A Non-linear Dynamics Approach to Classify Gait Signals of Patients with Parkinson's Disease.

P. A. Pérez-Toro[1*] J. C. Vásquez-Correa[1,2] T. Arias-Vergara[1,2]
N. Garcia-Ospina[1] J. R. Orozco-Arroyave[1,2] E. Nöth[2]

[1]Faculty of Engineering, University of Antioquia UdeA, Medellín, Colombia.
[2]University of Erlangen-Nüremberg, Germany.

paula.perezt@udea.edu.co

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August 8, 2019

Outline

Context

Parkinson's Disease

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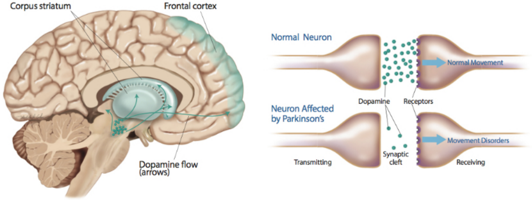
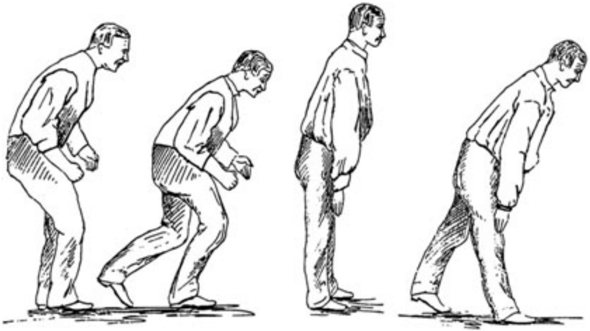
- Second neuro-degenerative disorder worldwide.
- 6.000.000 Parkinson's patients around the world. 220.000 are from Colombia.
- Neurologists evaluated PD according to MDS-UPDRS-III scale (Goetz et al. 2008).



https://tmrwedition.com/2017/03/23/the-future-of-parkinsons-disease-therapies/

Motor symptoms

- Resting tremor.
- Rigidity.
- Postural instability.
- Bradykinesia.
- Freezing gait.



https://allhealthpost.com/festinating-gait/

Hyphotesis and aims

- The aim of this study was to model components related with the stability during the walking process that cannot be characterized properly with the classical approach.
- Aging is an interesting aspect that deserves attention when patients with neurodegenerative diseases are considered.

Data

Gait Acquisition

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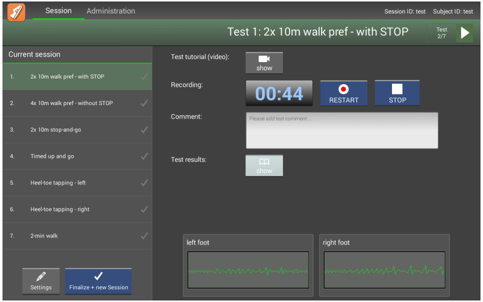

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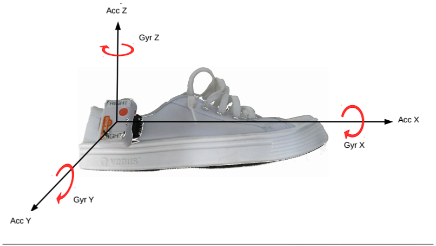

Gait signals were captured with the eGaIT system[1]

[1] Embedded Gait analysis using Intelligent Technology, http://www.egait.de/

General information about the gait data.

Table: General information of the subjects. **PD** patients: Parkinson's disease patients. **HC**: healthy controls. $\boldsymbol{\mu}$: mean. $\boldsymbol{\sigma}$: standard deviation. **T**: disease duration.

	PD patients		YHC subjects		EHC subjects	
	male	female	male	female	male	female
Number of subjects	17	28	26	18	23	22
Age ($\mu \pm \sigma$)	65 ± 10.3	58.9 ± 11.0	25.3 ± 4.8	22.8 ± 3.0	66.3 ± 11.5	59.0 ± 9.8
Range of age	41-82	29-75	21-42	19-32	49-84	50-74
T ($\mu \pm \sigma$)	9 ± 4.6	12.6 ± 12.2				
Range of duration of the disease	2-15	0-44				
MDS-UPDRS-III ($\mu \pm \sigma$)	37.6 ± 21.0	33 ± 20.3				
Range of MDS-UPDRS-III	8-82	9-106				

PD patients: Parkinson's disease patients.
HC: healthy controls (Elderly and Young)

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We considered two gait tasks :

- 2x10m: this consist of walk in a straight line 10 meters and turned around the right side returning back with a short pause.
- 4x10m: this consist of walk in a straight line 10 meters and turned around the right side returning back twice.

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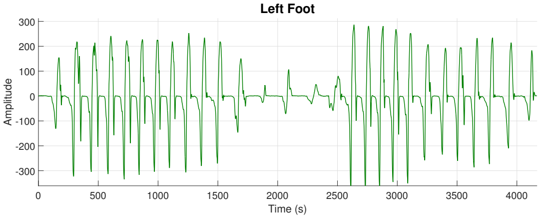
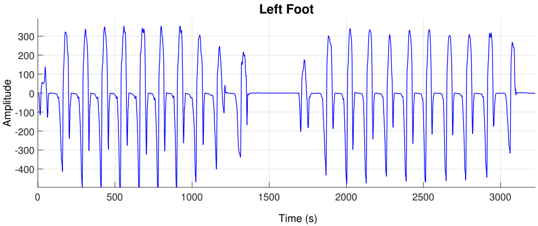
Female PD patient.
Age:*52.*
MDS-UPDRS=*49*



Female Young Healthy Control.
Age:*23*



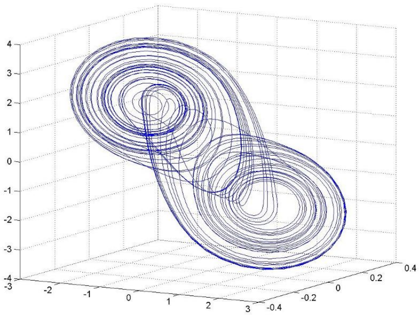
Gyroscope Z

Methods

Gait signals are not linear. This kind of signal shows a non-stationary behaviour.

We focus on non-linear Dynamics systems to describe patterns of gait complexity in patients with Parkinson's disease.

Non-linear Dynamics: Attractors (Phase Space)



Chua's Attractor

- In order to analyze the non-linear properties of the gait signals, the time series has to be projected into a high dimensional space, known as attractor (Taylor 2005).

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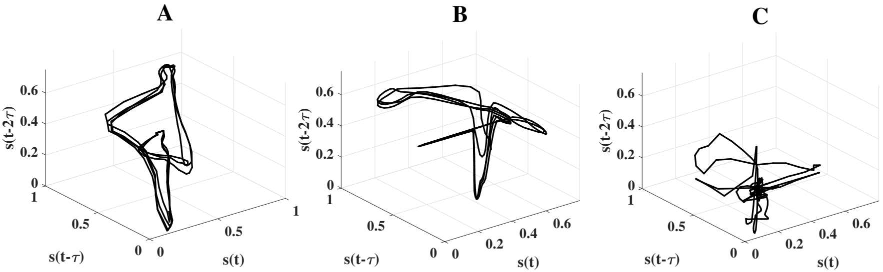
- From a single time series $\boldsymbol{S_t}$, a phase space can be constructed as follows:

$$\boldsymbol{S_t} = \left\{ s_t, s_{t+\tau}, ...s_{t+(m-1)\tau} \right\} \tag{1}$$

τ:delay-time.
m:embedding dimension, a point in the reconstructed phase space.



(A) Female YHC, age=23. (B) Female EHC, age=52. (C) Female PD patient, age=52, MDS-UPDRS=49.

Ten measures were computed. These measures are related with:

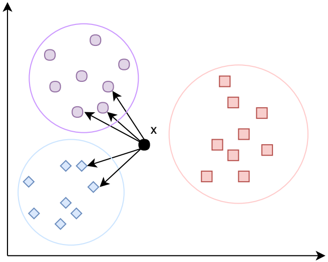
- Entropy.
- Space occupied by the attractor.
- Stability.
- Periodicity.
- Large-range dependency and trends.
- Repetitiveness patterns.

Table: Number of features per task

Foot	Task	Number of axes	Number of features	Total
Left	2x10m	6	10	60
Left	4x10m	6	10	60
Left	Fusion	6	20	120
Right	2x10m	6	10	60
Right	4x10m	6	10	60
Right	Fusion	6	20	120
Both	2x10m	12	10	120
Both	4x10m	12	10	120
Both	Fusion	12	20	240

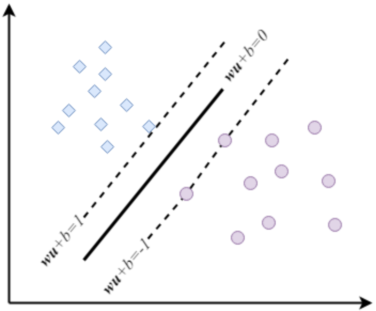
- KNN (Bishop 2006) uses a majority vote among the **k**, defining competencies as a distance measure d

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \ldots + (x_n - y_n)^2} \tag{2}$$



New input data in accordance with their distances

- SVM (Bishop 2006) outputs a class identity for every new vector **u**, by modeling best fitting hyperplane.



SVM Best fitting hyperplane

- A Gaussian kernel transforms the feature space into one linearly separable.

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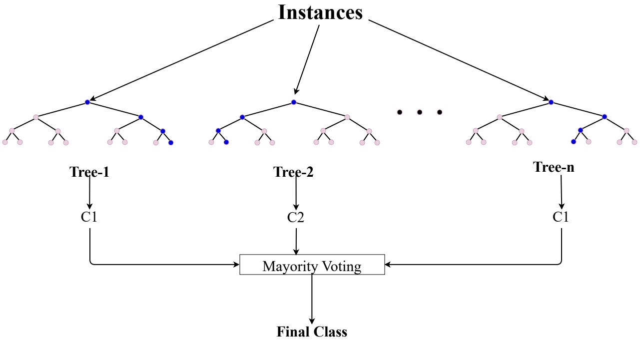
- Random Forest (RF) consists of a classification tree set.
- Each one contributes with one vote to assign a class.



Architecture of the random forest model

Experiment and results

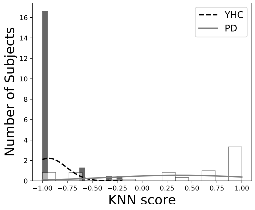
Five folds are chosen to perform the classification. These folds were balanced by gender and shoe type.

Table: Best KNN Classification: Fusion Both Feet

KNN Results

	Accuracy	Sen/Spe	AUC
PD vs. YHC	86.5%±2.9	73.3/100.0	0.93
PD vs. EHC	85.6%±5.0	77.8/93.3	0.89

Parameter estimation using grid–search with cross–validation



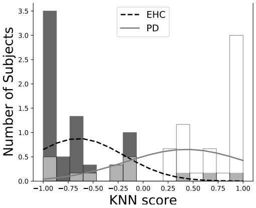


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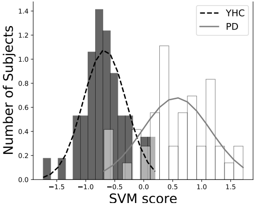
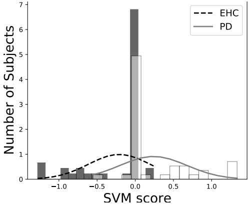
Table: Best SVM Classification: Fusion Both Feet

SVM Results

	Accuracy	**Sen/Spe**	**AUC**
PD vs. YHC	91.1%±4.9	84.4/97.8	0.96
PD vs. EHC	82.2%±4.6	71.1/93.3	0.86

Parameter estimation using grid–search with cross–validation





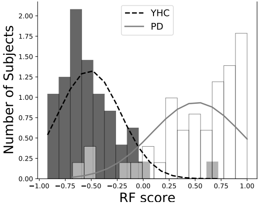
Five folds are chosen to perform the classification. These folds were balanced by gender and shoe type.

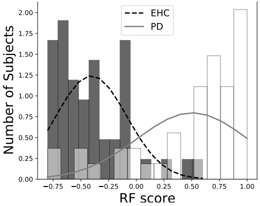
Table: Best RF Classification: Fusion Both Feet

RF Results

	Accuracy	Sen/Spe	AUC
PD vs. YHC	91.1%±4.9	84.4/97.8	0.96
PD vs. EHC	85.6%±2.5	80.0/91.1	0.91

Parameter estimation using grid–search with cross–validation





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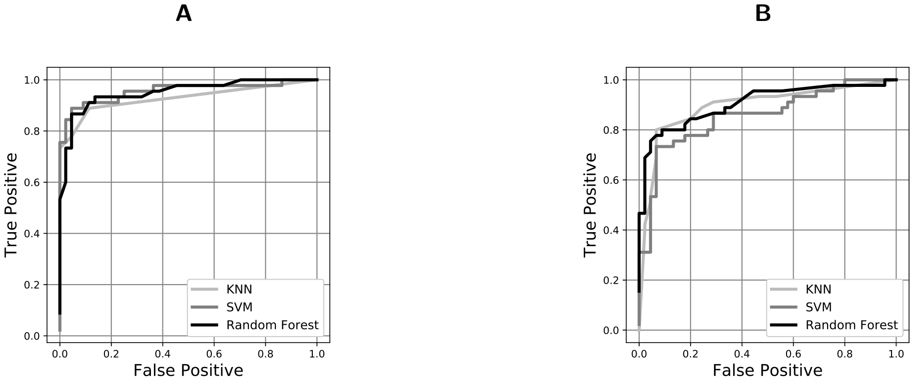

ROC curve graphics of the best NLD Features results. A) PD vs YHC. B) PD vs EHC. In both cases the fusion of features from both feet and both tasks are considered.

Conclusions

- An automatic discrimination between PD patients and two groups of HC subjects is performed to assess the impact of age in the walking process.

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- The fusion of several tasks is more effective in the classification process, i.e., both feet provide complementary information to discriminate between PD patients and HC subjects.

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- The fusion of several tasks is more effective in the classification process, i.e., both tasks provide complementary information to discriminate between PD patients and HC subjects.
- Results indicate the presence of the cross laterality effect(Sadeghi et al. 2000).

Future Work

- Further experiments will consider the evaluation of the neurological state of the patients by classifying patients in several stages of the disease according to the MDS-UPDRS-III score.
- Other NLD based features can also be considered.
- The proposed features might also be combined with standard kinematics features to improve the results.

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THANK YOU!!