

Cognitive Integration – How Task Representations Integrate Information from Multiple Sources

Stephanie C Leach (stephanie-leach@uiowa.edu)

Cognitive Control Collaborative (CCC)
Psychological and Brain Sciences Department, 340 Iowa Ave
Iowa City, IA 52242 United States

Hannah Morrow (hannah-morrow@uiowa.edu)

Cognitive Control Collaborative (CCC)
Psychological and Brain Sciences Department, 340 Iowa Ave
Iowa City, IA 52242 United States

Jiefeng Jiang (jiefeng-jiang@uiowa.edu)

Cognitive Control Collaborative (CCC)
Psychological and Brain Sciences Department, 340 Iowa Ave
Iowa City, IA 52242 United States

Kai Hwang (kai-hwang@uiowa.edu)

Cognitive Control Collaborative (CCC)
Psychological and Brain Sciences Department, 340 Iowa Ave
Iowa City, IA 52242 United States

Abstract: To facilitate cognitive flexibility, the human brain continuously integrates perceptual and internal state information to execute and switch between tasks. We developed a Bayesian model to investigate the neural and computational processes of integration. This model integrates the uncertainty of perceptual and internal state information into a posterior distribution, which jointly encodes beliefs of task-relevant inputs. Task decisions are then predicted by this posterior joint distribution. We designed a behavioral paradigm where subjects integrate a non-observable internal state with observable color perception to select or switch between two selective attention tasks. By applying the Bayesian model, we estimated the trial-by-trial color perception, state belief, and their associated uncertainty estimates, as well as the integrated to-be-performed task belief. This model successfully predicted human subjects' performance, outperforming several competing models. Using model derived predictors to analyze fMRI and EEG data, we found that the medial frontal, lateral middle frontal gyrus, and intraparietal sulcus, as well as theta-to-alpha band signals encoded statistical properties of this integrated posterior joint distribution. Our findings offer a computational account for cognitive integrative functions of the frontoparietal system.

Keywords: Cognitive Control; Integration; Bayesian Generative Model; Cognitive Flexibility

Introduction

The human brain is composed of distributed subunits that encode diverse sources of information (Damasio, 1989; Fuster, 2015). As such, the ability to integrate diverse information to guide behavior is integral to cognitive flexibility. For example, when navigating a new city, we integrate current visual inputs (external information) with procedural memories (internally maintained information) to successfully get from point A to B. However, how the human brain supports cognitive integration is not well understood.

This study proposes that the human brain integrates internal and external information by creating a joint distribution of task-relevant features, and the level of integration can be measured by calculating the entropy of this distribution. This posterior distribution jointly encodes multiple sources of task-relevant information in the form of an integrated task representation, in which down-stream systems can readout to guide goal-directed behavior.

Our study modeled the integration of two sources of information: (1) task state information (defined here as an internal representation organizing different stimulus-response mappings) and (2) an observable color input stimulus with varying levels of noise, or ambiguity. We

used a Bayesian generative model to estimate each subject's belief and uncertainty regarding task state, color perception, and to-be-performed task, as well as the prediction errors of these estimates and entropy of the posterior distribution. These estimates were then used as predictors for fMRI and EEG analyses to investigate the neurocognitive substrates of integration.

Methods

Twenty-six participants completed our paradigm while we collected functional brain scans with a 3T GE SIGNA Premier MRI scanner (TR=2.039, voxel size = 2.5 mm³). Seventeen participants completed the EEG version (Biosemi, 64 channels) of this experiment.

Task Design

To test cognitive integration of non-observable and perceptual information, we developed a paradigm (Fig. 1A) where participants had to integrate an external, noisy visual color cue with an internal "state" belief (Fig. 1B) to determine which selective attention task to perform (face or scene judgement; Fig. 1C). Each trial started with the onset of an array of randomly moving red and yellow dots. Participants first determined if there were more red or yellow dots in this array. After a delay, a partially transparent face image overlaid with a partially transparent scene image was presented, and participants performed either the face task (report if male or female) or the scene task (report if city or nature landscape). Task responses were split by hand so that the performed task could be inferred from the response. The mapping between the dominant color and to-be-performed task covertly reverses every 10-20 trials, creating two non-observable "states". Participants needed to integrate the current non-observable state and dominant color information to determine the to-be-performed task. Participants had to use feedback to infer the current state. Here, a "+" signals correct, and a "-" signals incorrect. We manipulated perceptual noise, or ambiguity, by varying the proportion of red and yellow dots. The dominant color ranged from 51%-67% of dots.

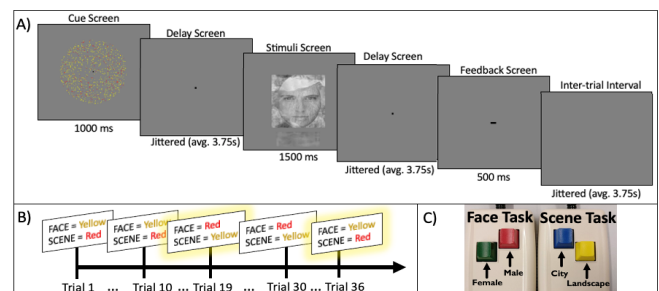


Figure 1: Task design. (A) Example task trial. (B) Non-observable state depiction. (C) Response setup.

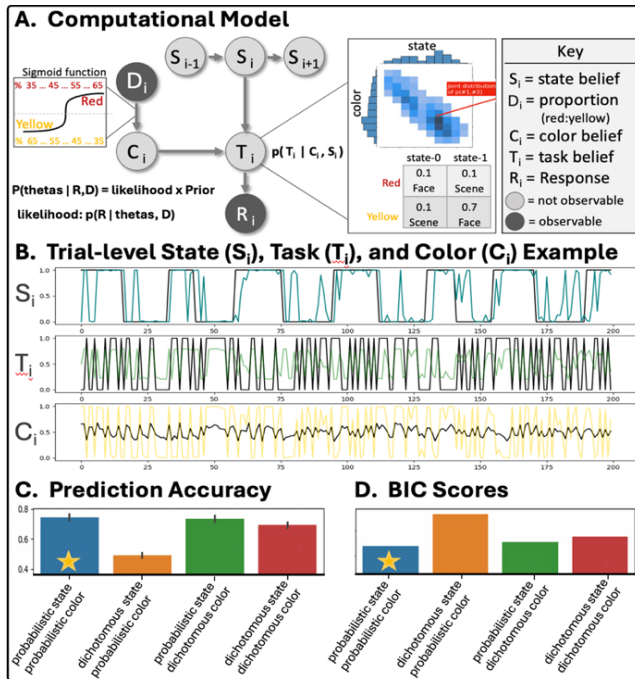


Figure 2: (A) Computational model integrating S_i and C_i into a joint distribution to determine T_i . (B) Model estimates of trial-wise state, task, and color beliefs from one example subject. (C-D) Model comparison.

Computational Model

We used a Bayesian model to investigate the cognitive integration of observable perceptual information with non-observable state information (Fig. 2A). On trial i , both the state (S_i) and color beliefs (C_i) are random variables. The joint distribution of (S_i) and (C_i) informs the task belief (T_i) on trial i . S_i and C_i are inferred from the only two directly observable variables: the true color proportions displayed (D_i) and the response (R_i) made. S_i , C_i , and T_i are latent variables in the Bayesian model. C_i is estimated from D_i using a sigmoid function. Using trial-wise values of observable variables, the generative model is inverted to infer latent variable distributions.

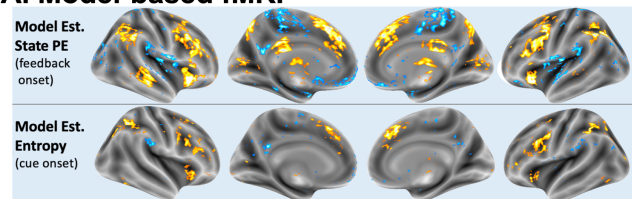
Neuroimaging and Model-based Analyses

We performed representational similarity analyses (RSA; Kriegeskorte et al., 2008) to identify brain regions and oscillatory signals that instantiate representations of color, state, and task beliefs. We also performed model-based fMRI and EEG analyses of key model-derived metrics, including the prediction error (PE) of state estimates, and the Shannon entropy of the posterior distribution. Briefly, we tested whether the trial-by-trial BOLD magnitude and the observed EEG oscillatory power (calculated by wavelet transformation) were modulated by trial-by-trial parametric regressors of these model estimates and derived metrics.

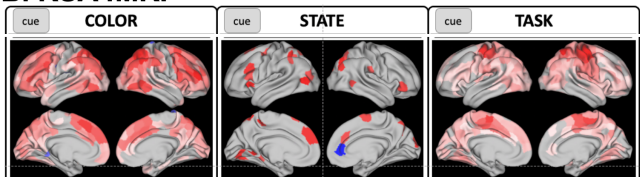
Results and Conclusions

Model Performance: The model estimated state, task, and color beliefs closely follow subjects' performance (Fig. 2B). Critically, the probabilistic model was compared to three alternative models (either/both of S_i and C_i is/are dichotomous). Protected exceedance probability analysis on Bayesian information criterion (BIC) showed strong preference of the integrative (S_i and C_i probabilistic) model (protected exceedance probability = 0.945, Bayes Omnibus risk < 0.001; Fig. 2C). The integrative model outperformed alternative models in predicting subjects' trial-wise performed tasks (Fig. 2C).

A. Model-based fMRI



B. RSA fMRI



C. EEG

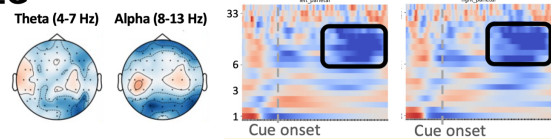


Figure 3: Neuroimaging results. (A) Model based fMRI results. (B) fMRI RSA results. (C) EEG results.

EEG/fMRI results: State PE and entropy estimates were associated with significant voxel clusters in the frontoparietal system (bilateral IPS and PFC) following cue onset; thereby indicating involvement in encoding a joint distribution of task-relevant features to determine what task to perform (Fig. 3A). The EEG counterpart of this signal was observed primarily in theta-to-alpha band oscillations (Fig. 3C). State and color beliefs were encoded across frontoparietal regions, while task belief was primarily read out from motor cortices (Fig. 3B).

Conclusion: Model-based analyses of fMRI/EEG data demonstrated that the frontoparietal system and theta-alpha band signals encode statistical properties of a joint distribution of task relevant features. Our results demonstrate how the frontoparietal system integrates observable and non-observable information to support cognitive flexibility.

Acknowledgments

Iowa Neuroscience Institute and the NIMH (R01MH122613) supported this research. The MRI instrument was funded by 1S10OD025025-01.

References

- Badre, D. & Nee, D. E. (2018). Frontal cortex and the hierarchical control of behavior. *Trends in Cognitive Science* 22(2), 170-188.
- Damasio, A. R. (1989). The brain binds entities and events by multiregional activation from convergence zones. *Neural computation*, 1(1), 123-132.
- Fuster J. M. (2015). The prefrontal cortex. Academic Press.
- Kriegeskorte, N., Mur, M., & Bandettini, P. A. (2008). Representational similarity analysis-connecting the branches of systems neuroscience. *Frontiers in systems neuroscience*, 2, 249.