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Empirical evaluation on multiple BCI datasets of the functional connectivity ensemble (FUCONE) method

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Introduction - Mastering Brain-Computer Interface (BCI) control via a voluntary modulation of the cerebral activity remains a learned skill that around 30 % of BCI users cannot develop control after completing a training program. Among the approaches adopted to circumvent this limitation is the design of more sophisticated classification algorithms to better discriminate the subjects' mental state [1]. Riemannian geometry-based methods are now the gold standard by notably improving the robustness of the performance [2]. One could consider the subjects' specificity by using alternative features that reflect the interconnected nature of brain activity. Functional Connectivity (FC), estimating the interaction between different brain areas, is a promising tool for BCI [3] relevant to discriminate subjects' mental states [4] and to study brain network reorganization underlying MI-based BCI training [5].

Material, Methods and Results - In this study, we propose a new framework that consists in combining functional connectivity estimators (namely Instantaneous and Imaginary coherences), Riemannian geometry, and ensemble learning. We compared our approach to the state-of-the-art methods (namely two pipelines relying on the use of the common spatial patterns [6], [7]; and a third one based on a purely riemannian method [8]). To assess the robustness and the replicability of our approach, we tested it through a large number of subjects, datasets, and motor imagery tasks. For a complete description of the pipeline[1] and the datasets used in the replicability study one can refer to [6].

Results - FUCONE performed significantly better than all state-of-the-art methods in a meta-analysis that aggregated results across datasets. In the case of the classification of 2 classes (right hand vs feet), for four over five datasets, FUCONE showed the bests results in terms of average accuracy from 0.82 to 0.91, and variability from +/-0.08 to +/-0.14 (see Figure 1). The performance gain is mostly imputable to the increased robustness of the ensemble classifier with respect to the inter- and intrasubject variability.

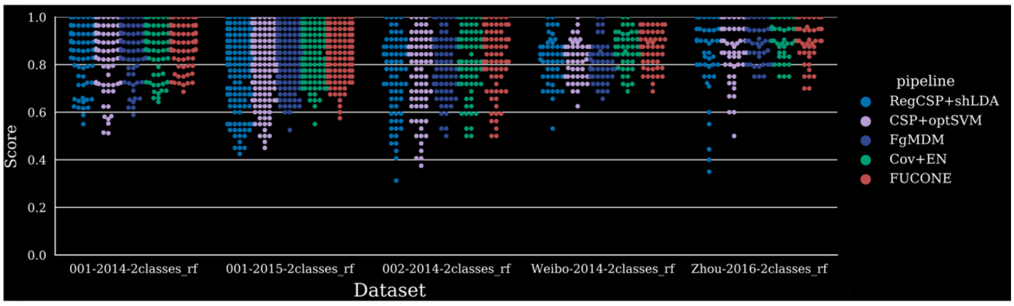

Figure 1 Replicability assessments and comparison with state-of-the-art pipelines. Analysis performed with 3-class (left hand vs right hand) datasets.

Discussion - Even though our approach enabled a reliable improvement of the BCI accuracy, we still observed an important inter-subject variability. Several elements can explain it: the strong diversity in terms of MI tasks and of the number of channels considered without preprocessing, and the variety in the possible ways to detect neurophysiological properties underlying the MI performance. Preliminary results in the source space, relevant to provide a description of the mechanisms underlying the control of a BCI, tend to demonstrate an improvement of the performance and a reduction of the inter-subject variability of our approach with respect to the state-of-the-art methods.

Significance: Our results offer new insights into the need to consider the interconnected nature of brain functioning to improve the BCI performance.

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[1] The code used to perform the analysis are publicly available in this Github repository: https://github.com/mccorsi/FUCONE.git