Neural Decoding Algorithms for robust design of Cortical Motor Prosthesis

by

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Abstract

Cortical Neural Prosthesis is a physical device that directly interacts with the motor cortical regions of the brain by implanting one or more electrode arrays, to identify repetitive patterns in its electrical activity which can be translated into motor command signals using decoding algorithms. While this technology, which will help in partially restoring limb function to amputees and locked-in patients, has been tested on mostly non-human primates in strictly controlled settings with big margins for prediction error, there are many concerns that need to be addressed before this technology can become clinically viable. This thesis focuses on improving the neural decoding algorithms in three different ways that can make them more robust.

First, a novel algorithm is developed to select a subset of “tuned” neurons from the entire recorded population, which contains maximum information towards decoding the particular motor task. In addition to reducing hardware complexity, this down selection of neurons has been shown to increase the predictive performance of the system. With more than 60% of recorded neural population reported irrelevant on an average, the problem of low prediction accuracy due to noisy input space is expected to grow as scientists continues to rely on implanting many arrays for multi-functional Neuroprosthetics. In order to facilitate the use of neuron selection algorithms, a utility called “*infoSense* neuron tracking utility” is developed.

While Single Unit (SU) activity has high temporal resolution, is not stable over time due to electrode-tissue degradation, Local field potentials (LFPs) are the summation of electrical fields around the electrode tip and provide a more stable but ambiguous information about the

underlying state. For the second challenge, we established that LFPs can be used to partially offset the loss of information from SUs by combining the features extracted from LFPs and SUs in single input space.

Third, a new concept of ‘Blind Decoding’ is introduced and demonstrated that in instead of training the user for every conceivable arm orientation, it is sufficient to train on a limited set of native states from which all possible movements can be “blindly” decoded. This has practical implications as it reduces the training time.