Brain shape analysis for predicting treatment remission in major depressive disorder

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Goal

Our goal is to classify patients into those who respond well to treatment or not based on brain shape analysis measures. In this work, we apply automated feature extraction and shape analysis algorithms from the Mindboggle software under development (www.mindboggle.info) to classify major depressive disorder (MDD) patients into remitters and non-remitters. Remitters are depressed subjects who have post-SSRI treatment Hamilton depression scores less than or equal to seven.

Shape analysis measures

Cortical thickness, curvature, and depth are examples of clinically relevant shape analysis measures. They have been used to help characterize disorders such as mild cognitive impairment and Alzheimer's disease [1]. Sulci have been used to compute global and local gyrification indices, which have been used to characterize schizophrenia [2] and early-onset vs. intermediate-onset bipolar disorder as well as bipolar and unipolar depression [3-5]. Pits, points of maximal depth or curvature in the sulci, may be well conserved structures formed early in development [6-7] and have been used to characterize conditions such as polymicrogyria [8]. Fundi run along the depths of the folds, and like pits are thought to characterize early stages of morphological development, and therefore may exhibit abnormalities in neurodevelopmental and heritable disorders.

Feature extraction and analysis

We generate a brain surface from T1-weighted MRI data using third-party software such as FreeSurfer. From a depth map of this surface (Fig.1), Mindboggle algorithms currently extract the following anatomical features related to folds in the surface of a brain (Fig.2): **sulci**, **fundi**, and **pits** [9]. Sulci are patches of the brain surface with positive curvature or below a certain depth. Fundi traverse the depth of the folds in a sulcus and run through the pits in that sulcus. For the present study we compute **fundus length** as well as **curvature**, **convexity**, **cortical thickness**, and **depth** [9-10] for each point on a sulcus (including points of the fundi and pits).

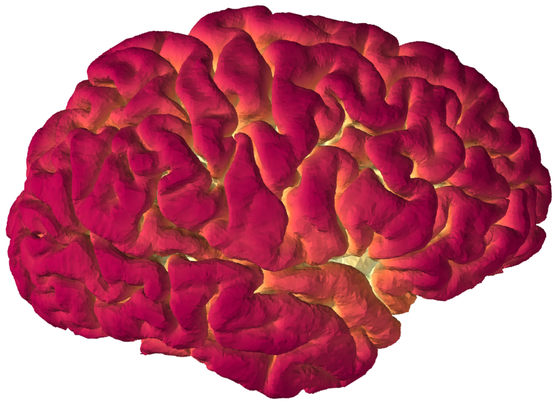

Fig. 1: Example depth map [10] of an exterior brain surface.

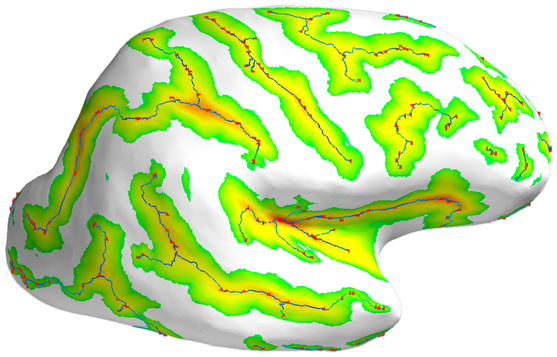

Fig. 2: Example inflated exterior surface with depth-based sulci (non-white surface patches of positive curvature), fundi (blue curves) and pits (red dots)

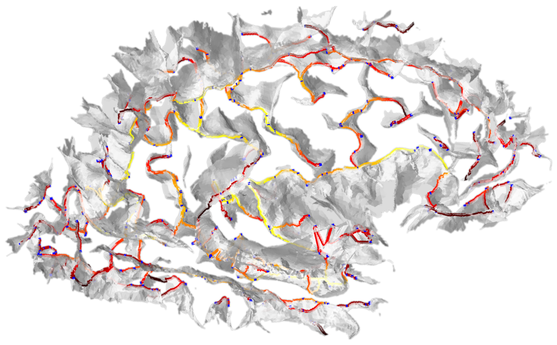

Fig. 3: Example exterior surface with depth-based sulci (gray surface patches), fundi (red-yellow curves) and pits (blue dots)

Data

T1-weighted MRI data from 24 healthy controls and 18 patients with major depressive disorder, of which 10 were non-remitters and 8 were remitters.

	Non-remitter (n=10)	Remitter (n=8)	p-value
Age	31.15 ± 11.28	34.30 ± 14.60	0.61^{+}
# Females (%)	7 (70.00%)	4 (50.00%)	0.63*
# Not Recently Medicated (%)	7 (70.00%)	7 (87.50%)	0.59*
# Suicide Attempters	4 (40.00%)	1 (14.29%)	0.31*
Hamilton Depression Rating Scale	24.40 ± 4.40	25.50 ± 7.09	0.69^{+}
Beck Depression Rating Scale	26.90 ± 8.50	23.75 ± 11.62	0.52^{+}
Genotype			
CC	1 (10.00%)	3 (28.57%)	0.53*
CG	6 (60.00%)	4 (57.14%)	
GG	2 (20.00%)	1 (14.29%)	

*p-value from fisher's exact test
$^{+}$p-value from 2 tailed Student's t-test

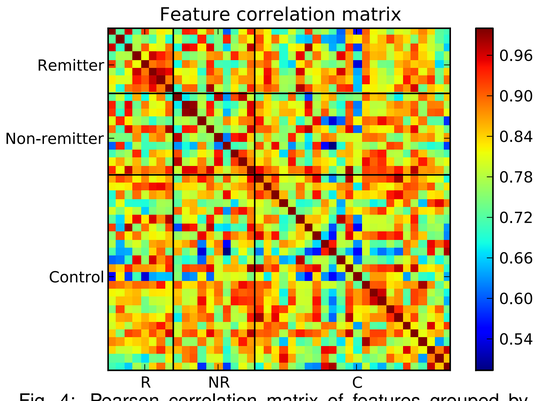

Fig. 4: Pearson correlation matrix of features grouped by type of subject. There is no visible block-diagonal structure, suggesting that multivariate approaches might help.

Results

We used scikits.learn [11] to train models and predict classes from these data (42 subjects x 8 sulci x 5 measures), chose classifier parameters through cross-validated search, and assessed classifier significance using a permutation test.

	precision	recall	f1-score	samples
Patients	0.60	0.67	0.63	18
Controls	0.73	0.67	0.70	24
avg / total	0.67	0.67	**0.67**	42
Remitter	0.75	0.75	0.75	8
Non-remitter	0.80	0.80	0.80	10
avg / total	0.78	0.78	**0.78**	18

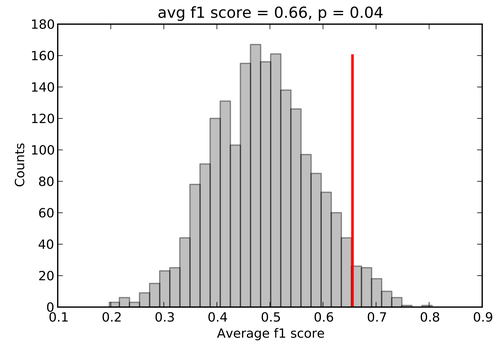

Fig. 5: Classification results using a KNearestNeighbor classifier to distinguish patients and controls. The gray histogram denotes the null distribution from a permutation test, while the red line indicates the performance of the classifier.

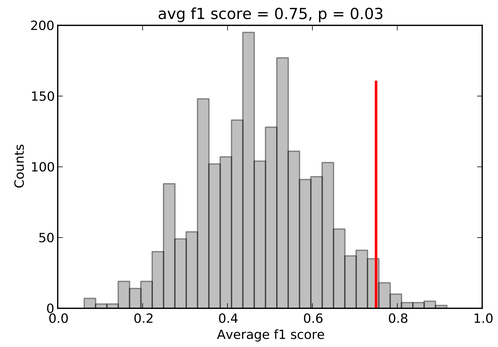

Fig. 6: Classification results using an SVM classifier with a polynomial kernel. The gray histogram again denotes the null distribution from a permutation test, while the red line indicates the performance of the classifier.

These are the first results that we know of using features extracted from anatomical MRI to predict treatment remission for MDD (Fig 6.).

Acknowledgements and References

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