Predicting Cognitive Scores from Resting fMRI Data and Geometric Features

Anand A. Joshi, Jian Li, Haleh Akrami and Richard M. Leahy

Signal and Image Processing Institute, University of Southern California, Los Angeles CA 90089

Abstract

The objective of this work is to predict cognitive scores of individuals, specifically, Performance IQ, Verbal IQ and ADHD index, using their resting fMRI (rfMRI) and structural T1 weighted (sMRI) imaging data. In this project, we use a deep learning approach for modelling relationship between rfMRI and sMRI data of individuals and their cognitive performance scores.

First, we process the rfMRI and sMRI data of subjects using our BrainSuite fMRI Processing (BFP) pipeline that performs the anatomical and functional preprocessing, resulting in a fMRI as well as geometric (anatomical) features represented in a standardized grayordinate system. Our neural network is a combination of convolutional and standard neural network where it processes the cortical data using convolutional layers and subcortical data using standard neural network.

The geometric and functional cortical data corresponding to the two hemispheres was transformed to 128x128 multichannel images and inputted to convolutional layers of a neural network while subcortical data was presented in a standard vector form and inputted to standard input layer of the network.

The neural network was implemented in Python using Keras library with TensorFlow backend. The training was done on 168 images and we used 90 images for testing. We observed significant correlation between predicted and actual values of the cognitive scores indicating significant predictivity of the scores from the MRI based imaging markers. The correlation values for combined anatomical and functional features-based prediction were higher than the individual features, while among anatomical and functional features, functional rfMRI based features were more predictive of the cognitive scores.

Description of Purpose

Anatomical (T1-weighted) and functional (fMRI) MRI techniques offer insight into structure and function of the human brain. Multiple studies have been able to identify brain regions associated with different cognitive scores such as IQ [1]. However, prediction of the cognitive scores based on these MRI imaging techniques remains a challenging task and has attracted attention recently [2], [3] because the relationship between high level cognitive functions revealed by cognitive scores and the brain structure and functional activations during resting state is highly unclear. The neural underpinnings of individual differences in intelligence is not well understood [4].

Here, we propose a deep learning approach that uses rfMRI data and geometric features extracted from anatomical T1 weighted MRI images to predict three cognitive scores, namely, verbal IQ, performance IQ and ADHD index.

Methods

We used the BrainSuite fMRI pipeline [5] to process the rfMRI subject data and generated grayordinate representation [6] of the preprocessed rfMRI signal. We used the BrainSync transform [7] to align rfMRI data in the subject population to a representative subject. This was followed by a dimensionality reduction along the temporal dimension to 21, using PCA, with the basis chosen from average signal from subjects. This results in a 21-dimensional vector representing functional features at each grayordinate point.

In order to generate geometric features we computed the shape index (S), mean curvature (C) and cortical thickness (T) [8]. These features were generated on the mid-cortex at 5 different smoothness levels, resulting in a 15-dimensional geometric feature at each point in the cortex. These features were mapped to the grayordinate system (Figure 1).

As input to the neural network model, we mapped the cortical hemispheres in the grayordinate systems to unit squares of size 128x128 (Figure 2). Additionally, the data from 31870 subcortical points was also inputted to the neural network. This forms the input of size 128x128xC (2 hemispheres) and 31870xC (subcortical) data as input, where C=15 for geometric features based prediction, C=21 for fMRI based prediction and C=36 for the combined prediction model.

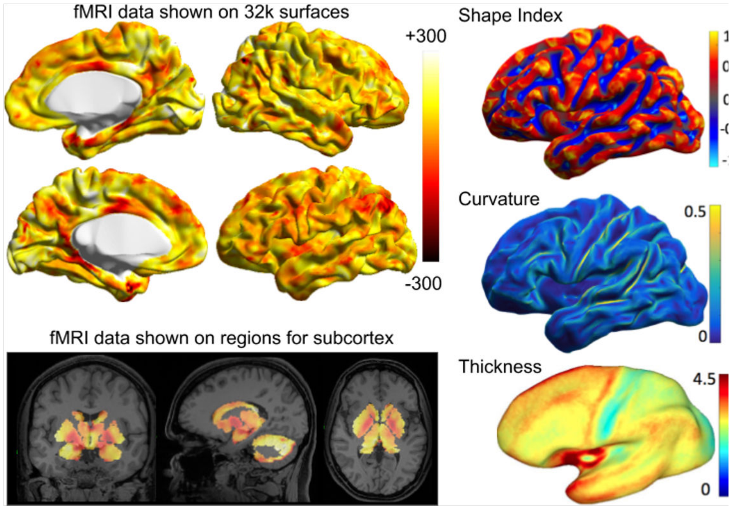

Figure 1: (Left) fMRI data mapped to cortex and subcortical regions for grayordinates. (Right) Shape index (S), curvature (C), and thickness (T).

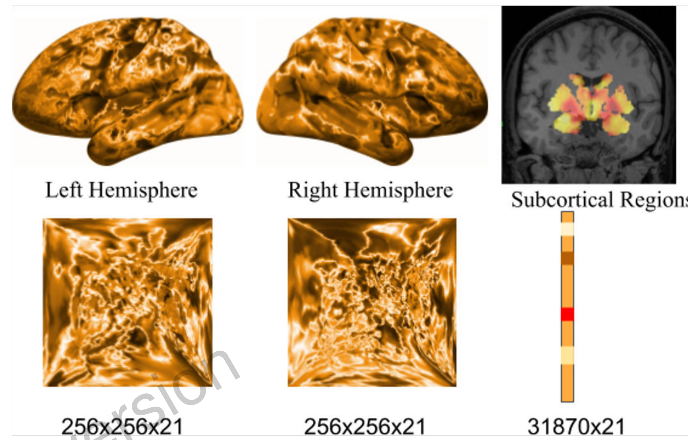

Figure 2: Input to the neural network. The cortical data was mapped to squares and subcortical data was vectorized according to grayordinate convention.

We used a neural network inspired from VGG model [9] that uses a combination of convolutional, fully-connected, dropout, pooling and flattening layers with ReLu activations. In addition to the convolutional layers from VGG model, we also added standard neural network model for the subcortical representations as shown in Figure 3. The neural network was implemented in Python using Keras library that uses TensorFlow backend. The Adam optimizer was used for training the network.

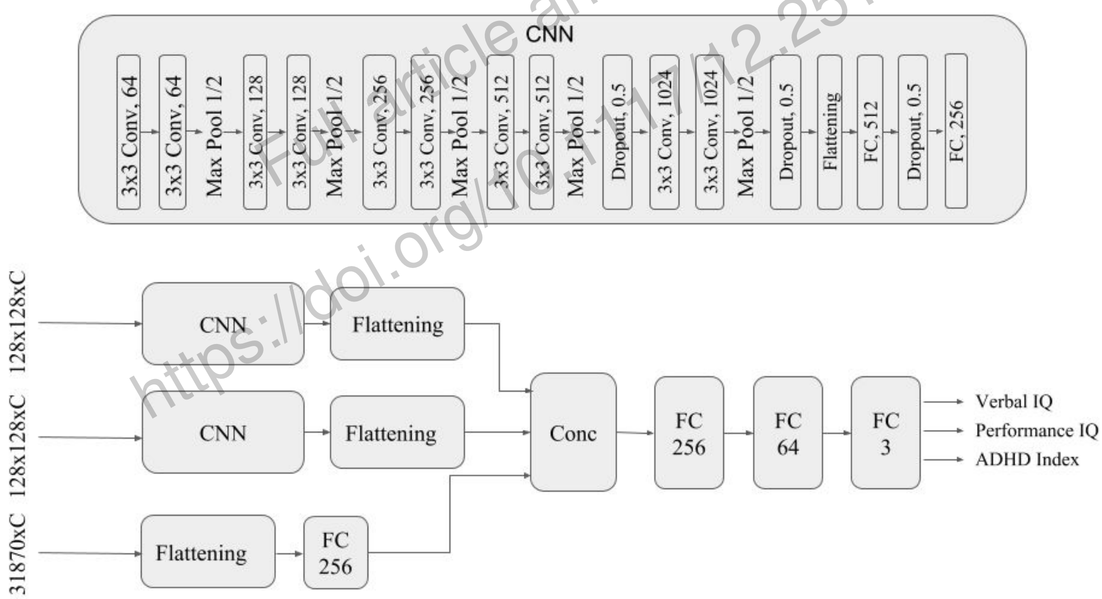

Figure 3: The Neural Network model is a combination of convolutional neural network and standard neural network. Geometric and functional features were mapped to the flat maps for the two cortical hemispheres and were inputted to a VGG style CNN, whereas standard neural network was used for data for the subcortical regions.

The study population comprise of 259 subjects (typically-developing controls: 146, ADHD combined: 46, ADHD inattentive: 66, ADHD hyperactive: 1) that were collected as a part of ADHD 200 competition [10]. In this study, we did not subdivide the population according to groups, but used their ADHD index as a cognitive measure to be predicted.

The subjects were scanned at the Peking University the fcon1000 protocol [10]: resting scan (TR=2 sec, 2mm isotropic 5 min) and an MPRAGE scan (1.2x1x1.2 mm) on a Siemens SIEMENS MAGNETOM trio 3T scanner.

The training was done on 169 subjects. For the Adam optimizer, a batch size of 10 was used with 8 subjects for computing the update to the weights and 2 subjects used for computing the cross-validation error. The weights were updates when the cross-validation error decreased. The small batch size was used in order to avoid overfitting. 20 Epochs were performed. The training was done on a 20 core Xeon computer. GPU acceleration was not used for this dataset. The training takes ~4 hours. Once the model is trained, it was used to predict the three cognitive scores on a test dataset of remaining 90 subjects.

Results

In order to analyze the performance of the predictions, we computed correlation between predicted values of the three cognitive scores and the actual values. This computation was performed for (1) functional features computed from rfMRI data, (2) geometric features computed from shape of the cortex, and (3) combination of both rfMRI and shape features. The results show that the combination of fMRI and geometric features results in an improved predictability of the cognitive features.

	Performance IQ	Verbal IQ	ADHD Index
Shape	0.25	0.18	0.21
rfMRI	0.32	0.34	0.32
Shape + rfMRI	0.47	0.41	0.57

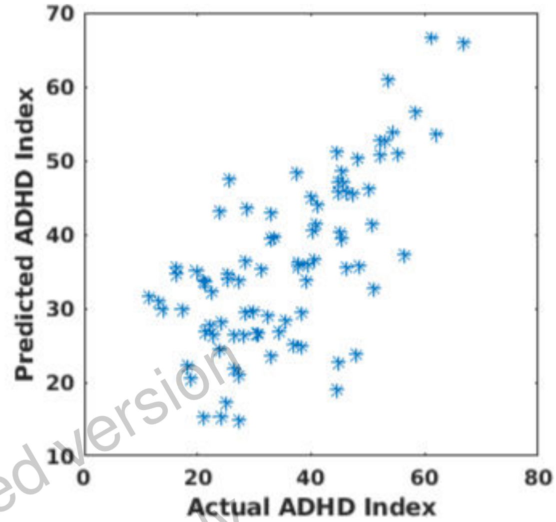

Figure 4: The table on the left shows correlation between actual and predicted cognitive scores for prediction based on shape features only, rfMRI features only, and the combination of the two. The plot on the right shows scatter plot of actual and predicted ADHD index using the combination of shape and rfMRI features, for the test population.

Conclusions

We observed significant correlation between predicted and actual values of the cognitive scores indicating significant predictivity of the scores from the MRI based imaging markers. The correlation values for combined anatomical and functional features-based prediction were higher than the individual features, while among anatomical and functional features, functional rfMRI based features were more predictive of the cognitive scores.

This study indicates the potential of rfMRI imaging as a screening test for various neurological and psychological conditions.

References

[1] D. M. Barch *et al.*, "Function in the Human Connectome: Task-fMRI and Individual Differences in Behavior," *NeuroImage*, vol. 80, pp. 169–189, Oct. 2013.

[2] J. C. Dubois, P. Galdi, L. K. Paul, and R. Adolphs, "A distributed brain network predicts general intelligence from resting-state human neuroimaging data," *bioRxiv*, p. 257865, May 2018.

[3] R. Kong *et al.*, "Spatial Topography of Individual-Specific Cortical Networks Predicts Human Cognition, Personality, and Emotion," *Cereb. Cortex*, Jun. 2018.

[4] N. Raz, "Aging of the brain and its impact on cognitive performance: Integration of structural and functional findings," in *The handbook of aging and cognition, 2nd ed*, Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers, 2000, pp. 1–90.

[5] "BFP: BrainSuite Functional Pipeline | BrainSuite." [Online]. Available: http://brainsuite.org/bfp/. [Accessed: 02-Aug-2018].

[6] S. M. Smith *et al.*, "Resting-state fMRI in the Human Connectome Project," *NeuroImage*, vol. 80, pp. 144–168, Oct. 2013.

[7] A. A. Joshi, M. Chong, J. Li, S. Choi, and R. M. Leahy, "Are you thinking what I'm thinking? Synchronization of resting fMRI time-series across subjects," *NeuroImage*, vol. 172, pp. 740–752, May 2018.

[8] S. P. Awate, R. M. Leahy, and A. A. Joshi, "Riemannian Statistical Analysis of Cortical Geometry with Robustness to Partial Homology and Misalignment," in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016*, 2016, pp. 237–246.

[9] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *ArXiv14091556 Cs*, Sep. 2014.

[10] "ADHD200." [Online]. Available: http://fcon_1000.projects.nitrc.org/indi/adhd200/. [Accessed: 04-Jan-2018].