Optimized Encoding of Sensation in Brain-Machine Interfaces

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Final Output:

Set of Characteristic

Within-Cluster: Which

Stimulation Parameter is

Most Characteristic?

INTRODUCTION

Sensory feedback in Brain-Machine Interfaces (BMI) currently rely on either *user-in-the-loop* calibration or *closed-loop algorithms* to *replicate desired neural responses* downstream of stimulation areas. However, both approaches are not practical or robust given time constraints in the clinic and variability in neural interfaces.

We propose an alternative algorithm that:

- 1) Quantifies the dissimilarity of downstream neural responses,
- 2) Schedules new applied stimulus patterns to efficiently identify clusters of patterns leading to similar responses.

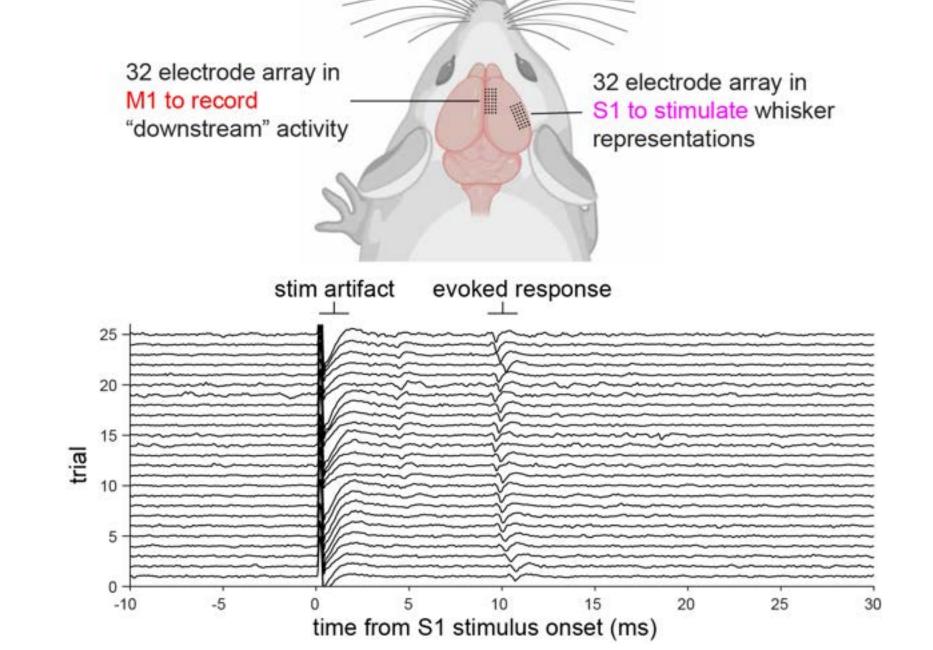
The set of identified stimulus patterns would maximize encoded information under the assumption that discriminable neural responses lead to discriminable percepts.

EXPERIMENTAL DATA

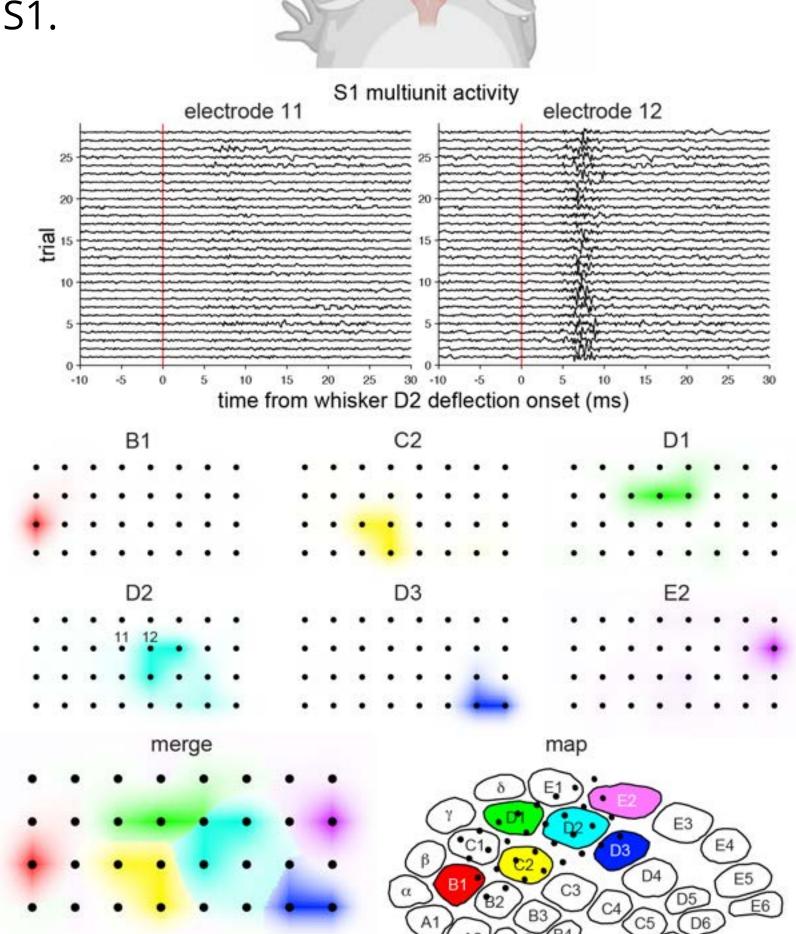
Electrical stim of whisker somatosensory cortex (S1) in anesthetized rats to encode sensations.

Downstream response recorded in motor cortex (M1) since often implanted in BMI and highly connected to S1.

Perceptual ground truth determined by mapping whisker representations ("barrels") in S1. We safely assume stimulation of different barrels evokes discriminable percepts.



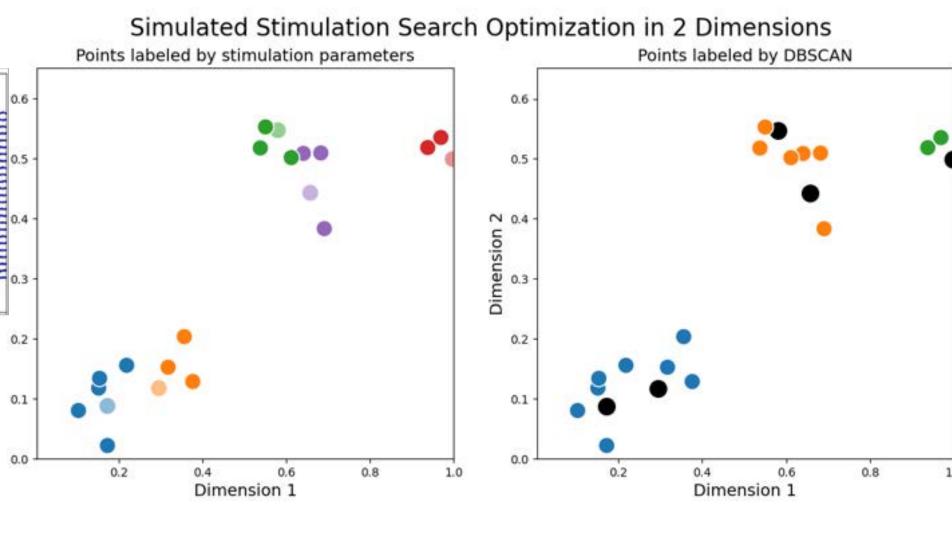
Our Stimulation Parameter Search Algorithm vs Previous Adaptive Closed-Loop Approaches Record "downstream" **Stimulate S1 Optimize Search:** Stimulate Patterns That Evoke Distinct Neural Responses **Cost Function:** Maximize Discriminability Among Multiple Responses **Cost Function: Machine Learning:** Minimize Error between **Generate New Stimulation Evoked and Desired** Pattern Response



32 electrode array in S1

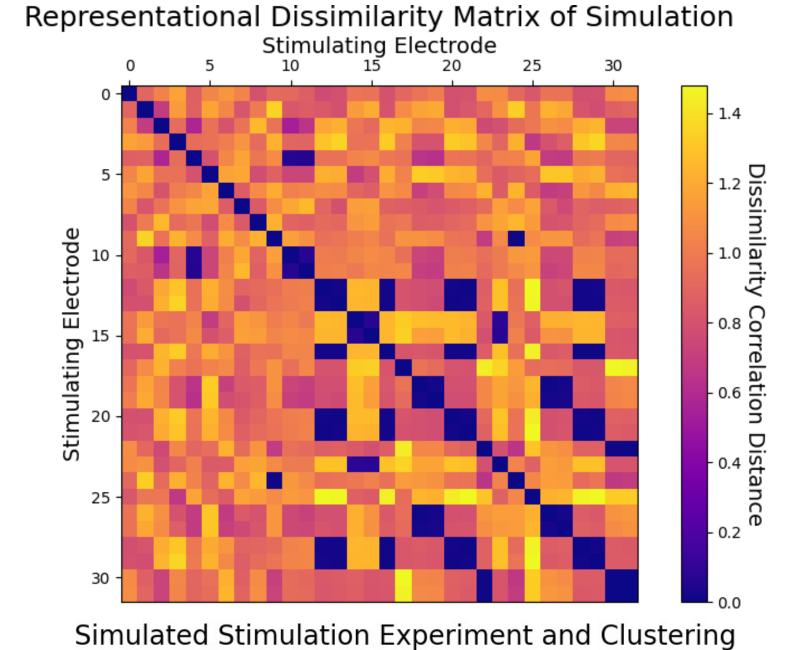
OPTIMIZATION WORKFLOW

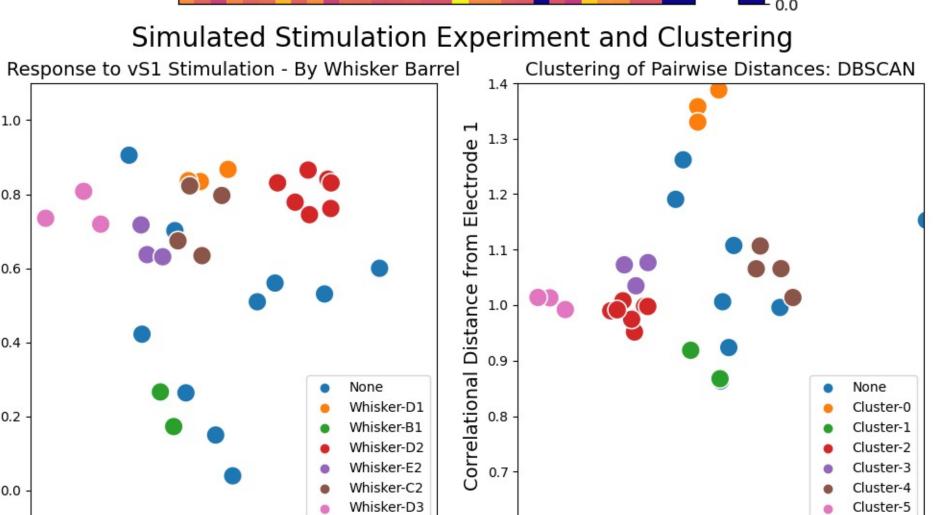
Simulated data to mimic the optimization workflow in two-dimensions.



DISSIMILARITY ANALYSIS

To date, the whisker mapping and M1 recording are from different animals. Thus, created simulated M1 responses corresponding to the mapping data.





0.7 0.8 0.9 1.0 1.1 1.2 1.3 1.4

Correlational Distance from Electrode 0

0.2 0.4 0.6 0.8

Average SNR for Electrode 0

Cluster-Silhouette

DISCUSSION

Good

Next Steps: Algorithm to be implemented in real-time and validated and expanded upon a full vS1-vM1 and Whisker Mapping dataset. To further test perceptual discriminability, rats will be trained on a three-alternative forced choice (3AFC) "oddity" task to validate in behavioral experiments.

Online Algorithm

Schedule: Stimulate

Ambiguous Patterns

Evaluate Clusters:

Unsure

Preprocessing:

Feature Extraction

Unsupervised

Clustering: DBSCAN

Algorithm: Future directions of the algorithm include different scheduling methods (Bayesian) and explicit mentioning of **stimulation parameter nature** to utilize parameter-specific features and/or physiological relevance.

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