Optimized Encoding of Sensation in Brain-Machine Interfaces

Toma Itagaki – University of Washington, Neuroscience, SUNFEST Fellow **Anusha Keshireddy** – University of Pennsylvania, Department of Bioengineering **Benjamin Ferleger** – University of Pennsylvania, Department of Neurosurgery **Andrew Richardson** – University of Pennsylvania, Department of Neurosurgery

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.

32 electrode array in M1 to record "downstream" activity

32 electrode array in whiske representations

stim artifact evoked response

time from S1 stimulus onset (ms)



Stimulate S1





Optimize Search: Stimulate Patterns That Evoke Distinct Neural Responses

Machine Learning: Generate New Stimulation Pattern





Our Stimulation Parameter Search Algorithm Simulated data to mimic the optimization vs Previous Adaptive Closed-Loop Approaches workflow in two-dimensions. **Record "downstream"** Simulated Stimulation Search Optimization in 2 Dimensions Points labeled by stimulation parameters Points labeled by DBSCAN Dimension Dimension **Cost Function: DISSIMILARITY ANALYSIS** Maximize Discriminability Among **Multiple** Responses To date, the whisker mapping and M1 **Cost Function:** recording are from different animals. Thus, Minimize Error between created simulated M1 responses **—**•••••• Evoked and Desired corresponding to the mapping data. Response Representational Dissimilarity Matrix of Simulation Stimulating Electrode vhisker deflectior 32 electrode array in S1 hisker D2 deflection onset (ms/ Simulated Stimulation Experiment and Clustering Response to vS1 Stimulation - By Whisker Barrel E2 None Whisker-D1 Whisker-B1 Whisker-D2 Whisker-E2 • • • • • Whisker-C2 Whisker-D3

0.2 0.4 0.6 0.8 1.0 Average SNR for Electrode 0

OPTIMIZATION WORKFLOW





Clustering of Pairwise Distances: DBSCAN





DISCUSSION

Next Steps: Algorithm to be implemented in realtime and validated and expanded upon a full vS1vM1 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.

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.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the support of the National Science Foundation, through NSF REU grant no. 1950720 and thank Dr. Sue Ann Bidstrup Allen for leading the REU.







