ARTICLE IN PRESS

NeuroImage xxx (2014) xxx-xxx



Contents lists available at ScienceDirect

NeuroImage



YNIMG-11349; No. of pages: 10; 4C: 4, 5, 6, 8

journal homepage: www.elsevier.com/locate/ynimg

Relating brain anatomy and cognitive ability using a multivariate multimodal framework

Q1 Philip A. Cook ^{a,*}, Corey T. McMillan ^b, Brian B. Avants ^a, Jonathan E. Peelle ^c, James C. Gee ^a, Murray Grossman ^b

Please cite this article as: Cook, P.A., et al., Relating brain anatomy and cognitive ability using a multivariate multimodal framework, NeuroImage

4 ^a Department of Radiology, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA 19104, USA

5 b Penn Frontotemporal Degeneration Center, Department of Neurology, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA 19104, USA

6 ^c Department of Otolaryngology, Washington University in St Louis, St Louis, MO 63110, USA

7 ARTICLE INFO

§6Article history:9Accepted 4 May 201410Available online xxxx

11 Keywords:

- Language
 Verbal fluency
- 14 Multimodal
- 15 FTD

ABSTRACT

Linking structural neuroimaging data from multiple modalities to cognitive performance is an important challenge for cognitive neuroscience. In this study we examined the relationship between verbal fluency perfor- 17 mance and neuroanatomy in 54 patients with frontotemporal degeneration (FTD) and 15 age-matched controls, 18 all of whom had T1- and diffusion-weighted imaging. Our goal was to incorporate measures of both gray matter 19 (voxel-based cortical thickness) and white matter (fractional anisotropy) into a single statistical model that 20 relates to behavioral performance. We first used eigenanatomy to define data-driven regions of interest 21 (DD-ROIs) for both gray matter and white matter. Eigenanatomy is a multivariate dimensionality reduction 22 Q2 approach that identifies spatially smooth, unsigned principal components that explain the maximal amount 23 of variance across subjects. We then used a statistical model selection procedure to see which of these 24 DD-ROIs best modeled performance on verbal fluency tasks hypothesized to rely on distinct components 25 of a large-scale neural network that support language: category fluency requires a semantic-guided search 26 and is hypothesized to rely primarily on temporal cortices that support lexical-semantic representations; 27 letter-guided fluency requires a strategic mental search and is hypothesized to require executive resources 28 to support a more demanding search process, which depends on prefrontal cortex in addition to temporal 29 network components that support lexical representations. We observed that both types of verbal fluency 30 performance are best described by a network that includes a combination of gray matter and white matter. 31 For category fluency, the identified regions included bilateral temporal cortex and a white matter region in- 32 cluding left inferior longitudinal fasciculus and frontal-occipital fasciculus. For letter fluency, a left tempo- 33 ral lobe region was also selected, and also regions of frontal cortex. These results are consistent with our 34 hypothesized neuroanatomical models of language processing and its breakdown in FTD. We conclude 35 that clustering the data with eigenanatomy before performing linear regression is a promising tool for mul- 36 timodal data analysis. 37

© 2014 Published by Elsevier Inc.

38 **40**

41

44

45

46 47

48

49

43 Introduction

One of the fundamental challenges of cognitive neuroscience is relating brain anatomy to cognitive processes. Most neuroimaging studies linking brain structure to behavior use mass univariate approaches, relying on a whole-brain regression framework in which the relationship between a dependent variable (e.g. gray matter density or fractional anisotropy; FA) and a behavioral measure is assessed at every voxel in

(2014), http://dx.doi.org/10.1016/j.neuroimage.2014.05.008

http://dx.doi.org/10.1016/j.neuroimage.2014.05.008 1053-8119/© 2014 Published by Elsevier Inc. the brain.¹ An advantage of this traditional approach is that it makes 50 few a priori assumptions about the location of the relationship, or the 51 spatial extent of the brain region(s) relating to behavior. However, 52 there are also some challenges. An obvious limitation is that, without 53 some sort of prior narrowing of focus, voxelwise methods result in a 54 large number of statistical tests that need correction for multiple com-55 parisons. A common strategy to address multiple comparisons is to ac-56 cumulate voxel data into larger regions of interest (ROIs). However, 57 ROIs are often difficult and labor-intensive to define for each applica-58 tion. For example, the cytoarchitectonic boundaries of Broca's area 59 involved in language are both structurally (Amunts et al., 1999) and 60 functionally (Clos et al., 2013) heterogeneous across individuals. The 61 anatomical boundaries of a particular label set may not align with 62

Abbreviations: AIC, Aikake Information Criterion; AICc, corrected AIC; bvFTD, behavioral-variant FTD; CVMSE, cross-validation mean squared error; FTD, frontotemporal degeneration; naPPA, non-fluent/agrammatic variant PPA; PPA, primary progressive aphasia; svPPA, semantic variant PPA.

^{*} Corresponding author at: PICSL, 3600 Market St, Suite 370, Philadelphia, PA 19104, USA.

E-mail address: cookpa@mail.med.upenn.edu (P.A. Cook).

¹ For parsimony we refer to "voxelwise" analyses, but this also applies to massunivariate surface-based analyses.

2

ARTICLE IN PRESS

P.A. Cook et al. / NeuroImage xxx (2014) xxx-xxx

functionally relevant areas or the concentration of pathological change 63 64 in a disease under study. These issues motivate the use of data-driven ROIs (DD-ROIs) that can be defined automatically on different popula-65 66 tions of images, have soft boundaries instead of the hard labeling of most manual label sets, and can be optimized based on criteria other 67 than visual anatomical boundaries. Such approaches have been used 68 for automated diagnosis of Alzheimer's disease (Klöppel et al., 2008) 69 70and the classification of primary progressive aphasia variants (Wilson 71et al., 2009). Variability of white matter across individuals has also 72been suggested to impact language performance (Berthier et al., 2012; 03 Flöel et al., 2009). Another important issue with ROI studies of white matter is the lack of available labels: while there are several dense 74parcellations of cortical gray matter available to researchers, there are 7576 few white matter atlases and those that are available focus on major tracts that can be delineated using diffusion tensor imaging. 77

In this report, we use a multivariate approach that aims to integrate 78 neuroimaging measures of gray matter and white matter in order to de-79 80 fine a large-scale neural network that accounts for linguistic performance. This approach relies on "eigenanatomy" (Avants et al., 2012a; 81 McMillan et al., 2013b, 2014), which is a recently proposed algorithm 82 for generating DD-ROIs. These soft ROIs are defined automatically by 83 maximizing the covariance of voxel-wise measurements normalized 84 85 to template space and collected into a matrix representation. There is no need for prior manual labeling of the subject images and one only 86 needs to define an anatomical domain of interest in the template, for ex-87 ample cortical gray matter for cortical thickness and white matter for 88 diffusion-tensor statistics. Eigenanatomy also addresses the need to 89 90 take into account spatial smoothness in the ROIs. Voxelwise approaches 91 do this in a post-hoc manner by considering clusters of contiguous re-92 sults. More recent multivariate approaches take spatial dependency as 93 a given, and seek to capitalize on this from the outset. We view this as 94a sensible assumption, given the continuous nature of the neural tissue, 95and the fact that processes such as neural development, age-related cortical thinning, and gray matter loss due to neurodegenerative disease all 96 show a significant degree of spatial localization. By capitalizing on these 97 dependencies, we should be able to better characterize variations in 98 99 brain shape and tissue structure. Further, theoretical arguments suggest that exploiting prior knowledge when solving challenging optimization 100 problems fundamentally improves results in terms of performance, 101 stability and interpretability (Wolpert and Macready, 1997). 102

In combination with eigenanatomy dimensionality reduction, we 103 104 apply a model selection procedure to determine which DD-ROIs in gray matter and white matter form the most efficient regression models 105 of behavioral measures. This approach combines information from 106 multiple imaging modalities in a principled manner within a single 107 regression framework while maintaining the interpretability of classic 108 109regression models. Although in theory researchers certainly appreciate the joint contribution of gray matter and white matter integrity to 110 behavioral performance, in practice it has proven difficult to study 111 these at the same time in the same set of subjects. In particular, it has 112 been challenging to quantitatively evaluate the relative contribution of 113 114 gray matter and white matter to behavior: if a patient has damage to 115both, which is the better predictor of performance?

To demonstrate the utility of our multivariate approach, we focus on 116the neural basis of language limitations in patients with frontotemporal 117 degeneration (FTD). The two most common forms of FTD yield either a 118 119 language disorder, primary progressive aphasia (PPA) (Gorno-Tempini et al., 2011), or a disorder of personality, social comportment, and exec-120utive dysfunction, behavioral-variant FTD (bvFTD) (Rascovsky et al., 121 2011). Within PPA there is a semantic variant (svPPA) that is character-122ized by difficulty with naming, word meaning, and object knowledge. 123This variant has been associated with considerable atrophy in the ante-124rior and ventral temporal lobe, more prominently on the left than the 125right, as well as disease in uncinate and inferior longitudinal fasciculi 126projections (Mahoney et al., 2013; Whitwell et al., 2010). There is also 127128 a non-fluent/agrammatic variant (naPPA), involving slowed, effortful speech with grammatical difficulty and this has been associated with 129 left-lateralized frontal and anterior–superior temporal cortical regions 130 and prominent white matter disease in corpus callosum and inferior 131 frontal–occipital fasciculus (Grossman, 2012; Grossman et al., 2012; 132 Mahoney et al., 2013). bvFTD is not associated with an obvious aphasia, 133 though executive-social limitations can have consequences on language 134 processing (McMillan et al., 2013a), and these patients have gray matter 135 frontal atrophy that is most prominent in ventral and medial frontal 136 regions and extends into dorsolateral frontal areas, with associated disase in white matter projections from these areas (Lillo et al., 2012; 138 Zhang et al., 2013). 139

Given the distributed localization of disease within the FTD variants 140 we hypothesize that distinct large-scale neural networks contribute to 141 patients' language limitations. Specifically, we focus on verbal fluency. 142 This is a complex task that involves mental search through the lexicon 143 of words that meet the criteria of a category. This process requires con- 144 ceptual knowledge of word meanings, lexical retrieval, and executive 145 resources involving a flexible mental search strategy. Verbal fluency 146 tasks are common neuropsychological measures that can be adjusted 147 to stress different cognitive processes and thus place different demands 148 on a large-scale neuroanatomical network. For example, a category flu- 149 ency task ("Name as many animals as you can") emphasizes knowledge 150 of lexical and conceptual information. By contrast, a letter fluency task 151 ("Name as many words as you can that begin with the letter F") requires 152 lexical information and additionally requires an advanced executive 153 search strategy to search through all words that begin with a specific 154 letter. In the context of FTD patients, svPPA patients have more difficulty 155 with category fluency than letter fluency and this has been associated Q4 with temporal cortex disease (Libon et al., 2009a). However, letter flu- 157 ency appears to be more associated with frontal cortex disease in FTD 158 and is compromised in bvFTD and nvPPA (Libon et al., 2009a). Assess- 159 ments of gray matter regions contributing to verbal fluency tasks have 160 been performed using a priori regions of interest (Amunts et al., 2004) 161 or regression analyses using voxel-based morphometry (Libon et al., 162 2009b). We are unaware of investigations evaluating the relative contri- 163 butions of gray matter and white matter disease to verbal fluency defi- 164 cits in FTD. 165

Together, we hypothesize that our novel multivariate approach and166model selection procedure will reveal a large-scale neural network that167supports verbal fluency, including fronto-temporal gray matter regions168as well as white matter projections between these brain regions, and169that the cortical-white matter network implicated in performance will170be tailored to the specific task. We test this in a multimodal imaging171study of FTD. These observations would provide proof-of-concept172evidence for utilizing this approach to better understand the relative173contributions of gray matter and white matter in the context of cog-174nitive neuroscience, and would improve our understanding of brain-175behavior relationships in neurodegenerative conditions like FTD.176

Materials and methods

Participants

We recruited 54 patients from the Penn Frontotemporal Degenera-179 tion Center and Hospital of the University of Pennsylvania Cognitive 180 Neurology Clinic who were native-English speakers and clinically-181 diagnosed with FTD by a board-certified neurologist using published 182 criteria of either PPA (Gorno-Tempini et al., 2011) or bvFTD (Rascovsky 183 et al., 2011). Other causes of dementia were excluded by clinical exam, 184 blood and neuroimaging tests. Exclusion criteria included other neuro-185 logic, psychiatric or medical conditions that can result in cognitive 186 change. Some patients may have been on a small, stable dose of a 187 non-sedating neuroleptic or anti-depressant medication. We also re-188 in age and education relative to the patient cohort. All subjects had T1and diffusion-weighted structural MRI scans. Thirty-eight subjects 191

Please cite this article as: Cook, P.A., et al., Relating brain anatomy and cognitive ability using a multivariate multimodal framework, NeuroImage (2014), http://dx.doi.org/10.1016/j.neuroimage.2014.05.008

177 178 Download English Version:

https://daneshyari.com/en/article/6027146

Download Persian Version:

https://daneshyari.com/article/6027146

Daneshyari.com