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Analysis of Interpretable Handwriting Features to Evaluate Motoric Patterns in Different Neurodegenerative Diseases

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Background

What are Neurodegener ative Diseases?

Encompass disorders involving brain, nerves and spinal cord which usually develop at older stages of life and are progressive in nature Problems with Diagnosis and treatment

- Difficult to Diagnose
- The gold standard tests is usually via autopsy which takes months and years for diagnosis
- Leading to :
 - Uncertainty among patients and caregivers
 - Delayed implementation of treatment strategies



• This study proposes a broad array of interpretable features which could aid the doctors for evaluation of their patients.



Literature Survey:

- Various methodologies approaches have been proposed to facilitate diagnosis:
 - Many algorithms have been developed to assess a **subject's gait** to monitor symptoms or assess disease type or severity.
 - Acoustics is used to extract features across different types of speech tasks.
 - Algorithms for recognizing **facial expressions** are being designed to identify the loss of verbal communication in ND subjects.
 - Some may use **eye tracking** data for the same.
- Handwriting data was also used by several researchers for this purpose, within this there are two kinds of analysis:
 - Online : Consists of Time-Series signals which capture the writing sequence,
 - Offline: Consists of Static Images

• This study deals with the online time series Handwriting Data



Data Description:



- The data set, Neuro Logical Signals (NLS), is an ongoing multi-modal corpus.
- Containing 3 types of modalities collected during various neuropsychological tasks at University-based sub-speciality clinics.
 - Speech
 - Eye Tracking
 - Handwriting



- Wacom One tablet
- Eye&Pen: For data visualization and cleaning
- Time sequences of both the pen's tip position [x,y] coordinates and on-tablet pressure of the pen tip.



- 85 individuals which included CTRL, PD, AD and PDM (Parkinson Mimics)
- Copy Text (CT), Copy Cube (CC), Copy Image (CI)
- The data from each of these tasks can be used to characterize various motoric and cognitive dysfunctions in the subjects.



Tasks









Data Analysis:



- where the task is carried out.
- broadly categorized into
 - Writing Analysis,
 - Kinematic Analysis ٠
 - Fluency Analysis and ٠ Micro



Feature Description:

Writing Analysis

Writing Analysis: Consists of features that measure the subject's writing capabilities

- Its set of features are: Total duration of writing (TD), height (H), length (L), width (W), number of changes in x (NCX) and y (NCY), the relative number of changes in x (RNCX) and y (RNCY), etc.
- The features proposed by us within this analysis: amount of data used AOD, pressure (μ) is the average pressure.

Kinematic Analysis

Kinematic Analysis: Assesses a subject's fine hand motor function:

- Features extracted included:
 - Writing speed, velocity, horizontal velocity, vertical velocity, acceleration, horizontal acceleration, vertical acceleration, jerk, etc.



The **fluency analysis** was meant to assess the ease in performing a handwriting task.

Features we created: Number of inversions in velocity (NIV), Number of inversions in acceleration(NIA), and Ratio of Decceleration Phase (RDP).

To analyze **Micrographia**, we propose a new feature (*MSlope*) to selectively characterize this condition in subjects with NDs.



Statistical Analysis: Hypothesis Testing

- After we were done with the feature extraction process. We conducted pair- wise Kruskal–Wallis H-tests for each family of features to determine if there were any statistically significant differences between experimental groups per each feature.
- The **Kruskal- Wallis** test was used as it is a non-parametric test whose null hypothesis is that the mean ranks of the groups are the same.
- To control for **false discovery rate (FDR)**, we applied **Benjamini–Hochberg** correction to each pair-wise comparison for each family of features.
- The error rate, α was set to 0.05. For each significant comparison, we report the corresponding p value and the area under the ROC curve (AUROC), as a criterion to measure the feature's discriminative ability.



Results and Discussion



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Writing Analysis								
Task	Sample (n)		<i>p</i> -value	AUROC				
	1	2	1					
AOD								
СТ	$\mathbf{CTRL}\ (n=36)$	AD $(n = 10)$	0.03	0.78				
	$\mathbf{CTRL}\ (n=36)$	PDM $(n=9)$	0.03	0.80				
CI	$\operatorname{CTRL}\left(n=36\right)$	AD $(n = 11)$	0.001	0.87				
	$PD\;(n=29)$	AD $(n = 11)$	0.003	0.85				
Pressure (μ)								
CT	$\mathbf{CTRL}\ (n=36)$	AD $(n = 10)$	0.046	0.75				
	$\mathbf{CTRL}\;(n=36)$	PDM $(n = 9)$	0.04	0.78				
CISP [(mm/s)]								
	CTRL $(n = 36)$	AD $(n = 10)$	< 0.001	0.88				
CT	$\mathbf{CTRL}\ (n=36)$	PDM $(n = 9)$	0.047	0.74				
	PDM $(n=9)$	AD (n = 10)	0.02	0.81				
	PD $(n=28)$	AD $(n=10)$	0.02	0.76				
	$\mathbf{CTRL}\ (n=36)$	AD $(n = 11)$	< 0.001	0.86				
CI	$\mathbf{CTRL}\;(n=36)$	PDM $(n = 9)$	0.02	0.75				
CI	$\mathbf{CTRL}\;(n=36)$	PD $(n = 29)$	0.01	0.68				
	$\mathrm{AD}\left(n=11\right)$	$\mathbf{PD}\;(n=29)$	0.02	0.75				
Horizontal Width (on-tablet)								
CI	$\mathbf{CTRL}\ (n=36)$	PD $(n = 29)$	0.02	0.71				
Horizontal Width (in-air)								
CI	$\mathbf{CTRL}\ (n=36)$	PD $(n = 29)$	0.02	0.72				
Total Duration								
CI	CTRL $(n = 36)$	AD $(n = 11)$	0.001	0.83				
	PD $(n = 29)$	AD(n = 11)	0.004	0.83				
Table, 1								



Results and Discussion

Kinematic Analysis



Kinematic Analysis [14]							
Task	Sample (n)		<i>n</i> -value	AUROC			
	1	2	p-value	nenoe			
Velocity (µ)							
CI	$\mathbf{CTRL}\;(n=36)$	AD $(n = 11)$	< 0.001	0.89			
	$\mathbf{PD}\ (n=29)$	$\mathrm{AD}\ (n=11)$	0.004	0.88			
CT	CTRL $(n = 36)$	PDM $(n = 9)$	0.04	0.80			
Acceleration (μ)							
CI	$\mathbf{CTRL}\;(n=36)$	AD $(n = 11)$	0.01	0.80			
	$\operatorname{CTRL}(n=36)$	PDM $(n=9)$	0.02	0.86			
	PD $(n = 29)$	PDM $(n=9)$	0.025	0.90			
	$\mathbf{PD}\;(n=29)$	AD $(n = 11)$	0.01	0.83			
CC	PD $(n = 15)$	AD $(n = 14)$	0.01	0.85			
Horizontal normalized jerk (HNJ) (μ)							
CI	$\mathbf{CTRL}\;(n=36)$	AD $(n = 11)$	0.001	0.83			
	$\mathbf{PD}\;(n=29)$	AD (n = 11)	0.01	0.76			
CT	PDM $(n = 9)$	$\mathbf{CTRL}\ (n=36)$	0.046	0.76			
CC	PD $(n = 15)$	AD $(n = 14)$	0.005	0.89			
Vertical normalized jerk (VNJ) (µ)							
CI	$\mathbf{CTRL}\;(n=36)$	AD $(n = 11)$	0.001	0.83			
	$\mathbf{PD}\ (n=29)$	AD(n=11)	0.01	0.75			
Speed							
CI	$\operatorname{CTRL}\left(n=36\right)$	AD (n = 11)	< 0.001	0.91			
	PD $(n = 29)$	AD $(n = 11)$	0.004	0.86			

Fig. 5

Table. 2

PDM (n = 9)

0.046

0.80

CT

CTRL (n = 36)



Results and Discussion

Fluency and Micrographia



Fluency Analysis and Micrographia								
Task	Sample (n)		n-value	AUROC				
	1	2	<i>p</i> -value	nenoe				
NIV acceleration								
СТ	$\operatorname{CTRL}\left(n=36\right)$	AD $(n = 10)$	0.02	0.76				
	$\mathbf{CTRL}\;(n=36)$	$PDM\ (n=9)$	< 0.001	0.80				
NIV velocity								
СТ	$\mathbf{CTRL}\;(n=36)$	AD $(n = 10)$	0.02	0.78				
	$\mathbf{CTRL}\;(n=36)$	PDM $(n = 9)$	< 0.001	0.81				
MSlope								
СТ	$\operatorname{CTRL}\left(n=36\right)$	AD $(n = 10)$	0.0457	0.74				
	$\mathbf{CTRL}\;(n=36)$	PDM $(n = 9)$	0.003	0.85				
	$\mathbf{CTRL}\;(n=36)$	PD $(n = 28)$	0.02	0.64				

Table. 3



Conclusions

The Features proposed and analyzed:

- Provide good differentiation
 Between several NDs
- Interpretable and Objective In nature
- The 3 sets of features successfully
- encoded cognitive and motoric impairments of the subjects
 - Thus, helping in assessing these
- impairments and clinical diagnosis



- Corpus in Progress
- → limited by subjects recorded
- We continue to balance these exp
 groups, and refine the cohort to be more representative of these groups



Use these features within Machine Learning framework to support development diagnostics tools to assess these patients.



Thank You

