The attractor states of the functional brain connectome

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Wednesday 28th June, 2023

Abstract

Abstract:
todo

Keywords

Key Points:

- We propose a high-level computational model of "activity flow" across brain regions
- The model considers the funcional brain connectome as an already-trained Hopfield neural network
- It defines an energy level for any arbitrary brain activation patterns
- and a trajectory towards one of the finite number of stable patterns (attractor states) that minimize this energy
- The model reproduces and explains the dynamic repertoir of the brain's spontanous activity at rest
- It conceptualizes both task-induced and pathological changes in brain activity as a shift on the "attractor landscape"
- We validate our findings on healthy and clinical samples (~2000 participants)

1 Introduction

Brain function is characterized by the continuous activation and deactivation of anatomically distributed neuronal populations. While changes in the activity of a single brain area is often associated with various tasks or conditions, in reality, regional activation never occurs in isolation (Bassett and Sporns [2017]). Regardless of the presence or absence of explicit stimuli, brain regions seem to work in concert, resulting in a rich and complex spatiotemporal fluctuation (Gutierrez-Barragan et al. [2019]). This fluctuation is neither random, nor stationary over time Liu and Duyn [2013], Zalesky et al. [2014]. It shows quasi-periodic properties (Thompson et al. [2014]), with a limited number of recurring patterns known as "brain states" (Vidaurre et al. [2017], Liu and Duyn [2013], Richiardi et al. [2011]).

Many recent studies (Smith et al. [2012], Vidaurre et al. [2017], Liu and Duyn [2013]) assess whole-brain dynamics and provide accumulating evidence supporting the neurobiological significance of these dynamics (Hutchison et al. [2013], Barttfeld et al. [2015], van der Meer et al. [2020]). However, the underlying driving forces remain elusive.

Questions regarding the origin and meaning of this dynamic repertoire are to be answered by computational models that hold promise to bring us from "correlational studies" to casual understanding. Traditional

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computational neuroscience approaches try to solve the puzzle all the way. They begin by considering the biophysical properties of single neurons and then aim to construct a model of larger neural populations, or even the entire brain (Breakspear [2017]). Although there have been numerous successful applications (Kriegeskorte and Douglas [2018], Heinz et al. [2018]), estimating all free parameters of such models proved to be a grand challenge, limiting success of these techniques to bridge levels of explanations from single neurons to complex behavior (Breakspear [2017]).

An alternative approach, known as "neuroconnectomism" (Doerig et al. [2023]) releases the aim of full bottom-up understanding of neural mechanisms and shifts the emphasis from "biophysical fidelity" of models to "cognitive/behavioral fidelity" (Kriegeskorte and Douglas [2018]) by using artificial neural networks (ANNs) that were trained to perform various tasks as brain models. This approach utilizes artificial neural networks (ANNs) trained for various tasks as brain models. While the approach has significantly contributed to expanding our understanding of the general computational principles of the brain (see Doerig et al. [2023]), the requirement of training ANNs for specific tasks poses inherent limitations in their capacity to explain spontaneous macro-scale dynamics of neural activity (Richards et al. [2019]).

In this work, we take the middle ground between traditional computational modelling and neuroconnectionism to address the phenomenon of brain dynamics. On one hand, similarly to neuroconnectionism, we do not aim for a full bottom-up understanding of neural mechanisms and use an ANN as a high-level computational model of the brain. On the other hand, we do not train our ANN for a specific task, but set its weights "manually", based on empirical data about the "activity flow" (Cole et al. [2016], Ito et al. [2017]) within the functional brain connectome, as measured with functional magnetic resonance imaging (fMRI). We use a neurobiologically motivated ANN architecture, a continuous-space Hopfield network. Within this architecture, the topology of the functional connectome naturally defines an energy level for any arbitrary activation patterns and a trajectory towards one of the finite number of stable patterns that minimize this energy, the so-called attractor states. Furthermore, it provides a natural account for brain state dynamics as the system, in the presence of a small amount of noise, can undergo bifurcation, i.e. spontaneously switch between attractor states.

In this simplistic yet powerful framework, the primary determinants of the system's dynamic behavior are the topology of the network spanned by the weights of the ANN. As these weights are directly inferred from brain data, we hypothesize that the system will closely mimic the dynamic repertoire of true activity patterns in the brain (as measured by fMRI) and capture activity changes induced by tasks and pathologies.

In the present work, we test our hypotheses in a series of experiments, on data from a total of n≈2000 individuals, to provide converging evidence for the validity of our model.

In the proposed framework, both spontaneous and task-induced brain dynamics can be conceptualized as a high-dimensional path that wanders on the reconstructed energy landscape in a way that is restricted by the "gravitational pull" of the attractors states. The framework offers a generative model for resting state and task-related brain dynamics and new perspectives on the mechanistic origin of resting state brain states and task based activation maps.

     ToDo: more on the significance

2   Results

- introduce the idea in more detail (fig 1)
  - attractor states and added noise
  - construcct validity
- attractor states (fig 1)
- face validity
- clinical validity

  Due to the known noise-tolerance of the applied eANN-s, the proposed approach can be expected to be highly robust/reliable/replicable, which we demonstrate with independent datasets (total n=xxx).
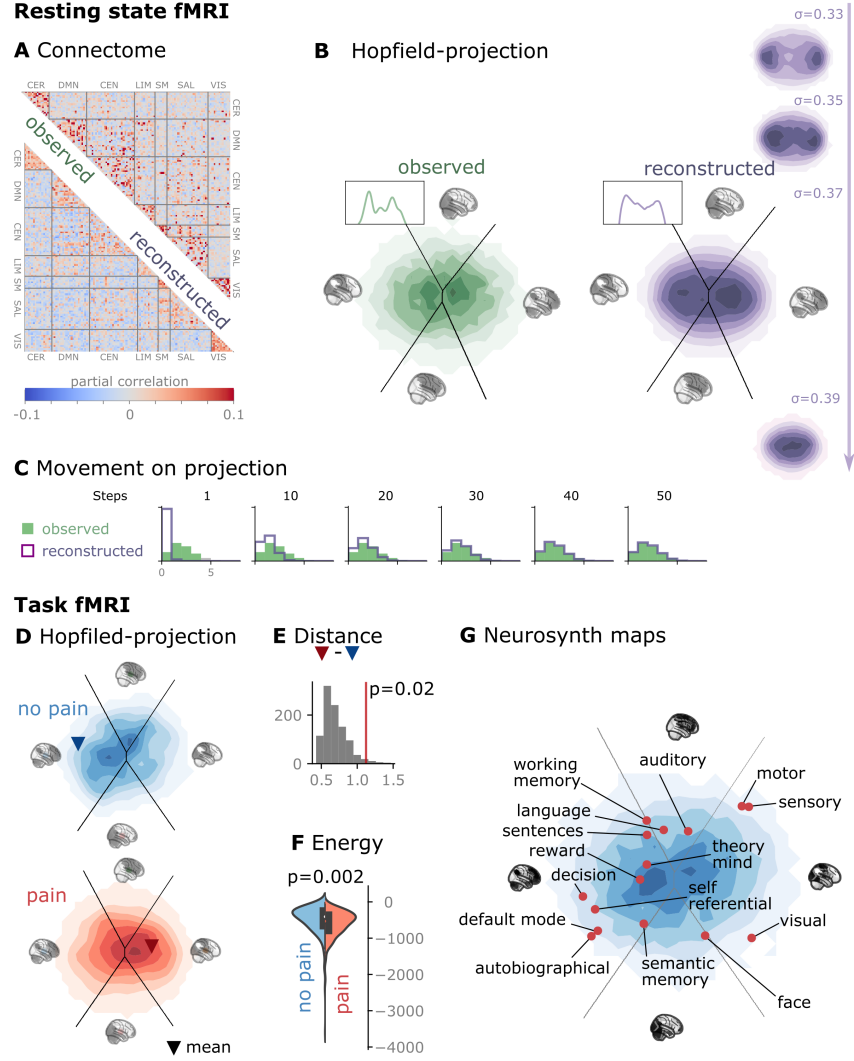
Here I refer to Figure 1.

Figure 1: Empirical Hopfield-networks reconstruct real brain activity.

3   Discussion

- significance

A further scenario rests on the role of ghost attractors [109](https://www.nature.com/articles/nn.4497#ref-CR109 "Deco, G. & Jirsa, V.K. Ongoing cortical activity at rest: criticality, multistability, and ghost attractors. J. Neurosci. 32, 3366–3375 (2012).", a dynamic landscape of remnant attractors each of which has an incomplete basin, hence allowing the system to 'wander' through large swathes of the phase space under the influence of weak noise 110.

4   Methods

Todo

Todo

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