

Task demand alters cortical network states ensuing integration and modularization

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INTRODUCTION

A graphical analysis of the brain, denotes regions as nodes while connections between regions as edges [5,6]. Node activation is dependent on the external environment, resulting in conformational changes: can be task and state dependent, though are largely individualistic [2,4]. An integrated network is such that there are connections between nodes across multiple regions. A modular network predominantly has nodal connections within specialized regions e.g. limbic. Shine [3] hypothesizes the brain is akin to an attractor landscape, where wells indicate stores of energy. In this domain a modular network indicates stores of energy within specialized regions while an integrated network has shallow wells with distributed energy stores. In this context the cerebellum (Cb) would drive network change to a modular pattern, while the basal ganglia (Bg) integration, through thalamic connections [3]. Integration is said to aid in accomplishing harder tasks while modularization easier [5,6].

Hypotheses:

1. Congruent (easier) task blocks will have higher cortical modularity than incongruent (harder).
2. The Bg will have greater influence during the incongruent task blocks, alternately the Cb in the congruent.

Figure 1. Subcortical regions basal ganglia and cerebellum are connected to cortex through gating of the matrix and core thalamus respectively. Image taken from Shine (2021).

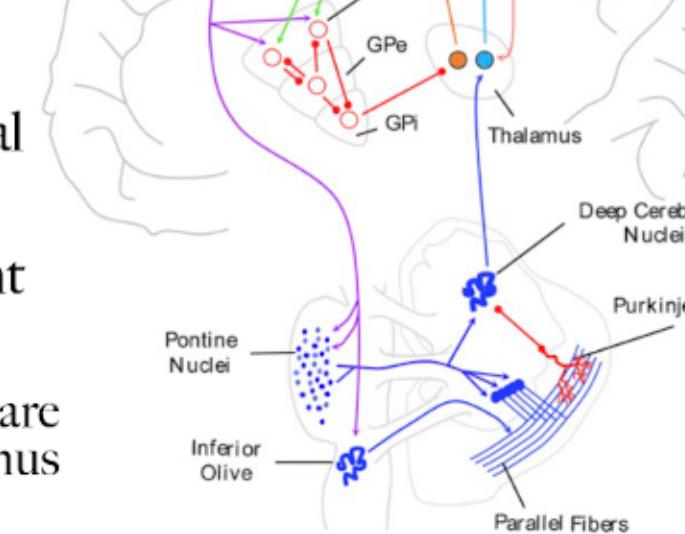
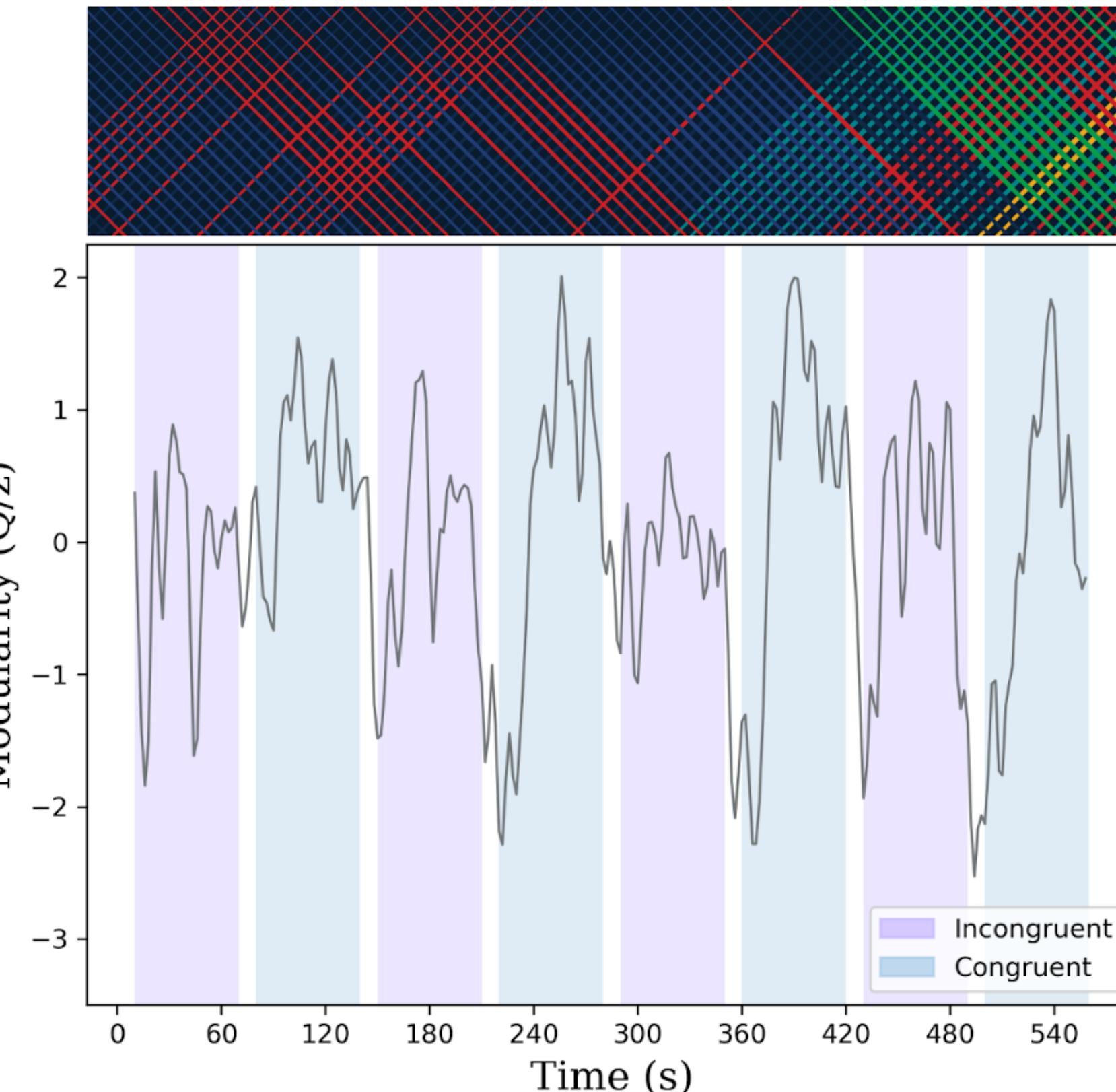


Figure 1. Modularity (Q/z)



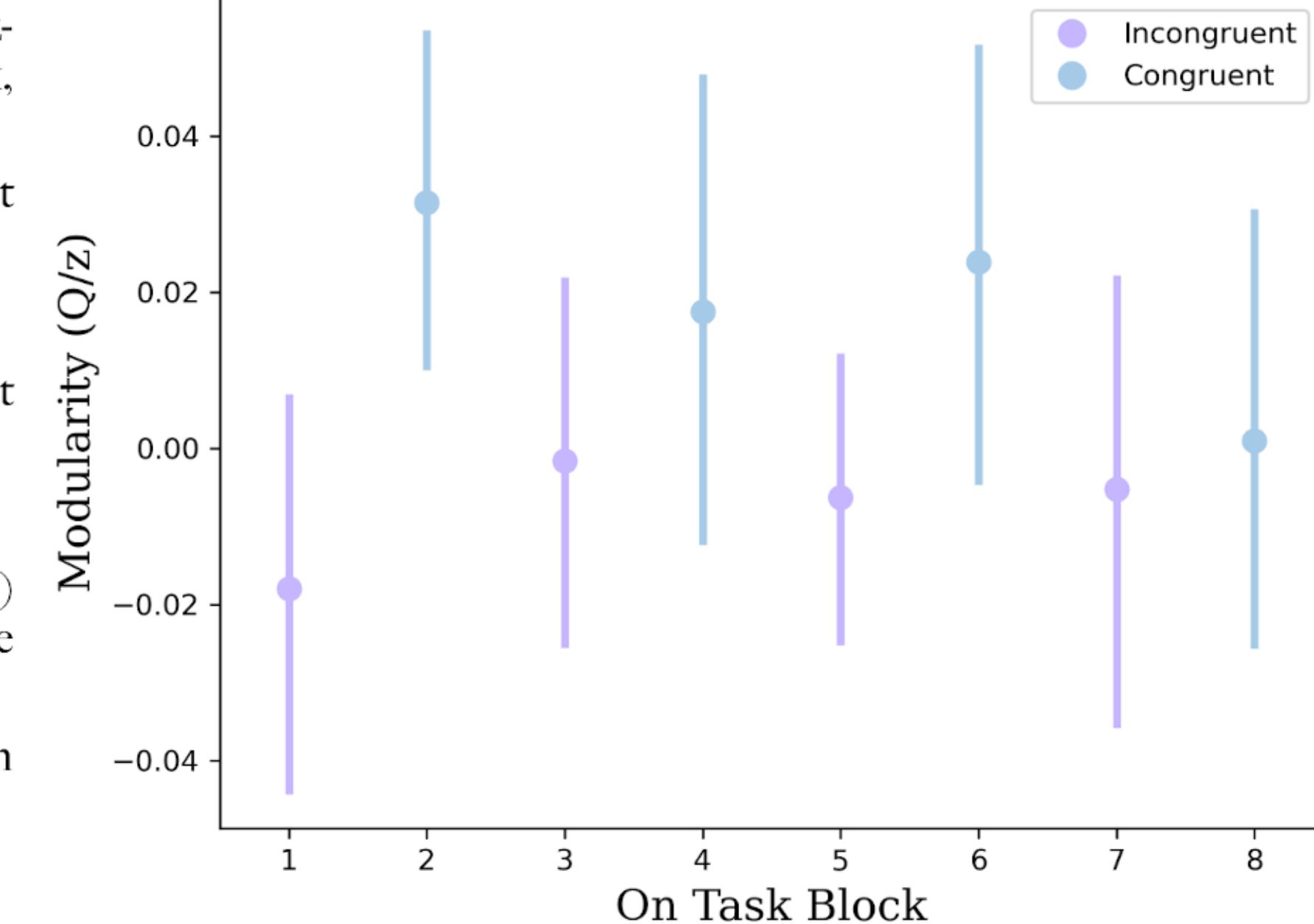
RESULTS

Figure 4. (left) Gaussian smoothed z-scored cortical modularity index, averaged across subjects.

- Higher modularity in congruent (easier) task blocks
 $\beta = 0.128$; 95% CI = 0.081, 0.175
- Lower modularity in incongruent (harder) task blocks
 $\beta = 0.072$; 95% CI = 0.028, 0.116

Figure 5. (right) Mean (ball) modularity index with confidence interval (stick).

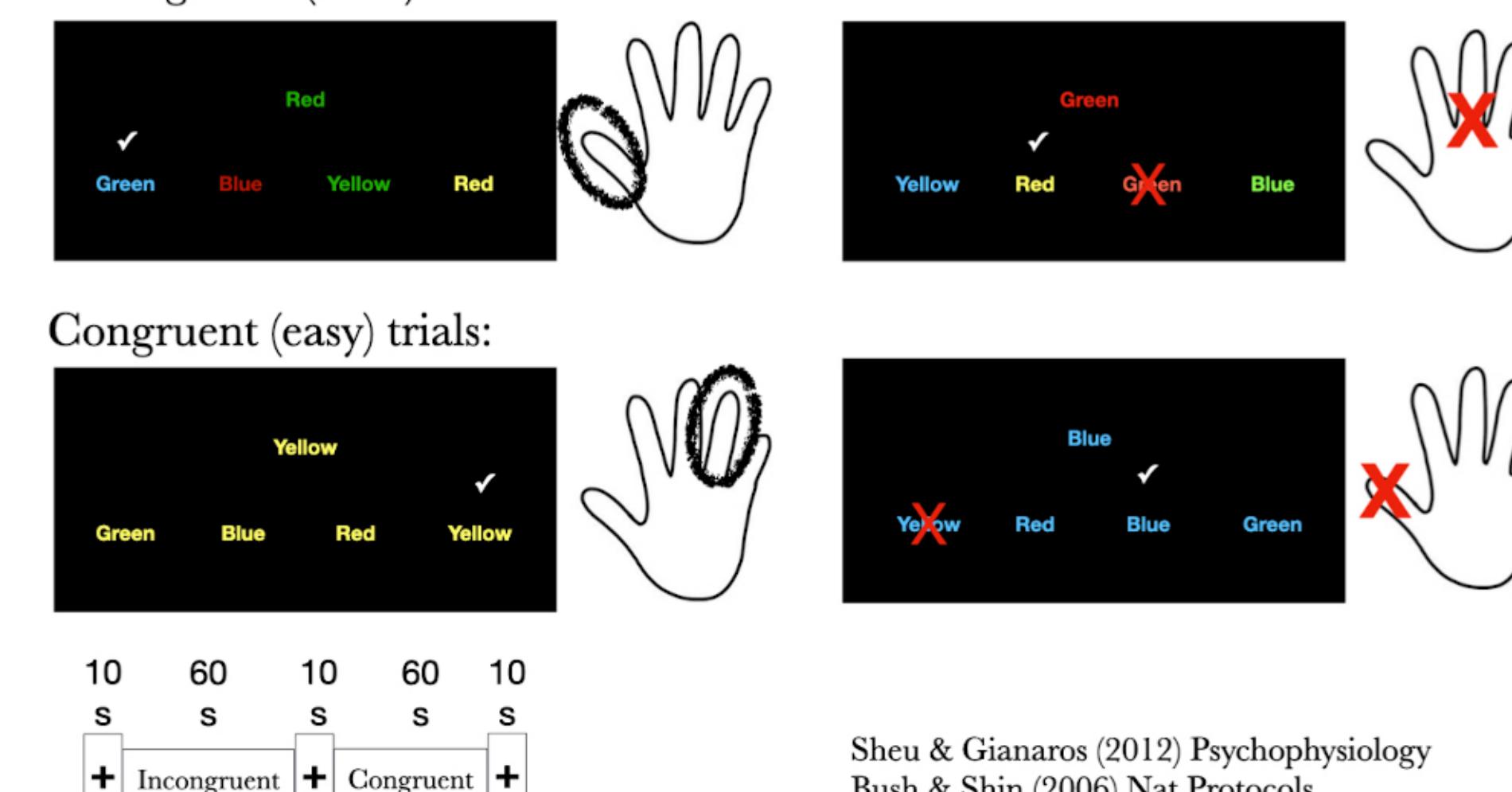
- Significant difference between incongruent and congruent trials
 $p = 0.014$, std = -0.056



METHODS

Color-word Stroop Task

Incongruent (hard) trials:



Congruent (easy) trials:

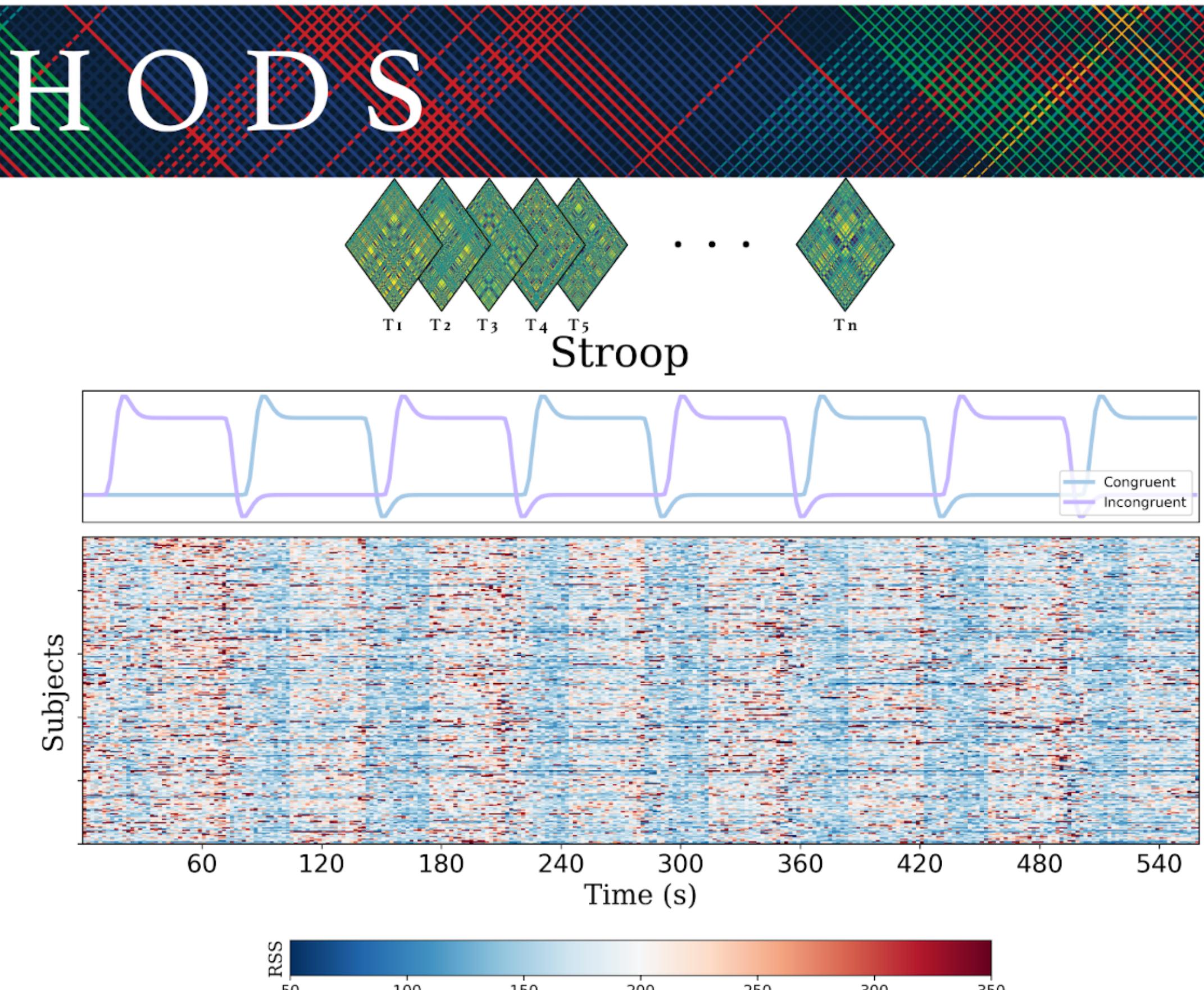


Figure 3. Stacked heat map of subjects (n=242) showing residual sum of squares (RSS) across the fMRI timescale (axis 2), with task paradigm (axis 1). Higher RSS indicates greater integration of networks, while lower RSS indicates less integration (modularization). Image adapted from Rasero et al. (2021).

Edge time series [1]:

$$\text{Let } c_{ij} = [z_i(1) \cdot z_j(1), \dots, z_i(T) \cdot z_j(T)]$$

Eigenvector centrality [7]: Modularity index [9]:

$$x_i = K_1^{-1} \sum_j A_{ij} x_j$$

$$B = A - P$$

$$Q^{\text{signed}} = \sum_{ij} [B_{ij}^+ - B_{ij}^-] \delta(\sigma_i, \sigma_j)$$

► A total of 242 subjects performed an adaptive Stroop task while being scanned for fMRI (female = 119, male = 123; mean age = 40 ± 6 ; min age = 30, max age = 51).

► The scanner used was a 3 Tesla Trio with 12-channel head coil. fMRI obtained was T2*-weighted with 3mm isotropic resolution (TR = 2s, ET = 28ms, Flip = 90°).

► For data analysis we used the Shen atlas for region segmentation and performed edge time series analysis [1]. Modularity index [9] was obtained for cortical regions and eigenvector centrality [7] for basal ganglia and cerebellum (cortical connected nodes only).

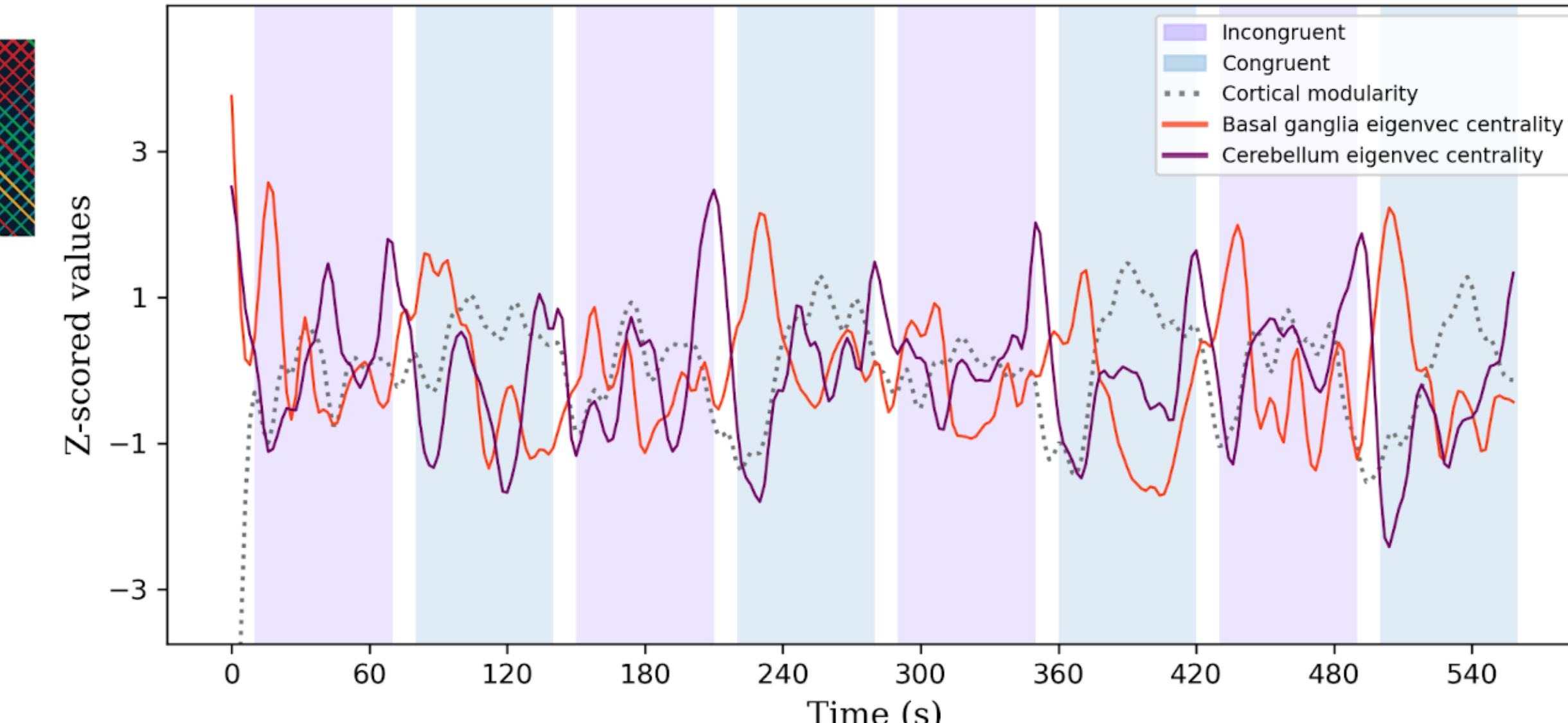


Figure 6. Gaussian smoothed z-scored basal ganglia (Bg) and cerebellum (Cb) eigenvector centrality values, averaged across subjects. The Bg and Cb exhibit an anti-correlated pattern across the timescale with Bg exhibiting more influence in the beginning of a task while Cb at the end.

CONCLUSION

1. We obtained patterns of modularity in cortical nodes consistent with prior studies [4,5].
2. The Bg and Cb seem to have opposite phase engagement during trials, but we need to explore further how these relate to modularity. The Shine [3] model may be more complex than initially hypothesized.

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