# Optimized encoding of sensory stimulation for brain-machine interfaces

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***Abstract*—Restoration of sensory feedback in Brain-Machine Interfaces (BMI) currently relies on user-in-the-loop calibrations or closed-loop approaches to replicate known neural responses corresponding to the target sensory perception. However, both approaches are not practically robust when considering the variability among users and neural interfaces. We propose an alternative, robust, and generalizable stimulus parameter search algorithm to 1) reduce the number of trials and total tuning time required to find discriminable sensory percepts, and 2) diversify the exploration of the stimulation parameter space.**

***Index Terms*—Somatosensory encoding, Brain-Machine Interfaces, Discriminable neural percepts**

## I. Introduction

Advances in brain-machine interfaces (BMI) show promise towards improving quality-of-life for amputees and patients with paralysis. However, BMI development has primarily focused on motor control, decoding motor intent from brain activity in the motor cortex to control a prosthetic limb or the peripheral nervous system. In the current state of BMIs, development has largely neglected the importance of tactile feedback [1] Thus, development of bi-directional BMIs that interface with both motor and sensory cortices are under investigation [2]. The current state of afferent neural interfaces providing somatosensation largely rely on user-in-the-loop methods. In other words, the user's subjective perception is the sole measure used to tune neural stimulation parameters. This tedious and time-consuming process is hampered by human errors and typically neglects the majority of the stimulus parameter space [3][4]. Consequently, evoked percepts can have little resemblance to natural sensory percepts [3].

Closed-loop approaches to tune stimulus parameters based on neural responses, rather than perceptual responses, have previously been explored. These algorithms assume that a spatiotemporal neural response corresponding to a certain percept is known [5]–[10]. Finding parameters to evoke these ground-truth neural responses sets up a straightforward controls problem. However, considering the variability between individuals and neural interfaces, these “target” neural activity patterns cannot be inferred from or generalized between the patient population [9], [11].

We propose an alternative, robust, and generalizable stimulus parameter search algorithm to 1) reduce the number tuning time required to find discriminable sensory percepts, and 2) diversify the exploration of the stimulation parameter space. Our hypothesis makes a key assumption that discriminable neural responses are related to unique sensory percepts. This assumption is supported by numerous studies linking neural population activity to perception [12].

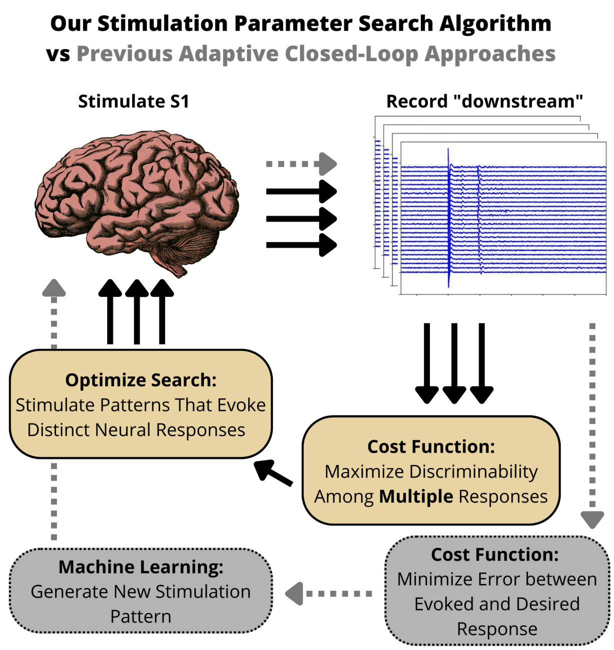


*Fig 1.* Workflow of proposed stimulation parameter search algorithm. *Grey*: past closed-loop approaches to adjusting stimulation parameters with a cost function to minimize the error between the recorded and “desired” response (to target sensation). *Beige*: proposed closed-loop approach simultaneously searches multiple stimulation patterns and implements a cost function to maximize the distance between the downstream responses.

## II. Background

Previous work surrounding closed-loop approaches to optimizing the encoding of specific neural percepts relies on a known neural response that corresponds with the target neural percept [5]–[10]. This creates a simple objective of reducing the spatiotemporal difference between the known activity and the evoked activity but considering the variability of each neural interface and individual’s brains, this approach does not offer a robust and scalable solution to encoding somatosensory feedback [11].

Considering these limitations, we propose a cost function to find the maximum number of stimulus encodings that have maximum dissimilarity from each other. This cost function now optimizes for discriminability of neural percepts with disregard for biomimetic experiences, based on the key assumption that dissimilar neural percepts downstream of the stimulation site results in discriminable neural percepts [13], [14]. Given the current understanding of sensory encoding, rather than chasing biomimetic percepts, evoking arbitrary neural percepts, and having users learn a new set of sensory mapping is more practical given the variability of every BMI.

Kriegeskorte's Representational Dissimilarity Matrix provides a framework in which neural responses can be evaluated as discriminable based on the correlational distance in the neural representational space – which becomes the basis of how the dissimilarity of neural activity will be evaluated in the proposed cost function [15]. After reducing the dimensionality of the spatiotemporal neural response, unsupervised clustering techniques will cluster the neural responses into groups related to discriminability; if two clusters are significantly distant in the response space, we assume that the stimulus parameters from each neural percept will evoke discriminable responses.

However, given the vastness of the stimulus parameter space, a brute force search and pairwise computation of dissimilarity would take significant time and likely, compute power considering that the algorithm is intended to be used online, in a closed-loop BMI. Furthermore, the noise in electrophysiological recordings will likely contain significant noise, requiring multiple passes and the averaging of neural responses to create a reliable representation in the neural response space. Given these challenges, the algorithm must efficiently search across a set of stimulus parameters whilst minimizing the number of passes for each stimulus set, calling for methods similar to active learning methods for unsupervised clustering in large datasets with a modified prioritization function [16].

## III.METHODS

Initial testing of the optimization algorithm was performed with data collected from acute experiments in anesthetized rats. Two sets of 32-electrode arrays (in 4 by 8 orientation) were implanted in vibrissal S1 (vS1) and vibrissal M1 (vM1). Stimulation was delivered in vS1 electrodes and the response in vM1 was recorded, to perform the representational similarity analysis between the responses in vM1 to different stimulation patterns in vS1.

### 3.1 Stimulation:

To evoke sensation, mircostimulation with a pulse width of 200 μs and amplitude of 50 μA was delivered in each of the 32 vS1 electrodes individually.

### 3.2 Whisker to vS1 Validation Experiment:

Initial stimulations were delivered in vS1 in the electrode location domain. To validate clusters from the search algorithm, we assumed that clusters of vS1 electrodes that respond to different whisker deflections result in discriminable percepts.

### 3.3 Preprocessing and Feature Extraction

The response in vM1 15 ms before and 50 ms after the stimulation was sliced. The stimulus artifact was removed prior to applying a bandpass filter between 300 and 5000 Hz to isolate multi-unit activity. Signal-to-noise (SNR) was calculated between with noise as the pre-stimulus window.

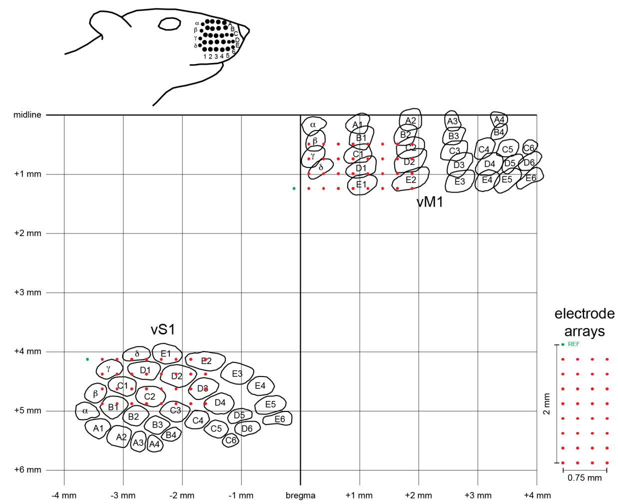


*Fig 2.* Stereotaxic coordinates of array implantation sites relative to approximate sensory and motor whisker representations.

## IV. ALGORITHM

The workflow of the algorithm is listed in Figure 3. An online implementation would stimulate a set of patterns which will be called a schedule. The response to each stimulation pattern is then processed, resulting in a 32-dimensional vector of SNR – one for each recording electrode. After each set of stimulation, the algorithm clusters the responses naïve to which stimulation pattern each response came from. The current implementation uses DBSCAN or density-based spatial clustering of application with noise due to its robustness with noise as well as the lack of a requirement of k, or the number of clusters.

Once the algorithm clusters the responses, the clusters are evaluated using a silhouette score which calculates the ratio between intra-cluster and inter-cluster distances. The denser and far away from other clusters, the higher the score. Based on a threshold, if a cluster exceeds the silhouette score requirement, the cluster contents are evaluated.

To evaluate cluster content, the ratio of responses resulting in that cluster is compared. For example, if a cluster contains 3 responses from stimulation pattern A and 6 responses from stimulation pattern B, and both stimulation patterns have been explored 6 times, then stimulation pattern B is the characteristic stimulation pattern for that cluster because 100% of stimulation pattern B resides in that cluster, compared to just 50%.

Furthermore, stimulation pattern A, in this case, is "pruned" from the search because a majority (greater than or equal to 50%) of stimulation pattern A resided in a cluster that was deemed good but was uncharacteristic for that cluster.

The final output of the algorithm is a set of characteristic stimulation patterns that result in disparate clusters in M1. The idea here is to reduce the number of trials necessary for each stimulation pattern by evaluating the responses in real-time.

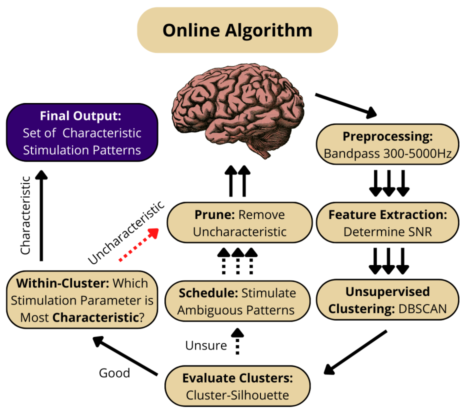


*Fig 3.* Workflow of algorithm in an online implementation.

## V. RESULTS

The online algorithm has not been deployed yet but has been tested in an offline simulation. The whisker to vS1 experimental data that corresponds to the vS1-vM1 dataset that was used in the simulated algorithm experiment did not exist, and thus it is hard to evaluate results.

Regardless, the clustering algorithm was able to find a single cluster even with a reduced number of trials per stimulation pattern from 25 in the brute force experiment to between 3 and 7. Based on "ground truth" clustering of this vS1-vM1 dataset, a single cluster seems to be a reasonable finding, although not a desired outcome.

## VI. DISCUSSION

Further testing on a validation dataset is necessary in order to fully understand the strengths and weaknesses of the proposed algorithm. Ideally, the number of whisker barrels that reside in the vS1 implants (based on the whisker-vS1 results) should be the minimum number of clusters that the vS1-vM1 experiment should be able to find.

In terms of further improvements to the algorithm, trying different methods of determining an eps value for DBSCAN may be necessary for clustering raw SNR values. Alternatively, normalizing the SNR values to fit a reasonable eps value could serve better than current methods.

Another implementation of this search algorithm could be to use SNR working average across trials instead of raw or normalized SNR values. The average SNRs can then be converted into a representational dissimilarity matrix and further clustered using DBSCAN with pairwise distances. This approach may serve as an alternative to normalizing the SNR, but does neglect the noise or spread of SNR across trials.

Further implementation of the algorithm should also consider specific properties of stimulus parameters. In the initial testing, the electrode location was considered discrete and independent from each other, but they are oriented in a grid where relative location could be fed into the algorithm to further reduce search time. For stimulation parameters such as amplitude, a threshold for response could simultaneously be calculated. Other parameters dimensions to test are pulse duration, number of pulses, frequency, stimulus shape (sine, box, etc.), etc.

Regardless, we are optimistic regarding the algorithm and hope to test with a full dataset as soon as it is ready.

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