Riemannian Geometry on Connectivity for Clinical BCI

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Riemannian geometry on connectivity for clinical BCI – RIGOLETTO

A participation to the IEEE WCCI BCI Clinical Challenge

#1374

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Controlling a brain-computer interface (BCI) requires time to achieve high performance [1]. Despite its clinical applications, one of the main drawbacks is the high inter-subject variability that could be noticed for performance. This is sometimes referred in the literature as the « BCI inefficiency » phenomenon [2] and affects its usability. Among the approaches adopted to tackle these issues are the search for neuromarkers, that potentially capture better the neurophysiological mechanisms underlying the BCI performance and the optimization of the classification pipelines, that could be robust enough to be applied to any subject.

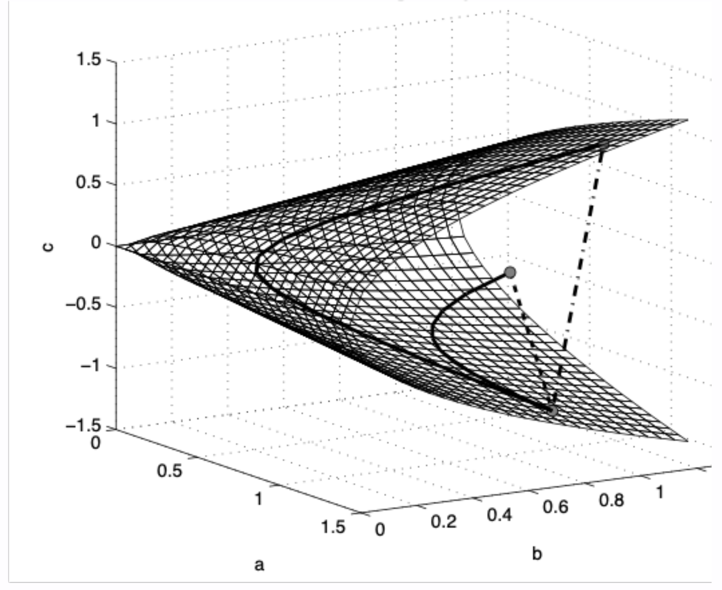
In this work, we proposed an original approach that combines functional connectivity estimators, Riemannian geometry and ensemble learning to ensure a robust classification. This methods was ranked First in the Clinical BCI Challenge-WCCI (within-subject category).

Riemannian geometry

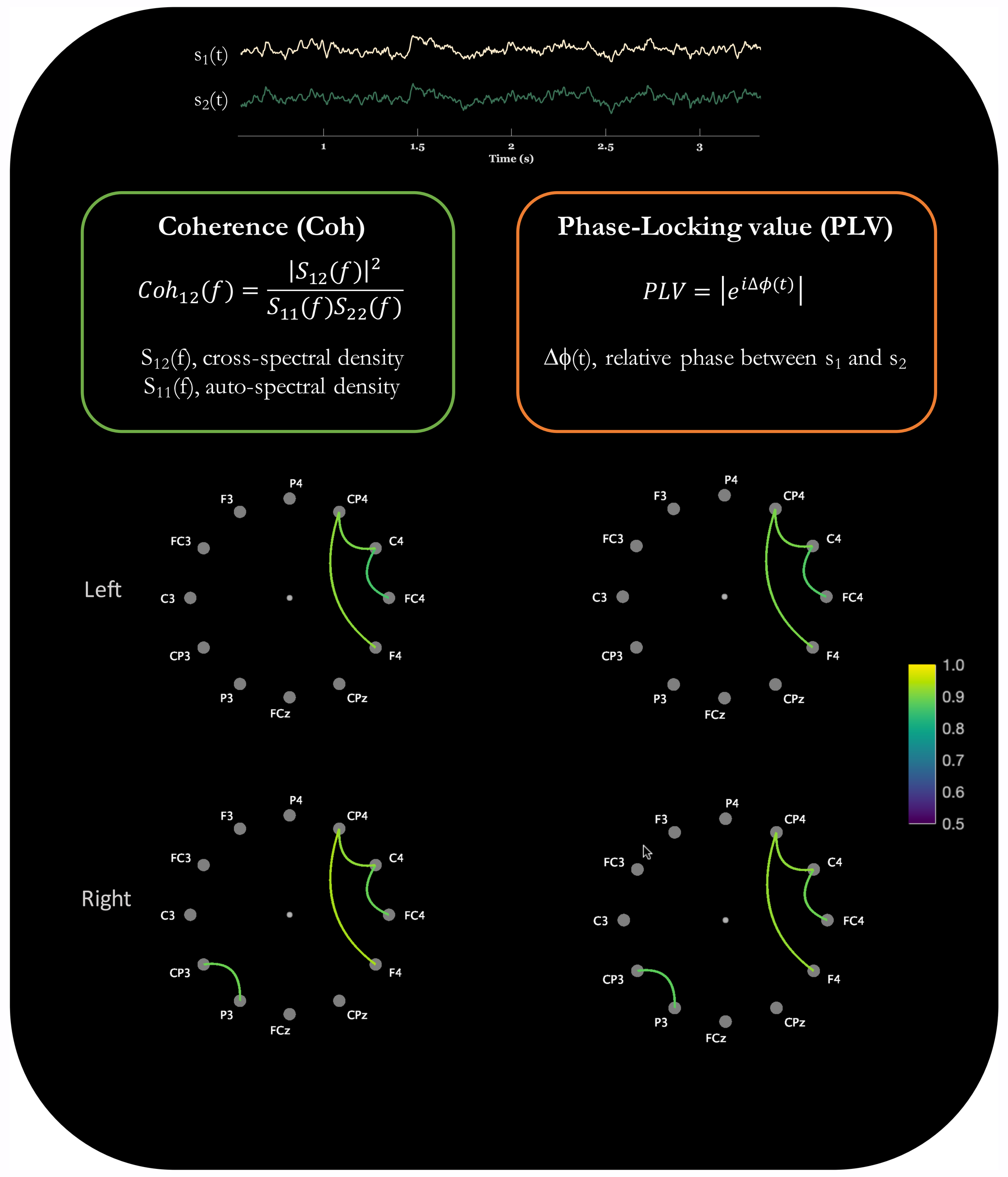
The diffusion of Riemannian geometry for motor imagery BCI has strongly increased in the past decade [3]. This method consists in the extraction of Symmetric Positive Definite (SPD) matrices, usually the covariance matrices among sensors, for each trial and in considering this as a curved space.

Here, to estimate the distance between two matrices A & B, we used the LogEuclidean distance via the Froebenius norm:

$$\delta_{LE}(A,B) = \|\log(A) - \log(B)\|_{\mathfrak{F}}$$



Functional connectivity



Two main estimates were computed within the alpha-beta frequency band (8-30Hz): the coherence (Coh) and the phase-locking value (PLV).

We also computed two other FC estimates: the amplitude envelope correlation (AEC) and the imaginary coherence (ICoh). For the sake of completeness, we report the results of AEC and ICoh although those features were not used in the final submission.

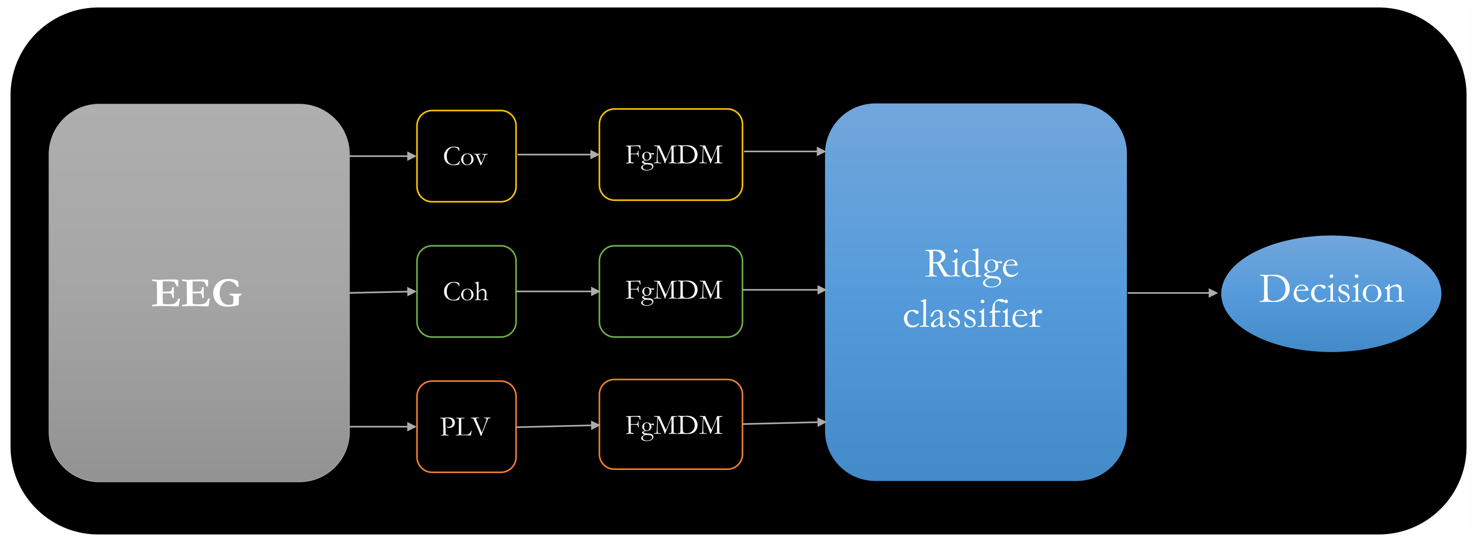
For an illustrative purpose, we represented the values obtained by averaging the FC estimators in each task separately in data obtained from one patient.

IEEE WCCI BCI Competition dataset

Item	Information
Participants	8 stroke patients
EEG dataset	12-channel montage
	Sampling rate 512Hz
	Left vs Right motor imagery
Tasks	Each trial lasts 8s
	MI task: 3-8s
Training/Testing set	80/40 trials

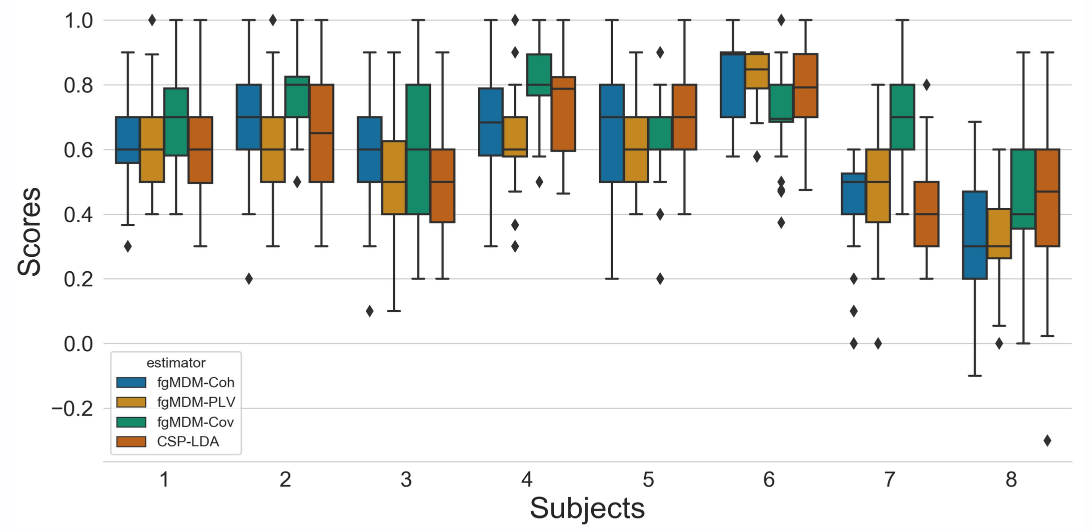
Ensemble classifier

Spatial covariance (Cov), coherence (Coh) and phase-locking value (PLV) are estimated from electroencephalographic (EEG) signals. A first level of classification was performed by FgMDM classifiers that yielded output decision probabilities to train a second level classifier, a ridge regression classifier, that provided the final decision. The associated code is available at https://github.com/sylvchev/wcci-rgcon.

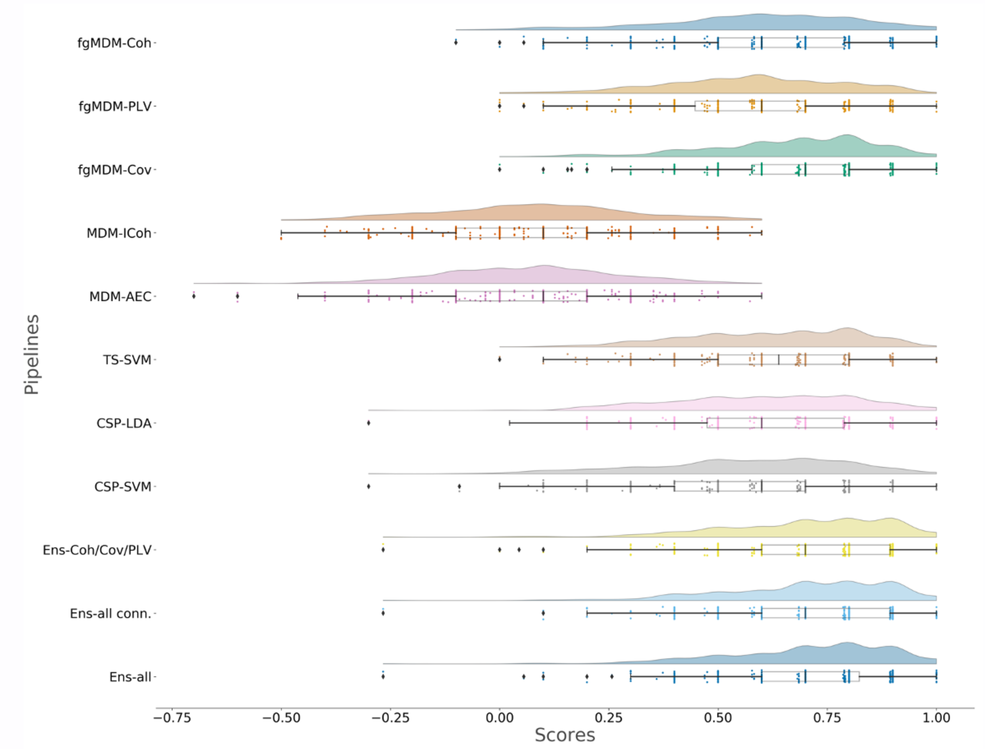


Proof of concept

To assess the performance of our approach we conducted a comparison of the estimators both at the individual and at the group level. For that purpose, we directly applied our approach to an EEG dataset obtained from 8 stroke patients, in the frame of the IEEE WCCI Clinical BCI Challenge.



There were 14 submissions to the competition from 12 different institutions around the world across 9 different countries spread across 3 continents.



Our approach got the first position on this task with a substantial margin, the following teams having respectively kappa scores of 0.49 and 0.47 and accuracies of 74.69% and 73.75%.

The kappa score obtained on validation is close to 0.68 and to the value obtained on training data with a 5-fold cross-validation. Our hypothesis is that this result is due to the robustness provided by a classification based on multiple sources.

Using FC estimators associated with an ensemble classifier gives the possibility to take into account the users' specificity. After participating to the competition, we identified different approaches to improve our method. Further investigation should be done regarding the follow-up to the MDM and the dimensionality reduction.. We plan to refine the selection of the frequency band of interest. Another promising lead would be to extract for each epoch several PSD matrices, each on a different frequency band, and to consider this set as a trajectory on the manifold.

References

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