Dynamic Neural State Transitions Underlying Visuospatial Planning and Execution in Rubik's Cube Solving: An EEG Microstate Study

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Abstract

EEG microstates provide a high-resolution temporal window into large-scale brain dynamics, yet their behavior during complex, real-world problem-solving remains underexplored. In this exploratory single-subject case study, EEG was recorded using a 19-channel system while the participant solved a Rubik's Cube across ten trials. Data were pre-processed in EEGLAB, artifact-corrected using independent component analysis and CleanRawData, and analyzed with the MicrostateLab plugin. Four microstate class structure (A–D) were identified. Microstates A and C accounted for the greatest proportion of time coverage, while Microstates B and D occurred less frequently during task performance. Analysis of microstate transitions revealed recurring, non-random patterns across trials. These findings are descriptive and correlational in nature and demonstrate the feasibility of applying EEG microstate analysis to a complex problem-solving task. The study provides preliminary observations to inform future research using larger samples and controlled experimental designs to examine task-related microstate dynamics.

Keywords: EEG, microstates, Rubik's cube, problem solving, executive function

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Human cognition is mostly experienced as a seamless and continuous phenomenon, but growing neuroscientific evidence suggests that this continuity is in part an illusion. Electrophysiological research has demonstrated many times that large-scale neuronal networks spontaneously self-organize into brief, quasi-stable states, each lasting on the order of tens of milliseconds, before giving way to another configuration. These transient but recurrent states, termed *EEG microstates*, are observed as stable topographic patterns of scalp potential maps that remain consistent over their duration before rapidly transitioning to a new configuration (Koenig & Michel, 2018). The microstates have been proposed as fundamental temporal units of large-scale brain dynamics (Lehmann, 1990).The sequence of microstates and their transitions have been proposed as a framework for describing large-scale neural dynamics, providing a grammar-like structure through which cognition is constructed in real time (Farzan, Khanna, Michel, &Pascual-Leone, 2015).

Although traditional neuroimaging approaches such as the Functional Magnetic Resonance Imaging (fMRI) have revealed the spatial organization of large-scale networks, but with limited temporal precision. EEG, conversely, affords millisecond-level temporal resolution but typically sacrifices spatial interpretability. Microstate analysis offers a middle ground: by focusing on global scalp topographies rather than isolated electrode activity, it captures whole-brain configurations while retaining temporal fidelity. Indeed, the canonical microstate classes identified at rest map onto core functional brain networks revealed by fMRI, such as the default mode and executive control networks, dorsal attentional networks and salience networks (Britz, Van De Ville, & Michel, 2010). This convergence reinforces the notion that microstates represent meaningful units of large-scale network coordination.

Despite the growing body of work on resting-state microstates, comparatively little attention has been directed toward understanding how these states unfold during active cognition. Most studies have investigated spontaneous activity in resting conditions, or contrasted resting microstate parameters across clinical populations such as schizophrenia, depression, or dementia (Koenig et al., 1999; Strik, Dierks, Becker, & Lehmann, 1995; Michel & Koenig, 2018). While these studies have yielded important insights into alterations in the basic architecture of mental states, they leave open the critical question of how microstates dynamically support complex cognitive functions. Cognition is not a random succession of mental events; rather, it is structured, recursive, and often goal-directed. To fully realize the potential of microstate research, it is therefore necessary to study their role not only in spontaneous mental activity but also in carefully defined problem-solving contexts.

The Rubik's Cube provides a uniquely rich paradigm for investigating these dynamics. Since its invention in the 1970s, the Cube has become emblematic of complex problem-solving. To solve it, individuals must engage in continuous cycles of sensory monitoring, visuospatial planning, working memory manipulation, and motor execution. Each move alters not only the current perceptual state of the cube but also the solver's strategy space, requiring ongoing adjustments in cognitive control.

The present study represents an initial step toward this goal by applying microstate analysis to EEG data recorded while a participant solved the Rubik's Cube. Our aim was to characterize the repertoire of microstates expressed during problem-solving and to identify whether their sequences reflect structured motifs corresponding to key cognitive subprocesses. We explored whether task-related microstate dynamics would differ from the largely stochastic patterns reported during rest. In doing so, we seek to demonstrate that microstate analysis can provide a foundation for future research into the temporal building blocks of human intelligence.

Methods

Participants

One healthy right-handed adult (age = 32 years; gender = male) participated in this study. The participant reported normal or corrected-to-normal vision, no neurological or psychiatric history, and no prior head injuries. Written informed consent was obtained before participation, in accordance with the Declaration of Helsinki. Given the exploratory and methodological nature of this work, the dataset is presented as a single-subject case study.

Ethical Approval

The Institutional Ethics Committee of Sarojini Naidu College for Women gave its first ethical approval on December 20, 2024. The study followed the ethical guidelines set out in the Declaration of Helsinki, and the subject gave their agreement before taking part.

Task and Procedure

The experimental paradigm consisted of solving a standard 3×3 Rubik's Cube across 10 separate trials. For each trial, the cube was scrambled using a fixed sequence to ensure task consistency across attempts. The participant was instructed to solve the cube as fast and accurately as possible using their habitual strategy. EEG was continuously recorded during each trial, beginning with the first move and ending upon cube completion. The participant's head was stabilized using a chin rest, and excessive body movements were minimized to reduce movement-related artifacts.

A fixed scrambling sequence, corresponding to a standard beginner-level solution algorithm, was used across trials. While this design ensured reproducibility, it likely introduced practice effects and increasing task automaticity across repetitions. Consequently, later trials may have involved changes in task strategy and increasing task familiarity, which could have influenced the observed microstate dynamics. To obtain sufficient data for microstate analysis, EEG data from the 10 trials were concatenated and analyzed as a continuous dataset.

EEG Recording

EEG was recorded using a Clarity Medical EEG system, with Ag/AgCl 19-channel electrodes (excluding reference and ground) positioned according to the international 10–20 system. Data were referenced online to the linked mastoids. Signals were acquired at a sampling rate of 256 Hz and filtered online with a 0.1–40 Hz bandpass. Additional electrooculographic (EOG) electrodes were placed to monitor eye movements and blinks. The impedances for all the electrodes were checked and kept below 10 kΩ.

Preprocessing

Preprocessing was conducted in **EEGLAB** (Delorme & Makeig, 2004). Raw data were first processed using the *CleanRawData* function to remove high-amplitude noise and transient artifacts. Independent component analysis (ICA) was done followingly, and ocular components (eye-blink and eye-movement artifacts) were identified and removed. Channels exhibiting persistent noise were interpolated, and the data were re-referenced to the common average reference. A bandpass filter (1–40 Hz) was applied, and the continuous EEG was segmented into epochs corresponding to the 10 problem-solving trials. These epochs were concatenated to form a continuous dataset for subsequent microstate analysis.

Microstate Analysis

Microstate segmentation was performed using the MicrostateLab plugin for EEGLAB (Poulsen et al., 2018). Global field power (GFP) peaks were extracted from the preprocessed data, and a modified k-means clustering algorithm was used for the identification of dominant scalp topographies. The optimal number of microstate classes was determined through cross-validation and global explained variance (GEV) optimization. Once the optimal class solution was established, the continuous EEG was back-fitted to the derived templates, labeling each time point with the best-fitting microstate.

The following temporal parameters were extracted for each microstate class: (1) mean duration (average persistence of each microstate in milliseconds), (2) occurrence (frequency of appearances per second), (3) time coverage (percentage of total time occupied), and (4) global explained variance (proportion of variance explained by each class). Additionally, transition probability matrices were computed to quantify sequential dependencies among classes, enabling the identification of structured motifs corresponding to perception–planning–action loops.

Results

Microstate Segmentation

Clustering analysis of the averaged EEG data across ten Rubik's Cube solving trials revealed a four-class solution that accounted for the majority of variance in the dataset. The resulting scalp topographies are presented in Figure 1, corresponding to canonical microstate classes A–D with task-specific adaptations. Microstate A displayed a posterior–anterior gradient, Microstate B a lateralized distribution, Microstate C a pronounced central–frontal pattern, and Microstate D a bilateral occipital–temporal configuration.

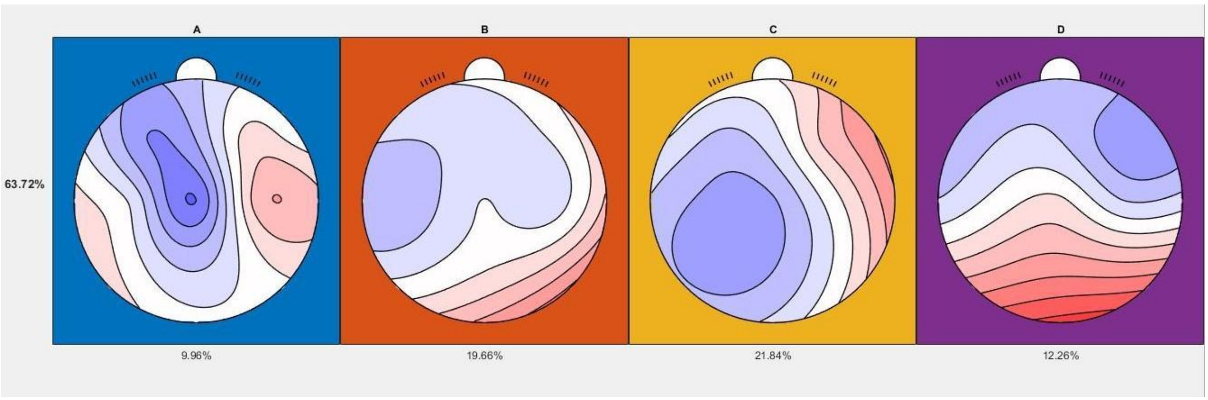

Figure 1. *Topographical maps of the four identified microstate classes (A–D) during Rubik's Cube solving.*

Temporal Parameters

The temporal dynamics of each microstate class are have been given in Figure 2. Mean duration values ranged from 70-120 ms across classes, with Microstate C persisting the longest, suggesting sustained frontal–executive engagement during problem solving. Occurrence rates varied between 5.84 and 7.45 per second, with Microstate A dominating in frequency, consistent with the constant visual monitoring required for cube manipulation. Time coverage showed that Microstates A and C jointly occupied the greatest proportion of total time, while Microstates B and D contributed smaller but contextually significant proportions. The global explained variance (GEV) of the four-class solution was 63.72%, reflecting a stable segmentation of the EEG signal during task performance.

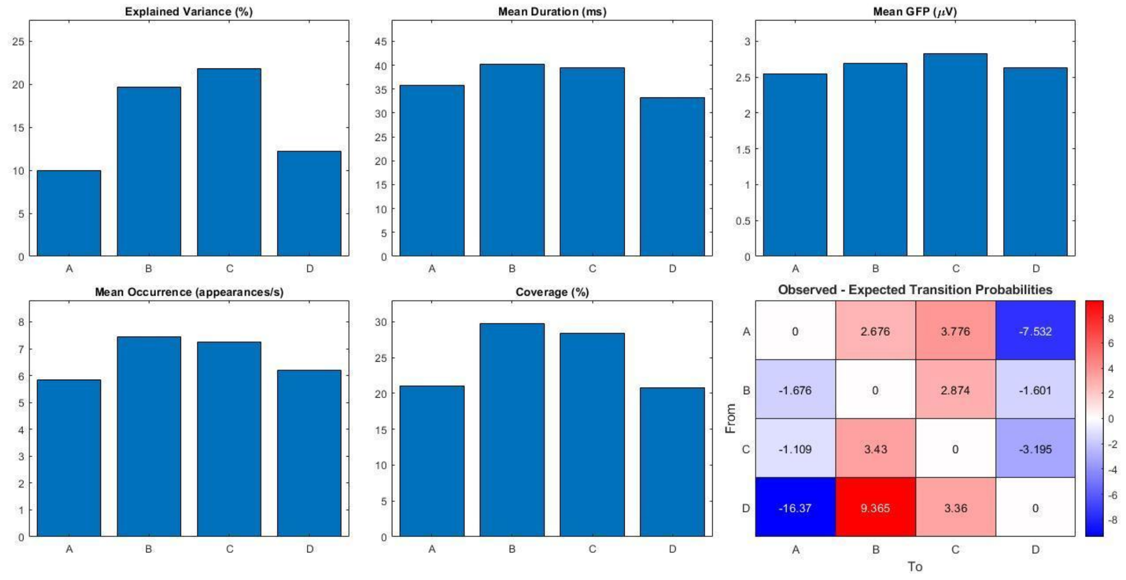

Figure 2. *Temporal parameters of microstate classes A–D, including mean duration (ms), occurrence (Hz), time coverage (%), and global explained variance (GEV, %).*

Transition Dynamics

Sequential dependencies among microstates revealed non-random transition structures (Figure 2). The most prominent motif involved transitions from Microstate A (visual monitoring) to Microstate C (executive control), followed by Microstate B (motor execution), and back to Microstate A. This recurring transition pattern, involving these microstates was observed across trials. Microstate D was more frequently observed following Microstate A during periods involving increased visuospatial demands.

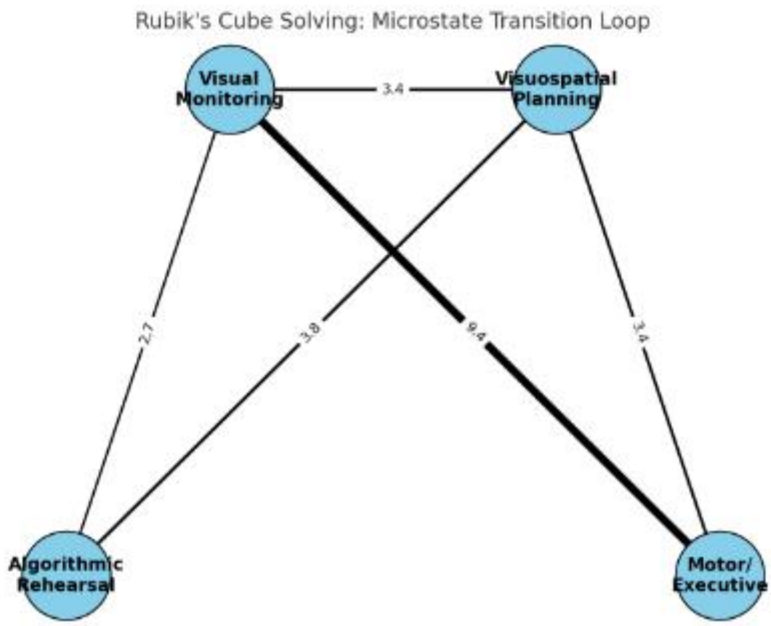

Figure 3: *Microstate transition loop during Rubik's Cube solving (These labels reflect descriptive associations rather than direct functional mappings.).*

The diagram illustrates the dominant transition cycle (A → B → C → D → B), previously associated with algorithmic rehearsal (A), visual monitoring (B), visuospatial planning (C), and motor/executive execution (D). The strongest connection was observed from D → B (9.4), reflecting frequent visual verification following motor actions. Additional transitions (A → C = 3.8; C → B = 3.4) indicate shortcut loops, suggesting non-linear pathways within the problem-solving process.

Discussion

Task Specific Microstate Properties

Rubik's Cube solving constitutes a complex, goal-directed task that requires the continuous integration of visual monitoring, visuospatial planning, memory-based strategy use, and motor execution. In contrast to resting-state conditions, where microstate sequences typically exhibit relatively unconstrained and scale-free dynamics (Van De Ville et al., 2010), the present exploratory case study observed recurring microstate patterns and non-random transition structures during task engagement. These observations suggest that active problem-solving may be accompanied by more constrained temporal organization of large-scale neural activity.

The microstate classes identified during task performance broadly resembled canonical microstate topographies reported in the literature, indicating that task engagement modulated the temporal expression of established large-scale neural configurations rather than giving rise to entirely novel states. Microstates associated with visual and fronto-central distributions occupied a larger proportion of time coverage, consistent with the sustained perceptual and planning demands of Rubik's Cube solving. Other microstates occurred less frequently but were repeatedly observed during phases involving motor actions and visuospatial transformations. These associations reflect temporal co-occurrence and should not be interpreted as one-to-one mappings between specific microstates and discrete cognitive operations.

Microstate Transitions During Problem-Solving

Analysis of microstate transitions revealed that certain sequences occurred more frequently than others, forming recurring motifs during task performance. In particular, transitions involving visually oriented and fronto-central microstates were prominent, consistent with the iterative nature of perceptual monitoring and action execution during cube manipulation. Such transition patterns indicate non-random temporal organization of large-scale neural states during active cognition.

Importantly, microstate transitions are correlational measures and do not imply causal or computational relationships between states. The observed transition motifs should therefore be interpreted as descriptive patterns of temporal association rather than as mechanisms or primitives underlying problem-solving. While these patterns may reflect task-related constraints on neural dynamics, they do not establish directional control or functional hierarchy among microstates.

Limitations and Future Directions

Several limitations should be considered when interpreting the present findings. First, the study is based on a single participant, precluding any assessment of inter-individual variability or generalizability. Second, the use of a fixed scrambling sequence across trials likely introduced practice effects and changes in task familiarity, which may have influenced microstate dynamics over repeated trials. Third, the limited number of trials restricts the stability of estimated microstate transition probabilities. Future studies should address these limitations by employing larger samples, randomized scrambling sequences, and trial-wise analyses to better disentangle learning effects from task-specific neural dynamics.

Conclusion

This exploratory study examined EEG microstate patterns during Rubik's Cube solving. Task performance was associated with recurring microstate patterns and non-random transitions, indicating that large-scale brain activity showed structured temporal organization during problem-solving. These findings are descriptive and correlational and should not be interpreted as evidence of causal mechanisms underlying cognition. Rather, the study demonstrates the feasibility of applying EEG microstate analysis to a complex, real-world problem-solving task. Future studies with larger samples and improved experimental designs are needed to examine the consistency and functional relevance of these patterns.

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