 DOI: 10.3217/978-3-85125-962-9-194

Decoding Visual Scenes from Visual Cortex Spikes Using Deep Learning

Alexander McClanahan[1*], Matthew Moench[1], Brian Kim[2]

[1] College of Medicine, University of Central Florida, Orlando, Florida, United States

[2]Bioelectronics Lab, Department of Electrical & Computer Engineering, University of Central Florida, Orlando, Florida

*6900 Lake Nona Blvd, Orlando, FL 32827, alexmcclanahan@Knights.ucf.edu

Introduction: Neural decoding has co-evolved in recent years the arrival of CMOS-fabricated electrophysiology probes (1) and miniaturized neural amplifier chips (2), both of which have enabled large scale neural recording. Machine learning-based neural decoding has shown incredible feats in recent years (3); namely, the decoding of: spatial coordinates of a rodent using hippocampal place cells, and motor activity (4). We explore the utility of deep learning in decoding images from neural spikes using various decoding time bin protocols, as well as across cortical and subcortical regions of the rodent brain.

Materials, Methods and Results: Electrophysiology recordings and stimulus presentations were obtained from the Allen Institute for Brain Sciences Visual Coding: Neuropixels Dataset using the AllenSDK. Three deep learning models were trained on spike counts across thousands of cortical and subcortical neurons and over 5,000 natural scene stimulus presentations. Models were tested on held-out test spikes and evaluated for image decoding accuracy.

Discussion: Three machine learning models were trained to decode and classify which image was shown to the animal solely from visual neural spiking activity. Each model's decoding accuracies were subsequently compared across various time bin durations and anatomical regions of the mouse visual system. In our analysis, time bin durations of 50 ms and greater appeared to capture neural information in the most robust way for decoding. Deep neural networks outperformed shallow neural networks and linear support vector machines across most conditions. These findings suggest possible avenues for future visual neural decoding efforts and offer insights into optimal neural decoding algorithm design.

Significance: While conventional neural decoding algorithms suffer from having to make assumptions about the encoding of neural representations, deep learning based neural decoding makes few assumptions. However, most of this deep learning-based decoding work has been done in motor cortex decoding. Accurate decoding of electrophysiology signals from brain structures involved in visual processing hold great promise in better informing our understanding of sensory processing, artificial intelligence, and BMIs for visual prosthetics.

References:

[1] Jun JJ, Steinmetz NA, Siegle JH, Denman DJ, Bauza M, Barbarits B, Lee AK, Anastassiou CA, Andrei A, Aydin Ç, et al. Fully integrated silicon probes for high-density recording of neural activity. *Nature* (2017) 551:232–236. doi:10.1038/nature24636.
[2] Harrison RR, Charles C. A Low-Power Low-Noise CMOS Amplifier for Neural Recording Applications. *IEEE J Solid-State Circuits* (2003) 38: doi:10.1109/JSSC.2003.811979.
[3] Glaser JI, Benjamin AS, Farhoodi R, Kording KP. The roles of supervised machine learning in systems neuroscience. *Prog Neurobiol* (2019) 175:126–137. doi:10.1016/j.pneurobio.2019.01.008.
[4] Tseng P-H, Urpi NA, Lebedev M, Nicolelis M, Tseng P-H, Urpi NA, Lebedev M, Nicolelis M. Decoding Movements from Cortical Ensemble Activity Using a Long Short-Term Memory Recurrent Network. *Neural Comput* (2019) 31:1085–1113. doi:10.1162/neco_a_01189

 Article ID: 144598