An OpenViBE Python-based framework for the efficient handling of MI BCI protocols

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A. Desbois, T. Venot, M.-C. Corsi, F. De Vico Fallani

ARAMIS LAB
BRAIN DATA SCIENCE

Sorbonne Université
Institut du Cerveau - Paris Brain Institute - ICM
CNRS, Inria, Inserm, AP-HP
Hôpital de la Pitié Salpêtrière, F-75013, Paris, France

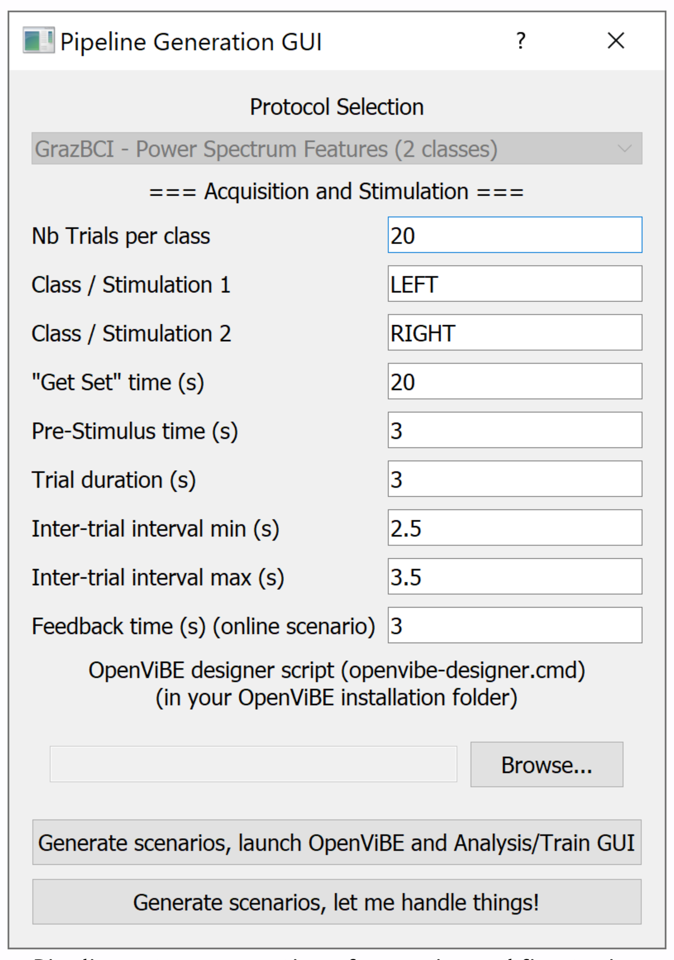
arthur.desbois@gmail.com AsteroidShrub ADesboisDev

A typical Motor Imagery (MI) experimental pipeline is composed of an EEG data acquisition phase, followed by an analysis phase to train a classification algorithm (such as LDA). The training uses features extracted from the acquired data such as spectral power for a subset of sensors and frequencies, in which desynchronization can be observed between the MI tasks.

The feature selection phase is crucial but can be a long step of trial-and-error, which is not acceptable in clinical settings. Training a classification algorithm can be challenging and time consuming as it may include multiple manipulations and datatype conversions with external softwares.

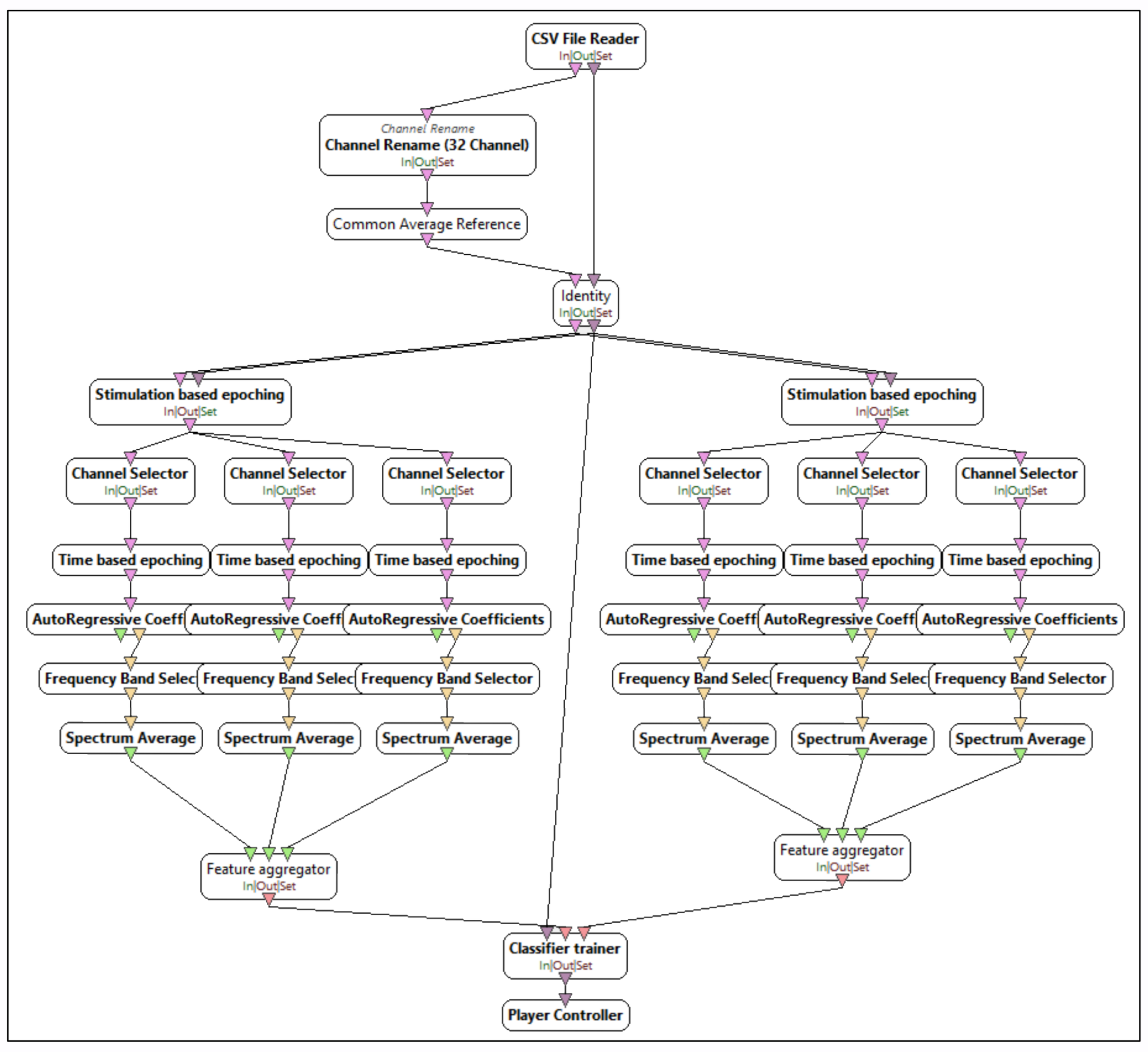
Here, we propose a new Python-based framework to manage the whole experimental pipeline smoothly, integrating seamlessly with OpenViBE.

Pipeline automation, simplified workflow



Pipeline setup: generation of scenarios and fine tuning of the acquisition step

- The experimental pipeline is set-up using templated scenarios, fine-tuned using pipeline-dependent parameters.
- This allows to provide a **clean, controlled and risk-free working environment** for non-technical clinician experimenters, removing the need for manually modifying OpenViBE scenario parameters.
- In the offline analysis & training steps, OpenViBE is used "in the background", hidden from the user, to make the experimental workflow as smooth and efficient as possible.
- Scenarios are modified on-the-fly, allowing to test various parameters (e.g., signal segmentation for spectral analysis, frequency resolution, channel of interest…) in a **trial-and-error oriented workflow.**
- We take advantage of the computational performance offered by OpenViBE, but we propose a framework which trades OV's flexibility and modularity for fixed, easy to manipulate scenarios.
- This framework was successfully validated using a Graz MI protocol with 2 classes, and an LDA classification algorithm with spectral power as discriminant feature.
- Integration of additional pipelines and methods is currently ongoing, following the same paradigm.



Training scenario: ex. of classifier training with 3 selected (channel; frequency band) spectral features

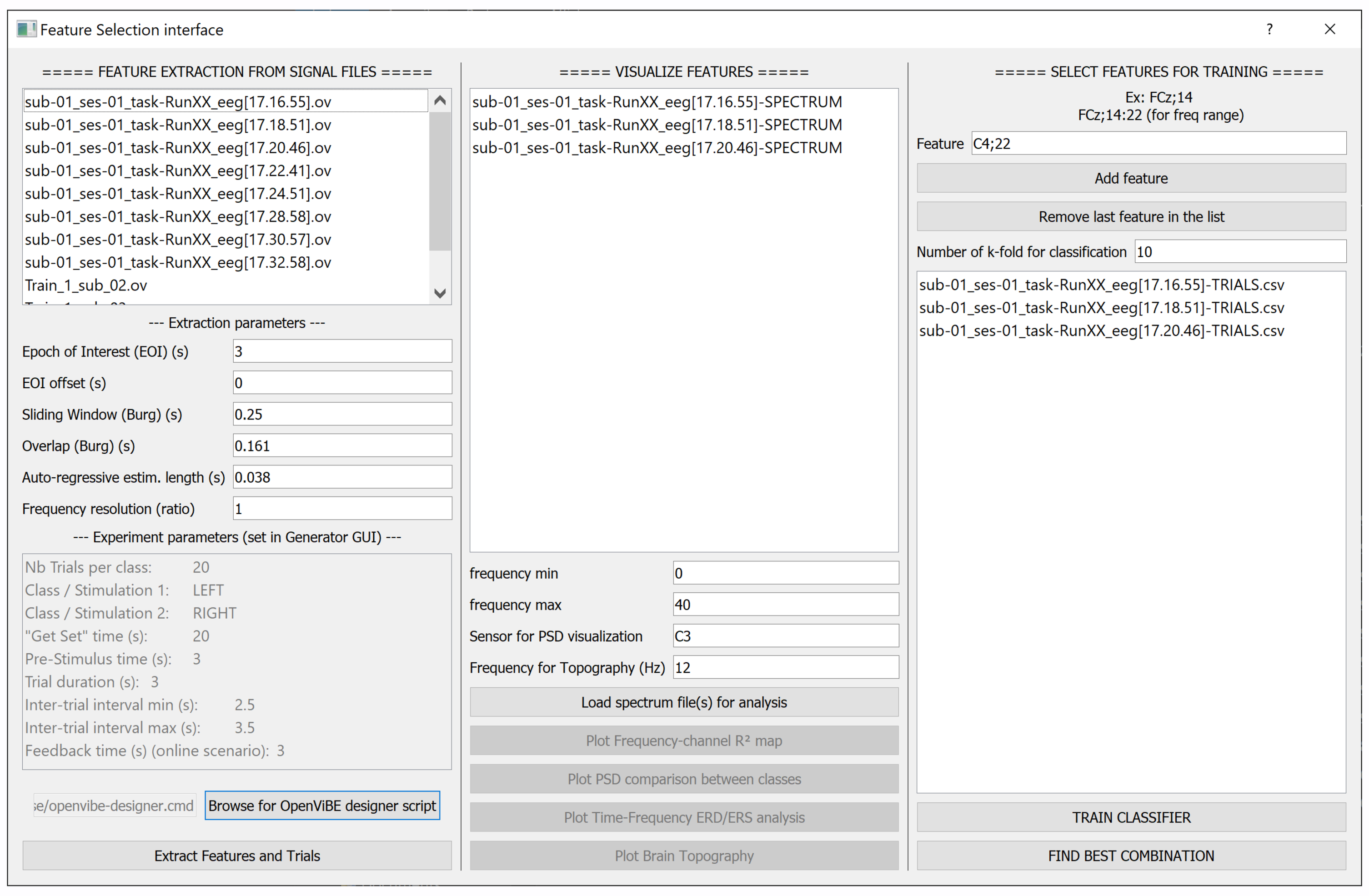
Key Features and Mechanisms

All offline capabilities (spectral feature extraction, visual analysis, classifier training) are available via a dashboard-like graphical interface.

Extraction of spectral features ①

- Runs of experimental data are displayed as they are recorded, and the user can choose during the acquisition phase of the experiment which signal(s) to analyse.
- This list can also be fed with pre-recorded signals, for analysis outside of the scope of an experiment.
- Extractions of spectral features useful for analysis, and of trials chunks for future training, are realized using OpenViBE in the background, with scenarios automatically modified using pipeline-dependent parameters.

① ② ③



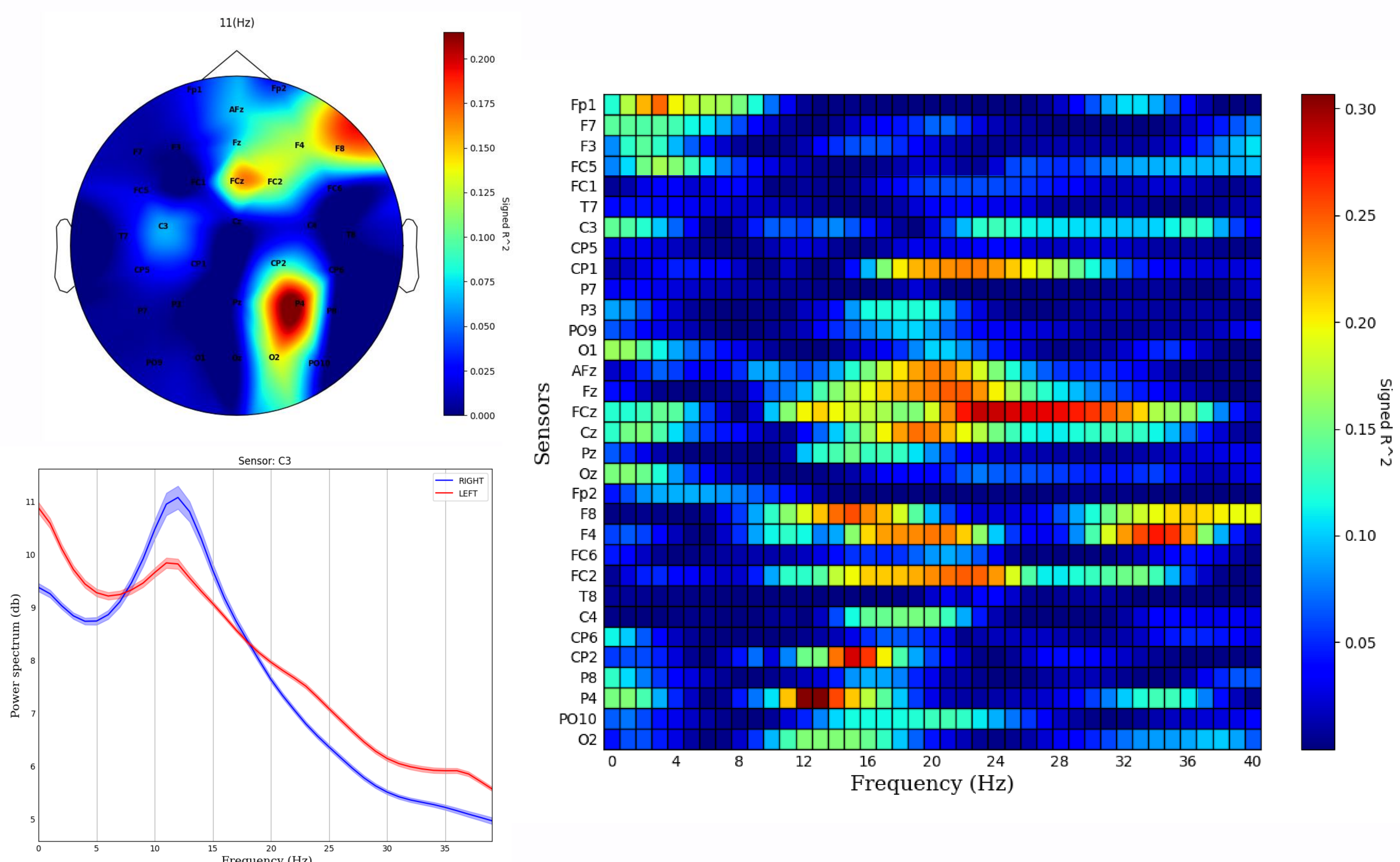
View of the Feature Extraction Interface

Visual analysis of spectral features ②

The classification algorithm is trained using a subset of sensors and frequency bands in which desynchronization can be observed between Motor Imagery tasks.

This selection is made easier through the use of visualization tools, allowing to display:

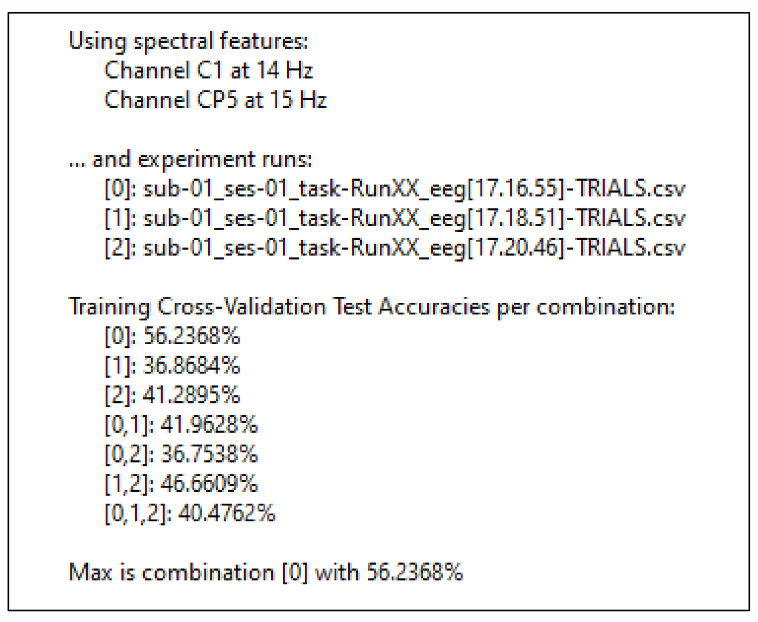
- **frequency/channel map of R²** values between the two tested conditions
- « **brain topography** » of R² values mapped on a scalp
- **compared PSDs** for the two conditions, for a given channel
- **time/frequency ERD/ERS analysis**, showing the difference in activity between baseline and task



Visualization tools for spectral features analysis

Classifier training, trials combinations ③

- The classification algorithm can be trained with a few clicks. Here again, OpenViBE scenarios are run in the background after being automatically updated with entered values.
- This mechanism allows running various training attempts. Multiple recorded sessions can be selected, their trials being then concatenating.
- After training, the accuracy is displayed to the user, and selected features and classifier weights are automatically updated in the "Online Testing" scenario, available directly without additional manipulation.
- A mechanism also allows for testing all possible combinations of selected sessions, to determine the best possible combination.



Using spectral features:
Channel C1 at 14 Hz
Channel CP5 at 15 Hz

... and experiment runs:
[0]: sub-01_ses-01_task-RunXX_eeg[17.16.55]-TRIALS.csv
[1]: sub-01_ses-01_task-RunXX_eeg[17.18.51]-TRIALS.csv
[2]: sub-01_ses-01_task-RunXX_eeg[17.20.46]-TRIALS.csv

Training Cross-Validation Test Accuracies per combination:
[0]: 56.2368%
[1]: 36.8684%
[2]: 41.2895%
[0,1]: 41.9628%
[0,2]: 36.7538%
[1,2]: 46.6609%
[0,1,2]: 40.4762%

Max is combination [0] with 56.2368%

Example of testing different combinations for training the classifier

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