Passive BCI hackathon - TEAM BCCYH
Ensemble learning based on functional connectivity and Riemannian geometry for robust workload estimation

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Context

Passive BCI (pBCI) has recently gained in popularity through its applications, e.g. workload and attention assessment[1,2]. Nevertheless, one of the main limitations remains the important intra- and inter-subject variability[2]. We propose a robust approach relying on ensemble learning, grounded in functional connectivity and Riemannian geometry to mitigate the high variability of the data with a large and diverse panel of classifiers.

Methods

Riemannian geometry

The use of Riemannian geometry (RG) has raised a growing interest within the BCI community in the last ten years to become the gold standard in specific paradigms such as motor imagery-based BCI[3,4]. Recent works have also used RG in the context of passive BCI[5].

The approach consists in estimating the covariance matrix of each epoch. Covariance matrices are symmetric positive definite (SPD), *i.e.* symmetric matrices with strictly positive eigenvalues. In Riemannian geometry, the distance δ between two SPD matrices Σ_1 and $\Sigma_2$is:

$$\delta\left(\Sigma_1,\ \Sigma_2\right) = \|Log(\Sigma_1^{-\frac{1}{2}}\Sigma_2\Sigma_1^{-\frac{1}{2}})\|_F\ .$$

A simple classifier for SPD matrices is the Minimum Distance to Mean (MDM) that could be combined with a geodesic filter. It is also possible to use any standard classifier in the tangent space.

The Riemannian geometry was applied on SPD matrices extracted from spatial covariances. In a contribution on motor imagery-based BCI, we adopted an alternative approach by computing SPD matrices from functional connectivity estimators that gave promising results[6]. In this submission, we aimed at applying this method in the frame of passive BCI.

Functional connectivity

Functional connectivity (FC) gives an estimation of the interaction between brain areas[7]. Such an approach has been proved to discriminate subjects' mental states and to elicit neurophysiological patterns of BCI training[8]. In this submission, for a given trial, we took into account the whole time window to estimate the FC and we averaged the FC values within two frequency bands: α-β (8-35Hz) and low-γ (30-45Hz) bands. In the following paragraphs, we defined the metrics computed between two given signals referred as $s_1(t)$ and $s_2(t)$ between two EEG sensors. We computed three complementary FC estimators: the coherence (Coh), the imaginary coherence (ImCoh), and the phase-locking value (PLV).

Coh and ImCoh are both computed from the coherency, defined as the normalized cross-spectral density obtained from two given signals. More specifically, they can be obtained as follows:

$$Coh_{12} = \frac{|S_{12}(f)|^2}{S_{11}(f).S_{22}(f)} \quad \text{and} \quad ImCoh_{12} = \frac{Im(S_{12}(f))}{\sqrt{S_{11}(f).S_{22}(f)}},$$

with $S_{12}(f)$ the cross-spectral density of s_1(t) and s_2(t) and $S_{11}(f)$ the auto-spectral density of s_1(t).

PLV gives access to the phase synchrony between s_1(t) and s_2(t). It corresponds to the absolute value of the mean phase between s_1 and s_2, defined as follows[9]:

$$PLV = \left| e^{i\Delta\varphi(t)} \right| ,$$

where $\Delta\varphi(t) = arg(\frac{z_1(t).z_2^*(t)}{|z_1(t)|.|z_2(t)|})$. It represents the associated relative phase computed between s_1 and s_2 and $z(t) = s(t) + i.h(s(t))$, represents the analytic signal obtained by applying the Hilbert transform h on the signal s(t).

Ensemble learning

No specific feature space emerges from the literature on workload and, in this challenge, an examination of the individual performance of classifiers shows that their performances are highly variable. We decided to combine the best classifiers (first-level) using an ensemble ridge classifier (second-level) as shown on Fig. 1: Those 10 first-level classifiers are: 6 filters Common Spatial Patterns + Support Vector Machine (CSP+SVM), Source Power Comodulation + ElasticNet (SPoC+EN), geodesic filtering MDM (fgMDM) on covariance for α-β band, fgMDM on covariance for low-γ band, fgMDM on coherence for α-β band, fgMDM on coherence for low-γ band, ElasticNet in tangent space (EN) for imaginary coherence in α-β band, EN for imaginary coherence in low-γ band, EN for PLV in in α-β band and EN for PLV in low-γ band. We used all electrodes available.

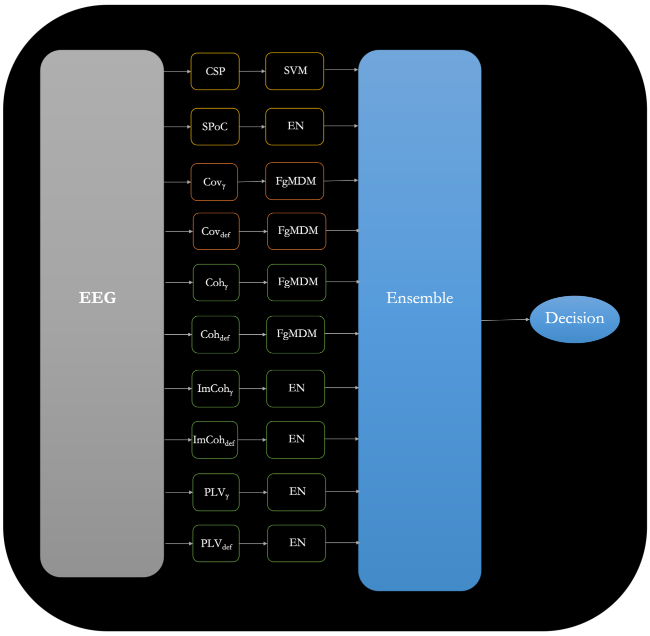

Fig. 1: Proposed architecture for ensemble learning.

Classification results for S1 & S2

The results obtained on training sessions, S1 and S2, are displayed below. The Fig. 2.A shows the balanced accuracy obtained with the ensemble classifier and each first-level classifier. The top rain plot displays the accuracy when training on S2 and testing on S1, the bottom plot displays the results for training on S1 and testing on S2. The performances of subjects with the ensemble classifier are shown on Fig. 2.B for each session.

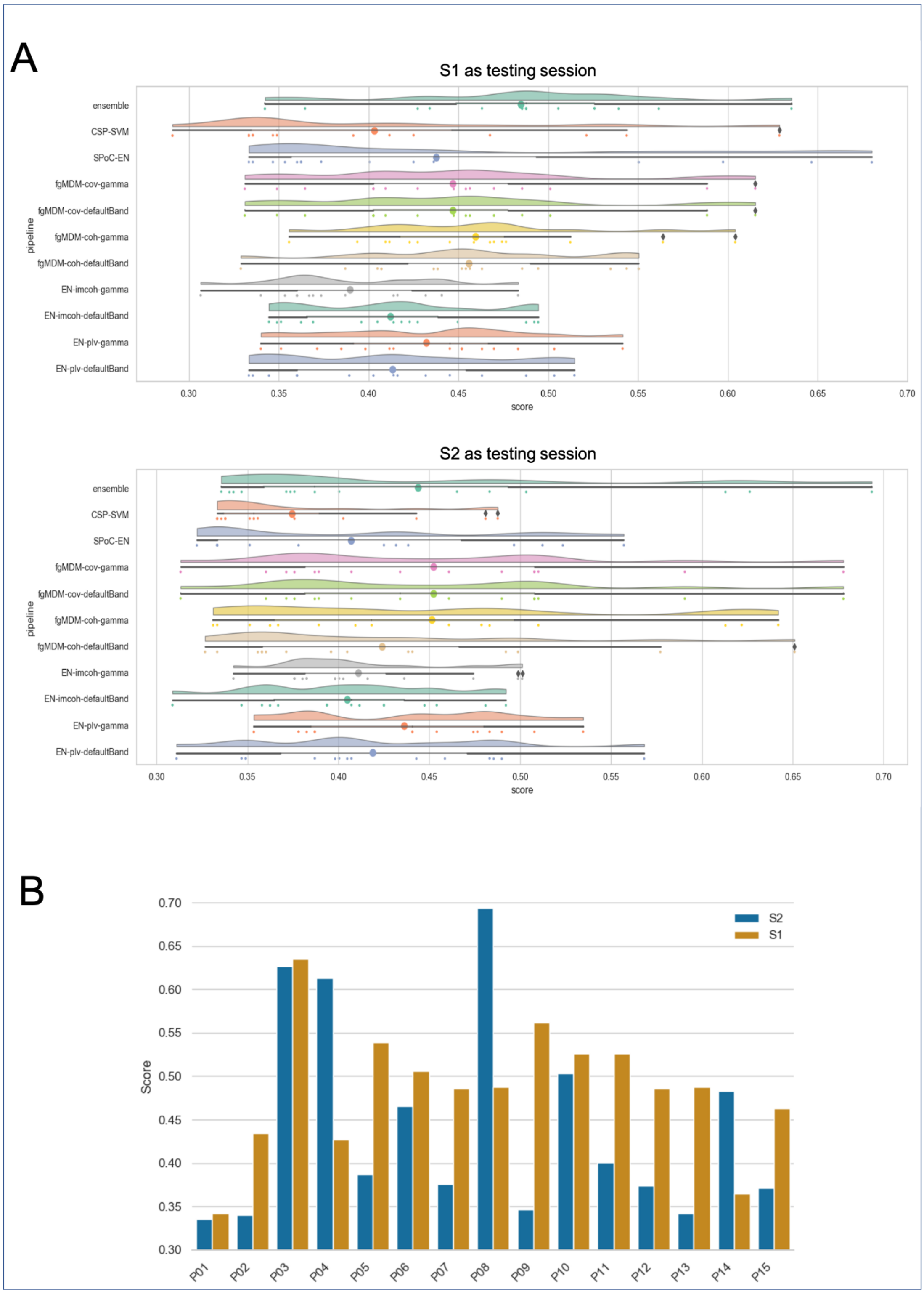

Fig. 2: Results obtained from the first two sessions. (A) Group-level results associated with all the tested classifiers. On the top, we classified the data from S1 by considering data from S2 as a training set. On the bottom, data from S2 were classified by considering S1 as the training set. (B) Individual-level results. Here we only presented results obtained from the ensemble classifier.

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