The spatio-temporal dynamics of personally-meaningful objects

Jasper J.F. van den Bosch, Ian Charest *Center for Human Brain Health, School of Psychology, University of Birmingham*

INTRODUCTION

Personally-meaningful visual objects involve repeated exposure, self-referential components, and are often associated with memorable events. At the level of the brain, this must involve richer representations in distributed cortical areas. Yet, the precise neural underpinnings of familiarity in object recognition are still being debated [1]. Familiar faces are recognized faster, more accurately and evoke stronger activity in the brain [2]. Famous faces also benefit from rapid and early representational enhancements [3]. Activity patterns elicited by personally-meaningful objects (including, but not limited to faces) also better predict semantic judgements about these objects [4].

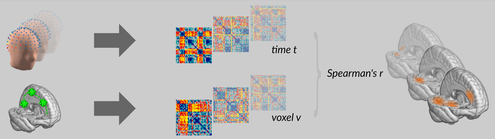
If familiar objects benefit from representational enhancements, what are the brain mechanisms supporting this? To better understand this, we presented participants with personally-meaningful and unfamiliar objects while measuring their brain activity with electroencephalography (EEG) and functional magnetic resonance imaging (fMRI). Using representational similarity analyses [5], and similarity-based fusion [6] of EEG and fMRI, we reveal largely distributed representational enhancements for personally meaningful objects across the human brain as they evolve in space and time.

METHODS

Stimuli

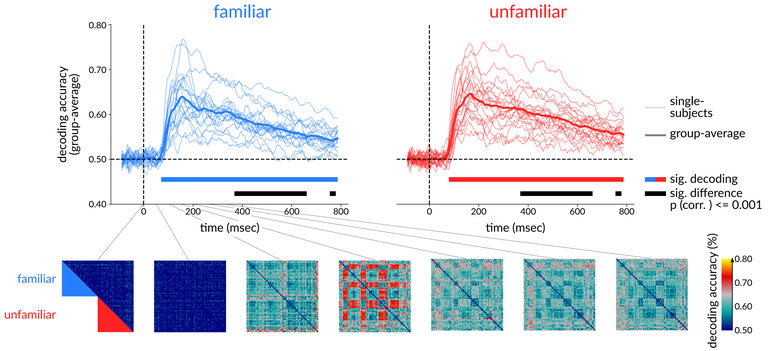
	Participants	*task & acquisition*	*preprocessing*	*patterns & distances*
EEG	• N = 20 (10 female) • age: 23,2 ± 6.11	• 20% catch trials • 30 trials per image • 5 % blink trials • 128 channel • duration: 500ms • SOA: 2s +- 250ms	• EEGLAB [7] • lowpass 0.01Hz • downsample 256Hz • referenced to linked mastoids • 500ms +1500ms	• MVPA-Light [8] • shrinkage-LDA for stimulus-pairs at each time-point • stratified K-fold crossvalidation
fMRI	• N = 20 (10 female) • age: 22.3 ± 4.12	• anomaly detection • duration 500ms • 3T Siemens Trio • 3x3x3.75mm voxels • TR: 2s ; TE: 30 ms; flip angle: 78°	• BIDS [9] • fmriprep [10] • Regions of interest [11] projected from fsaverage onto subject's EPI space.	• glmdenoise [12] • beta weigths converted to t-patterns [13] • pearson correlation distance

	pattern representations	*representational similarity analyses [14]*	*spatio-temporal fusion*
EEG	128 channel amplitudes as feature vectors	time t	Spearman's r
fMRI	ROI (or sphere) voxels' t-patterns as feature vectors	voxel v	

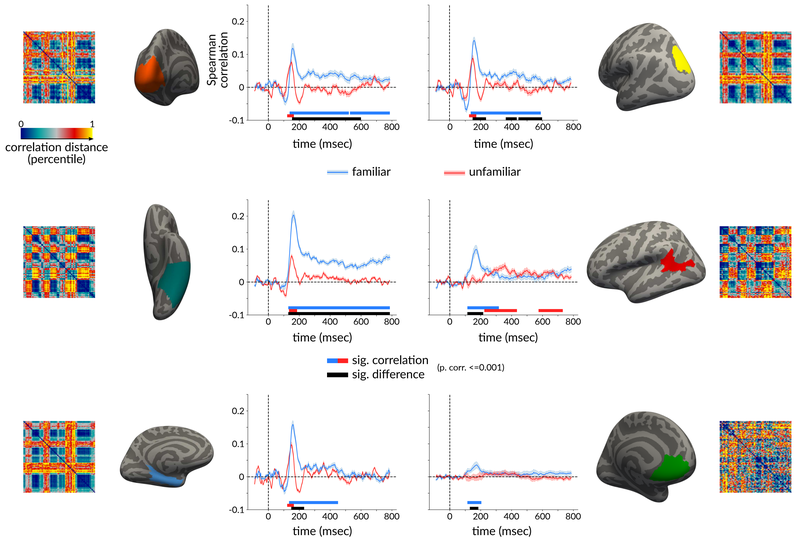


RESULTS

Object representations in EEG for familiar and unfamiliar images.

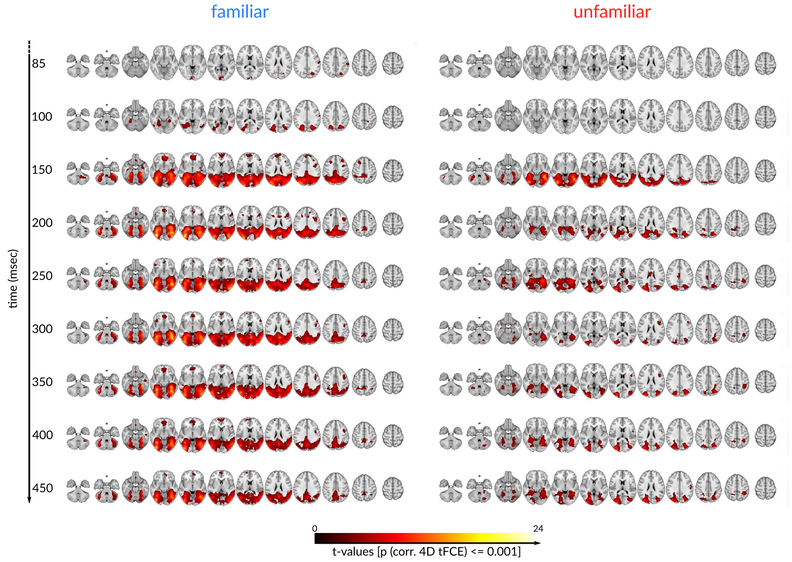


Region of interest similarity-based fusion of EEG and fMRI.



RESULTS

Searchlight similarity-based fusion of EEG and fMRI.



CONCLUSIONS

Using similarity-based fusion of EEG and fMRI data, we observed rapid local and distributed representational ehnancements in the visual ventral and dorsal streams, and in the medial temporal lobes in response to familiar objects. In addition, higher-order regions of the medial prefrontal cortex were only involved when objects were familiar. Finally, we see late and recurrent processes in the temporo-parietal junction when objects are unfamiliar. Critically, our results strengthen our understanding of the interactions between the visual ventral and dorsal streams, the medial temporal lobes, and the prefrontal cortex in recognising familiar and unfamiliar visual objects.

REFERENCES

[1] Op de Beeck, H. P., & Baker, C. I. (2010). The neural basis of visual object learning. Trends in Cognitive Sciences, 14(1), 22–30.
[2] Ramon, M., & Gobbini, M. I. (2018). Familiarity matters: A review on prioritized processing of personally familiar faces. Visual Cognition, 26(3), 179–195.
[3] Dobs, K., Isik, L., Pantazis, D., & Kanwisher, N. (2019). How face perception unfolds over time. Nature Communications, 10(1), 1258.
[4] Charest, I., Kievit, R. A., Schmitz, T. W., Deca, D., & Kriegeskorte, N. (2014). Unique semantic space in the brain of each beholder predicts perceived similarity. PNAS, 111(40), 14565–14570.
[5] Kriegeskorte, N., Mur, M., & Bandettini, P. (2008). Representational similarity analysis - connecting the branches of systems neuroscience. Frontiers in Systems Neuroscience, 2(November), 4.
[6] Cichy, R. M., Pantazis, D., & Oliva, A. (2014). Resolving human object recognition in space and time. Nature Neuroscience, 17(3), 455–462.
[7] A Delorme & S Makeig (2004) EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics. Journal of Neuroscience Methods 134:9-21
[8] Treder, M. (n.d.). MVPA Light. Retrieved from https://github.com/treder/MVPA-Light
[9] Gorgolewski, K. J., Auer, T., Calhoun, V. D., Craddock, R. C., Das, S., Duff, E. P., … & Handwerker, D. A. (2016). The brain imaging data structure, a format for organizing and describing outputs of neuroimaging experiments. Scientific Data, 3, 160044.
[10] Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., … Gorgolewski, K. J. (2019). fMRIPrep: a robust preprocessing pipeline for functional MRI. Nature Methods, 16(1), 111–116.
[11] Glasser, M. F., Coalson, T. S., Robinson, E. C., Hacker, C. D., Harwell, J., Yacoub, E., … Van Essen, D. C. (2016). A multi-modal parcellation of human cerebral cortex. Nature, 536(7615), 171–178.
[12] Kay, K. N., Rokem, A., Winawer, J., Dougherty, R. F., & Wandell, B. A. (2013). GLMdenoise: a fast, automated technique for denoising task-based fMRI data. Frontiers in Neuroscience, 7, 247.
[13] Charest, I., Kriegeskorte, N., & Kay, K. N. (2018). GLMdenoise improves multivariate pattern analysis of fMRI data. NeuroImage, 183, 606-616.
[14] van den Bosch, J., & Charest, I. (n.d.). pyRSA. Retrieved from https://github.com/Charestlab/pyrsa

email : J.J.F.VanDenBosch@bham.ac.uk