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

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September 2021

Abstract. *Objective* Brain co-processors[1] are devices which use artificial intelligence (AI) and 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 stimulation policies that optimize for (a) specific regimes of neural activities, or (b) external task performance. For example, it may seek to learn a complex stimulation policy, to aid a stroke victim in reaching 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, and explore some of the core algorithms that may allow them to succeed. *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. This initial proof-of-concept lays the foundation for a future demonstration *in vivo*.

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

1. Introduction

* Aided in part by application of advanced AI techniques, 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. ** Separately: advances in stimulation techniques and modeling have allowed us to probe neural circuit dynamics and learn to better drive neural circuits towards target dynamics (citations) ** Increasing interesting in combining decoding and encoding, for closed-loop control. BBCIs ** They have the potential to apply real-time, fine-grained control of neural circuits. ** Allows stimulation to be conditioned on a user's intention, sensory feedback, error signals, etc., to drive e.g. improvement in motor control after impairment due to TBI.

* Introduce the notion of a co-processor ** Use of AI and deep learning to determine a stimulation policy. ** Co-adapts policy to solve a task, together with the neural circuit ** Flexible model, allows for optimization of either brain activities or external task ** "These "neural co-processors" can be used to jointly optimize cost functions with the nervous system to achieve desired behaviors ranging from targeted neuro-rehabilitation to augmentation of brain function." ** Proposed approach here combines a learned stimulation model with a stimulation agent ** Learning allows for active adaptation to the neural circuit as it changes.

* BCIs: a single direction * Increasingly sophisticated ML techniques applied to decoding ** See 2019Raj citations * Encoding models, stimulation models (cite)

* Open loop control examples. [3]

* Learning stimulation models [4]

* Bi-directional BCIs (BBCIs) ** Closed loop control

- [5] Inception Loops: driving brain states
- [6] "Closed loop" here refers to when to apply stimulation, always of the same type and at the same site, based on memory performance.
- [7] ACLS

* 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? ** And how do we find activations that drive an intended task solution?

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. ** [8] Likeness of RNNs to natural circuits re: dynamics ** Cite Michaels, and those upstream from him (Susillo?) re: RNNs ** [9] 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

* EN architecture * CPN architecture

3. Results

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

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

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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6. Acknowledgements

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7. Ethical Statement

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8. References

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