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EEG Microstates: Unraveling the "Atoms of Thought" in Clinical Neuropsychology

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Introduction

Electroencephalography (EEG) has long served as a foundational tool in neuroscience and clinical neuropsychology, offering millisecond-level temporal resolution of brain activity. While traditional EEG analyses often focus on frequency bands (such as alpha, beta, and theta waves), an increasingly influential paradigm has emerged that captures the brain's moment-to-moment functional dynamics: EEG microstates.

EEG microstates are short-lived periods—typically lasting between 60 to 120 milliseconds—during which the spatial configuration of scalp EEG signals remains quasi-stable. These brief segments represent discrete "building blocks" or "atoms of thought" that together compose the stream of conscious and unconscious mental activity. First conceptualized by Dietrich Lehmann and colleagues in the 1980s, microstate analysis aims to understand how the brain transitions between functionally meaningful states over very short time scales [1].

Using topographic clustering techniques, researchers have consistently identified four canonical microstate classes—labeled A, B, C, and D—that recur across individuals during rest and task-free conditions. Each class is associated with distinct large-scale brain networks, as revealed through simultaneous EEG-fMRI studies. For example, microstate class B is often linked to auditory processing networks, while class C is associated with salience and attention networks. This correspondence between EEG microstates and resting-state networks has significantly advanced our understanding of how transient brain states reflect underlying functional organization.

Microstate analysis provides several quantifiable parameters, including **duration** (how long each state persists), **occurrence** (how frequently a state appears), **coverage** (the proportion of total time occupied by a state), and **syntax** (the transition probabilities between different states). These metrics offer a dynamic and non-invasive way to assess brain function in both healthy individuals and clinical populations [2].

In recent years, EEG microstates have garnered growing interest for their potential as biomarkers of neurological and psychiatric disorders, including schizophrenia, depression, Alzheimer's disease, and migraine. Their ability to capture fast neural transitions and correlate with symptoms or treatment outcomes highlights their clinical relevance. Moreover, because microstate analysis can be performed with standard EEG equipment and brief resting recordings, it holds promise for scalable and cost-effective neurodiagnostic applications.

As a rapidly evolving field, EEG microstate research bridges computational neuroscience, cognitive science, and clinical neuropsychology, offering novel insights into the brain's temporal organization and its perturbations in disease.

Historical Emergence and Key Concepts

The concept was pioneered by Lehmann and colleagues at the KEY Institute in Zurich, who found that rest-state EEG could be efficiently described as a sequence of recurring topographic maps labeled as four canonical classes—A, B, C, and D. These classes are highly reproducible across individuals and even across the lifespan. Microstates thus offer a method to compress continuous EEG into meaningful epochs indexing brain function [3].

Key measurable parameters include:

Duration: average length of each microstate epoch.

Frequency / Occurrence: how often each class appears per second.

Time coverage: percent of total recording covered by each class.

Syntax / Transition probabilities: likelihood of one microstate transitioning to another

Neural Correlates and Resting-State Networks

Simultaneous EEG–fMRI studies have mapped microstate classes onto canonical resting-state networks:

Class **B** aligns with the **auditory network**,

Class **C** maps onto the **executive control or salience network**,

Class **D** relates to **visual and salience networks**,

Class **A** is associated with visual networks as well

Microstates thus serve as rapid electrophysiological markers of large-scale brain network activity, bridging EEG's temporal resolution (~100 ms) with fMRI-derived slow hemodynamics [4].

Furthermore, PNAS researchers demonstrated that microstate sequences show **scale-free, long-range dependencies**, suggesting fractal-like dynamics in microstate transitions that correspond to brain-wide, temporally complex organization.

Clinical Applications: Neuropsychiatric and Neurological Disorders

Major Depressive Disorder (MDD)

Patients with MDD exhibit decreased duration and coverage of class D (attention/control network), and increased occurrence of classes A and B. Following eight weeks of SSRI treatment, these metrics partially normalized—especially a rise in microstate D parameters. Notably, transition dynamics shifted—for example, a reduction in D→A

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shifts—suggesting microstate patterns may serve as both diagnostic and prognostic biomarkers in depression [5].

Migraine Without Aura

In interictal migraine patients, increased coverage and occurrence of microstates B and D, and decreased presence of C, were reported. The mean duration of C was shorter, correlating negatively with headache-related disability scores. Syntax analysis revealed altered transition probabilities among B, C, and D, suggesting network dysfunction even between attacks [6].

Schizophrenia and Psychosis

Robust findings show elevated class C and reduced class D metrics in both first-episode psychosis patients and chronic schizophrenia cohorts. These microstate patterns are also found in unaffected relatives, supporting their use as potential endophenotypes. Additionally, individuals with higher class C tended to show more prominent emotion-regulation deficits, while reduced class D related to attentional control impairments [7].

Parkinson's Disease

Recent review literature highlights EEG microstate analysis as a promising approach for early detection, symptomatic profiling, and monitoring treatment effects in Parkinson's disease. Integrating AI-driven pattern recognition enhances sensitivity, though methodological variability and standardization remain obstacles [8].

Stroke Rehabilitation

Emerging research suggests microstate features correlate with motor symptom scales in post-stroke patients. Differences between stroke survivors and controls in microstate dynamics may offer objective correlates of recovery status and rehabilitation progress [9].

Ménière's Disease & Other Conditions

In Ménière's disease, elevated occurrence and coverage of microstate C (salience network) correlated with vertigo and balance impairments. A Support Vector Machine classifier achieved nearly 90% accuracy in distinguishing patients versus controls using microstate-based features—indicating potential as non-invasive biomarkers [10].

Reliability and Individual Specificity

A 2020 study found that resting-state microstate parameters (duration, coverage, occurrence, syntax) show moderate to high test-retest reliability across days when recordings exceed 2 minutes. Moreover, microstate C's duration and coverage correlated with fluid intelligence scores. More complex temporal dynamics (e.g. autocorrelation structure) provided even better individual specificity compared to traditional metrics.

Recent work further explored sequence complexity beyond first-order Markov models, revealing that microstate transitions exhibit rich, non-Markovian patterns. Complexity measures also varied with levels of consciousness—for example, microstate D differences distinguished vegetative versus minimally conscious states, and variations correlated with sleep quality or anesthetic state.

Methodological Considerations

Signal preprocessing: filtering (e.g. 2–20 Hz) and artifact control are essential before clustering microstate topographies.

Clustering methods: k-means remains standard; fuzzy c-means and probabilistic techniques are emerging alternatives.

Clustering classes: typically four canonical microstates suffice, explaining ~65–84% of variance; some studies explore additional classes (up to G) in task-specific contexts.

Standardization issues: variations in recording length, electrode montage (e.g. 10-20 or high-density), preprocessing, clustering parameters, and labeling conventions can affect reproducibility and cross-study comparisons.

Future Directions and Clinical Promise

EEG microstate analysis shows strong promise as a transdiagnostic biomarker—offering rapid, cost-effective, and high-temporal resolution insights into brain network dynamics. Key future challenges include:

Standardizing data collection and analysis pipelines to allow cross-site comparability.

Large-scale longitudinal studies in disorders like MDD, PD, epilepsy, dementia, and consciousness disorders.

Integration with AI / Explainable AI frameworks to automate pattern recognition while maintaining interpretability.

Extension into mobile or wearable EEG (e.g. ear-EEG systems) to enable ambulatory monitoring or remote follow-up.

Hybrid multimodal imaging, combining microstates with fMRI, MEG, or behavioral/clinical metrics to enrich neurobiological modeling.

Conclusion

EEG microstates represent a robust, temporally precise window into global brain dynamics. By clustering scalp topographies into four canonical states and measuring parameters like duration, occurrence, coverage, and syntax, researchers gain access to the sub-second dynamics underlying cognitive and clinical brain states. Consistent alterations in microstate patterns have been observed in depression, migraine, psychosis, Parkinson's disease, stroke recovery, and consciousness disorders—offering objective biomarkers and targets for intervention. Future work focusing on methodological harmonization, AI integration, wearable monitoring, and longitudinal clinical validation will further unlock the potential of microstates in both research and clinical settings.

References

1. Aviezer D, Shaaltiel Y, Hashmueli S, Bartfeld D, Mizrachi S, et al. (2009) A plant-derived recombinant human glucocerebrosidase enzyme – a preclinical and phase I investigation. PLoS One 4: e4792.
2. Oldham WM, Hamm HE (2008) Heterotrimeric G protein activation by G-protein-coupled receptors. Nat Rev Mol Cell Biol 9: 60-71.
3. Luft JR, Arakali SV, Kirisits J, Kalenik I, Wawrzak V, et al. (1994) A macromolecular crystallization procedure employing diffusion cells of varying depths as reservoirs to taylor the time course of equilibration in hanging drop and sitting drop vapour diffusion and microdialysis experiments. Journal of Applied Crystallography 27: 443-53.
4. Wilson LJ, Bray TL, Suddath FL (1991) Crystallization of proteins by dynamic control of evaporation. Journal of Crystal Growth 110: 142-7.
5. Bell SM, Wendt DJ, Zhang Y, Taylor TW, Long S, et al. (2017) Formulation and PEGylation optimization of the therapeutic PEGylated phenylalanine ammonia lyase for the treatment of phenylketonuria. PLoS One 12: e0173269.
6. Benjwal S, Verma S, Röhm KH, Gursky O (2006) Monitoring protein aggregation during thermal unfolding in circular dichroism experiments. Protein Sci 15: 635-639.
7. Bennett LL, Mohan D (2013) Gaucher disease and its treatment options. Ann Pharmacother 47: 1182-1193.

8. Blundell TL, Johnson LN (1976) Protein crystallography. London: Academic Press.

9. Wootten D, Christopoulos A, Marti-Solano M, Babu MM, Sexton PM, et al. (2018) Mechanisms of signalling and biased agonism in G protein-coupled receptors. Nat Rev Mol Cell Biol 19: 638-653.

10. Avramis VI (2011) Asparaginases: a successful class of drugs against leukemias and lymphomas. J Pediatr Hematol Oncol 33: 573-579.