Human Brain State Classification via Permutation Entropy of EEG Phase Dynamics

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Extended Abstract

Motivation.

Identifying and characterizing functional brain states from experimentally accessible signals like electroencephalography (EEG) remains a central challenge in neuroscience. Understanding the relationship between brain states and the statistical properties of brain wave signals is therefore of significant importance. In this study, we investigate whether the complexity of EEG phase dynamics can serve as a robust biomarker for different human brain states. We examine whether permutation entropy (PE) [1], an ordinal-pattern-based complexity measure that is robust to noise, can reliably distinguish between levels of consciousness and neurodevelopmental conditions like inattentive-type attention deficit hyperactivity disorder (ADHD). Understanding these dynamical signatures is important for clinical applications, such as ensuring patient safety during anesthesia and improving quantitative diagnostic tools for mental health conditions.

Approach and Methodology.

We analyze two independent EEG datasets: (i) recordings obtained during a general anesthesia protocol, including seven distinct states, namely, eyes-closed (EC), propofol injection (P), loss of consciousness (LOC), burst (B), suppression (S), post-burst/suppression (PBS), and recovery (ROC)) and (ii) eyes-open and eyes-closed resting state recordings from individuals with inattentive-type ADHD and healthy controls. After preprocessing the raw EEG signals, we compute the relative phase and apply principal component analysis to identify dominant modes of phase dynamics. We extract the principal mode $\beta_1(t)$, which reflects macroscopic anterior-posterior information flow [2,3]. The resulting $\beta_1(t)$is then mapped into the ordinal pattern sequence to compute the normalized PE, H, which is defined as the Shannon entropy of the ordinal pattern distribution. To evaluate the discriminative power of this measure, we further employ decision-tree-based machine learning classifiers using H as a single feature.

Results.

Our results [4] find that the distribution of the PE exhibits a clear dependence on brain state.

- **General anesthesia:** Unconscious states (LOC, B and S) show significantly higher mean entropy and lower standard deviation compared to conscious states (EC, ROC) and boundary states (P and PBS) (Figure 1 a,b). We also observe a negative correlation between the mean PE and the inverse participation ratio, supporting a link between entropy and consciousness depth. Using PE as a feature, the classifier distinguishes states with different levels of consciousness with an accuracy of 77–81% (Figure 1 c).
- **Resting States:** PE effectively differentiates eyes-open and eyes-closed conditions with 71–78% accuracy. Although in inattentive-type ADHD subjects exhibit lower mean entropy and higher standard deviations than controls—potentially reflecting attentional instability—the classifier could not reliably distinguish inattentive-type ADHD from healthy subjects due to overlapping distributions (Figure 1 d).

Conclusions and Outlook.
Our results demonstrate that permutation entropy derived from EEG phase dynamics provides a robust, data-driven indicator of brain dynamics, particularly effective for distinguishing states with different levels of consciousness and eyes-open/closed resting states. For inattentive-type ADHD, we observed differences in the mean and variance of the distribution, but the groups could not be distinguished based on a single measure.

References

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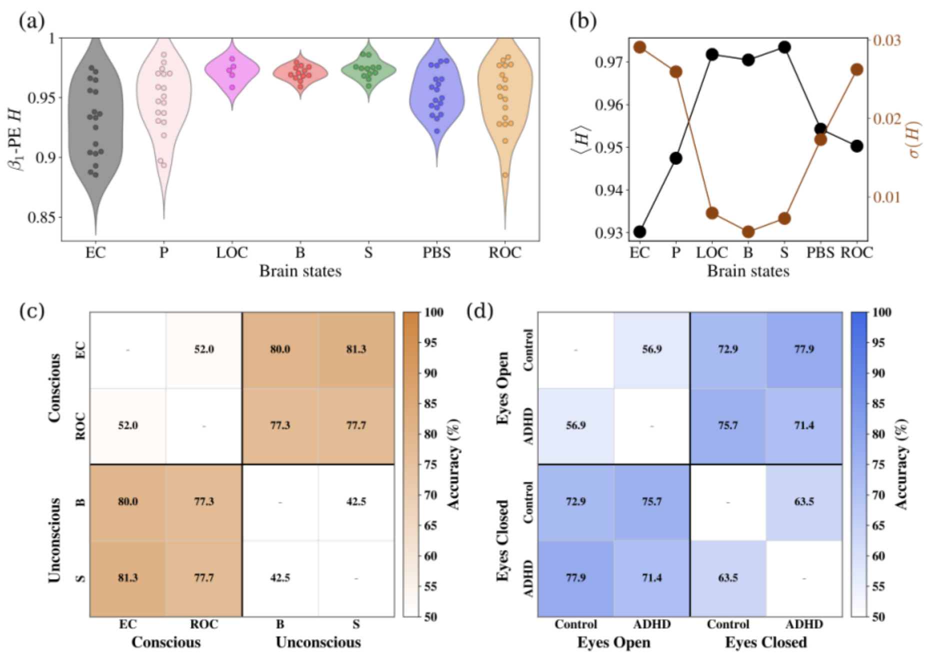

Figure 1: (a) Violin plots and symbols represent the distribution of the PE across subjects in the general anesthesia dataset. (b) Black and brown symbols indicate the mean and standard deviation of the PE, respectively. Classification accuracy (%) of classifier for distinguishing (c) conscious and unconscious states, and (d) resting states and inattentive-type ADHD condition.