 DOI: 10.3217/978-3-85125-962-9-213

Modeling local neural population responses to intracortical microstimulation.

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Introduction: Intracortical microstimulation (ICMS) is a primary tool for driving neural population activity, and may provide an avenue to create rich somatosensory percepts when delivered to the somatosensory cortex (S1) in intracortical brain-computer interfaces. However, current stimulation strategies, limited to fixed patterns of stimulation pulses, do not provide this rich feedback. These patterns can be coarsely optimized with participant reports about the evoked percepts, but this process is time-consuming and cannot be efficiently scaled to complex stimulation patterns, such as those using multiple electrodes [1]. We thus propose to characterize the evoked *neural response* as a step towards more sophisticated stimulation.
Materials, Methods, Results: We delivered ICMS trains in two participants, each of whom had two microelectrode arrays implanted in S1. During stimulation, we simultaneously recorded full bandwidth data (30 kHz) from these same electrodes using custom headstages (Blackrock Microsystems). Stimulation comprised 1-s trains of biphasic pulses; for each pulse we varied the amplitude (20-80 uA), timing (average rate 20-100 Hz), and electrodes (up to 5 electrodes in a trial) to study their effect on the recorded neural response.

We developed two models to characterize the spiking response to stimulation. First, we extracted the spiking response from the voltage recordings, which are contaminated with highly variable electrical artifacts. To do this, we created a deep network artifact estimator that re-enables spike detection within 1.3 ms of pulse offset. The observed spiking responses were diverse across stimulation parameters, consistent with previous studies on more limited stimuli [2]. Next, we developed a separate deep network model to capture the relationship between the commanded stimulation and observed response. Ablation studies confirmed that responses were affected by the choice of stimulating electrode, pulse amplitude and timing. These effects extend temporally beyond 200 ms and interact with the ongoing local population state.

Having quantified the complex neural response, we then considered practical strategies for exploring the exponentially large set of stimulation parameters. To do this, we designed a set of generalization experiments wherein models fit to one set of stimulation parameters were evaluated on trials collected with different parameters. We encouragingly find good generalization to novel pulse timing and amplitude (sampled from the same random distribution), but limited generalization to different electrodes. Finally, we find that multi-session data aggregation can potentially overcome practical performance limits in single sessions.
Discussion: We find that neural responses can be accurately modeled within practical experimental budgets. Characterization of high-electrode count stimulation remains a challenge, motivating the development of data aggregation strategies. Other next steps include developing stimulation controllers and modeling the relation between neural response and evoked percepts.
Significance: Our results lay groundwork for precise stimulation for neural population control.
Acknowledgments: JY is supported by the DOE Computational Science Graduate Fellowship. Experiments supported by NINDS NS107714 and NS123125.

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