Holographic EEG: multi-view deep learning for BCI

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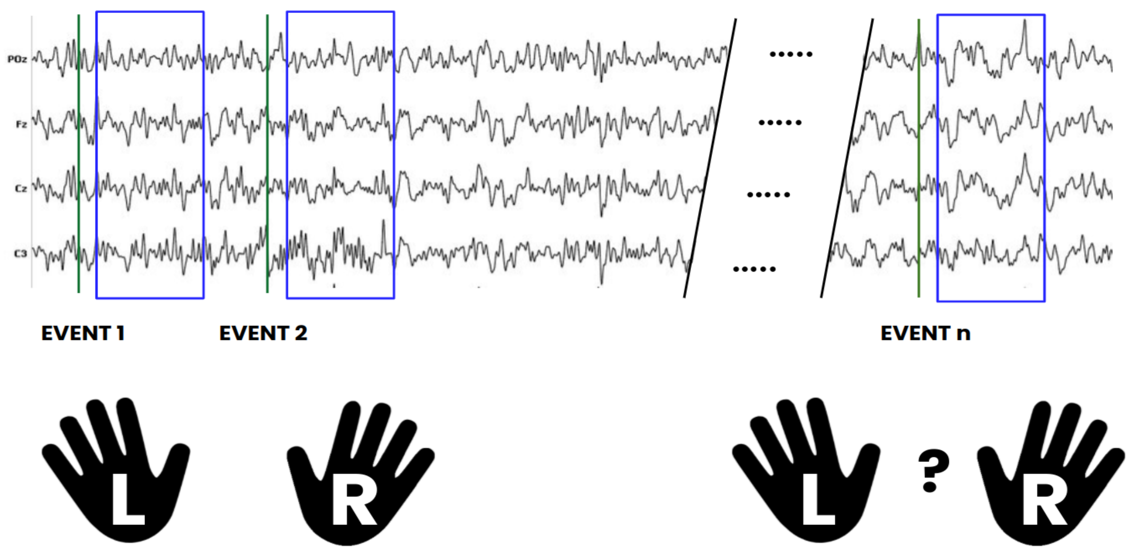
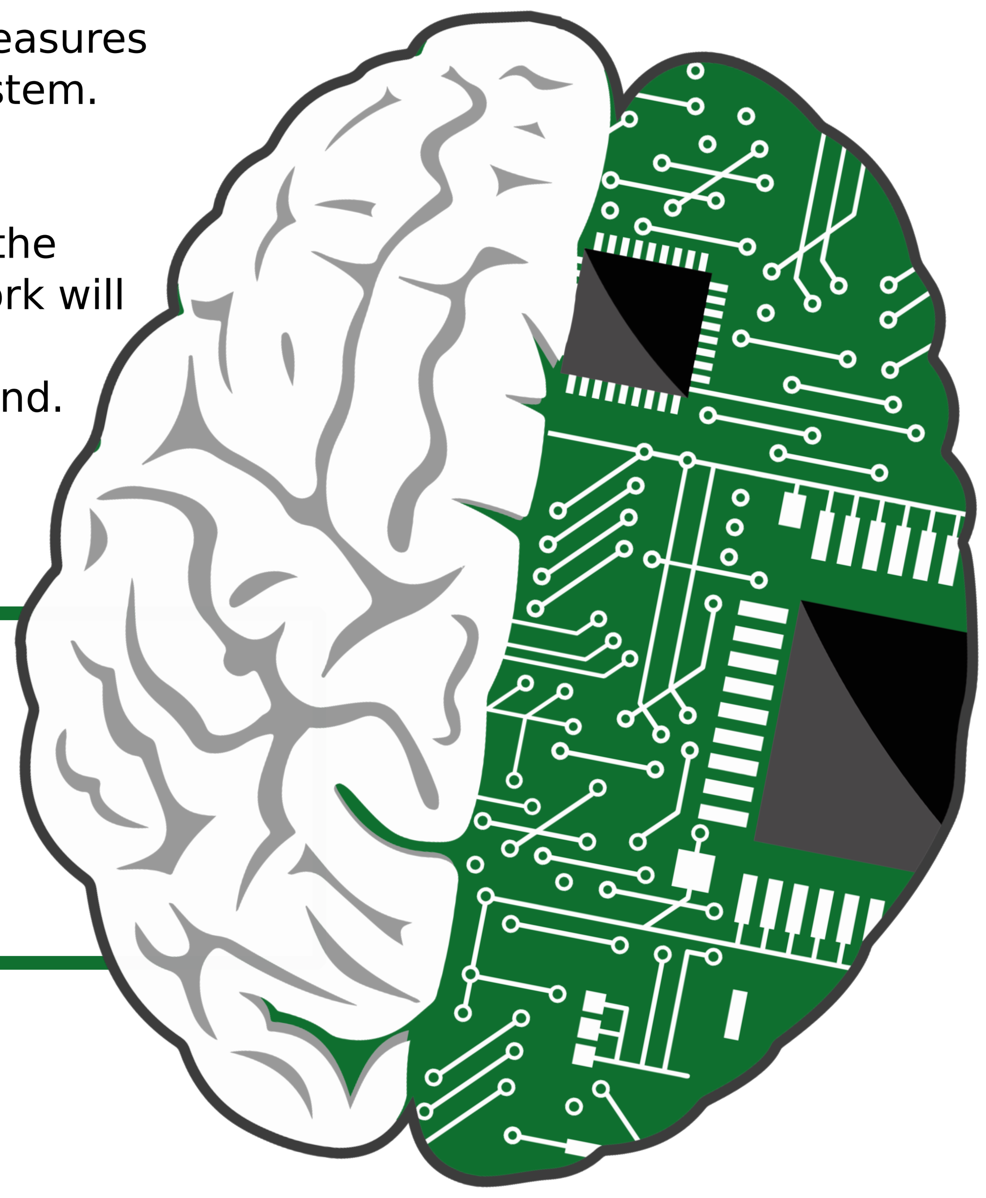
A b s t r a c t



Brain Computer Interfaces or **BCI** can be defined as a technology that measures brain activity and translates that activity into instructions for a digital system. We will focus on **non-invasive (EEG)-based BCI (BCI-EEG)**.

Let us consider a typical EEG signal after preprocessing. In the figure on the left, we show an EEG signal measured with 4 different electrodes. Our work will be focused on **Motor Imagery (MI) BCI**, so we want to understand if the subject, for example, is thinking about moving the left or the right hand.



Can we exploit multiple features to learn inherent SPD representations of the EEG data in a self-supervised manner, to later improve cross-subject classification ?

METHODS: Holographic-EEG

Stardard Riemann approach [1]:
Extract sample spatial covariances which are Symmetric Positive Definite (SPD) matrices and classify them using Minimum Distance to Mean (MDM) or classical machine learning procedure on the tangent space (SVM, LDA, ...)

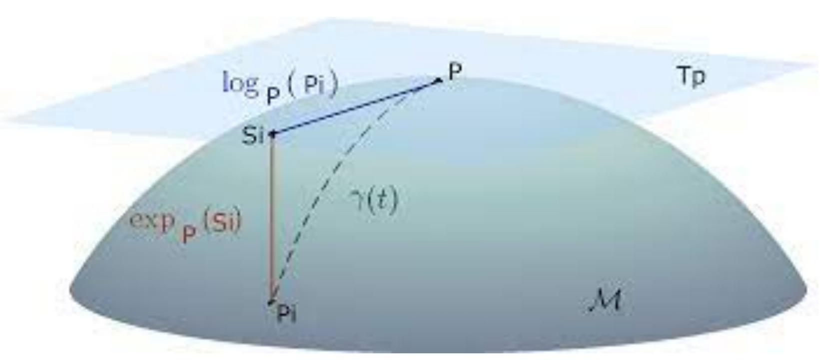
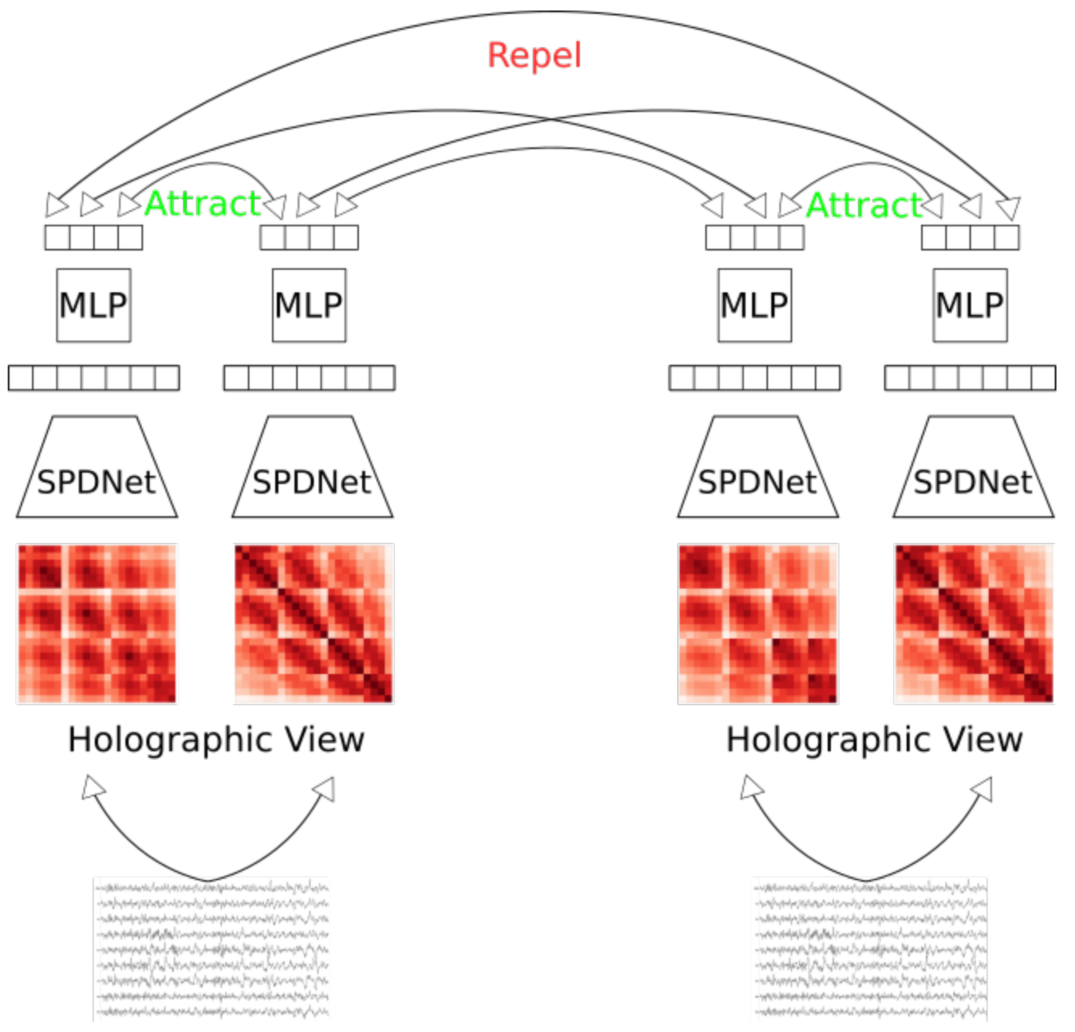


Figure extracted from [1]

From the EEG signal, we can extract different SPD matrices:
- Spatial covariance (as in the standard case).
- Augmented Covariance [2]
- Coherence [3]

Inspired by recent advances in Computer Vision [4], we want to use these different matrices in a **semi self-supervised contrastive framework**.

The idea is to **adjust the weights of the different SPDNet** [5] **Deep Learning networks in the architecture** (on the right) **so that the different SPD representations for a same data sample are pushed closer (maximizing the Mutual Information) while those of different samples are pushed apart.**



Use of **NT-Xent Contrastive Loss** [4]

$$\mathcal{L}^{\text{self}} = -\sum_{i\in I} \log \frac{\exp(z_i \cdot z_{j(i)}/\tau)}{\sum_{a\in A(i)} \exp(z_i \cdot z_a/\tau)}$$

We use the SPDNet architecture [5] instead of classical Convolutional Networks because we work with SPD matrices. Similarly, we are using the RiemannAdam optimizer [6] (instead of the standard Adam algorithm) because we need to constrain the weights in the BiMap layers to be on the SPD Riemannian manifold.

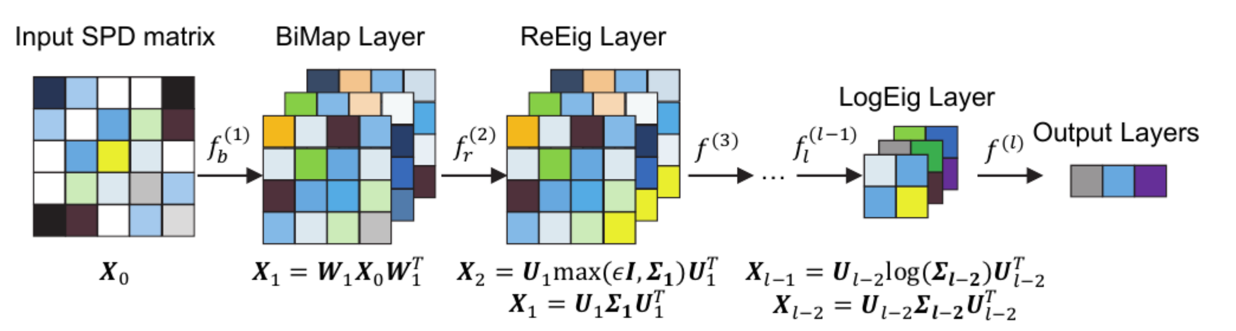
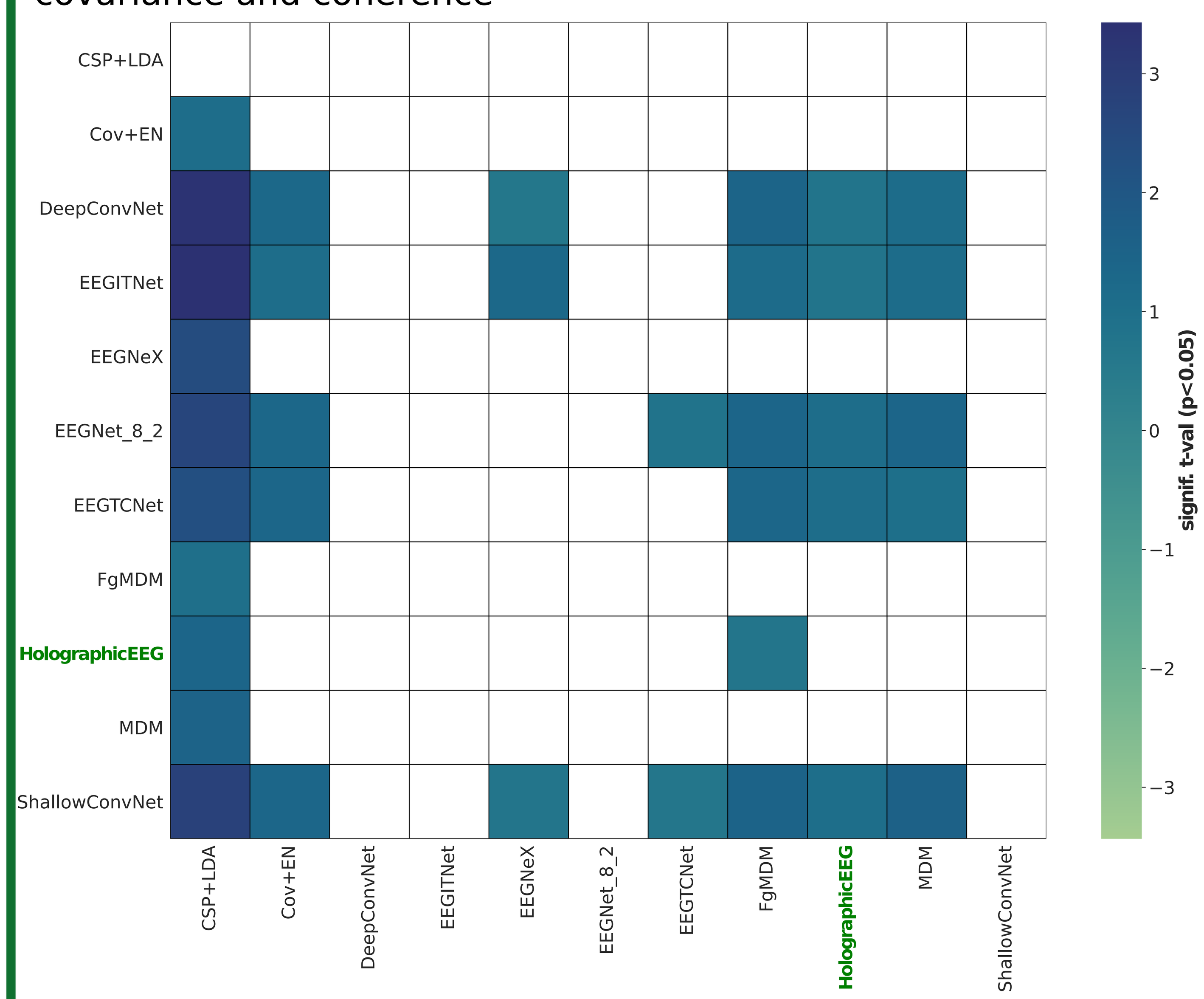


Figure extracted from [5]

The self-supervized learnt SPDNets are then used in a classification network which classification layer is trained for a specific task using a small labelled training set.

RESULTS

In order to test our approach and to increase the reliability of our results, we use the **MOABB framework** [7].
Results are preliminary and are tested only on **BNCI2014001 dataset** on task **right hand vs left hand** in a **cross subject evaluation. We compare the results against the state of the art algorithms [8]**. In this experiment, we use only spatial covariance and coherence



The state of the art algorithm use all labelled data to train the algorithm. Our self supervised **HolograpichEEG use only 20%** of the training labelled data.
No statistical differences between HolograpichEEG and other non deep learning ML algorithms can be seen. In some cases, our method is superior (CSP+LDA, FgMDM). DL architectures in general outperform HolograpichEEG (but with a 5 times bigger training set).

TAKE HOME MESSAGE

Contrastive learning can be used to **learn meaningful representations of EEG signals from different subjects**. Further research is required to fully explore the potential of self-supervised contrastive learning and really improve over the state of the art in EEG-BCI.

SCAN ME

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