Project outline

Project area title: Machine learning for biomedical signal analysis

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Possible project title: Motor Imagery-Based Brain-Computer Interface for Robotic Arm Control using Deep Learning

Scope

This project aims to develop a brain-computer interface (BCI) system that utilises EEG signals from the motor imagery (MI) paradigm to achieve control of the PX150 robotic arm. The primary source of EEG data for this research is the publicly available BCI Competition IV-2a dataset. A deep learning model will be developed and trained on this dataset to classify MI tasks accurately. The classification outcomes will then be mapped to specific control commands for the PX150 robotic arm within a ROS-based simulation environment (Gazebo). If time and technical resources permit, the system will be demonstrated using actual hardware deployment. Overall, this project will include EEG data preprocessing, deep learning model training, design of control mappings, and system integration and validation in a simulated robotic environment.

Motivation

Brain-computer interface technology opens transformative possibilities in areas such as assistive technology, neurorehabilitation, and hands-free human-machine interaction. Motor imagery is particularly compelling due to its intuitive user interaction and independence from external stimuli. However, challenges such as low signal-to-noise ratios, high inter-subject variability, and insufficient performance with traditional shallow classifiers persist, limiting MI-based BCIs' practical application and robustness (Non-invasive EEG-Based Intelligent Mobile Robots, IEEE, 2025).

Recent advancements in deep learning have provided promising avenues to address these limitations. Models such as convolutional neural networks (CNNs) have demonstrated strong capability for automatic extraction and classification of EEG signal features, achieving higher accuracy and better generalisation (Casson et al., 2018). The BCI Competition IV-2a dataset, featuring four distinct MI tasks (left hand, right hand, foot, and tongue), is widely recognised and extensively utilised in BCI literature, making it a reliable benchmark for algorithm validation. Moreover, the PX150 robotic arm, already available in the laboratory and compatible with ROS, offers intuitive, flexible, and visually appealing control demonstrations. Integrating these components—MI data, deep learning, and robotic control—provides a coherent platform for exploring the real-world potential and practicality of MI-based brain-machine interfaces.

Aims

The project has three main aims. First, to develop a deep learning-based classification model that accurately identifies the motor imagery tasks from EEG signals within the BCI Competition IV-2a dataset. Second, to design an intuitive mapping from classification outcomes to corresponding robotic actions for controlling the PX150 robotic arm. Third, to implement and demonstrate the effectiveness of the entire BCI-robot control system in a simulated environment using ROS-Gazebo, assessing overall feasibility and robustness.

Objectives

The specific research objectives for this project can be elaborated in detail as follows:

The first step involves preprocessing and analysing the BCI Competition IV-2a dataset. EEG data will undergo bandpass filtering (7–30 Hz), segmentation into specific task windows (such as 2–6 seconds post cue), and normalisation procedures, preparing the dataset effectively for subsequent deep learning modelling.

The second step entails developing a deep learning classification model based on convolutional neural network architectures such as EEGNet or EEGNeX, using Python and deep learning frameworks like PyTorch or TensorFlow. The model will be trained and validated to discriminate effectively between the four MI classes provided in the dataset: left hand, right hand, foot, and tongue.

In the third step, an intuitive mapping scheme from classified MI tasks to robotic control commands will be established. Specifically, motor imagery of the left hand will correspond to the PX150 robotic arm moving leftward, while right-hand imagery will correspond to the arm moving rightward. The exact mappings for foot and tongue imagery remain tentative, but these two tasks may be assigned to control robotic actions such as grasping and releasing objects. Further analysis during the project will help finalise these mappings clearly.

The fourth step is to integrate the classification and control mechanisms within a ROS-based simulation environment. The trained deep learning model will output MI classification results through ROS topics, directing the PX150 robotic arm in the Gazebo simulation platform. This integration will validate the practical performance of the entire brain-controlled robotic system under simulated but realistic scenarios.

The fifth step involves a thorough performance evaluation of the developed BCI system, including measures such as classification accuracy of motor imagery tasks, latency of command transmission, precision of robotic arm response, and the overall effectiveness of the control scheme. Outcomes from these evaluations will identify current limitations and guide potential system improvements.

Finally, the sixth step is to create a comprehensive demonstration video illustrating the successful control of the PX150 robotic arm via the motor imagery classification outcomes derived from the BCI Competition IV-2a dataset. This video will effectively showcase the project's results and provide clear visual evidence of the feasibility and efficacy of the developed system.