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Benchmarking one-class Riemannian EEG classifiers to detect wakefulness under general anesthesia

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Introduction: Current brain monitors for detecting Accidental Awareness during General Anesthesia (AAGA) remain debated, as robust evidence supporting their effectiveness in reducing AAGA's incidence is lacking [1]. To address this, we propose a new brain-computer interface based on Median Nerve Stimulation (MNS), a painless stimulation that elicits motor patterns, to monitor depth of anesthesia [2]. Specifically, we train our algorithm with post-MNS EEG patterns recorded while patients are awake, enabling the detection of the return to an arousal state during the surgery under anesthesia. Since the anesthesia data is unavailable pre-surgery for BCI calibration, we focus on One-Class (OC) approaches. In this study, we evaluate three OC Riemannian methods for this task: K-Means (OC-RKM) [3], Minimum Distance to the Mean (OC-RMDM) [5] and Support Vector Machine (OC-RSVM) [4, 6].

Material, Methods and Results: This study includes 12 patients (6 women; 50 ± 14.3 years) undergoing surgery under general anesthesia with propofol as the hypnotic agent, at CHU Brugmann in Belgium [7]. EEG data were collected in two sessions: preoperatively (awake) and intraoperatively (under anesthesia). Each session involves several recordings, each with 150 MNSs delivered at a frequency of 0.25 to 0.33 Hz. Features were extracted as covariance matrices 250 to 1000 ms post-MNS in the 8–30 Hz frequency band. Classification performances of the three OC Riemannian algorithms are summarized in Figure 1. A Student's t-test with Benjamini-Hochberg correction shows OC-RKM and OC-RMDM significantly outperform OC-RSVM ($p < 0.05$).

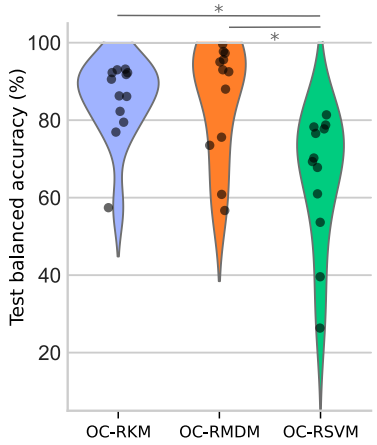

Figure 1: *Test balanced accuracies obtained with 12 patients using OC classifiers trained on data when patients are awake. Best results with OC-RKM are with 2 prototypes, and thresholds of median + 3 × median absolute deviation. For OC-RSVM, $\nu = 0.5$. For OC-RMDM parameters, see [5]. *p-value < 0.05.*

Conclusion: Results indicate that both OC-RKM and OC-RMDM effectively delimit an awake state in most subjects, though not all. In contrast, OC-RSVM has a lower performance, possibly due to the use of a Riemannian kernel reference point C_{ref} computed as the mean covariance matrix of the awake class, which may inadequately capture the geometry of both classes. Additionally, ν was not optimized, as its tuning in a one-class context remains challenging. Future work will assess performance regarding the number of electrodes, alternative C_{ref}, and comparisons with other one-class algorithms. An ensemble method will also be considered to improve robustness for depth of anesthesia estimation across subjects, leveraging the strengths of each model.

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