

#### Mixture Models for the characterization of brain abnormalities in "de novo" Parkinsonian patients

Verónica Muñoz Ramírez, Michel Dojat, Florence Forbes

#### ▶ To cite this version:

Verónica Muñoz Ramírez, Michel Dojat, Florence Forbes. Mixture Models for the characterization of brain abnormalities in "de novo" Parkinsonian patients. CNIV 2019 - 3e Congrès National d'Imagerie du Vivant, Feb 2019, Paris, France. pp.1-16. hal-02436886

HAL Id: hal-02436886

https://hal.inria.fr/hal-02436886

Submitted on 13 Jan 2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



# Mixture Models for the characterization of brain abnormalities in "de novo" Parkinsonian patients

Verónica Muñoz Ramírez

PhD directors: Michel Dojat & Florence Forbes





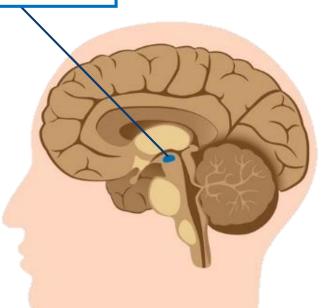






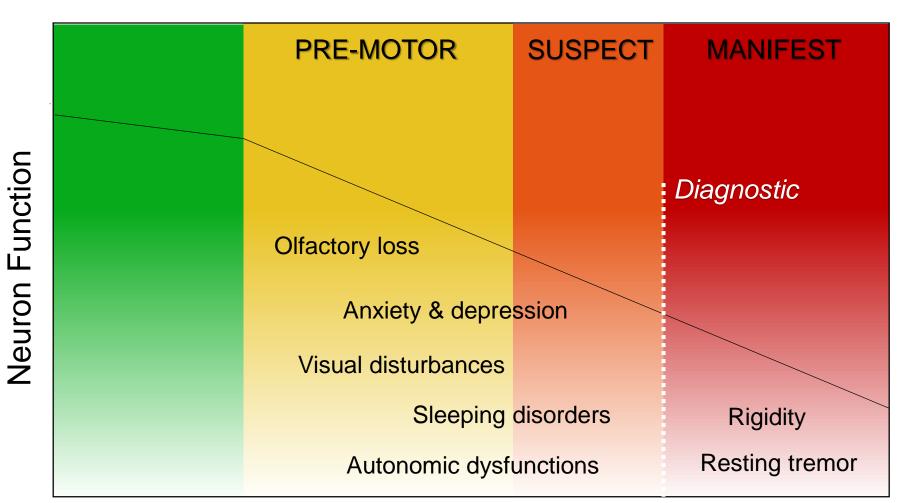
#### 1. A brief introduction to PD

- Degenerative disease
- 10 million cases worldwide
- Loss of dopaminergic neurons in the *substantia nigra*
- Perturbation of other subcortical structures
- Non-motor (silent) phase
- Motor phase leading to handicap
- No cure, but symptom management





#### 1. A brief introduction to PD



Time



### **Objectives**

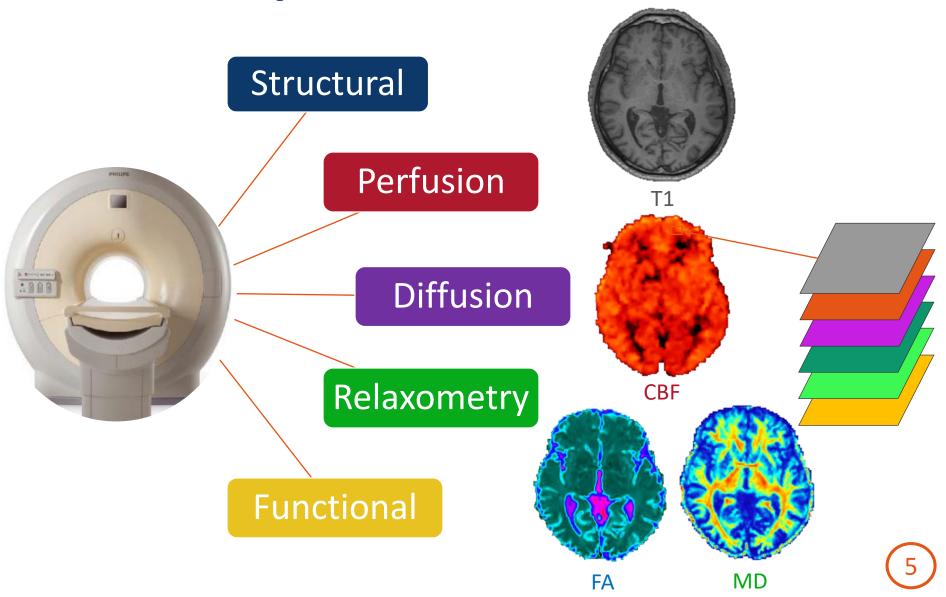
- ☐ To characterize the non-motor changes sustained by the Parkinsonian brain.
- ☐ To find new biomarkers for the early diagnosis of Parkinson's disease.
- ☐ To define specific classes of patients for personalized treatment

#### Tools:

- MR imaging (anatomical and quantitative data)
- Statistical classification methods (Mixture models, data mining)



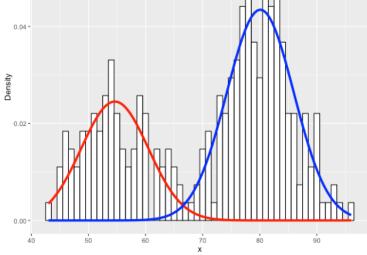
3. MRI parameters extraction





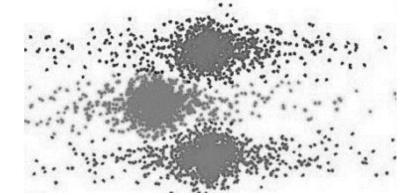
## 4. A word on mixture models

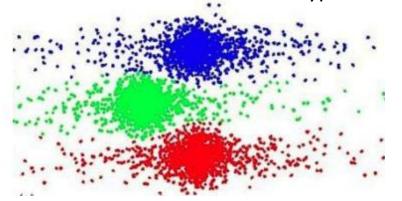
Mixture models are probabilistic models that represent subpopulations within an overall population.



#### Mixture of Multiple Scale t-distributions →

- More degrees of freedom
- Better classification of 'atypical values'

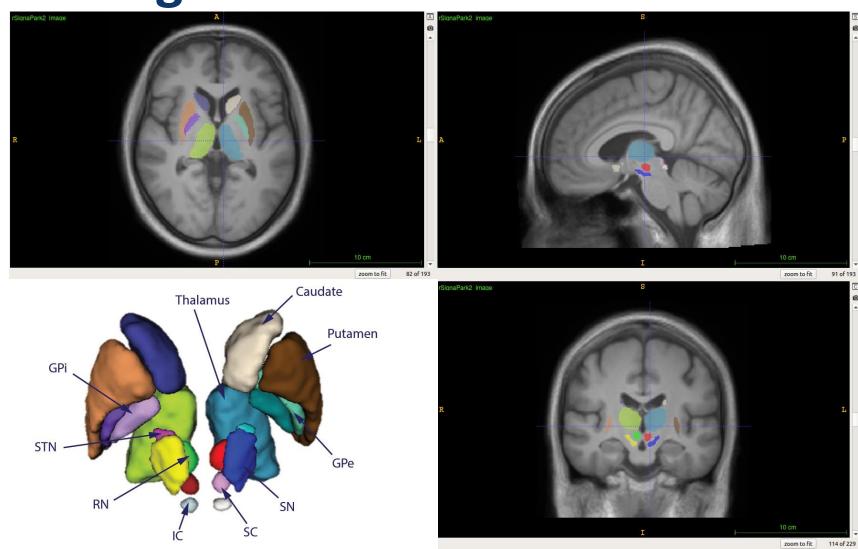




F. Forbes & D. Wraith (2014). A new family of multivariate heavy-tailed distributions with variable marginal amounts of tailweight: application to robust clustering. *Stat. Comput.*, vol. 24, 971–984.

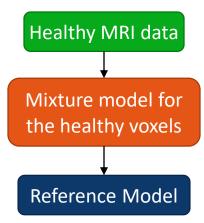


5. Segmentation atlas



Xiao, Y., Collins, D. L. & al. (2015). Multi-contrast unbiased MRI atlas of a Parkinson's disease population. *International Journal of Computer Assisted Radiology and Surgery*, *10*(3), 329–341.

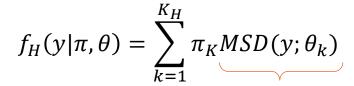




(Arnaud & al., 2017)

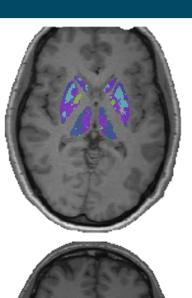
Healthy voxels group:

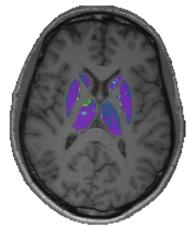
$$Y_H = \{y_v, v \in V_H\}$$

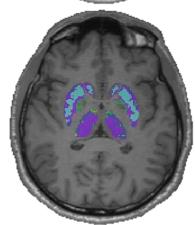


Probability distribution function of the estimated MMSD model

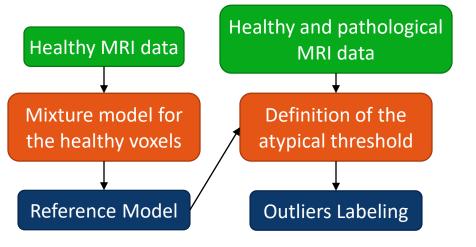
K\_H is determined by the BIC score ... or a slope heuristic







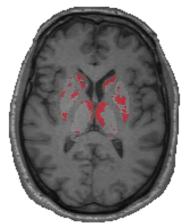


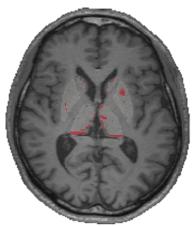


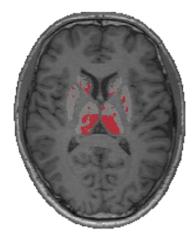
Patient voxels group :  $Y_P = \{y_v, v \in V_P\}$ 

$$P(\log(f_H(Y_v)) < \tau_\alpha) = \alpha$$

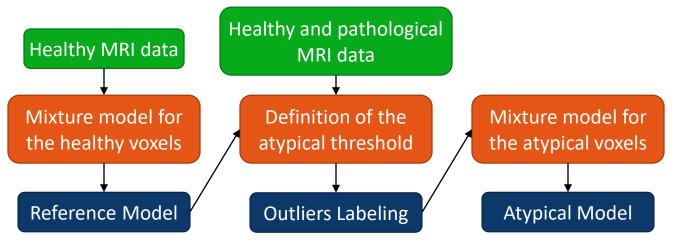
Where  $\alpha$  is the FPR











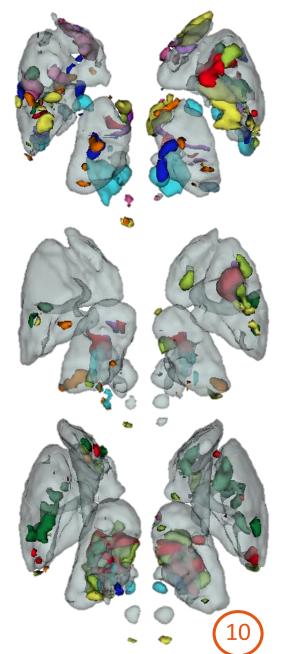
Atypical voxels group:

$$Y_A = \{y_v, v \in V_H \cup V_P\}$$
 such that  $\log(f_H(y_v)) < \tau_\alpha$ 

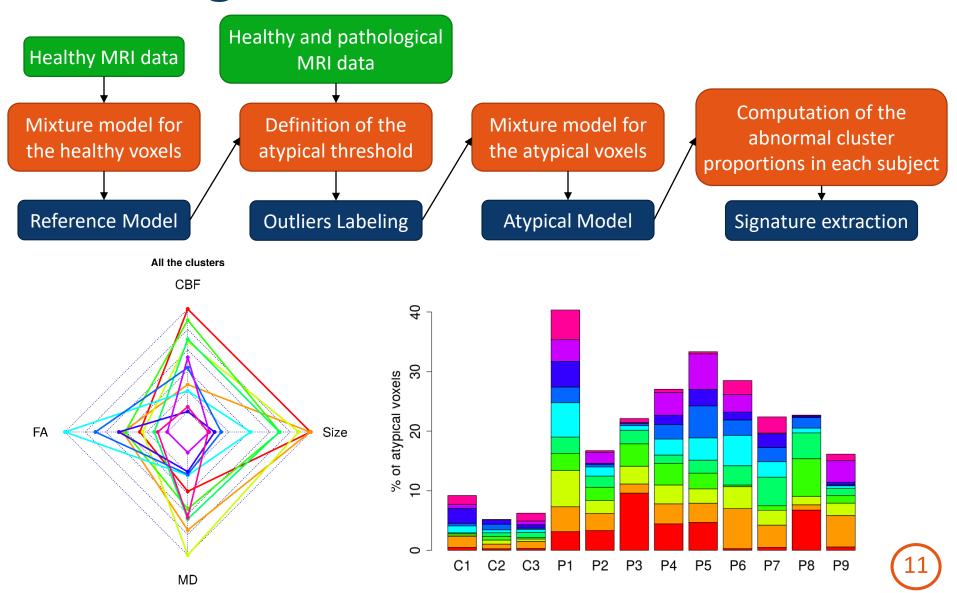
$$f_A(y) = \sum_{K=1}^{K_A} \eta_K MST(y; \phi_K)$$

For each subject S

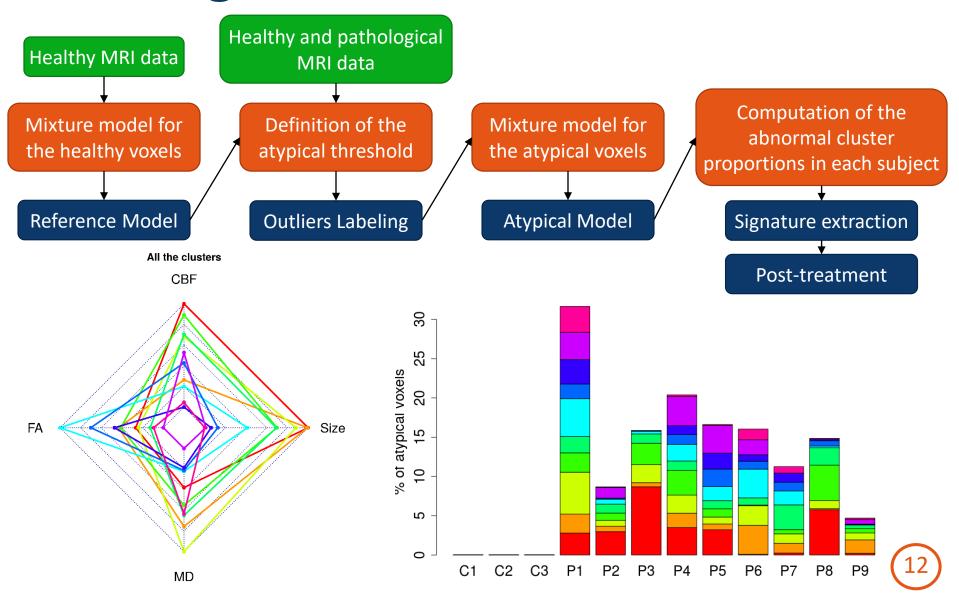
$$\rho^S = \left\{ \rho_1^S, \dots, \rho_{K_A}^S \right\}$$











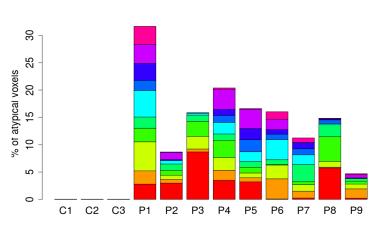


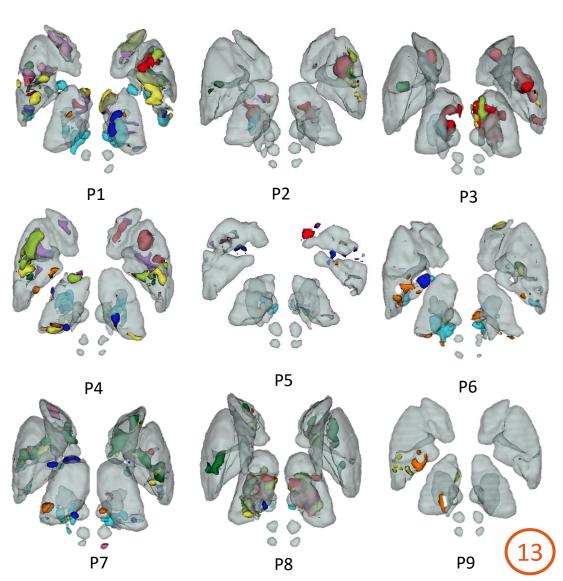
#### 7. Results

Subcortical structures CBF - FA - MD 9 patients K = 10

#### **Highligthed regions:**

- Substantia nigra
- Red nucleus
- Globus Pallidus







#### 7. Results

Brain

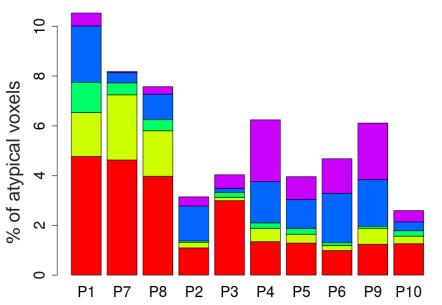
CBF – FA – MD

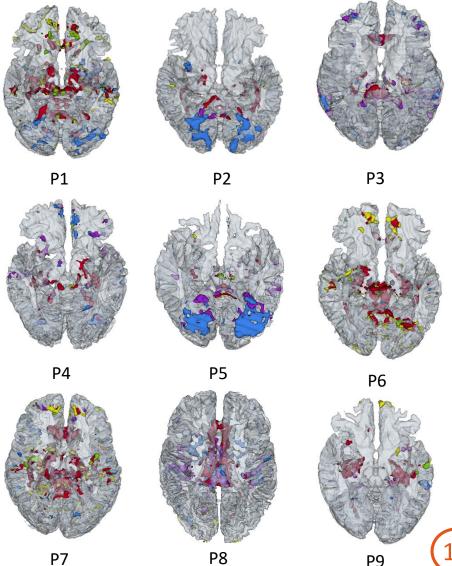
9 patients

K = 5

#### **Highligthed regions:**

- Brainstem
- Diencephalon
- Substantia nigra
- Transverse Temporal gyrus







## 8. Perspectives & Conclusion

Preliminary results show the potential of this approach, however we need to acquire more data to confirm our findings and build robust models.

#### **WORK IN PROGRESS:**

- Machine Learning approaches for anomaly detection
- Proof of robustness.
- Signature profiling



# Thank you!

veronica.munoz-ramirez@univ-grenoble-alpes.fr









This work is supported by a grant from NeuroCoG IDEX UGA in the framework of the "Investissements d'avenir" program (ANR-15-IDEX-02).