



**HAL**  
open science

# Toward everyday BCI: Augmented Covariance Method in a reduced dataset settings

Igor Carrara, Théodore Papadopoulo

► **To cite this version:**

Igor Carrara, Théodore Papadopoulo. Toward everyday BCI: Augmented Covariance Method in a reduced dataset settings. Neuromod Meeting 2023, Jun 2023, Antibes, France. hal-04161475

**HAL Id: hal-04161475**

**<https://hal.science/hal-04161475>**

Submitted on 13 Jul 2023

**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.

# Toward everyday BCI:

## Augmented Covariance Method in a reduced dataset settings

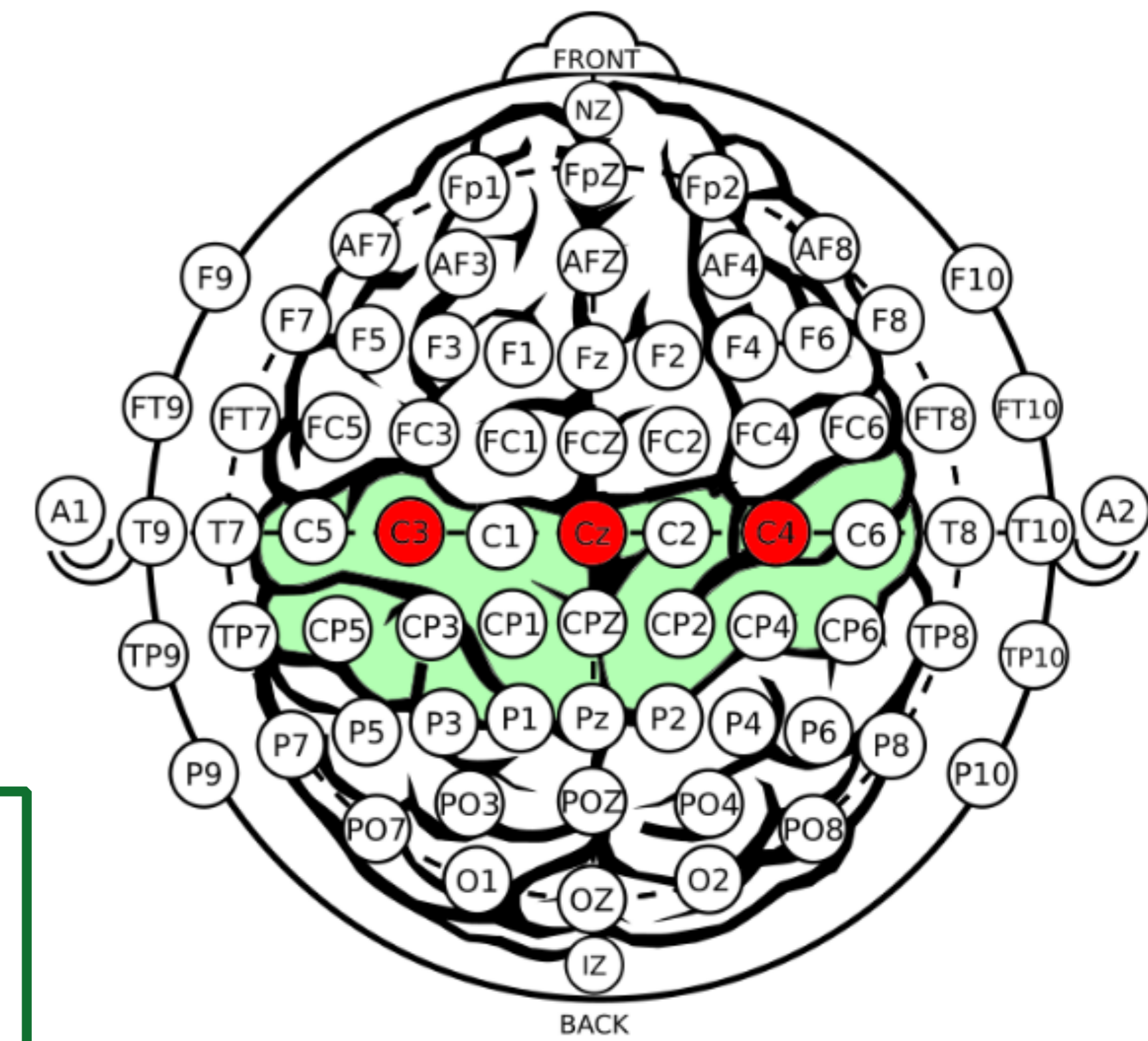
I. Carrara<sup>1,2\*</sup>, T. Papadopoulo<sup>1, 2</sup>

<sup>1</sup>Université Côte d'Azur (UCA), Nice, France, <sup>2</sup>Inria Centre at Université Côte d'Azur, Sophia Antipolis, France

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

A key goal of BCIs research is to make such devices comfortable and reliable for everyday life, so we need to solve several challenges to enable their widespread use. **As such, it is critical to achieve a high level of performance while reducing the number of electrodes and recuding the training data available.**

In fact having too many electrodes can introduce various problems: increased complexity, higher risk of noise; higher cost, and finally a decrease in the user comfort and longer calibration time. Collecting data can be a time-consuming process, as it involves recruiting participants, setting up the equipment, and ensuring that the data is of high quality.

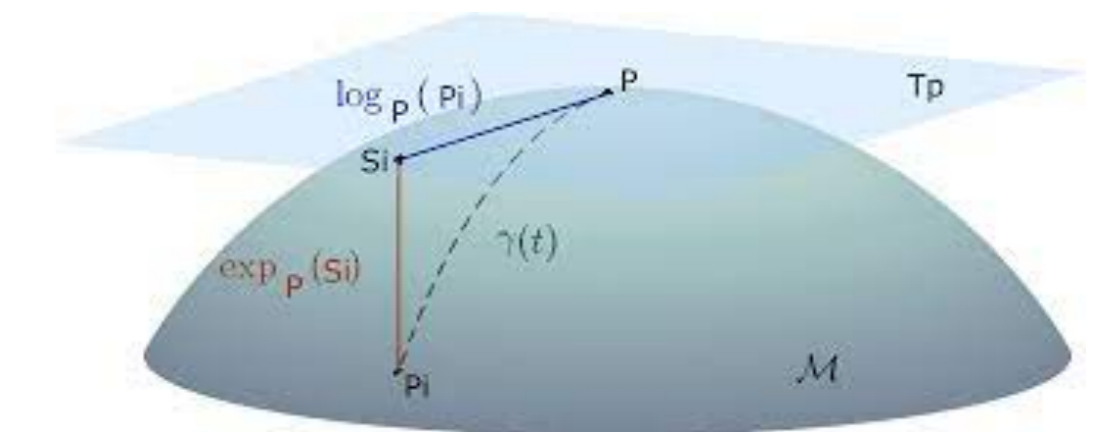


## Augmented Covariance Method (ACM) can improve the performance in a reduced dataset setting?

### METHODS

#### Standard Riemann approach [1]:

Extract sample spatial covariances which are Symmetric Positive Definite (SPD) matrices and classification using Minimum Distance to Mean (MDM) or classical machine learning procedure on the tangent space (SVM, LDA ...)



#### Autoregressive model formulation:

EEG signals can be modeled using an AR model



Sensor Space

$$\mathbf{X}_t = \sum_{i=1}^p \mathbf{A}_i \mathbf{X}_{t-i} + \varepsilon_t$$

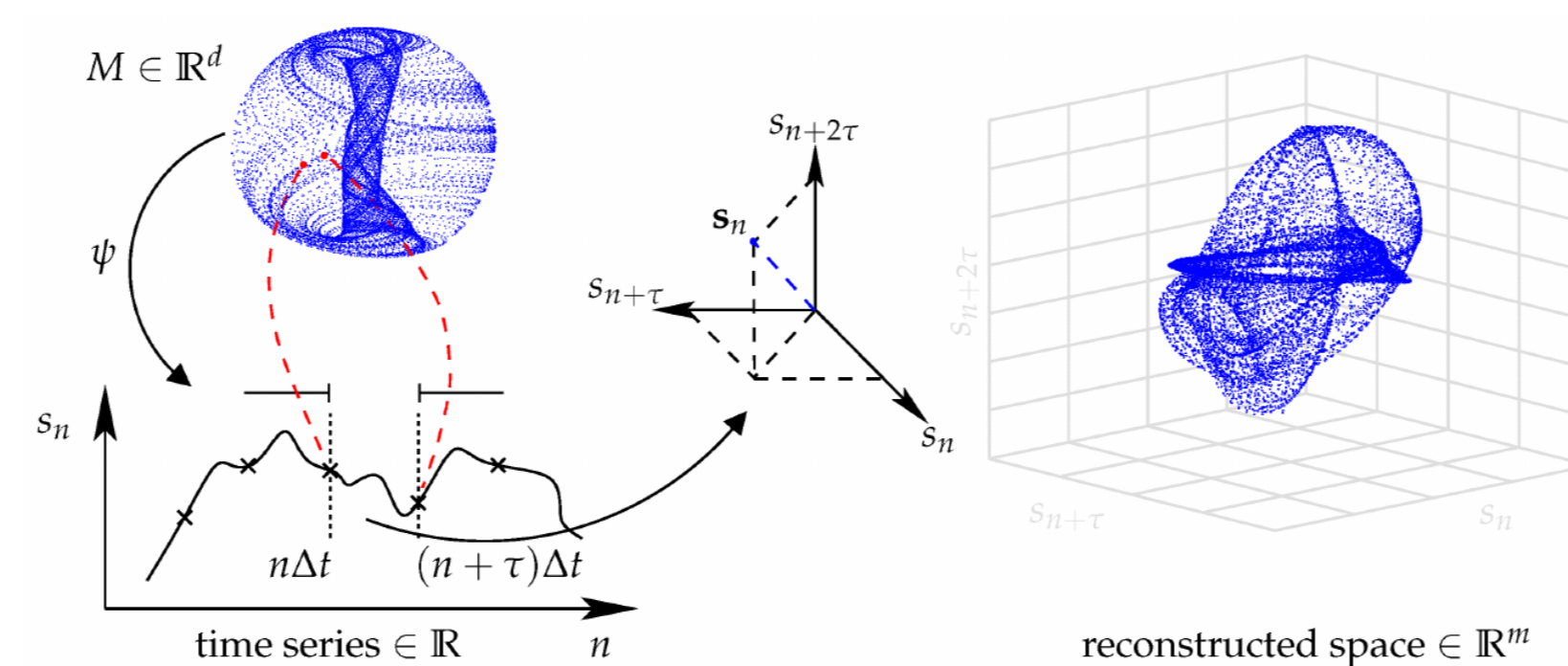
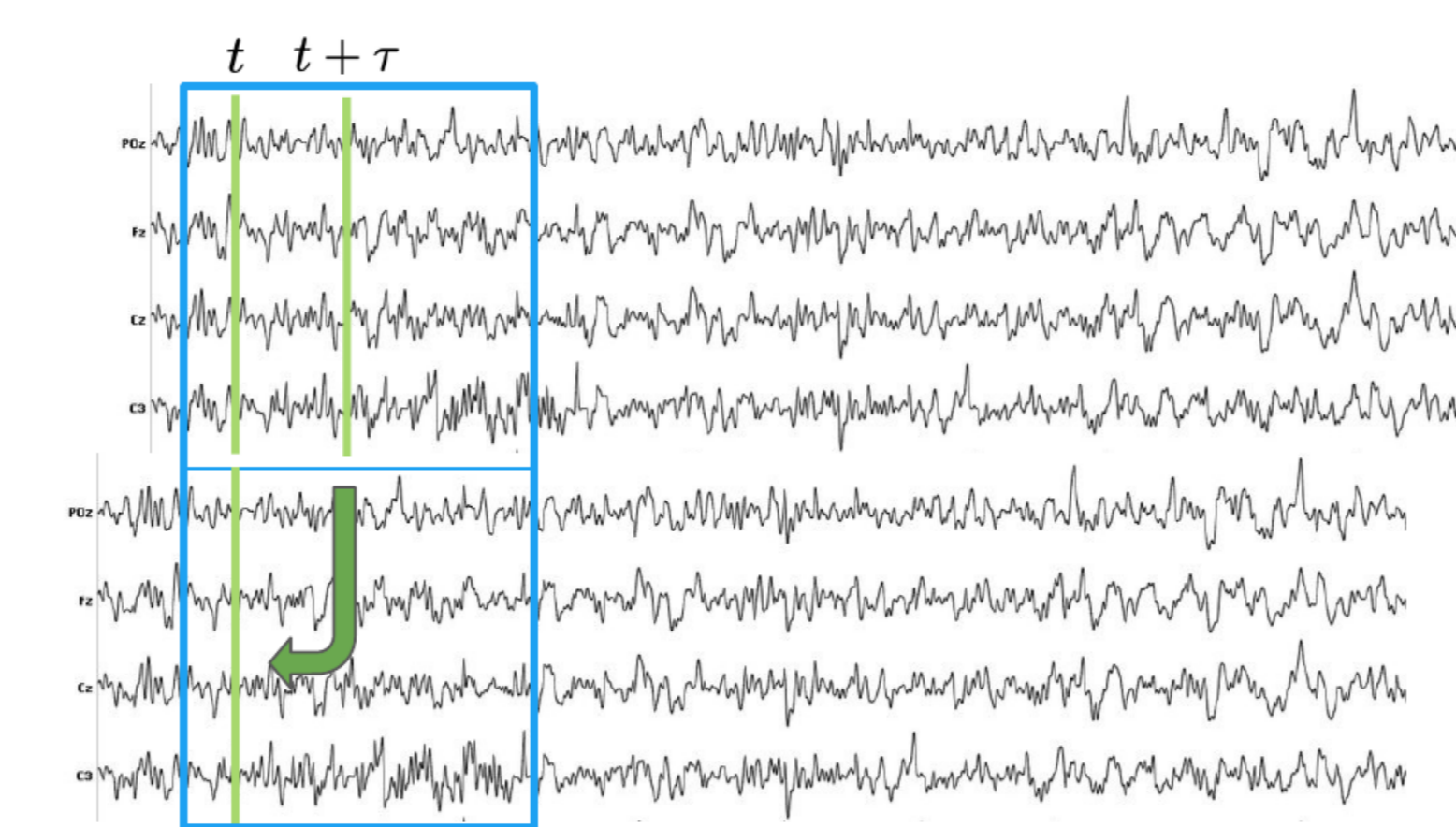
Derive the Yule-Walker equation that in matrix form:

SPD matrix

$$\begin{bmatrix} \Gamma_0 & \Gamma_{-1} & \Gamma_{-2} & \dots \\ \Gamma_1 & \Gamma_0 & \Gamma_{-1} & \dots \\ \Gamma_2 & \Gamma_1 & \Gamma_0 & \dots \\ \vdots & \vdots & \vdots & \ddots \\ \Gamma_{p-1} & \Gamma_{p-2} & \Gamma_{p-3} & \dots \end{bmatrix} \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \\ \mathbf{A}_3 \\ \vdots \\ \mathbf{A}_p \end{bmatrix} = \begin{bmatrix} \Gamma_1 \\ \Gamma_2 \\ \Gamma_3 \\ \vdots \\ \Gamma_p \end{bmatrix}$$

Augmented Covariance Matrix (ACM) [2]

#### Dynamical System Formulation:



#### Takens Theorem[4]

Let  $M$  to be a compact manifold of dimension  $m$ . For pairs  $(\Phi, Y)$ ,  $\Phi : M \rightarrow M$  a smooth diffeomorphism and  $Y : M \rightarrow \mathbb{R}$  a smooth function, it is a generic property that the map  $\varphi_{(\Phi, Y)} : M \rightarrow \mathbb{R}^{2m+1}$ , defined by

$$\varphi_{(\Phi, Y)}(x) = (Y(x), Y(\Phi(x)), \dots, Y(\Phi^{2m}(x)))$$

is an embedding; by "smooth" we mean at least  $C^2$ . We refer to the function  $Y$  as measurement function.

The ACM model [2] defined here depend on **2 hyper-parameters: order of the autoregressive model (p) and delay (tau)**.

To compute such parameters we apply 2 different strategies:

- Grid Search
- Approach based on Takens Theorem [4] (Traditional and Unified).

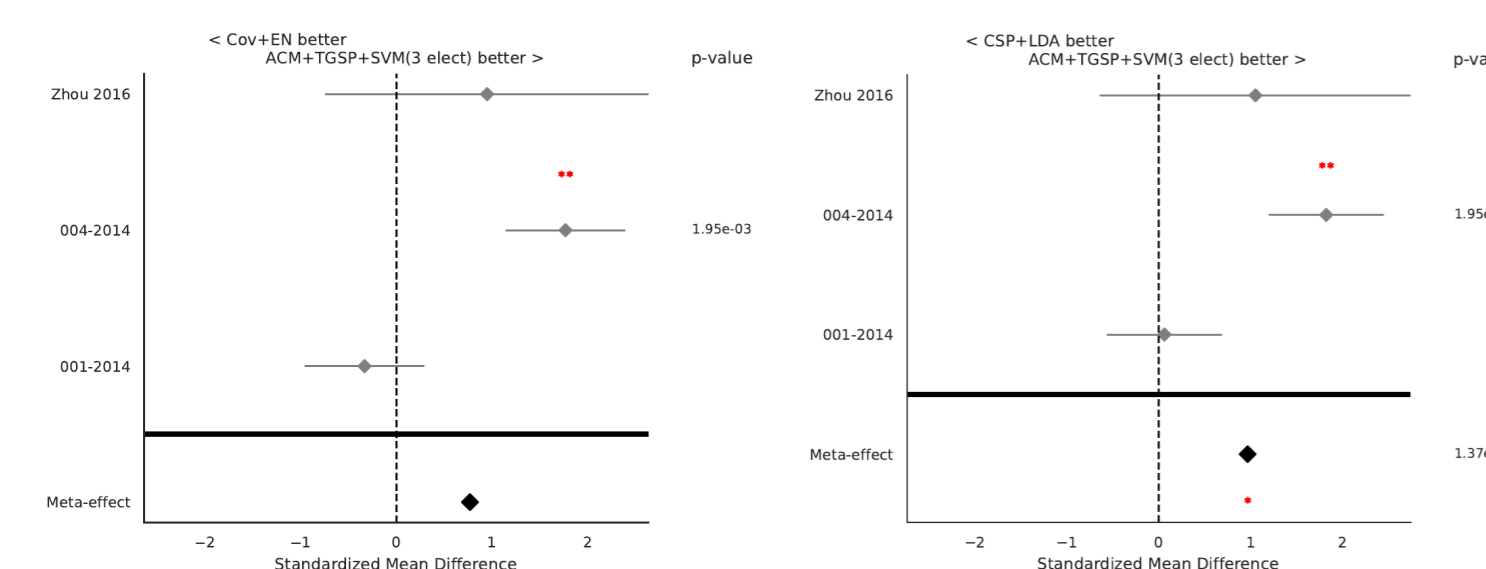
The approach of Grid Search shows better results, while the Takens approaches are more stable and robust regarding different subjects and datasets.

### RESULTS

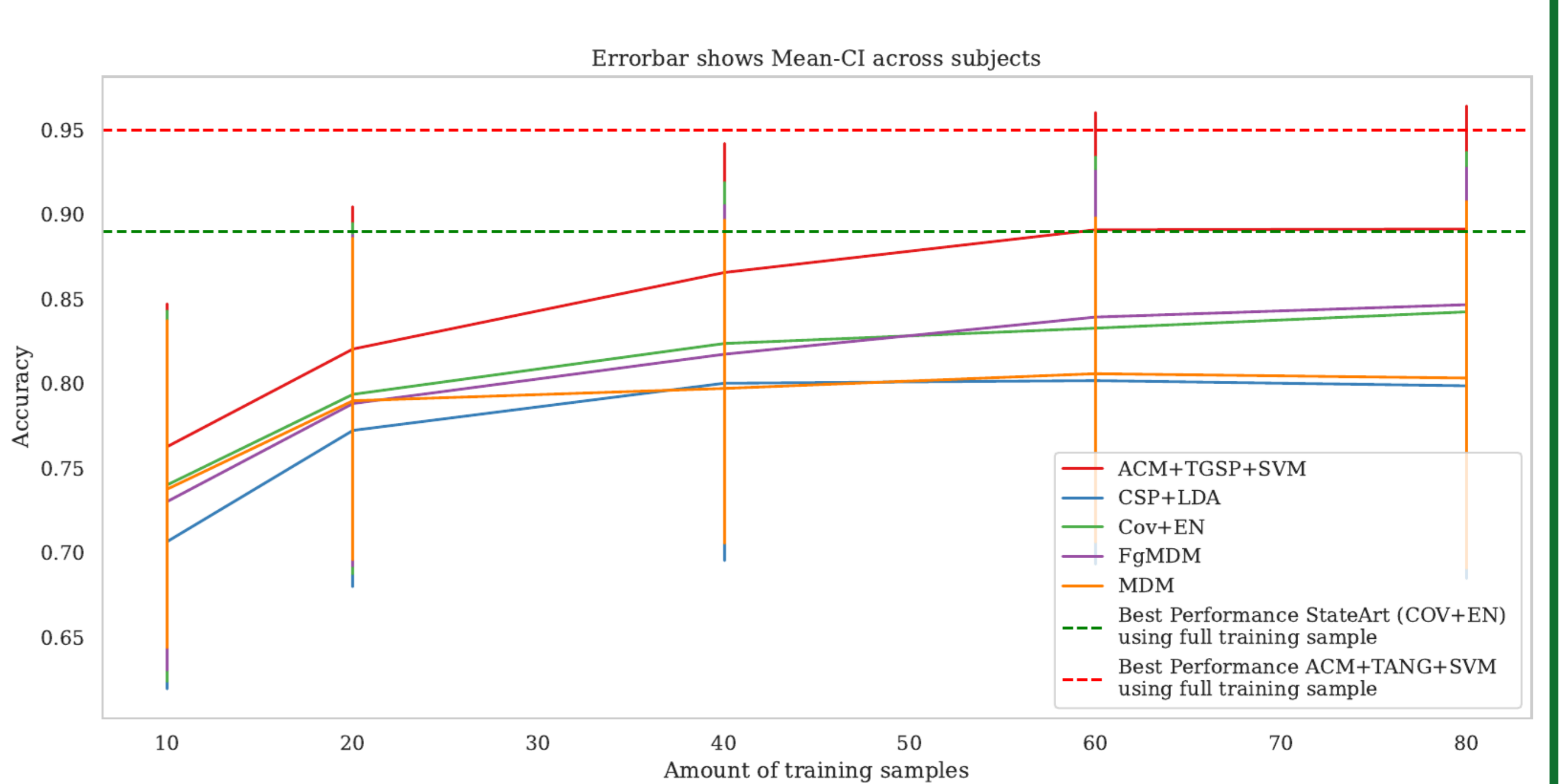
We consider multiple **Motor Imagery BCI dataset** consisting of several subjects for each datasets and several sessions. We test on **different task, different evaluation procedure**. In order to increase the reliability of our approach we use the **MOABB framework [5]**.

#### Reduced Number of Electrodes (C3, C4 and Cz)

| Pipeline              | Eval | BNCI2014001        | BNCI2014004        | Zhou2016           |
|-----------------------|------|--------------------|--------------------|--------------------|
| MDM                   | WS   | 0.76 ± 0.15        | 0.78 ± 0.16        | 0.90 ± 0.05        |
| COV+EN                | WS   | 0.78 ± 0.15        | 0.80 ± 0.15        | 0.93 ± 0.05        |
| FgMDM                 | WS   | 0.77 ± 0.15        | 0.79 ± 0.15        | 0.91 ± 0.05        |
| ACM + TANG + SVM      | WS   | <b>0.86 ± 0.10</b> | <b>0.89 ± 0.11</b> | <b>0.98 ± 0.03</b> |
| CSP + LDA             | WS   | 0.77 ± 0.16        | 0.80 ± 0.15        | 0.91 ± 0.06        |
| ACM + CSP + LDA       | WS   | <b>0.83 ± 0.12</b> | <b>0.85 ± 0.13</b> | <b>0.97 ± 0.02</b> |
| VECTORIZE + LDA       | WS   | 0.73 ± 0.15        | 0.80 ± 0.16        | 0.86 ± 0.08        |
| ACM + VECTORIZE + LDA | WS   | 0.79 ± 0.13        | 0.83 ± 0.15        | 0.92 ± 0.04        |
| MDM                   | CS   | 0.75 ± 0.16        | 0.79 ± 0.15        | 0.90 ± 0.04        |
| COV+EN                | CS   | 0.78 ± 0.14        | 0.81 ± 0.14        | 0.92 ± 0.06        |
| FgMDM                 | CS   | 0.78 ± 0.13        | 0.80 ± 0.14        | 0.91 ± 0.06        |
| ACM + TANG + SVM      | CS   | <b>0.84 ± 0.11</b> | <b>0.86 ± 0.14</b> | <b>0.97 ± 0.02</b> |
| CSP + LDA             | CS   | 0.77 ± 0.15        | 0.81 ± 0.14        | 0.92 ± 0.05        |
| ACM + CSP + LDA       | CS   | 0.81 ± 0.13        | 0.84 ± 0.14        | <b>0.97 ± 0.02</b> |
| VECTORIZE + LDA       | CS   | 0.74 ± 0.14        | 0.79 ± 0.15        | 0.85 ± 0.11        |
| ACM + VECTORIZE + LDA | CS   | 0.80 ± 0.12        | 0.84 ± 0.14        | 0.93 ± 0.03        |



#### Reduced Training Sample (All Electrodes)



### TAKE HOME MESSAGE

The ACM is effective in motor imagery EEG-BCI classification even with a low number of electrodes and reduced training samples.



SCAN ME

**Acknowledgements:** This work has been partially financed by a EUR DS4H/Neuromod fellowship.

- References:**
- [1] Alexandre Barachant et al. "Riemannian geometry applied to BCI classification". In: International conference on latent variable analysis and signal separation. Springer. 2010, pp. 629–636.
  - [2] Carrara Igor, and Théodore Papadopoulo. "Classification of BCI-EEG based on augmented covariance matrix." arXiv preprint arXiv:2302.04508 (2023).
  - [3] Javier de Pedro-Carracedo et al. "Phase space reconstruction from a biological time series: A photoplethysmographic signal case study". In: Applied Sciences 10.4 (2020)
  - [4] Takens, F. (1981). Detecting strange attractors in turbulence. Lect. Notes Math. 898
  - [5] Jayaram, Vinay, and Alexandre Barachant. "MOABB: trustworthy algorithm benchmarking for BCIs." Journal of neural engineering 15.6 (2018): 066011.