Catalyzing in silico neuroscience with a toolkit of accurate encoding models of the brain

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Abstract

In silico **neural responses generated from encoding models increasingly resemble *in vivo* responses recorded from real brains, enabling the novel research paradigm of in silico neuroscience. In silico neuroscience scales beyond what is possible with in vivo data, allowing to explore and test scientific hypotheses across vastly larger solution spaces. To catalyze this emerging research paradigm, here we introduce the Brain Encoding Response Generator (BERG), a resource consisting of multiple pre-trained encoding models of the brain and a Python package to generate accurate in silico neural responses to massive amounts of arbitrary stimuli with a few lines of simple code (https://github.com/gifale95/BERG). We show that BERG's encoding models accurately predict neural responses to visual stimuli, and that these in silico responses reproduce key neural signatures of visual processing. This opens the doors to using in silico neural responses for scientific discovery, which we envision will lead to a more efficient and reproducible science.**

Keywords: in silico neuroscience; fMRI; EEG; encoding models; vision; research resource

Introduction

Encoding models (Yamins & DiCarlo, 2022) generate *in silico* neural responses that increasingly resemble *in vivo* responses recorded from real brains, enabling the novel research paradigm of in silico neuroscience (Jain, Vo, Wehbe, & Huth, 2024). In silico neural responses are fast and cost-effective to generate, allowing researchers to explore and test scientific hypotheses across vastly larger solution spaces than possible in vivo. Novel findings from large-scale in silico experimentation are then validated through targeted small-scale in vivo data collection, in this way optimizing research resources.

To catalyze this emerging research paradigm, we introduce the Brain Encoding Response Generator (BERG), a resource consisting of multiple pre-trained encoding models of the brain and an accompanying Python package to generate accurate in silico neural responses to arbitrary stimuli with just a few lines of code. BERG includes a growing, well documented library of encoding models trained on different neural data acquisition modalities, datasets, subjects, stimulation types, and brain areas, offering broad versatility for addressing a wide range of research questions through in silico neuroscience.

Methods and Results

BERG's encoding models generate accurate in silico fMRI and EEG responses

BERG features encoding models trained on the largest and highest quality datasets of fMRI and EEG responses to naturalistic images. To allow for cross-subject validation of result and population-level inferences we trained separate models for each subject. For fMRI, we trained whole-brain encoding models using the Natural Scenes Dataset (NSD) (Allen et al., 2022), 7T fMRI responses from 8 subjects to over 70,000 naturalistic scenes from COCO (Lin et al., 2014), resulting in encoding accuracies (Pearson's r) of up to r = 0.75 across visual cortex (**Figure 1A**). For EEG, we trained time-resolved encoding models using THINGS EEG2 (Gifford, Dwivedi, Roig, & Cichy, 2022), EEG responses from 10 subjects to 16,740 naturalistic images of objects from THINGS (Hebart et al., 2019), resulting in an accuracy peak of r = 0.75 at 110 ms after stimulus onset, and sustained encoding accuracies for the remaining part of the EEG epoch (**Figure 1B**). Thus, BERG encoding models generate in silico fMRI and EEG responses that closely match in vivo neural data. Next, we show that these in silico responses reproduce key spatial and temporal signatures of visual processing in the brain.

BERG's in silico fMRI responses reproduce the tripartite organization of visual cortex based on animals, small objects, and big objects

We determined whether the in silico fMRI responses reproduce the tripartite organization of visual cortex into preference zones for animals, small objects, and big objects (Konkle & Caramazza, 2013). Using BERG, we generated in silico fMRI responses for 145 images from each of these three categories. We then averaged the responses within each category, and assigned each fMRI vertex to the category yielding the strongest response. This revealed a systematic topography across visual cortex reflecting preferences for animals, small objects, or big objects (**Figure 1C**). In line with previous work, these preference zones are duplicated on both the ventral and lateral surface of visual cortex, face- and body-selective areas fall mostly within the animal zones (75.28%, 60.90%, 75.61%, and 68.99% of vertices for FFA, OFA, EBA, and FBA, respectively), and place-selective areas fall mostly within the big object zones (92.13%, 84.06%, and 88.46% of vertices for PPA, OPA, and RSC, respectively). This shows that BERG's in silico fMRI responses reproduce key spatial signatures of vision, inviting the use of these in silico data to discover new space-resolved properties of visual processing.

BERG's in silico EEG responses reproduce the dynamics of object exemplar and animacy categorization

We determined whether the in silico EEG responses reproduce the dynamic of object exemplar and animacy categorization (Cichy, Pantazis, & Oliva, 2014). Using BERG, we generated in silico EEG responses for 200 object exemplars divided into 100 animate and 100 inanimate. We then applied a time-resolved decoding analysis (Haynes & Rees, 2006) to extract exemplar and animacy information from the EEG responses. Decoding performance peaked at 105ms for exemplar identity and at 200ms for animacy, in line with previous findings showing that object identity is processed earlier than animacy in the human brain (**Figure 1D**). This shows that BERG's in silico EEG responses reproduce key temporal signatures of vision, inviting the use of these in silico data to discover new time-resolved properties of visual processing.

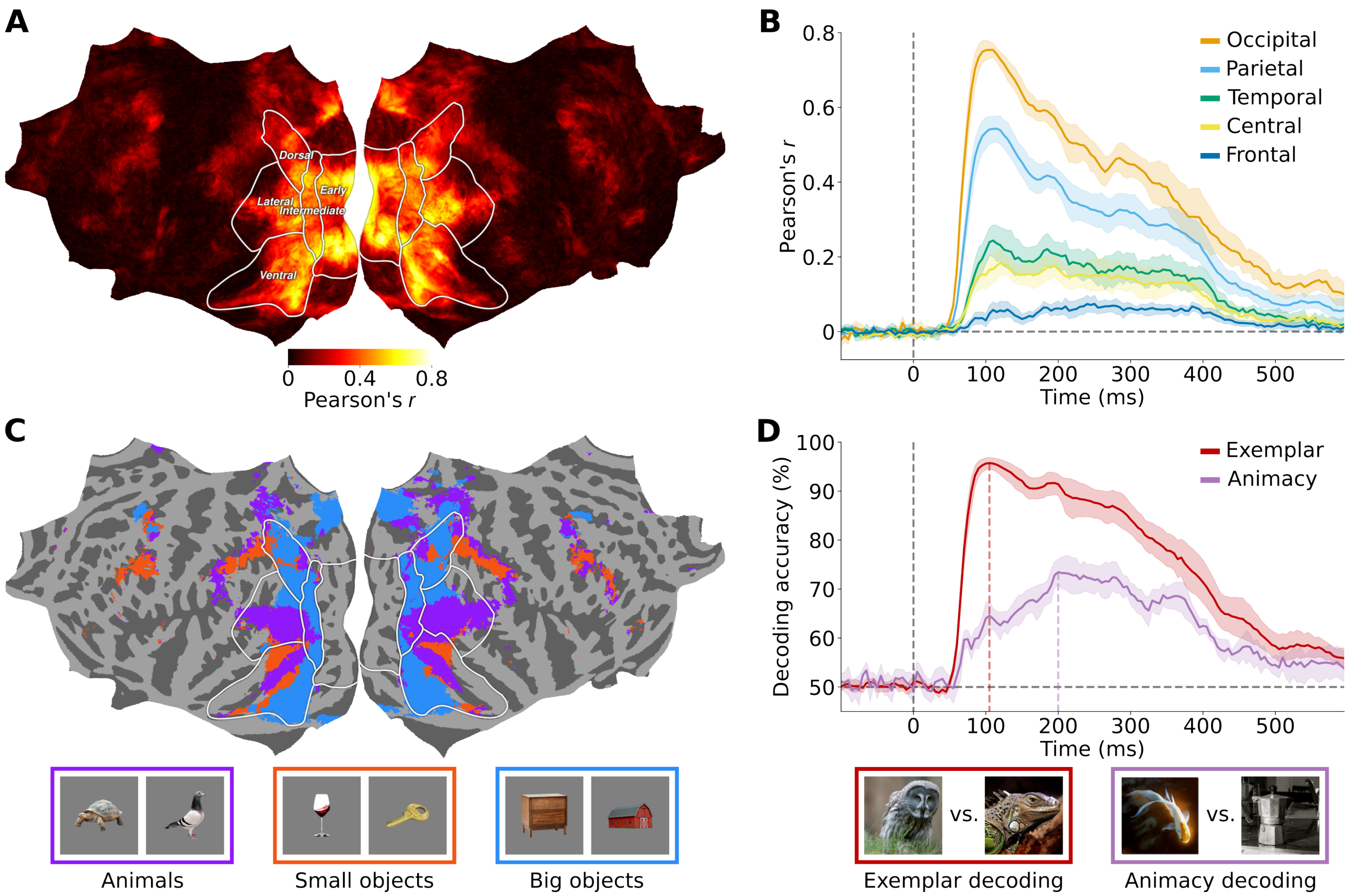

Figure 1: BERG's encoding models accurately predict neural responses that reproduce key neural signatures of visual processing. All results reflect subject averages. **A.** Prediction accuracy of BERG's fMRI encoding models, plotted on a flattened cortical surface. White contours indicate visual streams. **B.** Prediction accuracy of BERG's EEG encoding models, divided into channel groups. Error margins reflect 95% confidence intervals. **C.** BERG's in silico fMRI responses reproduce the tripartite organization of visual cortex by animals, small objects, and big objects. fMRI vertices are color coded based on their response preference for animals, small objects, or big objects. **D.** BERG's in silico EEG responses reproduce the different dynamics of object exemplar versus animacy categorization, as quantified by pairwise decoding using 28 occipital and parietal channels. Colored vertical dashed lines indicate the time point of peak exemplar and accuracy decoding

Discussion

We envision that BERG will catalyze in silico neuroscience research, resulting in two scientific advances. First, the fast and cost-effective generation of in silico neural responses will accelerate scientific discovery. Second, since BERG provides a common library of encoding models, it enables benchmarks similar to the ones in computer science that will increase reproducibility of scientific findings. As an example of in silico neuroscience for new discovery, we used BERG to develop relational neural control (RNC), a method to move from an atomistic understanding of visual cortical areas (i.e., *What does each area represent?*) to a network-level understanding (i.e., *What is the relationship between representations in different areas?*). Through RNC we generated and explored in silico fMRI responses for large amounts of images, identifying images that either align or disentangle responses across visual areas, thus revealing their shared or unique representational content. Closing the empirical cycle, we validated the in silico discoveries on in vivo fMRI responses from independent subjects (Gifford, Jastrzebowska, Singer, & Cichy, 2024).

The limitation of BERG lies in the component that empowers it: the encoding models generating the in silico neural responses do not predict all explainable neural signal, and generalize imperfectly beyond the distribution of the data they were trained on. However, the current push in the development of more accurate and robust encoding models (Schrimpf et al., 2018; Turishcheva et al., 2024; Gifford, Bersch, et al., 2024) using large in vivo data sets that also include out-of-distribution components (Gifford, Cichy, Naselaris, & Kay, 2025) promises increasingly accurate in silico neural responses. This, in turn, will increase the reliability of findings from experimentation on model-generated brain data.

We plan to expand BERG to more accurate encoding models from a larger variety of brains, species (e.g., monkey, mice), measurement devices (e.g., electrophysiology, MEG, ECoG), and stimuli (e.g., auditory, language, multimodal). This ever-growing richness makes BERG a versatile data-generation toolkit that empowers researchers to efficiently address new research questions. We warmly welcome models, ideas, and collaboration from the community.

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