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EEG-based classification of awareness in disorders of consciousness

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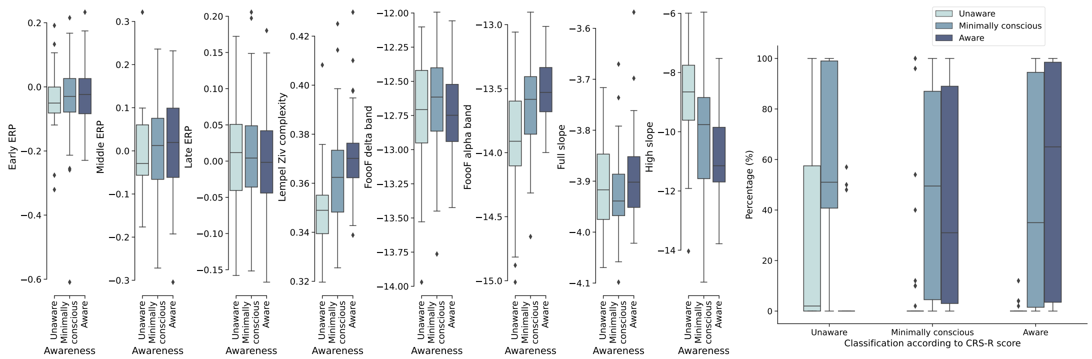
Introduction: Reliably assessing consciousness of patients with disorders of consciousness (DOC) is crucial for clinical decision-making. The Coma Recovery Scale-Revised (CRS-R) is commonly to differentiate between coma, minimally conscious state, and locked-in syndrome. Recent neuroimaging advancements allow motor-independent assessment of consciousness.

Material, Methods, and Results: EEG data were recorded from 84 patients with DOC (23 female, age range=18–84, CRS-R range=0–23). We excluded seven due to incomplete data. For the remaining n=77 patients, 202 sessions were available. One third of the sessions were reserved for testing. Full experimental and preprocessing details can be found in [1] and [2]. We used features including event-related potential (ERP) amplitudes (0–200, 200-500, and 500–1000 ms), Lempel-Ziv Complexity, the periodic component of delta (1-3.5 Hz) and alpha (8-13 Hz) bandpower computed with FoooF [3], and spectral slopes between 1–45 and 20–40 Hz [4]. We augmented our data by generating 50 bootstraps of size 50 from the auditory close trials from each session and averaged across each bootstrap (i.e., 50 “bootstrap trials”/session) and across electrodes for each feature. A random forest classifier was trained to categorize patients as Unaware, Minimally Conscious, or Aware. Distributions of feature amplitudes for each class are shown in Fig. 1a. Performance was evaluated with leave-one-session-out cross-validation, and classification results are shown in Fig. 1b.



(a) (b)

Figure 1: *(a) Distributions of feature values in the train set across all classes for each feature. (b) Percentages of bootstrap epochs that are classified as each of the classes, separately for each class.*

Conclusion: Our model performs well in distinguishing minimally conscious from aware states, but it shows misclassifications within the unaware category. Notably, for all classes, these errors tend to occur between adjacent classes (e.g., no unaware cases are misclassified as aware). Although no machine learning is perfect, there is always the possibility that some patients have been misdiagnosed. This dual challenge—imperfect machine learning and potentially noisy labels—underscores the importance of developing an objective alternative to the CRS-R to improve clinical utility.

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