

Automated individual-level parcellation of Broca's region based on resting-state functional connectivity

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Introduction

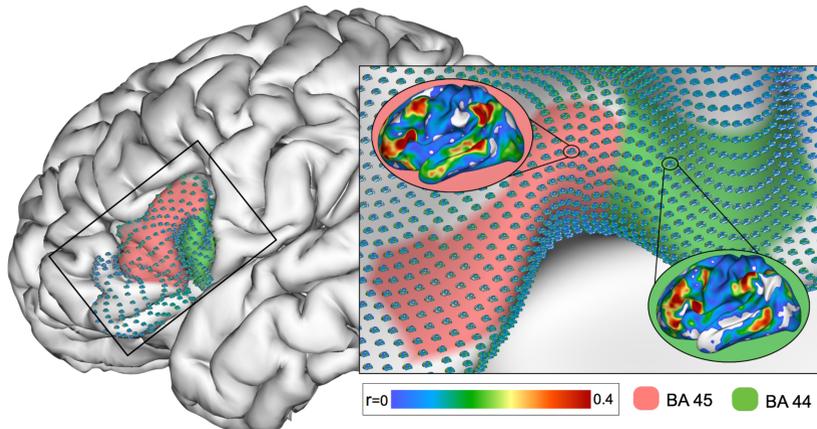
In previous work, Brodmann areas 44 and 45 were manually labeled in a large number of individual datasets using connectivity information mapped with functional connectivity glyphs^{1,2} (figures 1 and 2). The overarching aim of the current project is to use these manually labeled datasets to develop an automated individual-level parcellation method with comparable precision to the manual approach. The following work presents results from the initial steps in this process.

Methods

Data consisted of 109 ICA-FIX denoised resting-state fMRI datasets from the Human Connectome Project³. This included 101 previously labeled (BA 44 and 45) for training and 8 novel (previously unlabeled) datasets for testing.

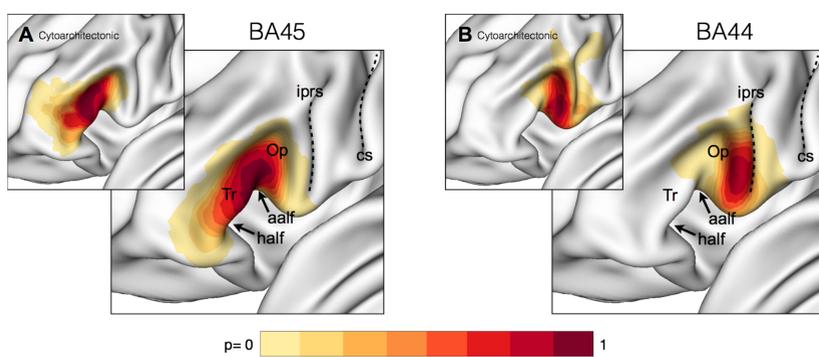
A decision tree classifier (CART algorithm⁴) was trained and cross-validated (figures 4) on connectivity information and geodesic distance maps of the 101 previously labeled datasets (figure 3). The resulting classifier was tested on 8 novel datasets (figure 5), which were then manually labeled for comparison (figure 6).

1 Manual labeling using functional connectivity glyphs



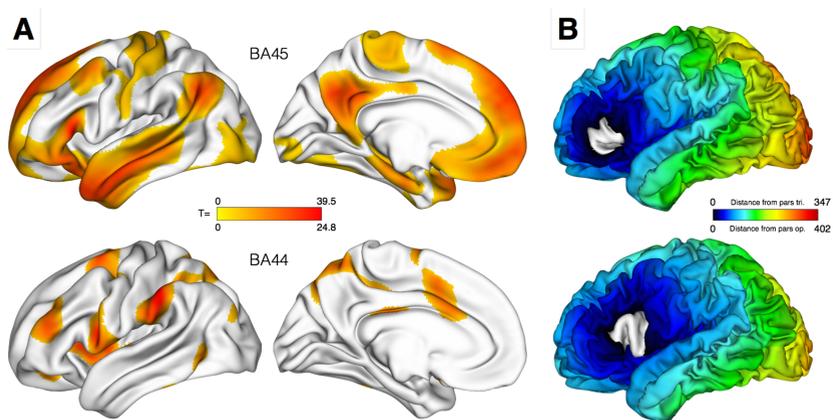
Manual labeling of areas 44 and 45 based on functional connectivity glyphs in one individual. Each glyph represents the connectivity of that node to the rest of the cortical surface. Areas 44 and 45 can be distinguished by differences in the anterior temporal and inferior parietal regions. Nodes are included in the labels based on their similarity to a region's known connectivity pattern.

2 Training data: manual labels



Probability maps of areas 44 and 45 across 101 manually labeled brains. (A) and (B) show cytoarchitectonic probability maps from the Juelich Brain Model⁵ for comparison. The 101 individual manual parcellations were included as labels in the training data.

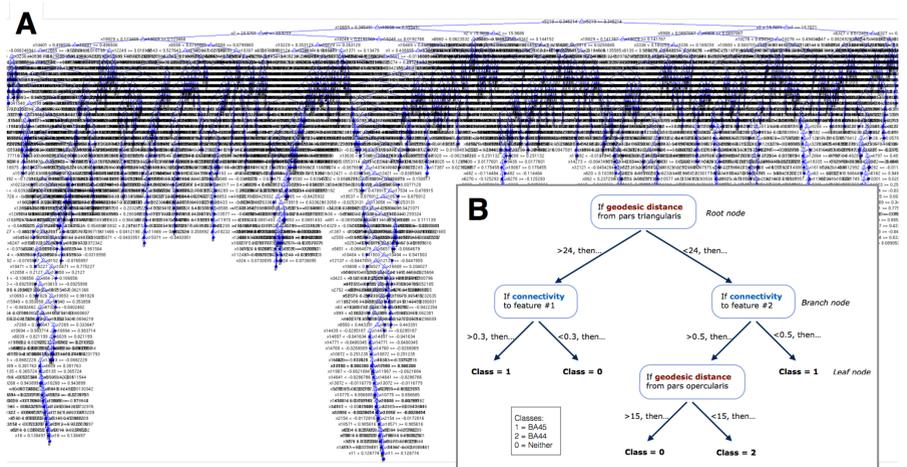
3 Training data: functional connectivity and geodesic distance features



(A) To reduce the size of the training data, connectivity features were reduced to those included in previously generated contrasted group-level connectivity maps of areas 44 and 45 (voxel-wise threshold of $p < 0.001$ and a cluster threshold of $p < 0.05$). (B) To incorporate knowledge of the anatomical locations of areas 44 and 45, the geodesic distances from the freesurfer labels corresponding to the pars opercularis and pars triangularis in each individual were included as additional features.

Results

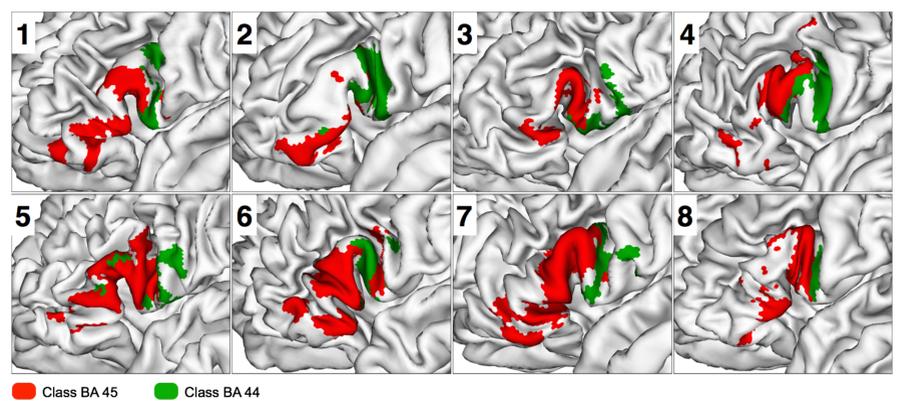
4 Decision tree and cross-validation



(A) The full unpruned decision tree resulting from CART⁴ classification of the training data of 101 subjects. (B) A schematic representation of the types of decisions made in the tree.

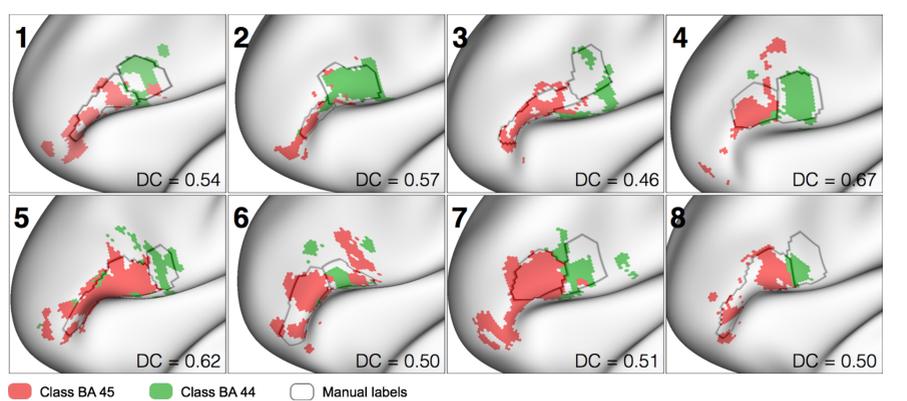
The 10-fold cross-validation procedure yielded a mean classification accuracy of 94% across the 10 folds.

5 Automated classification of testing data



Results of the automated classification of areas 45 (red) and 44 (green) in the testing datasets, presented on the individual un-inflated cortical surfaces. Each node was assigned to the most probable class according to the sum of the probabilities of its neighbors.

6 Comparison of automated classification results to manual labels



Spatial overlap of the results from the automated classification (red and green) and manual labeling (black outline) procedures for the testing datasets, presented on the individual inflated cortical surfaces. Spatial overlap of the two procedures was calculated using the Dice coefficient (DC).

Conclusions

- Areas 44 and 45 could be distinguished in the testing datasets using automated classification based on functional connectivity
- This approach could be applied to any cortical regions for which differences in functional connectivity have been established
- The current algorithm correctly identifies the boundary between areas 44 and 45, but results are limited in terms of spatial overlap with the manual labels due to the discontinuity of the automatically generated labels
- Future work will aim to optimize the classification results by integrating methods from existing parcellation pipelines to ensure spatial continuity of the labels

Abbreviations

aalf: anterior ascending ramus of the lateral fissure
cs: central sulcus

half: horizontal ascending ramus of the lateral fissure
iprs: inferior precentral sulcus
Op: pars opercularis
Tr: pars triangularis



<http://code.google.com/p/braingl>

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