

Characterizing Neural Adaptability Through Physiological Perturbation-Induced Reorganization of Human EEG Dynamics

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Abstract: EEG records the electrodynamics of the cortex with millisecond precision, and typical EEG protocols include eyes closed (EC), eyes open (EO), and hyperventilation (HV) as diagnostic ancillary measures. However, prevailing EEG analysis treats these conditions as static, separately characterized segments of neural activity and does not account for the transition periods during which the neural system is actively reorganizing; thus, the neuroplasticity of the brain is not methodologically characterized. This paper introduces a structured, repeatable framework to shift the focus from the discrete states of the neural system to perturbation transitions as the focus of analysis. The EEG recordings, already anonymized in archives, are divided into pre-perturbation, active-perturbation, and post-perturbation epochs, and a state-transition analysis based on principles of dynamical systems is used to quantify the trajectory of reorganization. The following four adaptability indices are defined: reorganization onset latency, reorganization completion time, trajectory coherence, and recovery time constant. The framework aims to, upon implementation, illustrate systematic and quantifiable signatures of neural adaptability as captured by EC–EO and EC–HV transitions that cannot be obtained by static analysis. The framework is immediately applicable to existing archival datasets and is transferable to other perturbation contexts, such as anesthetic induction, pharmacological challenge, sleep-state transitions, and more, connecting dynamical-systems engineering and clinical neurophysiology.

Keywords: Neural adaptability; EEG dynamics; Activation paradigms; Hyperventilation; State-transition analysis; Dynamical systems

Introduction

The human brain is constantly producing rhythmic and arrhythmic electrical activity that reflects the collective membrane-potential dynamics of large populations of neurons in the cortex, and the electroencephalogram (EEG) is a non-invasive window into this activity at millisecond resolution [1]. The spontaneous EEG oscillations are structured within characteristic frequency bands (delta, theta, alpha, beta, and gamma) that reorganize dynamically with changes in arousal, cognitive demand, and environmental context [1,3]. In the early decades of EEGs, physiological activation paradigms, such as eyes-closed (EC), eyes-open (EO), and voluntary hyperventilation (HV), have been part of routine clinical EEG. Event-related desynchronization of posterior alpha oscillations reliably occurs during the transition from EC to EO [2, 4], and HV triggers a transient hypocapnia, cerebral vasoconstriction, and characteristic reorganization in slow oscillations [5, 6]. These are reproducible, well-tolerated, and do not require specialized equipment; therefore, they are practical tools for probing neural dynamics in a graded and reversible fashion. Even though EEG has a long history, the dominant EEG analytical paradigm has stayed the same: epochs within each condition are characterized by their spectral content or connectivity and are considered as representatives of discrete states, whereas the transition periods between conditions are discarded as non-stationary artifacts [7]. This is a fundamental characteristic of neural computation: that it is dynamic and adaptive. Measurements of neural adaptability (the ability of neural dynamics to reorganize coherently in response to a perturbation while maintaining functional integrity [8]) are not of static pre- and post-perturbation features. The conceptual and experimental framework for characterizing neural adaptability was developed using routine multi-paradigm EEG recordings and by providing reference, widely used, and physiologically distinct perturbation stimuli: EC, EO, and HV.

Related Work

Features traditionally extracted from quantitative EEG studies have been based on temporally bounded, spectrally characterized epochs that were assumed to be stationary samples of discrete neural states [3, 9]. This convention has proven very fruitful for classification, brain–computer interfacing, and biomarker discovery [10] but has been used to view perturbation transitions as "noise" to be removed from the scientific signal. The time course and spatial propagation of posterior alpha suppression, viewed as an endpoint rather than a trajectory, has been comparatively little systematically addressed, especially in the context of the EC–EO transition. The transition of posterior alpha suppression has been one of the most well-described phenomena in clinical EEG, with eye opening reliably suppressing posterior alpha through event-related desynchronization [2,4], but the time course and spatial propagation of this suppression as a trajectory rather than an endpoint has received relatively less systematic attention. Likewise, HV has been routinely used for three minutes during clinical protocols to increase sensitivity for focal epileptiform abnormalities [5] and [6], but reorganization induced by HV is considered a provocation for diagnosis, not an index of adaptive capacity. There is also a parallel literature in dynamical-systems neuroscience that emphasizes the hierarchical organization of brain network dynamics over time and that brain networks are organized through adaptive self-organization [8–9]. A methodological framework, however, that could convert these principles into a repeatable analysis plan for routine, archival, multi-paradigm EEG recordings is currently lacking [10–14]. This gap is summarized in Table 1, compared to representative prior work.

Table 1. Comparison of this work with representative prior EEG activation-paradigm studies

Study	Within-condition characterization	Transition/reorganization analysis	Adaptability quantification
[4] Barry et al.	Yes	No	No
[5] Guaranha et al.	Yes	No	No
[10] Delorme et al.	Yes (toolbox)	Partial	No
This work	Yes	Yes	Yes

Key Contribution

This paper has four contributions. First, it shifts the focus of multi-paradigm EEG research from neural states to state-transition dynamics by suggesting that the EEG is primarily data on how the state transitions are happening rather than the states themselves. Second, it illustrates that EC, EO, and HV are already used in routine clinical and research protocols worldwide and are a standardized, low-barrier perturbation battery for research on adaptability, requiring no specific equipment or prospective recruitment and applicable to existing archival data post hoc. Third, it defines a distinct protocol for segmentation and phase identification that can be pre-registered, as well as four adaptability indices that can be quantified, namely reorganization onset latency, completion time, trajectory coherence, and recovery time constant, and that characterize the kinetics and structural coherence of neural reorganization across diagnostic categories. Fourth, it links the dynamical-systems engineering and clinical neurophysiology communities by extending state-space modeling within the context of control [8, 9] and making it both accessible to experiment and grounded in a physiological framework that allows direct connections between observational EEG data and state-transition mathematics.

Method, Experiments and Results

Dataset and activation paradigms. The framework is used for anonymous and archival EEG data collected during normal multi-paradigm EEG sessions with EC, EO, and HV conditions. The recordings are provided with no identifiable information, diagnostic labels, or clinical history; no inferences are made at the

individual level based on the recordings, and the dataset represents a collection of electrophysiological observations across transitions of activation paradigms. The resting reference is the EO (sensory-gating

perturbation), and HV (metabolic perturbation) is referenced against this. This provides two separate physiologically distinct perturbation pathways recorded in the same session.

Conceptual framework. The conceptual model employed in the analysis is summarized in Figure 1, and consists of four stages: (1) resting neural activity (EC baseline), (2) onset of physiological perturbation (EO/HV), (3) neural reorganization (transition phase), (4) characterization of adaptability (structure of the reorganization trajectory is converted to quantifiable measures).

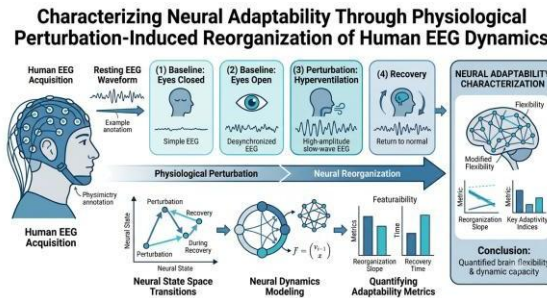


Figure 1. Conceptual pipeline linking physiological perturbation to quantified neural adaptability indices.

Analytical pipeline. The end-to-end analytical pipeline starts with EEG acquisition, followed by artifact removal and band-pass filtering, segmentation of the four experimental conditions, calculation of spectral (power spectral density, band power) and entropy features, computation of connectivity features, and computation of state transition analysis resulting in the neural adaptability indices.

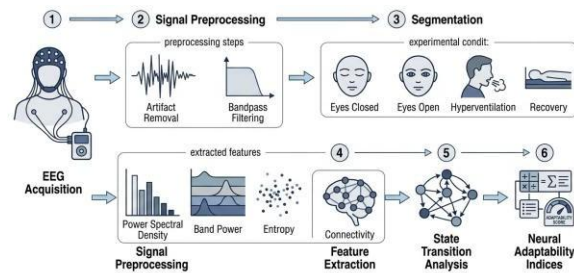


Figure 2. Analytical pipeline from EEG acquisition to neural adaptability index computation.

Segmentation strategy. Each recording consists of a 60 s eyes-closed baseline recording, 60 s eyes-open epoch, 60 s eyes-closed epoch, a 3-minute hyperventilation epoch, and a 60 s recovery epoch. Pre-perturbation epochs are collected from the last 60 s of the EC baseline; active-perturbation epochs are collected from the middle of each activation condition, excluding a 10-s window at the beginning and end of each condition; post-perturbation epochs are collected from the 60 s recovery window. The onset of reorganization is defined as the time when any of the candidate markers (dominant frequency, alpha power, delta power, amplitude) first falls outside of 1 standard deviation of the mean before reorganization, and the offset of reorganization is defined as the time the markers return to within 1 standard deviation of the baseline mean or to a new stable value.

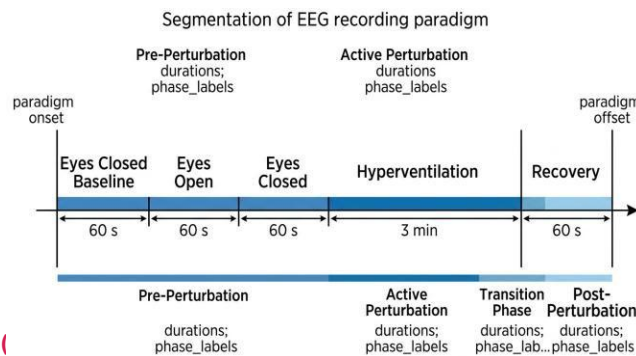


Figure 3. Temporal segmentation of the multi-paradigm EEG recording into pre-perturbation, active-perturbation, transition, and post-perturbation phases.

Illustrative reorganization patterns. Figures 4 and 5 show the expected pattern of reorganization from the four conditions in EEG. Eyes closed: posterior alpha is prominent; eye opening: this rhythm and topography desynchronises; hyperventilation: this generates diffuse slow-wave (theta/delta) activity, most marked over posterior and frontal areas; recovery: the alpha rhythm and topography returns gradually.

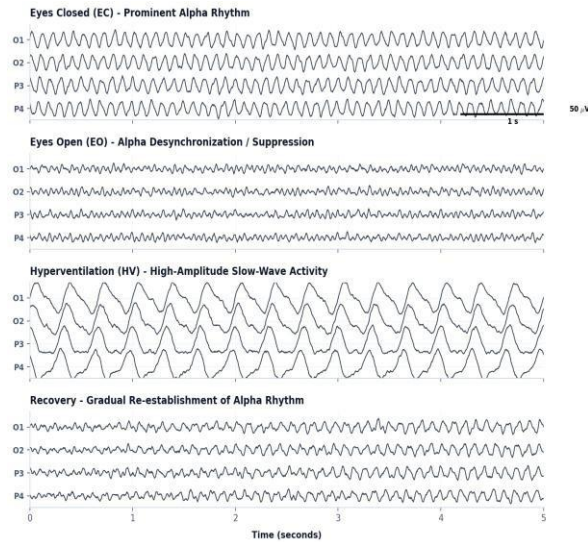


Figure 4. Representative multi-channel EEG waveforms (O1, O2, P3, P4) across eyes-closed, eyes-open, hyperventilation, and recovery conditions.

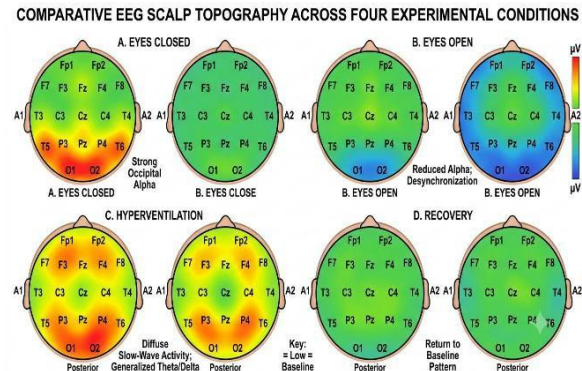


Figure 5. Scalp topography of EEG amplitude across the four experimental conditions, showing posterior alpha dominance at baseline, desynchronization on eye opening, diffuse slow-wave activity during hyperventilation, and return toward baseline during recovery.

Adaptability indices. The four proposed adaptability indices (AI) are defined in Table 2 for each of the reorganization windows identified above and compared at each of the within-paradigm, cross-paradigm (EO vs HV), and cross-recording levels using intraclass correlation to test for reproducibility.

Table 2. Proposed indices of neural adaptability within the EEG domain

Adaptability index	Definition	Expected behaviour
Reorganization onset latency	Time from paradigm onset to first significant EEG deviation from baseline	Shorter = faster adaptive response
Reorganization completion time	Duration of the active transition until a new stable EEG regime is established	Shorter = more efficient reorganization
Trajectory coherence index	Cross-channel correlation of spectral marker trajectories during the reorganization window	Higher = more structured adaptive response
Recovery time constant	Exponential time constant of EEG marker return to pre-perturbation baseline post-HV	Smaller = faster neural recovery

Discussions

This approach is different from a traditional focus on the individual condition and instead views perturbation transitions as the focal point of analysis, thereby shifting the focus of EC, EO, and HV from diagnostic adjuncts to standardized assessments of intrinsic neural adaptability. The coherence qualification is a must:

disorganized or erratic reorganization does not necessarily mean high adaptability, regardless of the amplitude change; only reorganization that is structured and correlated across channels and frequency

bands. The ability to identify both reorganization (EC–EO) and cerebral metabolic modulation (EC–HV) signatures in both perturbation conditions would be consistent with the proposed indices. The framework is built on clinical recordings that are routinely collected and archived, allowing for widespread retrospective use without prospective recruitment. The major drawback of this methodologically early stage is that it has been defined but not yet applied to a validation group; the sensitivity of the four indices to the presence of noise, electrode montage, and respiratory effort variability from individual to individual in hyperventilation has not yet been empirically determined.

Conclusions

1. Problem addressed: Static and segment-wise EEG analysis ignores the transitional period where neural reorganization is taking place, and neural adaptability is methodologically uncharacterized. 2. Method employed: A four-stage conceptual framework and a reproducible segmentation / state-transition analysis pipeline were defined and used on extant EC, EO, and HV recordings, operationalized with four adaptability indices. 3. Key findings: Reorganization onset latency, completion time, trajectory coherence, and recovery time constant directly characterize neural adaptability from routine clinical EEG protocols, in a diagnosis-independent manner, which can be quantified. 4. Limitations and future work: The framework is prospective and needs to be tested empirically on a multi-site cohort in the archival setting, and the perturbation battery will be expanded to other contexts such as the pharmacological and sleep-transition setting to examine cross-recording reproducibility.

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