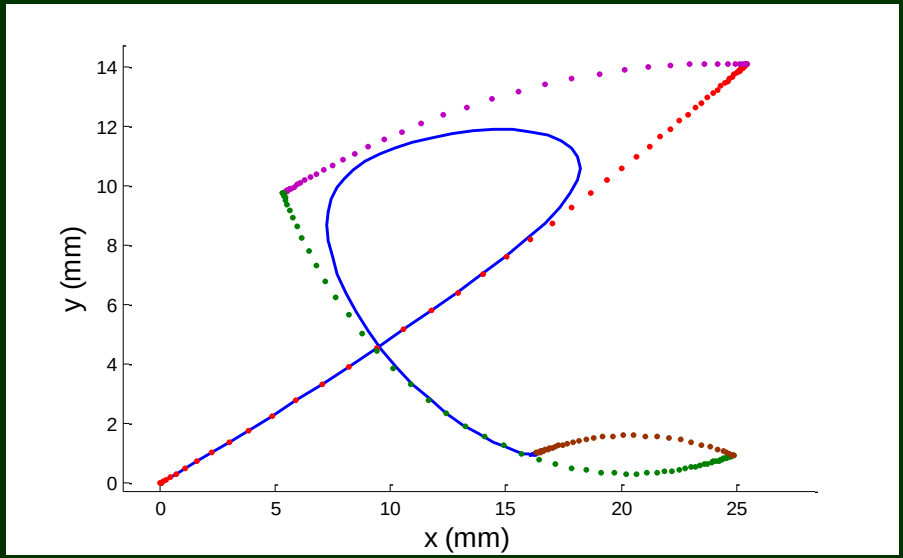
$$\vec{v}(t) = \sum_{i=1}^{L} \vec{v}_i(t) = \sum_{i=1}^{L} \vec{D}_i \Lambda\left(t; t_0, \mu_i, \sigma_i^2\right); \qquad L \geq 2$$

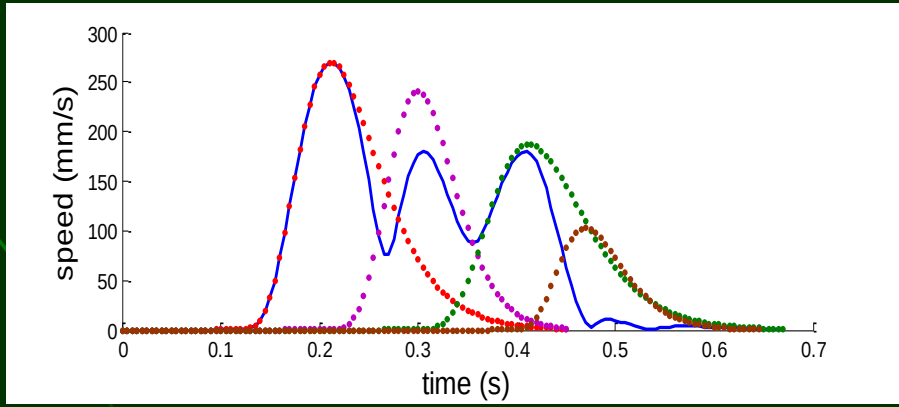
$$\theta_i(t) = \theta_{di} + \frac{\left(\theta_{fi} - \theta_{di}\right)}{2}\left[1 + erf\left(\frac{\ln\left(t - t_{0i}\right) - \mu_i}{\sigma_i\sqrt{2}}\right)\right]$$

$$x(t) = x_0 + \sum_{i=1}^{L} \int_{t_0}^{t} v_i(\tau)\cos\left[\theta_i(\tau)\right] d\tau$$

$$y(t) = y_0 + \sum_{i=1}^{L} \int_{t_0}^{t} v_i(\tau)\sin\left[\theta_i(\tau)\right] d\tau$$

Complex movement generation





Sigma-Lognormal model

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

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

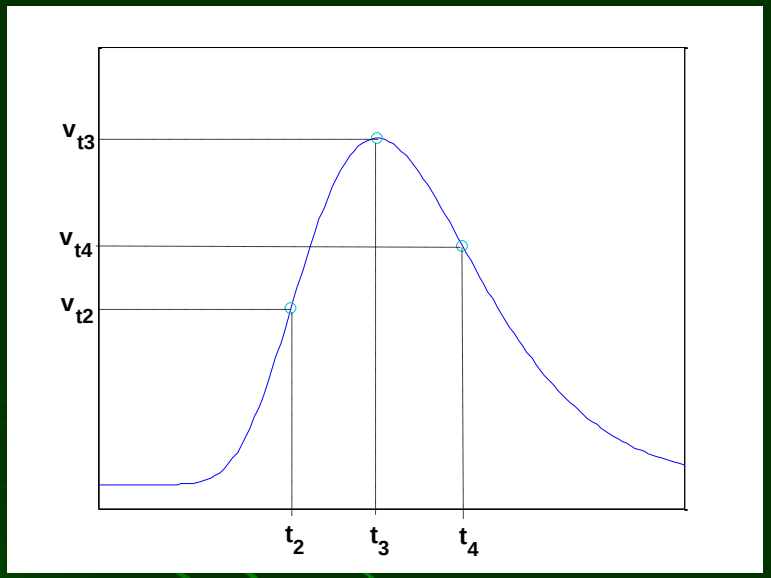
1. Conclusion: future trends.

Practical
Problem No 1

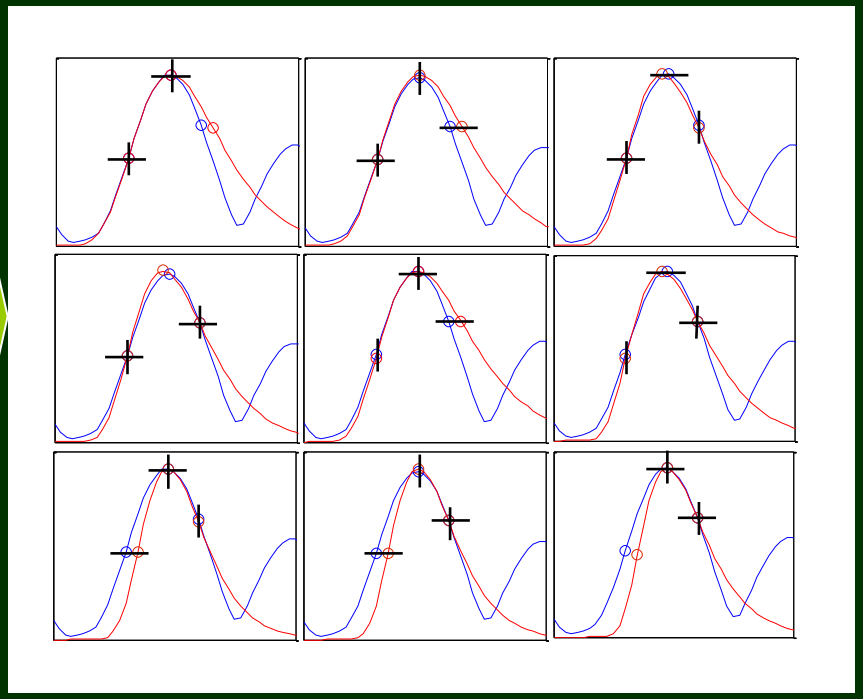
Sigma-Lognormal parameter extraction (Complex trajectories)

XZERO Robust Algorithm

Original XZERO

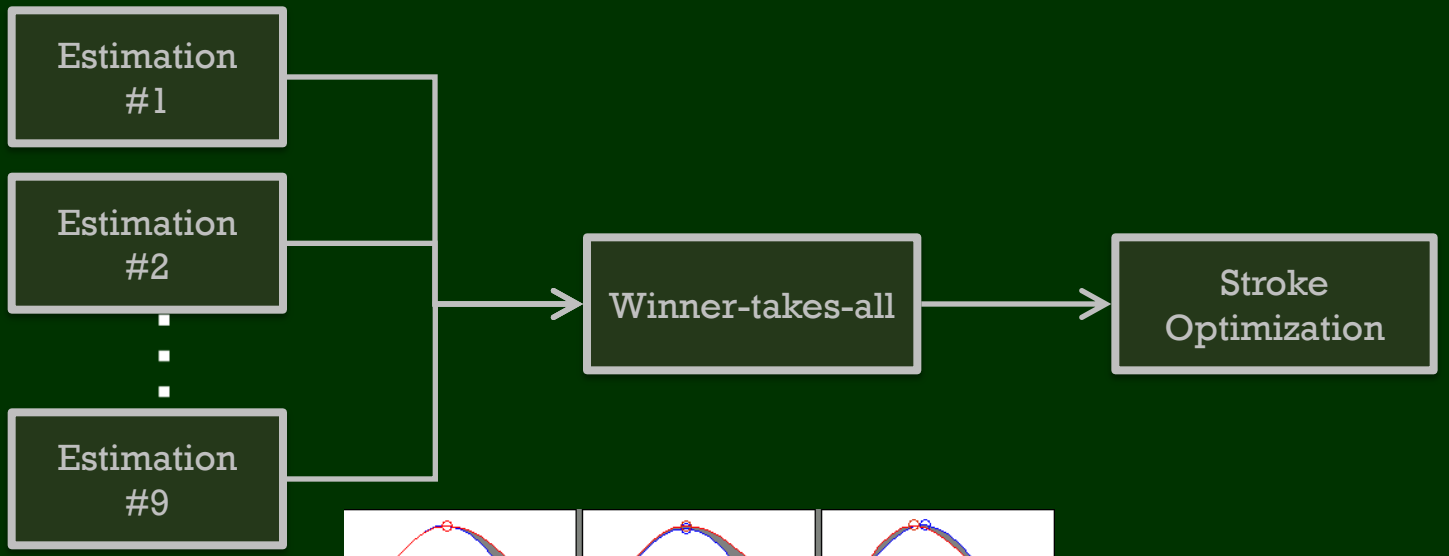


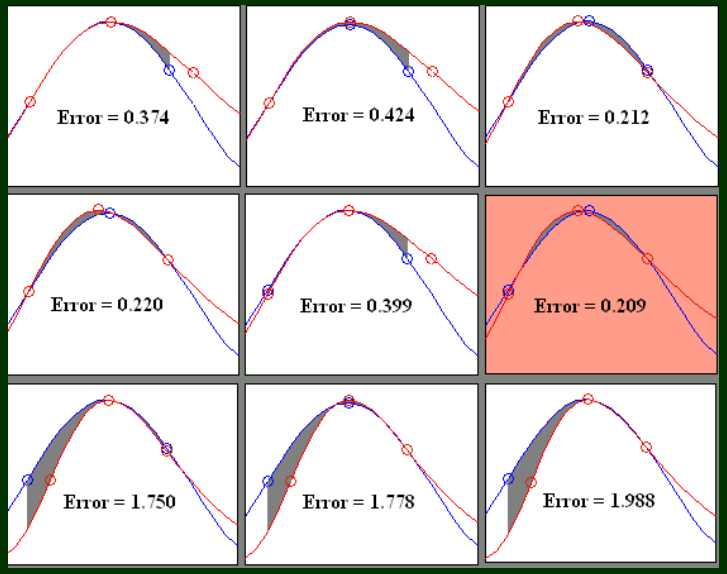
9 Analytic relationships for the initial estimation of the parameters



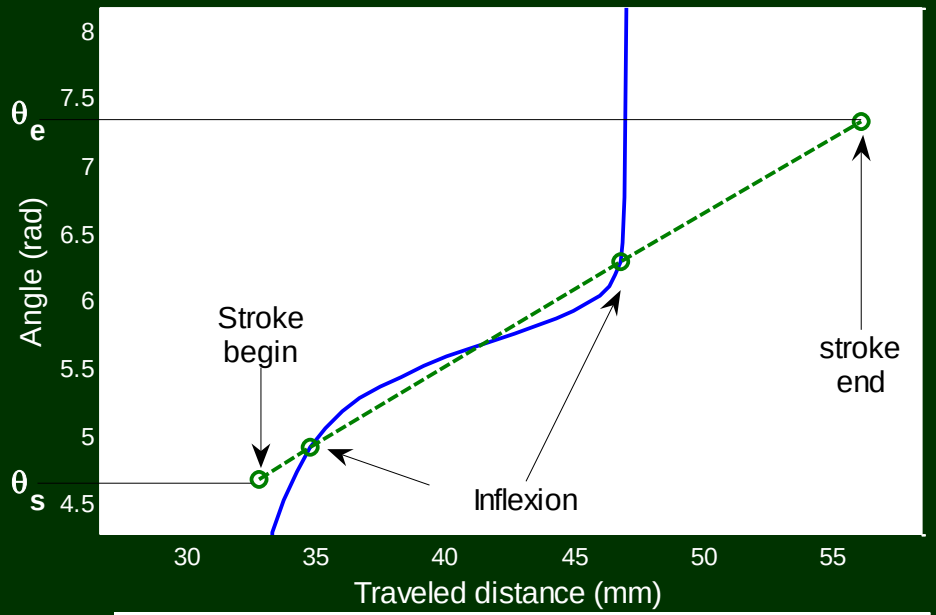
Ref : C. O'Reilly and R. Plamondon "Automatic Extraction of Sigma-Lognormal Parameters on Signatures," *Proceedings of the 11th Int. Conf. on Frontiers in Handwriting Recognition (ICFHR'08), Montréal*, vol. 11, pp. 216-222, 2008.

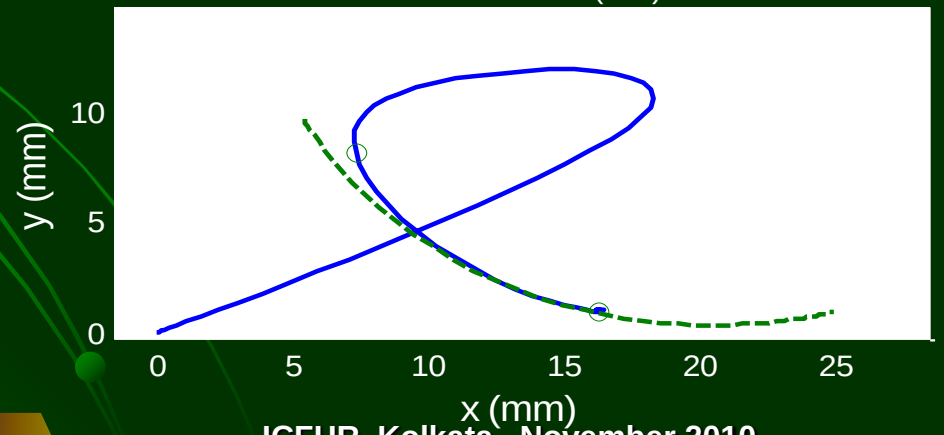
Sigma lognormal Parameter Estimation



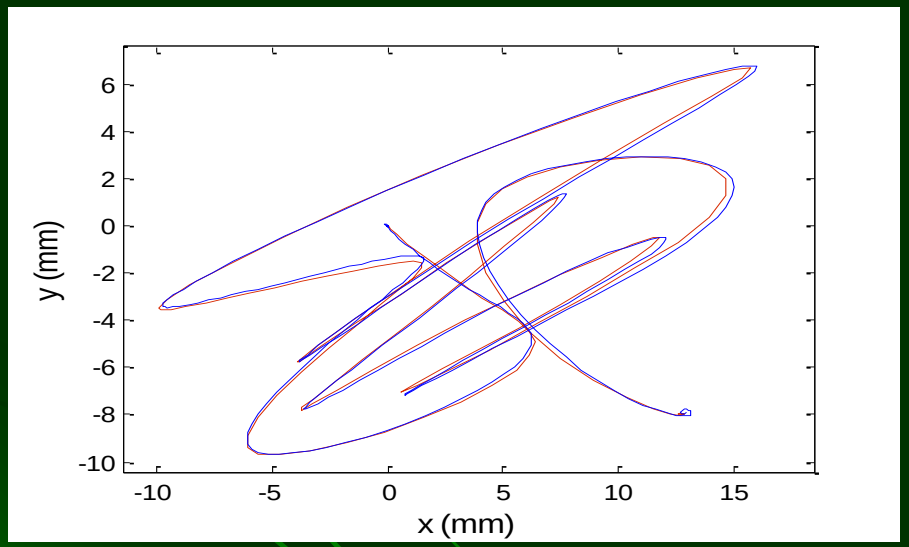


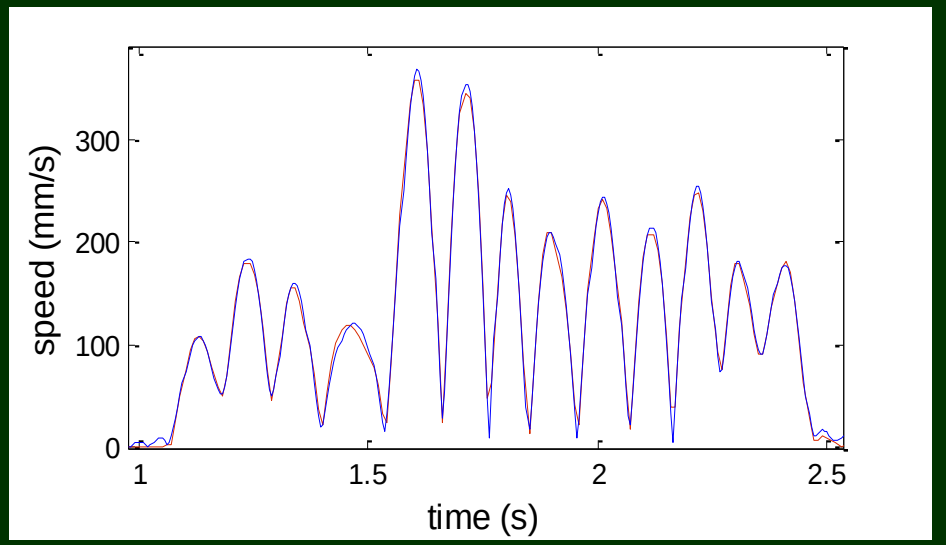
Angle Estimation



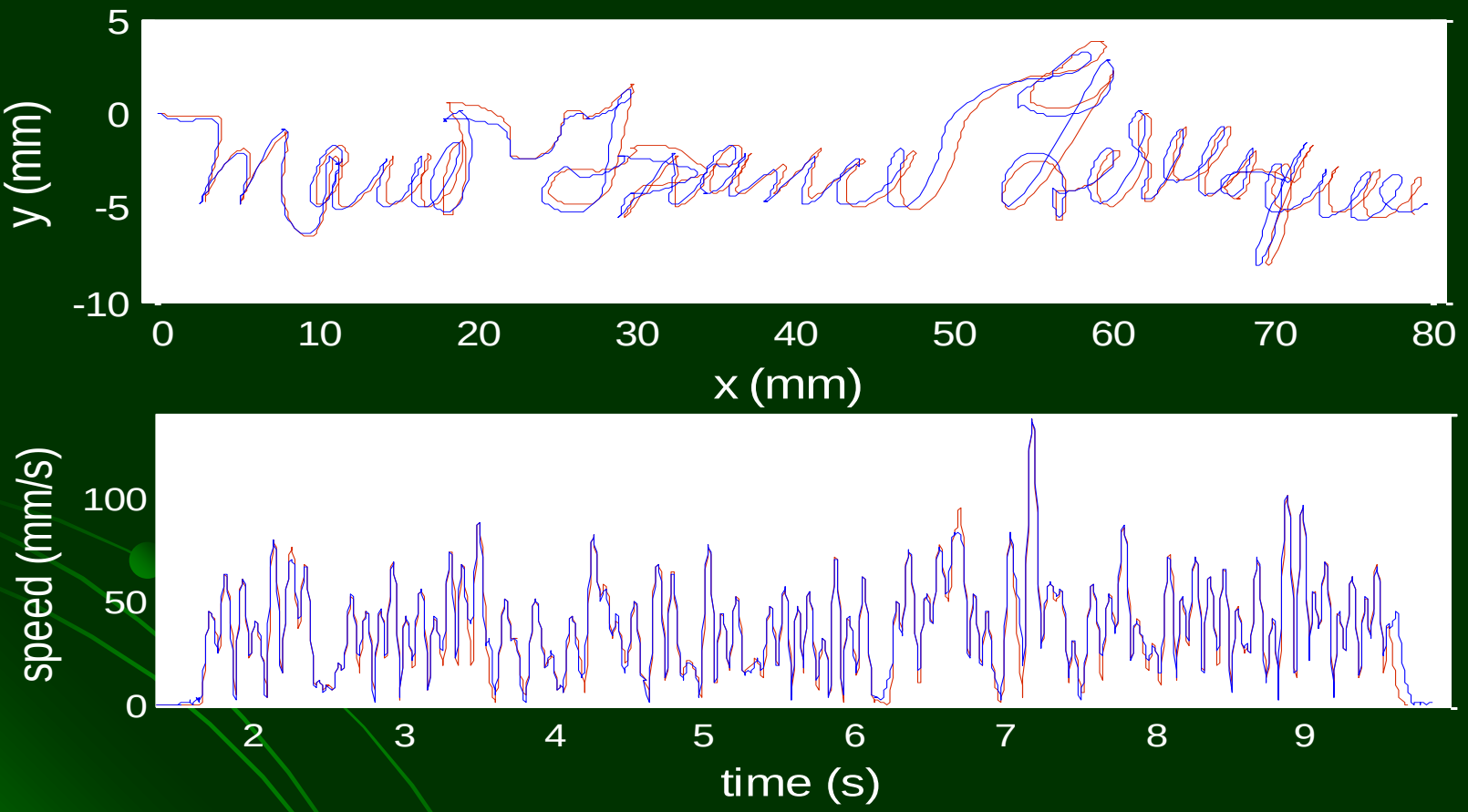


Typical results





Typical results



O'Reilly, C., Plamondon, R., "Development of a Sigma-Lognormal Representation for On-Line Signatures. **Pattern Recognition, Vol.42, pp. 3324-3337, (2009).**

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Conclusion: future trends.

Theoretical validation No 1

Analysis and Synthesis of handwriting variability

Potential sources of variability

Command Level: Action Plan

Time occurrence of the command : t_{0i} parameters

Trajectory Amplitude & Direction : $D_i, \theta_{di}, \theta_{fi}$ parameters

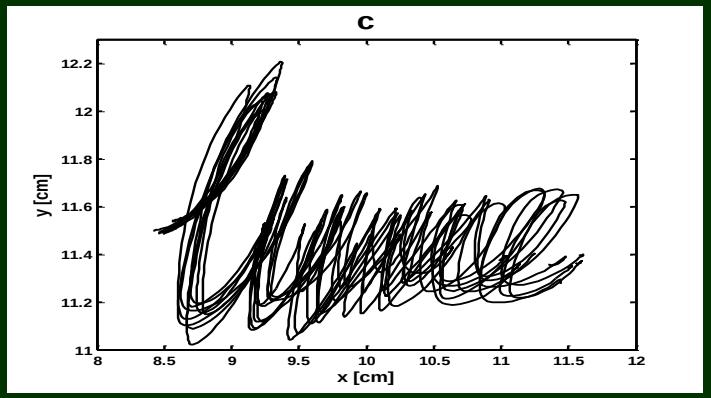
Response level : Peripheral System

Neuromuscular System Status : μ_i and σ_i parameters :

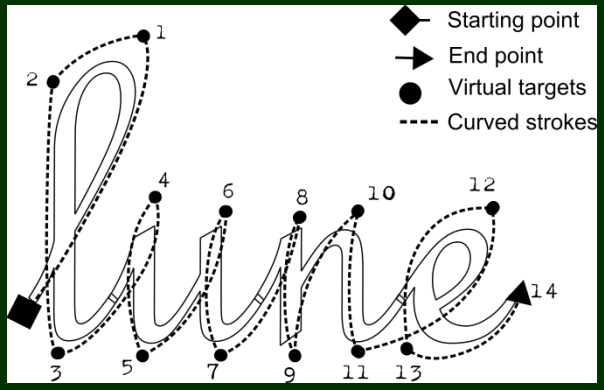
Ref : Djioua, M. & Plamondon, R. (2007). Analysis and synthesis of handwriting variability using the sigma-lognormal model. *Proceeding of the 13th Conference of the International Graphonomics Society (IGS2007)*. 13, 19-22.

Method and protocol

1. Three subjects wrote three times the word «lune» within a rectangle on a digitizer.

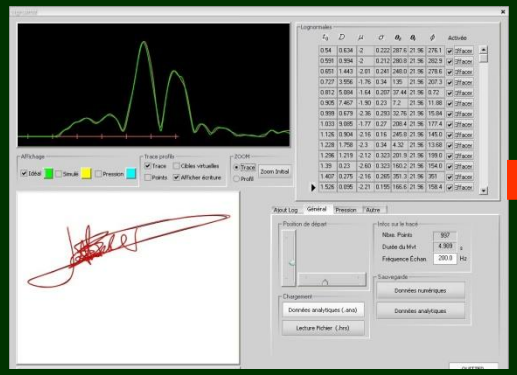


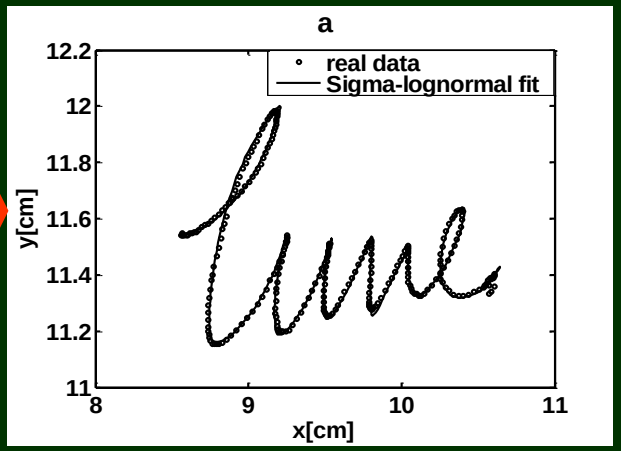
2. Using our software tool, we created a Sigma-Lognormal model of the word «lune» using 14 superimposed strokes.

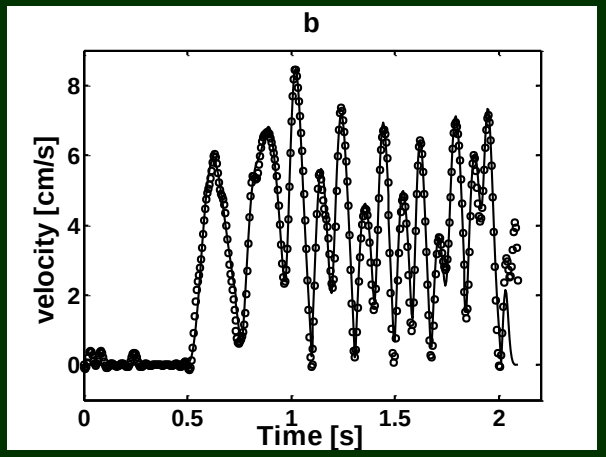


Method and protocol

3. Interactive extraction of the sigma-lognormal parameters on the real specimens



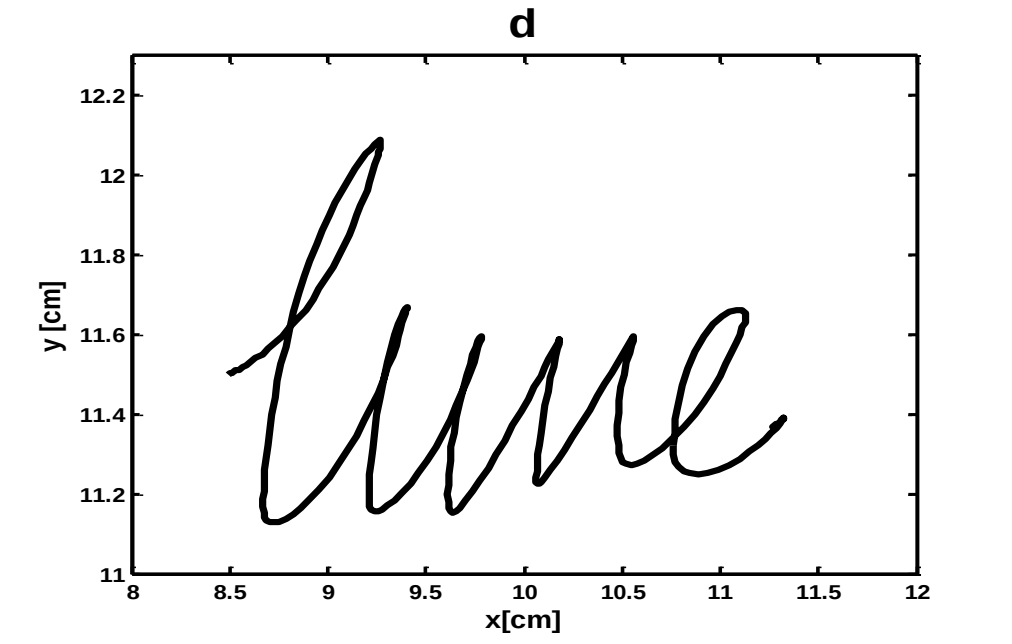




4. Delimitation of the handwriting variability by computing the variability intervals of the Sigma-Lognormal parameters.

Method and Protocol

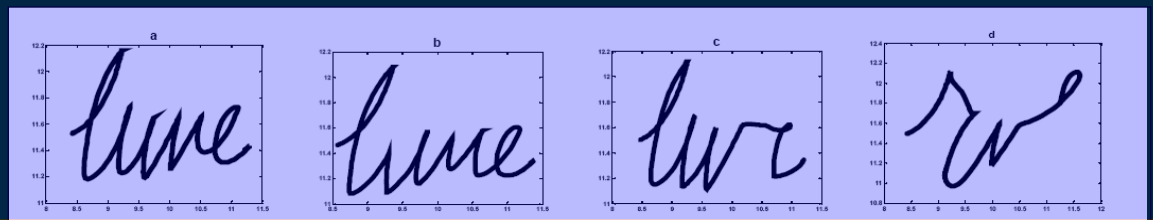
5. Construction of a REFERENCE PATTERN from the mean parameter values



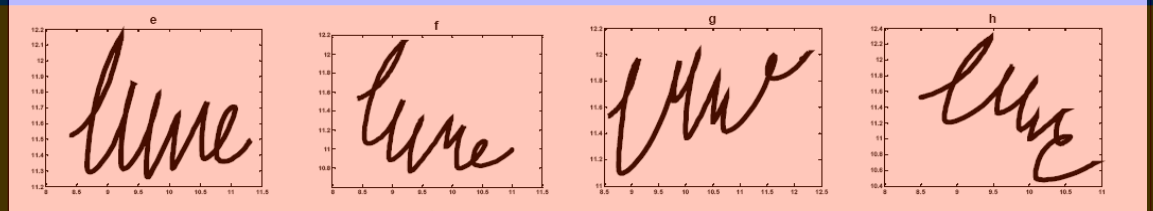
Effects of the command parameters on the variability of the fiducial profile

k=0.2 k=0.4 k=0.6 k=1

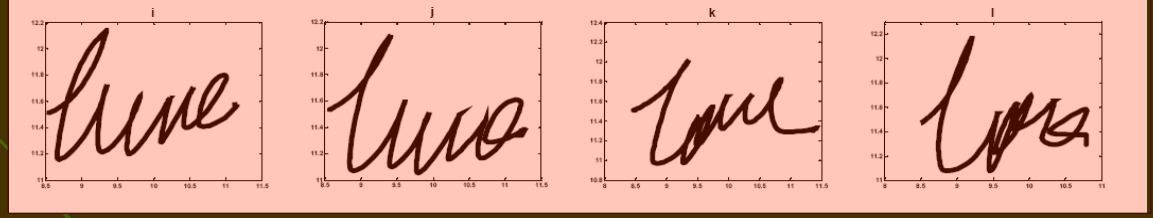
t_{0i} effects



D_i effects

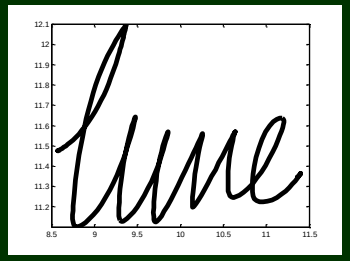
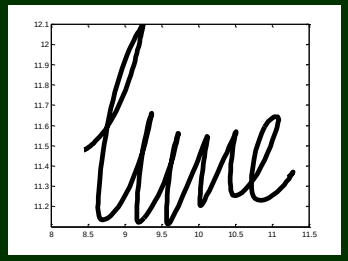
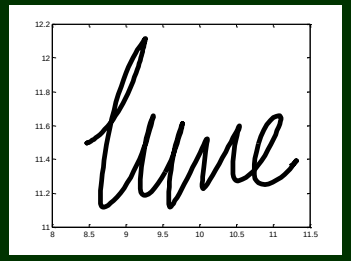
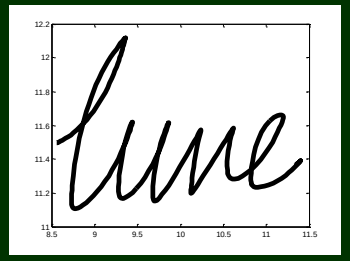
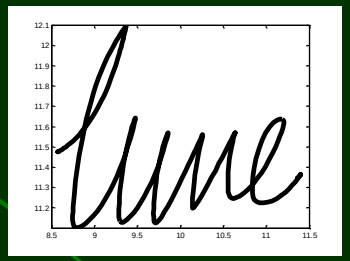
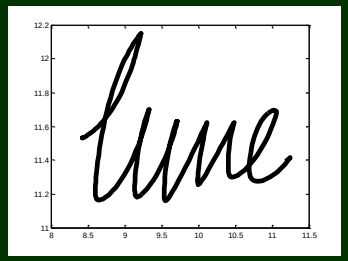
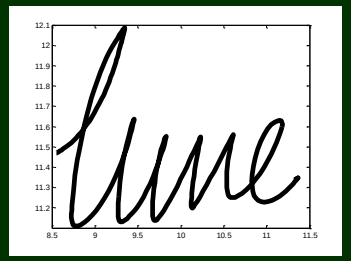
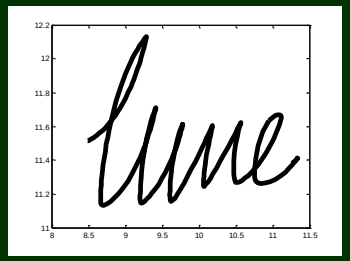


θ_i effects



k=1 k=2 k=3 k=4

Effects of the neuromuscular response parameters on the variability of the fiducial profile

	k=0	k=1	k=2	k=3
μ_i effects				
σ_i effects				

Summary: sensitivity to parameter fluctuations

Action Plan

Command time occurence : t_{0i}

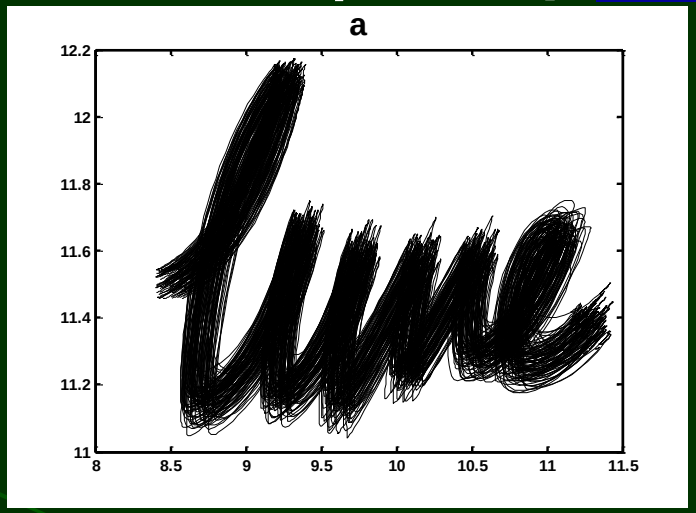
Amplitude and direction commands $D_i, \theta_{di}, \theta_{fi}$

Neuromuscular response μ_i, σ_i

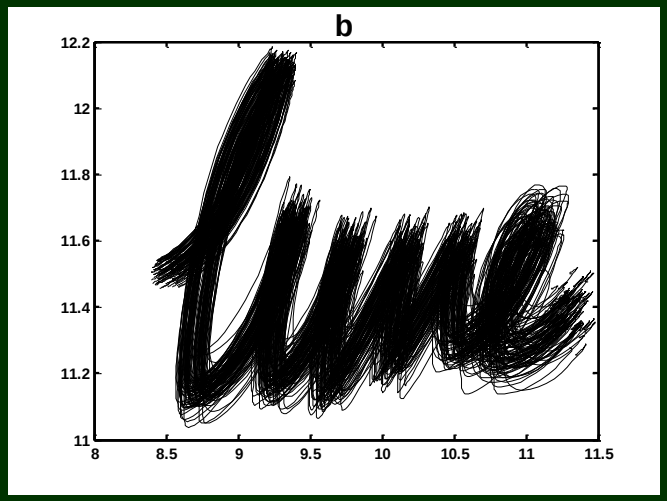
Very sensitive

Less sensitive

Effects of μ_i and σ_i $k \leq 2$



EXAMPLE :Effects of the peripheral parameter variability on the fiducial profile



EXAMPLE : Automatic Synthesis of 100 samples of the word «lune» from a random variation of the 6 sigma-lognormal parameters (k=0.2, for t_{0i} and k=1, for the others)

Djioua M., Plamondon R., "Studying the Variability of Handwriting Patterns using the Kinematic Theory" **Human Movement Science**, vol. 28, no. 5, (2009), pp. 588-601.

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Conclusion: future trends.

Practical Application No 1

Synthetic online signature generation

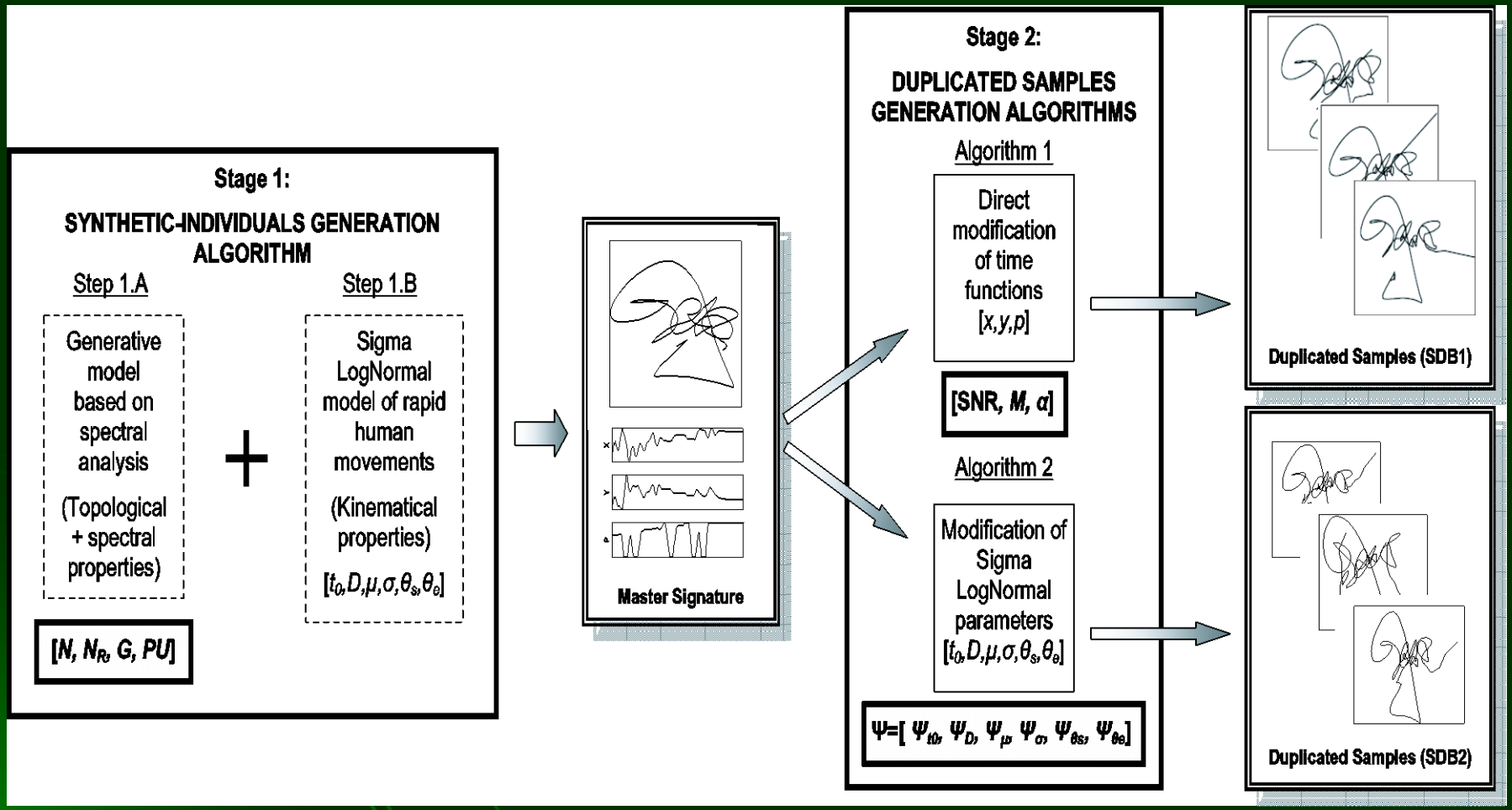
Collaboration with Profs. Javier Fierrez, Javier Ortega-Garcia and Dr. Javier Galbally, Universidad Autonoma de Madrid, SPAIN

CONTEXT

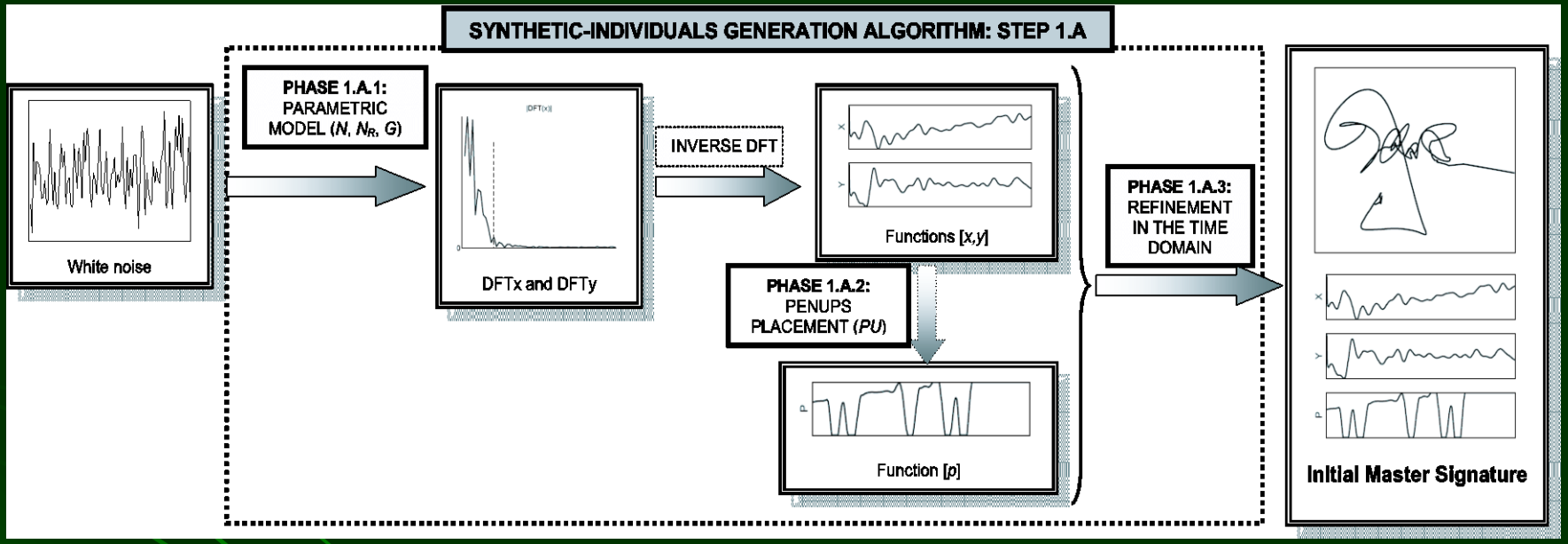
There is a need for the collection of new data that permit the objective and statistical evaluation of the performance of signature verification systems.

A solution: the generation of realistic synthetic signatures.

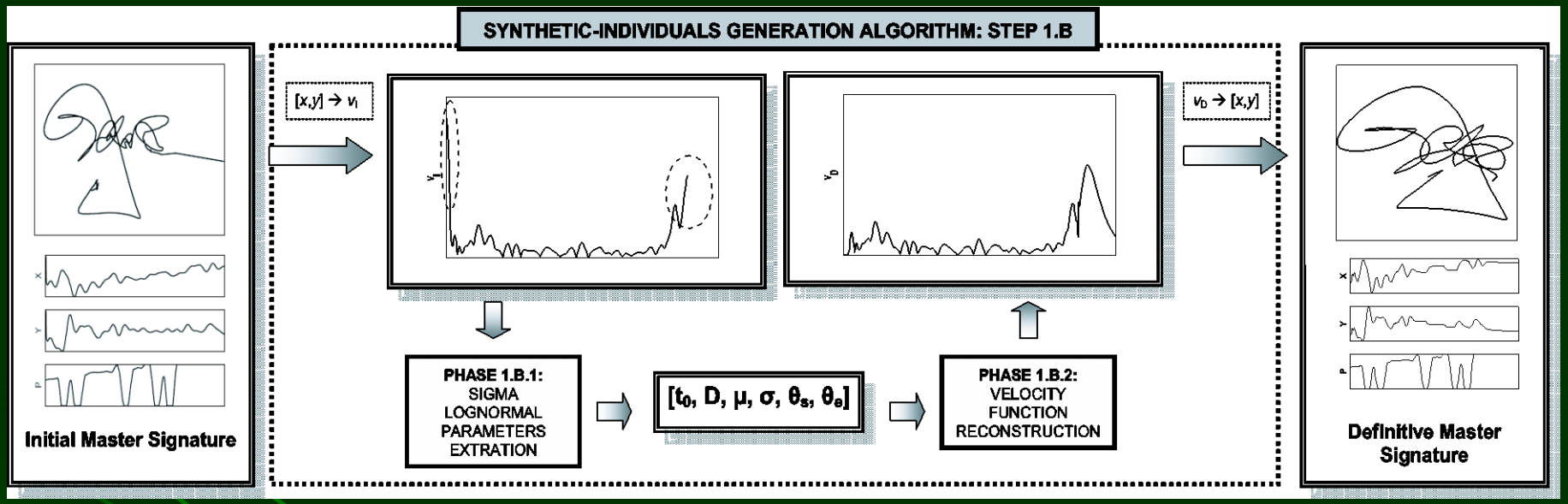
General Architecture



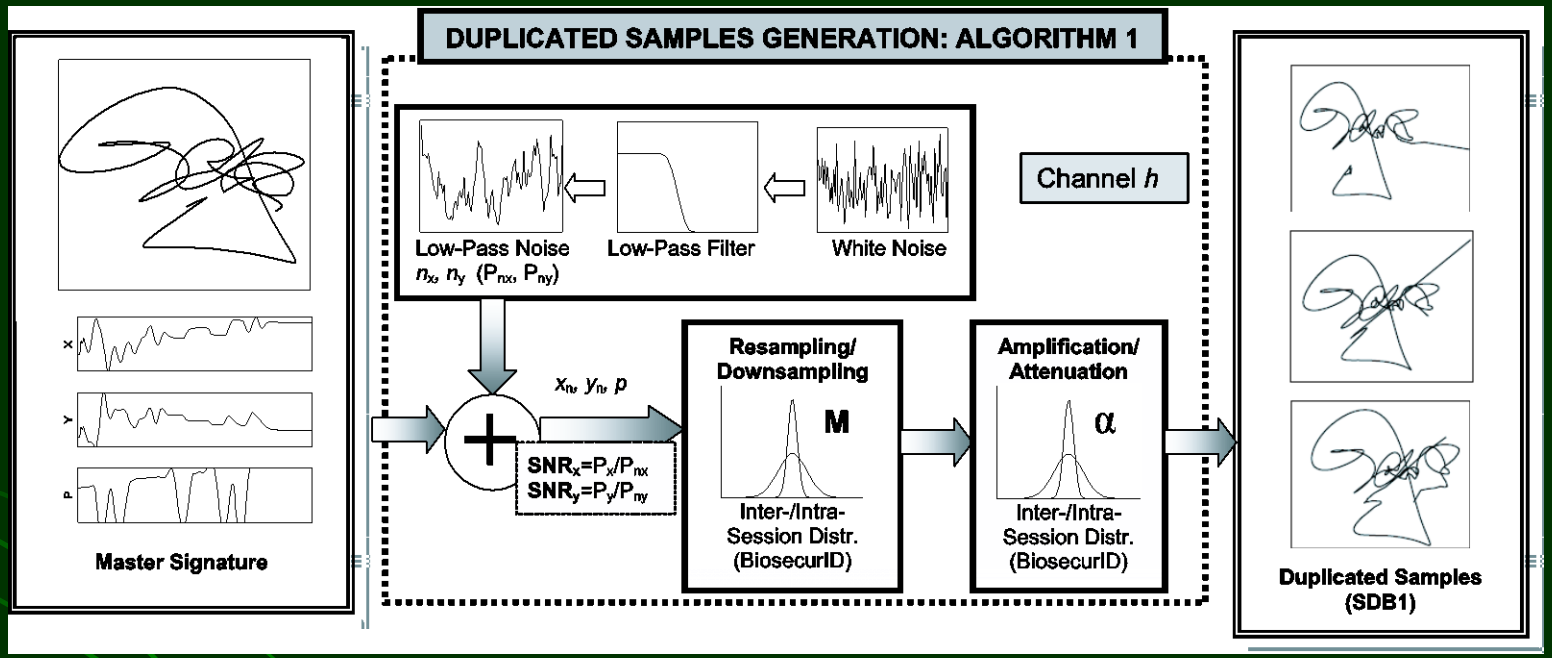
Step 1a


SYNTHETIC-INDIVIDUALS GENERATION ALGORITHM: STEP 1.A
White noise
PHASE 1.A.1: PARAMETRIC MODEL (N, NR, G)
DFTx and DFTy
INVERSE DFT
Functions [x,y]
PHASE 1.A.2: PENUPS PLACEMENT (PU)
Function [p]
PHASE 1.A.3: REFINEMENT IN THE TIME DOMAIN
Initial Master Signature

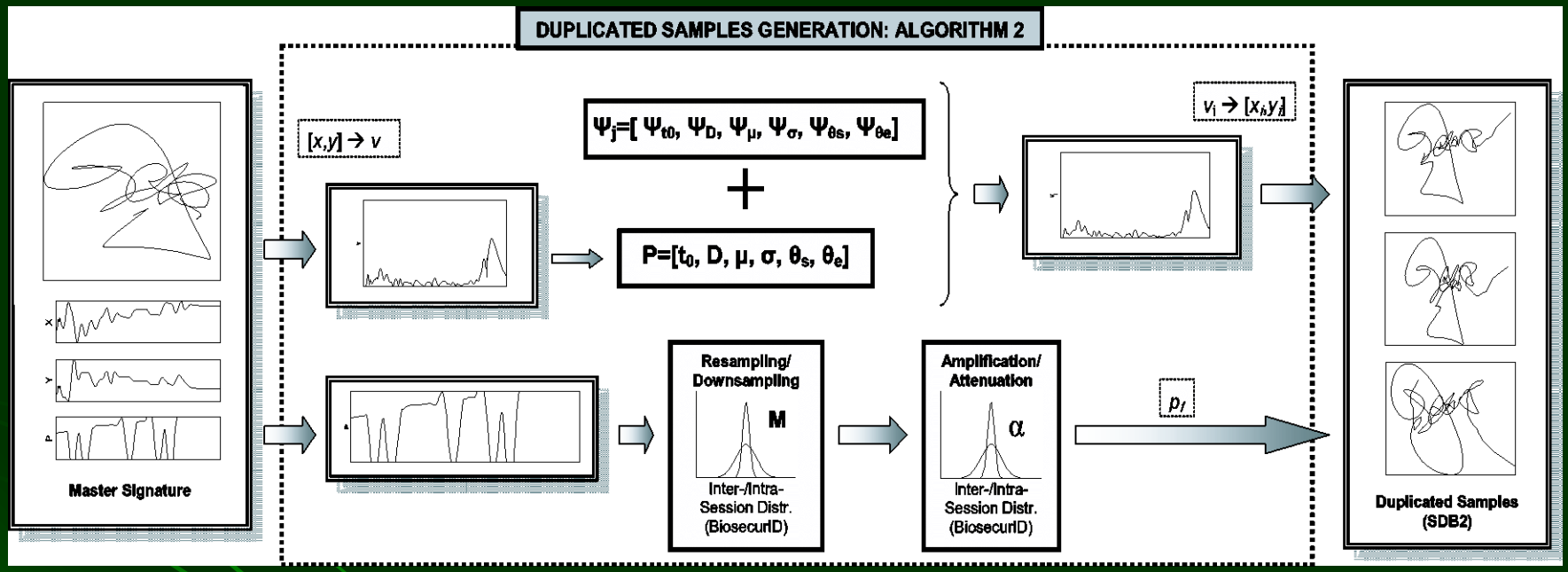
Step 1b


SYNTHETIC-INDIVIDUALS GENERATION ALGORITHM: STEP 1.B
Initial Master Signature
[x,y] → v1
v1
vD
vD → [x,y]
PHASE 1.B.1:
SIGMA
LOGNORMAL
PARAMETERS
EXTRATION
[t0, D, μ, σ, θs, θe]
PHASE 1.B.2:
VELOCITY
FUNCTION
RECONSTRUCTION
Definitive Master
Signature

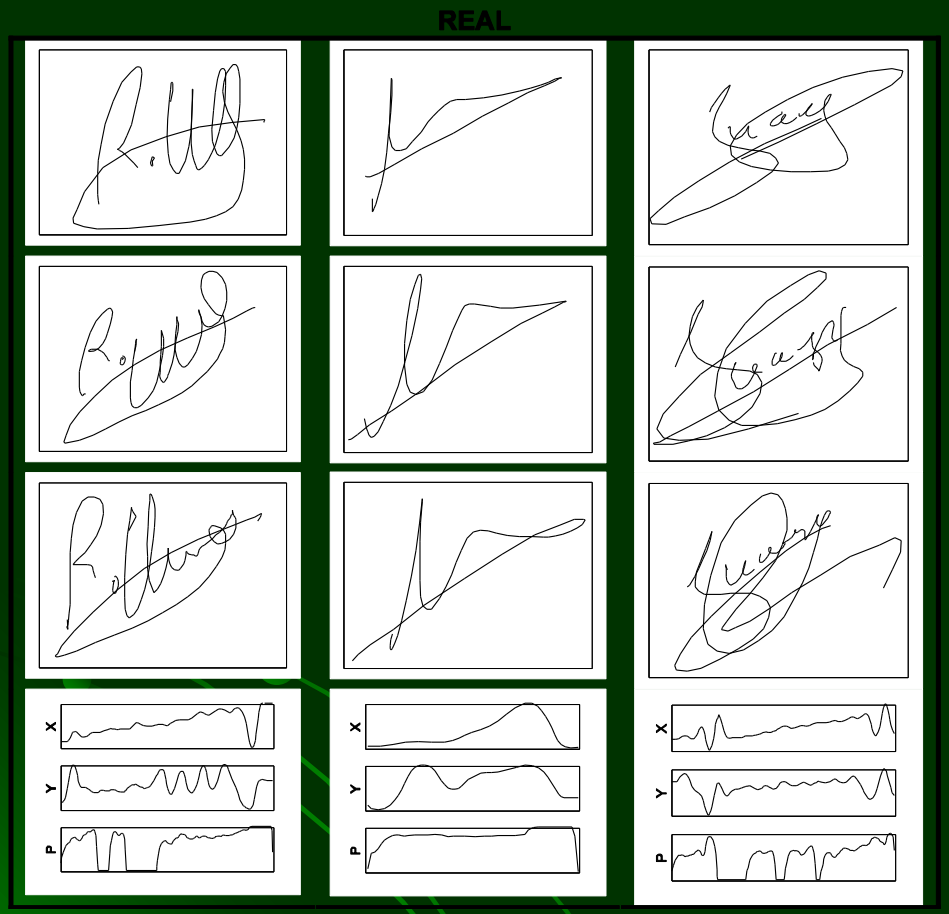
Duplicate sample generation #1



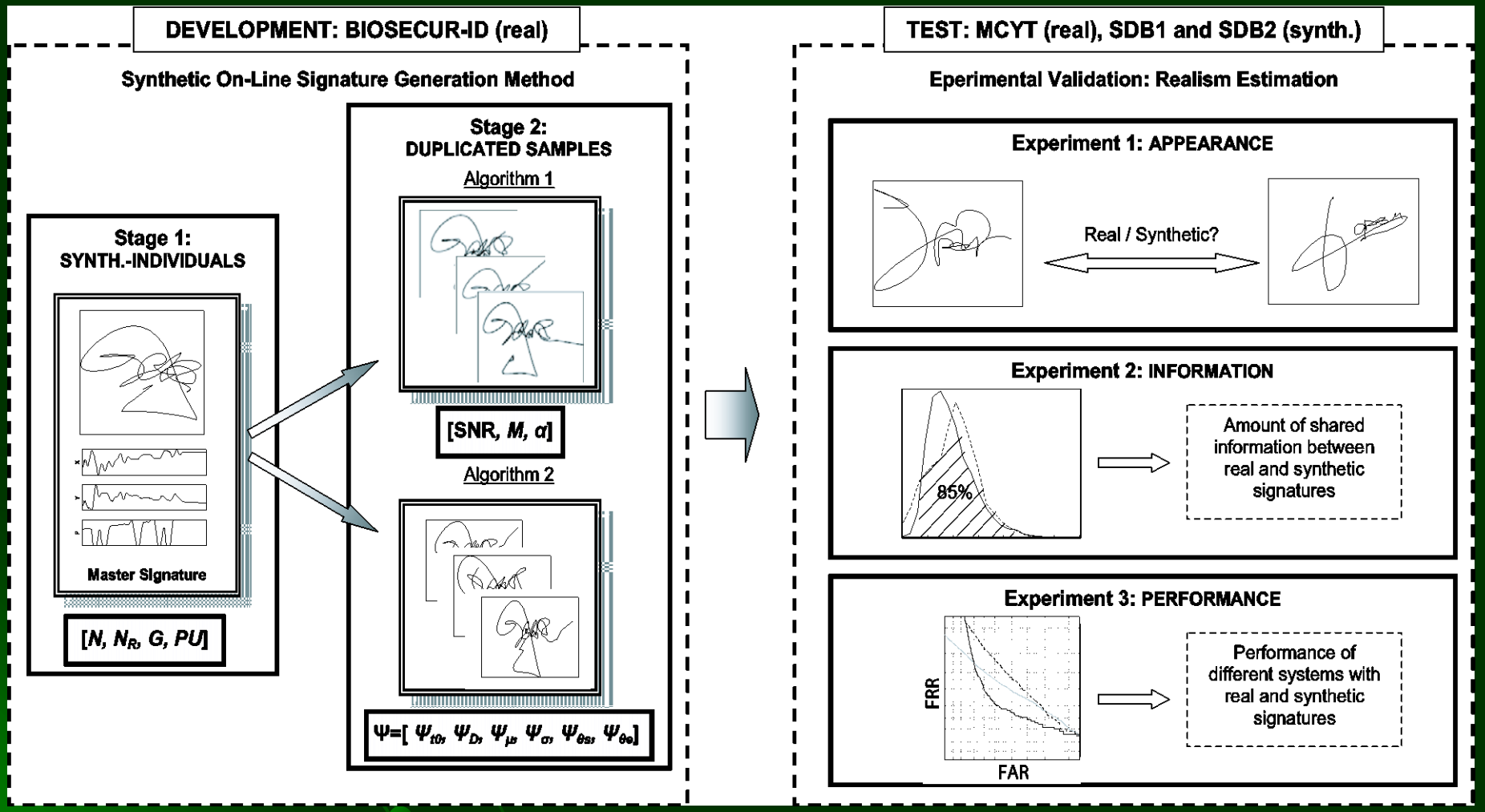
Duplicate sample generation #2



TYPICAL RESULTS



Validation strategy

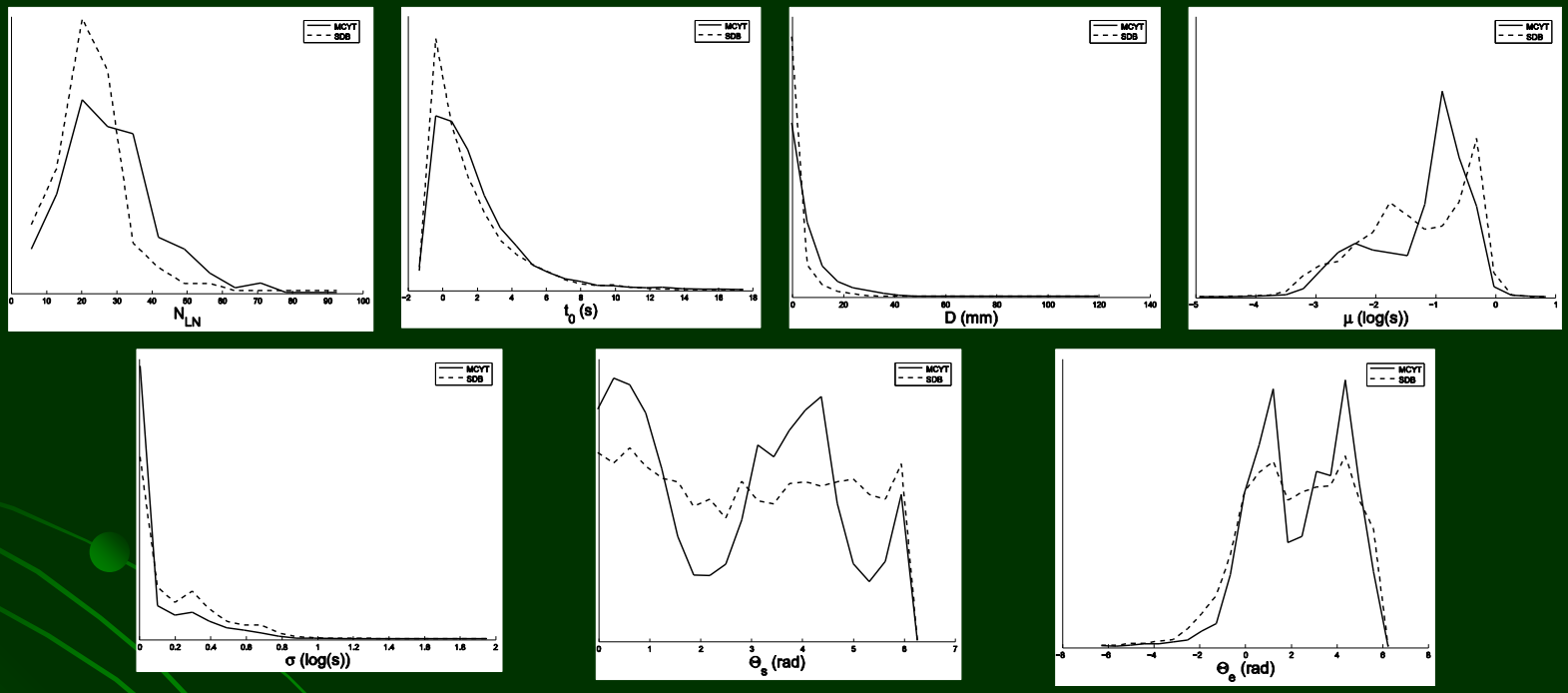


Appearance comparison

- 100 signatures (50real-50 synthetic)
- 25 subjects
- Quick inspection (less than 20 minutes)

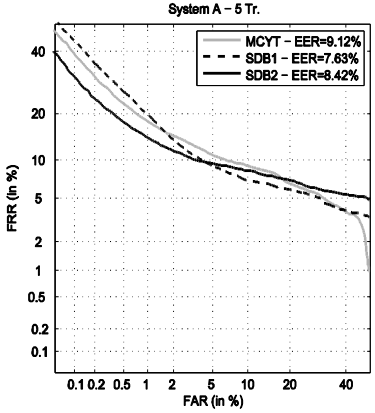
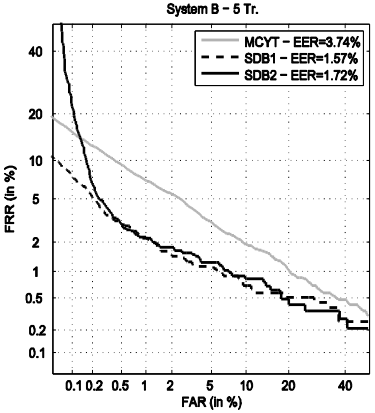
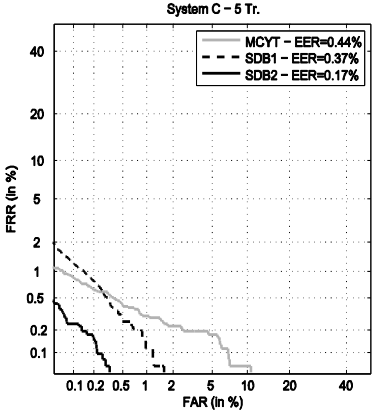
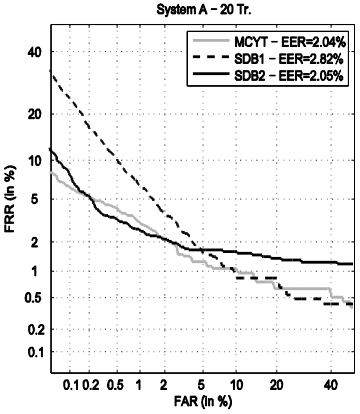
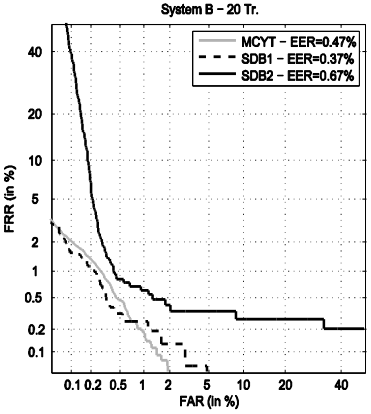
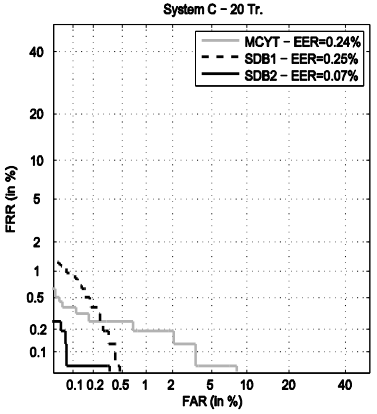
- 36% misclassified
- Similar FSR (35.28%) and FRR (36.72%)
- Similar perception of both types of signatures

Amount of shared information



Kinematical Analysis of Synthetic Dynamic Signatures Using the Sigma-Lognormal Model, J. Galbally, J. Fierrez, M. Martinez-Diaz, J. Ortega-Garcia, R.Plamondon, C. O'Reilly , Proc. ICFHR 2010

Detection error trade-offs

	System A	System B	System C
5 Tr.			
20 Tr.			

Practical Application No 2

Synthetic online handwriting generation

Collaboration with Prof. Éric Anquetil
and Abdullah Almaksour,
Université de Rennes I, FRANCE.

Incremental Learning of Handwritten Gesture Recognition Systems with few data

A. Almaksour E. Anquetil

- Context: online handwriting recognition systems for pen-based interfaces (PDAs, Tablet PCs.. Etc)
- Drawbacks
  - Writer-independent recognizer → high resource cost, low accuracy
  - Pre-defined alphabet (closed vocabulary)
    - Exhaustive alphabet → high cost, low accuracy
    - Limited alphabet → can't fit new user's needs
- Proposed Solution
  - Customized recognition system
  - No pre-defined learning alphabet (learning from scratch)
  - Writer-dependent
  - **Online and incremental learning**

Learning acceleration using synthetic data

- Synthetic handwritten gesture generation techniques can be used to overcome the problem of lack of examples when a new unseen class is added.

- Synthetic data can be generated by applying deformations on:

  - Coordinates level
    - Image scaling and slanting
    - Speed variation and curvature modification*

  - Lognormal profile level (much more realistic synthetic data)
    - Lognormal parameters variation within reasonable ranges
      - Predefined static variation ranges
      - Dynamic (incrementally estimated) variation ranges

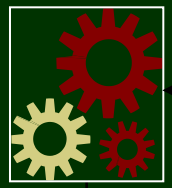
Predefined variation ranges

Real gesture

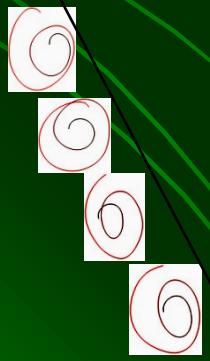
Original gesture profile

Expert, Statistics, ...

Incremental Learning Classifier



Predefined static variation ranges



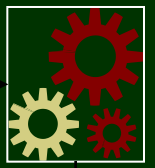
Synthetic gesture

Modified gesture profile

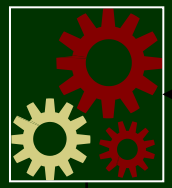
Dynamic variation ranges

Real gesture

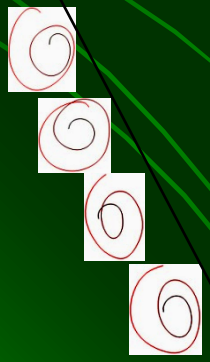
Original gesture profile



Incremental Learning Classifier



Dynamic variation ranges



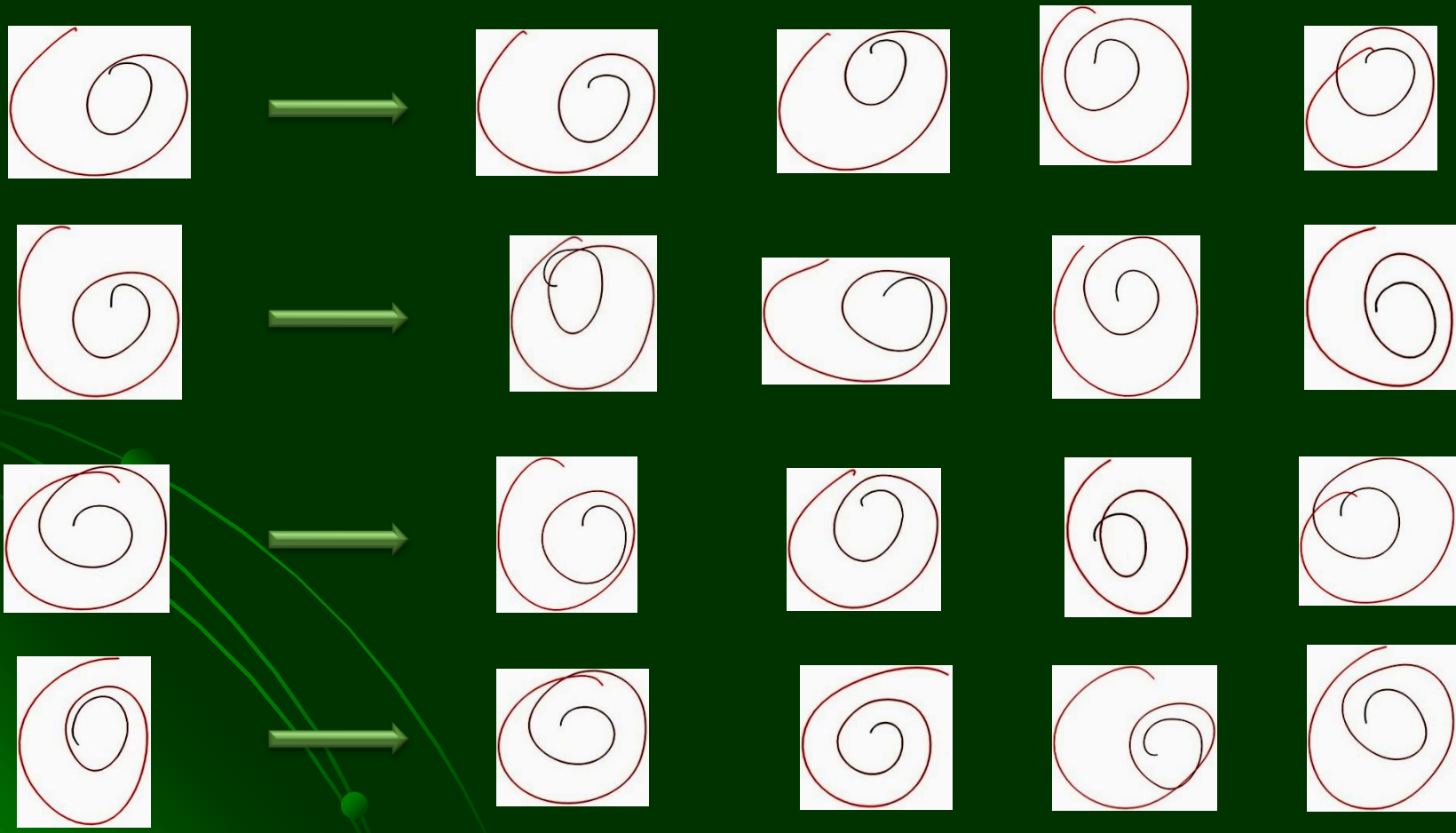
Synthetic gesture

Modified gesture profile

Lognormal-based handwriting generation (example)

Real gestures

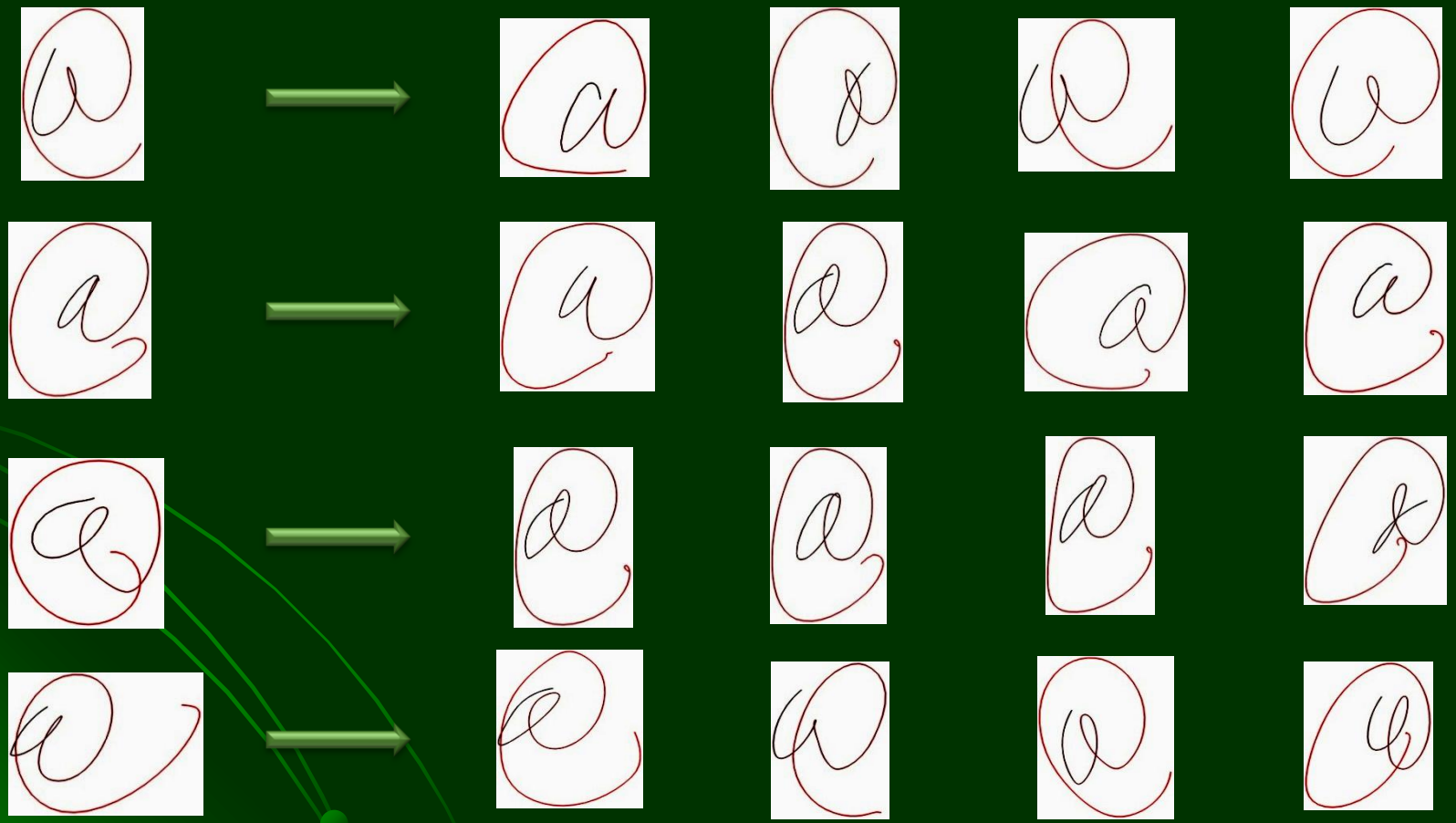
Synthetic gestures



Lognormal-based handwriting generation (example)

Real gestures

Synthetic gestures



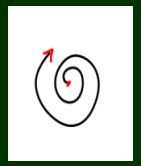
Experiments

- Need: To incrementally choose a group of gestures as handwritten shortcuts

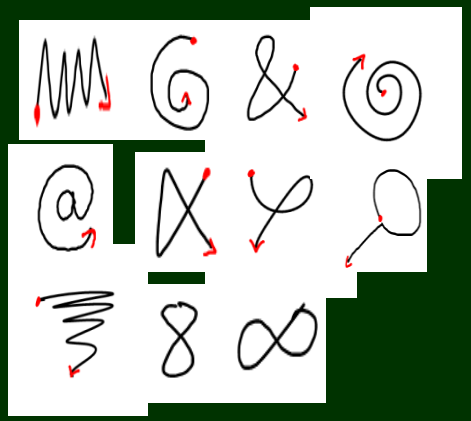
delete

copy

insert image

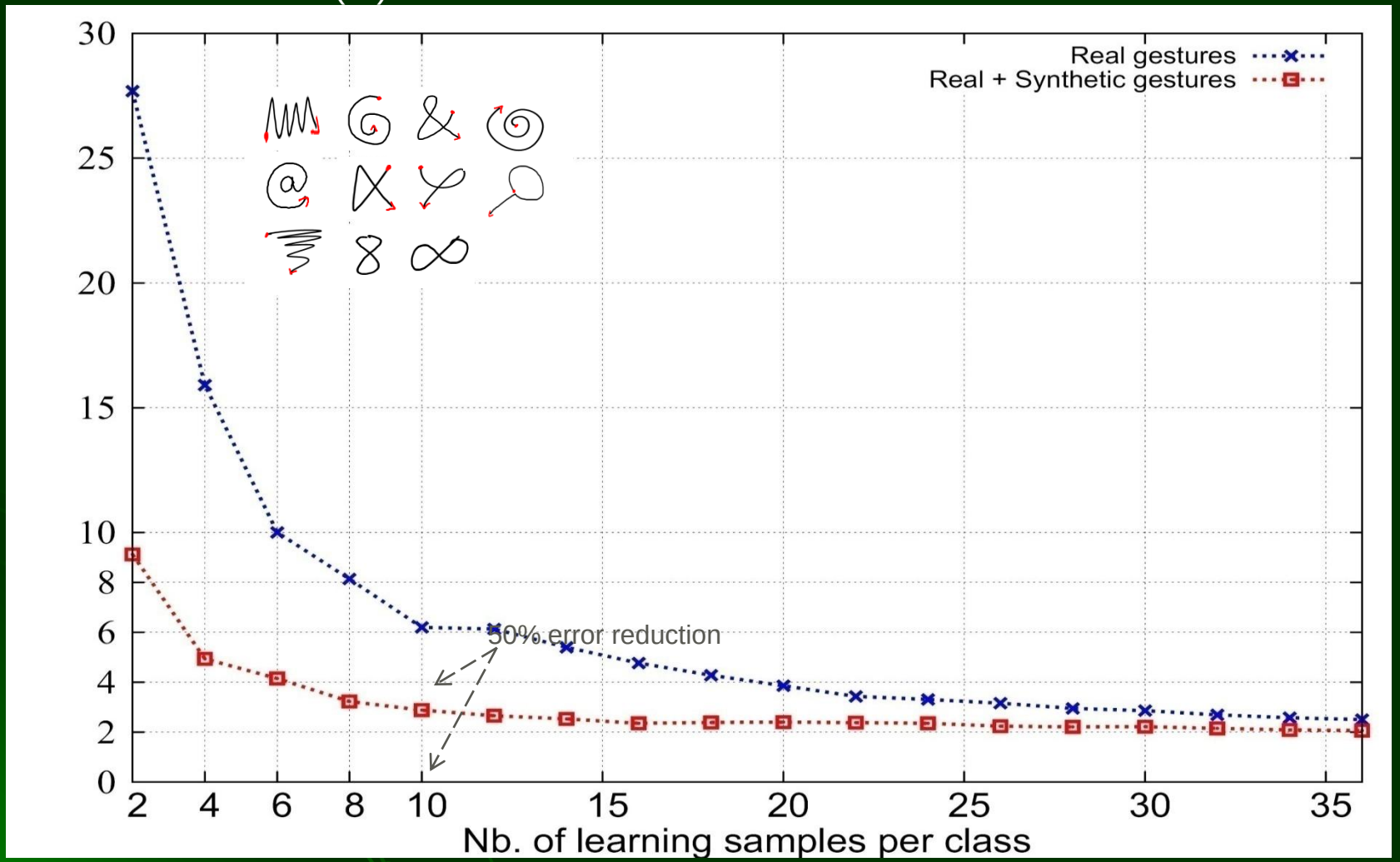


- Handwritten gesture dataset
  - 11 symbols
  - 10 features
  - 7 writer-specific datasets
    (mean results are shown)
  - 100 samples/symbol/writer
  - ~40% incremental learning, ~60% test
  - 10 generated synthetic gestures for each training sample



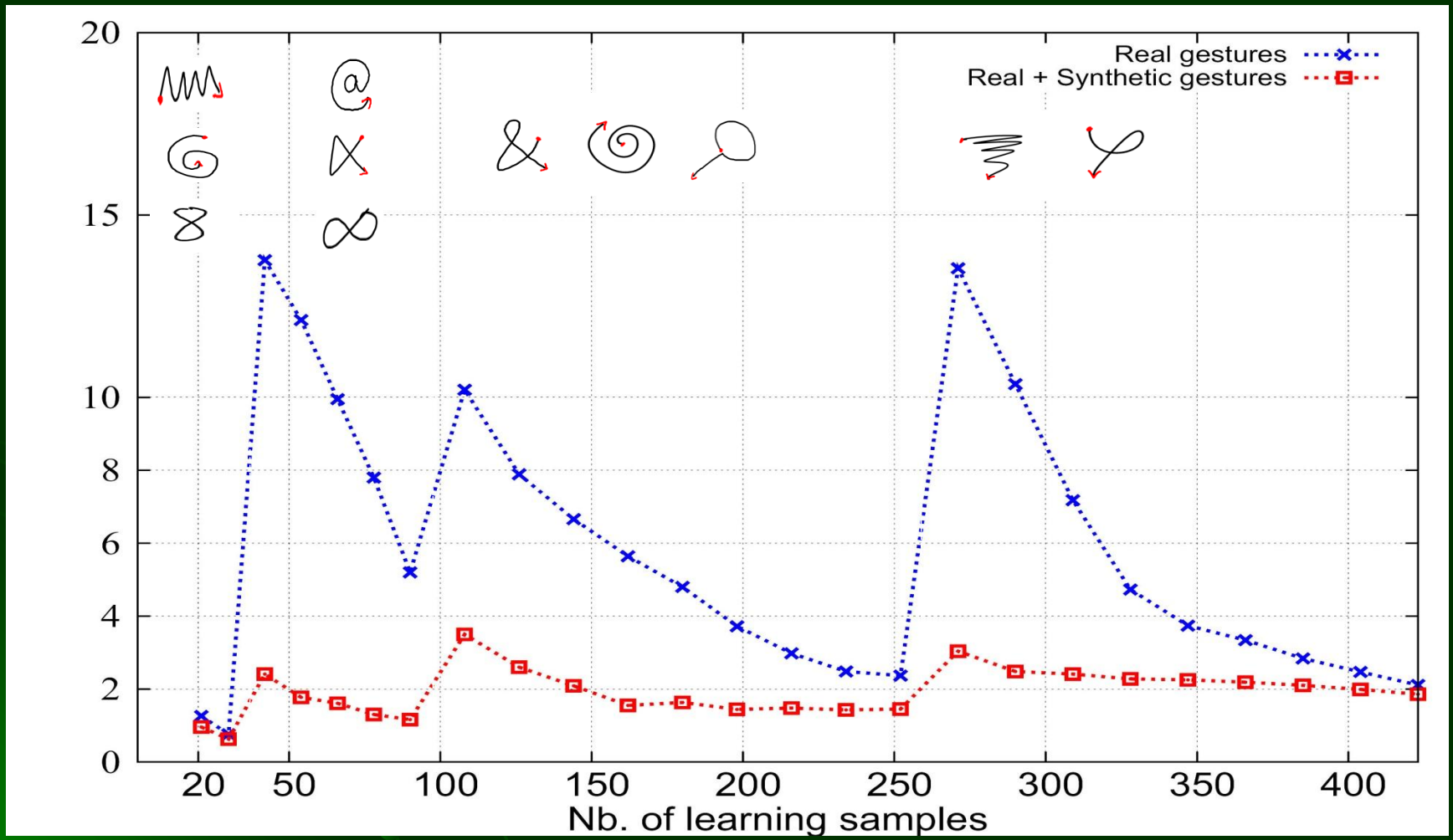
Results

Misclassification rate (%)



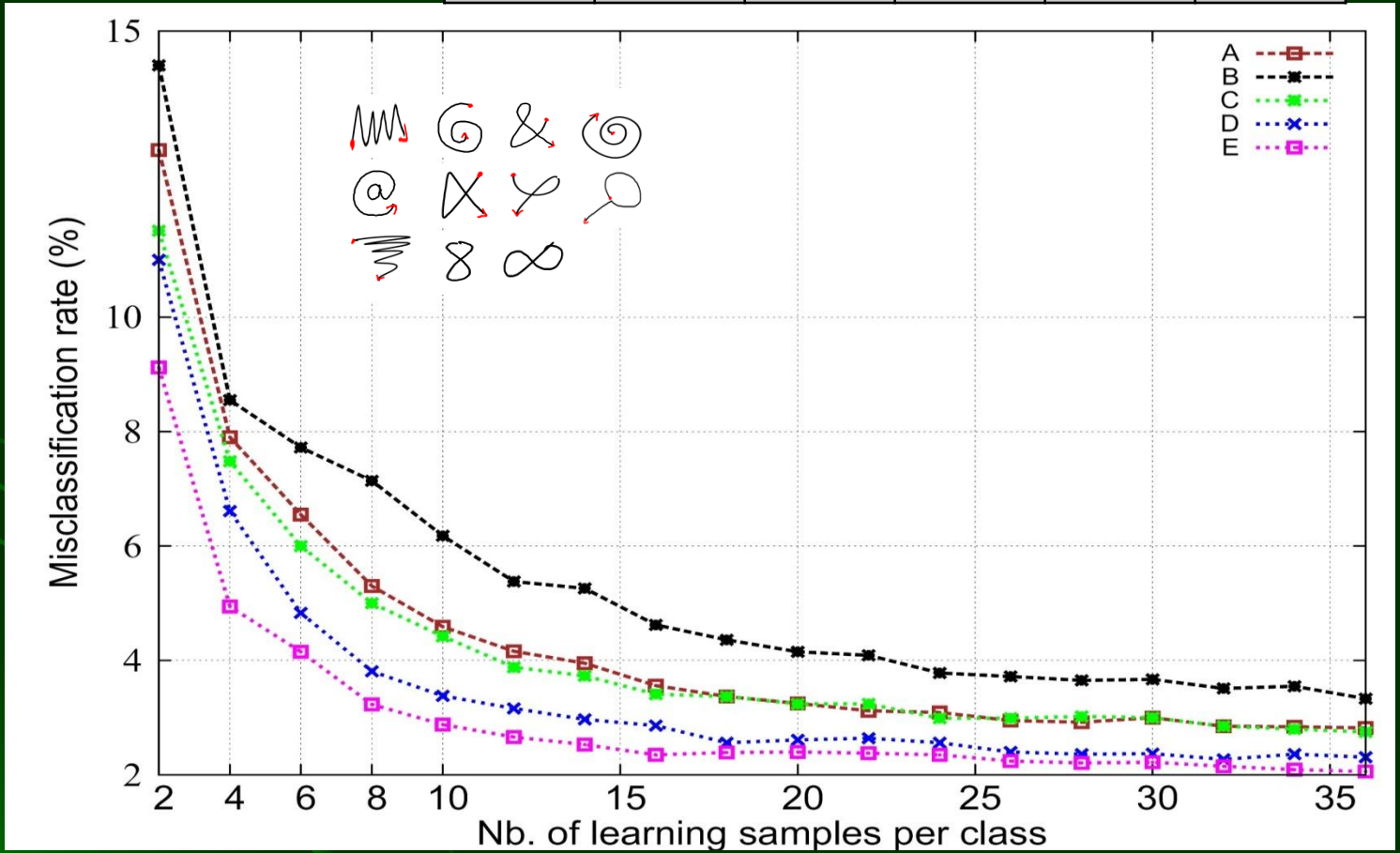
Results

Misclassification rate (%)



Predefined variation ranges

	Mu	Sigma	D	Téta1	Téta2
A	[-5%,5%]	[-5%,5%]	_	_	_
B	_	_	[-5%,5%]	_	_
C	[-5%,5%]	[-5%,5%]	[-5%,5%]	_	_
D	_	_	[-5%,5%]	[-20°,20°]	[-20°,20°]
E	[-5%,5%]	[-5%,5%]	[-5%,5%]	[-20°,20°]	[-20°,20°]



Practical Application No 3

Analysis of Cerebrovascular Accident Risk Factors

O'Reilly, C. Plamondon, R. "Impact of stroke risk factors on Human Movements"
In Press, **Human Movement Science**, August 2010.

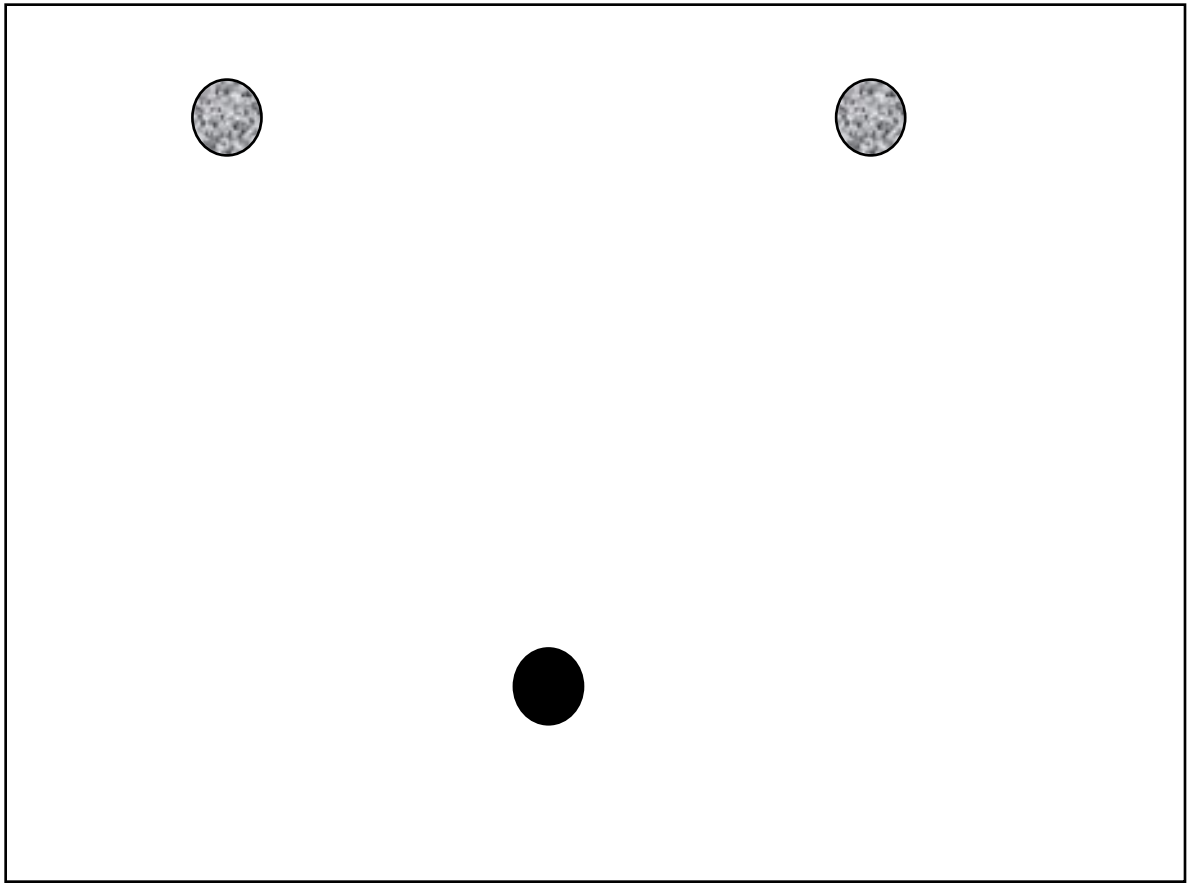
Goal

Investigate the relationships between cerebrovascular accident (CVA) risk factors and the Sigma-Lognormal characteristics of handwriting movements

O'Reilly, C., Plamondon, R., Lebrun, L.-H., Clément, B., & Mathieu, P. A. (2009).
"Sigma-Lognormal Analysis of a Complex Movements Neuromuscular Test."
Proc. 14th Conference of the International Graphonomics Society, Dijon, France, September 13-16.

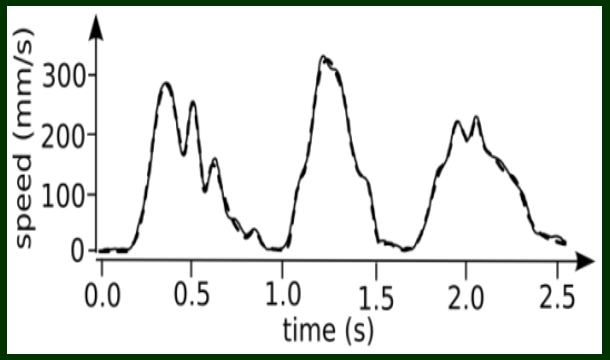
Experimental Protocol

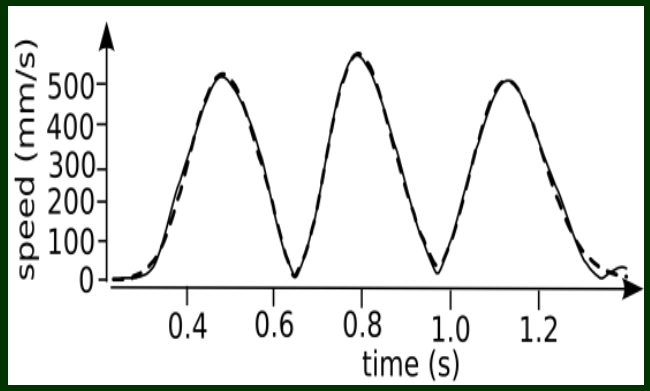
- Audio stimuli.
- Task: to draw a triangle as fast as possible.
- Three different sizes of triangles.
- Two different directions (Clockwise-counterclockwise).
- Two repetitions (12 movements per subjects).
- 120 subjects.
- 4 age groups (25-39, 40-54, 55-70, 70-85).
- 52 males, 68 females.
- 36 subjects with CVA risk factors.

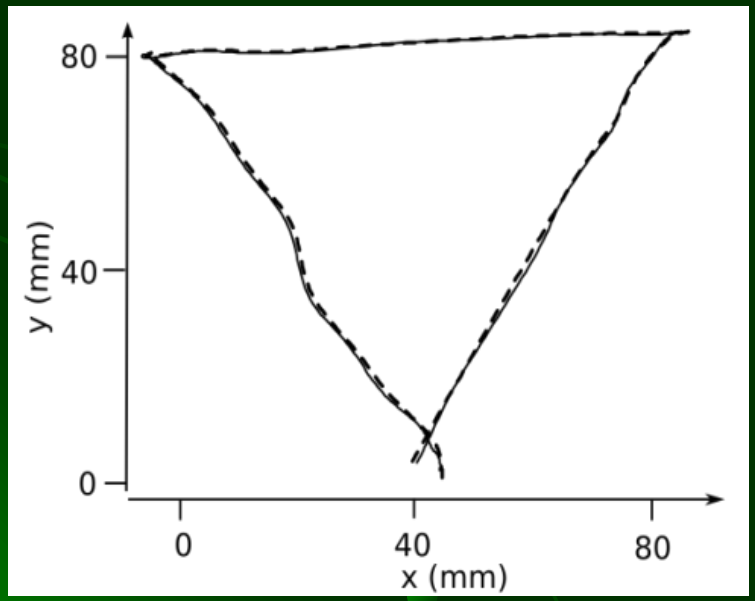


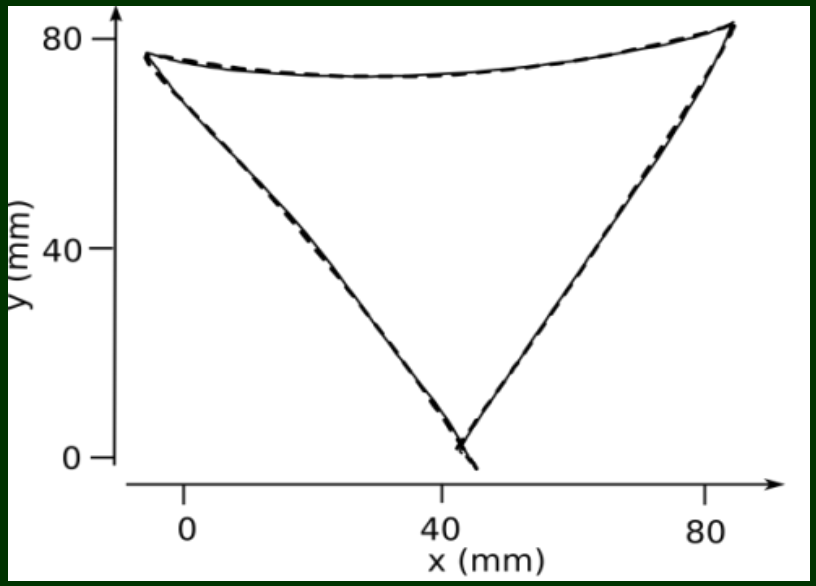
Targets are 15mm in diameter and are at the apex of an equilateral triangle with vertex of 135mm, 90mm or 45mm long.

TYPICAL EXTRACTION RESULTS



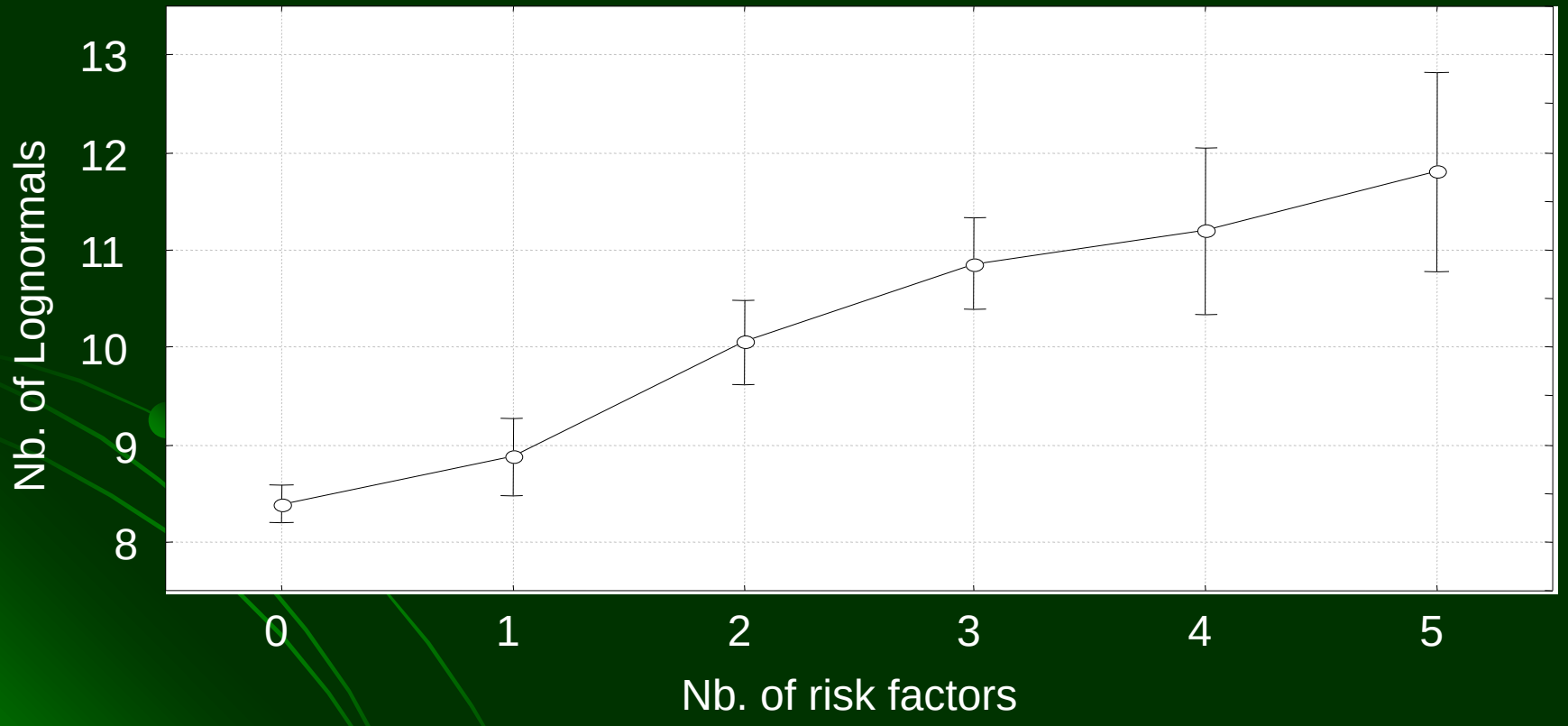




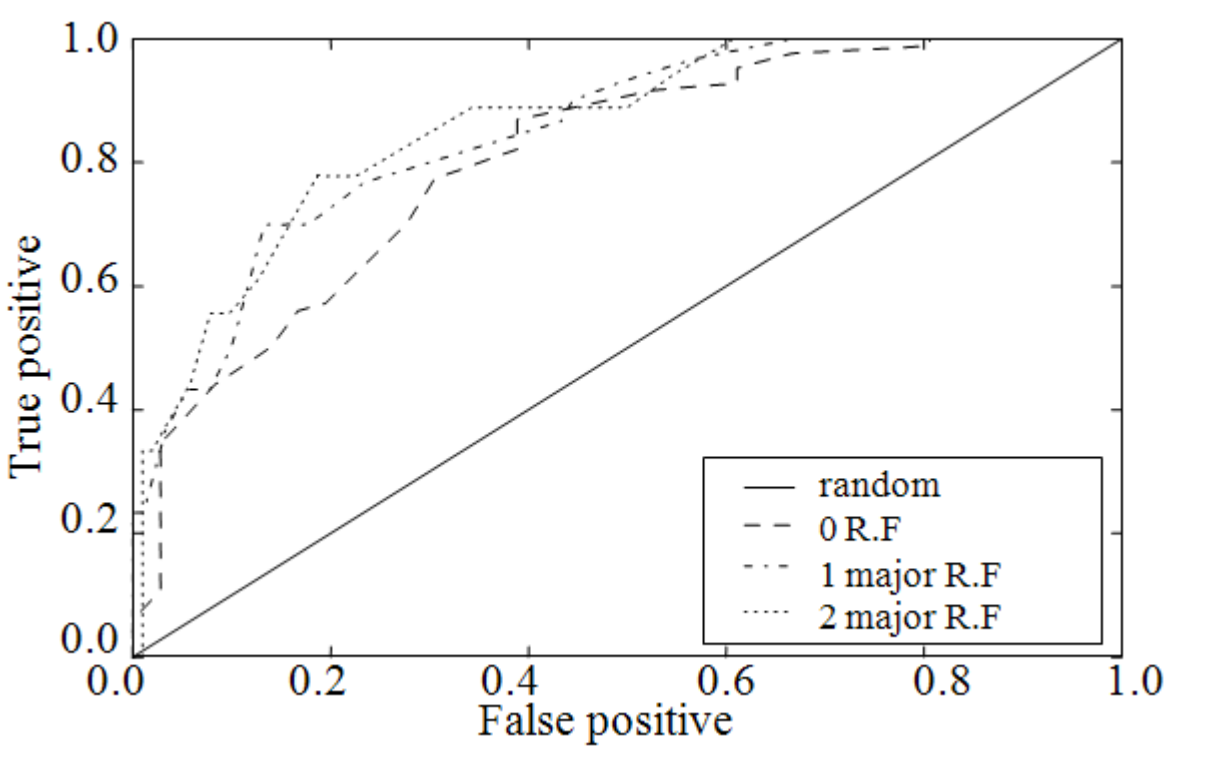


Risk factor effects

Effect: F(5, 1430)=27.025, p<0.0001
Vertical bars denote 0.95 confidence intervals



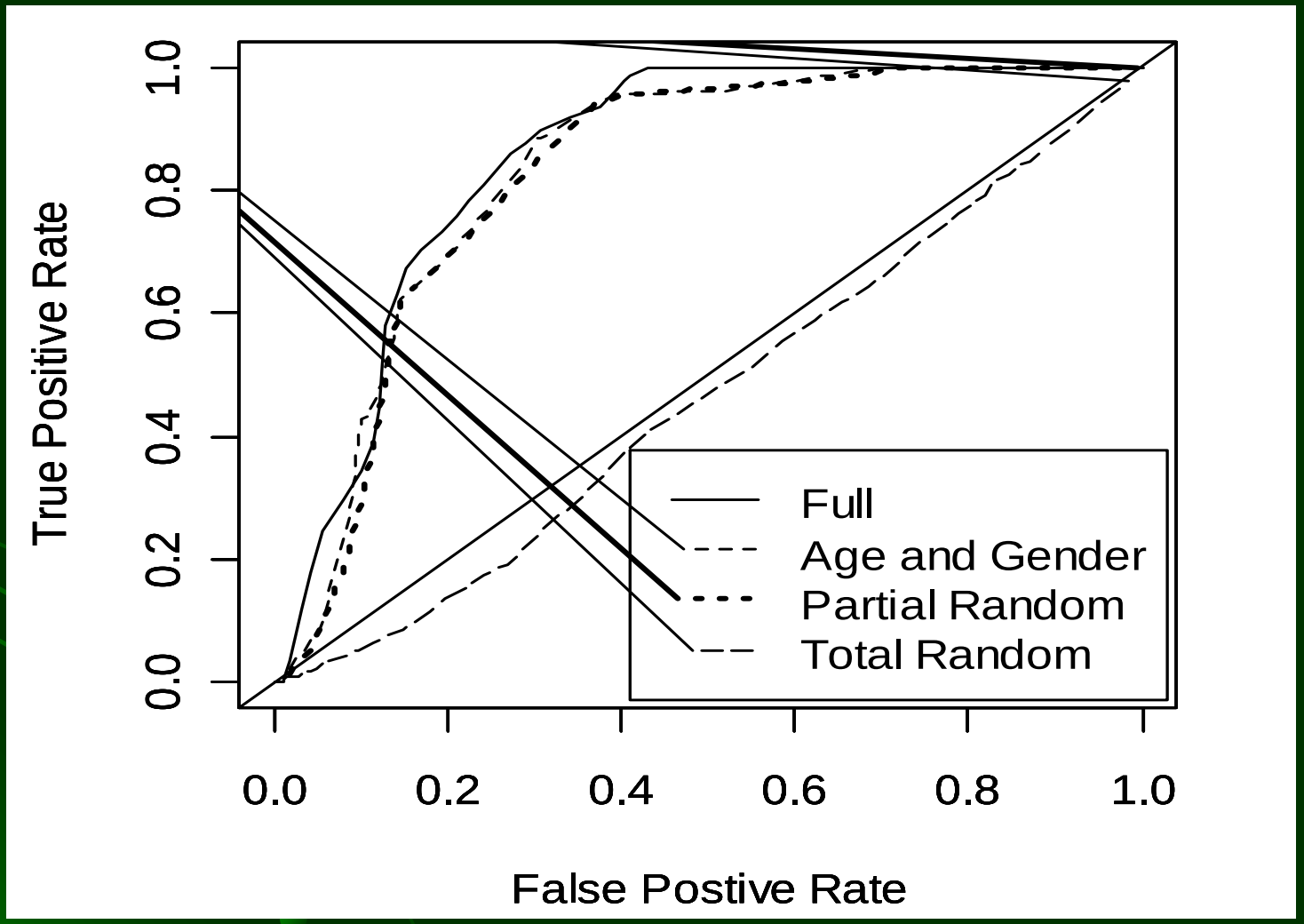
Risk factor predictability



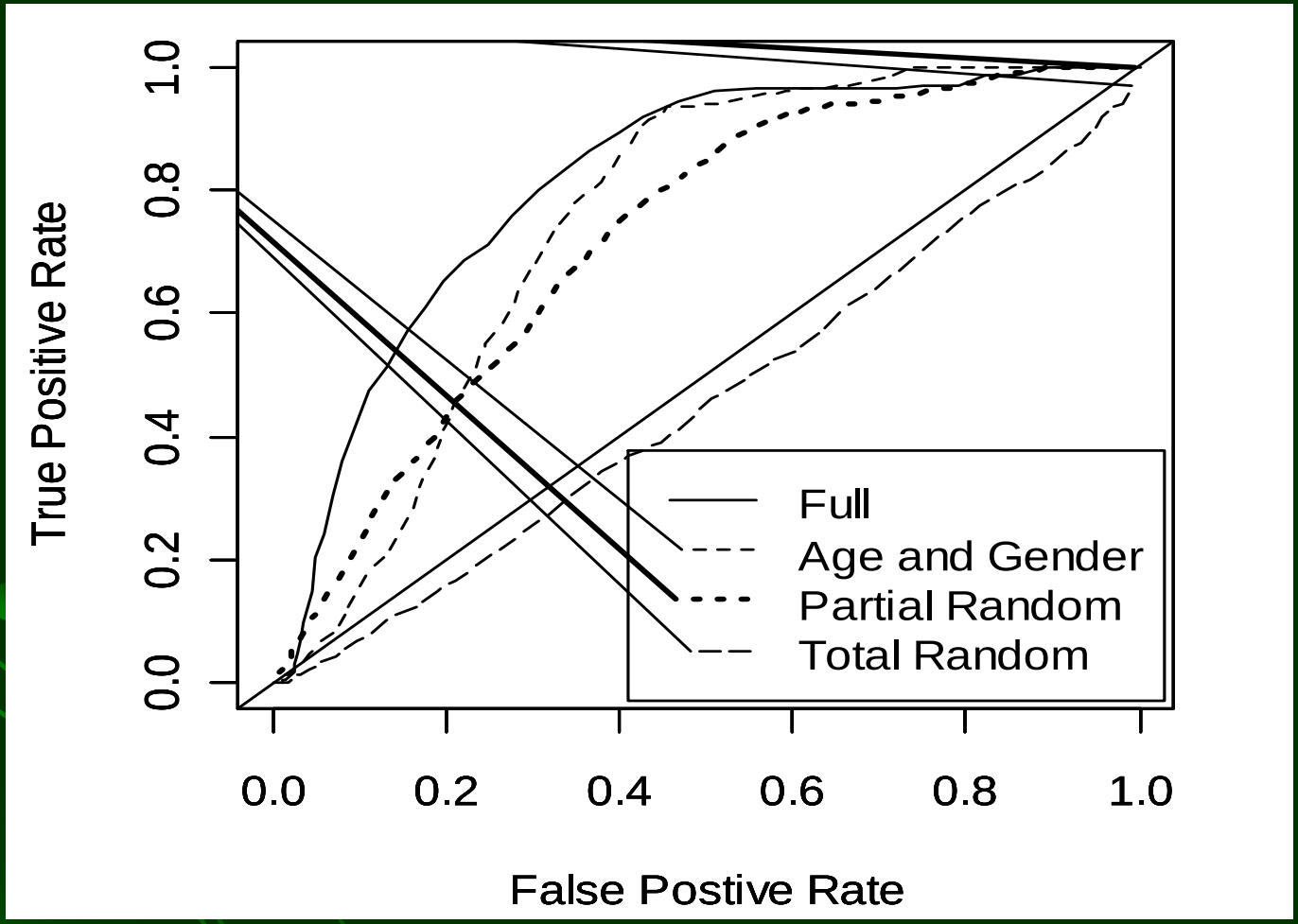
Prototype-based extraction

- From the 36 Sigma-lognormal parameters
- Scaling factor
- Time-shifting constant
- Snr reconstruction errors
- +age
- +gender

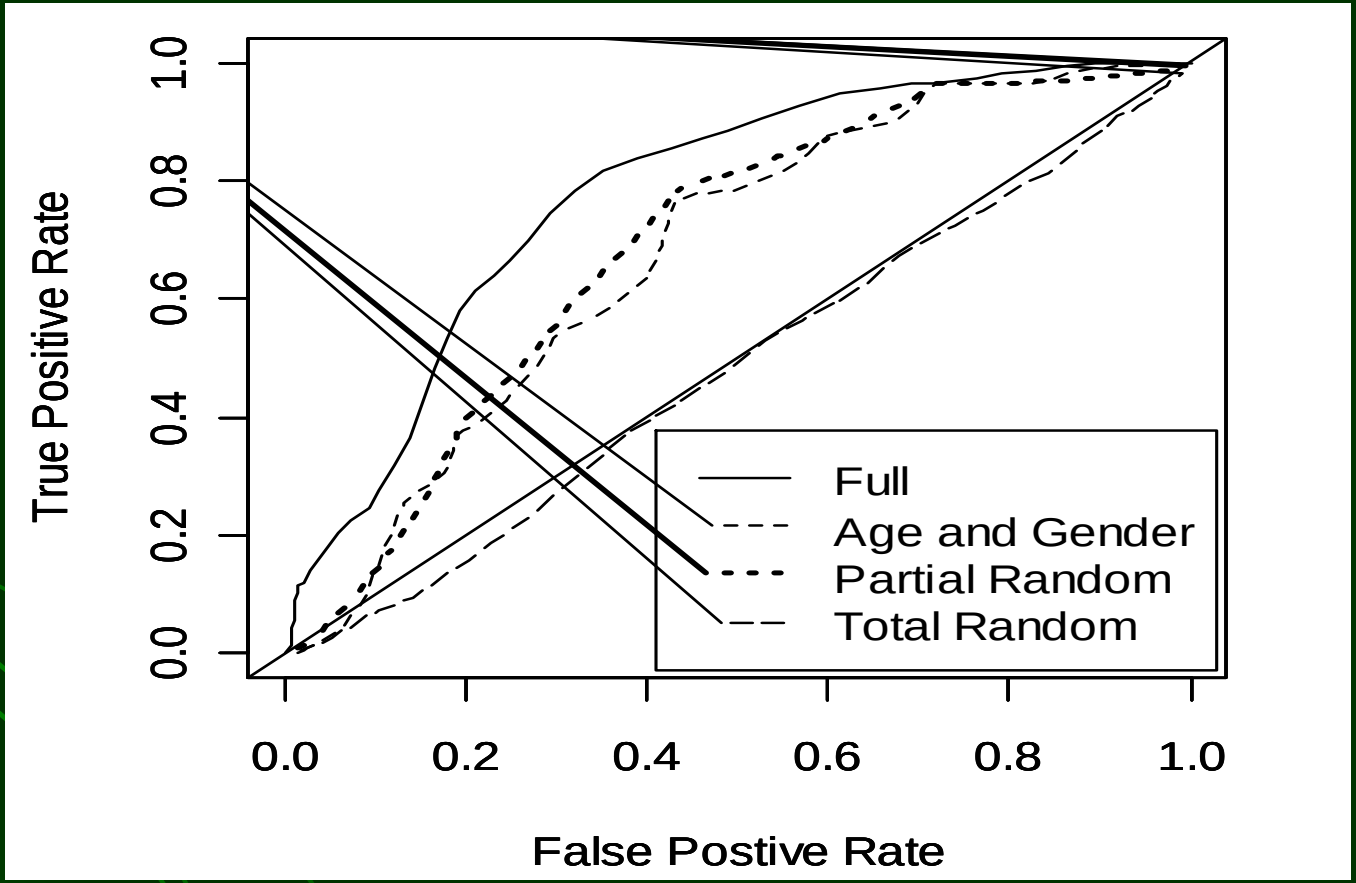
ROC CURVES: CARDIAC PROBLEMS



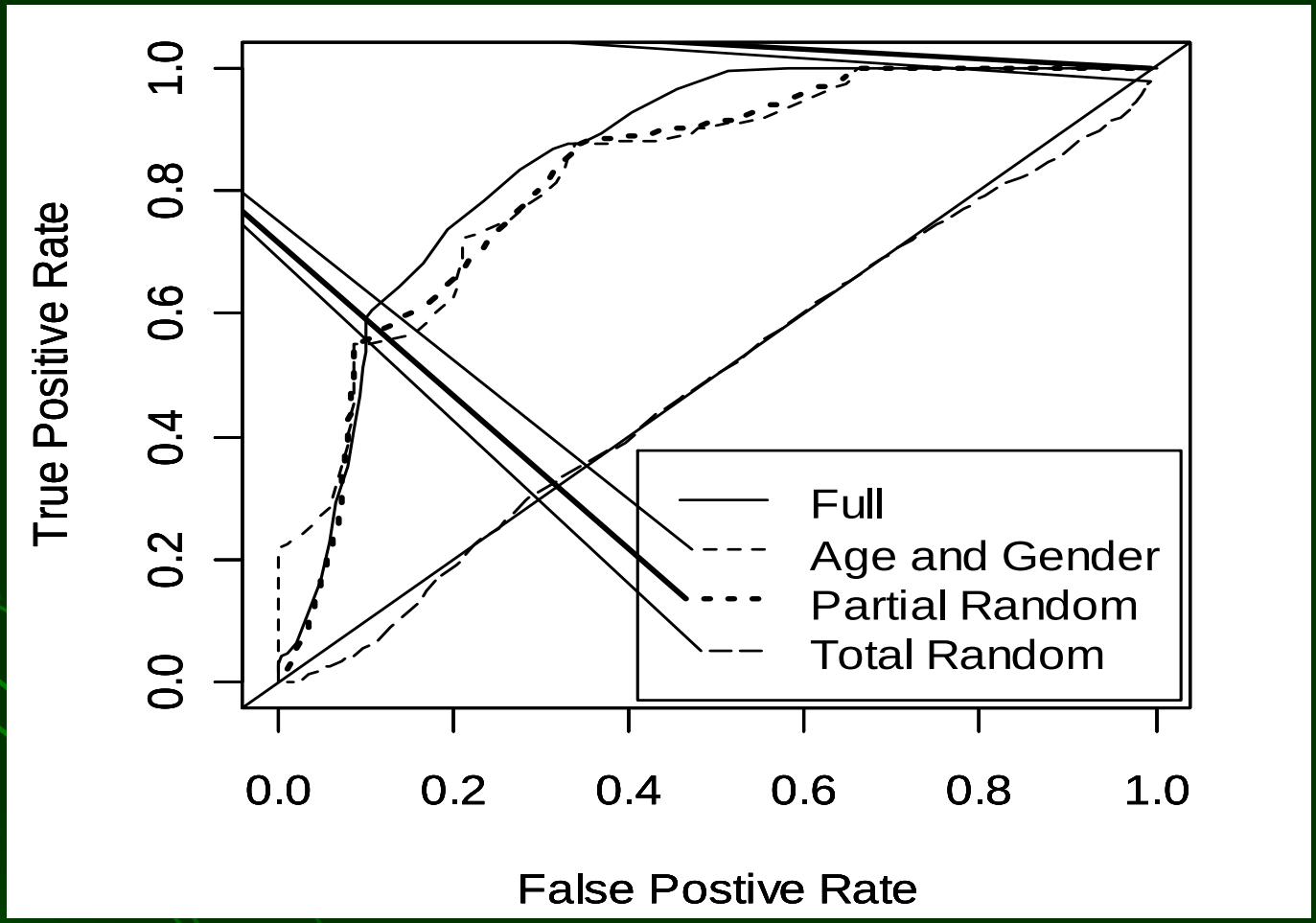
ROC CURVES: DIABETES MELLITUS



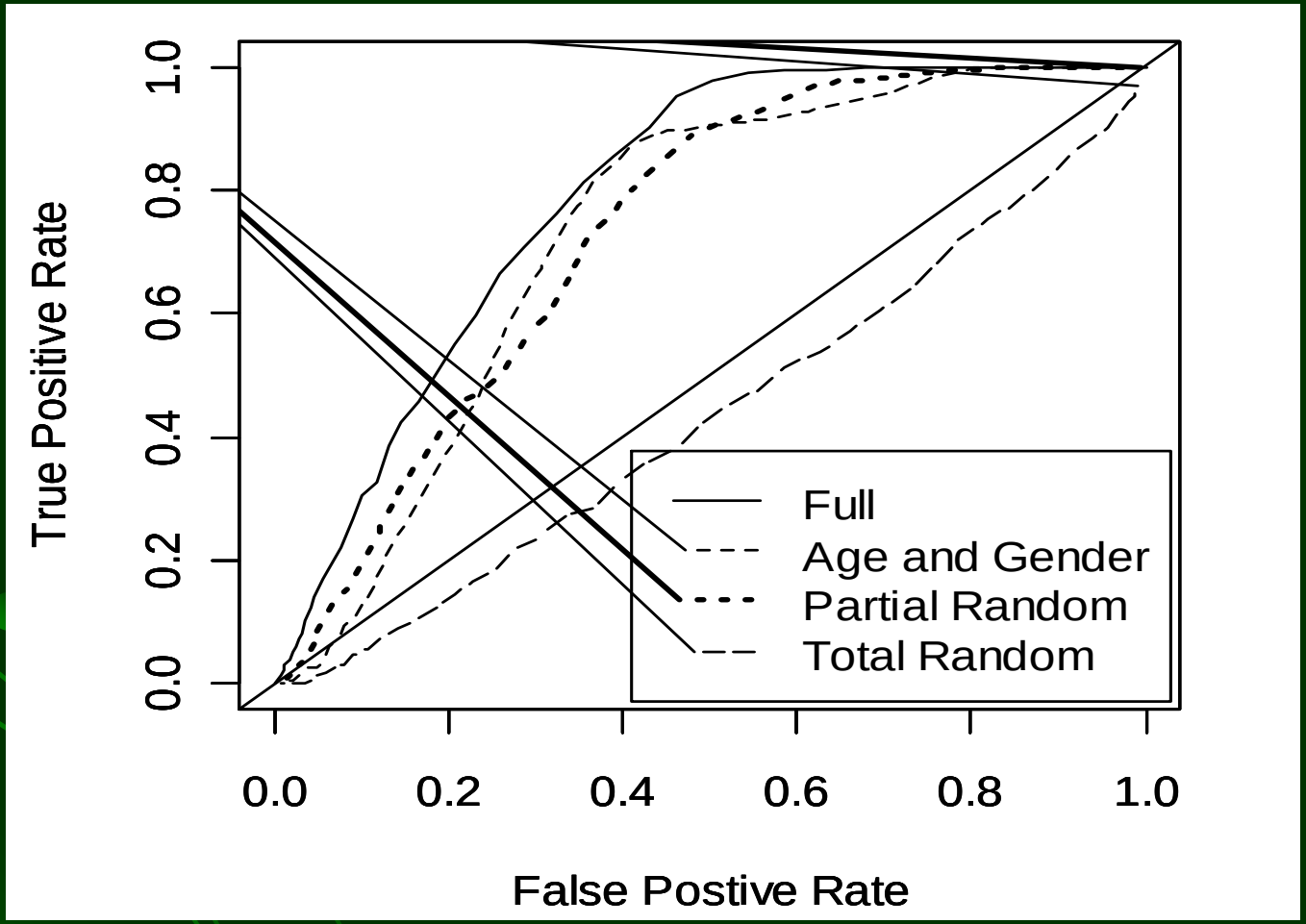
ROC CURVES: HYPERCHOLESTEROLIMIA



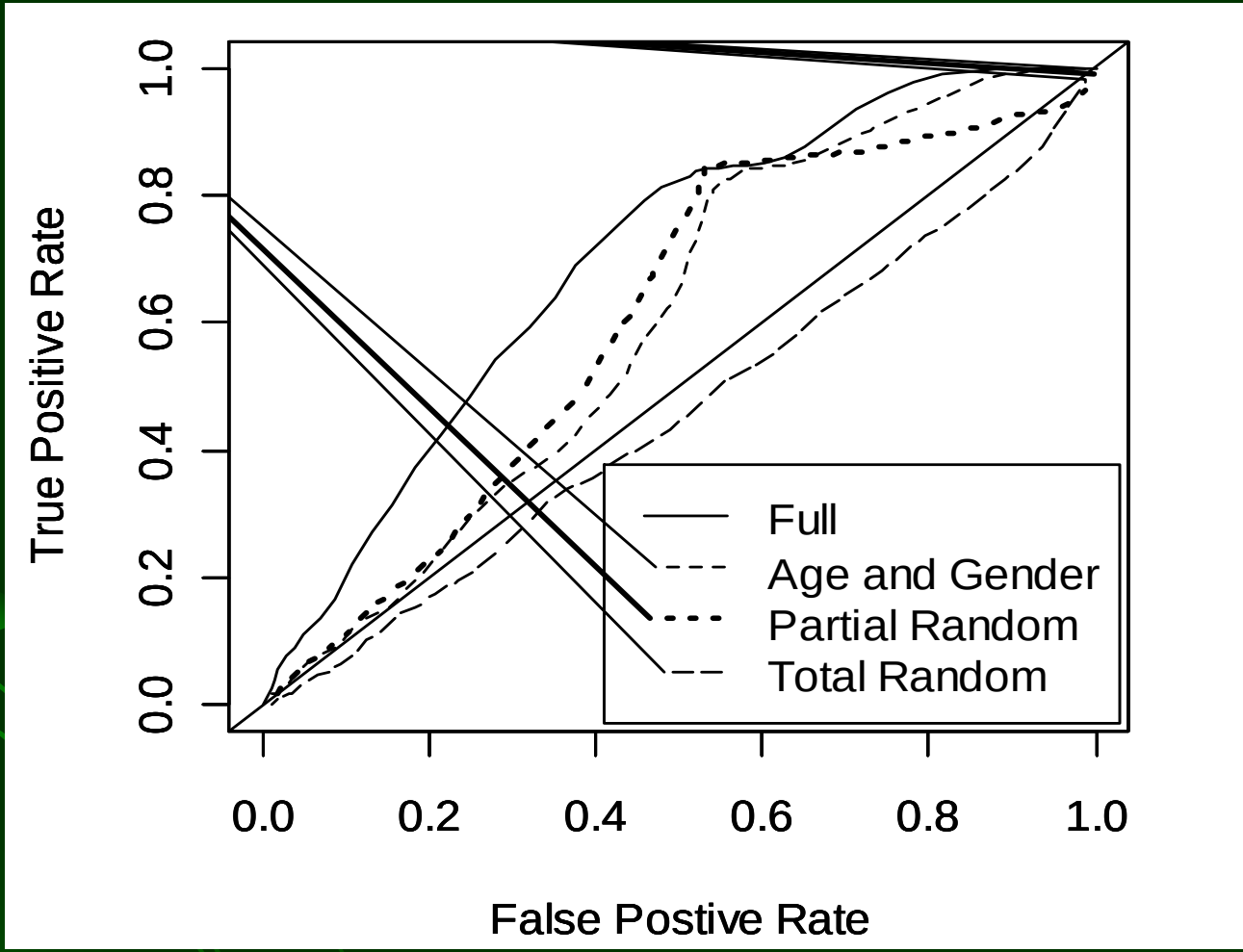
ROC CURVES: HYPERTENSION



ROC CURVES: OBESITY



ROC CURVES: CIGARETTE SMOKING



SUMMARY

- As area under the ROC curve of 0.68 to 0.82 have been obtained on the prediction of six of the principal CVA risk factors using only information extracted from the movements, there is a definitive relationship between the presence of stroke risk factor and the characteristics of human movements. Although, a large part of it may be attributed to the effect of the age and the gender, there are convincing evidences that these two factors does not account for all of it. Therefore, human movements seem to contain supplementary information related to the susceptibility of eventually suffering from a CVA which is neither attributable to the age nor the gender.

Conference Overview

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Conclusion: future trends.

Take home messages

1. Single stroke analysis: DELTA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

1. Multiple stroke analysis: SIGMA-LOGNORMAL MODEL

a) Parameter extraction

b) Theoretical validation

c) Practical applications

Potential Applications #n

- 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, new CAPTCHAs
- 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, Brain stroke)
- 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.

CONCLUSION

Nothing is more practical than a good theory!

HOLISTIC CONCLUSION

The whole human being might be hidden in a single stroke…

Neuromuscular Studies of Handwriting Generation and Representation

QUESTIONS?

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École Polytechnique de Montréal
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