

Discriminant BOLD Activation Patterns during Mental Imagery in Parkinson's Disease

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Introduction

During the past decades, advances in neuroimaging enabled the identification of biomarkers in dementia [1] or the characterization of patterns related to gait disturbances in Parkinson's disease [2]. More recently, machine learning based models [3] have been used in clinical applications, e.g. to provide an (early) diagnosis or monitoring the evolution of a disease. However, choosing a biomarker to detect the presence or absence of a disease is not straightforward, especially in the case of Idiopathic "Parkinson's Disease" (IPD) when compared to healthy subjects [4,5].

Aim: Investigate the mental imagery of gait as a biomarker of IPD.

Methods

Data and Design

14 patients (7M, 65.1 ± 9.5 y): IPD

15 controls (7M, 63.8 ± 8.1 y): CTRL

(A) Before fMRI:

- Walk at brisk and comfortable paces along a 25m path.
- Train mental imagery of gait.

(B) During fMRI:

- Standing on the path (STAND, 8 trials)
- Walking at a comfortable pace (COMF, 8 trials)
- Walking briskly (BRISK, 12 trials)

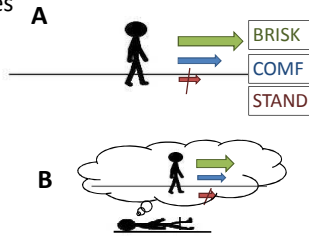
Analysis

- Pre-processing using SPM8.
- The parametric maps of each condition were computed using a General Linear Model [6]

→ 3 contrast images (STAND/COMF/BRISK) per subject.

A priori feature selection:

1. Whole brain.
2. Motor mask [7].
3. MLR (mesencephalic locomotor region + pedunculopontine nucleus, [2]).



Classification performed with PRoNTo [8] :

- binary Support Vector Machines (SVM, [9]) for between groups comparison (CTRL vs. IPD) or multiclass Gaussian Processes (GP, [10]) for between tasks comparison (STAND/COMF/BRISK).
- balanced, class accuracy and Positive Predictive values (PPV) were obtained using leave-one-subject out cross-validation.
- the significance of the results were assessed by random permutations (1000 for SVM, 100 for GP).

Results

Between group comparison

Conditions	Masks		
	Whole brain	Motor	MLR
STAND	14.3	34.5	72.6
COMF	58.3	62.1	76.0
BRISK	59.0	66.2	62.1
STAND+COMF	36.3	36.2	72.4
STAND+BRISK	36.7	39.7	65.4
COMF+BRISK	62.3	65.8	62.1
All	42.9	48.3	56.4

Table 1: Balanced accuracy (in %) for the IPD vs. CTRL classification for each combination of the three tasks (rows) and for each mask (columns). "All" represents the combination of the three tasks. Statistically significant results are highlighted in bold.

The MLR mask led to the best results, the highest performance being reached when considering the COMF condition. For this model, the balanced accuracy reached a value of 76% (p=0.01), with the class accuracies reaching 78.6% for IPD and 73.3% for CTRL (both significant at p<0.05 and a PPV of 78.6% for CTRL and 73.3% for IPD).

Between task comparison

Mask	Acc _b	STAND	COMF	BRISK
Whole brain	65.5	58.6 (65.4)	41.4 (75.0)	96.6 (62.2)
Motor areas	66.7	62.1 (64.3)	41.4 (70.6)	96.6 (66.7)
MLR area	32.2	89.7 (32.1)	0.0 (0.0)	6.9 (33.3)

Table 2: Balanced (Acc_b) and class accuracies (in %, PPV in brackets) of the multiclass GP model discriminating between the three tasks (STAND, COMF and BRISK) when considering both groups jointly. Significant results are highlighted in bold.

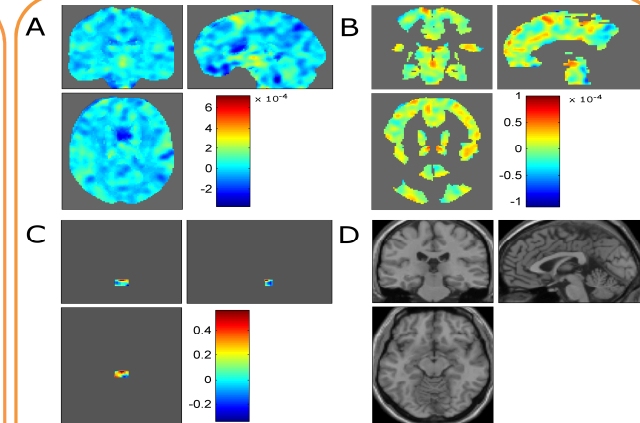


Figure 1: Weights of the CTRL (+1) vs. IPD (-1) model based on BRISK + COMF conditions, for **A** the whole brain, **B**, motor and **C** MLR masks **D** SPM single subject canonical structural image.

Conclusions

1. First ever significant discrimination between CTRL and IPD [4,5], with best results achieved with the MLR mask and COMF condition [2].
2. High within-group variability compared to between-group variability due to:
 - heterogeneity in gait disturbances?
 - overlap between mental imagery of disturbed gait and real disturbed gait?
3. Different results according to considered mask → need for specific feature selection?

References

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