

Spatial Graph Signal Interpolation with an application for Merging BCI Datasets with various Dimensionalities

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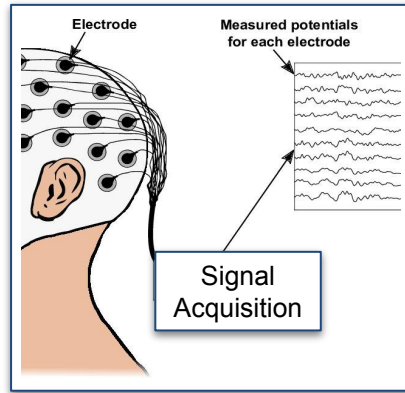
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ICASSP 2023

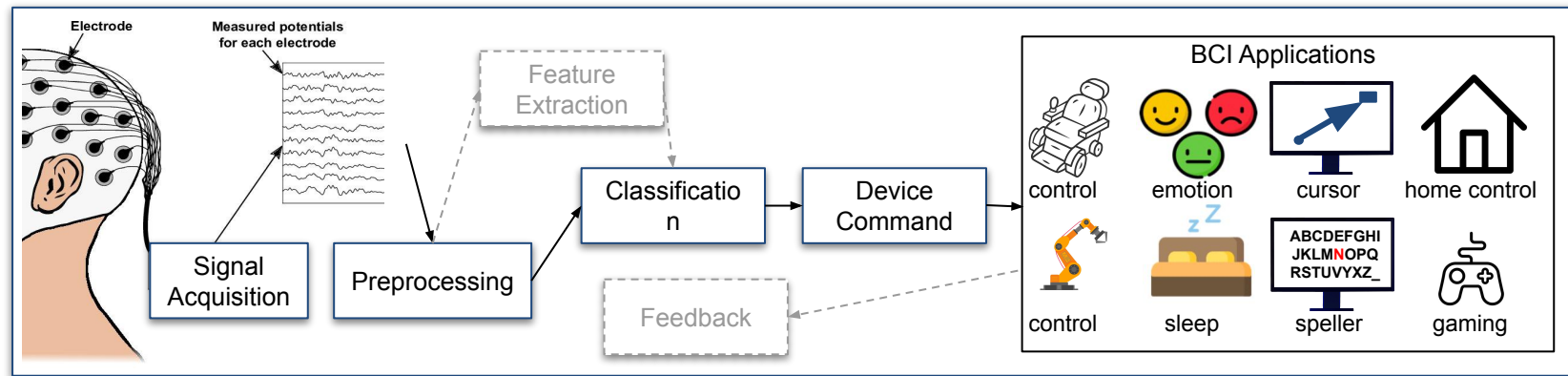


Context - Brain Computer Interface (BCI)

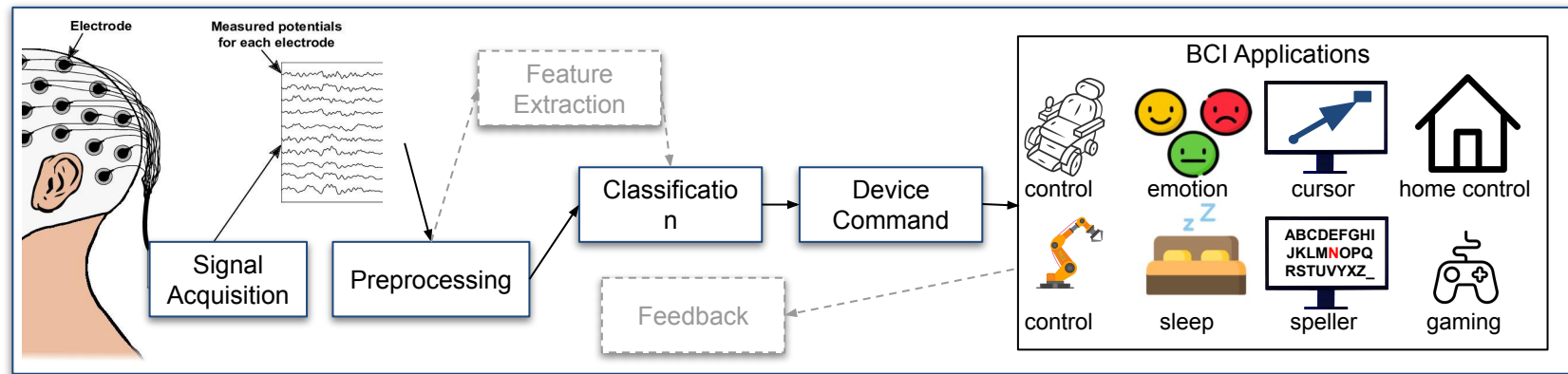


ElectroEncephaloGraphy (EEG)

Context - Brain Computer Interface (BCI)



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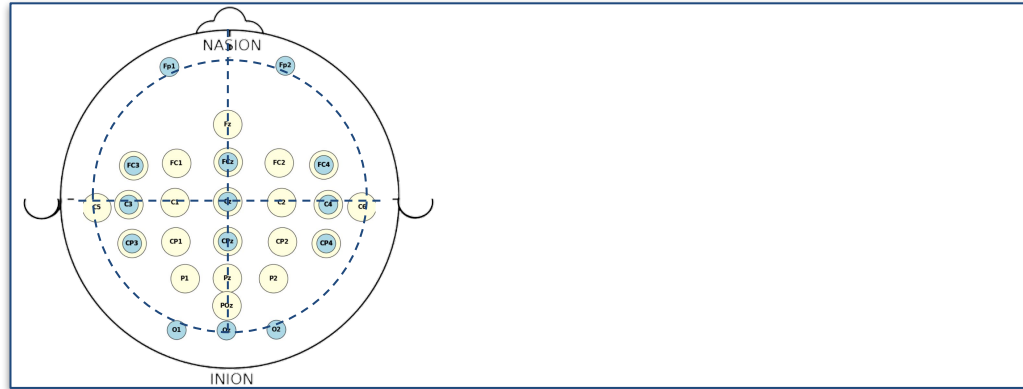
Challenges:

- Lack of big datasets.
 - Small dataset with different recording setups.
- Electrodes layout, sampling frequency, filters, ...



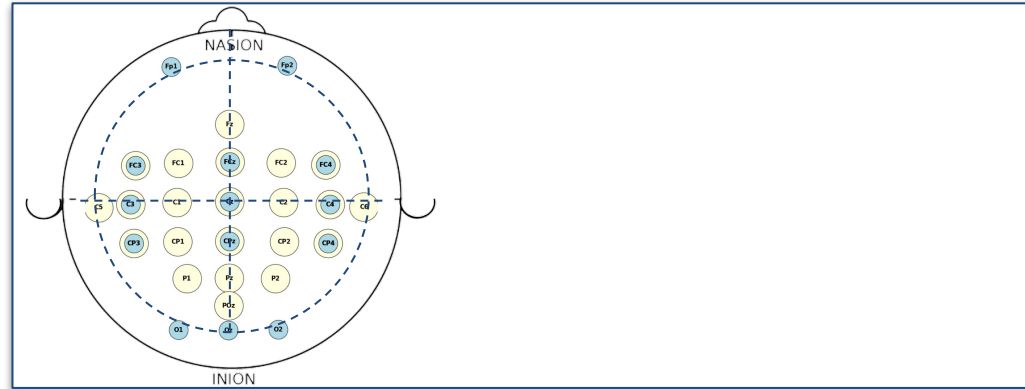
Context - Homogenize BCI datasets

However unifying the spatial aspect of the EEG setups remains a challenge.



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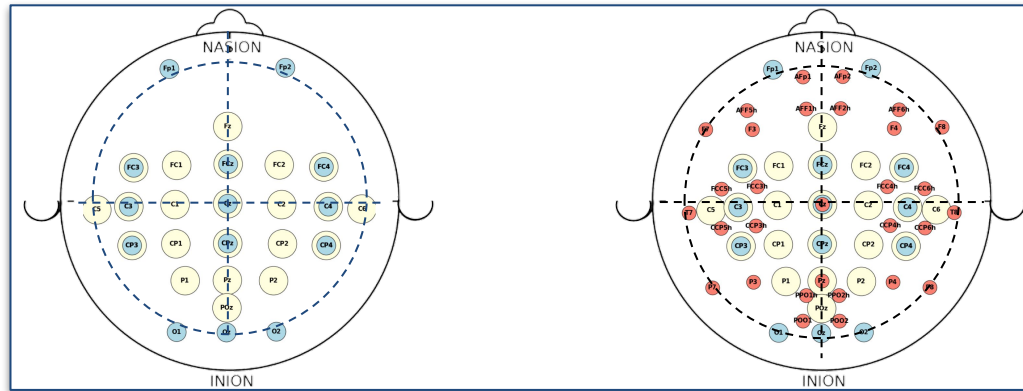


Few approaches have been proposed to unify the spatial aspect of the EEG setups.

- Reduce the spatial dimension:
 - Keeping the intersection
 - Dimension reduction methods (ex : PCA)

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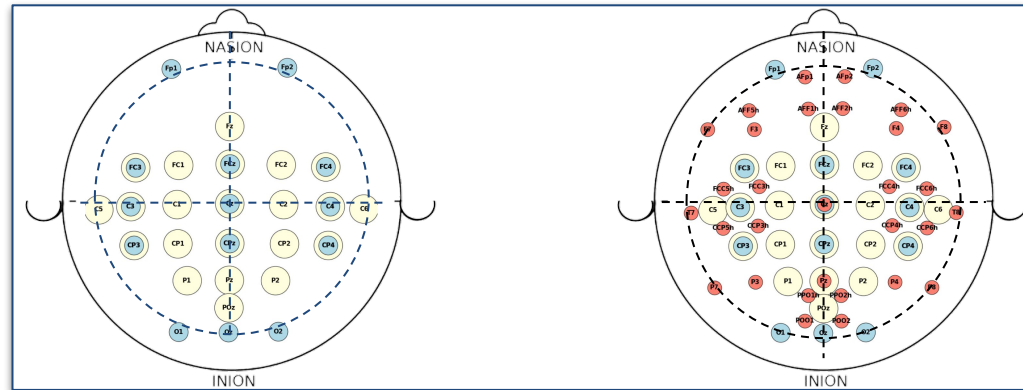


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 - Dimension reduction methods (ex : PCA)
- Increase the spatial dimension
 - Riemannian geometry

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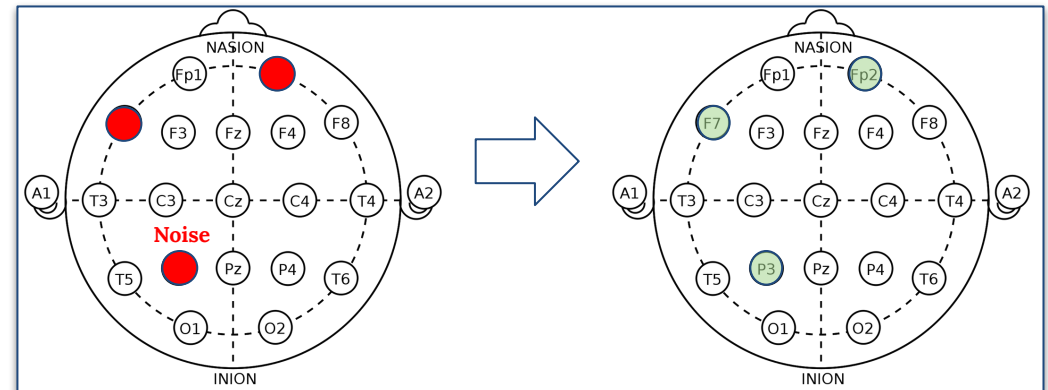
- Increase the spatial dimension
 - Riemannian geometry

No information loss

Context - Electrodes / Graph interpolation

Interpolating electrodes has been mainly used to recover signal from noisy electrodes

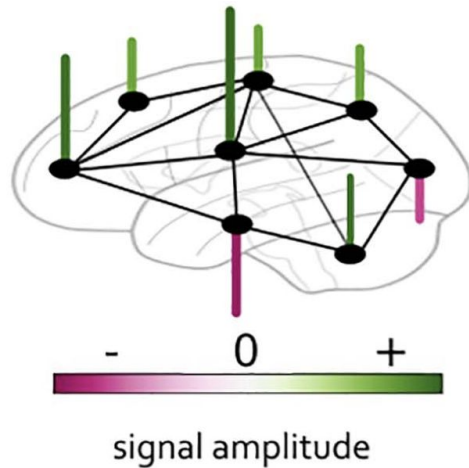
Mainly using is Spherical Spline [1]



[1] François Perrin, Jacques Pernier, O Bertrand, and Jean François Echallier, "Spherical splines for scalp potential and current density mapping," *Electroencephalography and clinical neurophysiology*, vol. 72, no. 2, pp. 184–187, 1989

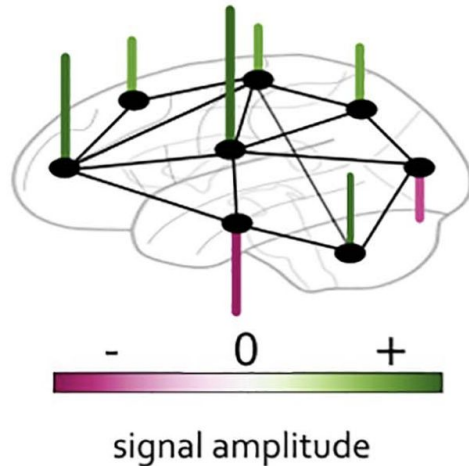
Scientific challenges

Our proposition: Interpolating spatial EEG using Graph Signal Processing



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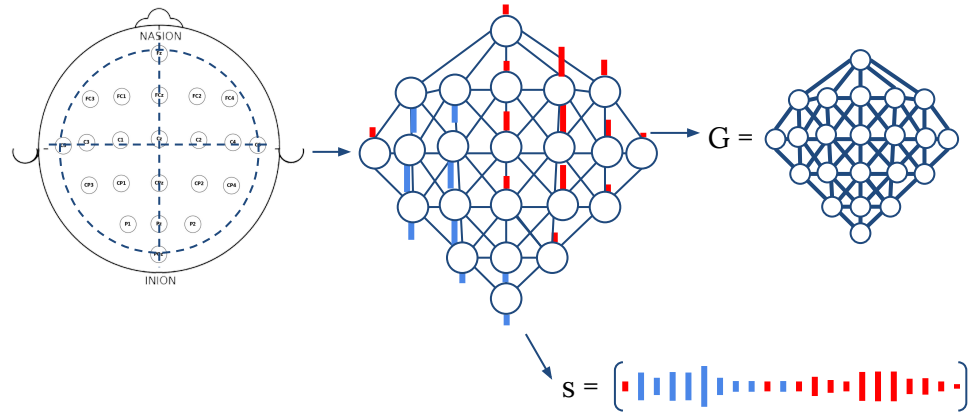


Research questions:

- 1) How to use GSP to interpolate electrodes?
 - Which graph?
 - Which interpolation criterion
- 2) Does unifying multiple EEG datasets with interpolation improve brain decoding?

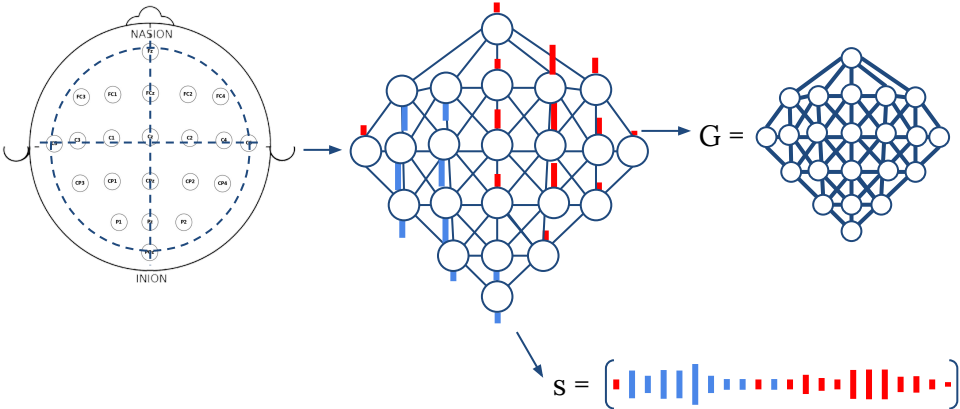
Methods

Few definitions:



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With D and W, the Degree and weights matrix of G, we have $\mathbf{L} = \mathbf{D} - \mathbf{W}$, with L the Laplacian

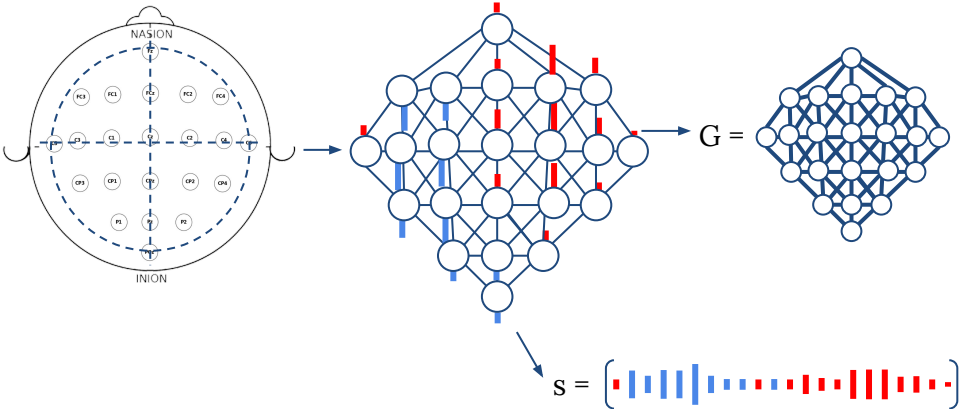
Smoothness of the signal over the graph is defined by:

$$\sigma(\mathbf{s}) = \mathbf{s}^T \mathbf{L} \mathbf{s} = \sum_{i=1}^{|\mathcal{V}|} \sum_{j=1}^{|\mathcal{V}|} W_{ij} (s_i - s_j)^2$$



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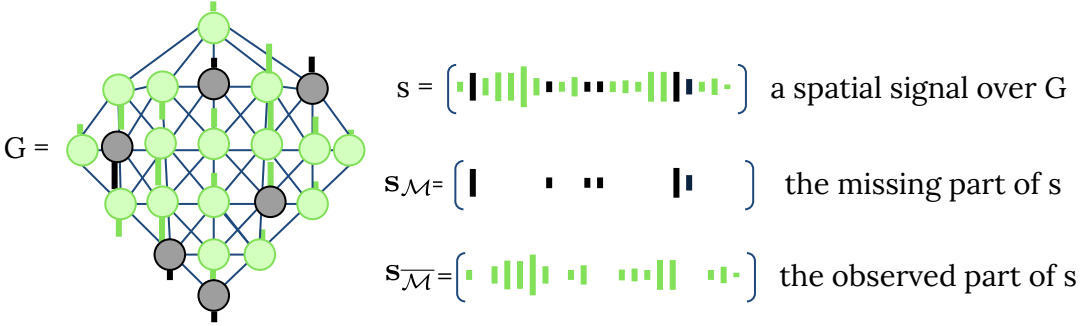


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Interpolation problem formulation:



- 1) How to find SM? Which interpolation criterion?
- 2) How to build a Graph?



1 How to find $\mathbf{s}_{\mathcal{M}}$?

Interpolation criterion : **smoothness**

$$\text{Minimizing } \sigma(\mathbf{s}) = \mathbf{s}^T \mathbf{L} \mathbf{s} = \sum_{i=1}^{|\mathcal{V}|} \sum_{j=1}^{|\mathcal{V}|} W_{ij} (s_i - s_j)^2$$

We found a closed form of $\sigma(\mathbf{s})$ that provides the optimal $\mathbf{s}_{\mathcal{M}}$

$$(A) \quad \mathbf{s}_{\mathcal{M}} = -\mathbf{L}_{\mathcal{M}}^{-1} \mathbf{L}_{\mathcal{M}\overline{\mathcal{M}}} \mathbf{s}_{\overline{\mathcal{M}}}$$

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2 How to build G?

We learn G, from real data using gradient descent.

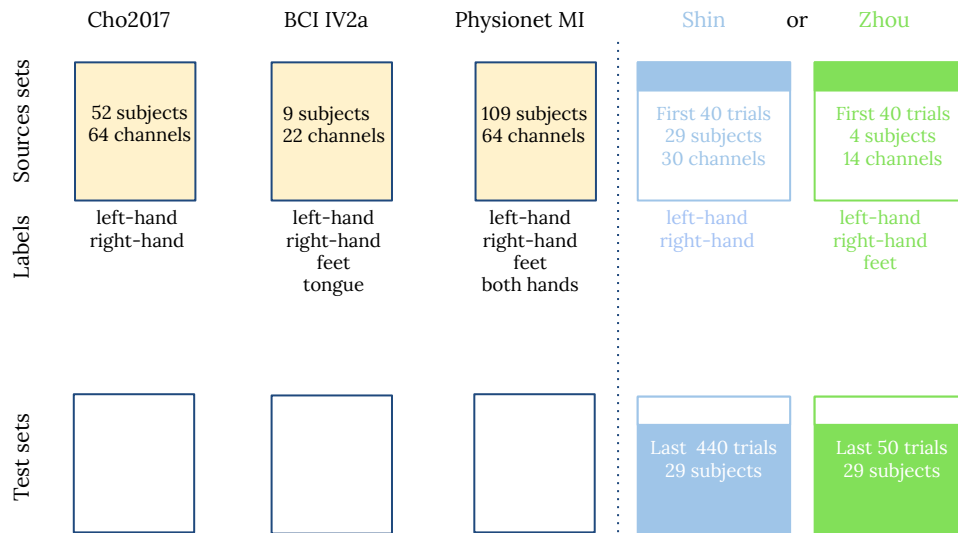
- 1) Initialize a connected graph G
- 2) Create virtual reconstruction problems
- 3) Reconstruct the signal using (A)
- 4) Update G based on the error of reconstruction
- 5) Repeat 2) to 4) until the error is low

Experiments

What is the added value brought by interpolated data?

Does unifying multiple EEG datasets with interpolation improve brain decoding?

We experiment brain decoding on the following realistic setup:



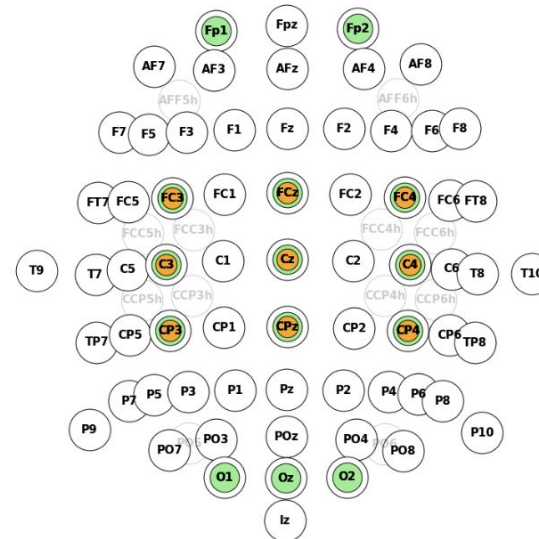
Results

Task : Brain decoding

	Cho2017	BCI IV2a	Physionet MI	Shin	or	Zhou
Sources sets	52 subjects	9 subjects	109 subjects	First 40 trials 29 subjects		First 40 trials 4 subjects
Labels	left-hand right-hand	left-hand right-hand feet tongue	left-hand right-hand feet both hands	left-hand right-hand		left-hand right-hand feet
Test sets				Last 440 trials 29 subjects		Last 50 trials 29 subjects

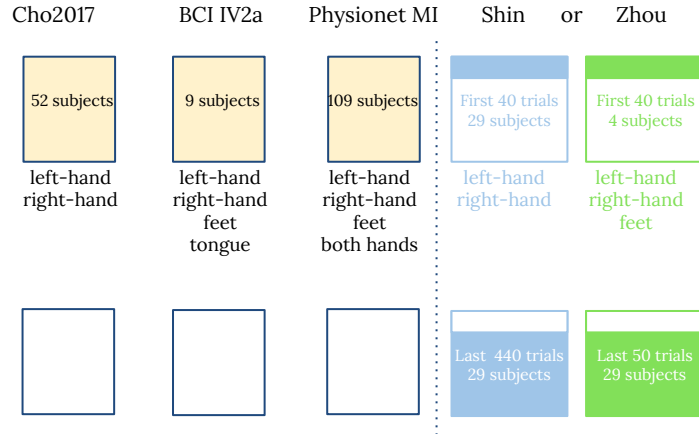
Classification accuracy

	Zhou	
	Acc	N
\cap	<u>61.2 ± 2.0</u>	<u>9</u>
Dataset	56.2 ± 4.8	14
\cup	46.4 ± 2.8	66



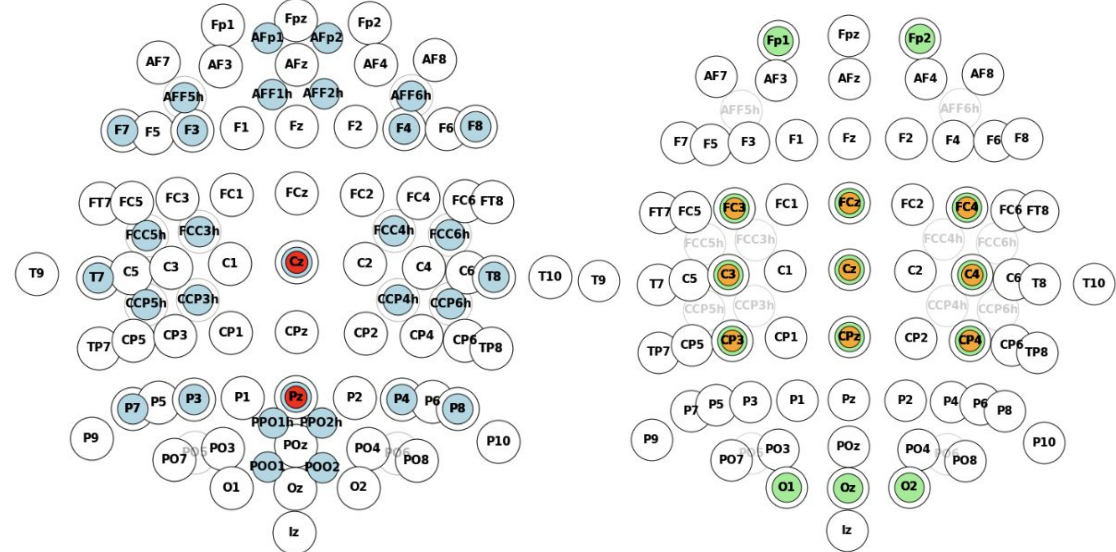
Results

Task : Brain decoding



Classification accuracy

	Shin		Zhou	
	Acc	N	Acc	N
\cap	53.2 ± 2.8	2	61.2 ± 2.0	9
Dataset	63.2 ± 2.3	22	56.2 ± 4.8	14
\cup	62.3 ± 2.1	76	46.4 ± 2.8	66



Conclusions

- New and efficient electrode interpolation technique exploiting GSP tools
- Illustrated the interest of our method to homogenize datasets
 - Our code is open
 - Many more details in our paper!

