Towards a Neural Co-Processor Which Restores Movement After Stroke: Modeling a Proof-of-Concept

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Abstract. *Objective* Brain co-processors[1] are devices which use artificial intelligence (AI) for closed-loop neurostimulation to shape neural activity and to bridge injured neural circuits for targeted repair and rehabilitation. The co-processor framework offers a flexible approach to learning closed-loop stimulation policies that optimize for (a) specific regimes of neural activity, or (b) external task performance. For example, it may seek to learn to stimulate the motor cortex of a stroke patient, conditioning the stimulation on upstream visual information, aiding the patient's attempt to grasp an object. Through the use of artificial neural networks (ANNs) and deep learning, the co-processor co-adapts with the neural circuit, allowing it to seek optimal stimulation policies, and adapt them as the neural circuit changes. The results presented here demonstrate a neural co-processor for the first time, through the use of a simulation. We explore some of the core algorithms that may allow co-processors to successfully learn and to adapt to non-stationarity in both the brain and sensors. *Approach* We provide the first proof-of-concept of a neural co-processor, through the use of a simulated neural circuit, which performs a reach-to-grasp task, based on visual input. It is designed to closely resemble a similar circuit in a primate brain [2]. We simulate a variety of lesions by altering the model, and then demonstrate a co-processor's ability to restore lost function through "stimulation" of that model. We further test the ability of a co-processor to adapt its stimulation as the simulated brain undergoes changes. *Main results* Our simulated co-processor successfully co-adapts with the neural circuit to accomplish the external reaching task. The co-processor framework demonstrated here adapts to a variety of lesion types, and to ongoing changes in the simulated brain. *Significance* The proof-of-concept here outlines a co-processor model, as well as our approach to training it, leading to insights on how such a model may be developed for *in vivo* use. We believe this co-processor design will allow for learning complex stimulation policies that help restore function to a stroke victim.

Keywords: brain-computer interface, neural co-processor, ai, machine learning, stimulation

1. Introduction

Aided in part by application of advanced AI techniques, brain-computer interfaces (BCIs) have made advancements over the last several decads, allowing for decoded brain signals to be used for control of a wide variety of virtual and physical prostheses [3] [4] [5] [6]. Separately: advances in stimulation techniques and modeling have allowed us to probe neural circuit dynamics **TODO: citations** and learn to better drive neural circuits towards target dynamics, by encoding and delivering information through stimulation **TODO: citations**. Recently, there has been increasing interest in building on these advances to combine decoding and encoding in a single system, for closed-loop stimulation of a neural circuit. Bi-directional BCIs (BBCIs) allow stimulation to be conditioned by decoded brain activity as well as external sensor data (e.g. camera), which can allow for the application of real-time, fine-grained control of neural circuits and prosthetic devices **TODO: citations**. These may lead, for example, to neuro-prostheses that are capable of restoring movement which was lost due to traumatic brain injury (TBI), to a degree not previously possible.

Motivated by that progress, we demonstrate here a flexible framework for combining encoding and decoding, which we term "neural co-processors" [1]. Neural co-processors leverage AI and deep learning to identify optimal, closed-loop stimulation patterns. The approach is flexible enough to optimize not only for particular neural activities, but also for tasks external to the subject. For example, they may be able to aid a stroke victim by finding a stimulation pattern of the motor cortex which helps restore lost limb function.

Additionally, the co-processor framework allows a neuro-prosthesis to actively adapt to a neural circuit as it changes with time. This framework is capable of co-adapting with the circuit, i.e. brain, by updating its stimulation regime, while at the same time the brain is updating its response to the stimulation, and changing due to natural plasticity, aging, etc. This allows the co-processor to continually optimize for the intended cost function, despite the signficant non-stationarity of the target circuit.

Here we provide a proof-of-concept in simulation for a co-processor that restores movement to a limb, after a subject has suffered a stroke affecting its ability to use that limb. It combines:

- A stimulation model, which models the relationship between decoded brain activity, stimulation, and task performance.
- An AI agent which determines the stimulation to apply in a closed-loop fashion, in real time.

Significant advances have been made in modeling the effects of electrical stimulation of the brain. Researchers have explored how information can be biomimetically or artificially encoded and delivered via stimulation to neuronal networks in the brain and other regions of the nervous system for auditory [7], visual [8], proprioceptive [9], and tactile [10, 11, 12, 13, 14], perception. Advancements have also been made in modeling the effects of stimulation over large scale, multi-region networks, and across time [15].

Some have additionally designed models which can adapt to ongoing changes in the brain, including changes due to the stimulation itself [16]. In our proof-of-concept outlined below, we will use a stimulation model, not unlike those cited here, which seeks to account for both network dynamics and non-stationarity. In addition to training the model to have strong predictive power, we additionally train it to be useful for then learning an optimal stimulation policy, which is a property somewhat distinct from predictive power alone.

Advances have also been made in both open loop stimulation [17] and closed-loop stimulation for aiding in learning new memories after some impairment [18, 19], replaying visually-invoke activations [16], and optogenetic control of a thalamocortical circuit [20], among others.

TODO: talk about: [21]

* Need for more complex stimulation policies, and need for optimizing task performance. ** i.e. what if we don't have a specific pre-recorded activation we want to drive towards? "Biomimetic" ** And how do we find activations that drive an intended task solution? ** We don't know a priori what the right stimulation is.

Begin with a proof-of-concept in simulation.

2. Method

* Proof-of-concept by way of simulation. ** Simulation allows for rapid, cheap exploration of learning algorithms. ** Potentially helpful to look for a simulated neural circuit which has internal dynamics, i.e. information propagation, which is demonstrably similar to natural circuits. ** [22] Likeness of RNNs to natural circuits re: dynamics ** Cite Michaels, and those upstream from him (Susillo?) re: RNNs ** [23] Simulation of spiking neural network, learning stimulation regime. Use of a biomimetic simulation to develop and evaluate a neural controller. Use of lesion model.

* Overview of test bed ** Michaels model [2] ** Lesion designs *** Lesion examples, i.e. hand velocity more affected than shoulder velocity. *** Disconnect modules vs lesion M1, and the effects ** Stimulation design *** Spatio-temporal smoothing ** Observation model

* EN architecture * CPN architecture

* Training ** Alternate training EN and CPN *** Train an EN **** Training the EN until predictive power reaches a threshold, based on current task performance **** Training regime based on most recent CPN, similar CPNS (noise added to params), and white noise stimulation **** Single batch of data from applying current CPN set and white noise to the brain, EN fit to "offline" it over maining epochs **** Predictive power alone is not sufficient for use in training the CPN: we need to form the batch as above, otherwise training is unstable. *** Train the CPN **** Backprop through the EN, effectively using the EN's prediction as ground truth

3. Results

* Task performance improves drastically * Fine tuning takes a long time * Object classes separate * Can co-adapt with the brain, as it changes

* Split by lesion design

* Show example where AIP/F5 lesioned and how that affects performance

* Any point in showing sensitivity to observation or stim dim?

* Try regularization variation?

* White noise and noised params ** Learning instability ** Predictive power isn't enough ** Illustrate this

* Training efficiency analysis

4. Discussion

* Training efficiency * Spectrum from simple low dimensional stimulation vectors today to higher dimensional future * Toward in vivo application

5. Conclusion

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7. Ethical Statement

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8. References

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