Print this Page

Neuroscience 2015

Presentation Abstract

Program#/Poster#:	748.04
Presentation Title:	"Neural hysteresis": Incorporating historical knowledge of neural dynamics to rescue decoder performance
Location:	N226
Presentation time:	Wednesday, Oct 21, 2015, 1:45 PM - 2:00 PM
Topic:	++D.18.c. Neuroprosthetics: Control of real and artificial arm, hand, other grasping devices

Authors: ***J. C. KAO**[1], S. I. RYU[6,1], K. V. SHENOY[1,2,3,4,5];
[1]Electrical Engin., [2]Neurobio., [3]Bioengineering, [4]Neurosciences Program, [5]Stanford Neurosciences Inst., Stanford Univ., Stanford, CA; [6]Dept. of Neurosurg., Palo Alto Med. Fndn., Palo Alto, CA

Abstract: Intracortical brain-machine interfaces (BMIs) convert spiking activity from neurons in motor cortex into control signals to guide prosthetic devices (e.g., a computer cursor or robotic arm). However, over time, the number of recorded spiking signals will decrease due to electrode array and biological failure (e.g., Barrese et al., JNE 2013). This decline reduces the performance (speed and accuracy) of the BMI to the point where a clinical intervention, such as replacing the electrode array, may be necessary. We asked if an algorithmic intervention, performed entirely in software, can rescue BMI performance and thereby postpone potential clinical intervention? To address this question, we sought to include historical data, recorded from an earlier point in the array lifetime when more neurons were observed, as additional prior information to augment the BMI decoder. We term this concept "neural hysteresis," because historical neural observations (memory) are used to improve the current decoder. We implemented this idea by using a decoder that models the dynamical properties of neural population responses in motor cortex (the neural dynamical filter or NDF, Kao et al., SFN 2013). We posit that if the neural dynamics accurately reflect properties of motor cortex, then having a better estimate of these dynamics should result in a better decoder. To obtain a "best estimate" of these dynamics, we used a historical training set (when more neurons were available) to learn a neural dynamical model. This neural dynamical model constituted our "memory" from a prior state. We performed an offline experiment where we simulated array failure by artificially removing neural channels. Beginning with 192 channels (all channels available), we proceeded to drop channels (in increments of 10), re-building the NDF with the remaining channels. Therefore, for the NDF, the neural dynamical model was inferred from only the remaining channels available. We observed a substantial decrease in performance as channels were lost. To test our approach to "neural hysteresis," we built a hysteresis-NDF (HNDF) that incorporated the neural dynamical model learned from a historical training set. Thus, the difference between the HNDF and the NDF is that the HNDF incorporates a better neural dynamical model, learned from many more neurons. We found that when 82 or fewer channels remained, the HNDF significantly outperformed the NDF in offline performance ($p < 0.01$, paired t-test). These results suggest that neural dynamics capture important features of the neural population responses in motor cortex, and that knowledge of these dynamics may rescue BMI performance as array signal quality degrades.

Disclosures: **J.C. Kao:** None. **S.I. Ryu:** None. **K.V. Shenoy:** None.

Keyword (s): brain-machine interface

neural dynamics

neural prosthesis

Support: NSF Graduate Research Fellowship

Defense Advanced Research Projects Agency (DARPA) Reorganization and Plasticity to Accelerate Injury Recovery (REPAIR) N66001-10-C-2010

US National Institutes of Health (NIH) National Institute of Neurological Disorders and Stroke (NINDS) Transformative Research Award R01NS076460

US National Institutes of Health (NIH) Director's Pioneer Award 8DP1HD075623-04