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► To cite this version:

Valérie Marissens Cueva, Sébastien Rimbert, Ana Maria Cebolla Alvarez, Mathieu Petieau, Iraj Hashemi, et al.. One-Class Riemannian EEG Classifier to Detect Anesthesia. 5th International Neuroergonomics Conference 2024, Jul 2024, Bordeaux, France. hal-04634709

HAL Id: hal-04634709

<https://hal.science/hal-04634709v1>

Submitted on 4 Jul 2024

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One-Class Riemannian EEG Classifier to Detect Anesthesia

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Synopsis

Accidental awareness during general anesthesia (AAGA) is a severe complication of anesthetic care. To prevent AAGAs, electroencephalograms (EEG) began to be employed, but current brain monitors still prove inadequate in detecting AAGAs. We aim to propose a new Brain-Computer Interface (BCI) that monitors the motor cortex via EEG, detects movement intentions (MIs) based on Median Nerve Stimulation (MNS) patterns, and alerts the medical team. Consequently, our first objective is to develop a classifier that distinguishes EEG patterns induced by MNS under two conditions: when a patient is awake vs under GA. Since the latter condition is unavailable pre-surgery for BCI calibration, we focused on one-class methods. A One-Class Riemannian Minimum Distance to the Mean trained with the awake data correctly differentiates between these two conditions (test balanced accuracy of 85.44%), significantly better than when the classifier is trained with the beginning of intraoperative data.

Background

Accidental awareness during general anesthesia (AAGA) is defined as an unexpected awakening during general anesthesia (GA) (Tasbihgou et al, 2018), highly stressful for the patients and potentially leading to significant psychological consequences (Leslie et al, 2010). The inability to predict AAGA using only clinical signs, has led to the use of brain activity monitors to study the depth of anesthesia, yet these monitors remain insufficient (Avidan et al, 2008).

The initial reflex of a patient experiencing AAGA is to attempt to move, alerting doctors of this terrifying situation (Pandit et al, 2014). However, in certain surgeries, the application of neuromuscular-blocking agents is necessary, inhibiting any movement of the patient. Thus, monitoring movement intentions (MI) may aid in detecting AAGAs. With current Brain-Computer Interfaces (BCIs) based on motor imagery, it is already possible to detect MIs with high accuracy based on EEG from the motor cortex. This accuracy is further improved when using Median Nerve Stimulation (MNS). When combined with MI, MNS patterns are significantly enhanced, additionally MNS serves as a trigger, easing MI detection compared to asynchronous BCI (Rimbert et al, 2019).

For this new BCI, it is necessary to construct a classifier capable of discriminating between EEG activities induced by MNS under two conditions: MNS while the patient is awake (MNS-awake), and MNS during a surgery under general anesthesia (MNS-anesthesia). To accomplish this objective, in previous works, we initially tested a Riemannian Minimum Distance to the Mean (MDM) classifier (Barachant et al, 2012) in a profound MNS-anesthesia vs MNS-awake classification task. Our (still unpublished) findings suggested that an MDM classifier is indeed

capable of distinguishing between these two classes with high accuracy, as the covariance matrices associated with the MNS pattern seem to evolve consistently with the patient's level of awareness. However, in a real situation, data from profound MNS-anesthesia will be unavailable for calibration. Hence, we opted for one-class methods (Khan et al, 2014), comparing the performances when relying solely on i) MNS-awake data, ii) the induction of MNS-anesthesia (when available), or iii) the beginning of profound MNS-anesthesia.

Methods

Offline performances of a one-class classification were analyzed. For this analysis, we utilized the MNS patterns of 15 patients who received propofol, an intravenous anesthetic, during surgery at CHU Brugmann, Belgium (Rimbert et al, 2023). Three subjects were excluded, either due to technical issues or because the surgery was canceled, resulting in only 12 subjects (6 females; 50 ± 14.3 years old) being included. For three of them (S11, S12, S13), we lacked the induction recordings. One recording, or run, consisted of 150 stimulations, spaced by 3 to 4 seconds.

For condition i), the One-Class Minimum Distance to the Mean classifier (OC-MDM) considers only preoperative data to compute an MNS-awake centroid using a Riemannian average, as in the MDM algorithm. A threshold based on the Riemannian distance to the MNS-awake centroid is then defined. Unseen trials that exceed this threshold are classified as an MNS pattern corresponding to an anesthetized patient (MNS-anesthesia). For conditions ii) and iii), OC-MDM computes an MNS-anesthesia centroid, and unseen trials situated too far from it are classified as MNS-awake.

First, the distances Δ between the training set covariance matrices and the one-class centroid are computed. The standard deviation σ_{Δ} and the median med_{Δ} are calculated. The class $\hat{k}$ of an unseen test EEG covariance matrix, with $\hat{\delta}$ its distance to the one-class centroid, is determined as follows:

if $\hat{\delta} > med_{\Delta} + 3 \sigma_{\Delta}$ then $\hat{k}$ is MNS-anesthesia in case i), or MNS-awake in cases ii) and iii).

Results

The OC-MDM classifier trained with these three conditions achieved an average balanced test accuracy of 85.44 %, 56.91 % and 73.14 % respectively (Fig. 1). According to a Student's t-test, the results obtained when trained with the induction are significantly inferior than with the other training runs (MNS-awake or the beginning of deep anesthesia).

We also observed the classifier's response evolution with anesthesia depth, in terms of distance between the learned centroid and covariance matrices of other trials throughout the surgery (Fig. 2).

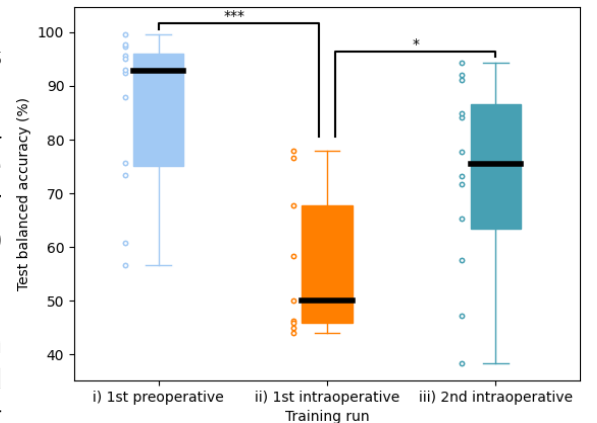


Figure 1: OC-MDM test balanced accuracies of the 12 subjects (9 for condition ii), with three training sets. The EEG signals were filtered in the mu+beta band (8-30 Hz), and all 64 electrodes were used. * p -value < 0.05, *** p -value < 0.001.

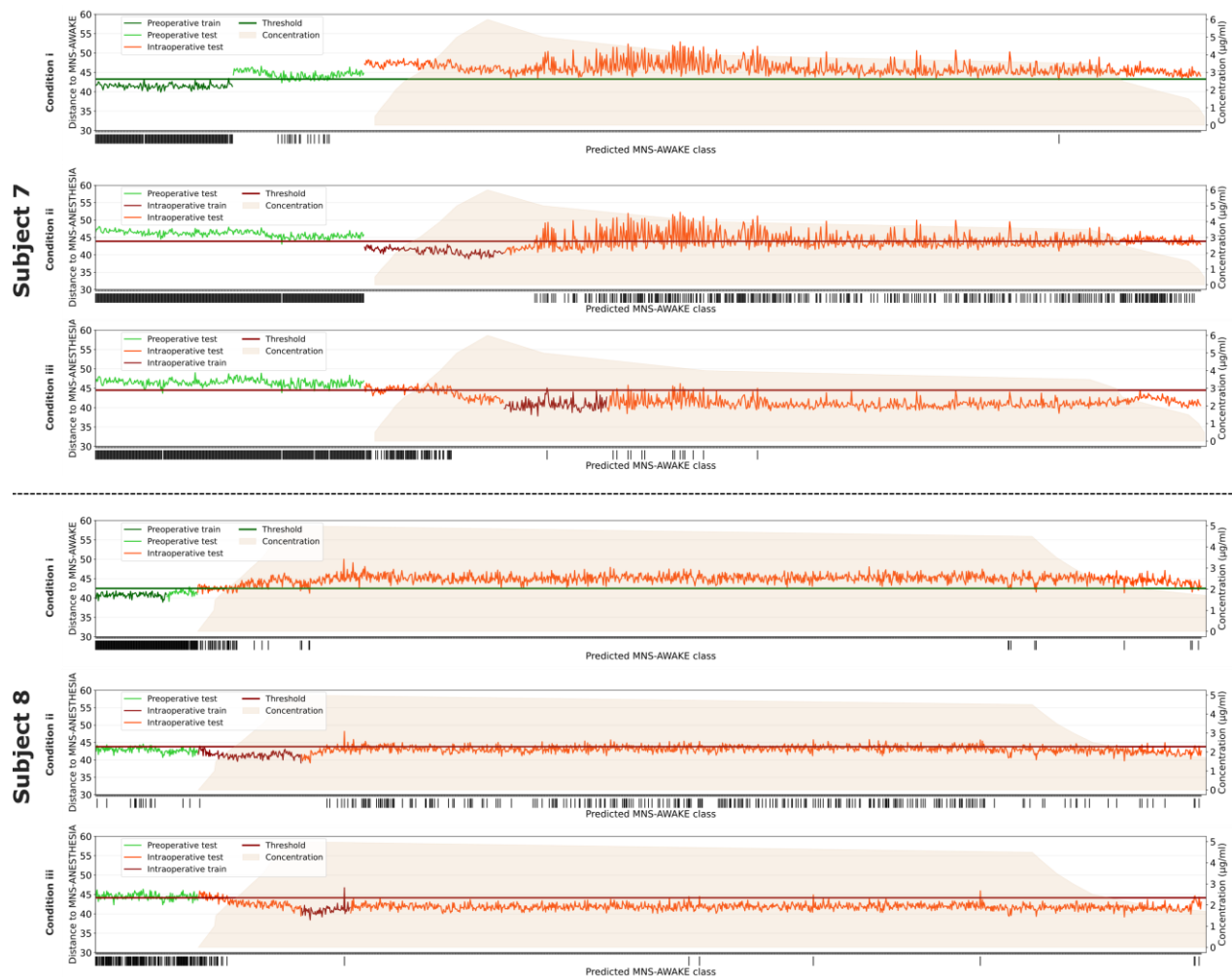


Figure 2: Distances between each test trial and i) the MNS-awake class centroid, or ii) and iii) the MNS-anesthesia class centroid, for subjects S7 and S8. The test balanced accuracies for S7 in each condition are 57%, 78% and 94%; and for S8 97%, 45% and 85%. The real labels are represented by colors: green for the MNS-awake, red for MNS-anesthesia. Darker colors are employed for training runs. Below, a bar indicates when the classifier predicted MNS-awake. The evolution of propofol target concentrations is presented by the shaded area in the background.

Discussion

The distance to the learned centroid seems to evolve consistently with the propofol concentration in conditions i) and iii), resulting in an improvement of the classifiers' output. Indeed, OC-MDM detects S8 as awake during the preoperative session, at the beginning of the induction and at the end of the emergence. However, in condition ii), when the MNS-anesthesia centroid is trained with the first intraoperative run (the induction), the centroid is less accurate and the accuracy plummets. While this condition would have been advantageous in a real-life setting for quicker calibration, the results indicate that this first intraoperative run cannot be used to effectively train the OC-MDM algorithm.

The subjects with the lowest accuracy in condition i), are those who had two different preoperative runs (e.g. S7). This may be due to different gel-drying conditions during the run used for training, or a different position of the arm (Fig. 2, S7, condition i).

In future work, to find the best classifier to distinguish between EEG activities induced by MNS-awake and MNS-anesthesia, we will compare different one-class algorithms trained solely on MNS-awake data.

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