

**PRE-MOVEMENT EEG BASED UPPER-LIMB INTENTION
MAPPING AND KINEMATICS PARAMETER ESTIMATION**

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**DEPARTMENT OF ELECTRICAL ENGINEERING
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PRE-MOVEMENT EEG BASED UPPER-LIMB INTENTION MAPPING AND KINEMATICS PARAMETER ESTIMATION

by

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DEPARTMENT OF ELECTRICAL ENGINEERING

Submitted

in fulfillment of the requirements of the degree of Doctor of Philosophy

to the



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Dedicated to
My Family



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CERTIFICATE

This is to certify that the thesis entitled “**Pre-movement EEG based Upper-Limb Intention Mapping and Kinematics Parameter Estimation**” being submitted by **Mr. Anant Jain** to the Department of Electrical Engineering, Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy** is the record of bonafide research work carried out by him under our supervision. In our opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis have not been submitted either in part or in full to any other University or Institute for the award of any degree or diploma.

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Anant Jain

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.

सारांश

ब्रेन-कंप्यूटर इंटरफ़ेस (बीसीआई) वृद्धि या पुनर्वास उद्देश्यों के लिए केंद्रीय तंत्रिका तंत्र (सीएनएस) सिग्नल के माप, डिकोडिंग और अनुवाद का एक एकीकरण है। तंत्रिका विज्ञान और मशीन लर्निंग एल्गोरिदम में प्रगति ने बीसीआई प्रणालियों को तंत्रिका संकेतों का उपयोग करके मोटर कार्यक्षमता की सहायता करने, बढ़ाने या पुनर्स्थापित करने के लिए सशक्त बनाया है। विशेष रूप से, बीसीआई प्रणालियों के कुशल नियंत्रण के लिए इलेक्ट्रोएन्सेफेलोग्राम (ईईजी) आधारित मोटर प्रक्षेपवक्र डिकोडिंग अपनी गैर-इनवेसिव प्रकृति और कम लागत के कारण अनुसंधान का एक सक्रिय क्षेत्र रहा है। यह ध्यान दिया जाना चाहिए कि मोटर निष्पादन कार्य से संबंधित मोटर जानकारी पूर्व-संचलन मस्तिष्क सक्रियण में एन्कोड की गई है। एक पूर्व-संचलन ईईजी-आधारित निरंतर गतिज अनुमान से सहायक उपकरणों का बेहतर प्रदर्शन और कुशल नियंत्रण प्राप्त होगा जिसमें तंत्रिका कृत्रिम अंग, एक्सोसूट या एक्सोस्केलेटन शामिल हैं। यह थीसिस मोटर अभिप्राय डिकोडिंग के लिए इलेक्ट्रोएन्सेफेलोग्राफी (ईईजी) संकेतों का लाभ उठाने वाले मस्तिष्क-कंप्यूटर इंटरफ़ेस (बीसीआई) सिस्टम के विकास की पड़ताल करती है। संबोधित की गई प्रमुख चुनौतियों में ईईजी सिग्नलों में अंतर्निहित कोलाहल, उपयोगकर्ताओं के बीच मॉडल की सीमित सामान्यीकरण और कम्प्यूटेशनल जटिलता शामिल है। प्रीमोवनेट और अन्य उन्नत गहन शिक्षण मॉडल पेश करके, यह थीसिस पूर्व-संचलन ईईजी का उपयोग करके ऊपरी-अंग संचलन के लिए अभिप्राय मैपिंग और किनेमेटिक्स पैरामीटर अनुमान के मुद्दे को संबोधित करती है। विशेष रूप से, ग्रेस्प-एंड-लिफ्ट (जीएएल) और बाइसेप्स-कल्ल मूवमेंट पर विचार किया जाता है।

पकड़ने और उठाने के कार्य के लिए, सार्वजनिक रूप से उपलब्ध डेटासेट, WAY-EEG-GAL, का उपयोग हाथ प्रक्षेपवक्र अनुमान के लिए किया जाता है। प्रक्षेपवक्र अनुमान के लिए गहन शिक्षण-आधारित तंत्रिका डिकोडर्स के साथ सेंसर-डोमेन ईईजी विशेषताओं का पता लगाया जाता है। प्रस्तावित डिकोडर पूर्व-संचलन मस्तिष्क सक्रियणों में एन्कोड की गई मोटर जानकारी को शामिल करने के लिए विभिन्न ईईजी समय अंतराल और खिड़की का उपयोग करते हैं। विषय-विशिष्ट और विषय-स्वतंत्र ईईजी विशेषताओं को सीखने के लिए प्रस्तावित तंत्रिका डिकोडर्स की क्षमता का पता लगाने के लिए अंतःविषय और अंतरविषय विश्लेषण किया जाता है। इसके अतिरिक्त, प्रक्षेपवक्र डिकोडिंग के लिए स्रोत-डोमेन ईईजी विशेषताओं का भी पता लगाया जाता है। फ्रंटोपेरिएटल कॉर्टिकल क्षेत्रों से ईईजी विशेषताओं को डिकोडिंग मॉडल के लिए इनपुट के रूप में लिया जाता है।

अंतःविषय और अंतर्विषय परिदृश्यों के साथ विभिन्न डिकोडिंग मॉडल के लिए ईईजी सेंसर और स्रोत डोमेन इनपुट विशेषताओं के लिए एक तुलनात्मक किनेमेटिक्स पैरामीटर डिकोडिंग विश्लेषण किया जाता है।

बाइसेप्स-कर्ल कार्य के लिए पूर्व-संचलन ईईजी का उपयोग करके किनेमेटिक्स मापदंडों को अतिरिक्त रूप से डिकोड किया जाता है। बाइसेप्स-कर्ल कार्य करते समय एक डेटासेट जिसमें एक साथ ईईजी और किनेमेटिक्स डेटा शामिल था, एकत्र किया गया था। फिर किनेमेटिक्स प्रक्षेपवक्र का अनुमान लगाने के लिए डीप-लर्निंग-आधारित न्यूरल डिकोडर के साथ विभिन्न ईईजी विशेषताओं का पता लगाया जाता है। विशेषताओं में पूर्व-संसाधित ईईजी डेटा, गोलाकार हार्मोनिक्स और हेड हार्मोनिक्स-आधारित विशेषताएं शामिल हैं। प्रस्तावित डिकोडिंग मॉडल की विषय-अनुकूलता का मूल्यांकन करने के लिए अंतः और अंतर-विषय प्रदर्शन विश्लेषण किया जाता है। पूर्वानुमानित कीनेमेटिक्स प्रक्षेपवक्र को मानव-मशीन इंटरफ़ेस (एचएमआई) सिमुलेशन प्लेटफ़ॉर्म के साथ भी एकीकृत किया गया है। एचएमआई सिमुलेशन प्लेटफ़ॉर्म का मस्क्युलोस्केलेटल मॉडल बाइसेप्स-कर्ल संचलन की नकल करने के लिए अनुमानित प्रक्षेपवक्र का उपयोग करता है। मजबूत प्रदर्शन और हल्का आर्किटेक्चर बीसीआई-आधारित पहनने योग्य रोबोटों को नियंत्रित करने के लिए माइक्रोकंट्रोलर पर तैनाती के साथ मॉडल के वास्तविक समय कार्यान्वयन की सुविधा प्रदान करेगा।

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List of Abbreviations

BCI	Brain Computer Interface
BEM	Boundary Element Method
BiLSTM	Bidirectional Long Short Term Memory
BI-SNN	Brain Inspired Spiking Neural Network
BTS	Band power Time Series
BWN	Baseline Wander Noise
CAM	Customized Attention Module
CMF	Caudalmiddlefrontal
CNN	Convolutional Neural Network
CNS	Central Nervous System
Conv	Convolutional
CV	Correlation Value
DCNet	DeepConvNet
DFT	Discrete Fourier Transform
DWS	Depth-Wise Seperable
EEG	Electroencephalogram
ELU	Exponential Linear Unit
EMG	Electromyogram
EOG	Electrooculography
ESI	EEG Source Imaging
FB	Frequency Band
FIR	Finite Impulse Response
H ²	Head Harmonics
HHT	Head Harmonics Transform
HMI	Human Machine Interface
ICA	Independent Component Analysis
IP	Inferiorparietal

KP	Kinematic Parameter
LOF	Lateralorbitofrontal
LSTM	Long Short Term Memory
MI	Motor Imagery
MKD	Motor Kinematics Decoding
MKP	Motor Kinematics Prediction
ML	Machine Learning
MLP	Multi Layer Perceptron
mLR	multi-variable Linear Regression
MOFL	Medialorbitofrontal
MRCP	Movement Related Cortical Potential
MRI	Magnetic Resonance Imaging
MSE	Mean Squared Error
MTD	Motor Trajectory Decoding
PCC	Pearson's Correlation Coefficient
PCL	Paracentral
PLS	Partial Least Square
PoCL	Postcentral
PreCL	Precentral
PTS	Potential Time Series
ReLU	Rectified Linear Unit
RMSE	Root Mean Square Error
ROI	Regions of Interest
SCNet	ShallowConvNet
SCP	Slow Cortical Potential
SF	Superiorfrontal
SFT	Spherical Fourier Transform
SH	Spherical Harmonics
SLiR	Sparse Linear Regression
sLORETA	standard Low-Resolution Electrical Tomography

SP	Superiorparietal
SR-UKF	Square-Root Unscented Kalman Filter
SVM	Support Vector Machine
WAY	Wearable interfaces for hAnd function recoverY
WPD	Wavelet Packet Decomposition