EEG-based Cross-Subject BCI Control System Using Deep Learning: Leveraging Feature Engineering and Feature Selection

Anas Taha, Mohamed Ahmed, Yousef Mohamed
Faculty of Science, Helwan University
Faculty of Computers and Artificial Intelligence, Cairo University

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Introduction

Many individuals with severe motor impairments are unable to interact with their environment in a normal way, which drives the need for assistive systems that can provide control without adding additional burdens. Brain–Computer Interface (BCI) systems offer a promising framework to help these individuals by leveraging neural signals recorded from the brain.

Problem Statement

EEG signals are inherently noisy, highly variable across subjects, and even vary between sessions for the same subject. Research in this field has increasingly focused on developing robust, subject-invariant EEG decoders that can generalize to new, unseen subjects. This remains a significant challenge due to the non-stationary nature of EEG data. Furthermore, in many practical scenarios, test labels are unavailable, which prevents subject-specific adaptation or fine-tuning during deployment.

To address these challenges, preprocessing and feature extraction stages must be carefully designed to maximize generalization across unseen subjects. Instead of relying on subject-dependent patterns, the focus is placed on extracting robust and discriminative features.

Objective

The objective of this project is to design and implement a pipeline capable of classifying both Motor Imagery (MI) and Steady-State Visually Evoked Potential (SSVEP) EEG signals for real-time control applications in a cross-subject setting. The system aims to achieve strong generalization across different subjects by leveraging:

- Rigorous preprocessing of raw EEG signals,
- Informative feature engineering techniques,

- Feature selection strategies, and
- Deep neural network architectures tailored for EEG.

This integrated approach is intended to provide a robust and efficient EEG-based control system that can be deployed in practical BCI applications without requiring subject-specific retraining.

Related Work

In our exploration of existing methods, we investigated a range of well-established EEG pipelines. One widely used technique is **Common Spatial Patterns (CSP)**, which is effective for subject-specific settings. However, CSP requires fitting per subject, making it inefficient for practical cross-subject scenarios. The high inter-subject variability present in our dataset further complicates the possibility of a single model fitting all users.

Filter Bank Common Spatial Patterns (FBCSP) filters have also been applied in the motor imagery (MI) setting. While FBCSP provides a richer feature set across multiple frequency bands, it still does not yield sufficiently discriminative features in our data.

We further experimented with several well-known deep learning frameworks from the *Braindecode* library, including **EEGNet** and **ShallowFBCSPNet**. Although these architectures have achieved success in other studies, the inherent variability and non-stationarity of our data limited their effectiveness, and they did not reach satisfactory performance in our cross-subject setting.

For motor imagery classification, recent advances such as **Cross-Subject DD** ("A Cross-Subject Brain-Computer Interface Algorithm", Xiaoyuan Li, Xinru Xue, Bohan Zhang) demonstrated promising results on our data. This approach leverages a universal feature extractor combined with pretraining and feature selection, resulting in improved generalization. Using this method, we achieved a linear separability of approximately 66% on our validation set.

For SSVEP analysis, we also examined **Filter Bank Canonical Correlation Analysis (FBCCA)** filters, which have been highlighted in numerous recent studies. FBCCA proved to be effective with our data, further supporting its suitability for steady-state visual stimuli in cross-subject BCI pipelines.

Challenges

Despite these advances, significant challenges remain:

- **Subject Variability:** The large differences between individual EEG patterns make it difficult to design a one-size-fits-all solution.
- **Session Variability:** Even within the same subject, signal characteristics fluctuate across sessions due to environmental factors and electrode placement.

- **Limited Discriminative Power:** Many traditional methods (e.g., CSP, FBCSP) fail to extract features that are sufficiently discriminative for robust cross-subject generalization.
- **Deep Model Sensitivity:** While deep architectures offer strong representation power, they are sensitive to data variability and require careful pretraining and feature selection.

Our pipeline directly addresses these challenges by combining universal feature extraction, statistical feature selection, and cross-subject training strategies, enabling more robust performance across unseen subjects.

Methodology

0.0.1 Motor Imagery:

Our proposed system follows a complete EEG processing and classification pipeline, designed to achieve robust cross-subject generalization for both Motor Imagery (MI) and Steady-State Visually Evoked Potential (SSVEP) tasks. The pipeline is composed of four main stages:

1. Preprocessing and caching of raw EEG signals,
2. Sliding window segmentation and augmentation,
3. Feature extraction and feature selection,
4. Model training and cross-subject classification.

Data Preprocessing

Raw EEG signals from multiple subjects and sessions are preprocessed using a custom `EEGPreprocessor` to remove noise and artifacts. The preprocessing stage includes:

- **Band-pass filtering:** A 4th-order Butterworth band-pass filter is applied with cutoff frequencies set to 8–30 Hz, targeting the Mu (8–13 Hz) and Beta (13–30 Hz) bands. These bands are known to contain discriminative information for motor imagery tasks. After band-pass filtering, the data is further processed with a 50 Hz notch filter to suppress power-line interference.
- **Power line interference:** Upon inspecting the power spectral density (PSD) distribution across the EEG channels, a prominent spike was observed at 50 Hz, indicating a significant presence of power-line noise. This is a common artifact in EEG recordings, particularly in countries where the electrical grid operates at 50 Hz (e.g., Egypt).

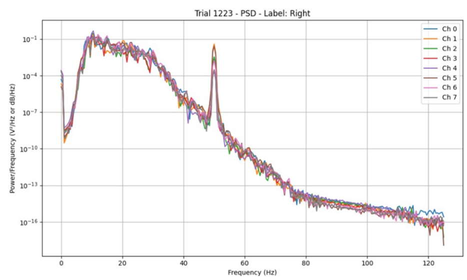

Figure 1: PSD for Trial Before Notch Filtering

- **ICA artifact removal:** Independent Component Analysis (ICA) is applied using the MNE library to identify and suppress artifact-related components, such as eye movements (EOG), muscle artifacts, or other stereotypical noise patterns. Although automated exclusion is possible, component 0 (`ICA000`) was manually identified and removed based on empirical observations.

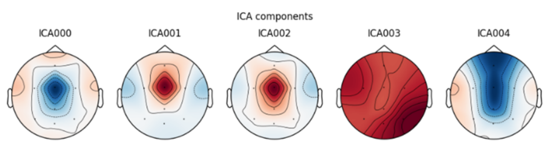

Figure 2: ICA decomposition results showing spatial topographies. Components such as ICA000 and ICA001 display spatial maps characteristic of artifacts (e.g., eye blinks).

- **Eye blink artifacts:** Upon inspecting the temporal waveforms of the ICA components, IC000 and IC001 show large-amplitude, sharp deflections, confirming their nature as prominent eye-blink artifacts. However, due to limited data and stability of ICA, only IC000 was removed.

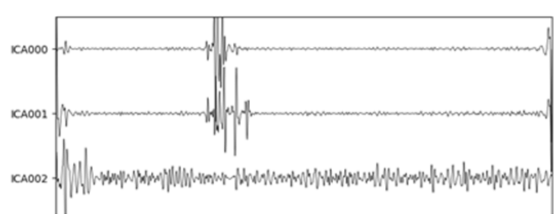

Figure 3: Temporal waveforms of ICA components. ICA000 and ICA001 exhibit large, sharp deflections, indicating eye blink artifacts.

- **Temporal cropping and Z-score Normalization:** Finally, the data is cropped to the time range 3.5–7.5 seconds after stimulus onset, as this window encompasses the critical period where motor imagery activity occurs and are also normalized.

Feature Extraction and Selection

Feature Extraction: After preprocessing and segmentation, each EEG window is passed through our proposed *Universal Feature Extractor (UFE)*. The UFE is a deep neural architecture specifically designed for EEG data. It employs multiple parallel temporal convolution branches with varying kernel sizes to capture oscillatory patterns across different time scales. These temporal features are then fused and processed through depthwise and pointwise spatial convolutions, effectively learning spatial filters over the EEG channels. Subsequently, a multi-head self-attention mechanism is applied to model long-range temporal dependencies and highlight discriminative time points. The resulting representation is passed through a lightweight convolutional encoder and projected into a compact 32-dimensional feature space, which serves as a subject-agnostic latent representation of each EEG window.

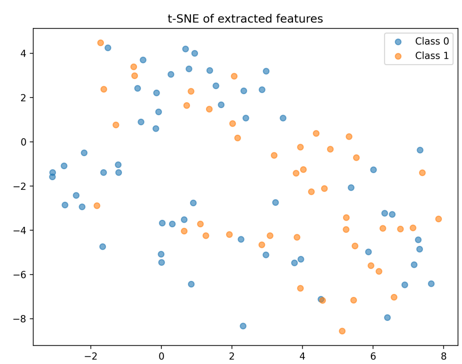

Figure 4: Validation data separation after feature extraction.

Feature Selection: Although the UFE provides good separation on validation data of 66%, not all dimensions are equally informative across subjects. To enhance cross-subject generalization, we train a lightweight differentiable filter network (*DDFilter*) on a per-subject basis to obtain relation spectra that indicate the contribution of each latent feature dimension. These spectra are aggregated across all training subjects, and a statistical analysis (one-sample t-tests) is performed to identify feature dimensions with consistently significant contributions.

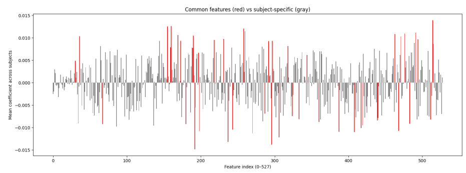

Figure 5: feature coefficients aggregated across all training subjects. Each vertical bar corresponds to a feature index in the latent feature space

Only features with p-values below a chosen threshold are retained, this resulting in a reduced subset of robust and discriminative features. This feature selection step removes subject-specific noise and improves the linear separability of classes, leading to better performance of the final cross-subject classifier.

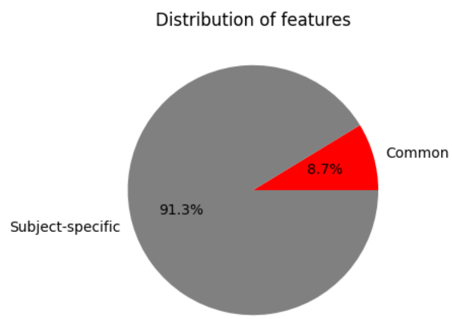

Figure 6: Common Features Distribution

Technical Details of Relation-Spectrum–Based Feature Selection

After training a lightweight Differentiable Filter Network (**DDFilter**) for each subject, we extract two key parameter matrices:

- $W_1 \in R^{32\times16}$: the weight matrix of the initial projection layer (`reduce.weight`), projecting the 32-dimensional latent representation into a 16-dimensional hidden space.
- $W_G \in R^{16\times16}$: the weight matrix of the filter layer (`dd.weight`), modeling feature interactions within the hidden space.

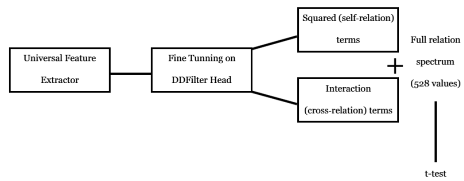

Figure 7: Diagram for the system architecture

Relation Spectrum Computation. For each subject, we compute a *relation spectrum* composed of two parts:

1. **Squared-term contributions** (α-coefficients):

$$\alpha_i = \sum_{k=0}^{15} W_G[k,k] \cdot (W_1[k,i])^2, \quad i = 0, \dots, 31$$

   These coefficients capture the individual contribution of each latent feature.

2. **Interaction-term contributions** (β-coefficients):

$$\beta_{ij} = \sum_{k=0}^{15} \sum_{\substack{l=0 \\ l \neq k}}^{15} W_G[k,l] \cdot W_1[k,i] \cdot W_1[l,j],$$

   for all pairs (i,j) with $0 \leq i < j < 32$. These coefficients capture the pairwise interactions between latent features.

The final relation spectrum is:

$$\text{Spectrum} = [\alpha_0, \alpha_1, \dots, \alpha_{31}, \beta_{0,1}, \beta_{0,2}, \dots, \beta_{30,31}] \in R^{528}.$$

Index Decoding. Each index in the spectrum can be mapped back to its original term:

- $0 \leq \text{idx} < 32$: corresponds to the squared term f_i^2,
- $\text{idx} \geq 32$: corresponds to an interaction term $f_i \times f_j$.

Aggregation Across Subjects. We collect spectra from all training subjects:

$$S \in R^{N \times 528},$$

where each row is a spectrum from a subject. This allows us to statistically evaluate which coefficients are consistently significant across subjects.

Statistical Feature Selection. A one-sample t-test is performed on each spectrum dimension across all subjects to test:

$$H_0 : \mu = 0,$$

where μ is the mean coefficient across subjects. Dimensions with p-values below a chosen threshold (e.g., $\alpha = 0.1$) are selected as **common robust features**.

$$\text{Selected} = \{ \, d \mid p\text{-value}(d) < \alpha \, \}.$$

These selected indices correspond to a reduced subset of features (both squared and interaction terms) that are consistently discriminative across subjects, improving cross-subject generalization.

Training and Validation

The system is trained in two main stages. First, the Universal Feature Extractor (UFE) is trained on the training set in a fully supervised manner to learn a subject-agnostic latent representation. The training dataset consists of windowed EEG segments obtained from multiple subjects, with each window labeled according to the corresponding motor imagery task. The model is optimized using the cross-entropy loss and the Adam optimizer, with a learning rate schedule and dropout regularization applied to prevent overfitting.

During training, batches of size 64 are sampled from the `SlidingWindowEEGDataset`, ensuring shuffling to improve generalization. Validation is performed after each epoch on a held-out validation set processed in the same way as the training data. Performance metrics such as accuracy and loss are tracked throughout training to monitor convergence and detect overfitting.

After the UFE is trained and frozen, subject-specific DDFilter models are fine-tuned using data from individual subjects to derive relation spectra for feature selection. The aggregated spectra are then used to select a stable subset of discriminative features. Finally, a lightweight Cross-Subject Classifier is trained on the transformed features using the same training and validation protocol, with the selected feature subset as input, further improving generalization across unseen subjects.

Key Results and Discussions

The model performed significantly better than the Phase-1 code that used AdaBoost and other traditional machine-learning classifiers. The cross-subject generalization achieved through feature selection and latent projections proved to be effective and noticeably improved the model's ability to generalize. Our UFE extractor also outperformed EEGNet with multi-head attention as well as purely statistical and PSD-based approaches. Although additional time for hyperparameter tuning could have led to even better feature extraction, the current approach already demonstrated strong and reliable performance, showing clear potential for further improvement.