Assignment #2: Classifying between two motor activities using the Common Spatial Patterns (CSP) component space and spectral features obtained by estimation of spectra using parametric modelling - autoregressive (AR) parameters using eeg signals

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***Abstract*—This study aimed to develop an algorithm for distinguishing between two motor states—fist opening and closing—using EEG signals from the EEG Motor Movement/Imagery Dataset. The dataset includes recordings from 109 participants, with each providing three 2-minute EEG recordings captured from 64 electrodes during motor tasks. The method involved several steps: band-pass filtering the signals to isolate the Mu rhythm, applying spatial filtering using the Common Spatial Pattern (CSP) technique, and extracting features such as variance, autoregressive parameters, and power spectral characteristics. These features were then used to train and evaluate six different classifiers: Linear Discriminant Analysis (LDA), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Logistic Regression, Decision Trees, and Naive Bayes. Results showed that, while classifier performance varied, none of the models exhibited strong classification accuracy.**

I. Introduction

The goal of this assignment was to develop an algorithm capable of distinguishing between two distinct motor states: the opening and closing of either the right or left fist. To achieve this, EEG signals from the EEG Motor Movement/Imagery Dataset [1] were utilized. The dataset includes recordings from 109 participants, with each individual providing three 2-minute EEG recordings, captured from 64 electrodes while performing fist-opening and fist-closing tasks. These signals were analyzed to differentiate the motor states.

II. Methodology

Band-pass filtering

Upon reading the signals, all 64 channels were filtered using a 500th-order FIR band-pass filter. The filter had a low cutoff frequency of 8 Hz and a high cutoff frequency of 13 Hz to detect the Mu rythm.

Spatial filtering based of CSP Next, spatial filters were designed using the CSP method [2]. First, the average covariance matrices for each state were calculated (using two intervals of the same motor activity for each). Then, generalized eigenvalue decomposition was performed, and the eigenvectors corresponding to the largest and smallest three eigenvalues were selected as filters, forming a filter matrix. This matrix was applied to the signal matrix, resulting in a component space with 6 signals. The first 3 signals maximized variance for the first state and minimized it for the second, while the last 3 signals exhibited the opposite behavior. We can see an example of the first an last signal on Figure 1.

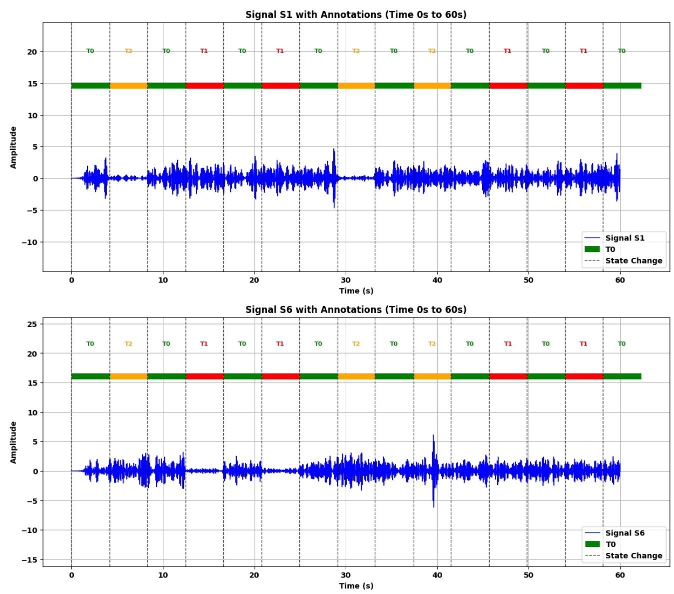

Fig. 1. First and last signal in the component space after CSP, with annotated states

Feature extraction After obtaining signals in the component space, features for each interval of the two tasks were extracted from all 6 component signals. The first feature was the logarithmic value of the variance of each signal over the observed interval. Then, autoregressive parameters were computed for each signal in the interval using the statsmodels Python library [3]. Additionally, power spectral features, including peak amplitude, median frequency, and highest power frequency, were also extracted.

Classification

After feature extraction, the data was split into a 50% train-test split. The classifiers tested included Linear Discriminant Analysis (LDA), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Logistic Regression, Decision Trees, and Naive Bayes. To asses the classification Sensitivity and Specificity were calculated.

III. Results and Discussion

A. Results

In Table I, we present the sensitivities and specificities for each mentioned classifier, which were computed by averaging the sensitivities and specificities calculated for each individual in the database.

B. Discussion

The results show that, while the classifiers exhibited some variation in performance, none of them achieved strong classification accuracy. Although certain models, such as Naive Bayes and Logistic Regression, performed slightly better in terms of sensitivity and specificity, the overall performance across all classifiers was modest.

Classifer	Sensitivity	Specificity
LDA	0.52 ±0.13	0.52 ±0.14
RF	0.48±0.17	0.54 ±0.17
XGBOOST	0.51±0.18	0.53±0.16
Logistic Regression	0.51±0.13	0.54 ±0.13
Decision trees	0.50 ±0.22	0.54 ±0.22
Naive Bayes	0.54 ±0.22	0.51 ±0.23

TABLE I
Comparison of performance metrics of different classifers

IV. Conclusion

In this assignment, we developed and tested an algorithm to distinguish between two motor states—fist opening and closing—using EEG signals from the EEG Motor Movement/Imagery Dataset. Various steps were taken, including band-pass filtering, spatial filtering using the Common Spatial Pattern (CSP) method, feature extraction, and classification using several machine learning models. Despite the differences in classifier performance, none of the tested models demonstrated strong classification accuracy.

References

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