2024 OHBM abstract

Title

Compositional representation of tasks in human multiple-demand cortex

Authors and affiliations

Jinkang (Derrick) Xiang[1], Moataz Assem[2], Geoffrey Ngo[1], John Duncan[2]*, Marieke Mur[1,3,4]*

*indicates co-senior authors

1 Western Institute of Neuroscience, University of Western Ontario, Canada

2 MRC Cognition and Brain Sciences Unit, University of Cambridge, UK

3 Department of Psychology, University of Western Ontario, Canada

4 Department of Computer Science, University of Western Ontario, Canada

Introduction

The execution of complex cognitive tasks activates an extensive network of frontal and parietal regions, known as the multiple-demand (MD) system, whose distributed activity patterns carry information about the task (Cole et al., 2011; Duncan, 2010; Woolgar et al., 2011). However, the functional organization of task representation remains unclear. Do certain tasks elicit more similar activity patterns than others? If so, what drives the functional organization? Computational work suggests that tasks may be represented in a compositional fashion in prefrontal cortex, where the representation of a task can be expressed as the algebraic sum of vectors representing the underlying sensory, cognitive and motor processes (Yang et al., 2019). Empirical evidence for compositional coding is limited (Cole et al., 2011; Reverberi et al., 2012). It remains to be tested if this principle generalizes to tasks that require context-dependent decisions.

Methods

We approach these questions by conceptualizing tasks as combinations of features (Cole et al., 2011; Mante et al., 2013; Rigotti et al., 2013). The feature dimensions define a task space, and points in this task space correspond to multivariate activity patterns elicited by tasks composed of different combinations of features. We designed a delayed-match-to-sample experiment where the task space was spanned by two feature dimensions: attended sensory modality and match rule (Fig. 1A). We measured brain activity of 32 healthy young adults while they performed the tasks in a 3T fMRI scanner (2D echo-planar imaging, 46 slices, voxel size: 2.5 mm^3, TR: 1.53 s, TE: 30 ms).

To compare the neural response elicited by different tasks, we estimated representational dissimilarity matrices (RDMs) using cross-validated Mahalanobis distances for each participant. To probe into the representational content of the data RDMs, we first created model RDMs based on single task features and their interactions. Next, we fitted the model RDMs to the data RDMs using linear combinations of task features, then additionally included their interactions, using non-negative weights (Jozwik et al., 2016). Model performance was evaluated by the cosine similarity between data RDMs and predicted RDMs (Diedrichsen et al., 2021). We compared performance across models for different regions of interest (Assem et al., 2020) (Fig. 1C). If adding interaction terms to the model does not improve performance, this provides evidence for compositional coding (Fig. 1E, F).

Results

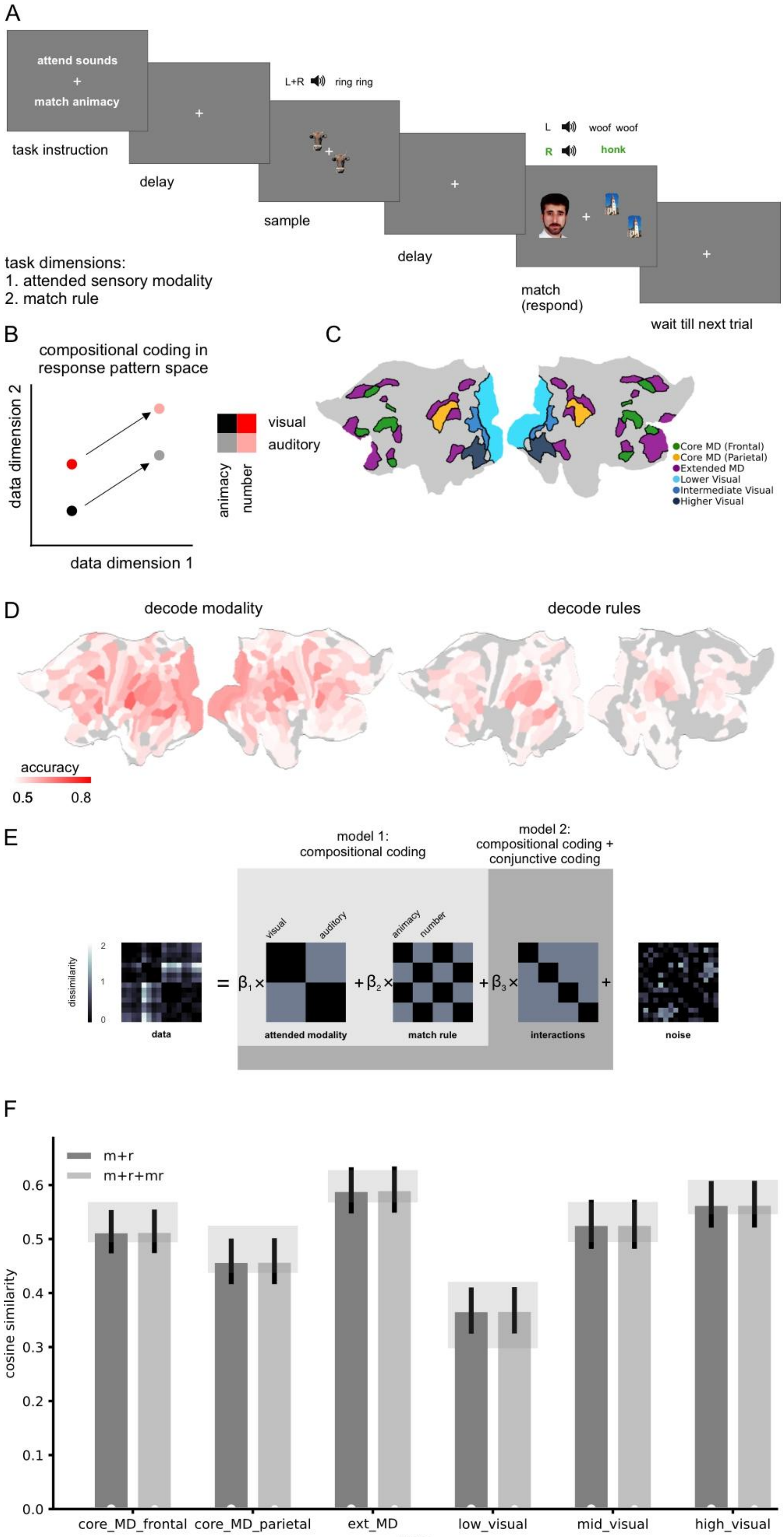
Our tasks strongly engage the MD system and both the attended sensory modality and the match rule are decodable from cortical regions comprising the MD system (Fig. 1D). Attended sensory modality is more widely decodable than match rule, consistent with the presence of attentional effects in sensory regions. Furthermore, representations in the MD system and higher visual regions are better modeled by task dimensions than those in lower visual regions. Importantly, across regions of interest, the interaction between task dimensions does not explain the task representation over and above their linear combination (Fig. 1E, F). These results suggest that tasks are represented in the MD system in a compositional fashion.

Conclusions

The representation of tasks differs across the cortical hierarchy. Early processing regions show a representation that is more strongly dominated by attended sensory information and less by abstract task rules, while later processing regions such as the MD system show a representation that carries a broad array of task information. In addition, task representations can be modeled as a linear combination of the representations of task features, while their interactions do not contribute significantly, supporting the compositional coding strategy. Future work should test for compositional coding in a broader range of tasks and across spatial scales.

(3919 characters)

Figures


A
attend sounds
match animacy
task instruction
delay
L+R ring ring
sample
delay
L woof woof
R honk
match
(respond)
wait till next trial
task dimensions:
1. attended sensory modality
2. match rule
B
compositional coding in
response pattern space
data dimension 2
data dimension 1
visual
auditory
animacy
number
C
Core MD (Frontal)
Core MD (Parietal)
Extended MD
Lower Visual
Intermediate Visual
Higher Visual
D
decode modality
decode rules
accuracy
0.5
0.8
E
model 1:
compositional coding
model 2:
compositional coding +
conjunctive coding
dissimilarity
data
= β1 ×
visual
auditory
attended modality
+ β2 ×
animacy
number
match rule
+ β3 ×
interactions
+
noise
F
m+r
m+r+mr
cosine similarity
core_MD_frontal
core_MD_parietal
ext_MD
low_visual
mid_visual
high_visual
ROIs

A. Delayed-match-to-sample task. The participants were asked to indicate the side (left or right) of the competing stimuli that matched the stimulus sampled in the same modality (visual or auditory) while applying the same rule (animacy or number).
B. Schematic showing compositional coding where tasks can be represented as a sum of vectors representing attended sensory modality and match rule.
C. Regions of interest (ROIs) (Assem et al., 2020).
D. Multivoxel pattern decoding accuracies for attended sensory modality and match rule. Multivoxel patterns for each HCP parcel were extracted using t-values against baseline then fed into a Linear Discriminant Analysis classifier using leave-one-run-out cross-validation for individual participants. Decoding results were averaged across participants and thresholded using a one-sided t-test (against chance level, 0.5), corrected for multiple comparisons across all HCP parcels.
E. Schematic showing how to model data RDMs using feature RDMs.
F. Cross-validated RDM model performance across ROIs. Dark gray: model including RDMs for modality and rule only; light grey: model including RDMs for modality, rule, and their interaction. Error bars show standard error of the mean across bootstrap resampled participants. White half circles at the bottom indicate above-zero model performance (bootstrap test, $p < 0.05$, uncorrected). Horizontal gray shaded areas show the noise ceiling. Neither model performed significantly worse than the lower bound of the noise ceiling across ROIs (bootstrap test, uncorrected). Model performance did not significantly differ in any ROI (bootstrap test, uncorrected).

References

Assem, M., Glasser, M. F., Van Essen, D. C., & Duncan, J. (2020). A Domain-General Cognitive Core Defined in Multimodally Parcellated Human Cortex. *Cerebral Cortex*, *30*(8), 4361–4380. https://doi.org/10.1093/cercor/bhaa023

Cole, M. W., Etzel, J. A., Zacks, J. M., Schneider, W., & Braver, T. S. (2011). Rapid Transfer of Abstract Rules to Novel Contexts in Human Lateral Prefrontal Cortex. *Frontiers in Human Neuroscience*, *0*. https://doi.org/10.3389/fnhum.2011.00142

Diedrichsen, J., Berlot, E., Mur, M., Schütt, H. H., Shahbazi, M., & Kriegeskorte, N. (2021). *Comparing representational geometries using whitened unbiased-distance-matrix similarity* (arXiv:2007.02789). arXiv. https://doi.org/10.48550/arXiv.2007.02789

Duncan, J. (2010). The multiple-demand (MD) system of the primate brain: Mental programs for intelligent behaviour. *Trends in Cognitive Sciences*, *14*(4), 172–179. https://doi.org/10.1016/j.tics.2010.01.004

Jozwik, K. M., Kriegeskorte, N., & Mur, M. (2016). Visual features as stepping stones toward semantics: Explaining object similarity in IT and perception with non-negative least squares. *Neuropsychologia*, *83*, 201–226. https://doi.org/10.1016/j.neuropsychologia.2015.10.023

Mante, V., Sussillo, D., Shenoy, K. V., & Newsome, W. T. (2013). Context-dependent computation by recurrent dynamics in prefrontal cortex. *Nature*, *503*(7474), Article 7474. https://doi.org/10.1038/nature12742

Reverberi, C., Görgen, K., & Haynes, J.-D. (2012). Compositionality of Rule Representations in Human Prefrontal Cortex. *Cerebral Cortex*, *22*(6), 1237–1246. https://doi.org/10.1093/cercor/bhr200

Rigotti, M., Barak, O., Warden, M. R., Wang, X.-J., Daw, N. D., Miller, E. K., & Fusi, S. (2013). The importance of mixed selectivity in complex cognitive tasks. *Nature*, *497*(7451), Article 7451. https://doi.org/10.1038/nature12160

Woolgar, A., Thompson, R., Bor, D., & Duncan, J. (2011). Multi-voxel coding of stimuli, rules, and responses in human frontoparietal cortex. *NeuroImage*, *56*(2), 744–752. https://doi.org/10.1016/j.neuroimage.2010.04.035

Yang, G. R., Joglekar, M. R., Song, H. F., Newsome, W. T., & Wang, X.-J. (2019). Task representations in neural networks trained to perform many cognitive tasks. *Nature Neuroscience*, *22*(2), 297–306. https://doi.org/10.1038/s41593-018-0310-2