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

Igor Carrara, Théodore Papadopoulo

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Toward everyday BCI:

Augmented Covariance Method in a reduced dataset settings

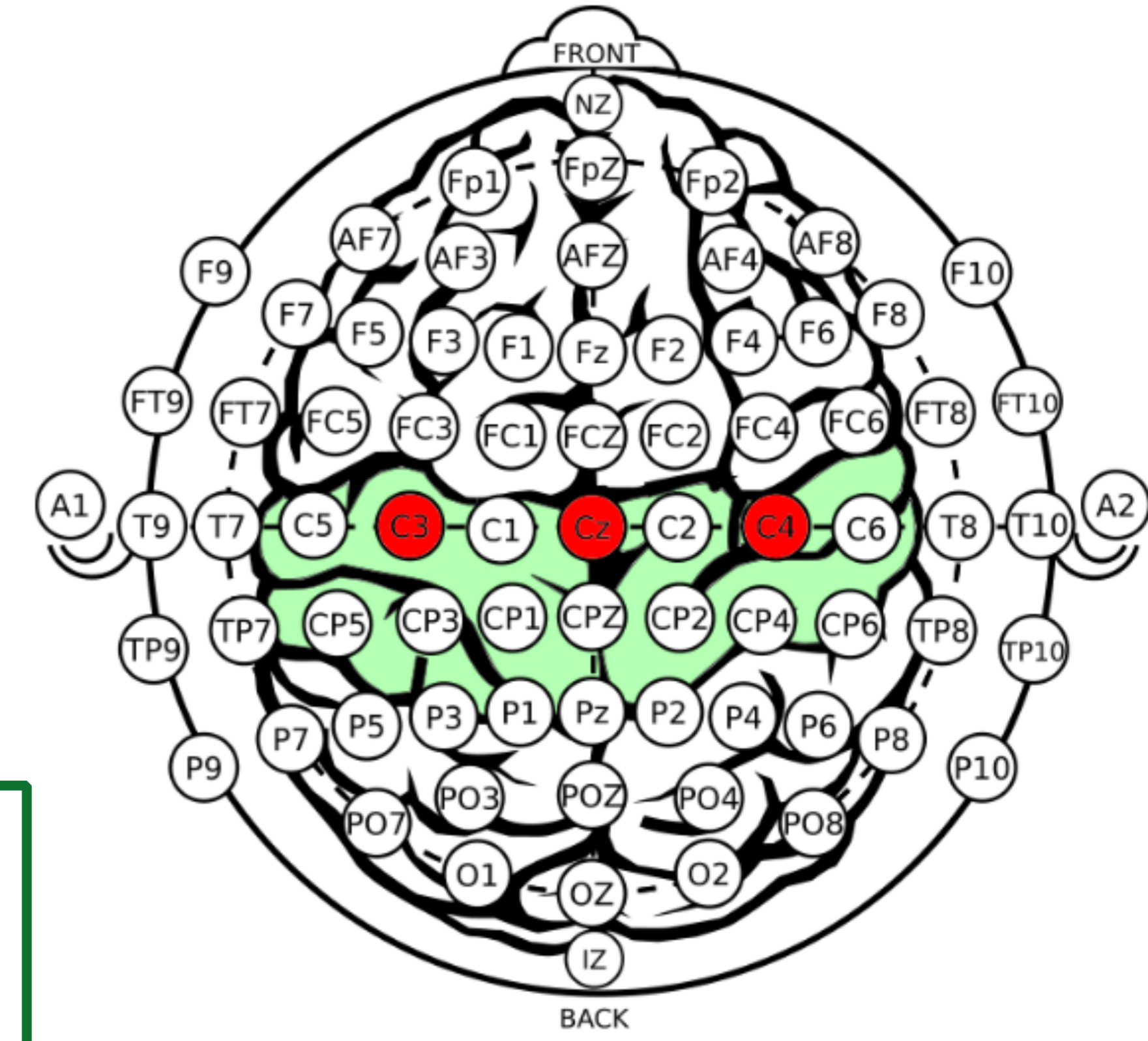
I. Carrara^{1,2*}, T. Papadopoulo^{1,2}

¹Université Côte d'Azur (UCA), Nice, France, ²Inria 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.

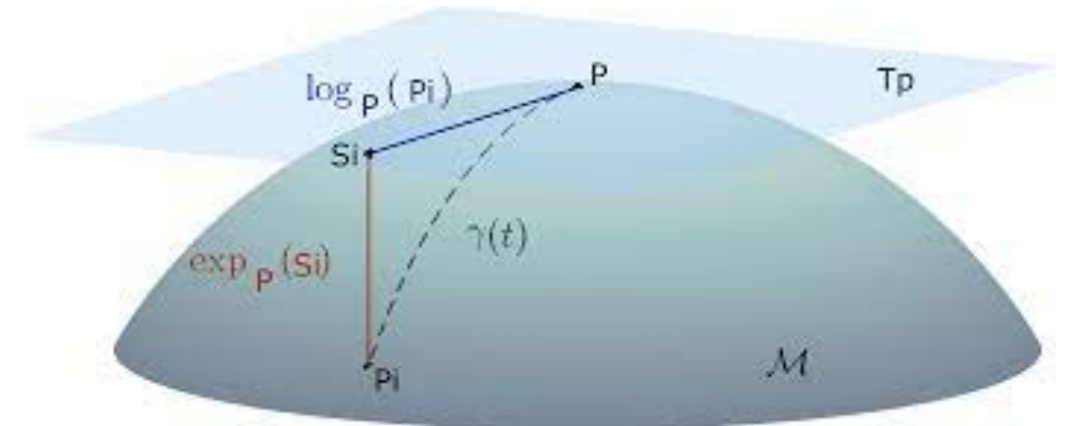


Augmented Covariance Method (ACM) can improve the performance in a reduced dataset setting?

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

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

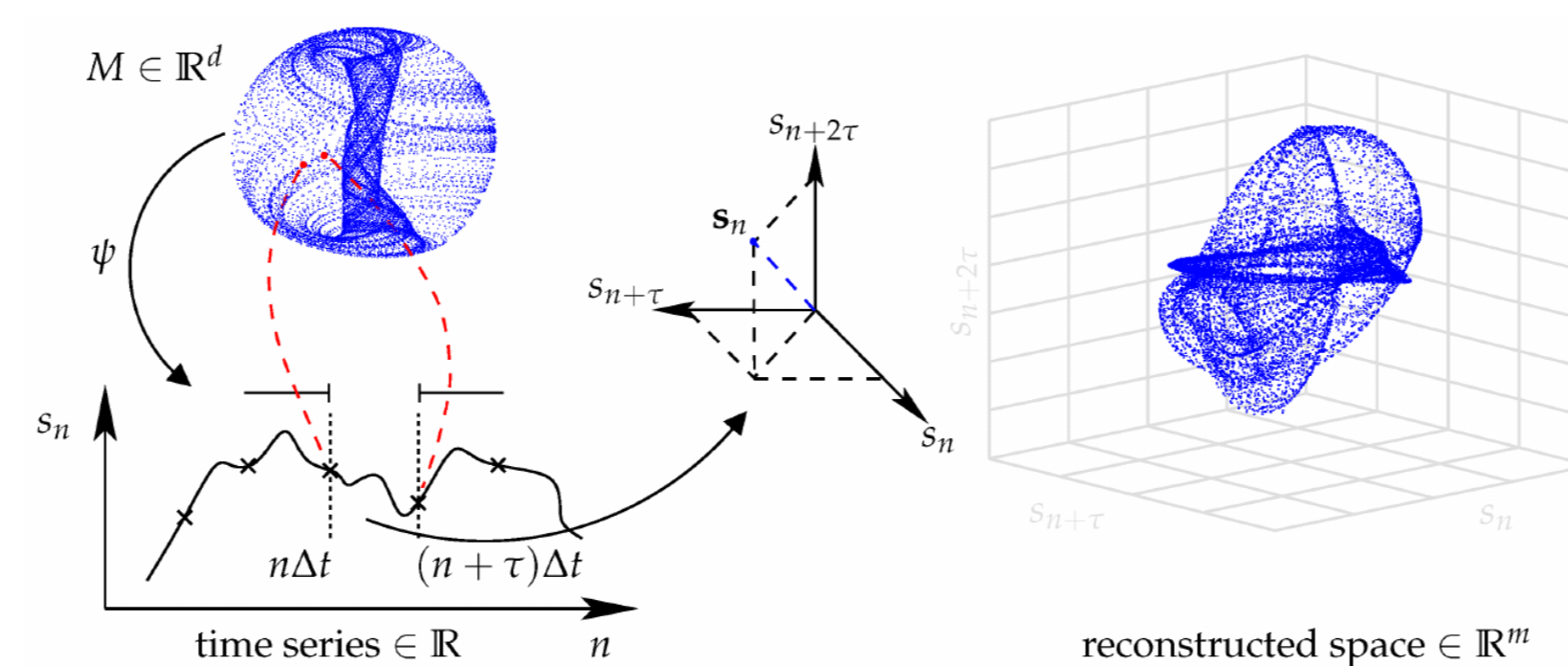
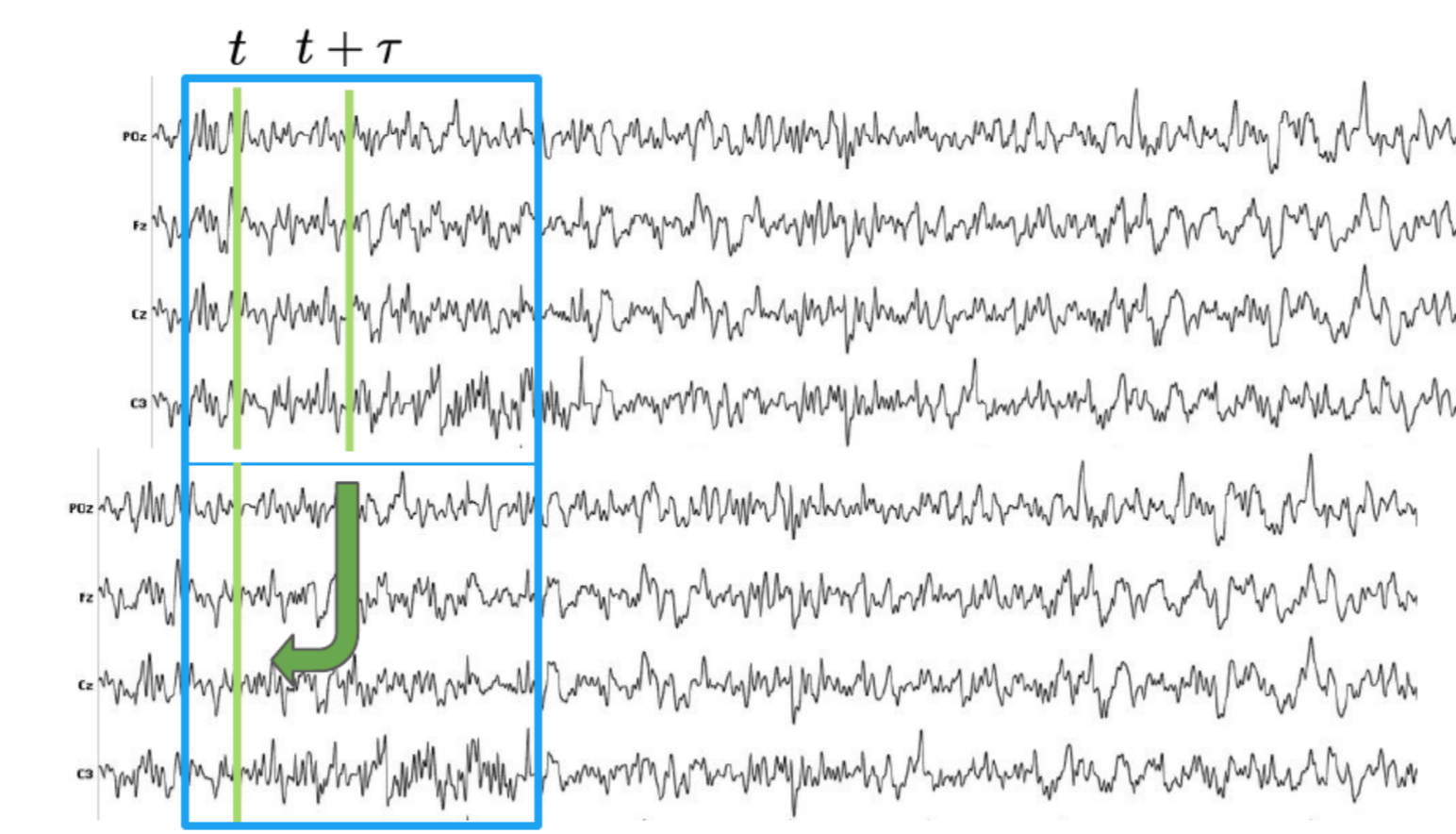
Derive the Yule-Walker equation that in matrix form:

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 (Φ, 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).

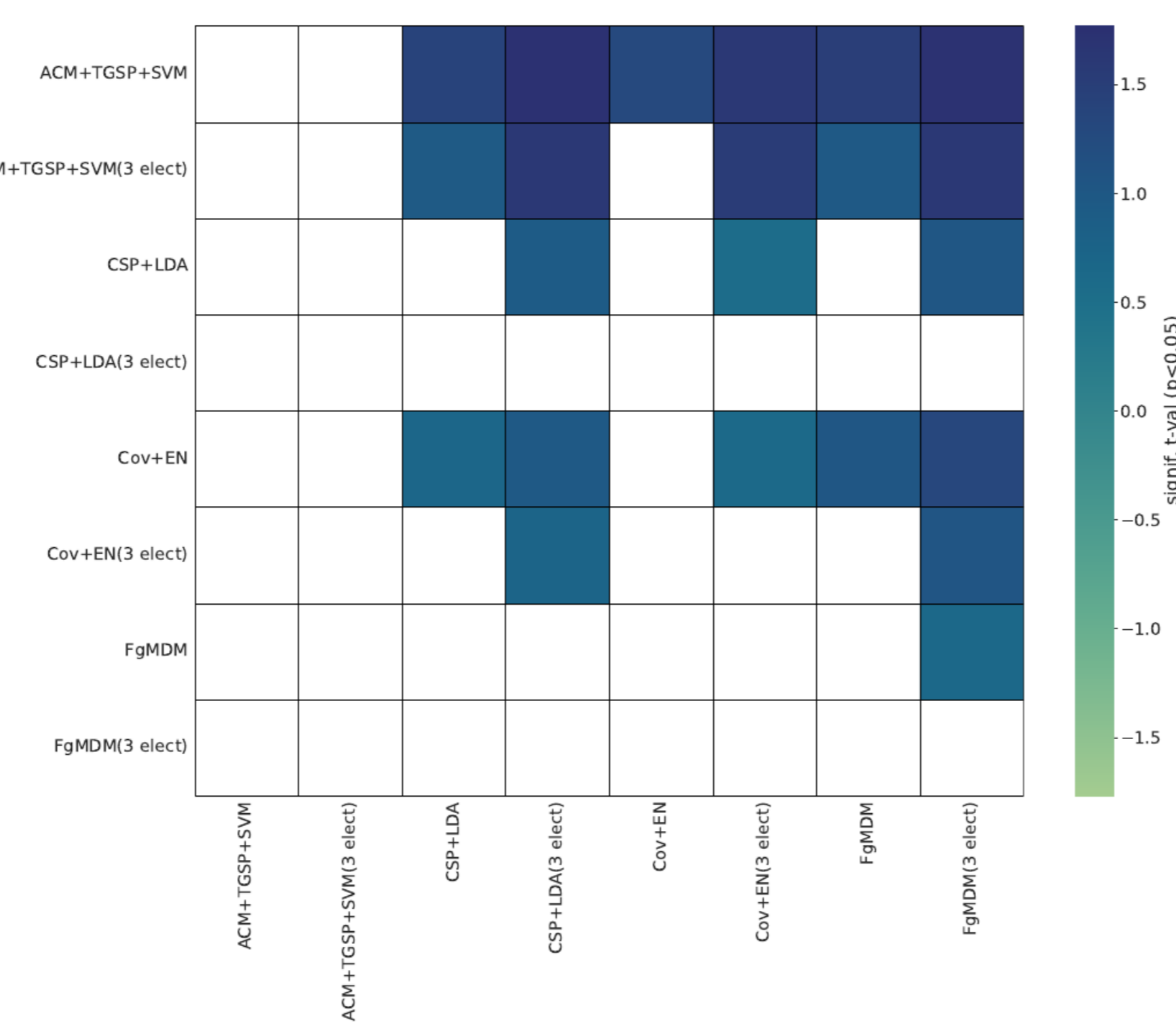
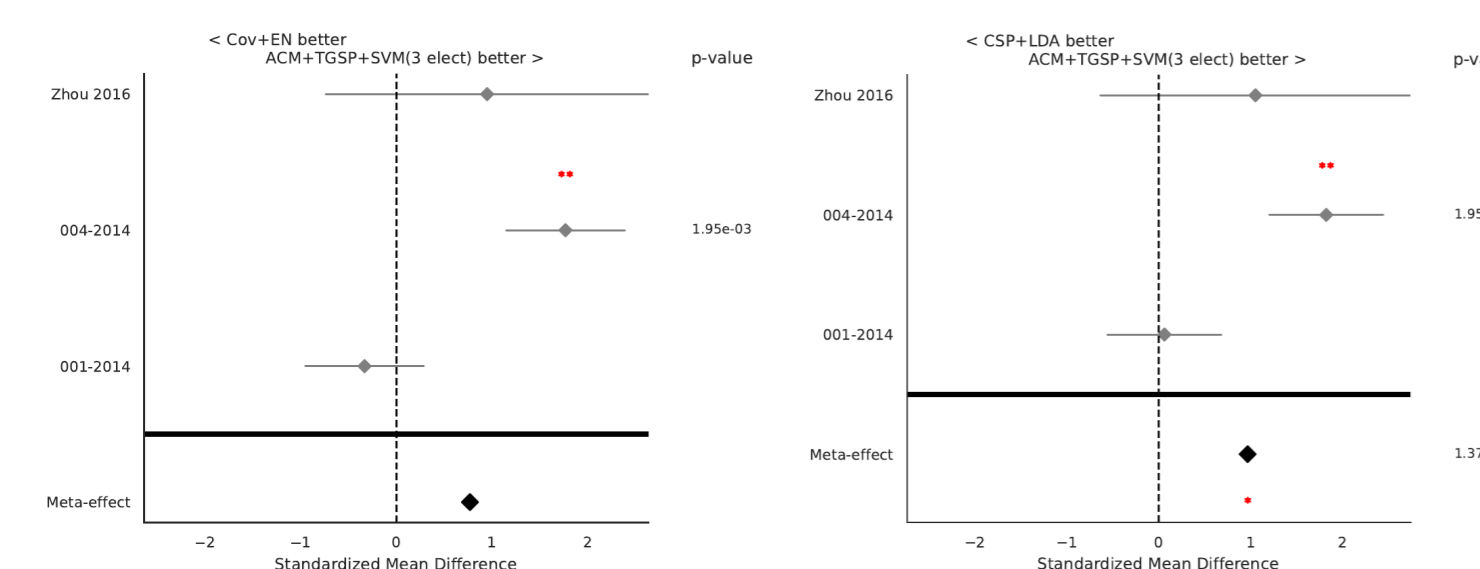
The approach of Grid Search shows better results, while the Takens approaches are more stable and robust regarding different subjects and datasets.

RESULTS

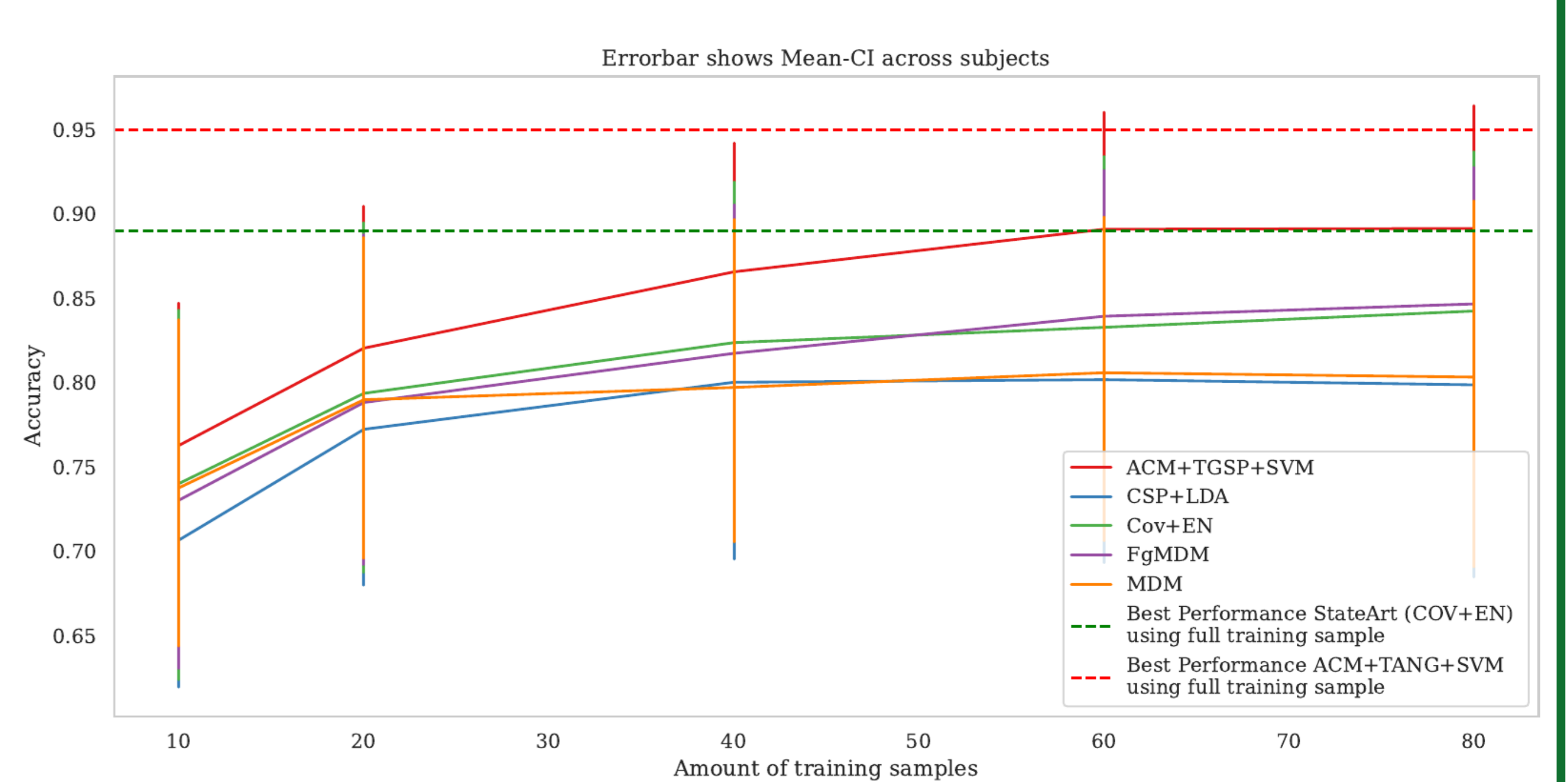
We consider multiple **Motor Imagery BCI dataset** consisting of several subjects for each datasets and several sessions. We test on **different task, different evaluation procedure**. In order to increase the reliability of our approach we use the **MOABB framework [5]**.

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	0.86 ± 0.10	0.89 ± 0.11	0.98 ± 0.03
CSP + LDA	WS	0.77 ± 0.16	0.80 ± 0.15	0.91 ± 0.06
ACM + CSP + LDA	WS	0.83 ± 0.12	0.85 ± 0.13	0.97 ± 0.02
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	0.84 ± 0.11	0.86 ± 0.14	0.97 ± 0.02
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	0.97 ± 0.02
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

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