ABSTRACT

Brain-computer interface (BCI) is an integration of the measurement, decoding, and translation of the central nervous system (CNS) signal for augmentation or rehabilitation purposes. Advancements in neuroscience and machine learning algorithms have empowered the BCI systems to assist, augment, or restore motor functionality by harnessing neural signals. In particular, Electroencephalogram (EEG) based motor trajectory decoding for efficient control of BCI systems has been an active area of research due to its non-invasive nature and low cost. It is to be noted that the motor information corresponding to the motor execution task is encoded in the pre-movement brain activations. A pre-movement EEG-based continuous kinematic estimation would yield enhanced performance and efficient control of assistive devices that include neural prostheses, exosuits, or exoskeletons. This thesis explores the development of brain-computer interface (BCI) systems leveraging electroencephalography (EEG) signals for motor intention decoding. Key challenges addressed include the inherent noise in EEG signals, the limited generalizability of models across users, and the computational complexity. By introducing PreMovNet and other advanced deep learning models, this thesis addresses the issue of intention mapping and kinematics parameter estimation for upper-limb movement using pre-movement EEG. In particular, grasp-and-lift (GAL) and biceps-curl movements are considered.

For the grasp-and-lift task, a publicly available dataset, WAY-EEG-GAL, is utilized for hand trajectory estimation. Sensor-domain EEG features are explored with deep learning-based neural decoders for trajectory estimation. The proposed decoders utilize various EEG time lags and windows to incorporate motor information encoded in the pre-movement brain activations. The intra-subject and inter-subject analyses are performed to explore the ability of the proposed neural decoders to learn subject-specific and subject-independent EEG features. Additionally, source-domain EEG features are also explored for trajectory decoding. The EEG features from frontoparietal cortical regions are taken as input for the decoding models. A comparative kinematics parameter decoding analysis is performed for the EEG sensor and source domain input features for different decoding models with intra-subject and inter-subject scenarios.

Kinematics parameters are additionally decoded using pre-movement EEG for the biceps-curl task. A dataset comprising simultaneous EEG and kinematics data was collected while performing the biceps-curl task. Various EEG features are then explored in tandem with the deep-learning-based neural decoder to estimate the kinematics trajectory. The features include pre-processed EEG data, spherical harmonics, and head harmonics-based features. Intra- and inter-subject performance analyses are performed to evaluate the subject-adaptability of the proposed decoding model. The predicted kinematics trajectory is also integrated with the human-machine interface (HMI) simulation platform. The musculoskeletal model of the HMI simulation platform makes use of the predicted trajectory for imitating the biceps-curl movement. The robust performance and lightweight architecture will facilitate the real-time implementation of the model with deployment on a microcontroller to control BCI-based wearable robots.