



HAL
open science

Ensemble learning based on functional connectivity and Riemannian geometry for robust workload estimation

Marie-Constance Corsi, Sylvain Chevallier, Quentin Barthélemy, Isabelle Hoxha, Florian Yger

► **To cite this version:**

Marie-Constance Corsi, Sylvain Chevallier, Quentin Barthélemy, Isabelle Hoxha, Florian Yger. Ensemble learning based on functional connectivity and Riemannian geometry for robust workload estimation. Neuroergonomics conference 2021, Sep 2021, Virtual event, Germany. hal-03359257

HAL Id: hal-03359257

<https://hal.inria.fr/hal-03359257>

Submitted on 30 Sep 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Passive BCI hackathon - TEAM BCCYH

Ensemble learning based on functional connectivity and Riemannian geometry for robust workload estimation

[Marie-Constance Corsi¹, Sylvain Chevallier², Quentin Barthélemy³, Isabelle Hoxha⁴, Florian Yger⁵]

[¹Aramis project-team, Inria Paris, Paris Brain Institute, Paris, France]

[²LISV, UVSQ, Univ. Paris-Saclay, Versailles, France]

[³Foxstream, Vaulx-en-Velin, France]

[⁴CIAMS, Univ. Paris-Saclay, Orsay, France]

[⁵LAMSADE, Univ. Paris-Dauphine, Paris, France]

Keywords: Riemannian geometry, functional connectivity, ensemble learning

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 variability². 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 BCI⁵.

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 Σ_2 is:

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

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 results⁶. 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 areas⁷. Such an approach has been proved to discriminate subjects' mental states and to elicit neurophysiological patterns of BCI training⁸. 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:

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

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 follows⁹:

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

where $\Delta\varphi(t) = \arg\left(\frac{z_1(t) \cdot z_2^*(t)}{|z_1(t)| \cdot |z_2(t)|}\right)$. It represents the associated relative phase computed between s_1 and s_2 and $z(t) = s(t) + i \cdot h(s(t))$, 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 α - β band and EN for PLV in low- γ band. We used all electrodes available.

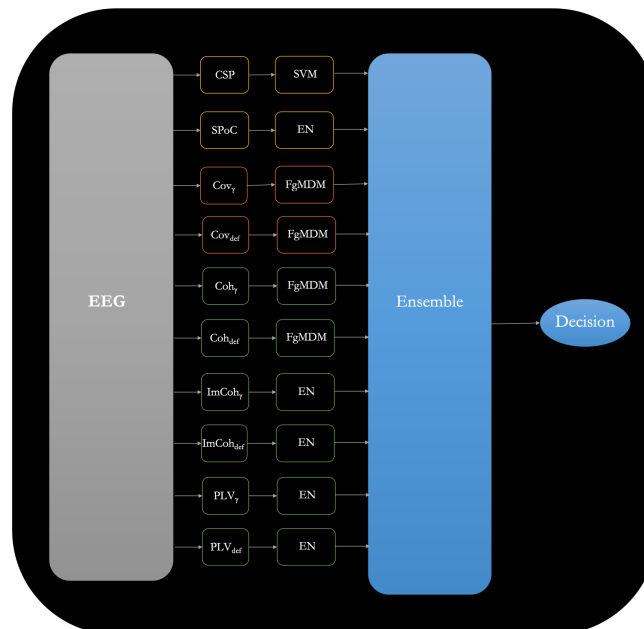


Fig. 1: Proposed architecture for ensemble learning.

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.

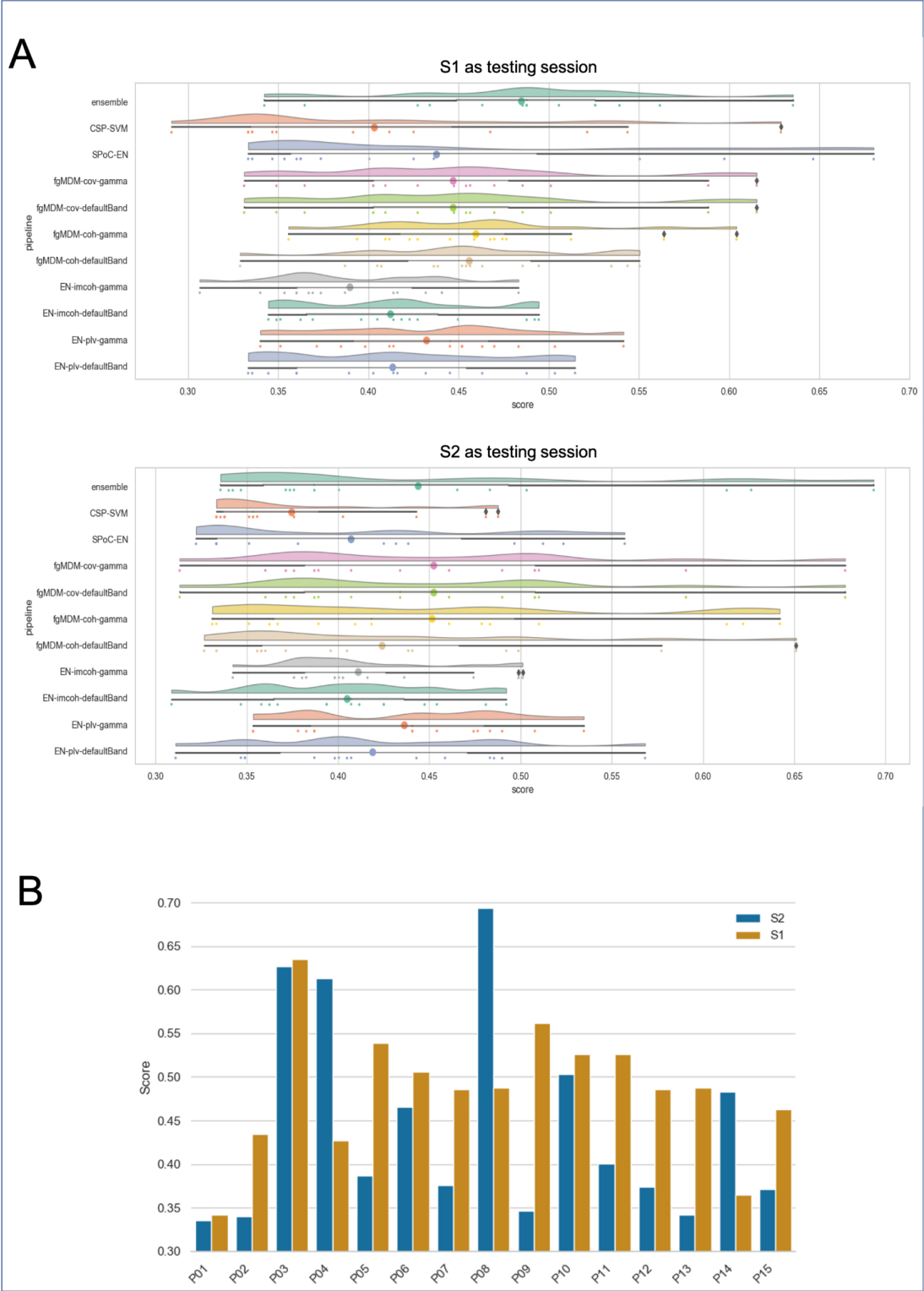


Fig. 2: Results obtained from the first two sessions. (A) Group-level results associated with all the tested classifiers. On the top, we classified the data from S1 by considering data from S2 as a training set. On the bottom, data from S2 were classified by considering S1 as the training set. (B) Individual-level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

References

1. Roy, R. N., Bonnet, S., Charbonnier, S. & Campagne, A. Mental fatigue and working memory load estimation: Interaction and implications for EEG-based passive BCI. in *IEEE EMBC* 6607–6610 (2013).
2. Aricò, P., Borghini, G., Flumeri, G. D., Sciaraffa, N. & Babiloni, F. Passive BCI beyond the lab: current trends and future directions. *Physiol. Meas.* **39**, 08TR02 (2018).
3. Yger, F., Berar, M. & Lotte, F. Riemannian Approaches in Brain-Computer Interfaces: A Review. *IEEE TNSRE* **25**, 1753–1762 (2017).
4. Congedo, M., Barachant, A. & Bhatia, R. Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review. *Brain-Computer Interfaces* **4**, 155–174 (2017).
5. Appriou, A., Cichocki, A. & Lotte, F. Modern Machine-Learning Algorithms: For Classifying Cognitive and Affective States From Electroencephalography Signals. *IEEE Systems, Man, and Cybernetics Magazine* **6**, 29–38 (2020).
6. Corsi, M.-C., Yger, F., Chevallier, S. & Noûs, C. Riemannian Geometry on Connectivity for Clinical BCI. in *IEEE ICASSP* 980–984 (2021).
7. De Vico Fallani, F., Richiardi, J., Chavez, M. & Achard, S. Graph analysis of functional brain networks: practical issues in translational neuroscience. *Philos Trans R Soc Lond B Biol Sci* **369**, (2014).
8. Gonzalez-Astudillo, J., Cattai, T., Bassignana, G., Corsi, M.-C. & De Vico Fallani, F. Network-based brain computer interfaces: principles and applications. *J. Neural Eng.* (2020)
9. Lachaux, J.-P., Rodriguez, E., Martinerie, J. & Varela, F. J. Measuring phase synchrony in brain signals. *Human Brain Mapping* **8**, 194–208 (1999).