Decoding 3D Upper Limb Motion Using EEG and Motion Capture Integration: A Deep Learning Approach

Mohamad Hoteit[1], Richard van Dijk[1], Matthijs van Leeuwen[1], and Tessa Verhoef[1]

Universiteit Leiden, Leiden, Netherlands
{m.hoteit, m.k.van.dijk, m.van.leeuwen, t.verhoef}@liacs.leidenuniv.nl

Abstract. This project aims to demonstrate the feasibility of decoding 3D trajectories of both left and right upper limbs using EEG and motion capture data, with minimal preprocessing. We investigate decoding imagined trajectories and explore the role of different motion representations, such as position and velocity. Our findings suggest potential improvements for continuous control applications, aligning with advancements in non-human primate studies. This work could impact prosthetic control, rehabilitation, and BCIs by offering real-time decoding of motor execution and imagery tasks.

Keywords: EEG decoding · 3D motion capture · Upper limb trajectories · Motor imagery · Real-time BCI

1 Introduction

Decoding human motor activity from brain signals, specifically for the upper limbs, is a rapidly evolving field with profound implications for brain-computer interfaces (BCIs), rehabilitation, and prosthetic control. Non-invasive BCIs based on electroencephalography (EEG) provide a relatively safe avenue for studying motor functions without invasive procedures.

The main objective of this project is to demonstrate the feasibility of decoding 3D trajectories of both upper limbs using a research-grade EEG device and state-of-the-art motion capture system. This is achieved with minimal preprocessing, leveraging deep learning to automate feature learning. Additionally, we aim to investigate the decoding of imagined trajectories (motor imagery), expanding on successful motor execution decoding.

2 Related Work

Non-invasive BCIs such as EEG offer high temporal resolution, making them practical for real-time motor decoding, though they have lower spatial resolution.

Traditional EEG decoding focused on classification tasks, such as distinguishing left vs. right-hand movements, which lacks continuous control, thus motivating regression-based models better suited for prosthetic control. Deep learning approaches have recently demonstrated improved accuracy in decoding continuous 3D motion with minimal preprocessing.

Early work in this domain concentrated on 2D trajectories; however, modern efforts, including those of [2] and [1], have advanced to decoding 3D limb motion. Recent studies show that velocity, a proprioceptive signal, may offer improved decoding accuracy over position alone, particularly when decoding motor imagery tasks, which is a central focus of this research.

3 Methodology

3.1 Experimental Design

Participants will be seated 1.5 meters from a screen where targets appear at random locations. During each 3-second period, participants extend a designated arm toward the target without contact. This randomized target presentation, adapted from Meta's engagement experiments [5], aims to introduce dynamic task variability.

The experiment consists of four runs, with each run having blocks for actual and imagined movements, where participants either perform or imagine reaching the targets. Imagined movement tasks require participants to keep their arms at rest, imagining movement in synchrony with stimuli, as adapted from [4].

3.2 Data Collection

EEG signals will be recorded using a 32-electrode system, synchronized with kinematic data from a motion capture system. Kinematic data will capture 3D trajectories of hand, elbow, and shoulder joints during movement trials, providing reference templates for imagined movement decoding. Hardware-clock synchronization will ensure precise alignment of EEG and motion data streams.

4 AI Implementation

Traditional methods like multivariate linear regression (MLR) have shown the feasibility of motor decoding, but recent deep learning models, such as CNN-LSTM architectures, significantly outperform traditional techniques, achieving correlation coefficients up to 0.84 compared to MLR's 0.67 [1]. Transformer-based models, such as [3], effectively capture long-term dependencies, achieving remarkable accuracies on EEG-based motion decoding, highlighting the potential of these architectures in complex motor trajectory tasks. This project will test hybrid CNN-LSTM models and transformer-based networks for their capability in handling the temporal and spatial complexities of EEG signals in motor decoding.

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