
The Neuromodulation Connectivity Dataset: Cross-Modal Data for Closed-Loop Brain Stimulation

Anonymous Author(s)

Affiliation

Address

email

Abstract

1 Neuromodulation enables the precise modulation of human brain circuits, with
2 promising therapeutic applications and providing a causal probe of brain function.
3 It includes a wide range of techniques, from invasive methods such as deep brain
4 stimulation (DBS), vagus nerve stimulation (VNS), and responsive neurostimula-
5 tion (RNS), to non-invasive approaches such as transcranial focused ultrasound
6 (tFUS), transcranial magnetic stimulation (TMS), and transcranial electrical stim-
7 ulation (tES). A key shift in the field is moving from open-loop to closed-loop
8 strategies, where stimulation is dynamically adjusted based on neural activity.
9 However, closed-loop modulation requires accurate modelling of how differing
10 stimulation protocols affect brain functional connectivity (FC), and how those
11 changes in FC result in clinical or behavioural outcomes. The field is currently
12 hindered by heterogeneous, modality-specific datasets that impede generalisable
13 model development. We propose an expanded cross-modality dataset linking
14 stimulation protocols, EEG activity, standardised FC readouts, and behavioural or
15 clinical outcomes. Such a dataset would enable real-time, personalised stimulation
16 and provide deeper circuit-level biological insight.

1 Background

18 Neuromodulation uses technology to impact the neural interface and modulate the function of the
19 central, peripheral or autonomic nervous system [Yan et al., 2024]. Invasive approaches such as
20 deep brain stimulation (DBS), vagal nerve stimulation (VNS), and responsive neurostimulation
21 (RNS) have been used for a wide range of pathological diseases such as epilepsy, movement and
22 psychiatric disorders [Nagel and Najm, 2009, Saillet et al., 2009, Dhaliwal et al., 2025]. Recently,
23 non-invasive methods have increased in prevalence. Transcranial magnetic stimulation (TMS) is a
24 well-established method to causally perturb the cortex, transcranial electrical stimulation (tES) can
25 modulate oscillations, and transcranial focused ultrasound (tFUS) allows deep, focal modulation with
26 growing human evidence [Davidson et al., 2024]. Symptoms in various disorders often arise not from
27 isolated nodes, but rather from dysfunctional communication across distributed networks.

28 Recent advances in stimulation and sensing hardware, along with low-latency neuroinformatics
29 modelling, have enabled a shift from open-loop, where therapy is delivered according to fixed settings
30 regardless of changes in symptoms or disease state, to closed-loop strategies that use real-time
31 EEG feedback to capture dynamic brain activity and provide more adaptive responses [Sun and
32 Morrell, 2014]. Closed-loop strategies fundamentally depend on robust predictive models that can
33 link stimulation parameters to changes in network connectivity and even clinical outcomes. However,
34 heterogeneous, modality-specific datasets and limited longitudinal depth of studies hinder model
35 accuracy and generalizability.

36 Because stimulation effects propagate along circuits, the network context of a target is important.
37 Functional connectivity (FC), the statistical coupling between brain regions, has driven the char-
38 acterisation of the brain connectome in both typical healthy populations and various pathological
39 groups such as stroke, epilepsy, neurodegenerative and psychiatric conditions, providing meaningful
40 insights into the neural basis of diverse pathological and behavioural traits [Mohanty et al., 2020]. FC
41 therefore provides actionable targets for stimulation and means of measuring the effects of stimulation
42 protocols and guiding neuromodulation.

43 2 Dataset rationale

44 We will combine diffusion MRI tractography (structure) with EEG/MEG/ECoG/fMRI (function) to
45 quantify FC and its change under stimulation. Crucially, stimulation parameters capturing frequency,
46 amplitude and electrode configuration would be required. These parameters dictate the specific neural
47 circuits that are engaged, how stimulation effects unfold, and thereby enable clinicians to accurately
48 tune these parameters accordingly.

49 The dataset would include multimodal data: diffusion MRI for structural tractography, EEG/MEG or
50 ECoG recordings for neural responses, and detailed stimulation logs (frequency, amplitude, pulse
51 width, electrode configuration). A wide range of patients will be included to capture heterogeneity.
52 Metadata would label subject demographics, electrode locations and stimulation parameters to provide
53 reproducibility and interpretation.

54 2.1 Conceptual flow of the dataset:

- 55 1. **Perturbation** – Apply stimulation to a specific neuroanatomical region.
- 56 2. **Stimulation parameters** – Vary frequency, amplitude, and pulse width.
- 57 3. **Neural readout** – Record responses via EEG/MEG or ECoG, capturing voltage fluctuations
58 over time.
- 59 4. **Functional connectivity (FC) derivation** – Compute statistical relationships between
60 signals from different brain regions under the same stimulation conditions, producing
61 pre-/post-stimulation FC matrices.
- 62 5. **Integration with structural connectivity** – Overlay FC matrix onto diffusion MRI tractog-
63 raphy. This would validate whether functional links align with known white-matter tracts,
64 and whether evoked responses propagate along expected anatomical pathways.
- 65 6. **Outcome Link** - Align FC deltas with clinical/behavioural change and side-effect thresholds.

66 2.2 Interpretation / Outcome link

67 This dataset will link stimulation protocols to FC changes, and link those FC changes to clinical or
68 behavioural outcomes. Predictive models trained on these datasets will enable parameter-response
69 mapping to recommend stimulation settings and support closed-loop optimisation. Because it spans
70 multiple neuromodulation modalities, the dataset provides a cross-modal reference frame, and models
71 can be trained on pooled data and learn correspondences across TMS, tES, DBS, and ultrasound. This
72 is particularly important in a field where data and approaches are heterogeneous and lack a common
73 frame. The dataset makes previously siloed modality-specific datasets interoperable, substantially
74 expanding the volume of usable training data and enabling modality-agnostic ML models. Finally,
75 the dataset enables a mechanistic and biological understanding of how changes in FC are linked to
76 behavioural or clinical outcomes.

77 2.3 Dataset Expansion

78 Various published datasets and public archives exist that provide datasets spanning EEG, MEG,
79 fMRI and intracranial stimulation, including OpenNeuro, the Human Connectome project (HCP),
80 and UK Biobank. The resources alongside NeuroVault [Gorgolewski et al., 2015], an open-science
81 neuroinformatics online repository of a range of brain statistical maps, atlases and parcellations,
82 could be used to create connectivity derivatives.

83 Stimulation parameters for perturbation including coil position, pulse train, and ultrasound focus
 84 are also found within literature, and will be identified using natural language processing. Extraction
 85 of this data will be done where available. For datasets that lack explicit stimulation metadata,
 86 reconstruction of parameters will be done by combining reported coordinates with electric-field
 87 modelling tools, such as SimNIBS. These will then be seeded on structural connectomes to generate
 88 synthetic functional responses.

89 The overall workflow involves a staged process: scoping eligible datasets, automated discovery and
 90 triage, acquisition and harmonisation into BIDS-compliant formats, and generation of derivatives
 91 such as stimulation-region electric fields, and parcellated structural and functional connectomes.

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