Neuromappr

Brain-Computer Interface Movement Decoding Using Support Vector Machines

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Table of contents

1 Introduction

1.1 Background

Since the creation of machines and computers, the human interaction with them has been evolving and sometimes quite challenging. For instance, the first computers were operated using punch cards, which required a lot of effort to input data. As technology advanced, we moved to keyboards and mice, which made it easier to interact with computers. However, these methods still require physical movement and can be limiting for individuals with disabilities or injuries. This interaction with computers has been a challenge investigated for researchers and engineers for decades in the field of Human-Computer Interaction (HCI) [1].

The goal of HCI is to create systems that are easy to use and understand, allowing users to interact with computers in a natural and intuitive way. This has led to the development of various input devices, such as touchscreens, voice recognition, and even brain-computer interfaces (BCIs), the focus of this project.

Brain-Computer Interfaces (BCIs) are systems that enable direct communication between the human brain and devices, bypassing the need for physical movement and control, which can be particularly beneficial for individuals with disabilities or injuries. Among other data, BCIs can use electroencephalography (EEG) signals to decode brain activity and translate it into commands for controlling devices.

BCI technology has the potential to revolutionize the way we interact with computers and other devices, making it possible for individuals with disabilities to regain control over their environment. Central to the efficacy of BCIs is the accurate interpretation of electroencephalogram (EEG) signals, particularly those associated with motor imagery—the mental simulation of movement without actual execution as described by Costantini et al. (2009) [2].

From a machine learning standpoint, the classification of EEG signals for motor imagery tasks presents several intricate challenges:

- **High Dimensionality with Limited Samples**: EEG data are inherently high-dimensional, often involving recordings from numerous electrodes (e.g., 102 in this project), each capturing complex temporal dynamics. However, the number of labeled training samples is typically limited, leading to the "curse of dimensionality," where models risk overfitting and poor generalization.
- **Non-Stationarity and Noise**: EEG signals are susceptible to various artifacts (e.g., muscle movements, eye blinks) and exhibit non-stationary behavior, complicating the extraction of consistent features across sessions and subjects.
- **Inter-Subject Variability**: There is significant variability in EEG signals across different individuals, which can affect the performance of machine learning models trained on data from a single subject. This variability necessitates the development of robust algorithms that can generalize well across different users.
- **Temporal Dynamics**: EEG signals are time-dependent, and capturing the temporal dynamics of brain activity is crucial for accurate classification. This requires the use of advanced techniques that can model temporal relationships effectively.

Support Vector Machines (SVMs) have been extensively employed in this domain due to their effectiveness in high-dimensional spaces and robustness to overfitting. For instance, Costantini et al. (2009) [2] demonstrated the utility of SVMs in classifying EEG signals for BCI applications, emphasizing their capacity to handle complex, high-dimensional data.

1.2 Objectives

In this project, we aim to implement and evaluate SVM-based classifiers for distinguishing between left and right-hand motor imagery using EEG data. By addressing the aforementioned challenges through appropriate preprocessing, feature extraction, and model selection, we seek to contribute to the development of reliable and efficient BCI systems.

1.2.1 Spedific Objectives

1. Implement a Support Vector Machine (SVM) classifier for EEG data.
    - Evaluate the performance of the SVM classifier using various kernel functions (linear, polynomial, and radial basis function).
    - Optimize the SVM hyperparameters using grid search and cross-validation techniques.

2. Compare the performance of the SVM classifier with Overt and Imagined Motor Imagery (MI) tasks.
   - Analyze the classification accuracy, precision, recall, and F1-score for both tasks.
   - Investigate the impact of different EEG feature extraction methods on classification performance.
3. Visualize and interpret the results of the SVM classifier, including feature importance and decision boundaries.
   - Provide insights into the EEG features that contribute to the classification performance.
   - Visualize the decision boundaries of the SVM classifier in the feature space.

1.3 Dataset overview

The dataset utilized in this project comprises EEG recordings from a Brain-Computer Interface (BCI) experiment designed to distinguish between left and right-hand movements. The recordings are categorized into two distinct types:

1. **Overt Motor Imagery (OMI)**: This task involves participants imagining moving their left or right hand while EEG signals are recorded.
2. **Imagined Motor Imagery (IMI)**: In this task, participants are instructed to imagine moving their left or right hand without any actual movement.

Moreover, the dataset provides the XY coordinates of the electrodes, which are crucial for visualizing the spatial distribution of EEG signals across the scalp. The dataset is organized into two main folders: `data`.

The data is organized on the following files:

- `data/BCIsensor_xy.csv`: Contains the XY coordinates of the electrodes.
- `data/feaSubEImg_1.csv`: Contains the EEG data for the IMI task for one direction (left).
- `data/feaSubEImg_2.csv`: Contains the EEG data for the IMI task for the other direction (right).
- `data/feaSubEOvert_1.csv`: Contains the EEG data for the OMI task for one direction (left).
- `data/feaSubEOvert_2.csv`: Contains the EEG data for the OMI task for the other direction (right).