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# THE ATTRACTOR STATES OF THE FUNCTIONAL BRAIN CONNECTOME

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## Abstract

**Abstract:**  
todo

### *Keywords*

### **Key Points:**

- We propose a high-level computational model of "activity flow" across brain regions
- The model considers the functional 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 repertoire of the brain's spontaneous 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 accompanied by the 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 (ref). Regardless of the presence or absence of explicit stimuli, brain regions seem to work in concert, resulting in a rich and complex spatiotemporal fluctuation over time. This fluctuation shows quasi-periodic properties ([Thompson et al. \[2014\]](#)), with a limited number of recurring states known as "brain states" ([Gutierrez-Barragan et al. \[2019\]](#), [Vidaurre et al. \[2017\]](#)). These states are often interpreted as sporadic intervals during which information can be efficiently exchanged between a characteristic subset of brain regions ([Hutchison et al. \[2013\]](#), [Liu and Duyn \[2013\]](#), [Zalesky et al. \[2014\]](#)). Brain state dynamics can be assessed with multiple techniques, including independent component analysis (ref), co-activation patterns ([Liu and Duyn \[2013\]](#)) and hidden markov models ([Vidaurre et al. \[2017\]](#)).

While such efforts, by their nature, do not shed light on the driving forces of the complex spatiotemporal dance of brain activity, they provide accumulating evidence for the neurobiological relevance of these dynamics, with promising perspectives for facilitating the clinical translation of functional neuroimaging techniques ([Lee et al. \[2021\]](#)).

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Why does such interregional communication manifest in co-activation? Which activity configurations does the brain visit and which not? How do these relate to each other? How does this dynamic repertoire of activation patterns result in task-related activity maps, as obtained with functional magnetic resonance imaging? What is the meaning of activity and connectivity differences across individuals or in various clinical conditions?

Traditional tools of computational neuroscience try to address these and similar questions with methods of varying complexity from those based on the Fokker–Planck equation, to neural mass and neural field models. Commons amongst these models is the assumption that spatiotemporal patterns of neural dynamics arise from interactions between functionally specialized cell populations connected by a topologically complex array of short- and long-range axonal connections (Bullmore and Sporns [2009], Yuste [2015]), the latter often being estimated at macroscopic scales by diffusion magnetic resonance imaging (dMRI).

These models have found broad success in modeling seizures [11], encephalopathies [12, 13], sleep [14], anesthesia [15], resting-state brain networks [16, 17] and the human alpha rhythm [18, 19], and as a tool for multimodal data fusion [20]. Technical advances in model inversion (estimating the likelihood and parameters of a model from empirical data) place mean field models within reach of widespread application to cognitive neuroscience [21].

*Nevertheless, there is no broadly accepted mathematical theory for the collective activity of neuronal populations and such models have shown limited success to bridge levels of explanations from single neurons to complex behavior, mainly due to the grand challenges of estimating all free parameters.*

Todo: shorten and focus on the fact that most comp models aim to solve the task all the way: to construct a "biophysical model" that accounts for empirical brain data and behavior.

Thus, the penetration of dynamic models of large-scale brain activity into mainstream neuroscience has been slow, and they may be unknown to many neuroscientists.

An alternative approach: Neuroconnectomist approach (Doerig et al. [2023])

A further scenario rests on the role of ghost attractors [109] (<https://www.nature.com/articles/nm.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].

In this work, we aim for:

- simplest, highest-level generative computational model: a multistable dynamic system with **maximal empirical validity**
- bypass the challenges of estimating parameters, by building on the activity flow
- **no mechanistic model, not aiming to explain biophysical background**
- links to Neuroconnectomism

multistable dynamical systems theory

Our framework - with minimal and reasonable assumptions about the "activity flow" (ref: Cole-papers) between two, functionally connected regions - considers the stationary functional brain network as an already-trained artificial neural network. In the proposed framework, the topology of the stationary brain connectome defines a cost (energy) for any arbitrary brain activation patterns and a trajectory towards one of the finite number of stable patterns that minimize this cost (so-called attractor states).

- noise

Here we propose these attractor states as robust and neurobiologically relevant characteristics of the functional brain connectome, with a wide variety of potential applications.

We demonstrate that the proposed attractor states highly resemble to the dynamic brain states commonly observed by dynamic functional connectivity methods (e.g. CAP-analyses (ref)) and provide a proof-of-concept for the biomedical validity of our framework, by showing that the average brain activations corresponding to the attractor states during resting state display manifold significant associations to cognition.

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).

List all the aims: hierarchy, generalizability etc

## 2 Results

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

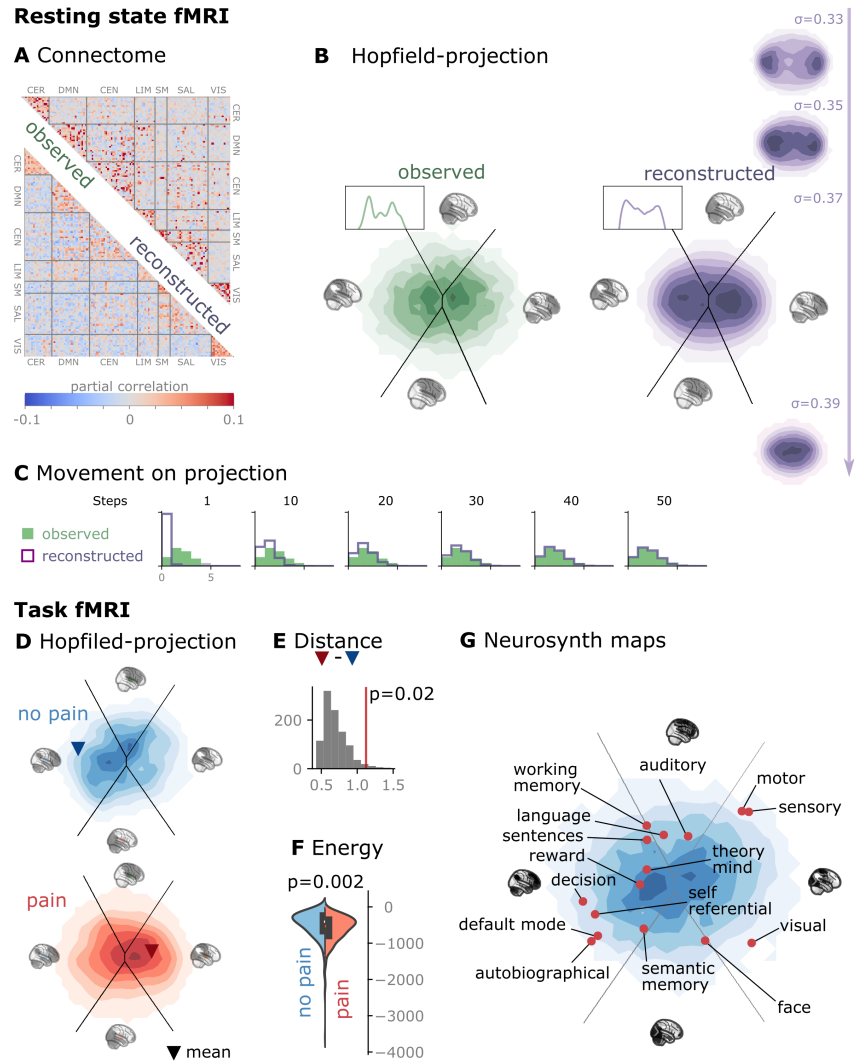


Figure 1: Empirical Hopfield-networks reconstruct real brain activity.

Here I refer to Figure 1.

### 3 Discussion

- significance

### 4 Methods

Todo

Todo

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