Neural Measures of Inter- vs Intra-individual Differences in Sustained Attention

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Abstract:

Sustaining attention to a task results in variability due to intra-individual fluctuations in performance and inter-individual differences in overall task ability. What are the neural and cognitive bases of this variability? Attention is thought to play a central role by facilitating the representation and communication of stimulus information within and across sensory, attentional, and executive networks. Here we ask two questions: (a) Does performance variability correspond to changes in the fidelity and/or connectivity of stimulus representations? and (b) Do intra- and inter-individual differences correspond to the same underlying neural changes? Using a large fMRI dataset (N = 227; 511 task runs) from multiple studies we used Representational Similarity Analysis (RSA) to quantify the representational fidelity (RF) and representational connectivity (RC) of stimulus representations during the gradual onset Continuous Performance Task (gradCPT) and related these neural variables to intra- and inter-individual differences in performance. We found increased RF and RC related to better performance within and across a network of brain regions in the visual, frontal, and parietal cortices. Interestingly, inter-individual differences involved visual cortex while intra-individual differences involved parietal and frontal regions, suggesting differential neurocognitive mechanisms underlying inter- and intra-individual variability in sustaining attention.

Keywords: sustained attention; individual differences; fMRI; representational similarity analysis

Introduction

When doing a task that requires prolonged engagement, inter- and intra-individual differences in task performance emerge. Here we examined whether the cognitive and neural states involved in trial-to-trial fluctuations in task performance are the same that explain individual differences in performance. While the underlying neurocognitive causes of inter- and intra-individual variability are probably partially task specific, the ability to sustain attention likely plays a key role in both. Generally, theories of attention posit that attention boosts performance by potentiating the representation of relevant stimulus features while suppressing irrelevant or distracting information (e.g., Peelen & Kastner, 2014). This effectively increases the fidelity of stimulus representations in cortical regions where the stimulus-feature representations are stored (e.g., Rothlein, DeGutis, & Esterman, 2018). Further, to enable efficient and accurate task-directed behavior, attention facilitates the integration of stimulus-feature representations with task-rule representations by broadcasting information about the stimulus throughout large-scale cortical networks that are generally localized to frontal and parietal cortices (e.g., Buschman & Kastner, 2015).

Previous research has examined sustained attention using fMRI-based measures like functional connectivity and univariate activation; however, the resulting interpretations were limited by ambiguities inherent to univariate comparisons (i.e. many factors could be driving both neural and behavioral variability). Further, variability due inter- vs. intra-individual differences were rarely compared. Given the importance of stimulus-based information processing in cognitive models of attention, Representational Similarity Analysis (RSA) was used to isolate and quantify the representational fidelity (RF) and representational connectivity (RC) of stimulus representations from multi-voxel patterns of BOLD activation during the gradCPT, a sustained attention task. We related these neural measures to measures of inter- and intra-individual task variability and revealed striking differences in the brain regions involved in each type of variability.

Methods

Participants

A total of 227 individuals were recruited from the Boston area to participate in one of 4 different studies. These studies consisted of Esterman et al., (2013) (N = 16), Esterman et al., (2017) (N = 16), Fortenbaugh et al., (2018) (N = 146), and Kucyi et al., (2016) (N = 28) with an additional cohort of individuals with ADHD (N = 21) who completed the same protocol but were not included in the published study. All studies were approved by their respective IRBs.

Experimental Paradigm – the gradCPT

The gradCPT is a sequential go/no-go task consisting of photographs of city and mountain scenes (10 exemplars of each), and participants were instructed to respond (button press) to frequently occurring city scenes (90% of trials) and withhold to mountain scenes (10% of trials). Images gradually transitioned from one to the next, with each transition occurring over 800 ms (1300 ms for data from the Kucyi et al., (2016) protocol). Participants repeated ~8 min. runs of task (1 to 5 runs) resulting in 511 total runs. A subset of the data had rewarded blocks (Esterman et al., 2017) or thought probes (Kucyi et al., 2016). However, these components were ignored for the purposes of this study.

To infer instantaneous attentional state for the intra-individual analyses, response times (RTs) to correct city trials were used to compute variance time courses (VTCs) that measured trial-to-trial variations in RT. Higher VTC values reflected periods of greater deviations from the mean RT and indicated a worse attentional state (Esterman et al., 2013). To infer individual attentional ability, d' (a measure of accuracy) was used because it is highly reliable and is related to several other measures of attentional ability (Fortenbaugh et al., 2015).

fMRI-Representational Similarity Analysis

Scanning was performed across 3 different equipment configurations (for details, see citations for each study) and accordingly, all results accounted for study as a covariate. Standard functional data preprocessing steps were performed, and the preprocessed data was smoothed (6mm FWHM) and normalization to Talairach space. The preprocessed time courses underwent further cleaning by running a GLM using a set of nuisance regressors—specifically, white matter and CSF signal time courses; six head-motion parameter time courses; linear, quadratic, and cubic trends (-polart 3 in AFNI)—and saving the resulting residuals.

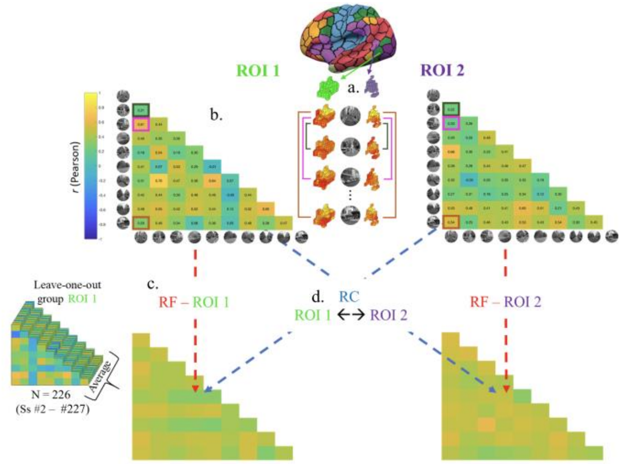

Figure 1: Using RSA to estimate representational fidelity (RF) and representational connectivity (RC). a. Activation patterns were computed for each of the 10 city exemplars via GLM (t-values). b. Pairwise similarity of activation patterns for each city exemplar were used to form representational similarity matrices (RSMs). c. Each participant's RF was quantified as the correlation coefficient between that participant's RSM and the leave-one-subject-out (LOSO) group average RSM from the same ROI. d) Each participant's RC was computed using the correlation between a participant's RSM from ROI 1 and the LOSO group average RSM from ROI 2.

Representational similarity analysis was performed on the city exemplars by estimating exemplar-specific activation patterns consisting of beta coefficient t values from a GLM (Fig. 1a) that modeled each participants cleaned time courses (concatenated across runs) with 11 event-related regressors—one for each of the 10 city exemplars and one for all mountain trials. The resulting exemplar-specific beta-t maps served as the activation values for RSA that was carried out using inhouse code run in MATLAB (Mathworks, Inc.). Parcellation-based RSMs were generated for each ROI (i.e. node) in both the Yeo 7 Network and Schaefer 100 parcellations (Schaefer et al., 2018) (Fig. 1b). Pairwise correlation coefficients (Pearson) were computed for each pair of city-exemplar activation patterns and these comprised the similarity values of the RSM.

Parcellation-based RSMs were used to estimate the representational fidelity (RF) and connectivity (RC) within and between each ROI respectively. Both RF and RC were computed using a leave one subject out (LOSO) reliability procedure whereby each participant's RSMs were correlated (Pearson) with the remaining participants' group average RSM from either the same ROI (RF, Fig. 1c) or a different ROI (RC, Fig. 1d). This process yielded participant-specific RF/RC values for each ROI/ROI-pair in the parcellation and these values were used for the inter-individual differences analysis.

Estimating the Intra-individual Fluctuations in Attentional State

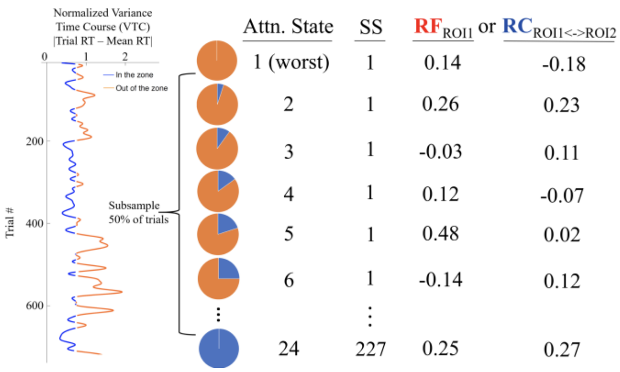

Figure 2: VTC-based subsample procedure to estimate state-specific RF and RC values. A sample participant's VTC is shown on the left. 50% of trials were sampled according to the VTC such that subsamples linearly stepped through 24 different attentional states from 1 (worst) to 24 (best). For each subsample, parcellation-based RF and RC values were computed.

To estimate how intra-individual differences in attentional state related to the parcellation-based measures of RF and RC, a behavior-based subsampling procedure was employed. This involved using the VTC as a proxy for attentional state and pseudo-randomly subsampling 50% of trials to have a target average VTC value. Specifically, we computed 24 target average VTC values consisting of equal increments from the maximum possible subsample (i.e. worst attentional state) to the minimum (best) and used an iterative algorithm to identify subsamples that minimized error from the target VTC value. This was done separately for each city exemplar to ensure that each subsample had an equal distribution of exemplars. Parcellation-based RF and RC values were computed for each subsample following the same procedure described in Fig. 1 but with 50% of trials. Each subsample (except the min. and max) was repeated 10 times and the RF and RC used for the intra-individual differences analysis consisted of the average RF and RC of these 10 repetitions.

Results

Inter-individual Differences in RF and RC

We sought to determine how RF and RC related to individual differences in attentional ability (estimated with gradCPT d'). To do this, d' values were fit using separate mixed-effects models for each ROI (RF) and ROI pair (RC) that also included motion and study as confound variables. The RF or RC coefficient value measured the extent to which the fidelity of stimulus processing within that ROI or the connectivity of stimulus information between ROIs related to individual differences in performance. As Fig. 3a shows, RF in the visual network (bonf. $p < 0.05$) and to a lesser extent, RC between the visual and dorsal attention network (DAN; $p < 0.05$) related to individual differences in attentional ability. This suggests that the ability to activate reliable representations of stimulus features was important for overall performance on the gradCPT.

Intra-individual Differences in RF and RC

We additionally sought to determine how RF and RC related to intra-individual fluctuations in attentional state (estimated by computing RF and RC within VTC-based subsamples). To do this, VTC-based attentional state values (1 to 24) for each participant were fit against the corresponding subsample RF and RC values using separate mixed-effects models for each ROI/ROI-pair. Motion and study were included as confound variables and random slopes were estimated by participant and by study. As Fig. 3c shows, increased RF in the ventral attention (VAN) and executive networks (EN) as well as increased RC between the DAN, DMN, VAN and EN were associated with better intra-individual measures of attentional states (bonf. $p < 0.05$). Fig. 1d. shows that the RF effect is largely right lateralized. This suggests that the representation of stimulus information within and broadcasting of this information across large-scale, domain general brain networks is related to one's instantaneous attentional state.

Conclusion

We found that both RF and RC changed as a function of inter-and intra-individual differences in attention suggesting the neurotopography of stimulus information processing was associated with attentional ability and state. Trait-like inter-individual measures of attentional ability were associated with changes in visual regions while state-like attentional fluctuations were associated with changes within and across large-scale brain networks often associated with domain general processing. The differences suggest that the ability to potentiate task-relevant stimulus-features underlie individual differences in attentional ability while the broadcasting of this stimulus information is reflective of one's instantaneous attentional state.

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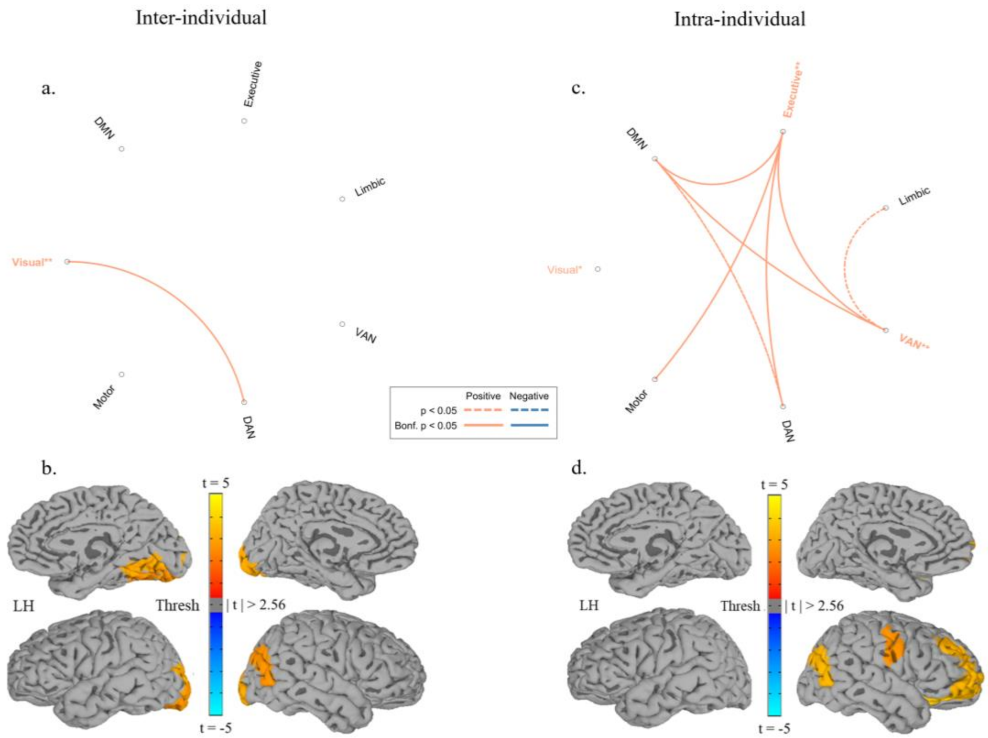

Figure 3: The relationships of RF and RC with inter- and intra-individual differences in sustained attention. a. A circular plot depicting networks from the Yeo 7 parcellation where RF and RC related to d'. b. A brain map depicting significant inter-individual RF from the Schaefer 100 parcellation. c. A circular plot depicting where RF and RC relates to intra-individual attentional state. d. A brain map (Schaefer 100) depicting where RF significantly relates to intra-individual fluctuations in attentional state. *p < 0.05; **bonf. p < 0.05.

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References

Buschman, T. J., & Kastner, S. (2015). From behavior to neural dynamics: An integrated theory of attention. *Neuron*, 88(1), 127–144.

Esterman, M., Noonan, S. K., Rosenberg, M., & DeGutis, J. (2013). In the zone or zoning out? Tracking behavioral and neural fluctuations during sustained attention. *Cerebral Cortex*, 23(11), 2712–2723.

Esterman, M., Poole, V., Liu, G., & DeGutis, J. (2017). Modulating reward induces differential neurocognitive approaches to sustained attention. *Cerebral Cortex*, 27(8), 4022–4032.

Fortenbaugh, F. C., DeGutis, J., Germine, L., Wilmer, J. B., Grosso, M., Russo, K., & Esterman, M. (2015). Sustained attention across the life span in a sample of 10,000. *Psychological Science*, 26(9), 1497–1510.

Fortenbaugh, F. C., Rothlein, D., McGlinchey, R., DeGutis, J., & Esterman, M. (2018). Tracking behavioral and neural fluctuations during sustained attention: A robust replication and extension. *NeuroImage*, 171, 148–164.

Kucyi, A., Esterman, M., Riley, C. S., & Valera, E. M. (2016). Spontaneous default network activity reflects behavioral variability independent of mind-wandering. *Proceedings of the National Academy of Sciences*, 113(48), 13899–13904.

Peelen, M. V, & Kastner, S. (2014). Attention in the real world: Toward understanding its neural basis. *Trends in Cognitive Sciences*, 18(5), 242–250.

Rothlein, D., DeGutis, J., & Esterman, M. (2018). Attentional fluctuations influence the neural fidelity and connectivity of stimulus representations. *Journal of Cognitive Neuroscience*, 30(9), 1209–1228.

Schaefer, A., Kong, R., Gordon, E. M., Laumann, T. O., Zuo, X.-N., Holmes, A. J., Eickhoff, S. B., & Yeo, B. T. T. (2018). Local-global parcellation of the human cerebral cortex from intrinsic functional connectivity MRI. *Cerebral Cortex*, 28(9), 3095–3114.