ALWRITE

ALzheimer Writing Walking Talking Empowerment

Etude de l'identification de paramètres de l'écriture, la voix et la marche chez des patients MCI et MA stade débutant

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Soutenir la recherche pour prévenir les risques

Langage dans la MA débutante

- Dégradation de la qualité d'écriture manuscrite (motricité fine)
- **Manque de mots**: noms propres, dates, mots moins familiers+++
- Circonlocutions, paraphasies.
- Habitudes de lecture et **écriture affectées** Ex. chèque
- **Erreurs dans la compréhension de l'intention** de l'interlocuteur (sarcasme, métaphores)

Fonctions exécutives, praxiques, langagières, mémoire sémantique,...

Macoir et al (2014)
Barkat-Defradas et al (2008)
Croisile (2005)

Objectif principal

- Identifier des indicateurs discriminant trois groupes : PA sans trouble cognitif (Contrôle), MCI et MA débutant.

Objectifs secondaires

- **Evaluer la corrélation** entre les paramètres d'écriture, voix et marche et les performances neuropsychologiques.
- **Mesurer la valeur prédictive** des indicateurs à M0 par rapport aux modifications des performances cognitives et aux modifications des mesures multimodales à M12

Méthode

- Etude monocentrique, longitudinale, exploratoire.
- 3 groupes de 50 personnes:

- **M0 – M12** : Protocole d'évaluation de l'écriture, de la voix et de la marche (~1h) + bilan neuropsychologique HDJ

Protocole d’acquisition d’écriture et de voix

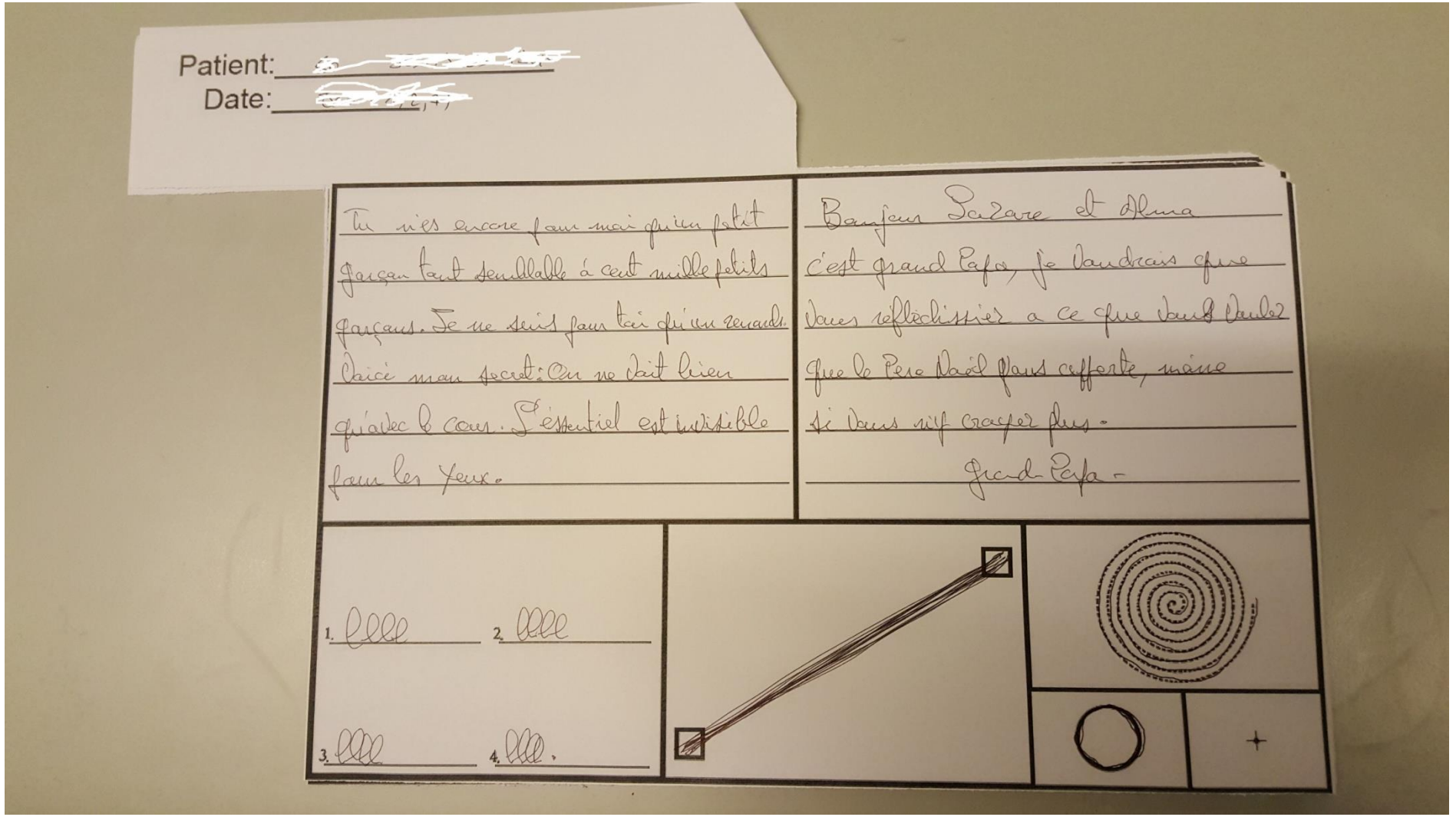
1. 4 séries de 4 lettres *ℓ* cursives
2. Recopier un texte imposé de quelques lignes.
3. Lire le même texte imposé.
4. Écrire un texte spontané et non connu a priori.
5. Lire un texte spontané et non connu a priori
6. Tracer des cercles, une spirale, des lignes, et maintenir sur un point fixe le stylo durant quelques secondes.

Tablette WACOM

Sony Voice Recorder

Olympus Voice Recorder

Exemple d'acquisition de données manuscrites



7. Remplir sur la tablette une simulation de chèque et de courrier postal.

Banque

Neuf cent quatre-ving-trois euros et vingt-cinq

Centimes

A Ecole de Sainte Geneviève

€

€ 983,25

N° du compte

A

Le

Signature

Protocole d’acquisition (gestes fins et marche)

8. Effectuer dans l’air des gestes fins

(Chiffres + formes géométriques simples)

9. Marcher sur le tapis GAITRite

selon le protocole de Broca

Uncovering Major Age-Related Handwriting Changes by Unsupervised Learning

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Uncovering Major Age-Related Handwriting Changes by Unsupervised Learning

Outline

- Introduction
- Proposed Approach
    - Feature Extraction
    - Unsupervised Two Layer Scheme
- Experimental Setup & Results
- Conclusions & Perspectives

Handwriting (HW) Activity

- HW is a fine motor task requiring high cognitive skills
- HW is intrinsic to each writer
- HW evolves over the years
- HW is affected by many disorders
  (i.e. Parkinson, Alzheimer, MCI) [1-2]

- **Objective:** study the link between age and HW
  - Changes due to age vs. changes due to early pathologies

State of the Art: Age & HW

- Not many studies
- Studies based on descriptive statistics [3-6]
    - Multiple Regression, Pearson's correlation

- Limitations
    - Assumption that all persons show the same HW evolution patterns

- Our Approach
    - All persons do not necessarily have the same HW evolution patterns
    - Seek to detect elder groups with similar HW styles

2 Layers Approach

- Feature Extraction
  - Layer 1: *Low Level* signal Information from *words*
  - Layer 2: *High Level* information (*stability*) from *writers*

- Unsupervised Age Characterization
  - Clustering without using age information
  - Using K-means and Hierarchical Clustering algorithms
  - Automatic estimation of the number of clusters: Silhouette criterion

Handwritten Online Samples

- Acquired using a digital tablet (Wacom)

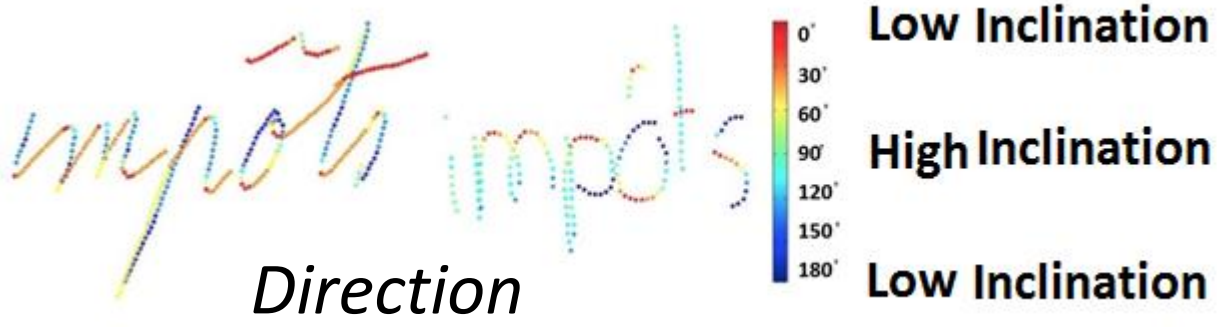
- Sampled at 100Hz
- Register HW as a sequence of points $(x(t),y(t),p(t))$
- Advantages
  - Possible to study the dynamics of HW
  - Acquire information about pressure

Feature Extraction: 1st Layer

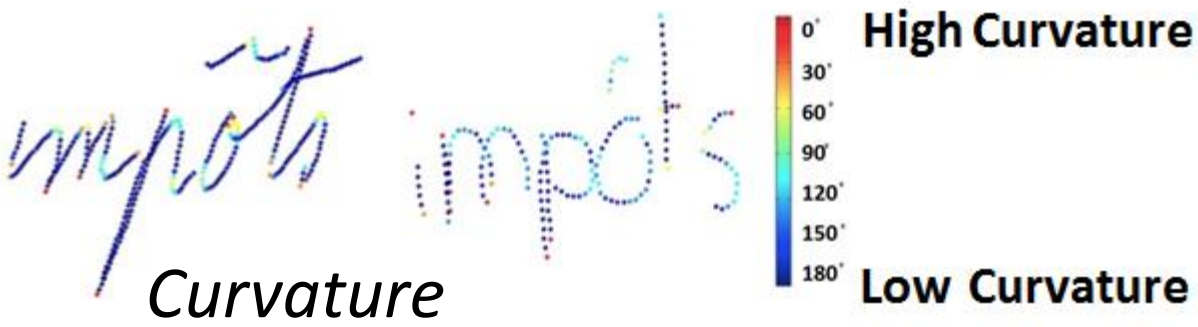
- 33 *Dynamic Features*: *speed, acceleration, jerk, pressure, time on air, etc.*

Speed

- 21 *Spatial Features*: *direction* histogram, *curvature* histogram, etc.



Direction

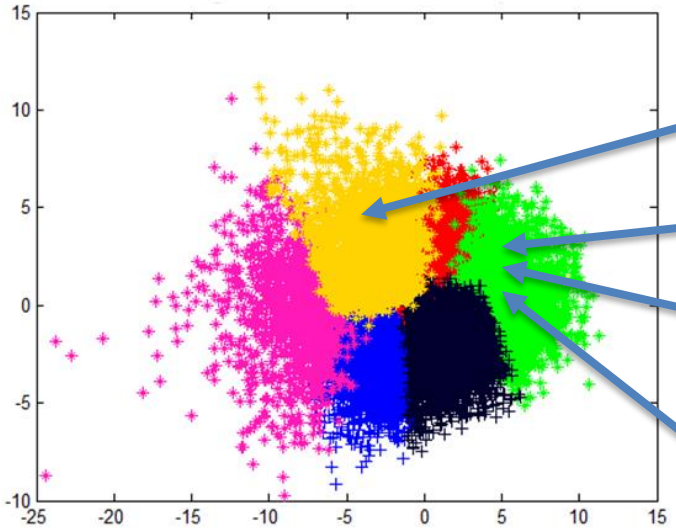


Curvature

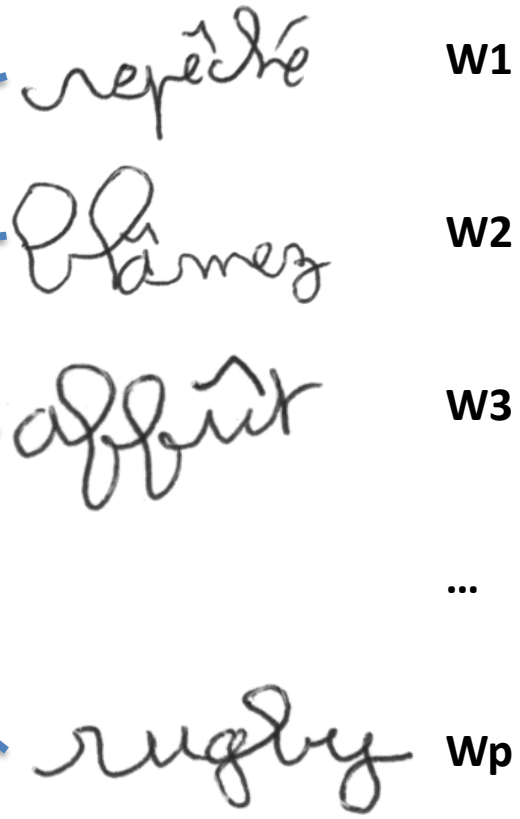
- Feature vector of dimension 54

Feature Extraction: 2nd Layer Features

- Each writer *p* → Set of W_p words → W_p feature vectors
  - Distribution of the W_p words over the 1st layer's clusters (9 features)



1st Layer Clusters



W1

W2

W3

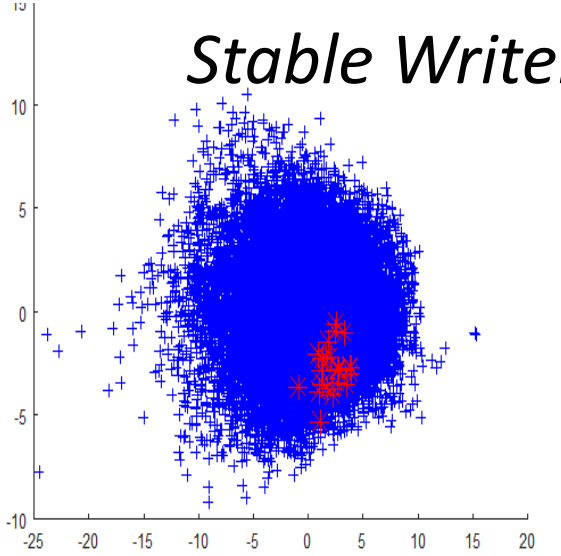
…

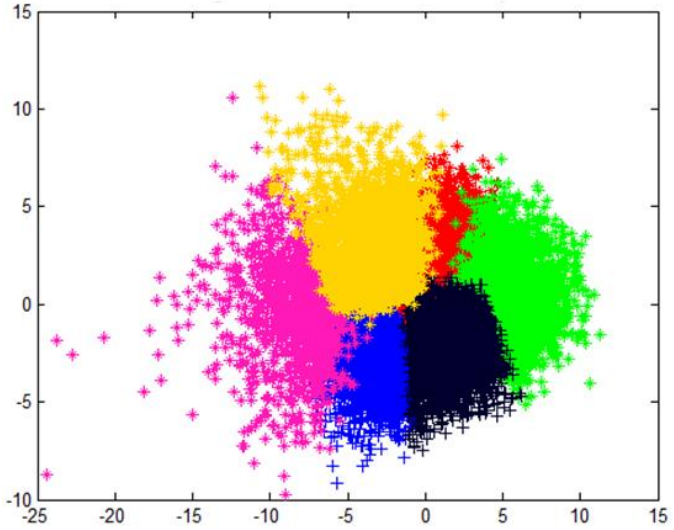
Wp

Feature Extraction: 2nd Layer Features

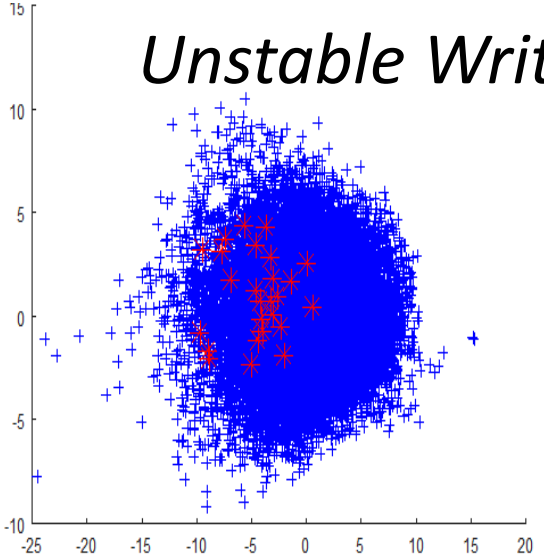
- Each writer *p* → Set of W_p words → W_p feature vectors
  - Histogram of pairwise distances between W_p words (5 features)

Stable Writer





Unstable Writer



Word Distribution in the 54-dim. feature space

- Final feature vector of dimension 14

Unsupervised Clustering

- Objective
  - Automatically detect HW styles and study their correlation with age
- 1st Layer Clustering
  - Performed on *words* using *low level* descriptors
  - Writer Independent
  - k_1 word clusters
- 2nd Layer Clustering
  - Performed on *writers* using *high level* descriptors
  - Distribution of each writer's words over the 1st layer clusters
  - Stability measures
  - k_2 writer clusters

Experiments

- Database: IRONOFF + Broca Hospital Dataset.
- 905 writers from 11 to 86 years old.
- Each writer has written between 20 to 50 words.
- 6 Age groups were defined.

Name	Age Range	Number of Writers
Teenagers (A1)	11 – 17 years old	68 Writers
Young Adults (A2)	18 – 35 years old	639 Writers
Middle Age Adults (A3)	36 – 50 years old	133 Writers
Mature Adults (A4)	51 – 65 years old	43 Writers
Seniors (A5)	66 – 75 years old	14 Writers
Elders (A6)	76 – 86 years old	8 Writers

- Problem: persons between 18 and 50 years old are overrepresented.

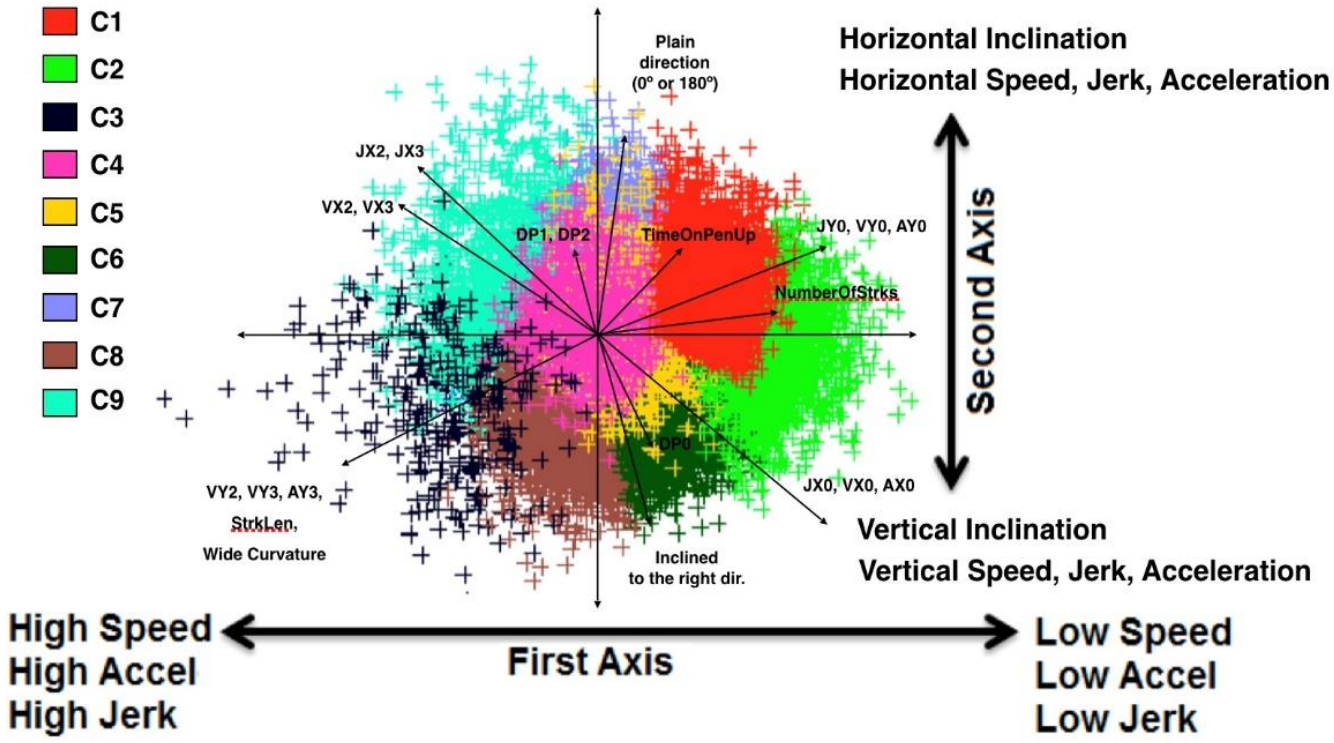
Experimental Setup

- Aim: increasing the “number” of elders and teenagers
  - Each person *p* has from 20 to 50 words
    - Generate from *p* a set of virtual writers with 10 to 15 words each
    - i.e. a writer with 25 words splits in 2 writers of 13 and 12 words

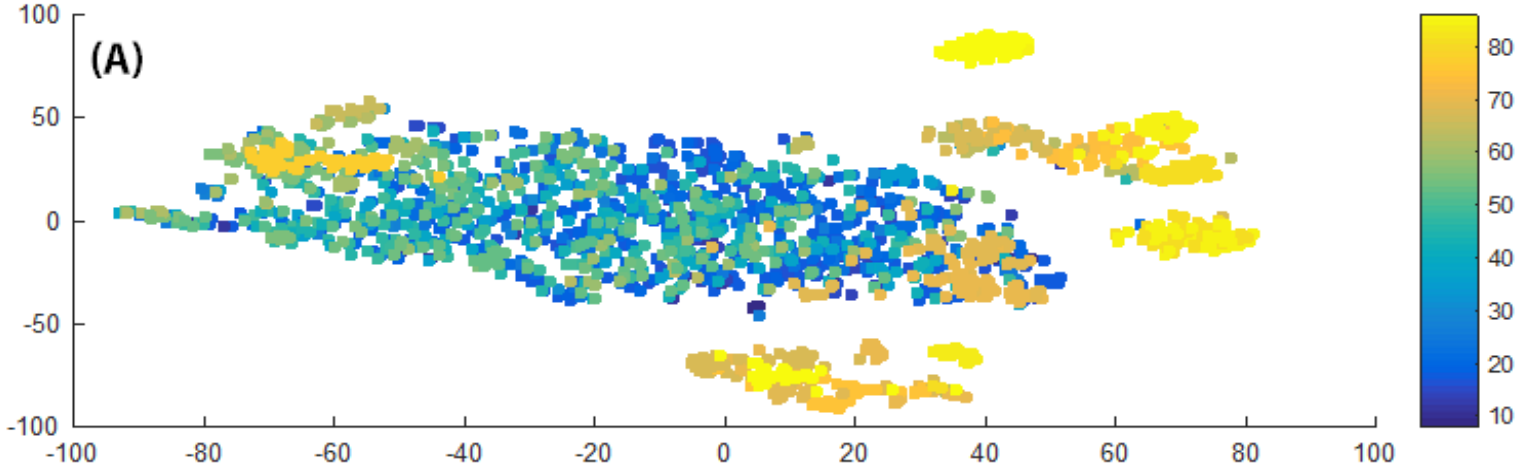
- Balancing the database age distribution:
  - Ensure the same number of writers per age group
  - 26 writers for each age group considered → Total: 156 writers
  - Allow sound comparisons

Results: 1st Layer Clustering

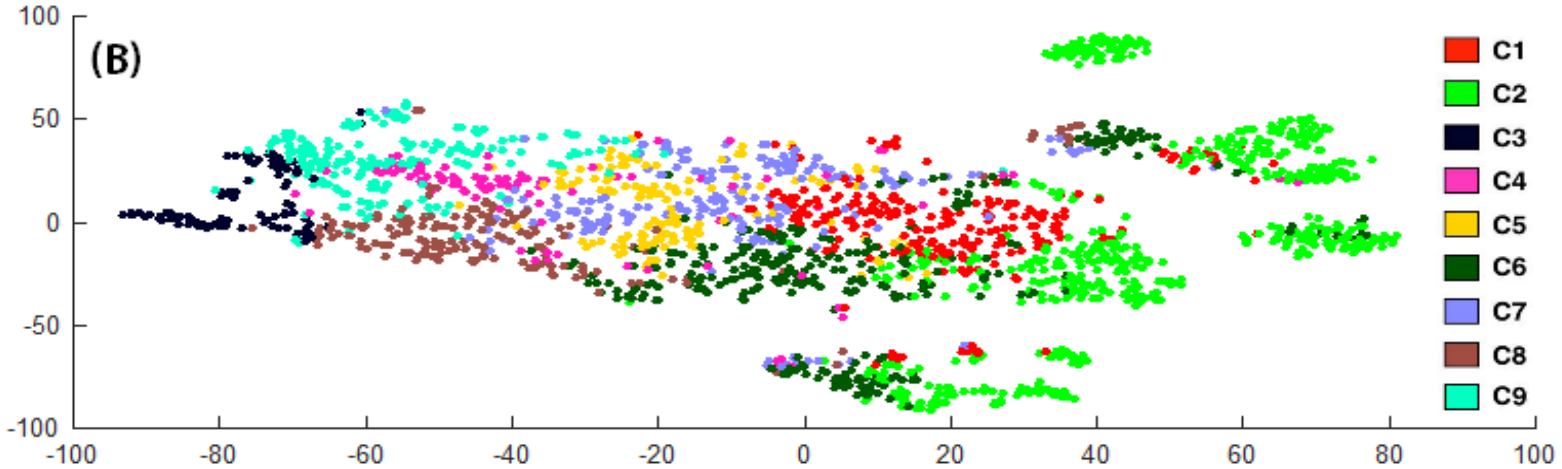
- First Layer Clustering: k_1 = 9 Clusters of words
  - Using 27,683 words
  - Automatic determination of k_1 via Silhouette method



Visualization of 1st Layer through SNE



← AGE DISTRIBUTION



← CLUSTER DISTRIBUTION

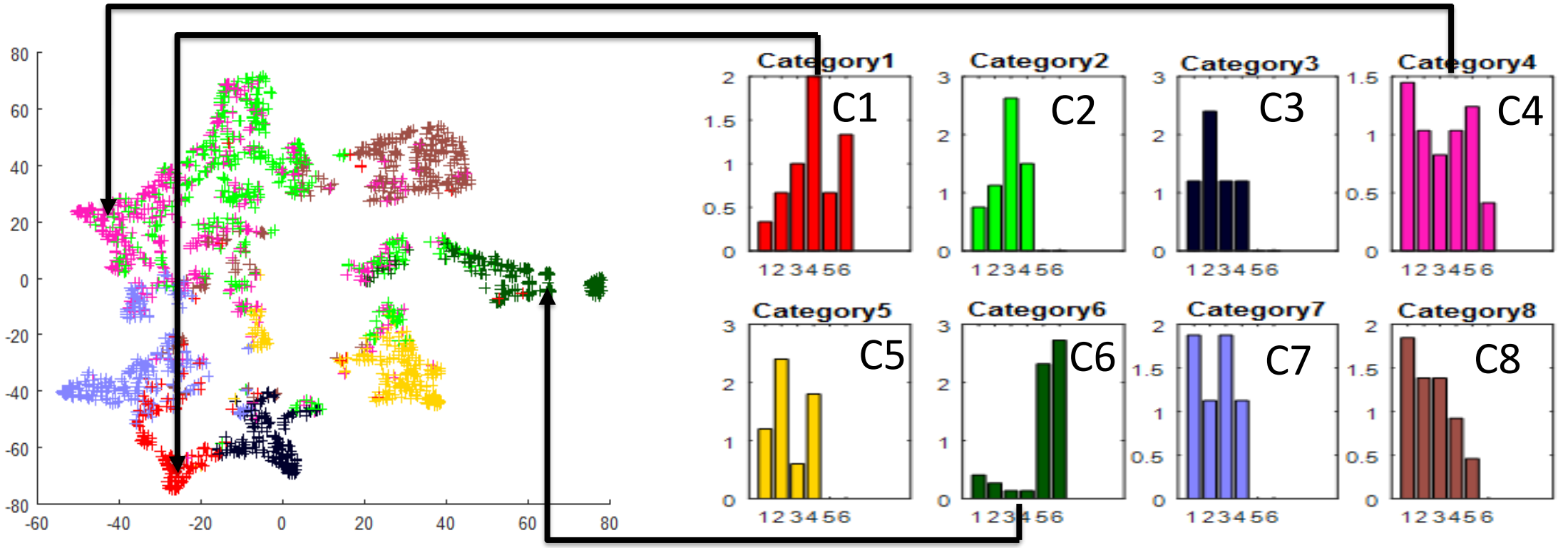
	Dynamics	Inclination	Pressure	Curvature	Pen-up
Cluster 1	Low Speed, Accel, Jerk	Straight	Average	Round Strokes	Average
Cluster 2	Low Speed, Accel, Jerk	Straight	Low	Round Strokes	Many
Cluster 3	High Speed, Accel, Jerk	Inclined Right	Average	Straight Strokes	Very Few
Cluster 4	Average Speed, Accel, Jerk	Inclined Right	High	Straight Strokes	Average
Cluster 5	Average Speed, Accel, Jerk	Straight	Average	Average	Many
Cluster 6	Average Dyn. on Y Low Dyn. on X	Straight	Average	Average	Average
Cluster 7	Average Speed, Accel, Jerk	Straight	Average	Round Strokes	Average
Cluster 8	High Dyn. on Y Average Dyn. on X	Straight	Average	Straight Strokes	Few
Cluster 9	Very High Speed, Accel, Jerk	Inclined Right	Average	Straight Strokes	Average

Results: 2nd Layer Clustering

- 2nd Layer Clustering: k_2 = 8 Categories of writers
  - Categories **C1** & **C4** & **C6** show a large concentration of aged people

    C1 & **C4** → 29% of aged people → *fast* HW with a very *large* instability.

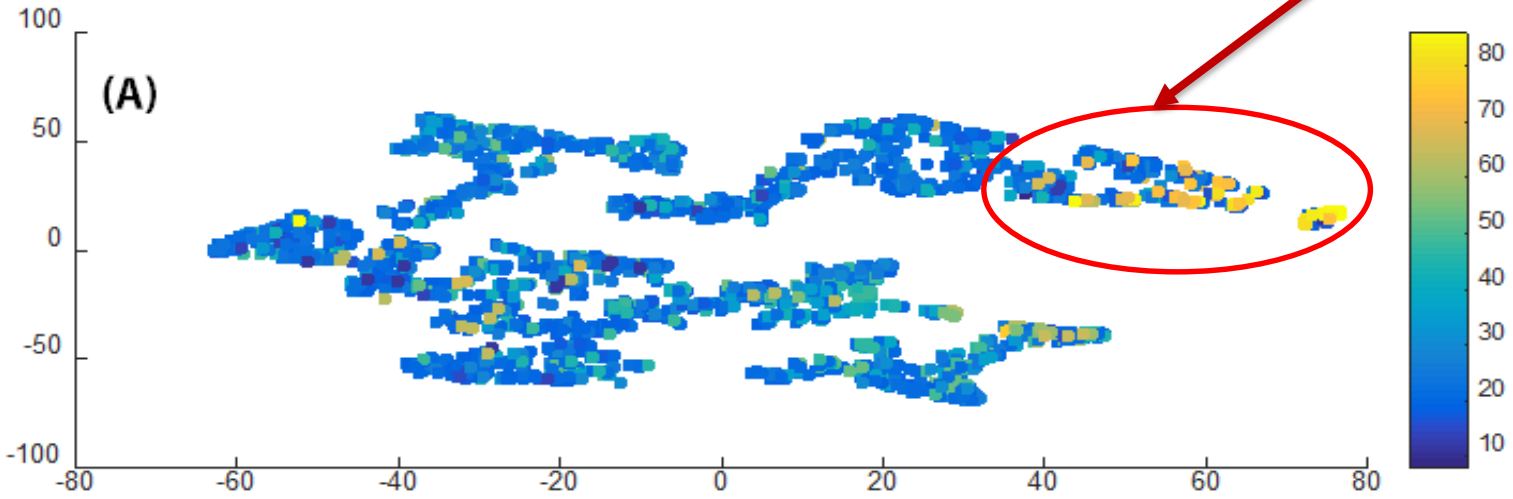
    C6 → 71% of aged people → *very slow* HW with *low* instability.



Age Groups

Results: 2nd Layer Clustering

71% of the Aged Population



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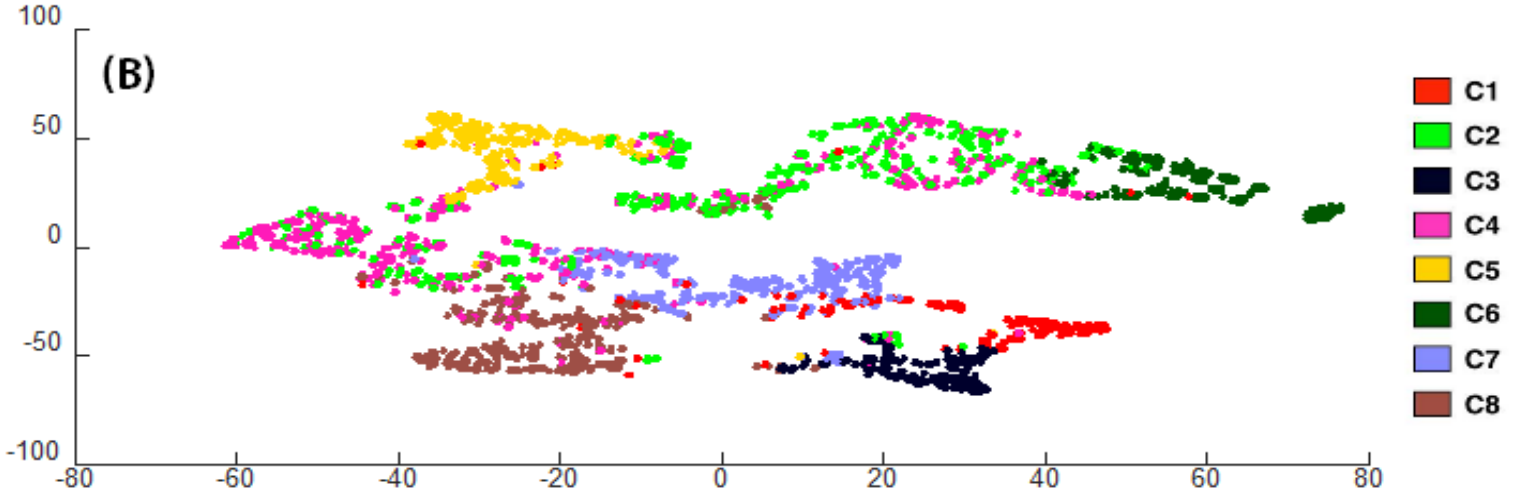
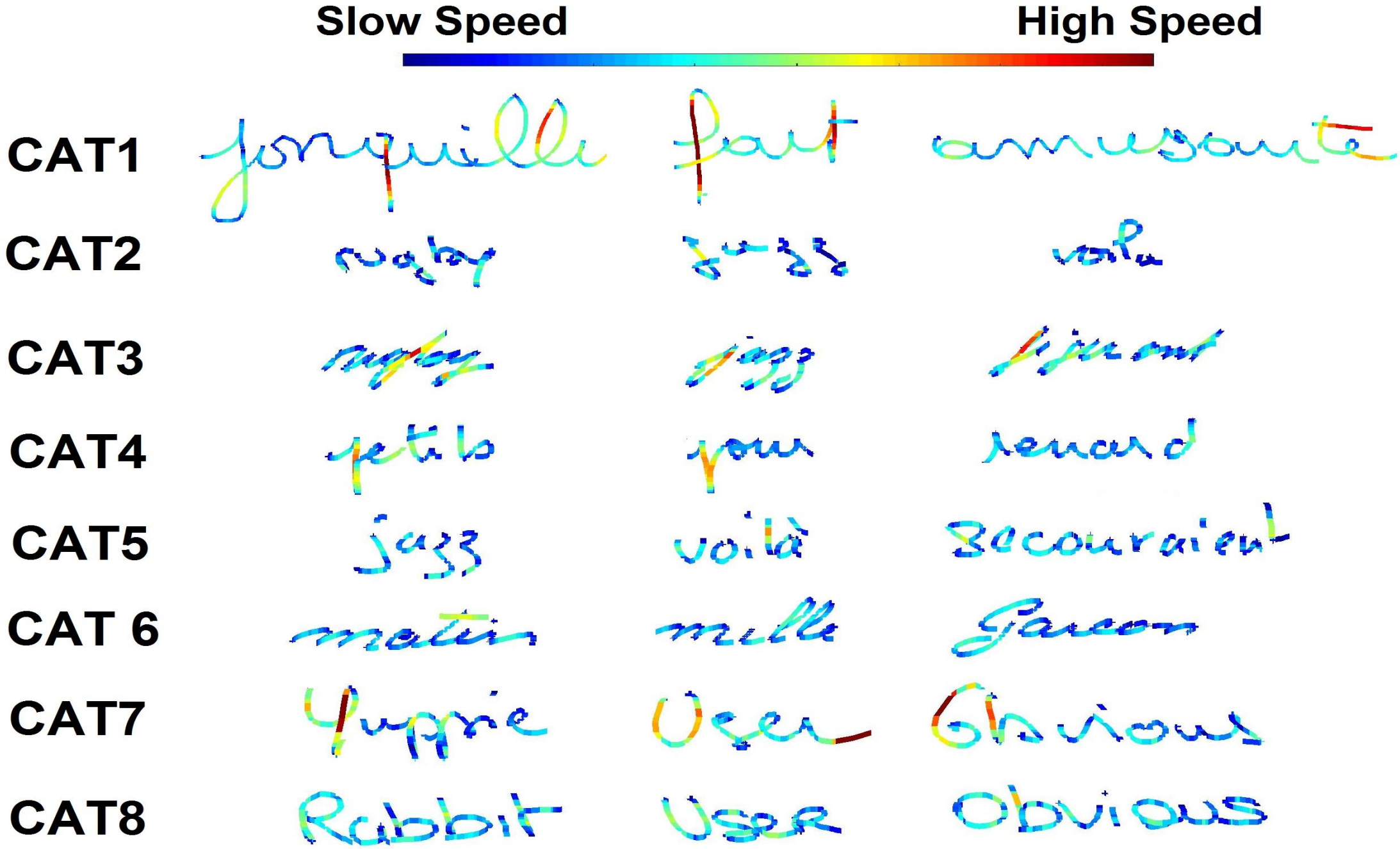


← CLUSTER DISTRIBUTION


Slow Speed
High Speed
CAT1
CAT2
CAT3
CAT4
CAT5
CAT 6
CAT7
CAT8
Rabbit
User
Obvious

Entropy Efficiency

- Entropy efficiencies $\eta(C_k)$ $\eta(A_k)$ E[η]
  - $\eta(C_k)$ Measures the effectiveness of cluster C_k to predict an age group
  - $\eta(A_k)$ Measures the sparsity of the age group A_k through the clusters
  - E[η] Measures the average entropy efficiency w.r.t the clusters

$$\eta(C_k) = \sum_{i=1}^{N_A} \frac{p(A_i|C_k)\log_2(p(A_i|C_k))}{\log_2(N_A)} \qquad \eta(A_i) = \sum_{k=1}^{N_C} \frac{p(C_k|A_i)\log_2(p(C_k|A_i))}{\log_2(N_C)}$$

N_A → Number of Age Groups

N_C → Number of Clusters

$$E[\eta] = \sum_{k=1}^{K} \frac{|C_k|}{\left|\bigcup_{j=1}^{M} C_j\right|} \eta(C_k)$$

- If age groups are equally distributed across the clusters → $E[\eta] = 1$
- If each age group is identified to one different cluster → $E[\eta] = 0$

Results: Entropy Efficiency

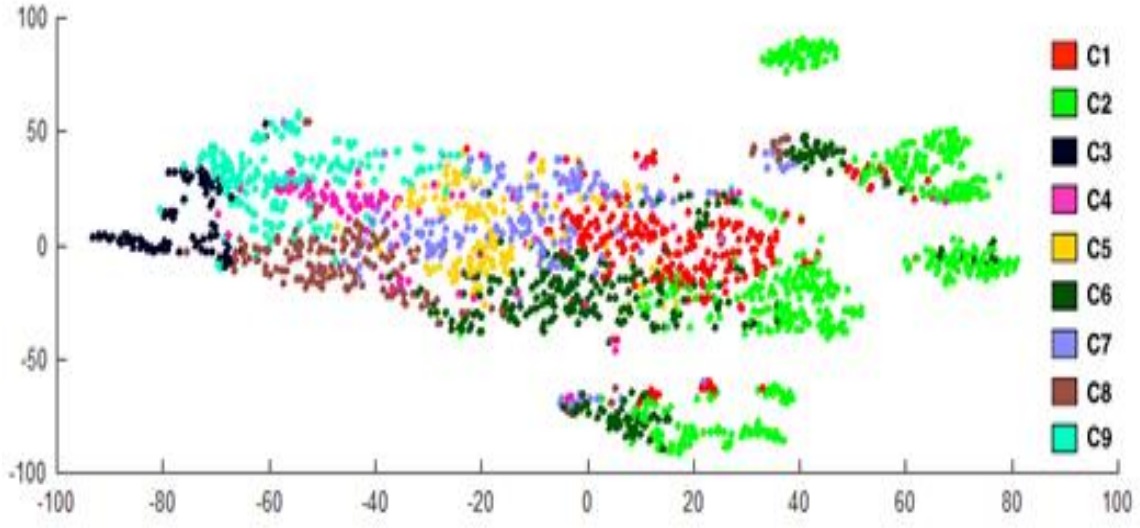
- Entropy decreases at each clustering layer

$$E[\eta] = \sum_{k=1}^{K} \frac{|C_k|}{|\cup_{j=1}^{M} C_j|} \eta(C_k)$$

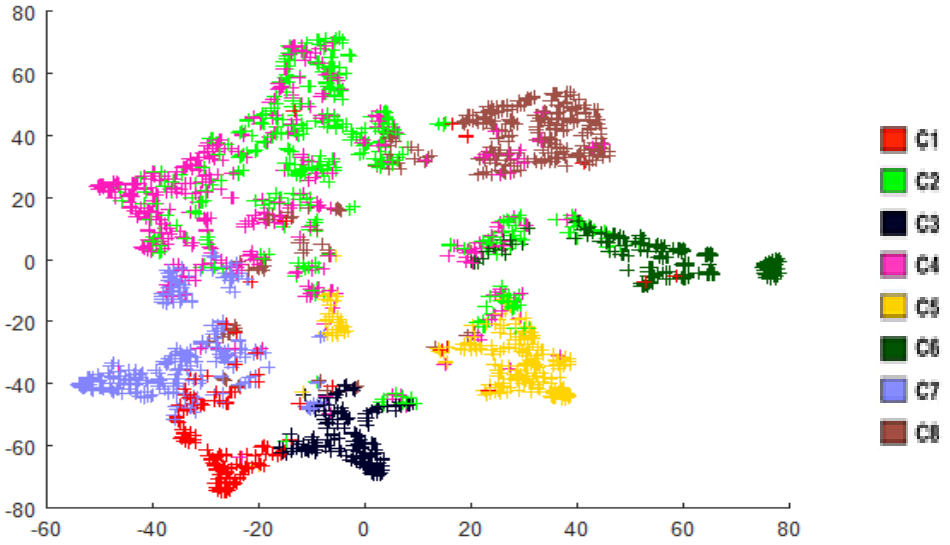
Total Entropy Efficiency Across Layers

	Layer 1	Layer 2
Entropy Efficiency E[η]	0.8365	0.7935

1st Layer



2nd Layer

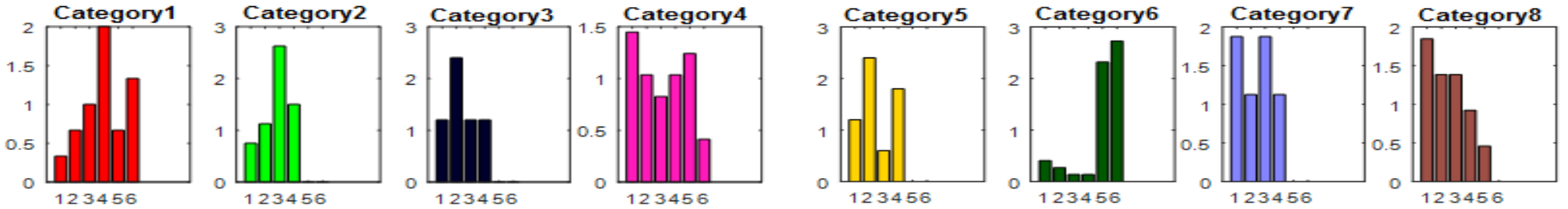


Results: Entropy Efficiency

- Category 6 with high concentration of elders has less entropy

Entropy Efficiency at each Category

	CAT 1	CAT 2	CAT 3	CAT 4	CAT 5	CAT 6	CAT 7	CAT 8
$\eta(C_K)$	0.92	0.72	0.74	0.97	0.71	0.68	0.76	0.85



Results: Entropy Efficiency

- Groups A5 & A6 (aged people) show significantly lower entropy

Entropy Efficiency at each Age Group

	A1	A2	A3	A4	A5	A6
$\eta(A_K)$ Layer1	0.91	0.96	0.96	0.96	0.56	0.42
$\eta(A_K)$ Layer2	0.92	0.98	0.92	0.94	0.45	0.33

Teenagers

Young Adults

Middle Age Adults

Mature Adults

Seniors

Elders

Conclusions

- Our 2 level approach uncovers different HW **profiles** through age
  - Adults → average stability regardless of writer's style and dynamics
  - Similar HW styles for people up to 65 years old
  - For aged population (+65) there are **3 tendencies**:
    - ***Category 6 (71,2% of aged people): Very slow dynamics, high time on air, stable HW across words, many pen-ups.***
    - ***Category 1 (11,5% of aged people): Highest velocity, acceleration and jerk, Very high instability across words.***
    - ***Category 4 (15,4% of aged people): Average velocity, high instability across words.***

- **Several** HW patterns for the elderly → Instead of 1 tendency

Work in Progress

- **Consider persons with psychomotor disorders**
  - Data Collection under way → Broca Hospital, Paris.
  - Target disorders: Alzheimer and Mild Cognitive Impairment (MCI).

- **Add new parameters to study HW on the population**
  - Consider size parameters, baseline stability.
  - Topological features (loops, ascenders, descenders, etc.).

- **Study of hand drawings**
  - Spirals, circles, continuous loops, psychomotor control and grip posture tests.
  - Analysis of hand drawing tasks associated with psychomotor disorders.

References

1) Judie Walton. “Handwriting changes due to aging and Parkinson’s syndrome”. Forensic Science International 88:197–214, 1997.
2) A. Schröter, R. Mergl, et al. “Kinematic Analysis of Handwriting Movements in Patients with Alzheimer’s Disease, Mild Cognitive Impairment, Depression and Healthy Subjects”. Dement Geriatr Cogn Disord 15:132–142, 2003.
3) M. Faundez-Zanuy, E. Sesa-Nogueras et al. “A Preliminary Study on Aging Examining Online Handwriting”. 5th IEEE CogInfoCom, 2014.
4) Roland Mergl, Peter Tigges et al. “Digitized analysis of handwriting and drawing movements in healthy subjects: methods, results and perspectives”. Journal of Neuroscience Methods 90:157–169, 1999.
5) S. Rosenblum, B. Engel-Yeger, Y. Fogel. “Age-related changes in executive control and their relationships with activity performance in handwriting”. Human Movement Science 32:1056–1069, 2013.
6) A. P. Accardo, M. Genna et al. “Development, maturation and learning influence on handwriting kinematics”. Human Movement Science 32:999–1009, 2013.

Travail en cours et Perspectives

- Travail en cours
  - Recueil de données d'une centaines de participants (MA débutant, MCI, contrôle)
  - Analyse de la dégradation des paramètres spatio-temporels de l'écriture manuscrite (thèse en cours, début oct. 2015)
- Perspectives
  - Analyse linguistique de l'écriture manuscrite
    - Erreurs orthographiques, syntaxiques, grammaticales, sémantiques, Récupération lexicale → Reconnaissance de l'écriture manuscrite
  - Analyse similaire sur la voix

Autres applications

- Aide à la détection précoces d'autres pathologies
  - Parkinson, Sclérose en plaque, Huntington, etc.
- Aide à la détection de syndrome envahissants de type autiste
  - Stage M2 en cours en collaboration avec Pr Carole Tardif, Professeur de Psychologie, Aix-Marseille Université, Centre PsyCLÉ (E.A. 3273) d.
- Aide à l'apprentissage pour enfants
  - Adaptation de l'apprentissage en fonction des difficultés
    - Dyslexie, Dysgraphie, etc.