Aperiodic-Aware EEG Features for Cross-Subject Acute Sleep Deprivation Detection

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Abstract. Acute sleep deprivation impairs vigilance and cognitive stability. Resting-state electroencephalography (EEG) is a potential approach, although traditional bandpower features may be confounded by broadband aperiodic activity. In this study, the authors assessed whether aperiodic-aware EEG characteristics could serve as useful indicators for detecting acute sleep deprivation across subjects. Eyes-open resting-state EEG recordings from the OpenNeuro ds004902 dataset were analyzed. Within-subject statistical tests demonstrated that the aperiodic exponent increased under sleep deprivation in both reduced-channel and all-channels configurations and that this trend persisted in a strict sensitivity subset. Neither session order nor age was significantly associated with the primary exponent change. By contrast, cross-subject discrimination with lightweight classifiers was only moderate, implying that generalization remains difficult despite the repeatability of the physiological change. These results provide a feasible basis for future EEG-based monitoring analyses.

Keywords: EEG; aperiodic-aware EEG characteristics; monitoring.

1 Introduction

Acute sleep deprivation is associated with impaired vigilance and cognitive stability. These impairments create greater safety hazards on roads, in health care, and in other work settings, and sleep deprivation has been associated with a broad range of impairments in attention, executive function, and psychomotor performance [1, 2, 3]. Robust monitoring is challenging because conventional evaluations rely on self-reports or controlled laboratory assessments. In contrast, electroencephalography (EEG) provides a direct measure of brain state. Resting-state EEG is also feasible because it requires minimal participant activity and can be repeated.

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Most EEG research on acute sleep deprivation summarizes signals within predefined frequency bands. Common features include delta, theta, alpha, and beta power, as well as theta-to-alpha ratios. This approach is simple and well established in the literature [4]. Band-limited power, however, has a critical limitation: it combines periodic peaks with a broadband aperiodic background. The aperiodic component can be described as a 1/f-like process. As its slope or offset varies, power may shift across frequency bands without a corresponding increase or decrease in actual rhythmic activity. This may make physiological interpretation difficult. It may also affect feature stability across subjects and sessions. These concerns apply to machine learning (ML) pipelines that focus on cross-subject generalization.

An alternative is spectral parameterization, which provides an aperiodic-sensitive representation. In this approach, the power spectrum is modeled as the sum of an aperiodic component and periodic peaks. It provides parameters including the aperiodic offset and exponent, as well as peak properties (e.g., alpha center frequency and bandwidth). Past studies have suggested that these variables are sensitive to arousal and changes in cognitive state [5]. However, results are not consistent across protocols. Variability in the duration of wakefulness, resting conditions, preprocessing choices, and sample characteristics may all contribute [6]. For this reason, it is useful to compare aperiodic-sensitive features in a clear and reproducible workflow using an open dataset.

Meanwhile, EEG-based ML has been proposed for monitoring fatigue and sleepiness. Most studies have reported positive performance, although evaluation approaches vary [7, 8]. Compared with within-subject classification, cross-subject classification is often more difficult, and baseline performance can vary [9]. Related EEG-based methods have also sought to infer behavioral effects of sleep deprivation, such as changes in reaction time, from electrophysiological characteristics [10]. Lightweight models remain appealing for practical implementation, but they rely on strong and interpretable feature sets. It is therefore important to directly compare conventional bandpower features with aperiodic-aware features. This comparison can identify which signal components contain the most information about sleep deprivation. It can also inform the design of simple models without unnecessary complexity.

This research analyzed acute sleep deprivation effects using the OpenNeuro ds004902 resting-state EEG dataset. This dataset includes two sessions per participant under normal sleep (NS) and sleep deprivation (SD), with counterbalanced session order recorded. The analysis focused on eyes-open resting EEG because this condition is less dependent on drowsiness-related eye closure and is more applicable to real-world monitoring; prior resting-state work has also suggested that eyes-open and eyes-closed conditions may differ in sleep-deprivation-related EEG effects and their associations with psychomotor vigilance performance [6]. Two feature families derived from power spectra were evaluated: conventional bandpower summaries and spectral parameterization features, with particular emphasis on the aperiodic exponent and offset. Within-subject changes in aperiodic metrics were assessed using paired statistical tests and confidence intervals. Cross-session discrimination of NS versus SD was also evaluated using lightweight classifiers, including logistic regression and linear support vector machines. In addition, session order and age were examined as basic potential confounds.

2 Methods

2.1 Dataset and study design

The OpenNeuro dataset ds004902 was analyzed in this study. It contains resting-state electroencephalography (EEG) recordings collected under NS and SD. Each participant completed two sessions, one in each condition, and session order was counterbalanced and recorded as NS->SD or SD->NS. The dataset consists of 71 participants, with a total of 142 sessions (71 NS and 71 SD). The current analysis targeted eyes-open resting-state EEG because this condition is practical for monitoring and less dependent on eye closure.

EEG was recorded at 500 Hz using 61 scalp channels. Each session contained approximately 300 s of recording. The dataset metadata indicated that FCz was used as the reference and that the power-line frequency was 50 Hz. A subset of sessions included behavioral data. All 142 sessions had eyes-open EEG files, and 67 sessions had trial-level psychomotor vigilance task (PVT) files. PVT data were not included in the primary analyses.

2.2 Data organization

The dataset follows the Brain Imaging Data Structure (BIDS), with subject and session folders. EEG data were stored in EEGLAB format as paired .set and .fdt files. An intermediate session-level manifest was created to standardize file discovery and downstream processing. Each row represented one session and contained the subject identifier, session identifier, condition label, session order, and path to the eyes-open EEG file. Eyes-closed EEG and PVT trial files were also identified and recorded in the manifest when available. Feature extraction and model evaluation were performed based on this manifest.

2.3 Epoching and spectral estimation

EEGLAB file support in MNE was used to load the EEG files. A few sessions required additional file-integrity handling because of loading inconsistencies. To ensure that feature extraction could be completed without excluding sessions, these sessions were retained through a standardized recovery procedure.

The EEG recordings were divided into contiguous, non-overlapping epochs for each session. The target segmentation generated 15 epochs per session. In practice, there were minor differences in the number of epochs per session (range, 11–18; mean, 14.83) because of minor variations in the amount of usable data in individual recordings.

The PSD for each epoch was estimated using Welch's method. PSDs were then averaged across epochs to obtain a stable session-level spectrum. Features were calculated using two channel configurations. The all-channels configuration used the maximum available number of EEG channels. The min8 setting used a smaller montage of eight predefined EEG channels.

2.4 Traditional bandpower characteristics

Traditional spectral summaries were derived from the epoch-averaged PSD. These features included absolute and relative bandpower in standard frequency bands (delta, theta, alpha, and beta). Bandpower ratio features, including the theta-to-alpha ratio, were also included. Bandpower features were calculated for both the all-channels and min8 configurations and arranged in a session-level feature table.

The aperiodic offset and exponent of each session-level spectrum were estimated. Alpha peak parameters were also obtained when a valid alpha peak was identified. These parameters included alpha center frequency, peak power, and bandwidth. As expected, some sessions did not yield alpha peak parameters under the model criteria.

Spectral parameterization features were calculated for the all-channels and min8 configurations and summarized in a session-level feature table containing the subject, session, condition, parameter values, and number of epochs included in the PSD estimate.

Several checks were conducted to assess data completeness and feature stability. First, the number of epochs across sessions was summarized. Second, the feature tables were examined for missing values. The aperiodic exponent and offset were available for all sessions in the final dataset, but alpha peak parameters were missing for some sessions.

To minimize heterogeneity in the number of epochs, a strict sensitivity subset was also established. Only sessions containing 15 epochs were selected (strict15), yielding 130 sessions. For paired analyses, subjects were also required to have both NS and SD sessions in the strict15 subset. The resulting paired subset comprised 59 subjects (118 sessions). The initial paired analyses were replicated in this subset.

3 Statistical analysis

Within-subject differences in the aperiodic exponent between SD and NS were the primary outcomes and were calculated independently for the min8 and all-channels configurations. Paired t-tests and Wilcoxon signed-rank tests were performed for each endpoint. Cohen's dz was reported as the paired effect size. Nonparametric bootstrap confidence intervals based on 10,000 subject-level resamples were used to quantify uncertainty.

Secondary paired analyses were performed to investigate a limited number of other features, such as selected bandpower summaries and peak-related measures. When several features were tested, the false discovery rate (FDR) was controlled to reduce false positives.

3.1 Machine learning testing

For session-level discrimination between NS and SD, lightweight machine learning models were compared. The main models were logistic regression and linear support vector machines. In exploratory comparisons, a random forest classifier was also evaluated. Performance was assessed by cross-validation and summarized as the mean and standard deviation across folds. Reported metrics included balanced accuracy, receiver operating characteristic area under the curve (ROC AUC), and F1 score.

Feature configurations were compared to examine the contribution of aperiodic-aware features. The baseline configuration used bandpower features only. Augmented configurations combined bandpower with aperiodic offset and exponent, with optional inclusion of alpha peak center frequency in some variants. A within-subject-centered version of the feature matrix was also evaluated. In this setting, each subject's features were mean-centered across sessions to reduce stable between-subject offsets and emphasize within-subject condition-related variation.

3.2 Confound checks

To assess possible confounding by session order, Δexponent was computed for each subject as exponent (SD) − exponent (NS), and values were compared between the NS->SD and SD->NS groups using independent-samples tests. Age was also examined as a potential covariate by calculating Spearman correlations between age and Δexponent.

Software

All analyses were performed in Python within a reproducible conda environment. EEG loading used MNE with EEGLAB file support, and spectral parameterization used FOOOF (version 1.1). Statistical analyses and machine learning models were implemented with standard scientific Python libraries.

4 Results

4.1 Data completeness and quality checks

A total of 142 sessions from 71 participants were analyzed, including 71 NS sessions and 71 SD sessions. Eyes-open EEG was available for all sessions (142/142). Trial-level PVT files were available for a subset of sessions (67/142), based on the session manifest, but PVT measures were not included in the primary analyses reported here.

Epoch counts were close to the target in most sessions. Across all sessions, the mean number of epochs was 14.83 (SD = 0.79), with a range of 11 to 18. Twelve sessions did not contain exactly 15 epochs. A strict sensitivity subset was therefore defined by retaining only sessions with exactly 15 epochs, resulting in 130 sessions. For paired strict analyses, subjects were further required to have both NS and SD sessions in this subset, yielding 59 subjects (118 sessions).

4.2 Primary paired effect in the reduced montage: min8 aperiodic exponent

The primary endpoints were the aperiodic exponents estimated from session-level spectra. Within-subject changes from NS to SD were evaluated, and differences are reported as SD − NS.

For the reduced-channel configuration (min8), the aperiodic exponent was higher under SD than under NS. The mean within-subject difference was 0.1566. The paired t-test was significant ($p = 0.00699$), and the Wilcoxon signed-rank test supported the same direction of effect ($p = 0.00745$). The paired effect size was Cohen's dz = 0.3298. Bootstrap uncertainty estimates were also consistent with a positive shift. The 95% confidence interval (CI) for the mean difference was [0.0486, 0.2674], and the 95% CI for dz was [0.1020, 0.5916].

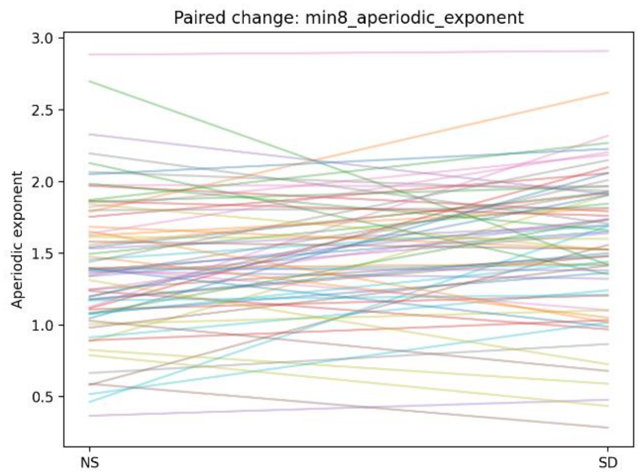

Figure 1: Paired change for the min8 aperiodic exponent (NS vs. SD)

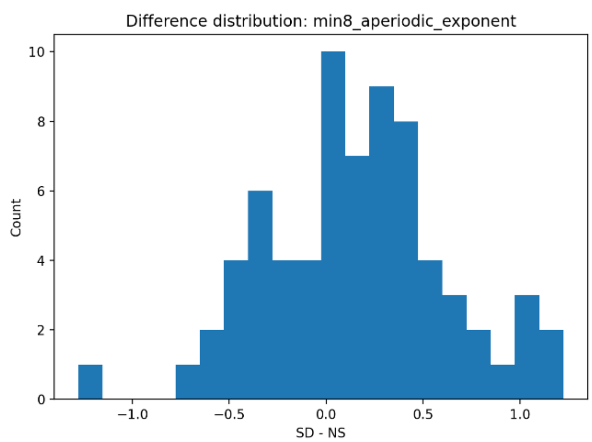

Figure 2: Difference distribution for the min8 aperiodic exponent (SD − NS). Photo/Picture credit: Original

As shown in Figure 1, the paired trajectories indicate substantial inter-individual variability. Many participants showed higher exponent values under SD, although decreases were also observed in a subset of subjects. Figure 2 further shows that the distribution of SD − NS differences was centered above zero, despite a negative tail. Together, these plots support the statistical result that the min8 aperiodic exponent tended to increase under sleep deprivation, while also highlighting heterogeneity across individuals.

4.3 Primary paired effect in the full montage: all-channels aperiodic exponent

The all-channels configuration showed a similar pattern. At the within-subject level, the aperiodic exponent was higher under SD than under NS. The mean difference was 0.1233. The paired t-test was significant ($p = 0.0142$), and the Wilcoxon signed-rank test again supported this result ($p = 0.00993$). Cohen's dz was 0.2986. Bootstrap intervals were also consistent with a positive mean shift. The 95% CI for the mean difference was [0.0264, 0.2165], and the 95% CI for dz was [0.0608, 0.5697].

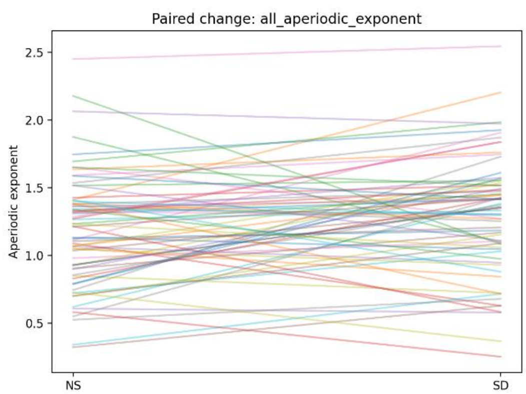

Figure 3: Paired change for the all-channels aperiodic exponent (NS vs. SD). Photo/Picture credit: Original

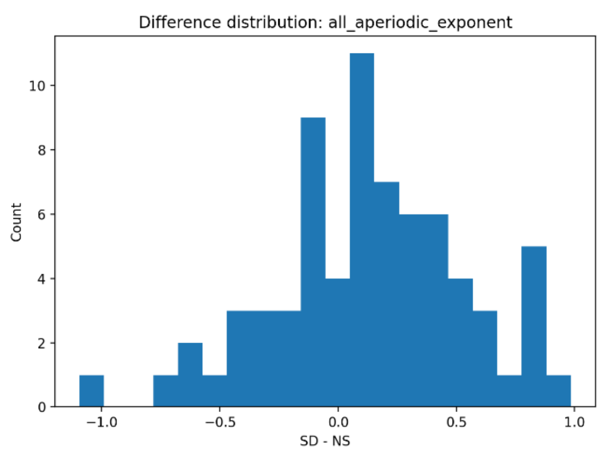

Figure 4: Difference distribution for the all-channels aperiodic exponent (SD − NS). Photo/Picture credit: Original

A similar pattern can be seen in the full-montage visualizations. Figure 3 shows that many paired trajectories shifted upward from NS to SD, although the increase was not uniform across all participants. Figure 4 shows a difference distribution with a positive central tendency and substantial individual variation. These visual patterns are consistent with the statistical evidence for a modest but reliable increase in the all-channels aperiodic exponent under SD.

4.4 Sensitivity analysis: strict paired subset

The paired exponent analysis was repeated in the strict paired subset ($n = 59$) to reduce heterogeneity in epoch count. The direction of effect remained consistent.

For the all-channels exponent, the mean difference was 0.1305 with $dz = 0.3073$ (paired t-test $p = 0.0216$; Wilcoxon $p = 0.0178$). For the min8 exponent, the mean difference was 0.1635 with $dz = 0.3455$ (paired t-test $p = 0.0102$; Wilcoxon $p = 0.00843$). Taken together, these results indicate that restricting the analysis to sessions with the target epoch count did not remove the primary SD-related increase in aperiodic exponent.

A small core set of features, including the exponent and selected bandpower-derived summaries, was also examined. In this screening table, the exponent features yielded the smallest p-values. However, their false discovery rate (FDR)-adjusted q-values were 0.0839 for the min8 exponent and 0.0849 for the all-channels exponent. Other screened features showed weaker evidence after correction. These results support the exponent as a comparatively consistent signal within this feature set, while indicating that inference across multiple tested features should remain conservative.

Possible confounding by session order was also examined using Δexponent = exponent(SD) − exponent(NS). Group differences were not statistically significant. For all-channels Δexponent, $p = 0.317$ by t-test and $p = 0.292$ by Mann-Whitney test. For min8 Δexponent, $p = 0.180$ by t-test and $p = 0.147$ by Mann-Whitney test. Age was also not significantly correlated with Δexponent (Spearman $r = 0.152$, $p = 0.206$ for all-channels; $r = 0.098$, $p = 0.417$ for min8). These checks did not suggest strong confounding by session order or age in the present dataset.

5 Conclusion

This paper assessed acute sleep deprivation using eyes-open resting-state EEG from the OpenNeuro dataset (ID: ds004902), combining conventional bandpower and spectral parameterization features with statistical testing and lightweight machine-learning analyses.

Several findings emerged from the current analysis. First, within subjects, the aperiodic exponent consistently increased under sleep deprivation compared with normal sleep in both reduced-channel and all-channels configurations. Paired t-tests, Wilcoxon signed-rank tests, and bootstrap confidence intervals supported this effect, indicating that the result was not tied to a single statistical method. Second, the direction of the effect remained consistent in the strict paired subset, which included only sessions with the target number of epochs, indicating that small variations in epoch count were unlikely to explain the main finding. Third, exploratory screening of the small set of core features showed that exponent-based features produced the smallest p-values, although the associated false discovery rate-adjusted results remained conservative. Finally, neither session order nor age was significantly associated with the primary change in the exponent, suggesting that the observed change was not explained by these simple confounds.

Meanwhile, cross-subject discrimination remained modest even when aperiodic-aware features were included. This outcome suggests that a consistent physiological change does not necessarily produce a high degree of cross-subject generalization. Future studies should examine independent datasets, include behavioral measures such as psychomotor vigilance task performance, and evaluate the value of aperiodic-aware features under broader recording conditions. These markers may also generalize to other performance domains affected by sleep loss beyond laboratory vigilance paradigms. Overall, this study contributes to the interpretable use of the aperiodic exponent as an indicator of acute sleep deprivation and provides a useful benchmark for future EEG monitoring studies.

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