ONE-CLASS RIEMANNIAN WRAPPED GAUSSIAN CLASSIFIER: APPLICATION TO ANESTHETIC STATE DETECTION

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One-class classification in BCIs

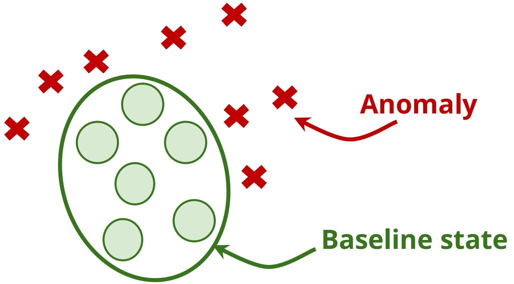
Several BCI problems are inherently **one-class**: the system must detect rare deviations from a baseline state

Mason & Birch, IEEE Trans. Biomed. Eng., 2000
Mason et al, Tech. Rep., 2006.
Lotte et al, IEEE Int Conf Patt Recogn, 2008
Lopes-Dias et al, J Neural Eng., 2021
Hernández-Del-Toro et al, Biomed. Sig. Proc. Control, 2021

One-class classification in BCIs

Several BCI problems are inherently **one-class**: the system must detect rare deviations from a baseline state

- **Asynchronous BCI:** brain switch, self-paced [*Mason & Birch, 2000; Mason, 2006; Lotte, 2008; Lopes-Dias, 2021; Hernández-Del-Toro, 2021*]
- **Clinical monitoring scenarios**: detection of anomalous respiratory states [*Navarro-Sune, 2017*], epileptic seizures [*Tran, 2022*], sleep apnea [*Barnes, 2022*], awareness under anesthesia [*Rimbert, 2023*]



Mason & Birch, IEEE Trans. Biomed. Eng., 2000
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Hernández-Del-Toro et al, Biomed. Sig. Proc. Control, 2021

Navarro-Sune et al, IEEE Trans. Biomed. Eng., 2017
Tran et al, Diagnostics. 2022
Barnes et al, PLOS One, 2022
Rimbert et al. JMIR Res. Protoc, 2023

Data from a clinical protocol

19 patients (10 females; 47 ± 12.51 years old)

Median-Nerve Stimulation based BCI

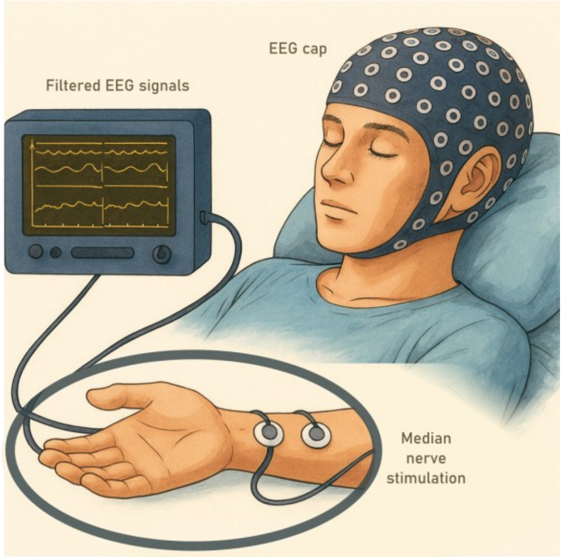

Figure inspired by Sigl and Chamoun, J Clin Monit, 1994

Rimbert et al. JMIR Res. Protoc, 2023.

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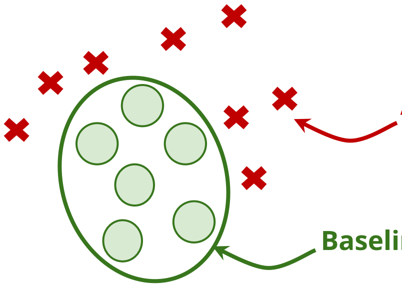
Awake vs. under anesthesia

TRAIN	TEST
Awake	Awake or Anesthesia?
150 trials	400 to 1500 trials

preoperative session | change of room | intraoperative session

0  ~1h — beginning of the surgery  end of the surgery



From EEG to covariance matrices

$\mathbf{E}_1, \dots \mathbf{E}_N$

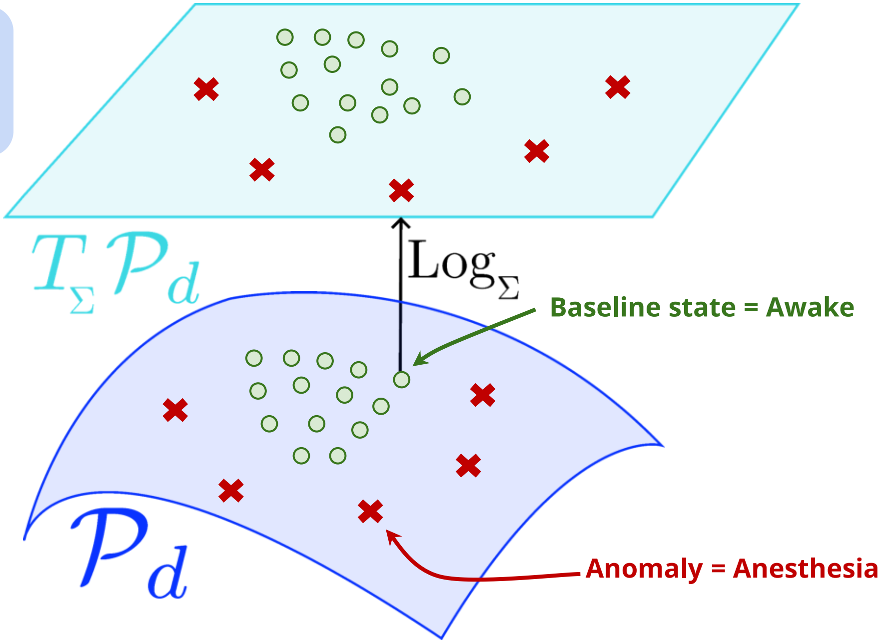
EEG

$\Sigma_1, \dots, \Sigma_N$

Covariance matrix

$$\delta_R(\Sigma_1, \Sigma_2) = \| \log(\Sigma_1^{-1/2} \Sigma_2 \Sigma_1^{-1/2}) \|_F$$

Riemannian distance



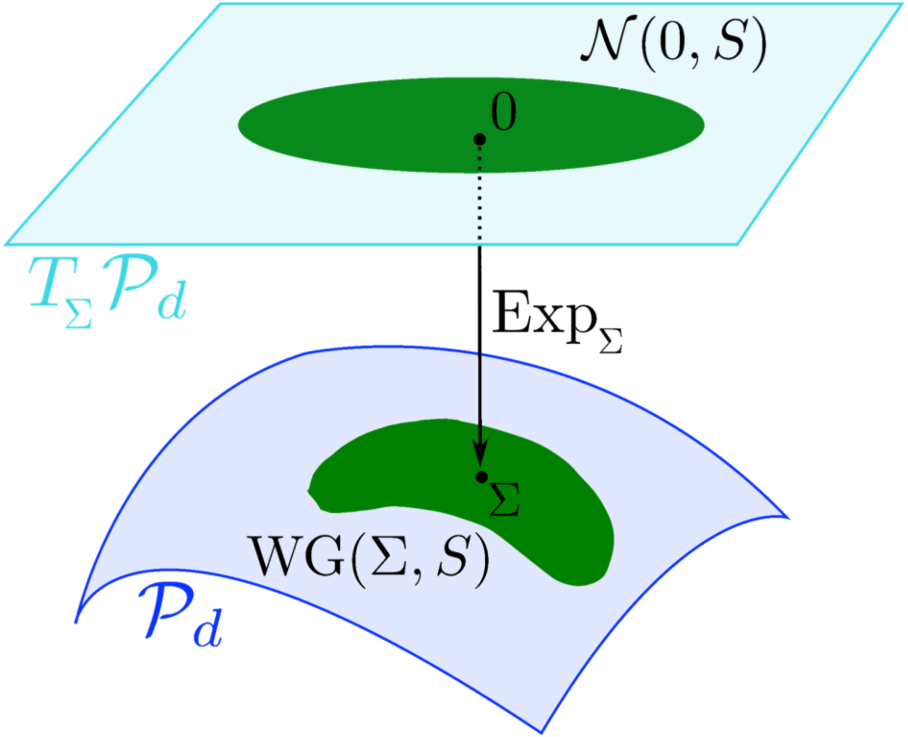
The wrapped Gaussian

Definition (Wrapped Gaussian)

A random variable $X \in \mathcal{P}_d$ follows a *wrapped Gaussian* $\mathrm{WG}(\Sigma, S)$ if

$$X = \mathrm{Exp}_\Sigma(t), \quad t \sim \mathcal{N}(0, S)$$

We know:
- Its density
- How to estimate its parameters



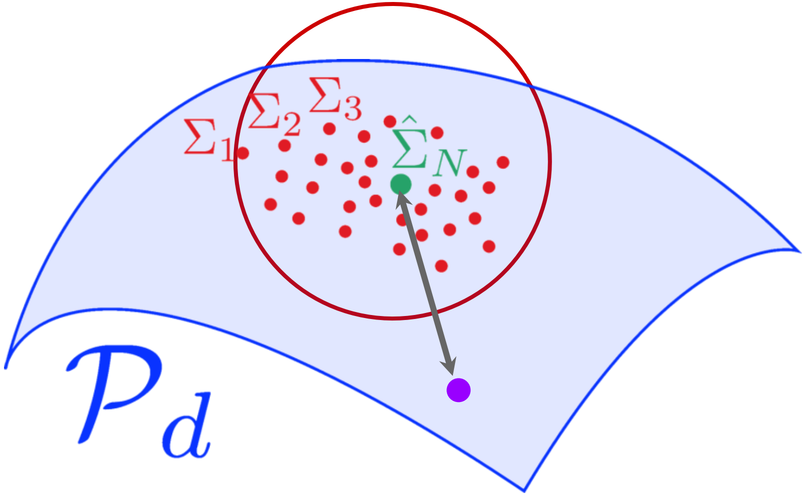
de Surrel T, Lotte F, Chevallier S, Yger F. *Wrapped Gaussian on the manifold of symmetric positive definite matrices.* ICML, 2025.

One-Class Minimum Distance to the Mean (OC-MDM)

- Model uses the **Riemannian mean** $\hat{\Sigma}_N$ of the class awake

- **Decision**: log-likelihood threshold

$$\delta_R(\Sigma, \hat{\Sigma}) \leq \mathrm{median}_{\Sigma \in \mathcal{P}_d} \left(\delta_R(\Sigma, \hat{\Sigma})\right) + 3\, \mathrm{std}_{\Sigma \in \mathcal{P}_d} \left(\delta_R(\Sigma, \hat{\Sigma})\right)$$



...but assumes **isotropic** structure

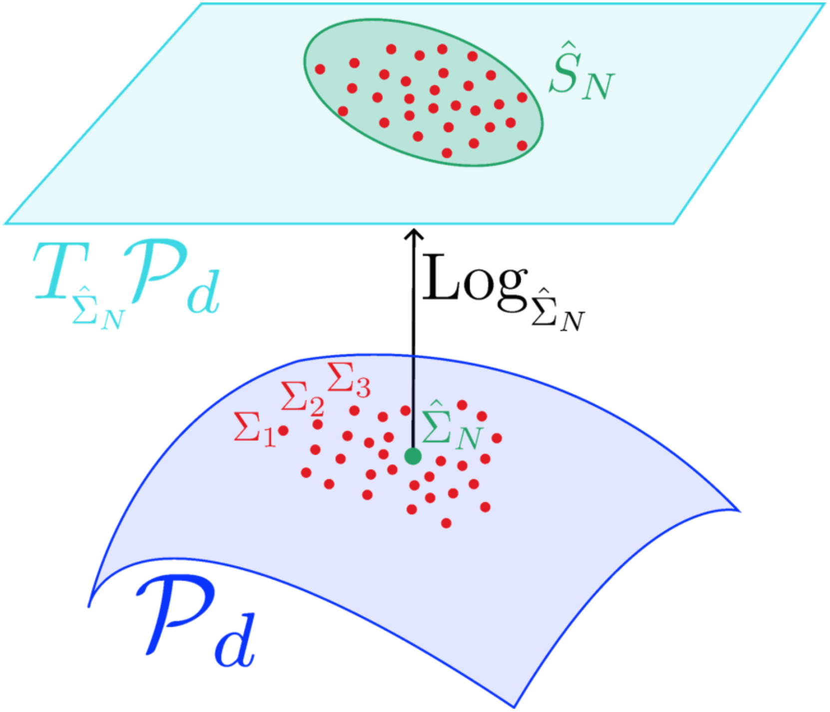
One-Class Wrapped Gaussian (proposed)

- Model uses a **wrapped Gaussian** $\mathrm{WG}(\hat{\Sigma}_N, \hat{S}_N)$ where
  - $\hat{\Sigma}_N$ is the Riemannian mean of the class awake
  - the dispersion $\hat{S}_N$ is estimated by

$$\hat{S}_N = \frac{1}{N}\sum_{i=1}^{N} \mathrm{Log}_{\hat{\Sigma}_N}(\Sigma_i)\mathrm{Log}_{\hat{\Sigma}_N}(\Sigma_i)^\top$$

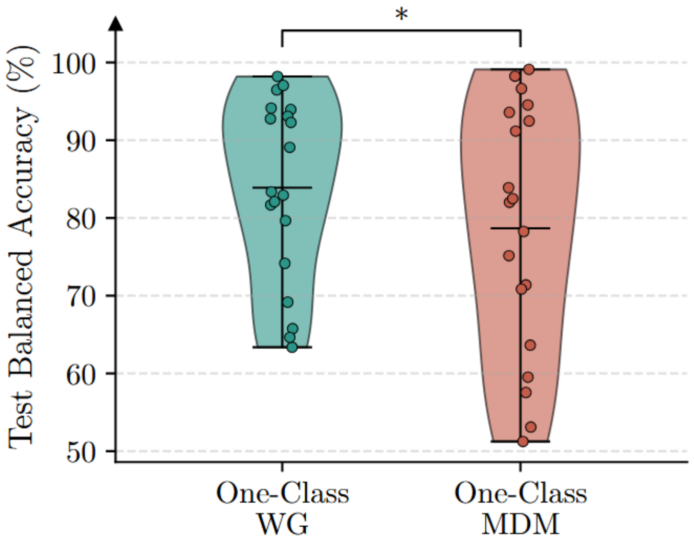
- **Decision**: log-likelihood threshold

Compared to the One-Class MDM:
- Anisotropy in the dispersion
- Equal to the One-Class MDM if $S = \alpha I$



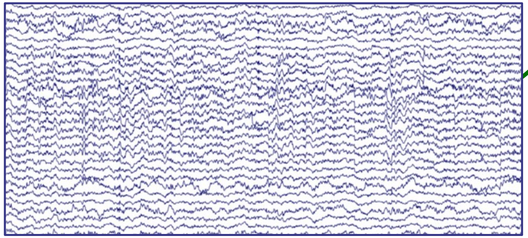
Classification results (5 electrodes)

Electrodes: Cz, C3, C4, FC3, FC4

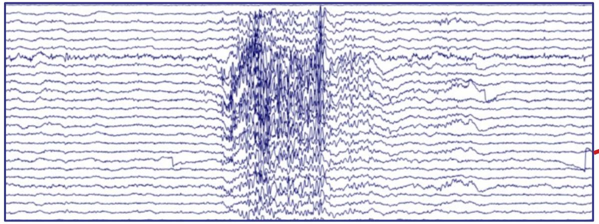


In **13/19** subjects One-Class WG improves One-Class MDM

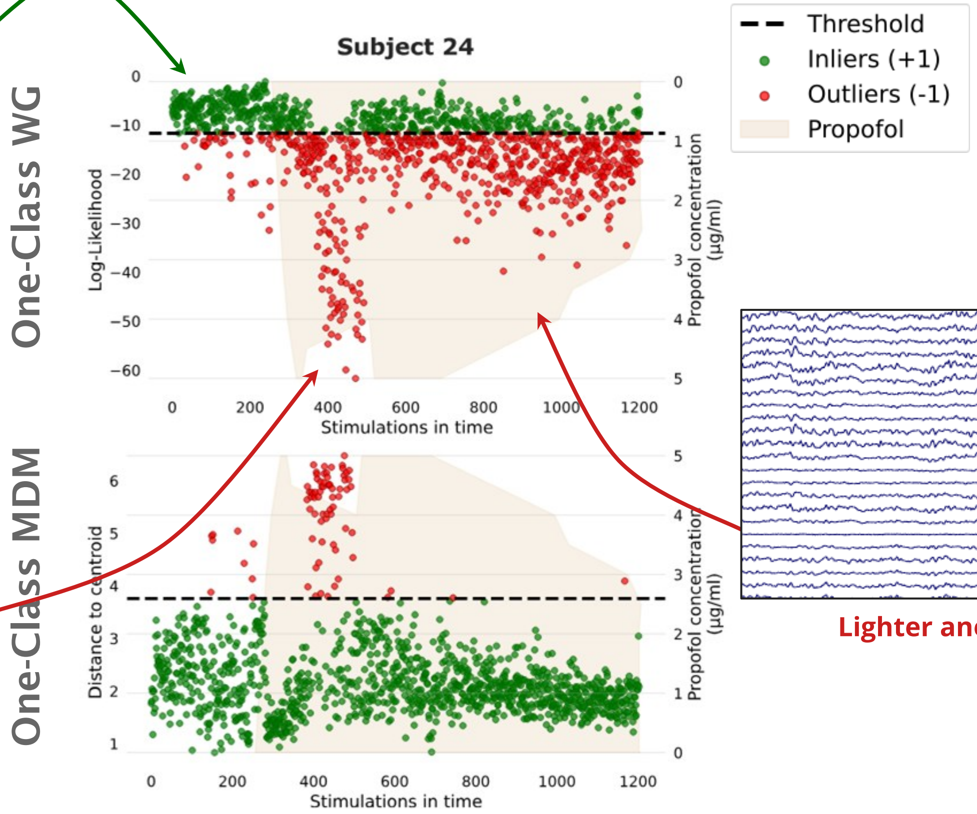
Effect of anesthesia depth

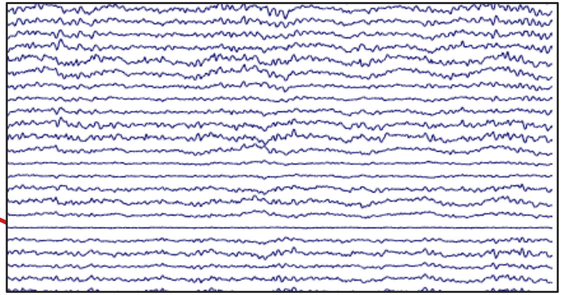


Awake



Deep anesthesia: burst suppression
[Pawar and Barreto, 2022]





Lighter anesthesia

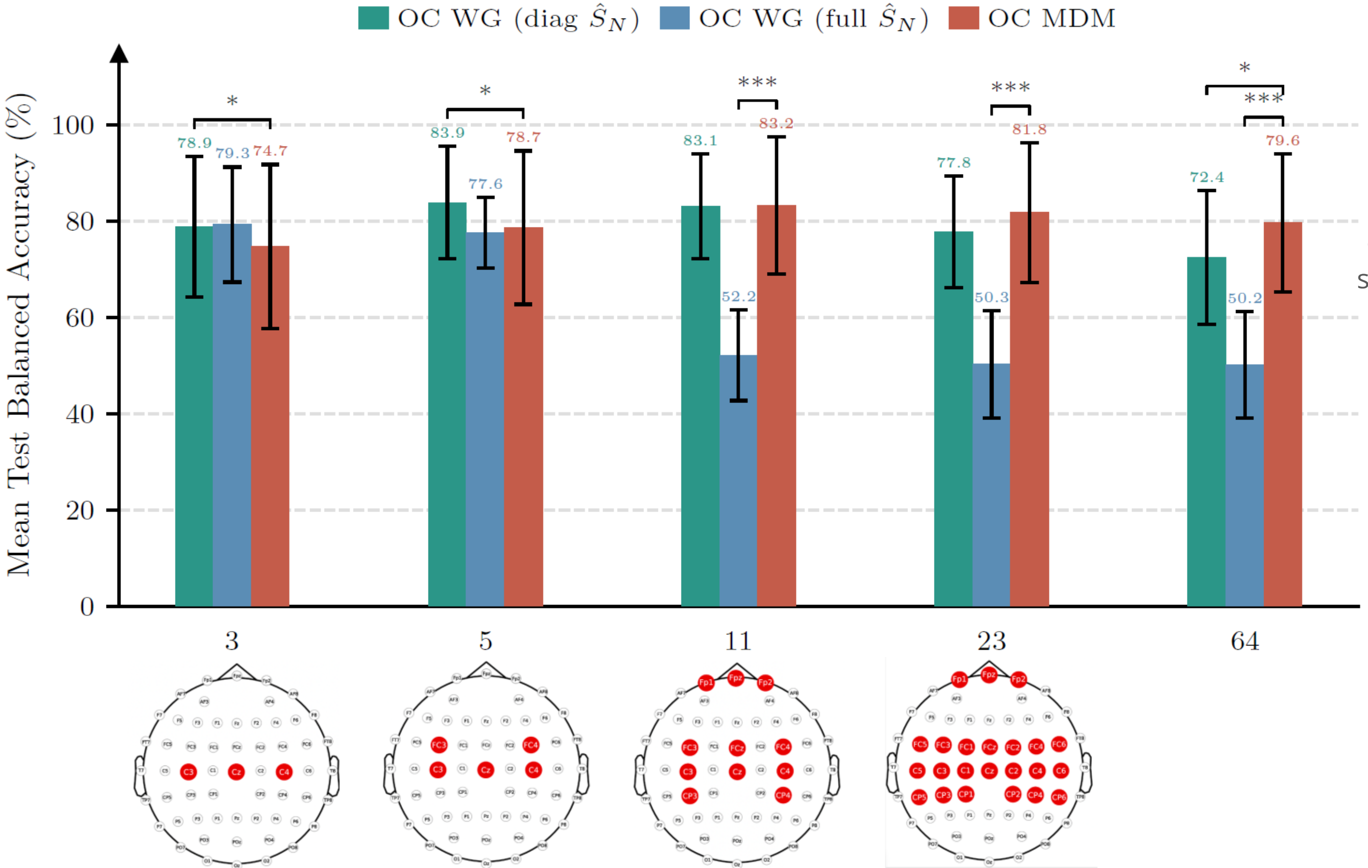
Pawar and Barreto. Front. Syst. Neurosci., 2022

Importance of the montage

Number of coefficients to estimate when the montage has d electrodes:

- One-Class MDM: $O(d^2)$
- One-Class WG: $O(d^4)$
- One-Class WG with a diagonal $\hat{S}_N$: $O(d^2)$

Importance of the montage



Mean test balanced accuracy across different electrode setups. Statistical significance was assessed using a two-sided paired t-test (*p < 0.05, **p < 0.01, ***p < 0.001).

Takeaways

- New **probabilistic One-Class Riemannian** algorithm
- Generalization of One-Class Riemannian Minimum Distance to the Mean
- Suitable for a real-world BCI with **fewer electrodes**: clinical scenarios such as the detection of awareness under anesthesia

Perspectives:

- Validation on additional EEG datasets
- Comparison with other one-class algorithms [*Ruff et al, 2021*]
- In this application case: exploration of change-point detection algorithms [*Wang et al, 2025*] & further analyses of burst suppression states [*Purdon et al, 2015*]

Ruff et al, Proc IEEE, 2021
Wang et al, IEEE EUSIPCO, 2025
Purdon et al, Anesthesiology; 2015

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BCI4IA project
2022-2026

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BCI4IA project
2022-2026


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Thank you for your attention!

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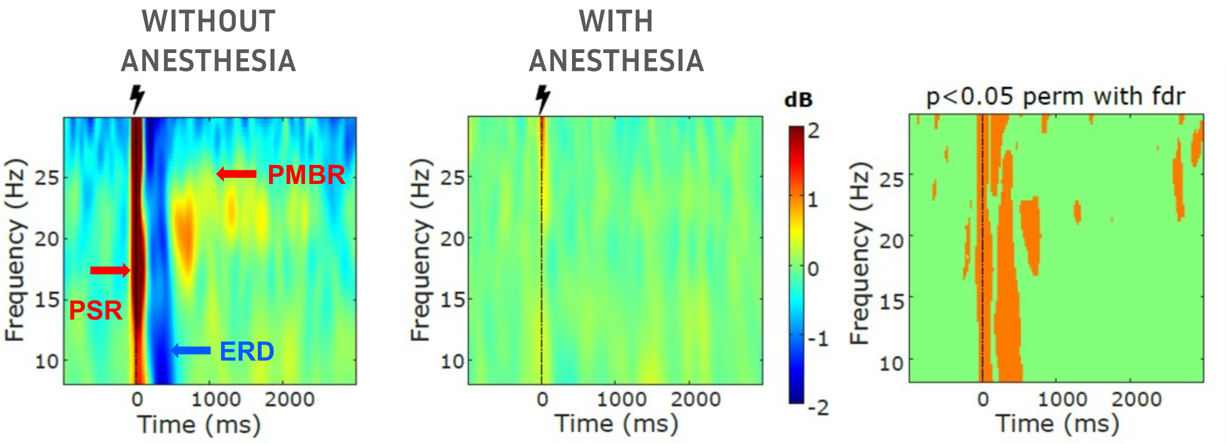
Median Nerve Stimulation-based BCI to monitor anesthesia

MNS induces sensorimotor modulations visible via EEG and variable with the depth of anesthesia.

IDEA: Follow this pattern through the anesthesia.



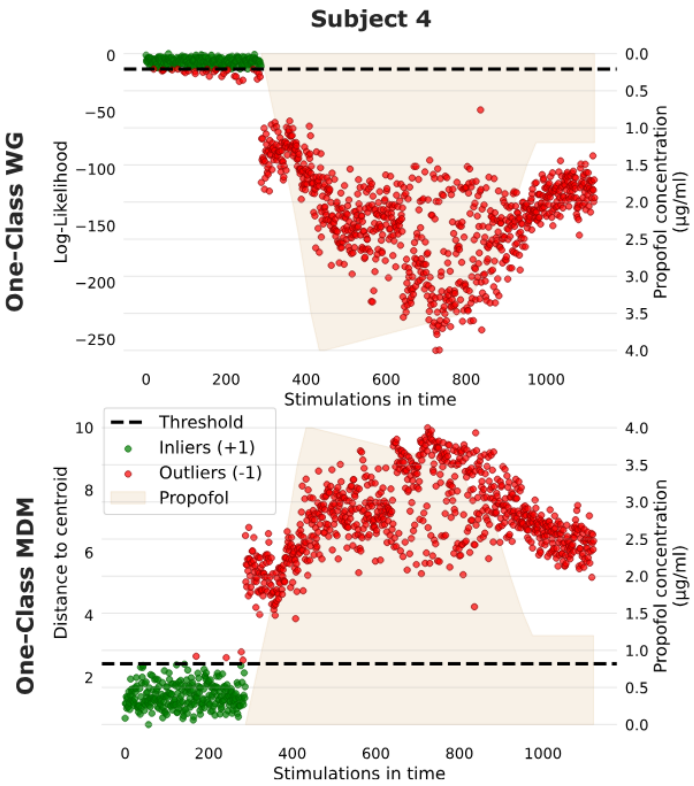
Grand average time frequency analysis across 8 subjects for electrode C4

PSR: Post-Stimulation Rebound
ERD: Event Related Desynchronization
PMBR: Post-Movement Beta Rebound

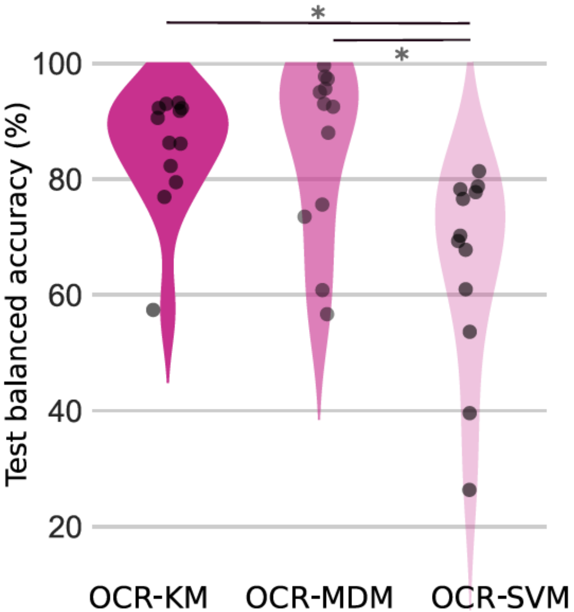
Marissens Cueva et al. 9th Int.. Graz BCI Conf. 2024.

With different depth of anesthesia?

-5.2



Comparison of One-Class Riemannian classifiers

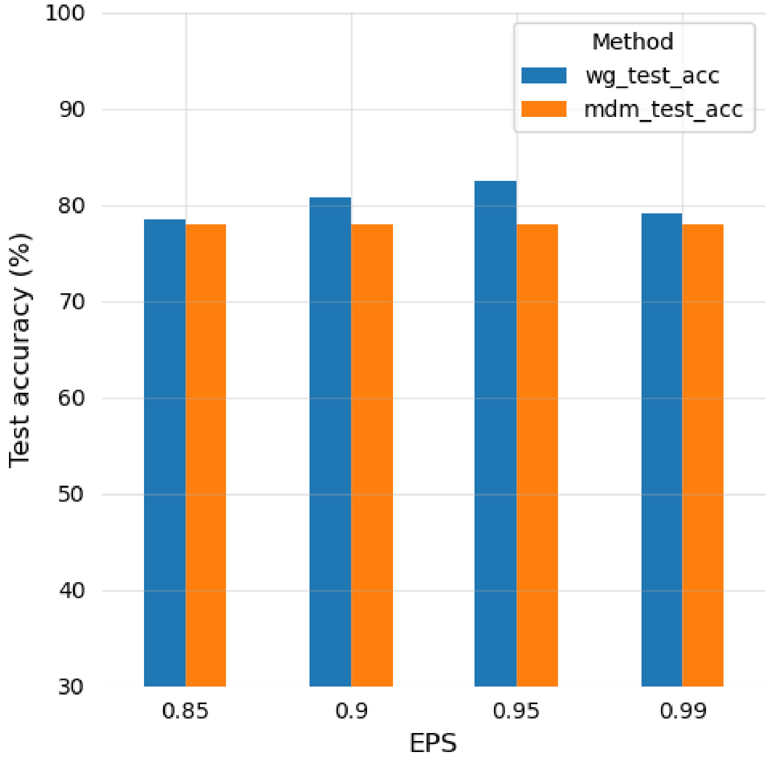


With ϕ the Riemannian kernel:

$$K_{i,j} = \mathrm{tr}\left(\log\left(\boxed{C_{ref}^{-1/2}} X_i \boxed{C_{ref}^{-1/2}}\right) . \log\left(\boxed{C_{ref}^{-1/2}} Y_j \boxed{C_{ref}^{-1/2}}\right)\right)$$

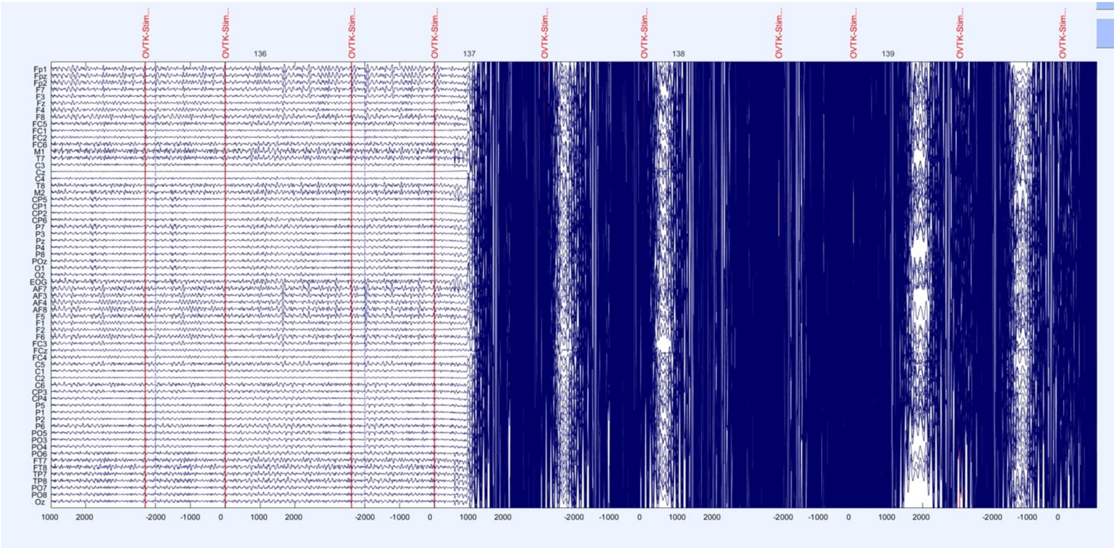
Test balanced accuracies of **OC classifiers trained on data when patients are awake** (12 subjects). Best results with OC-RKM are with 2 prototypes, and thresholds of median + 3 × median absolute deviation. For OC-RSVM, ν = 0.5.*p-value < 0.05

Différents epsilons (log-likelihood threshold)



Preprocessing

- DS 128 Hz
- BP 8-30 Hz
- Artifacts manually rejected
- Epochs 250:1000 ms post MNS



The density of the wrapped Gaussian

Theorem (Then density of the wrapped Gaussian)

The density $f_{p,\mu,\Sigma}$ *of the wrapped Gaussian* $\mathrm{WG}(p,\mu,\Sigma)$ *exist and is:*

The density of $\mathcal{N}(\mu,\Sigma)$

$$\forall x \in \mathcal{P}_d,\ f_{p,\mu,\Sigma}(x) = \frac{g_{\mu,\Sigma}(\mathrm{Vect}_p(\mathrm{Log}_p(x)))}{|J_p(\mathrm{Log}_p(x))|}.$$

The Jacobian determinant of Exp_p

Proposition (The Jacobian determinant of the exponential map)

The Jacobian determinant of the exponential map Exp_{I_d} *at the identity is:*

$$J_{I_d}(u) = 2^{d(d-1)/2} \prod_{i<j} \frac{\sinh\left(\frac{\lambda_i(u)-\lambda_j(u)}{2}\right)}{\lambda_i(u)-\lambda_j(u)}$$

where $(\lambda_i(u))_i$ *are the eigenvalues of* u*. Then, for any point* $p \in \mathcal{P}_d$*:*

$$J_p(u) = J_{I_d}(p^{-1/2}up^{-1/2}).$$

STIM-PSI clinical protocol

C H U | U V C
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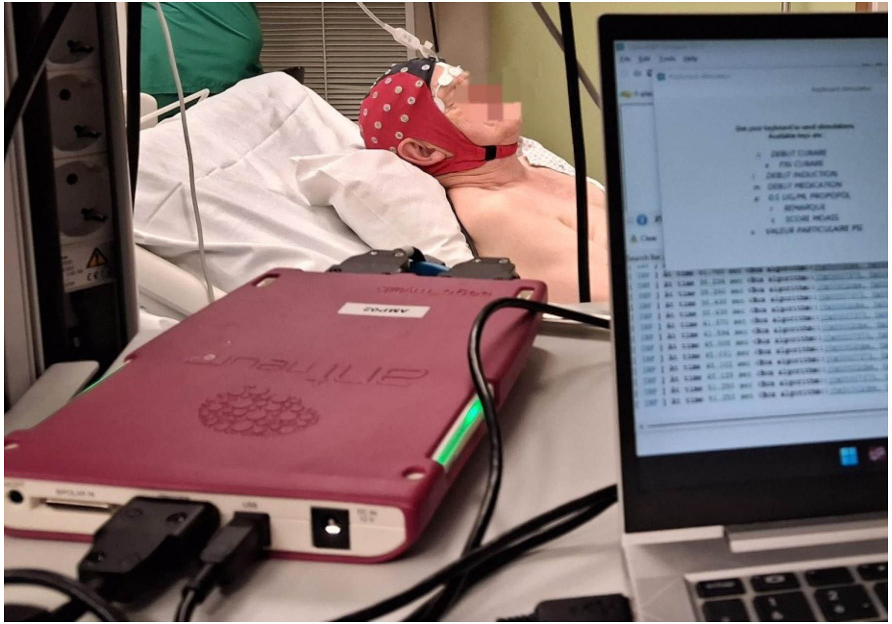

SedLine monitor
www.masimo.fr