Brain-machine interfaces (BMIs) can help spinal cord injury (SCI) patients by decoding neural activity into useful control signals for guiding robotic limbs, computer cursors, or other assistive devices. BMI in its most basic form maps neural signals into kinematics, then closes the loop to enable direct neural control of kinematics. Such systems have shown promise in helping SCI patients; however, improving performance and robustness of these systems remains challenging. Even for simple movements, such as moving a computer cursor to a target on a computer screen, decoding performance can be highly variable over time.

Furthermore, most BMI systems currently run on high-power computer systems. Clinical translation of these systems will require decoders that can adapt to changing neural conditions, and which operate efficiently enough to run on mobile—even implantable—platforms. Recently, machine learning algorithms have shown promise in attaining high performance and robustness in BMIs. Therefore, to address a number of these challenges, we propose a deep multi-state Dynamic Recurrent Neural Network (DRNN) architecture. The DRNN is used for predicting Cartesian representation of kinematics from the open-loop neural data recorded from the posterior parietal cortex (PPC) of a human subject over 39 days in a BMI system. We design the algorithm to achieve a reasonable trade-off between performance, robustness, and to reduce the memory that is required to store the weights for hardware implementation. To achieve a better prediction performance and robustness, we generalize our model by feeding the predictions of the network back to the input. To solve the statistical distribution mismatch between the ground-truth and predictions, we apply a scheduled sampling approach to the model. By configuring the DRNN to operate without history, we reduce the number of memory accesses which has shown to consume the most significant power in neural network accelerators (Watmough et al., 2018). We compare our algorithm with the state-of-the-art methods in the literature to show that it performs favorably: DRNN achieves average correlation coefficients of (0.75, 0.88) for position (X, Y) and (0.74, 0.87) for velocity in X and Y directions. To the best of our knowledge, this is the first demonstration of applying deep learning-based decoders to human PPC data. The results show that multi-state...
DRNN has the potential to model the non-linear relationships between the neural data and the kinematics for robust BMIs.

Abstract Citation