Behavior-driven effective connectivity analysis of motor learning

G. A. James[1,2], G. He[2], Y. Liu[1,2]

[1]Neuroscience, University of Florida, Gainesville, FL, United States, [2]Psychiatry, University of Florida, Gainesville, FL, United States

Introduction: Functional neuroimaging allows the modeling of effective connectivity networks between brain regions mediating cognitive tasks. Although neural networks for dynamic processes such as motor learning have been established (Toni *et al.*, 2002; Sun and D'Esposito, 2003), the connectivity analyses do not directly incorporate the behavioral data acquired from participants. Rather, behavioral measures of learning are merely used as markers for the beginning and conclusion of the learning phase. The loss of information inherent in such oversimplifications impedes our capacity for modeling learning's dynamic cognitive component. In this study, response times are incorporated into our connectivity analyses and used as a seeding point; thus, we are able directly measuring the neural correlates for motor learning.

Participants/Materials: Ten graduate students (five female; mean (sd) age = 24.6 (2.1) years) participated in this study in accordance with Institutional Review Board policy. Participants underwent functional imaging in a 3T Siemens Allegra head dedicated scanner (Siemens). Proton-density weighted anatomical images (matrix=256x256, TR=5.24s, TE=13ms, FA=150^o, FOV=240mm, 36 slices, slice thickness=3.8mm without gaps) were obtained for co-registration with EPIBOLD functional images (matrix=64x64, TR=3s, TE=25ms, FA=90^o, FOV=240mm, 36 slices, slice thickness=3.8 mm without gaps) obtained while participants performed a serial reaction time (SRT; Nissen and Bullemer, 1997) explicit motor learning task. Stimuli presentation was coded in E-Prime (Psychology Software Tools) and displayed to participants by LCD screen (MRI Devices). Participant behavioral responses were recorded in E-Prime with a response button glove (MRI Devices).

Data Processing: Motion correction and linear detrending were performed in Brain Voyager (Brain Innovations). All subsequent analyses were performed in Matlab (MathWorks). The 36 slices for each functional volume were combined into a single volume. White matter voxels were used as a baseline for intersession intensity normalization. For each volume, artificial voxels representing the participant's mean reaction time, accuracy, and percent of responses made were inserted into the image body. The reaction time voxels were then used as seed points with the WICA method (He *et al.*, 2003).

Results: During random (non-sequenced) trials, RT correlated positively with the bilateral cerebellum and left primary motor strip (M1). No notable negative correlations were found. During sequential trials, RT correlated negatively with the cerebellum (bilateral with trend toward widespread right hemisphere activation), left M1, left somatosensory cortex (S1), left supplementary motor area (SMA), bilateral basal ganglia, and prefrontal cortex (BA6; bilateral with trend toward widespread left hemisphere activation). No noteable positive correlations were found. Figure 1 depicts positive and negative correlations between reaction time and activity for the cerebellum, M1, S1, and BA6 for a representative participant.

Discussion: In the SRT task, decreases in response time reflect improvements in performance due to learning. We propose this novel approach for analyzing effective connectivity through direct incorporation of behavioral data into our functional analyses. The increased activity in brain regions as RT decreases (as expressed through negative correlation) during sequential trials inarguably implicates these regions as contributors to motor learning. The observed positive correlations during both trial conditions could represent any number of factors, including fatigue, frustration, or failure to attend to stimuli; further correlational analysis with accuracy and response rate may clarify their significance. Nonetheless, the observed negative correlations during sequential trials (and double dissociation of positive correlations during nonsequential trials for the cerebellum and BA6) validate this modification of the WICA seeding method for analyzing neural networks for learning. The incorporation of behavioral data into other WICA components (especially a dynamic analysis of temporally changing connectivity) will give us a comprehensive <u>behavior-driven</u> understanding of effective connectivity patterns for motor learning.

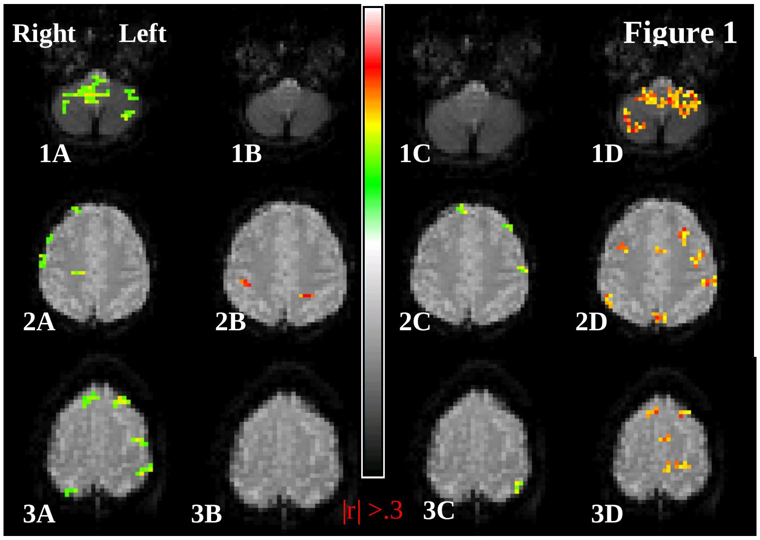

Figure 1: Connectivity correlation map using reaction time as a seed. (1) Cerebellum (z = -38 mm), (2) M1/S1 (z = +20 mm), and (3) prefrontal/BA6 (z = +46 mm). A: Positive correlations during random trials. B: Negative correlations during random trials. C: Positive correlations during sequential trials. D: Negative correlations during sequential trials. All images are in radiological convention (participant's left is viewer's right). Absolute values for correlations are color-coded ranging from green (r =.3) to red-white (r = 1).

References:

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