Deep clustering as a unified method for explainable representation learning and clustering of EEG data for microstate theory.

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Abstract

EEG microstates have distinct scalp potential topographies, often captured by four microstate maps explaining 64-84% of brain dynamics variance using clustering methods. Recent research suggests 5-15 cluster maps are needed to account for 80% of the variance. The clustering algorithms employed are typically chosen arbitrarily, with tools like Cartool and EEGLAB only supporting a limited range of shallow clustering methods. Such methods can be suboptimal for complex, high-dimensional data. While deep clustering has shown promise in fields like computer vision and NLP, its potential for EEG microstates remains underexplored. This study examines the efficacy of deep clustering on EEG microstates, proposing a unified framework that combines representation learning and clustering for improved microstate analysis.

Keywords

EEG Microstates, Deep clustering, Convolutional Autoencoders, K-means, Resting state networks, Task State Networks

1. Introduction

Microstates are pivotal in revealing the intricate temporal and spatial nuances of multichannel, fluctuating EEG signals [1, 2]. These EEG microstates are semi-stable phases enduring between 60 to 120 ms [3]. While early microstate analyses were centered on alpha-filtered EEG signals [4, 5, 6], contemporary methods have evolved to focus on a broader range of signals, including both broadband and select narrowband signals [7, 8]. This broadening scope enables a deeper understanding of varying spectral profiles during rest, tasks, and specific activities. Furthermore, EEG microstates have the unique ability to depict global brain patterns that change dynamically over time [9]. Microstate computation involves a series of well-defined steps, as illustrated in Figure 1 [10, 11]. The process begins by preprocessing raw EEG signals to derive the Global Field Power (GFP), essentially representing the standard deviation of all electrodes at a specific time point, as indicated in part B of the figure. The next step involves identifying the local maxima in the GFP over time. These maxima's corresponding electrode values then serve as input for clustering algorithms, such as k-means and hierarchical clustering

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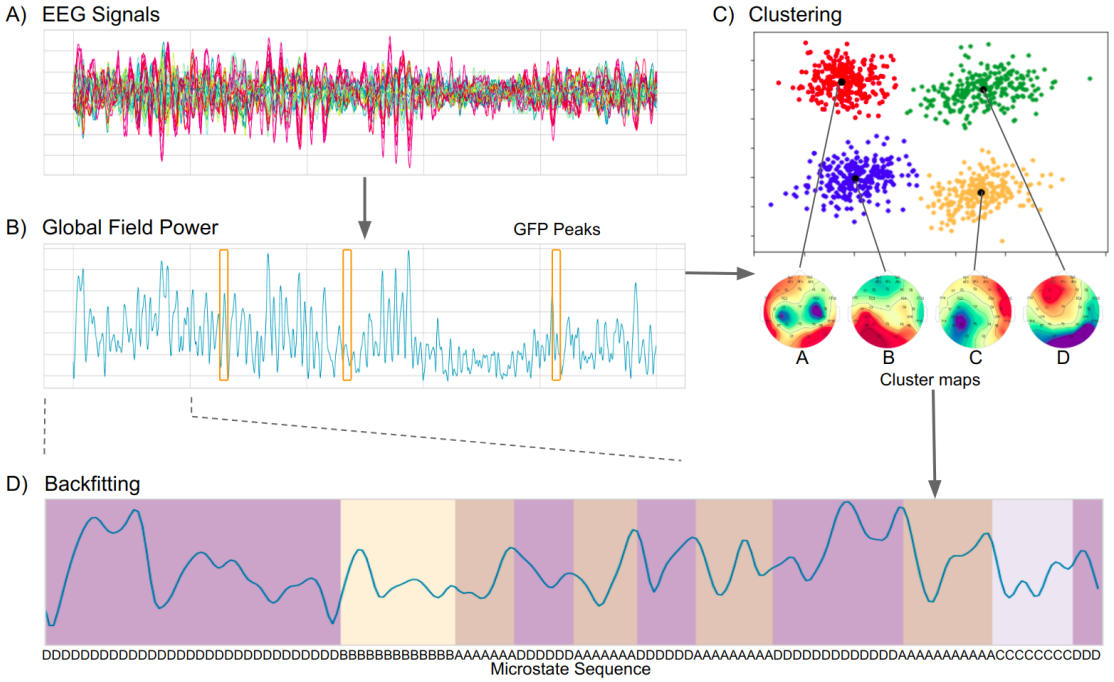

Figure 1: Illustration of the current state-of-the-art microstate architecture pipeline.

[12]. These algorithms yield several distinct cluster maps, highlighted in part C of the figure. The process culminates with back fitting, where each time point from the original signal is labelled based on spatial similarity to the identified cluster maps. This generates microstates, offering a dimensionally reduced sequence of topographies for the initial EEG signal [9].

Microstates offer distinct scalp potential mappings that encapsulate the spatial and temporal dimensions of EEG brain signals[13]. Typically, clustering methods produce four key microstate maps, accounting for 64-84% of the variance in brain dynamics. Each map corresponds to specific brain regions [14, 15]. For instance, Microstates A and B are linked to the brain's temporal and occipital areas. Microstate C represents areas like the anterior cingulate cortex (ACC), dorsolateral prefrontal cortex (DLPFC), and insula. In contrast, Microstate D pertains to the right dorsal and ventral brain regions. Although EEG microstates are widely recognized tools, several ambiguities persist in their computation [16]. Many studies suggest that the four principal cluster maps account for up to 80% of the global variance. Yet, research by Seitzman indicates that these maps only explain between 62% and 69% of this variance [10]. Recent findings also suggest that between five to fifteen cluster maps may be necessary to capture 80% of the variance. Additionally, selecting clustering algorithms for generating these maps often seems arbitrary. While traditional choices like modified k-means and agglomerative hierarchical clustering are prevalent [12], the broader clustering research field has unveiled hundreds of specialized algorithms [17]. And while deep clustering techniques have demonstrated superior performance in contemporary image datasets [18, 19, 20], their integration into the microstate

computation process remains uncharted territory. There's also a pressing need for a comprehensive framework in the microstate domain that allows for interactive and iterative representation learning and clustering.

2. Problem Statement

The assumption of microstate theory is the existence of a finite number of non-overlapping, quasi-stable brain activation states leading to microstates. However, the problem within microstate theory is the lack of stability in the number of cluster maps learnt from shallow clustering (modified k-means, hierarchical clustering) and the resulting EEG microstates, which can explain up to 80% of the variance from the input EEG signal. To the aforementioned problem statement, the Research Question (RQ) is formulated as follows:

(RQ)- To what extent do deep clustering methods improve the identification and stability of cluster maps and enhance the efficiency of microstate sequences across multiple resting and cognitive states over shallow clustering?

The remaining sections of the report are devoted to articulating the precise research hypothesis and the experimental details necessary to address the previously defined research question.

3. Design and Methods

A secondary experiment is designed using quantitative research methods with deductive reasoning to test the following research hypothesis.

Hypothesis - IF deep clustering methods (autoencoder-based) are used to form cluster maps across person and activity-specific and agnostic experimental configurations for high-dimensional EEG signals acquired with multiple resting and cognitive conditions, THEN the stability of these cluster maps and the efficiency of microstates will be significantly higher than those cluster maps and microstates obtained by applying shallow clustering methods (modified k-means clustering).

3.1. Research Objectives

A comprehensive set of general and specific research objectives is meticulously crafted to test the research hypothesis and realise the research aim.

1. To select a distinct EEG dataset.
    - To identify an EEG dataset with multiple resting and cognitive state activities [21].
2. To prepare and pre-process EEG data
    - To pre-process EEG signals from the selected dataset in accordance with Makoto's pre-processing pipeline.

3. To implement microstate generation pipeline using pre-processed EEG signals involving multiple resting and cognitive conditions [22].
    - To implement person-specific and activity-specific microstate generation pipeline.
    - To implement person-agnostic and activity-agnostic microstate generation pipeline.
    - To implement person-specific and activity-agnostic microstate generation pipeline.
    - To execute person-agnostic and activity-agnostic microstate generation pipeline.
4. To formulate microstate cluster maps.
    - To generate cluster maps using shallow clustering methods (modified k-means and agglomerative hierarchical clustering).
    - To generate cluster maps using deep clustering methods (autoencoder-based).
5. To perform hyperparameter tuning
    - To optimise hyperparameters, including the number of layers and kernels for convolutional autoencoders, optimisation, regularisation and dropout rates by performing tuning.
6. To measure the microstate's efficiency
    - To evaluate the microstate's efficiency using microstate parameters: Global Explained Variance(GEV), mean duration, and time coverage.
7. To evaluate the outcome of distribution comparison and test the research hypothesis
    - To run Friedman Fr test between clustering techniques.

3.2. To measure the microstate's efficiency

The efficiency of the generated microstate formed using multiple shallow and deep clustering methods can be evaluated from the microstate's temporal parameters

1. Global Explained Variance (GEV): is the global variance accounted for by each microstate, which is the ratio of the summation of variances to the GFPs for all time points.
2. Duration (ms): provides the stable microstate period in milliseconds, which is the mean time when a label is present without interruption.
3. Coverage (%): is the contribution of a microstate expressed in percentage, representing the fraction of recording time that a label is present.

3.3. Explainability in 2D Topographic Maps and Deep Clustering for EEG Microstates

EEG microstates provide stable configurations of scalp electric fields and are thought to be the atoms of thought of human information processing [4]. As such, any methodology targeting the identification and analysis of microstates requires not just precision but also a high degree of transparency and interpretability. Our novel approach of applying deep clustering to 2D topographic maps for microstate generation brings unique challenges and opportunities in this domain.

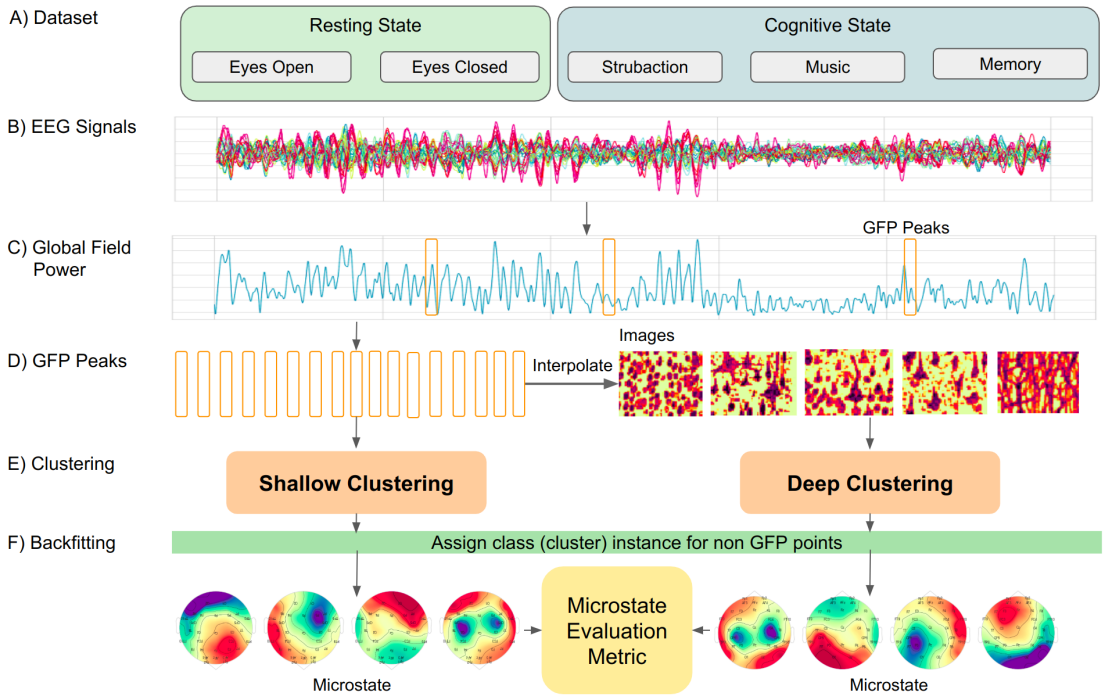

Figure 2: Illustration of EEG microstate sequence generation architectural pipeline for shallow and deep clustering. A) Dataset consisting of multiple resting and cognitive states. B) Raw EEG signal with 64 channels. C) Generate Global Field Power (GFP) peaks for shallow clustering. In contrast, interpolate EEG signals to generate topographic input maps for deep clustering. D) Identify the local maxima of GFP and provide it as an input to shallow clustering, while topographic input maps are fed to deep clustering. E) Compute cluster maps using multiple shallow and deep clustering methods. F) Backfitting to assign cluster labels for non-GFP points for shallow clustering.

1. *2D Topographic Maps as Inputs:* Traditional methods using 1D vector representations of EEG data for clustering abstracted the spatial intricacies of brain activity. Using 2D topographic maps, we preserve the spatial domain knowledge crucial for understanding neural source activations and their topological distributions. This spatial resolution becomes a source of explainability:
    a) *Spatial Activation Patterns:* by analysing which regions of the 2D map the autoencoder focuses on, we can infer the most salient spatial features that define specific microstates [23].
    b) *Comparison with Known Electrode Activations:* by juxtaposing our activation patterns with traditionally known electrode activations for specific cognitive tasks, we can validate and interpret the spatial significance of our findings [24].
2. *Deep Clustering vs. K-means:* Transitioning from traditional k-means clustering to deep clustering introduces additional layers of complexity. However, the hierarchical nature of deep neural networks allows us to understand EEG data at multiple levels of abstraction:
    a) *Hierarchical Feature Learning:* As the data progresses through the autoencoder layers, the network learns increasingly abstract features. By examining activations

at different layers, we can understand granular and high-level patterns that define microstates [25].

b) *Cluster Activation Analysis:* Post clustering, analysing which nodes or features activate for specific clusters can provide insights into the defining characteristics of each microstate cluster. This is a more nuanced approach than the often binary partitioning seen in k-means [26].

4. Concluding remarks and expected contributions

Microstate analysis provides a finite number of whole-brain representative maps with distinct topographies that capture the spatiotemporal characteristics of EEG brain signals with varying degrees of explained variance. However, there are uncertainties with the number of dominant cluster maps representing the coverage of the global explained variance. Moreover, the choice of algorithms to compute cluster maps is limited, primarily using shallow clustering methods. Deep clustering has produced substantially better results than shallow clustering for image data with self-supervision. The research conducted in the context of this doctoral project is one of the earlier studies to assess the effectiveness of deep clustering techniques on EEG microstates without supervision. Deep clustering methods are incorporated to enhance the stability of microstates for intra and inter-person and task-conditioned resting and cognitive data. The efficiency of the proposed method is compared against the existing pipeline using microstate parameters. Friedman Fr test is performed to evaluate the significance of the proposed method.

The primary contribution anticipated from this doctoral research is the demonstration of the suitability of deep clustering methods incorporated into the microstate generation pipeline, which performs representation learning and clustering interactively and iteratively. The proposed pipeline with deep clustering is expected to improve the stability of microstates, which are demonstrated across four distinct cases, namely person-specific activity-specific, person-agnostic activity-specific, person-specific activity-agnostic, person-agnostic activity-agnostic using multiple resting and cognitive conditions. Moreover, testing the pipeline with data from multiple resting and cognitive conditions is expected to validate the robustness of the microstate generation pipeline across varied natural and dynamic conditions. In addition, the proposed pipeline might be offered to the microstate community for performing microstate analysis with alternative input modalities, such as 2D topographic input maps, as opposed to the trivial 1D vector, which fails to capture the spatial characteristics of the input EEG data.

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