An adaptive watershed by flooding algorithm for an atlas of brain parcellations.

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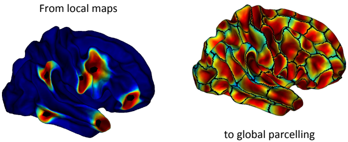
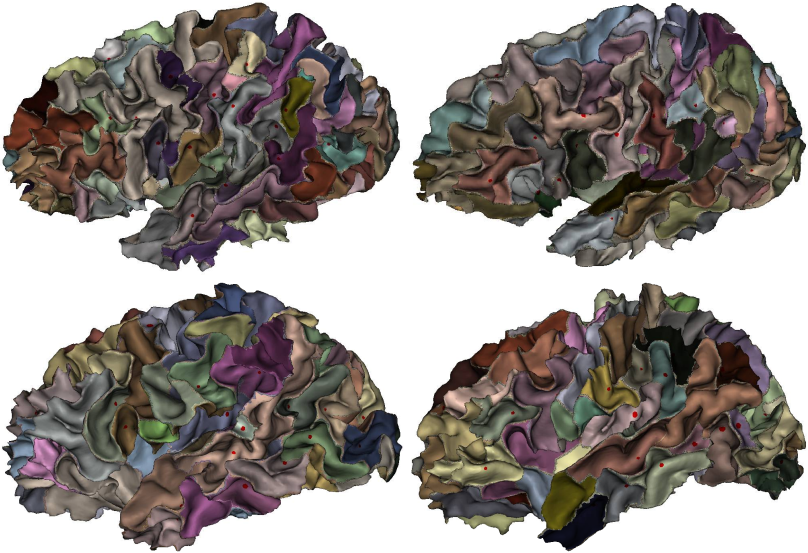
January 2018

Adaptive watershed by flooding



Variability of the cortical surface

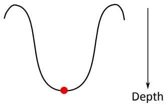


Cortical folding

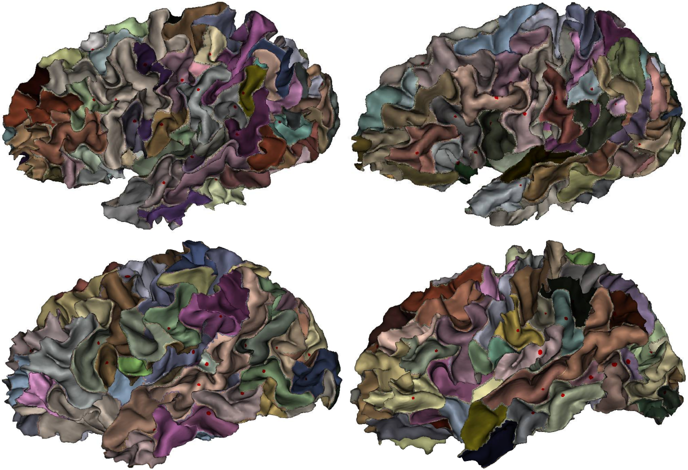
1. Cortical folds :
   - Name : *sulcus* (pl. *sulci*)
   - Common organization
   - Highly variable geometry and topology

2. **Sulcal basins** :
   - Subdivisions of the sulci
   - 1 sulcal pit in each basin

3. Sulcal pits :
   - **Robust landmark**
   - Point of maximal depth in each basin $\longrightarrow$
   - 100 ± 5 pits by subject



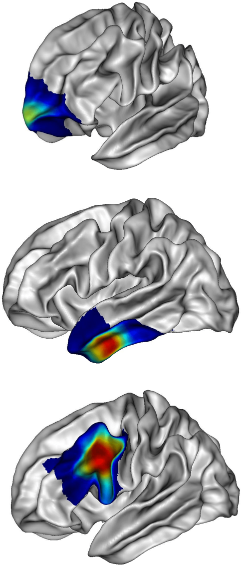
How to establish the correspondences between these parcels ?



and how to build an atlas parcellation in order to

- define a nomenclature of the sulcal basins
- have an insight on the average shape of these basins

Heuristic to build an atlas of sulcal basins

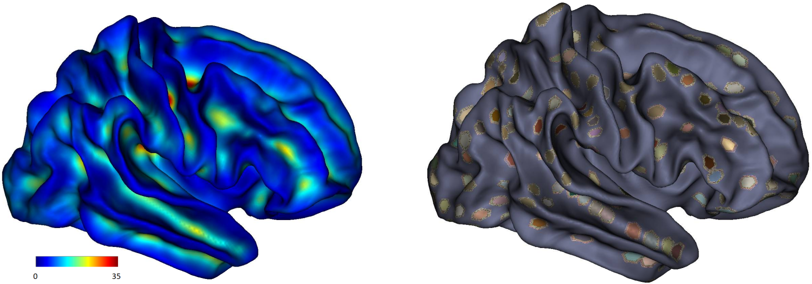


After registration, the density maps of homologous sulcal basins contain the geometry of these basins. These maps require yet to identify these basins across the population.

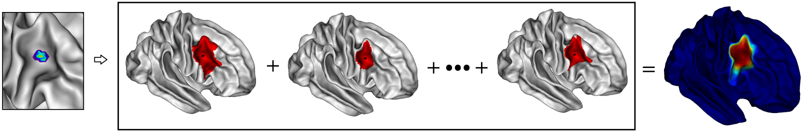
Aim: to jointly build an atlas map of sulcal basins and to identify individual basins with respect to this atlas.

Method: a watershed by flooding algorithm on the density maps of sulcal basins.

Initialization of the clusters

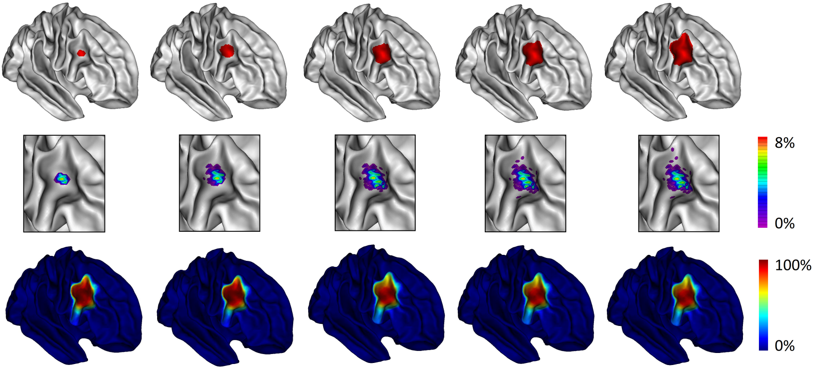


Density map of sulcal pits and clusters initialized with a small neighborhood around the maximums of the density map.

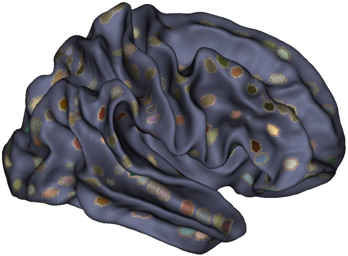


Identification of the first sulcal pits and extraction of associated sulcal basins.

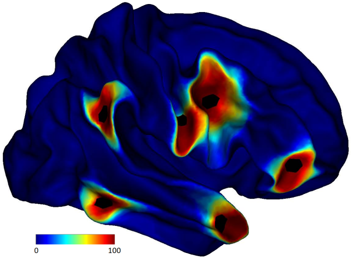
Growing cluster and learning of the influence map



Some initial influence maps

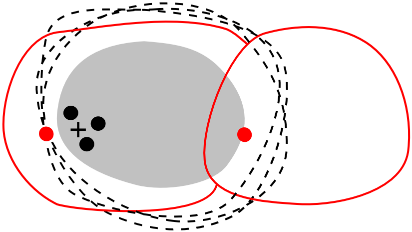


Initial clusters.



Some estimated **normalized density maps of sulcal basins**, called influence maps, (merged in one texture) with their respective **cluster in black**.

Improved learning of the influence maps



In order to improve the **robustness of these influence maps**, we filter the new pits assigned to a cluster according to a **geometrical criterion**:

- a new basin candidate (e.g. right red basin) must contain the seed "+" of the cluster (its first vertex)

This also ensures labeling uniqueness for each subject !

Clusters' filtering

The irregularity of the density map of sulcal pits produces too many seeds: we have about 170 **clusters when subjects have about** 100 **sulcal basins**.

Underlying minimization problem:

$$\min_{(N,C,\gamma)} \sum_{\text{subject } i} \sum_{k \in \mathrm{Def}(\gamma_i)} d\Big(B_i(\gamma_i(k)), C(k)\Big)^2 + \lambda \sum_{j \notin \mathrm{Im}(\gamma_i)} \ell\Big(B_i(j)\Big)$$

where the unknown variables are

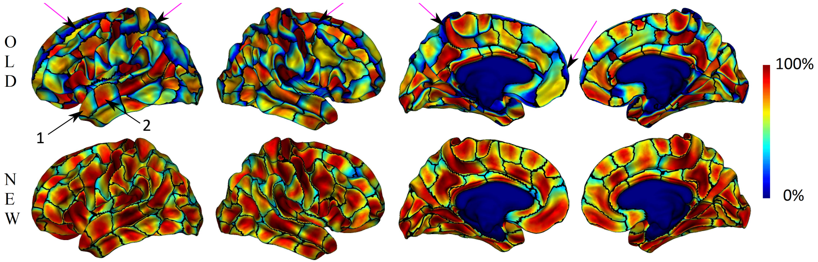
- the number of clusters $N > 0$
- the shape of these clusters C
- the mappings γ between clusters and individual sulcal basins

and where d measures the similarity between the individual basins and the clusters and ℓ penalizes the rejected individual basins.

λ **defines the trade-off between matching accuracy and the number of unlabeled sulcal basins. It regulates the flexibility of the model with respect to minor patterns of sulcal basins**.

In practice: we iteratively delete the clusters that induce the smallest pits lost with a stop criterion grounded on the minimal % of subjects associated to each cluster.

Results on 137 adults: comparison with a clustering method on sulcal pits

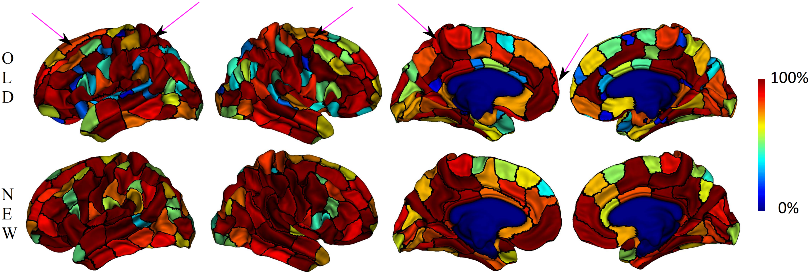


Merged influence maps for the old pipeline (first row) and new pipeline (second row).

For more details, see

I. Kaltenmark, G. Auzias, L. Brun, J. Lefèvre, C. Deruelle, and O. Coulon. Cortical inter-subject correspondences with optimal group-wise parcellation and sulcal pits labeling, *(available on Hal)*.

Results on 137 adults: frequency in each cluster



Final N_1 scores, percentage of subjects that have a pit associated to a given cluster. First row: old method. Second row: new method.