ElectroEncephaloGraphic signal processing & classification for Brain-Computer Interfaces

$$\frac{wC_1w^T}{wC_2w^T}$$

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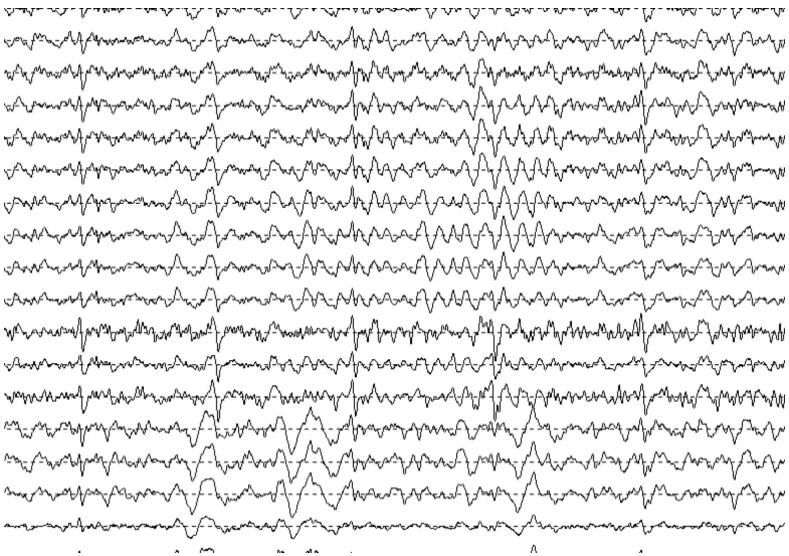
Potioc team

From ElectroEncephaloGraphy (EEG)…

EEG signals acquisition

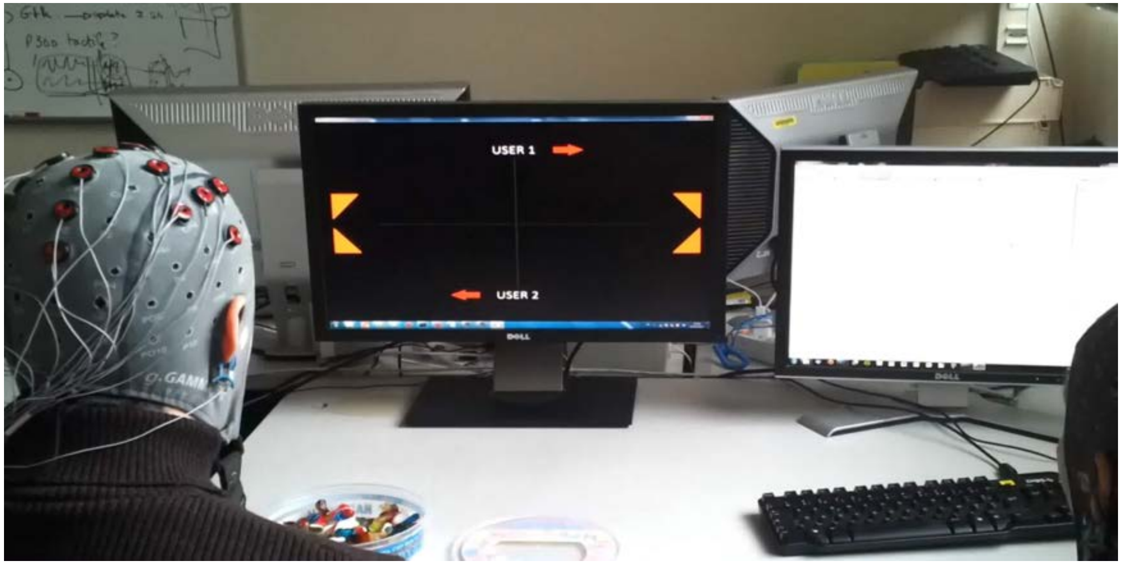


Example of EEG signals

Berger, H., *Ueber das Elektroenkephalogramm des Menschen,* Archiv für Psychiatrie und Nervenkrankheiten, 1929,
Niedermeyer, E. & da Silva, F. L., *Electroencephalography: basic principles, clinical applications, and related fields,* Lippincott Williams & Wilkins, ISBN 0781751268, 2005

…to Brain-Computer Interface (BCI)

System translating measures of brain activity
into commands or messages for an interactive application



Ex: Motor Imagery BCI-based [Bonnet, Lotte, Lécuyer, 2013]

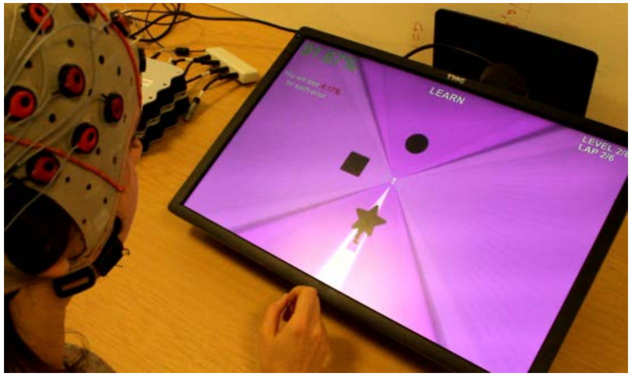
JR Wolpaw, EW Wolpaw, "*Brain-Computer Interfaces: principles and practice*", Oxford University Press, 2012
F. Lotte, L. Bougrain, M. Clerc, "*Electroencephalography (EEG)-based Brain-Computer Interfaces*",
Wiley Encyclopedia on Electrical and Electronics Engineering, 2015

EEG-based BCI: a promising technology

Communication & control

Gaming

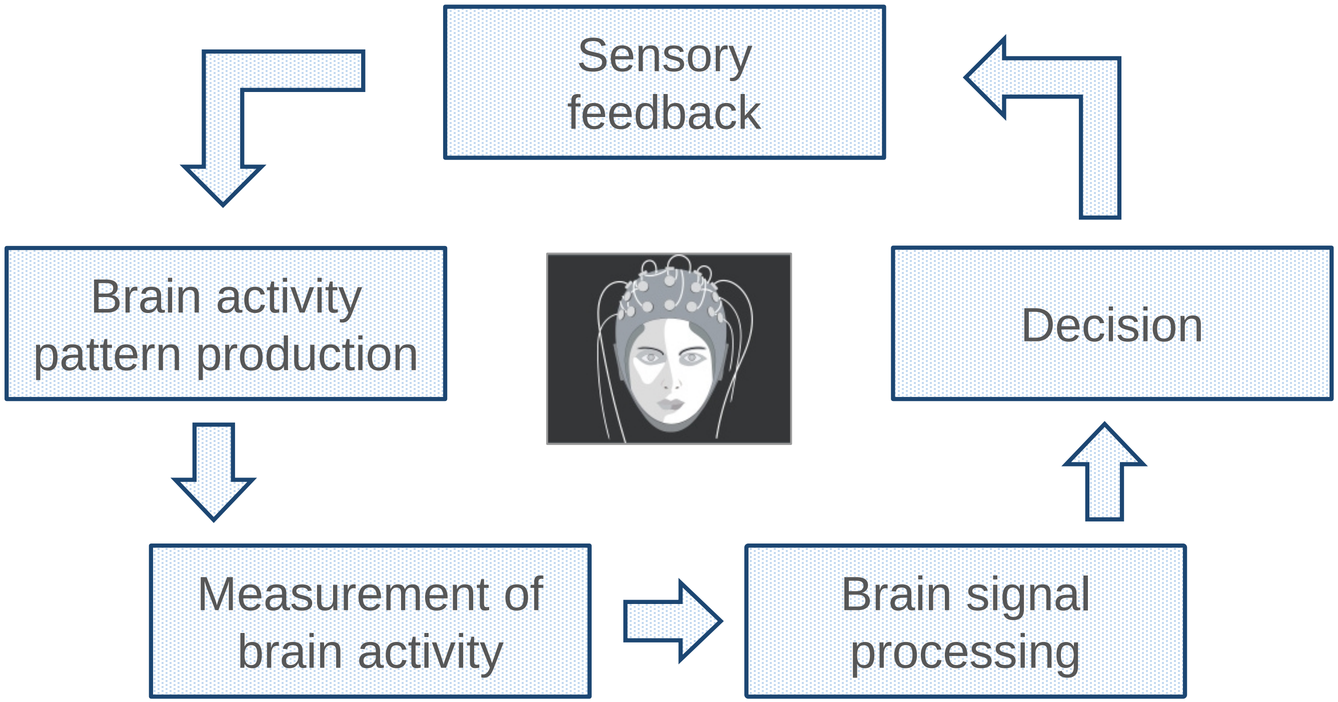
Stroke rehabilitation



Neuroadaptive technologies

M. Clerc, L. Bougrain, F. Lotte, “*Brain-Computer Interfaces 2: Technology and Applications*", ISTE-Wiley, 2016

BCI principle



M. Clerc, L. Bougrain, F. Lotte, “*Brain-Computer Interfaces 1: Foundations and Methods*", ISTE-Wiley, 2016

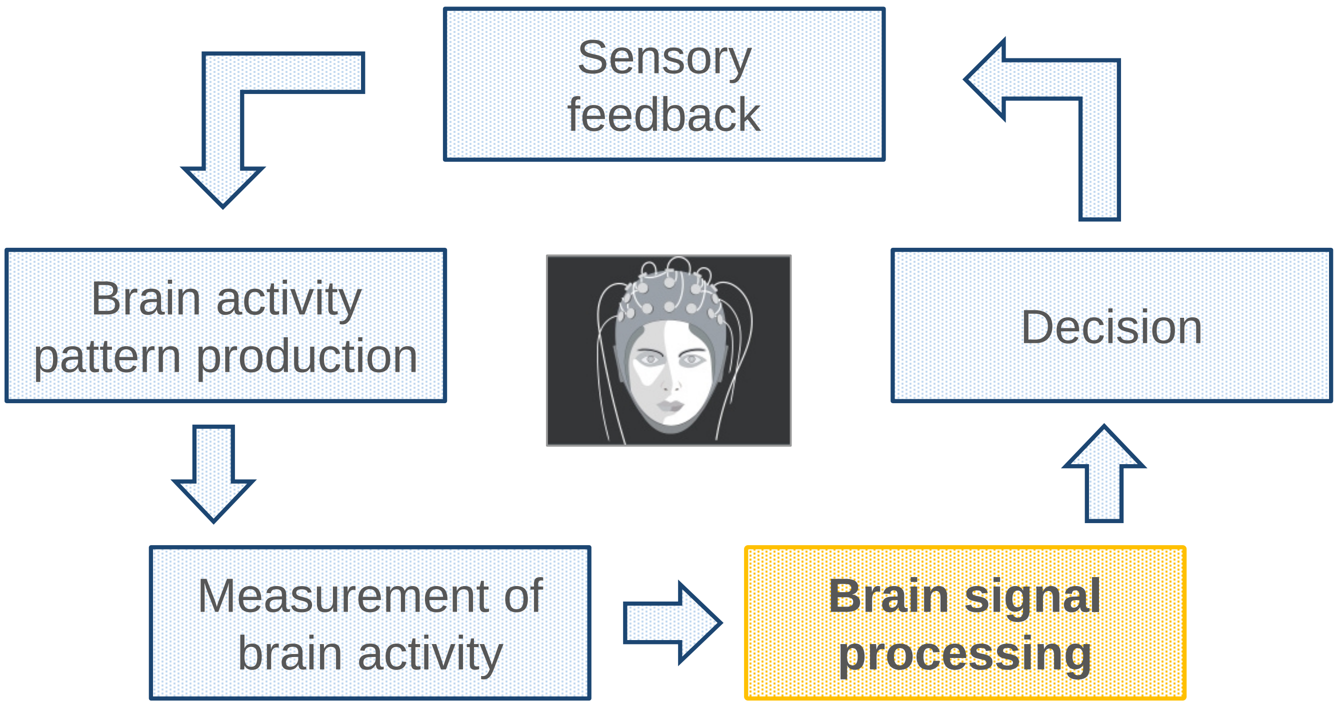
BCI are promising but not reliable enough

High error-rate
[Guger 2003]
[Blankertz 2010]

~10-30% of users cannot control a BCI
[Allison 2010]

⇒We need more reliable BCI!

Making BCI reliable at the signal processing level



M. Clerc, L. Bougrain, F. Lotte, “*Brain-Computer Interfaces 1: Foundations and Methods*", ISTE-Wiley, 2016

Challenges in EEG signal processing for BCI

Noisy data
[Goncharova 1999]

Between-user variability
[Guger 2003, Guger 2012, Ahn 2015]

Limited amount of training data
[Lotte 2015]

Within-user variability
[Grosse-Wentrup 2013]

Krusienski, D. J., Grosse-Wentrup, M., Galán, F., Coyle, D., Miller, K. J., Forney, E., & Anderson, C. W. *Critical issues in state-of-the-art brain–computer interface signal processing*. Journal of neural engineering, 2011

Outline

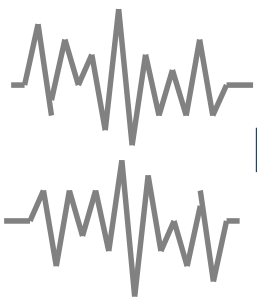
1. Standard EEG signal processing in BCI
2. Dealing with between-user variability
3. Dealing with noise
4. Dealing with limited training data
5. Dealing with within-user variability
6. Conclusion & perspectives

1

Standard EEG signal processing for BCI

Standard signal processing for Mental Imagery-based BCI

$$x' = \sum_i w_i x_i = wX$$



Spatial filtering → Frequency filtering → Features → Classifier → Class

Raw EEG signals e.g., corresponding to imagined movements

Ex: Laplacian filters

e.g., 8-30 Hz for motor imagery

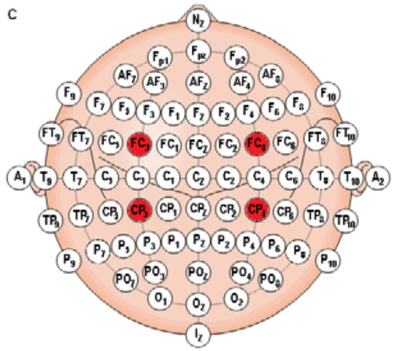
Standard: Band Power

Standard: Linear Discriminant Analysis (LDA)

Basic spatial filters

Bipolar filters

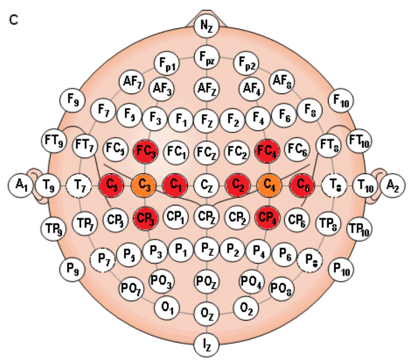
- C3’ = FC3 - CP3



Bipolar C3 & C4

Laplacian filters

- C3’= 4*C3 - FC3 - C5 - C1 - CP3



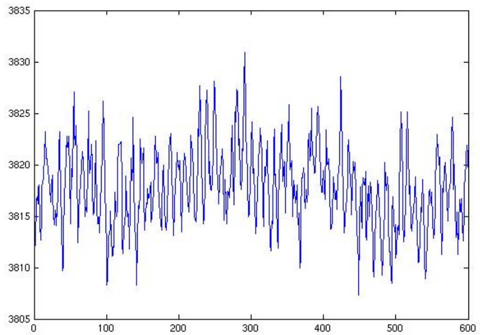
Laplacian C3 & C4

Emphasize localized activity and reduce diffuse spatial activity

[McFarland et al, EEG and Clinical Neurophysiology, 1997]

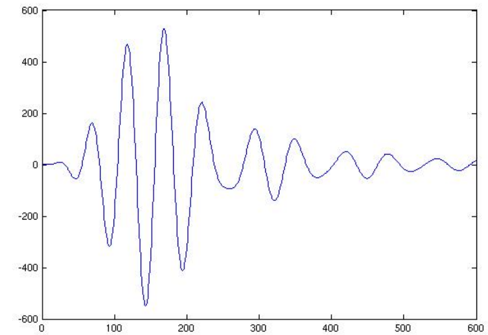
Band power features

Signal power in a given frequency band (here μ=8-12Hz)

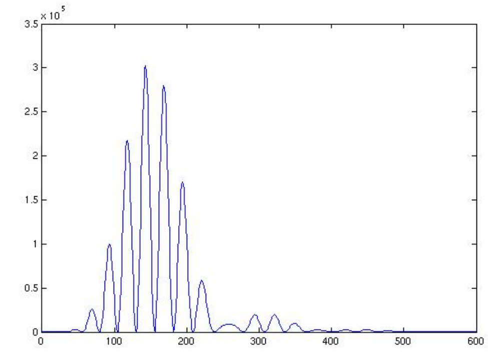


1s of raw EEG at C3
(left motor cortex)

Band-pass filtering in 8-12 Hz (μ)



Power estimation (squaring)

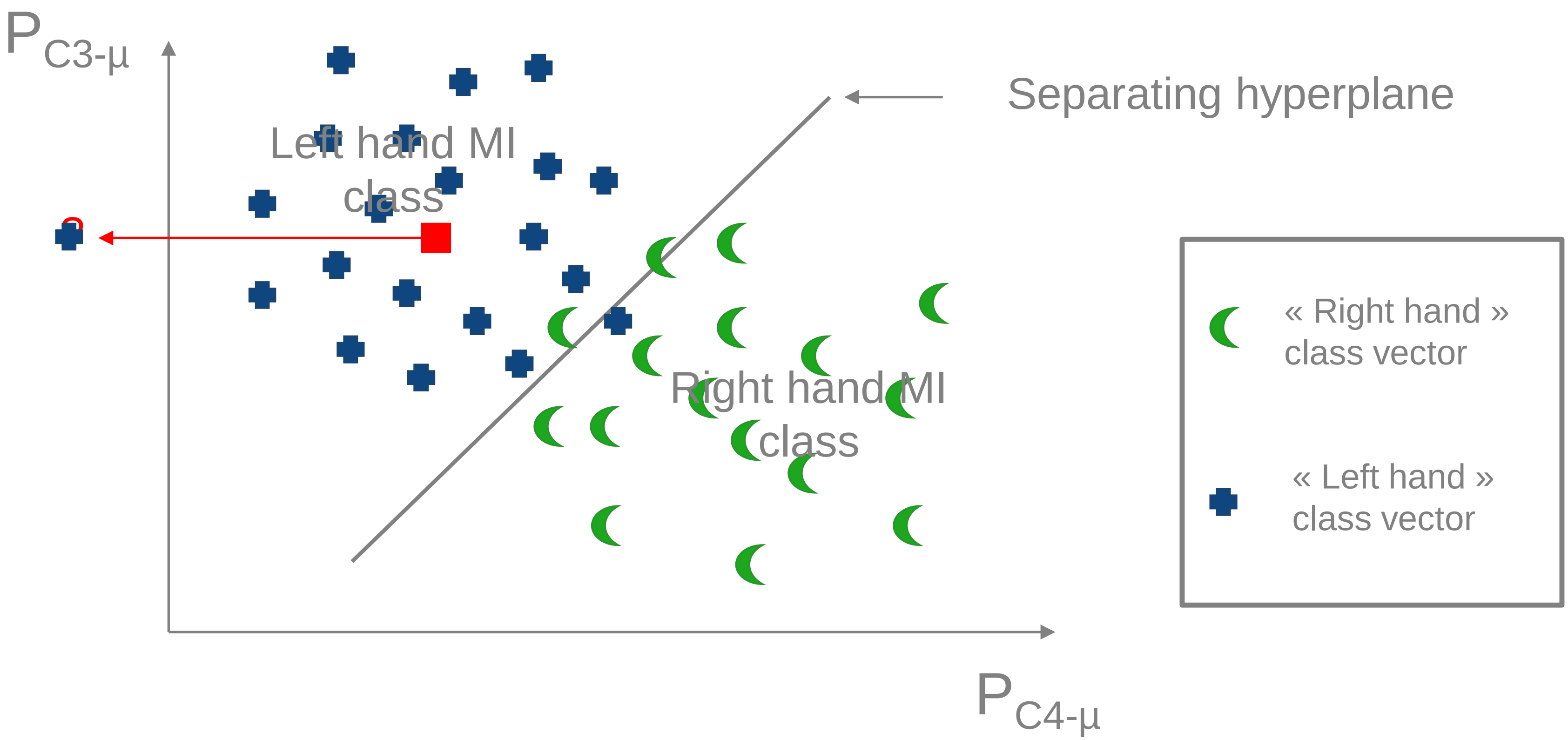


Temporal average

1 feature:
μ band power for channel C3
($P_{C3\text{-}\mu}$)

Classification

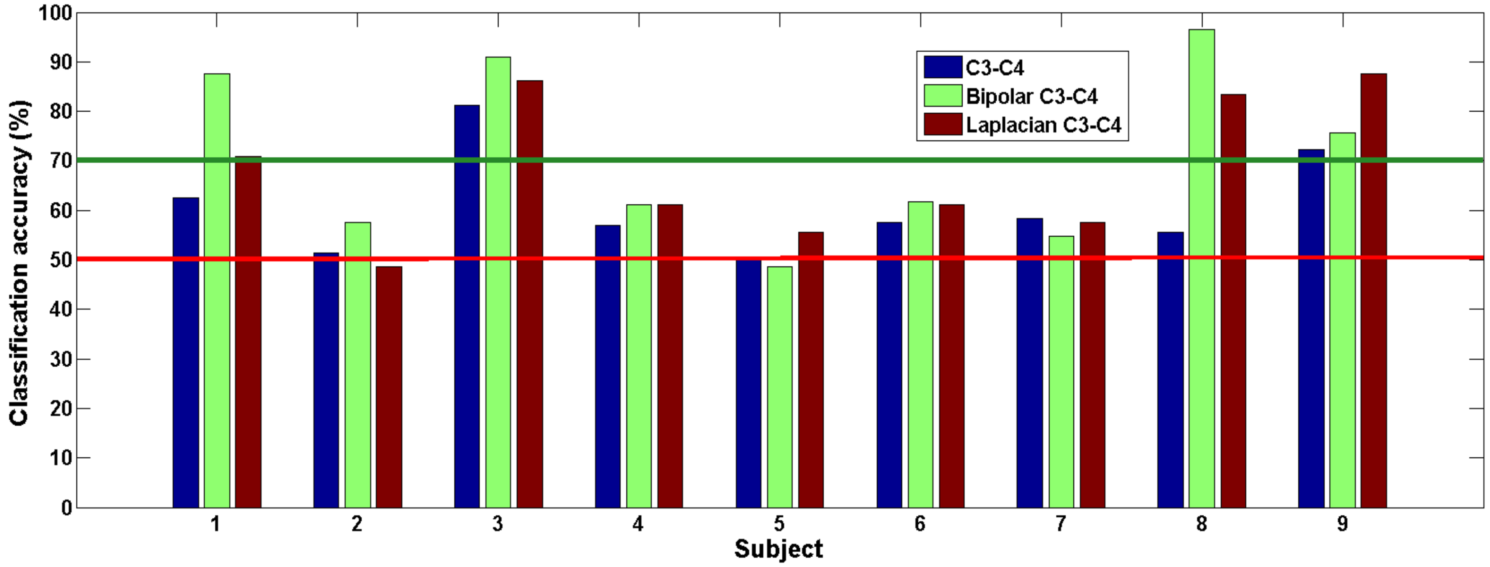
- Linear Discriminant Analysis (LDA)
  - Need for « training » examples



F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, B. Arnaldi, A Review of Classification Algorithms for EEG-based Brain-Computer Interfaces, Journal of Neural Engineering, 2007

Performance examples

- BCI competition IV, data set IIa (Tangermann et al, Frontiers, 2012)
  - 9 users, Left vs right hand motor imagery
  - 72 trials per class for training and testing
  - different spatial filters + 8-30 Hz band power + LDA



Average Accuracy:

C3-C4: **60,7%**

Bipolar C3-C4: **70,5%**

Laplacian C3-C4: **68%**

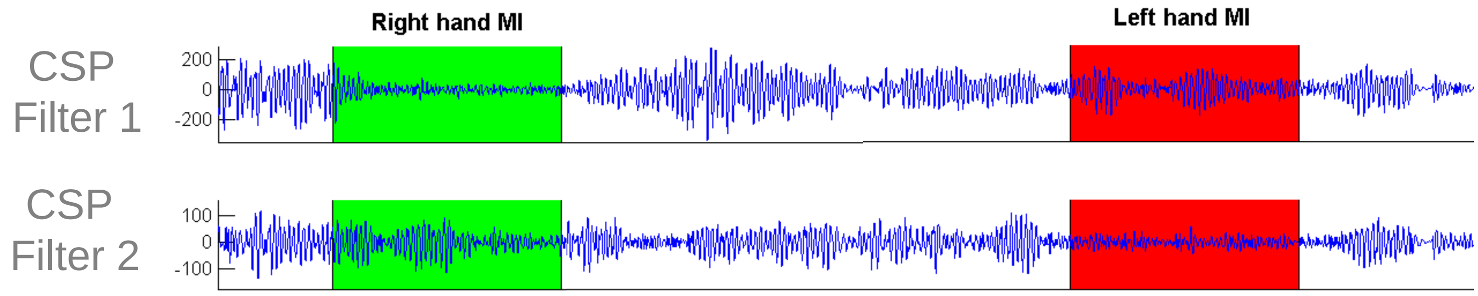
⇒ Still modest performances, huge between-user variability

2

Dealing with between-user variability

Using user-specific, data driven spatial filters: Common Spatial Patterns (CSP)

- Find spatial filters *w* such that the variance of the filtered signal is maximal for one class and minimal for the other



- It consists in extremizing

$$J(w) = \frac{wX_1X_1^Tw^T}{wX_2X_2^Tw^T} = \frac{wC_1w^T}{wC_2w^T}$$

Spatially filtered signal from class 2

Variance of the spatially filtered signal

w: spatial filter to optimize

***X**$_i$*: multichannel EEG signals from class i

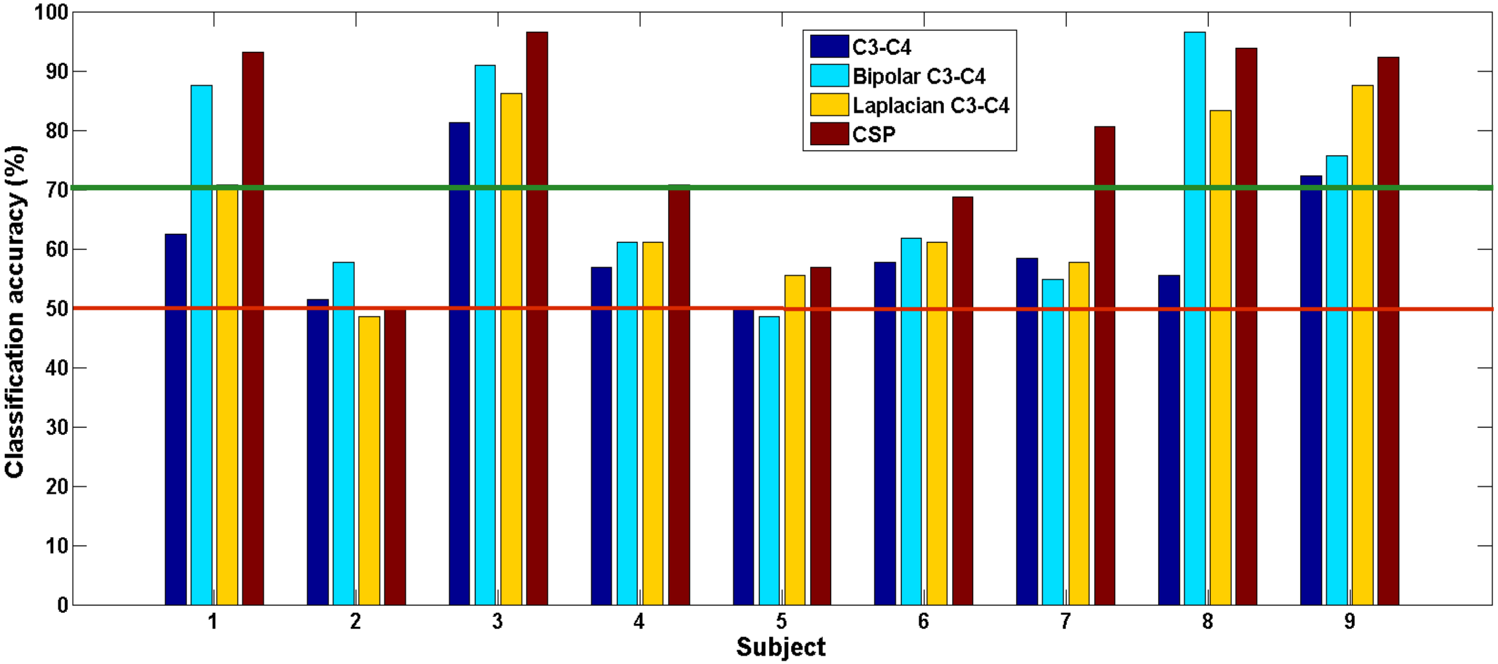
***C**$_i$:* covariance matrix from class i

Features = variance of the spatially filtered signals = $\log(wXX^Tw^T) = \log(wCw^T)$

Ramoser et al, IEEE Trans. On Rehab. Eng., 2000, Blankertz et al, IEEE Sig. Proc. Mag., 2008

CSP performance examples

- BCI competition IV, data set IIa
  - 9 subjects, left vs right hand motor imagery
  - 8-30 Hz band power+LDA, different spatial filters



Average Accuracy:

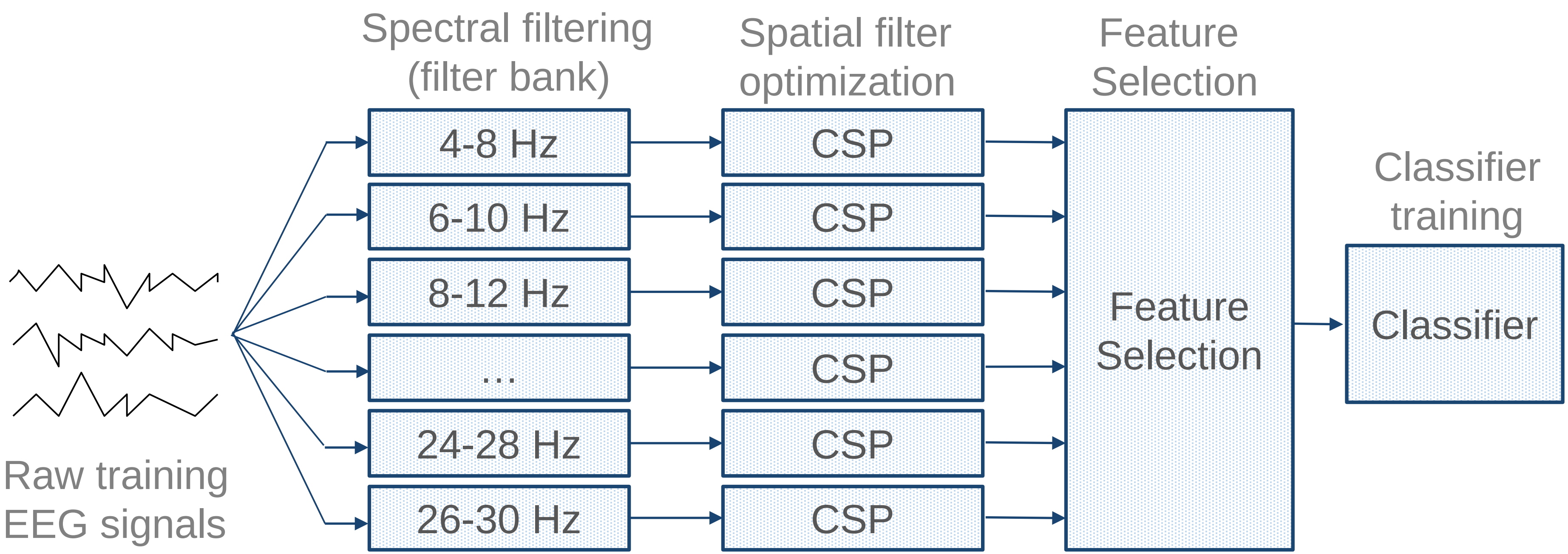
C3-C4: **60,7%**

Bipolar C3-C4: **70,5%**

Laplacian C3-C4: **68%**

CSP: **78,1%**

Using user-specific frequency bands: The Filter Bank CSP (FBCSP)



Ang et al, « Filter Bank Common Spatial Patterns in Brain-Computer Interfaces », IJCNN, 2008

FBCSP Results

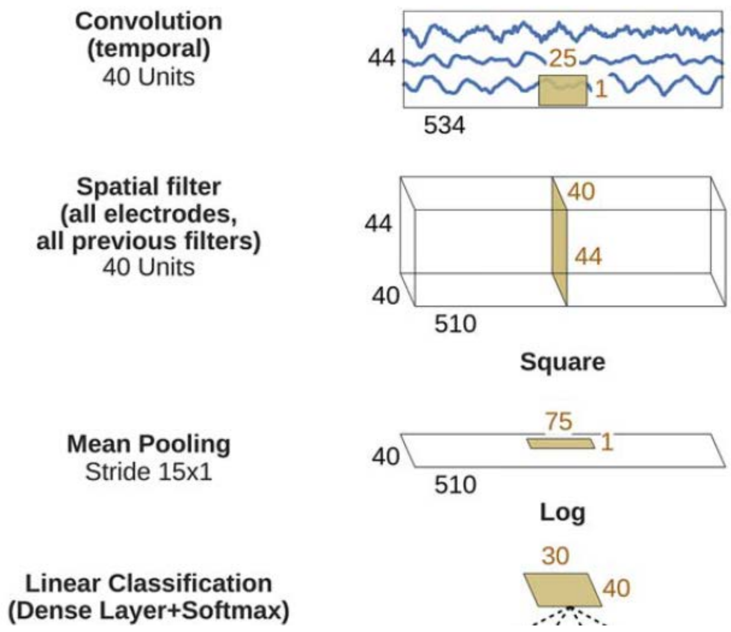
Method	Classification accuracy (%)	
	Data Set I (5 subjects)	Data Set II (11 subjects)
CSP	86.6	73.3
FBCSP	**90.3**	**81.1**

Efficiency of FBCSP (from Ang et al, IJCNN, 2008)

Winning algorithm of BCI competition 2008 on all EEG data sets
Ang et al, Pattern Recognition, 2011

Deep Learning

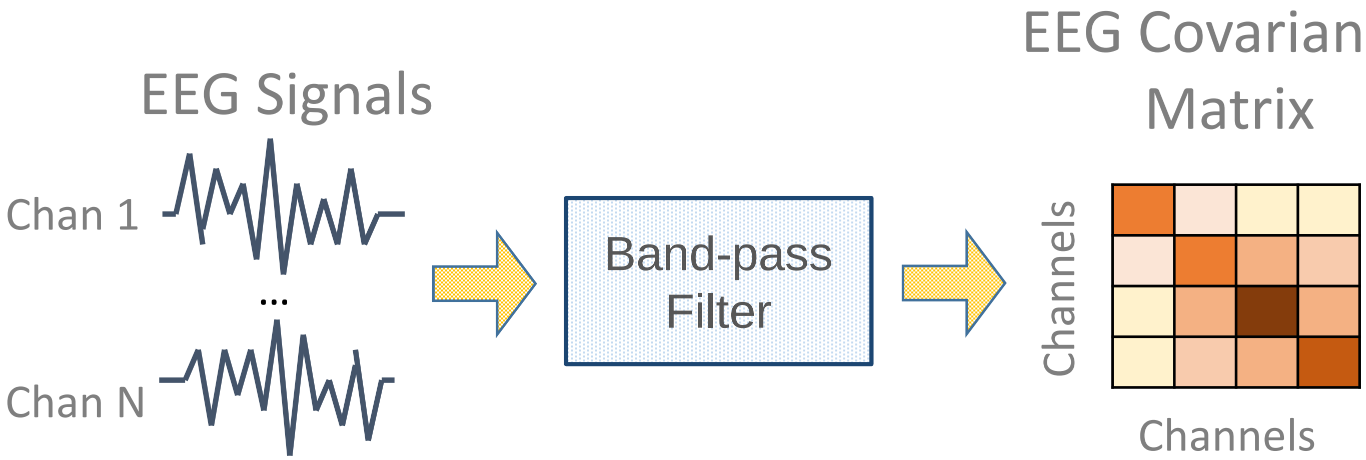
- Shallow ConvNet:
  A (not so) deep Network to learn FBCSP-like features



Shallow ConvNet
[Schirrmeister et al,
Human Brain Mapping, 2017]

Riemannian geometry for BCI

- Manipulating EEG oscillations as covariance matrices

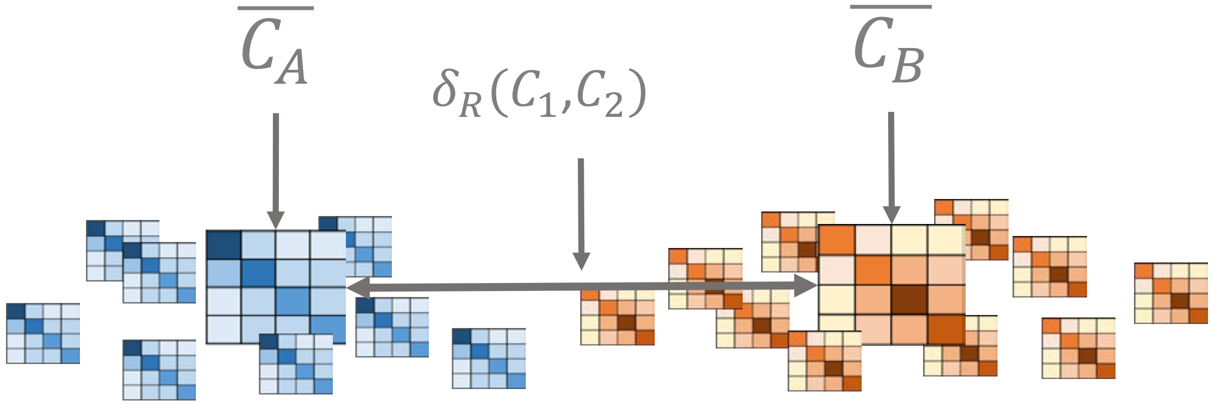


Note: we (indirectly) represent EEG with covariance matrices when using CSP

$$f = \log(wCw^T)$$

F. Yger, M. Bérar, F. Lotte, *"Riemannian approaches in Brain-Computer Interfaces: a review"*, IEEE Trans Neural System and Rehabilitation Engineering, 2017

Tools of Riemannian geometry



Riemannian Distance

$$\delta_R(C_1, C_2) = \left\| \log\left(C_1^{-1/2} C_2 C_1^{-1/2} \right) \right\|_F$$

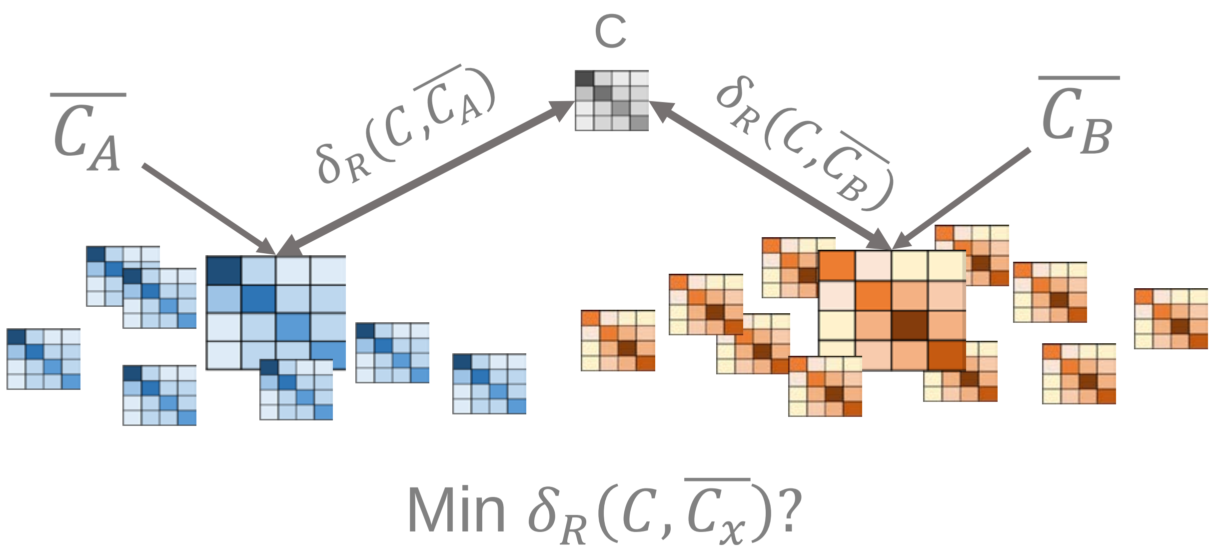
Invariant to full
rank linear transformation!

Riemannian Mean

$$\bar{C_i} = \min_{C_i} \sum_{t_i} \delta^2{}_R(C_i, S_{t_i})$$

F. Yger, M. Bérar, F. Lotte, *"Riemannian approaches in Brain-Computer Interfaces: a review"*, IEEE Trans Neural System and Rehabilitation Engineering, 2017

Minimum Distance to the Mean (MDM) classifier based on Riemannian geometry



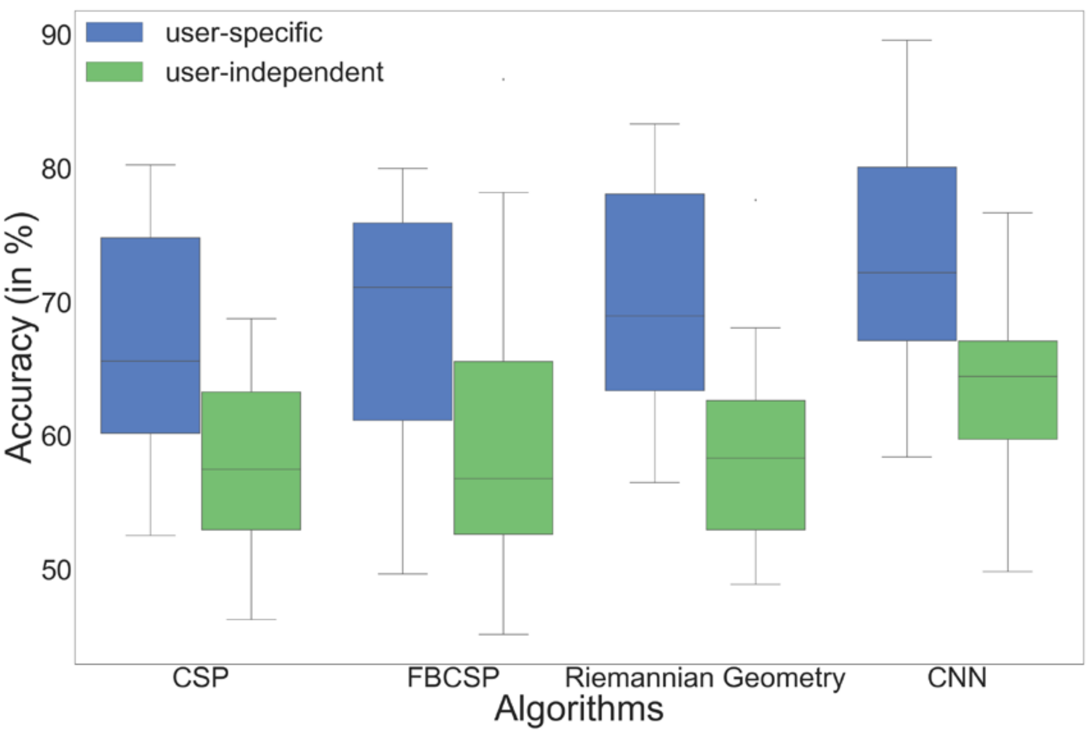
Riemannian classifiers won 5 international brain signal classification competitions!

F. Yger, M. Bérar, F. Lotte, *"Riemannian approaches in Brain-Computer Interfaces: a review"*, IEEE Trans Neural System and Rehabilitation Engineering, 2017

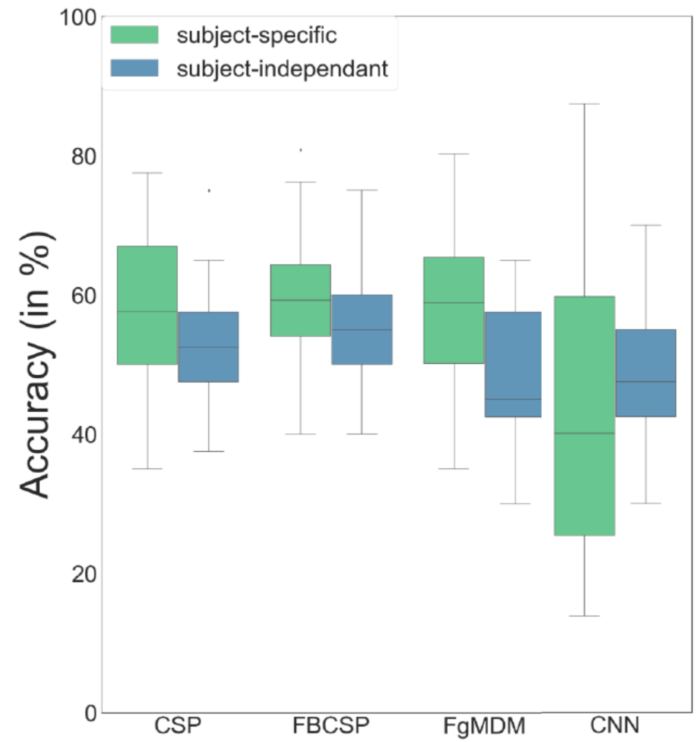
Congedo, M., Barachant, A., & Bhatia, R. « *Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review* ». Brain-Computer Interfaces, 2017

Comparing algorithms for workload & emotions estimation in EEG signals

Workload classification



Emotion (valence) classification



A. Appriou, A. Cichocki, F. Lotte,
"*Towards Robust Neuroadaptive HCI: Exploring Modern Machine Learning Methods to Estimate Mental Workload From EEG Signals*", ACM CHI Late Breaking Work, 2018

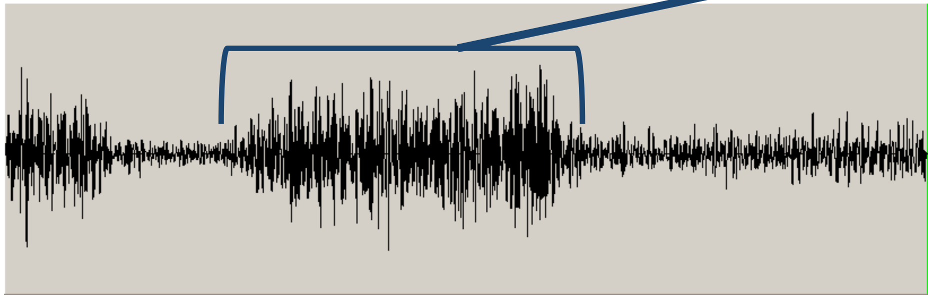
3

Dealing with Noise

Examples of noise

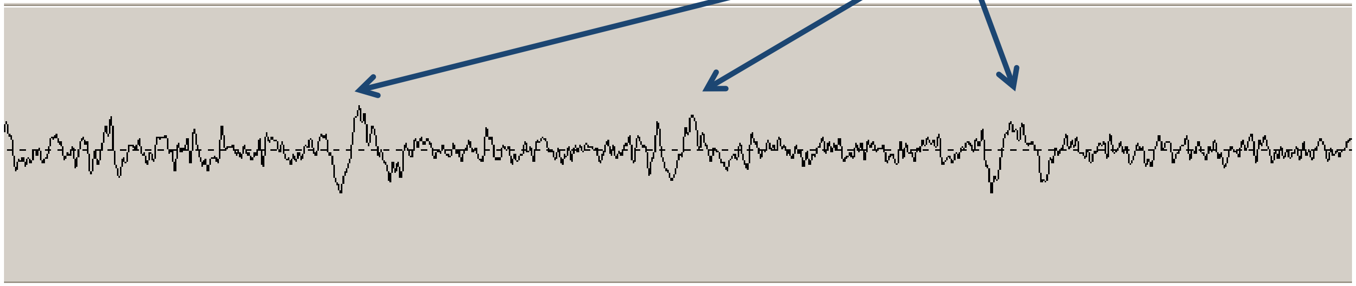
- ElectroMyoGraphy (EMG):
  - Measure of muscles activity

EMG signals measured by an EEG sensor (Jaw clenching)



- ElectroOculoGraphy (EOG):
  - Measure of eye movements

EOG signals measured by an EEG sensor (blinks)



Noise-robustness with a Regularized CSP (RCSP)

CSP	RCSP
Goal: extremizing $$\frac{wC_1w^T}{wC_2w^T}$$	Goal: maximizing $$\frac{w\tilde{C}_1w^T}{w\tilde{C}_2w^T \boxed{+ \alpha P(w)}} \text{ and } \frac{w\tilde{C}_2w^T}{w\tilde{C}_1w^T \boxed{+ \alpha P(w)}}$$ Penalty term
	with $$\tilde{C}_i = (1-\beta)C_i \boxed{+ \beta G_i}$$ Stabilization term

Lotte & Guan, *IEEE Trans. BioMed. Eng.*, 2011

What prior knowledge to use? Spatial knowledge to deal with noise

- Neighboring neurons are responsible for similar brain functions + EEG is smeared due to volume conduction

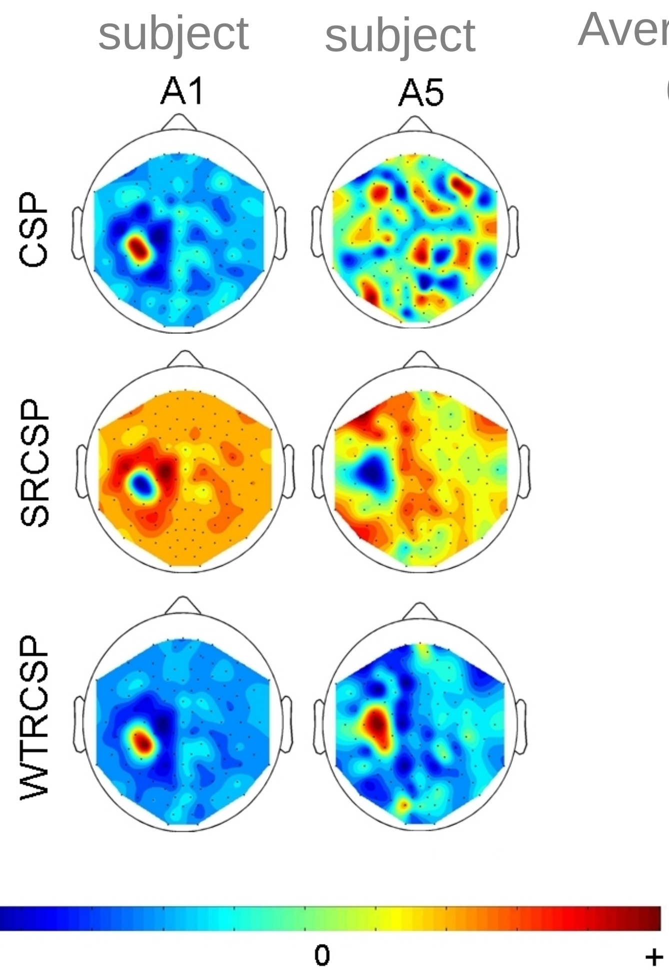
=> Spatially smooth filters

$$P(w) = \sum_{i,j} \underbrace{G(i,j)}_{\text{proximity of two electrodes}} \underbrace{(w_i - w_j)^2}_{\text{weight difference between electrodes}}$$

- For a given task, not all brain areas are involved

$$P(w) = w^T D w \ \text{ with } \ D(i,j) = \begin{cases} \text{channel } i \text{ "uselessnes"} & if \ i = j \\ 0 & if \ i \neq j \end{cases}$$

Spatial filters obtained



Average classification accuracy (%)
(n = 12 subjects, 2 classes)

73.1 %

78.7 %

77.6 %

Lotte & Guan, *IEEE Trans. on Biomedical Engineering*, 2011

4

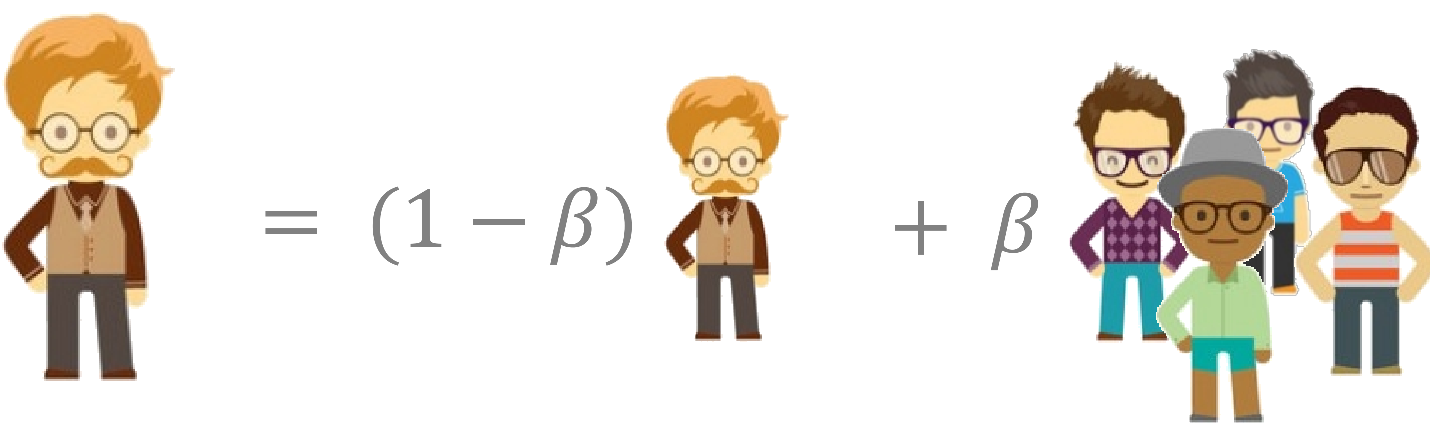
Dealing with Limited training data

Regularization terms to reduce calibration time

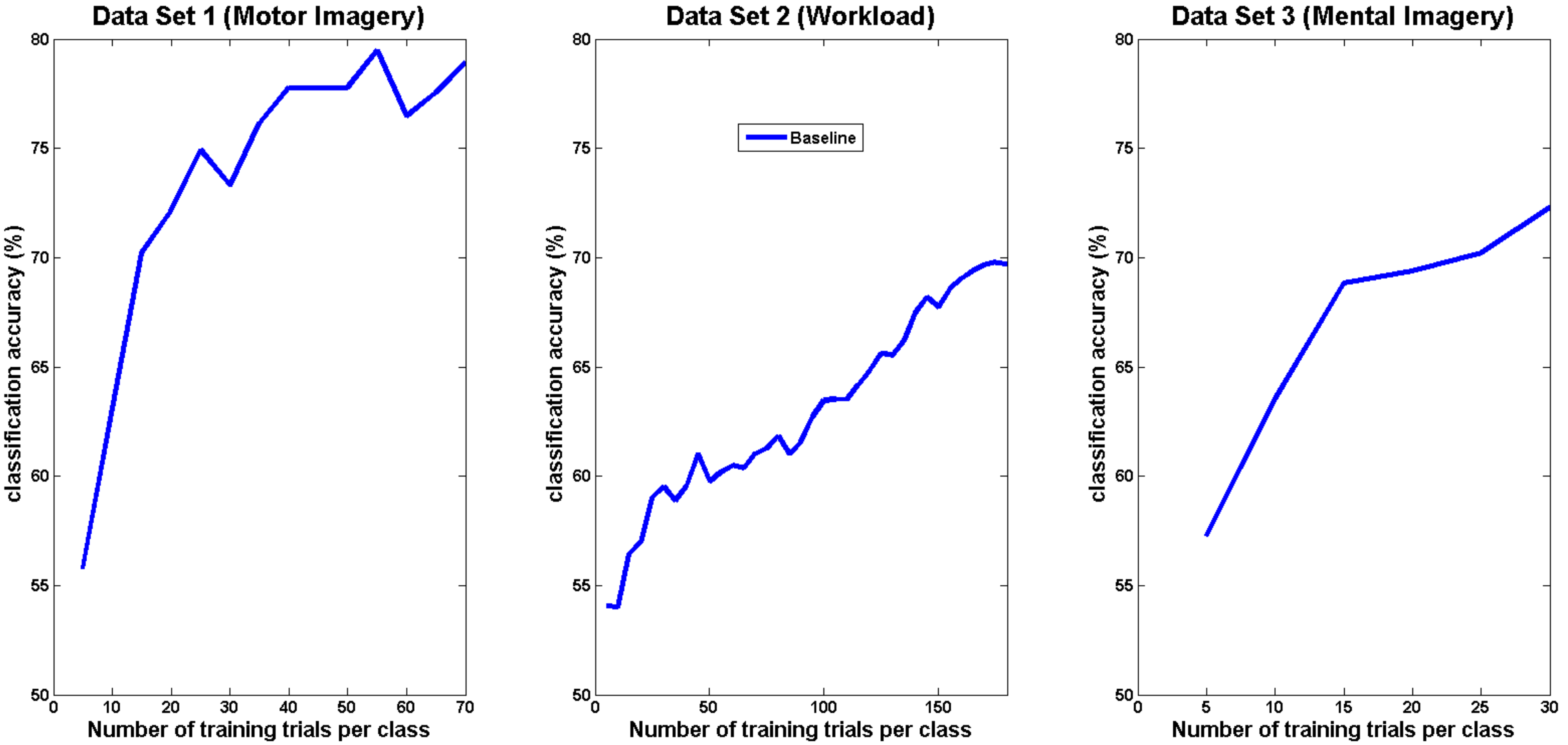
- Automatic covariance matrix shrinkage [Ledoit & Wolf 2004]

$$\tilde{C}_i = (1 - \beta) C_i + \beta I$$

- Using data from other users (previously recorded) as the stabilisation term [Lotte & Guan, ICASSP 2010 - Lotte, Proc. IEEE 2015]

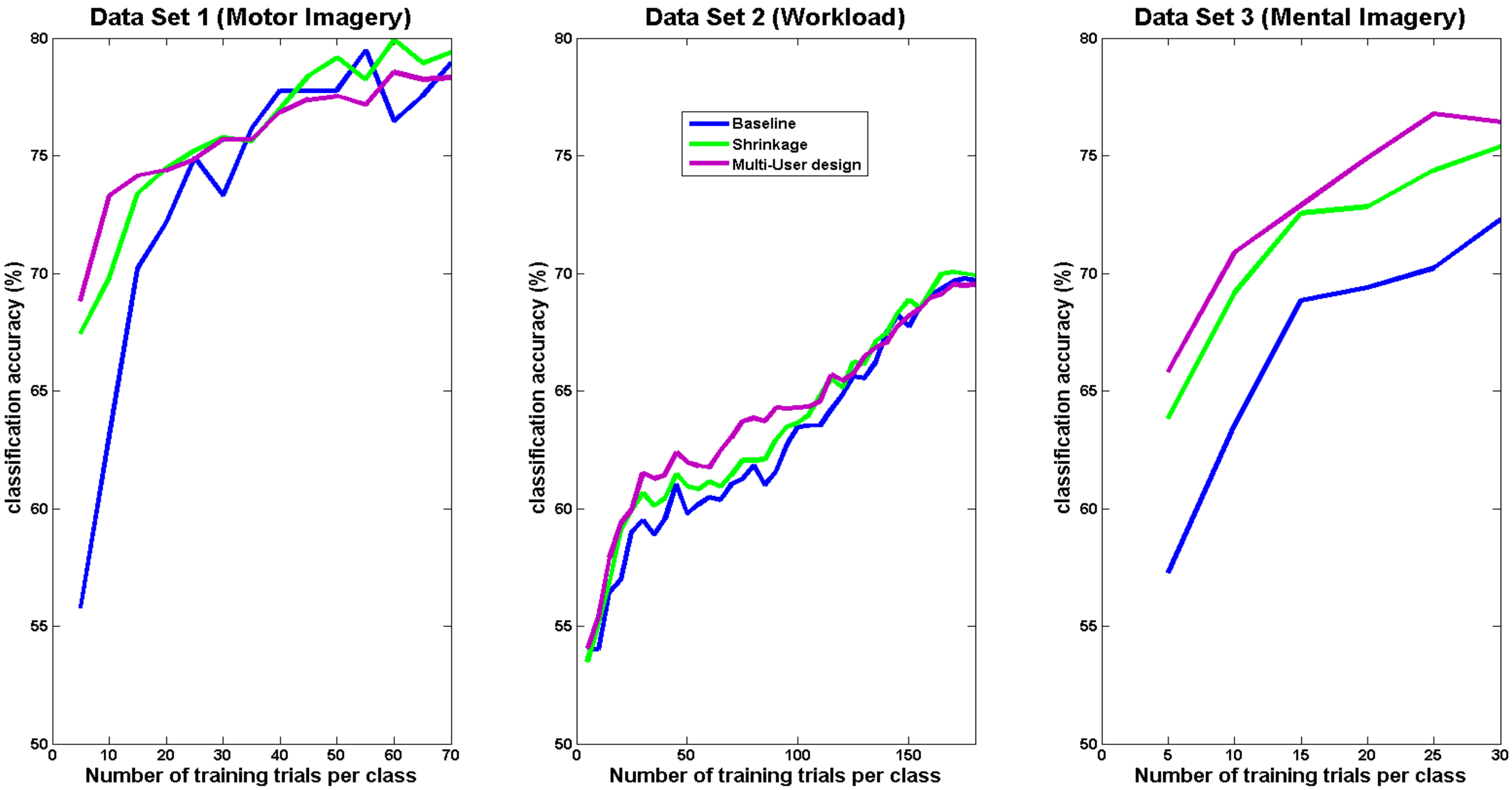


Evaluation



[Lotte, Proc. IEEE, vol. 103, no. 6, 2015]

Evaluation



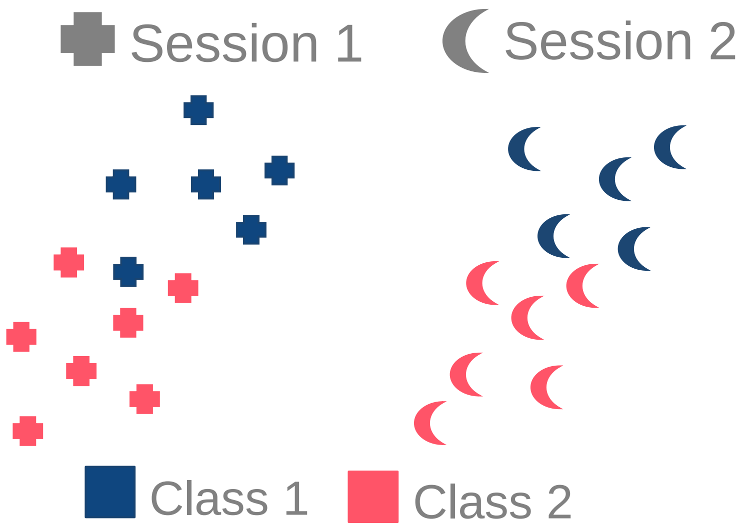
[Lotte, Proc. IEEE, vol. 103, no. 6, 2015]

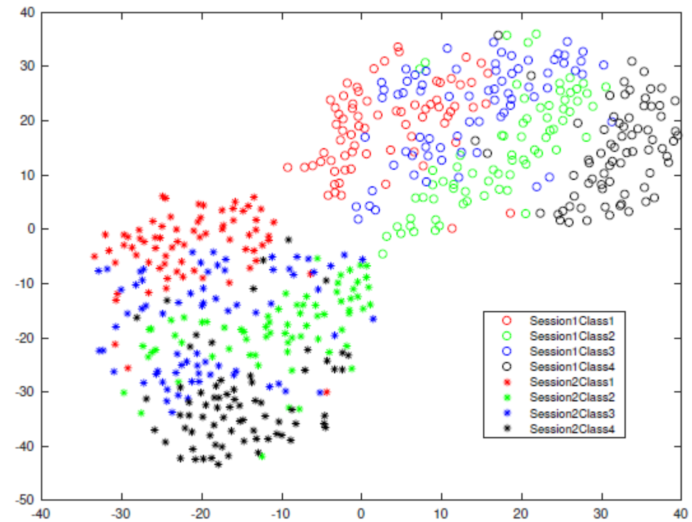
5

Dealing with non-stationarity

Non-stationarity in Brain-Computer Interfaces

- EEG signals/features distributions shift over time



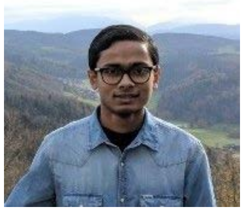


Real data (EEG covariance matrices)

- A solution: using adaptive classifiers, which updates their parameters as new EEG data are processed

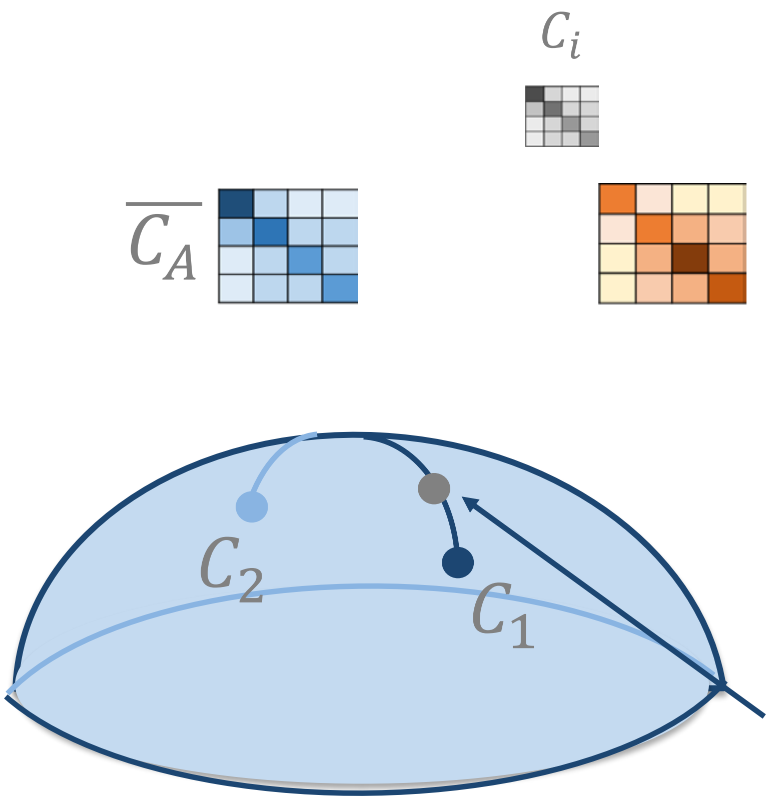
Shenoy, P et al, *Towards adaptive classification for BCI*. J Neural Eng., 2006
Lotte, F et al. *A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update*. J Neural Eng, 2018

Ex: Adaptive Riemannian Classifiers



With Satyam Kumar

- Retrain: incremental update of the prototype covariance matrix of each class



Covariance matrices manifold

- Geodesic interpolation of the prototype covariance matrices
  - Supervised: we update the true class prototype
  - Unsupervised: we update the estimated class prototype

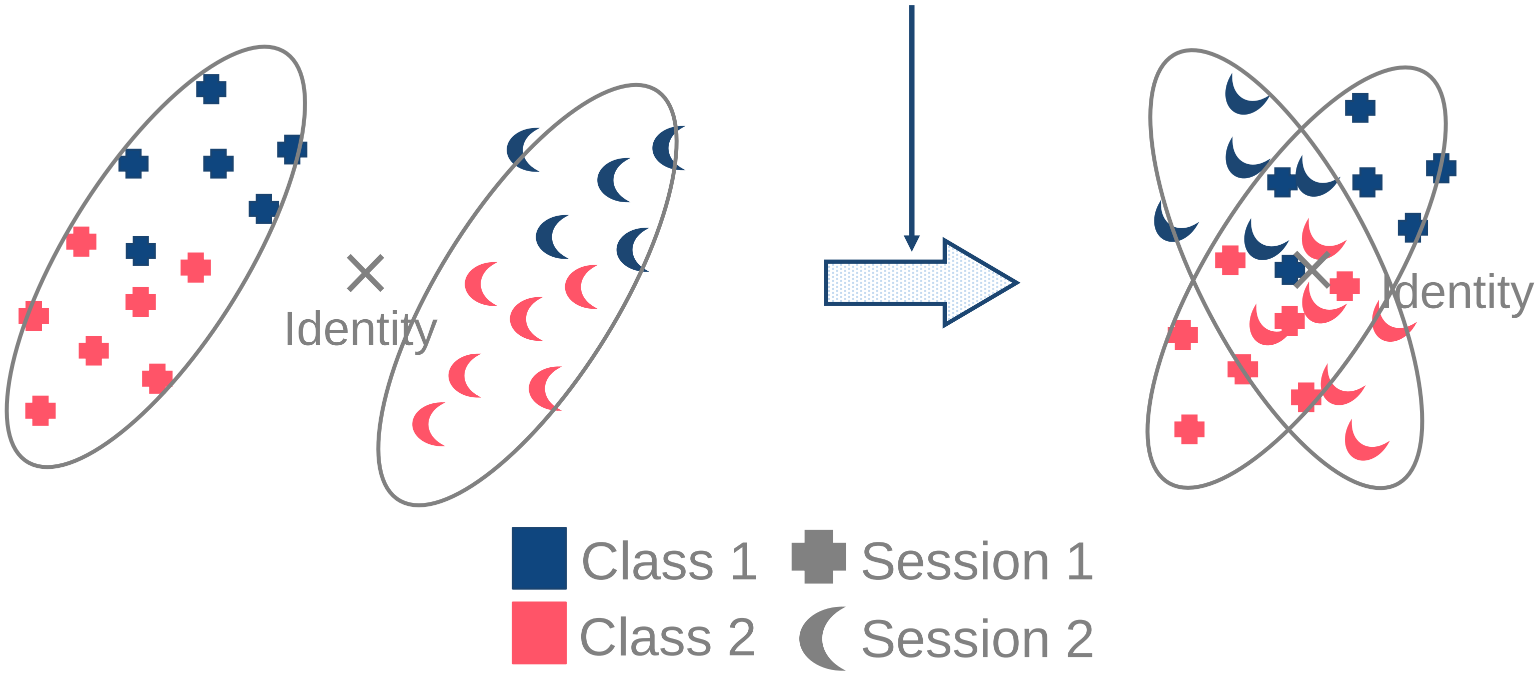
$$\overline{C_{B\_New}} = \gamma\left(\overline{C_B}, C_i, \frac{1}{N_{\overline{C_B}} + 1}\right)$$

$$\gamma(C_1, C_2, t) = C_1^{\frac{1}{2}}\left(C_1^{-\frac{1}{2}} C_2^{\frac{1}{2}} C_1^{-\frac{1}{2}}\right)^t C_1^{\frac{1}{2}}$$

Rebias: projecting to a common reference point

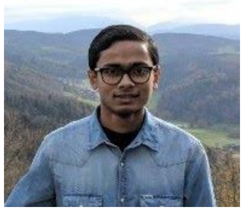
$$R_i^{Test} = \gamma\left(R_{i-1}^{Test}, C_i, \frac{1}{i-1}\right)$$

$$C_i^{Rebiased} = R^{-\frac{1}{2}} C_i R^{-\frac{1}{2}} \quad R \in \{R^{Train}, R^{Test}\}$$



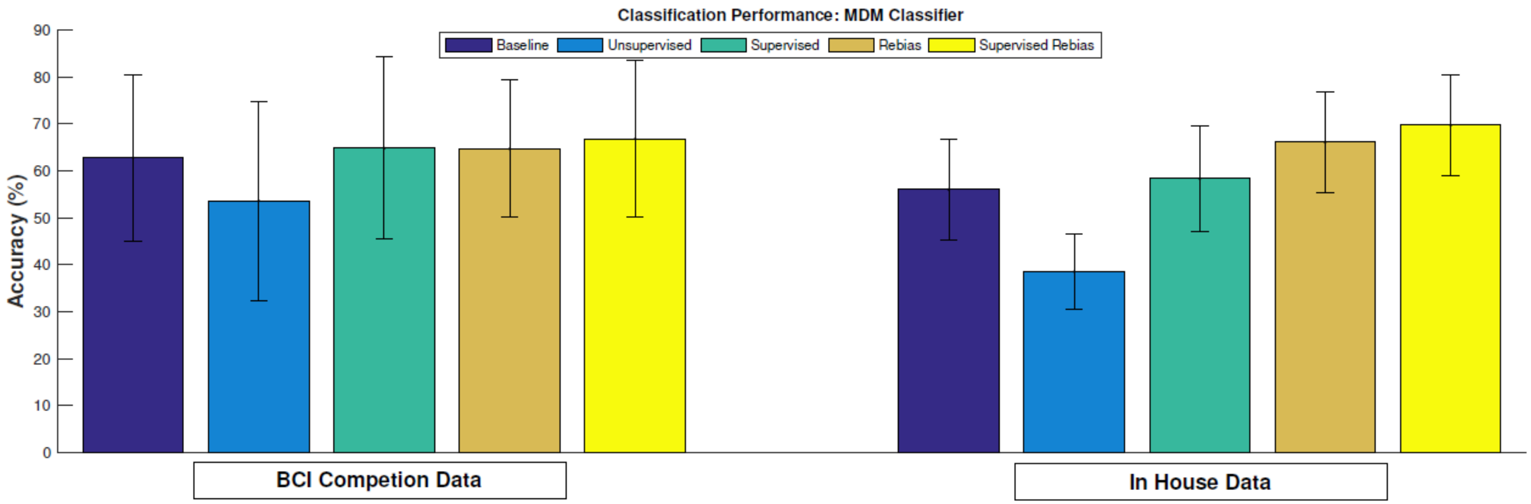
Zanini, P., Congedo, M., Jutten, C., Said, S., & Berthoumieu, Y. *Transfer learning: a Riemannian geometry framework with applications to brain–computer interfaces*. IEEE Transactions on Biomedical Engineering, *2018*

Performance of Adaptive Riemannian Classifiers



With Satyam Kumar

- Comparison on non-adaptive MDM, Retrain (supervised and unsupervised), Rebias and Retrain+Rebias



9 subjects, 2 sessions
4 motor imagery classes

18 subjects, 6 sessions
3 mental imagery classes

S. Kumar, F. Yger, F. Lotte, "*Towards Adaptive Classification using Riemannian Geometry approaches in Brain-Computer Interfaces*", IEEE Int Winter Conf on BCI, 2019

Conclusions & Perspectives

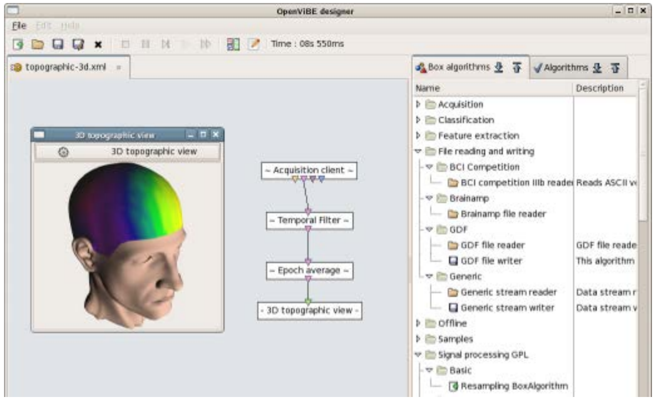
Summary

- BCI can decode EEG signals in real time
- Designed using Machine Learning and Signal Processing
  - Spectral & spatial filtering, feature extraction, classification
- Numerous EEG processing challenges
  - Between-user variabilities: using user-specific filters
  - Noise: using regularization
  - Limited data: transferring data across users
  - Within-user variabilities: using adaptive classifiers

Real-time EEG signals processing for everyone with OpenViBE!

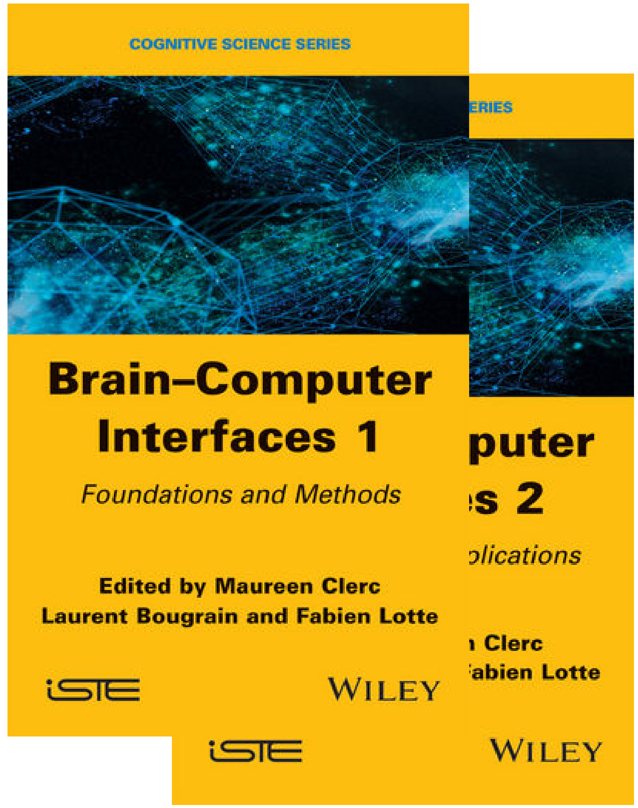
OpenViBE is a software platform for

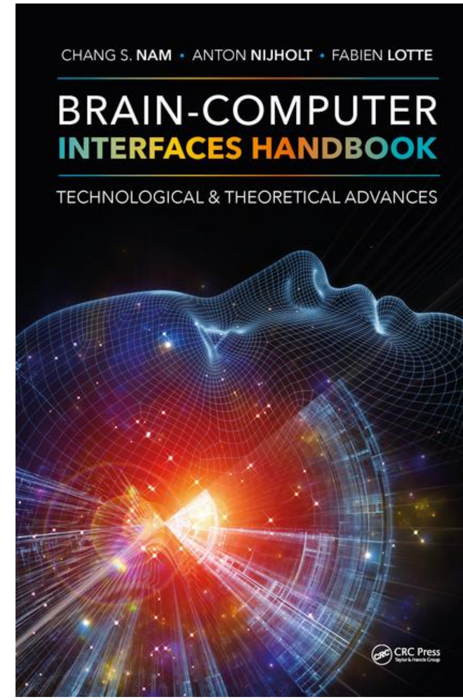
- Easily designing, testing and using BCI
- Real-time and online processing of brain signals
  acquisition, processing, visualization, …
- Free and open-source! **http://openvibe.inria.fr/**



Renard, Lotte, Gibert, Congedo, Maby, Delannoy, Bertrand, Lécuyer, *Presence*, 2010

Brain-Computer Interfaces: the books





Clerc, Bougrain, Lotte - ISTE-Wiley - 2016

Nam, Nijholt, Lotte
CRC Press, 2018

Perspectives

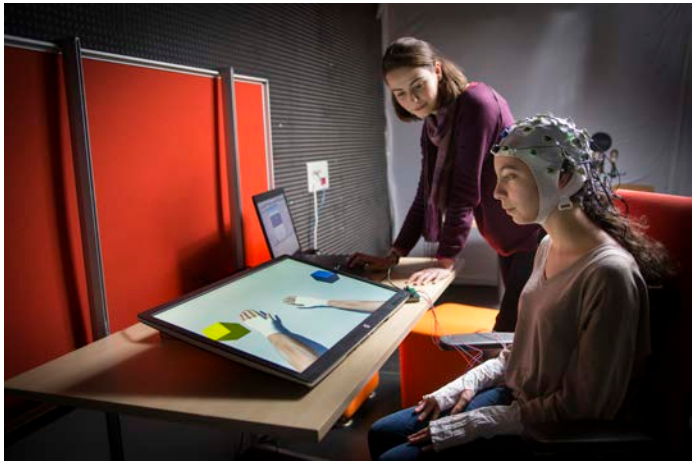
- Need for models explaining noise and variabilities

  LR Krol, J Pawlitzki, F Lotte, K Gramann, TO Zander, "*SEREEGA: Simulating Event-Related EEG Activity*", Journal of Neuroscience Methods, vol. 309, pp. 13-24, 2018

- Need for online studies with the designed algorithms

- BCI reliability can and should be improved at other levels
  - Brain activity sensors
  - Human-computer Interaction
  - User training

  ⇒ the ERC BrainConquest project



F. Lotte, C. Jeunet, J. Mladenovic, B. N'Kaoua, L. Pillette, « *A BCI challenge for the signal processing community: considering the human in the loop* », IET Book 'Signal Processing and Machine Learning for Brain-Machine Interfaces, 2018

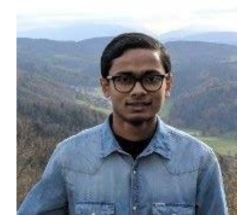
Thank you for your attention!

Andrzej
Cichocki

Florian
Yger

Cuntai
Guan

Any question?



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