Intelligence 54 (2016) 105–116

Contents lists available at ScienceDirect

Intelligence

Structural efficiency within a parieto-frontal network and cognitive differences

José Angel Pineda-Pardo [a,*], Kenia Martínez [b,c], Francisco J. Román [b], Roberto Colom [b,**]

[a] hmCINAC, Hospital Puerta del Sur, Hospitales de Madrid, Móstoles, and CEU-San Pablo University, Madrid, Spain
[b] Department of Biological and Health Psychology, Universidad Autónoma de Madrid, Ciudad Universitaria de Cantoblanco, Madrid, Spain
[c] Instituto de Investigación Sanitaria Gregorio Marañón Madrid, Spain

ARTICLE INFO

Article history:
Received 3 August 2015
Received in revised form 7 December 2015
Accepted 7 December 2015
Available online xxxx

Keywords:
Connectivity
Graph theory
P-FIT
Cognition
Diffusion tensor imaging

ABSTRACT

Here we compute the association between cognitive differences and variations in brain efficiency within a predefined structural network. The regions comprised by the network of interest were selected according to the parieto-frontal integration theory (P-FIT) (Jung & Haier, 2007). Local and global efficiency was quantified for this network. The former reflects specialization within the network, whereas the latter benefits long-distance interactions and reflects integration over the whole network. Fluid reasoning, working memory capacity, and processing speed were the measured cognitive factors. Forty-two young healthy women were the participants in the present study. These were the main findings: a) the precuneus, the middle frontal gyrus, the pars triangularis, and the superior frontal gyrus showed the greatest connectivity indices, supporting the special role of discrete parietal and frontal regions within the network, b) network efficiency was remarkably related with variations in working memory capacity, c) fluid reasoning showed positive correlations with network efficiency, and d) processing speed was unrelated with network efficiency. The findings underscore brain network analyses for studying cognitive differences.

1. Introduction

There are a number of reports addressing whether it is possible to reliably identify neural substrates of cognitive differences using various structural and functional neuroimaging approaches (Colom, Karama, Jung, & Haier, 2010; Colom & Thompson, 2011; Deary, Penke, & Johnson, 2010; Nisbett et al., 2012; Yarkoni et al., 2011). Jung and Haier (2007) proposed the parieto-frontal integration theory (P-FIT) for highlighting the commonalities underlying published neuroimaging studies of general cognitive ability (intelligence) and reasoning. This model has been used as a framework for interpreting a range of research findings (Basten, Hilger, & Fiebach, 2015; Cole, Yarkoni, Repov, Anticevic, & Braver, 2012; Colom et al., 2009; Ebisch et al., 2013; Langer et al., 2012; Santarnecchi, Rossi, & Rossi, 2015; Wang et al., 2011).

These studies are mainly exploratory and results are under the influence of several sources of variability, such as the nature of the sample analyzed, the brain property measured, the neuroimaging approach employed or the cognitive construct studied. The direct consequence is a mixture of findings hardly interpretable in terms of reliable brain architecture and mechanisms underlying individual differences in cognitive performance, as reviewed by Colom (2014).

In this regard, using fMRI Cole et al. (2012) underscored the role of the lateral prefrontal cortex. Also relying on fMRI, Ebisch et al. (2013) proposed that the network comprised by the anterior insular cortex, the dorsal anterior cingulate cortex, and the medial frontal cortex contributes to the integration of common high-order cognitive requirements. Considering high-density EEG, Langer et al. (2012) highlighted the central role of the parietal cortex. Applying voxel-based morphometry (VBM) and surface-based morphometry (SBM), Colom et al. (2013) found that the middle frontal gyrus seems to support both fluid intelligence and working memory capacity. Large-scale voxel-based lesion structural studies supported the P-FIT model underscoring the basic role of frontal and parietal regions along with their communication pathways (Barbey et al., 2012; Barbey, Colom, Paul, & Grafman, 2014; Gläscher et al., 2010).

As pointed out by Martínez et al. (2015), these exploratory analyses are informative and increase our knowledge, but observed results are open to varied interpretations (Haier et al., 2014a & 2014b; Hampshire & Owen, 2014; Hampshire, Highfield, Parkin, & Owen, 2012). The brain is a general-purpose complex dynamic system (Burgaleta, Johnson, Waber, Colom, & Karama, 2014, Colom et al., 2013; Fjell et al., 2013; Schnack et al., 2014) and different individuals might rely on distinguishable brain networks for coping with a given cognitive requirement (Karama et al., 2011). But there are still further possibilities. For instance, not all brain properties may be equally

---

* Correspondence to: J.A. Pineda-Pardo, hmCINAC — Hospital Puerta del Sur, Móstoles, Avenida Carlos V, 70, 28938, Madrid, Spain.

** Correspondence to: R. Colom, Department of Biological and Health Psychology, Universidad Autónoma de Madrid, Ciudad Universitaria de Cantoblanco, 28049, Madrid, Spain.

E-mail address: joseangel.pineda@ctb.upm.es (J.A. Pineda-Pardo).

http://dx.doi.org/10.1016/j.intell.2015.12.002
0160-2896/© 2015 Elsevier Inc. All rights reserved.

relevant for explaining cognitive differences (Vuoksimaa et al., 2014) and different neuroimaging approaches might not capture individual differences in brain structure and function with the same sensitivity (Martínez et al., 2015). Finally, variability in tissue composition or activations of discrete brain regions might be unrelated with behavioral individual differences (Escorial et al., 2015, Mueller et al., 2013). Perhaps the key is how these regions communicate for working in an integrated way (Barbey et al., 2014; Santarnecchi et al., 2014).

Based on this latter perspective, the main research question addressed in the present study is: are the interactions among specific gray matter processing units through white matter pathways related with cognitive differences? Finding an answer requires using a network approach. There are some reports analyzing functional networks, mainly derived from resting state records (Shehzad et al., 2014; Song et al., 2008; Van den Heuvel, Mandl, Kahn, Pol, & Hilleke, 2009) and, again, inconsistencies can be seen in the reported results (Li & Tian, 2014, Santarnecchi et al., 2014). Network analyses relating variations in structural connectivity with cognitive performance differences are still rare. Li et al. (2009) hypothesized that intelligence differences are associated with brain structural organization (greater global efficiency of the brain physical network). Their report found a positive correlation between local efficiency and IQ in several regions of the brain: parietal, temporal, occipital, and frontal lobes, along with three subcortical structures. These results can be interpreted as consistent with the P-FIT framework.

Here we select a set of discrete regions of interest (ROIs) specifically nominated by the P-FIT model[1]* (Fig. 1). These regions were organized according to successive stages involved in information processing: 1) processing of sensory information (temporal and occipital regions), 2) symbolism, abstraction, and elaboration (parietal areas), 3) hypothesis testing (frontal lobes), and 4) response selection (anterior cingulate) (Appendix 2 lists the selected regions/nodes). Local and global network efficiency was evaluated. Latora and Marchiori (2001) introduced the concept of network efficiency by quantifying variations in information flow within the network: "by using efficiency, small-world networks are seen as systems that are both locally and globally efficient". Afterwards, we computed the relationship between individual differences in structural efficiency within the predefined network and cognitive differences (as assessed by fluid reasoning, working memory capacity, and processing speed). As noted, small-world networks are locally and globally efficient, and, therefore, individuals with better cognitive scores will show greater fault tolerance (local efficiency) and better long-distance interactions (global efficiency) (Latora & Marchiori, 2001). From this perspective, we predict substantial associations between structural efficiency within the P-FIT network and cognitive differences: the higher the efficiency, the better the cognitive performance.

2. Method

2.1. Participants

Forty-two young women (mean age = 18.3, SD = 1.2) participated in the study. They were psychology undergraduate paid volunteers with no history of psychiatric or neurological illness. Written informed consent was obtained in accordance with regulations of Fundación CIEN-Fundación Reina Sofía (Madrid). The local ethical committee approved the study.

2.2. Psychological measures

Participants completed a set of tests and tasks measuring fluid reasoning (Gf), working memory capacity (WMC), and processing speed (PS). Gf represents the ability for abstract reasoning and novel problem solving (Cattell, 1987). WMC is devoted to the mental manipulation of varied amounts of information in the short-term. This cognitive mechanism is usually measured by dual tasks combining processing and storage requirements (Colom, Abad, Quiroga, Shih, & Flores-Mendoza, 2008, Martínez et al., 2011). PS captures the speed by which simple mental operations can be completed and it is measured by reaction time in the face of low-level processing requirements (Colom et al., 2008).

These psychological constructs were measured by three tests or tasks each for obtaining representative aggregated scores beyond the specificities associated with the concrete measures (Colom et al., 2013; Haier et al., 2009). The Raven Advanced Progressive Matrices Test (RAPM; Raven, Raven, & Court, 2004a), the inductive reasoning subtests from the Primary Mental Abilities Battery (PMA-R; Thurstone & Thurstone, 1968a), and the abstract reasoning subtest from the Differential Aptitude Test Battery (DAT-AR; Bennett, Seashore, & Wesman, 2005a), measured fluid intelligence (Gf). WMC was assessed by the (verbal) reading span task (Kane et al., 2004a), the (numerical) computation span task (Ackerman, Beier, & Boyle, 2002a), and the (spatial) dot matrix task (Miyake, Friedman, Rettinger, Shah, & Hegarty, 2001a). Finally, processing speed was measured by simple verbal, numerical, and spatial tasks. A detailed description of these tests and tasks can be found in Appendix 1.

2.3. MRI data acquisition

Participants were scanned (after psychological assessment) on a 3 T General Electric MR scanner (General Electric Healthcare, Fairfield, CT), using a whole-body radiofrequency (RF) coil for signal excitation and quadrature 8-channel brain coil for reception. The acquisition protocol consisted of: (1) High resolution 3D T1-weighted Gradient Echo-SPGR with TR/TE/flip angle of 9.1 ms/4.1 ms/10°, FoV = 256 mm, matrix = 256 × 256 and slice thickness of 1 mm yielding a 1 mm^3 voxel size; (2) diffusion weighted images (DWI) in 45 non-collinear encoding directions and a b value of 1000 s/mm^2 with a single-shot spin echo echo-planar sequence with TR/TE of 12,700/88.3 ms, NEX = 2, FoV = 240 mm, reconstruction matrix of 96 × 96 and slice thickness = 2.4 mm resulting in $2.5 \times 2.5 \times 2.4\ \text{mm}^3$ voxels, and two additional images with no diffusion sensitization $b = 0\ \text{s/mm}^2$ (b_0); (3) two gradient echo images with different echo times, 6.5 and 8.5 ms, TR of 600 ms and flip angle of 45° and same spatial resolution as the DWI.

2.4. Brain parcellation

We used Freesurfer (version 5.1.0) to segment each subject's cortex in 66 anatomical cortical regions and 16 sub-cortical regions (Fischl et al., 2004) (Appendix 2). From these 82 regions, twelve regions by each cerebral hemisphere, nominated by the P-FIT network, were selected (Jung & Haier, 2007). The selected twenty-four regions are depicted in Fig. 1.

2.5. Structural connectivity

DWI images were pre-processed using the FMRIB's Diffusion Toolbox (FDT). Correction for motion and geometrical distortion due to eddy currents was performed with the *eddycorrect* tool in FDT, taking as the reference image the average of the two b_0 volumes. Non-brain tissue from the average b_0 image was removed using the FMRIB's Brain Extraction Toolbox, BET (Smith, 2002). The obtained brain mask was applied to the rest of the DWI images. We build the inhomogeneity fieldmap using the two gradient echo images with different echo times. Using FUGUE-FSL, we considered the fieldmap image to unwarp the DWI images, in order to correct the geometric distortion and signal loss due to the magnetic field inhomogeneities. The Diffusion Toolkit (DTK — http://www.trackvis.org) was used to fit the diffusion tensor model using a least squares approach.

---

[1] *We thank Richard J. Haier and Rex E. Jung for their careful checking of the ROIs selected for the present study. After their revision, we can state that the selected ROIs provide a proper operationalization of the P-FIT model according to the parcellation scheme used in the Freesurfer pipeline.