Code conflict in an event file task is reflected by aperiodic neural activity

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We investigated the relationship between aperiodic electroencephalography (EEG) activity and code conflict, hypothesizing that the former might serve as an indicator of the latter. We analyzed EEG and behavioral outcomes of a sample performing the event file task, which assesses code conflict in co-occurring or temporally overlapping stimulus and response features. To quantify aperiodic activity, we employed the fitting oscillations & one-over-f algorithm. The behavioral results revealed a typical partial-repetition cost effect, indicating that performance is impaired if the stimulus repeats while the response alternates, or vice versa. This suggests that the previously combined shape and response were stored in an event file and retrieved when any one of these components was repeated. Notably, this effect was also evident in the aperiodic exponent, which was lower for partial repetitions than for full repetitions or alternations, implying increased cortical noise, a higher excitatory *E/I* ratio, and noisier decision-making processes. The scalp distribution of this effect aligns with its sensorimotor characteristics. Thus, we interpret these findings as promising preliminary evidence that the aperiodic exponent may serve as a valuable neural marker of code conflict. *NeuroReport* 36: 337–341 Copyright © 2025 Wolters Kluwer Health, Inc. All rights reserved.

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Introduction

Heider [1] and Treisman [2] emphasized that even though our primary cortices code sensory input in terms of its separable features, like shape or pitch, our eventual perceptual experience always refers to complete, integrated objects. The same holds for actions, which do not target individual features but fully integrated goal objects [3]. To account for this discrepancy, the theory of event coding (TEC) claims that the basic units of human cognition consist of *event files* [4] – bundles of codes of co-occurring or temporally overlapping stimulus and response features [5].

The most popular paradigm to study event files has participants carry out two responses to two stimuli in a row (Fig. 1a) [6]. The first (R1) is precued by a response cue that signals a left or right keypress, say, which is carried out as soon as the actual stimulus (S1) appears. TEC assumes that the co-occurrence of S1s features (e.g. its red color and horizontal shape) are integrated with the codes of R1 into an S1/R1 event file. Next, S2 appears to signal R2 according to an instructed mapping (e.g. a horizontal/vertical shape indicates a left/right keypress). Repeating one or multiple features of the S1/R1 file should retrieve this file and reactivate its codes, which can create code conflict. If all features are repeated (if S1 = S2 and R1 = R2) the S1/R1 file would be retrieved, but the reactivated feature codes would not conflict with the S2/R2 codes. If all alternate (if S1 shares no feature with S2, and R1 none with R2), no code would be reactivated. However, if some features repeat while others alternate (e.g. S1 = S2, but R1 ≠ R2, or S1 ≠ S2, but R1 = R2), feature codes would conflict with each other, which should create uncertainty and prolong decision-making. Hence, partial (but not complete) feature repetition should induce cognitive conflict.

Behavioral and neuroscientific studies provide strong evidence for such *partial-repetition costs* in reaction-time (RT) studies [4,6–8] and functional MRI studies [9,10], which demonstrated that partial feature repetition reactivates previously integrated features. However, diagnosing feature conflict by assessing partial-repetition costs remains indirect, and employing brain scanning to identify reactivations is costly and not overly convenient, and fails to provide the temporal resolution that is necessary to monitor the dynamics of code conflict over time. Accordingly, we sought a more convenient and better time-resolved procedure to assess code conflict.

Aperiodic electroencephalography (EEG) activity has been shown to vary systematically across development and aging [11,12], between sleep and wake stages [13,14], and during cognitive tasks such as attentional processes [15], sensory integration [16], and working memory [17]. Interestingly, tasks involving response conflict (e.g. Go/No-go or Flanker tasks) elicit cognitive control adjustments, manifested as an increase in the aperiodic exponent [18–20]. Furthermore, aperiodic activity decreases significantly during task switching compared with task

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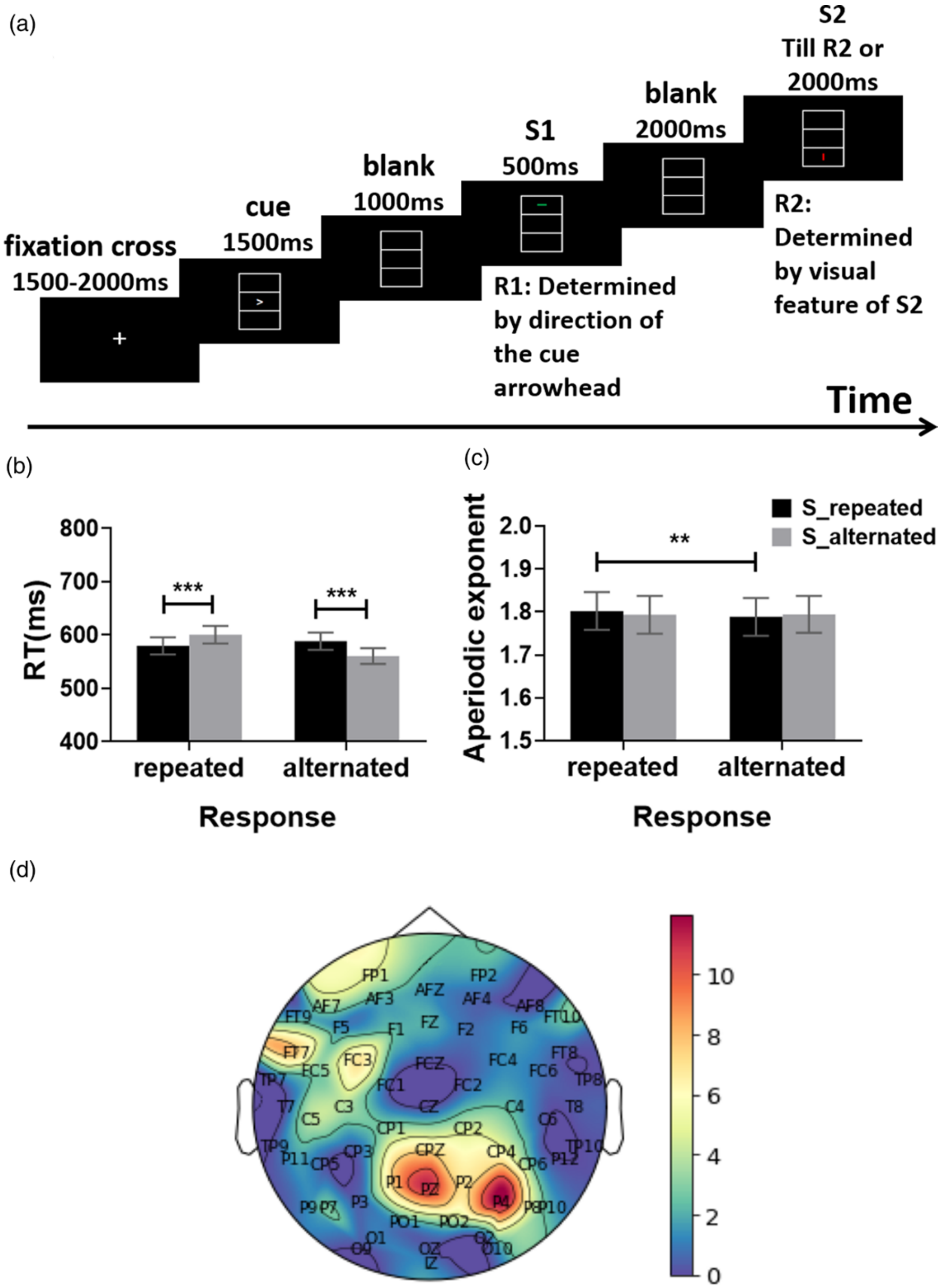
Fig. 1



(a) Illustration of displays and timing of task. (b) Shape × response interaction in RTs. (c) Shape × response interaction in aperiodic exponent. Error bars in (c) and (d) represent SEM; ***$P < 0.001$, **$P < 0.01$. (d) Scalp distribution of significant shape × response interactions in the aperiodic exponent. Colors indicate cluster-level summed F values. RT, reaction time.

repetition, suggesting that task switching requires a more flexible cognitive state [21]. Here, we tested whether the aperiodic exponent, which corresponds to the negative $1/f$ slope of the logarithmic transformation of the power spectrum [22], might serve as a convenient proxy to diagnose code conflict. This exponent has been taken to indicate 'neural variability' (i.e. the brain's ability to flexibly adjust to situational demands [23]) and to reflect the so-called 'E/I ratio' – which expresses the relationship between excitatory and inhibitory brain processes. Given that code conflict should create decision-making uncertainty and induce a dominance of excitatory over inhibitory processes, which in turn implies a weaker signal-to-noise ratio and a noisier decision-making process [24], more code conflict in the sense of TEC may be reflected by the aperiodic exponent. As lower values of this exponent indicate higher noise levels and greater dominance of excitatory processes, we expected that greater code conflict would be associated with a lower exponent. While many codes can be involved in code conflict [6], here we focused on the two task-relevant feature codes: the instructed S2 feature (horizontal or vertical shape) and the instructed R2 feature (left or right location).

Materials and methods

Participants

Data from 74 healthy participants, originally collected for a different research purpose [25], were reanalyzed (48 males, 26 females; mean age: 19.16 ± 9.96 SD; 8–49 years). Two participants were excluded from the behavioral data analysis because of having zero correct responses in several conditions and six from the EEG analyses, because of errors, poor EEG quality, or different channel settings. All participants underwent a standardized clinical assessment to gather lifetime clinical information, which included a clinical neuropsychiatric interview, screening for neuropsychiatric disorders, and IQ testing. Only those without clinically significant neuropsychiatric issues at the time of the study and with an IQ above 80 were included. For more details, see Adelhöfer *et al.* [25]. The study and all procedures were conducted in accordance with the Declaration of Helsinki and received approval from the Ethics Committee of the Medical Faculty of the TU Dresden.

Apparatus and stimuli

Participants were seated approximately 60 cm from a computer screen. A vertically aligned 6.7 × 2.8 cm white rectangle was displayed at the center of a black screen. It was divided into three 2.2 × 2.8 cm sections. The central section showed the arrowhead cue indicating a left or right R1. The upper and lower sections showed S1 and S2, which consisted of a vertical or horizontal line (relevant shape feature) in red or green color appearing in the top or bottom location. EEG data were recorded using 60 equidistant Ag/AgCl electrodes mounted on an elastic cap. The data were sampled at 500 Hz, with the reference electrode at Fpz, the ground electrode at $\theta = 58$ and $\phi = 78$, and the impedances less than 10 kΩ throughout.

Procedure and design

Participants executed two speeded responses per trial: R1, a left or right keypress as indicated by the arrow cue, carried out upon presentation of S1 (regardless of its shape, position, or color), and R2, a left or right keypress as indicated the S2 shape. 50% of the participants pressed the left/right key in response corresponding to a vertical/horizontal shape, while the other 50% had this mapping reversed. After an intertrial interval (see Fig. 1a for timing), a fixation cross appeared at the screen center, followed by the arrow cue indicating R1, a blank to prepare the response, and S1 to trigger R1. S2 appeared for 2000 ms or until R2 was made. There were three blocks of 128 trials each, totaling 384 valid trials. Each block was made up by repeating twice the factorial combination of the two shapes (vertical and horizontal), the two colors (green and red), and the two positions (top and bottom) of S2, with repetitions of shape, location, color, and response varied, leading to 128 different combinations ($2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2$). The trials within each block were presented in random sequence, with an optional break after each block.

EEG recording and preprocessing

As reported in the original study [25], an initial manual review of the raw data was conducted to eliminate significant technical artifacts, followed by the application of a band-pass filter set to 2–40 Hz (slope: 48 dB/oct). Independent component analysis, utilizing the infomax algorithm, was then performed to detect and remove periodically occurring artifacts, including horizontal and vertical eye movements, as well as pulse artifacts. The EEG data were segmented based on the onset of the S2 stimulus. Separate segments were created for every possible combination of stimulus feature overlap and response type (repetition versus alternation), with each segment lasting 4000 ms and starting 2000 ms before the S2 stimulus onset. Only trials that resulted in correct responses to both the cue and the S2 stimulus were included in the analysis. During artifact rejection, epochs were discarded if any of the following criteria were met: amplitudes exceeding 200 μV or dropping below −200 μV, voltage spikes greater than 200 μV within a 200-ms interval, or activity levels falling below 0.5 μV in a 100-ms period. To remove the reference potential from the data, a current source density transformation was applied. Finally, the data underwent baseline correction within a time interval from −200 to 0 ms.

Parameterization of spectral data

Of 1000 ms after the onset of the S2 was identified to be a specific time windows for analysis. On the basis of previous research, which utilized a 0.25-s Hamming window with 50% overlap, the power spectral density for each frequency was calculated using the ‘pwelch’ function in MATLAB (version R2024a, Mathworks, https://ww2.mathworks.cn). These calculations were conducted separately for each participant, electrode, and condition. The EEG power spectra were then analyzed using version 1.0.0 of the Python-based FOOOF toolbox (available at https://github.com/fooof-tools/fooof). It decomposes the power spectrum into aperiodic activity and periodic (oscillatory) activity and represents it as a linear combination of these two components. The mathematical expression for the aperiodic component, *L(f)*, is defined as: $L(f) = b - \log [f^x]$. It includes the aperiodic offset ‘*b*’, indicating the overall shift in broadband power, and the aperiodic exponent ‘*x*’, which reflects the slope of the power spectrum when plotted on a log–log scale (for further details, see Donoghue *et al.* [22]). We computed this exponent for each participant and electrode using the aperiodic-only signal. Given the lack of prior assumptions regarding the distribution of aperiodic neural activity on the scalp, we employed the ‘global’ exponent for our statistical evaluations [26]. We first calculated the average exponent values across 60 electrodes for each participant to observe the overall trends in variation over different periods, and then performed a cluster-based permutation test to analyze the distribution of aperiodic components on the scalp. This nonparametric statistical method is specifically designed for examining high-dimensional EEG/magnetoencephalography data and aimed to detect significant differences between electrodes while accounting for multiple comparisons [27]. The method involves creating clusters based on the adjacency of thresholded sample-level *F* values, with a significance level set at 0.05). We utilized MNE-Python (https://mne.tools/stable/index.html) to conduct the permutation cluster test (for further details, see Maris and Oostenveld [27]).

Results

Behavioral results

A 2 (shape = repeated/alternated) × 2 (location = repeated/alternated) × 2 (color = repeated/alternated) × 2 (response = repeated/alternated) analysis of variance (ANOVA) on RTs revealed significant main effects for location ($F_{(1,71)} = 4.94$, $P < 0.05$, $\eta_p^2 = 0.07$) and response ($F_{(1,71)} = 14.41$, $P < 0.001$, $\eta_p^2 = 0.17$). Both factors were involved in numerous interactions, which mostly indicated partial-repetition costs. Most importantly for our purposes, the significant interaction of shape and response ($F_{(1,71)} = 45.62$, $P < 0.001$, $\eta_p^2 = 0.39$) indicating that RT was significantly shorter when both shape and response repeated (580 ± 16) or both alternated (560 ± 15) than when shape alternated but response repeated (600 ± 16) or shape repeated but response alternated (589 ± 16; Fig. 1b).

Aperiodic exponent

A four-factor repeated-measures ANOVA revealed one significant interaction between shape and response ($F_{(1,67)} = 4.68$, $P < 0.05$, $\eta_p^2 = 0.07$). Simple effects analysis showed a significant decrease in the aperiodic exponent with alternated (1.79 ± 0.04) as compared with repeated responses (1.80 ± 0.04) when the shape was repeated ($F_{(1,67)} = 4.68$, $P < 0.05$, $\eta_p^2 = 0.07$), but no significant difference when the shape was alternated, see 1C. A cluster-based permutation test examined the distribution of the aperiodic components on the scalp, where the shape × response interaction was significant over central and posterior areas (cluster: C4/CP4/P2/Pz, $F_{(1,67)} = 3.98$, $P < 0.05$, $\eta_p^2 = 0.75$; Fig. 1d).

Conclusion

The behavioral outcomes demonstrate a classical partial-repetition cost effect [4,6–8], showing that the repetition of either shape or response and for performance if the other feature alternates. This pattern indicates that the previous shape/response combination was integrated into an event file, which was retrieved upon the repetition of at least one of these two components.

In this study, the aperiodic exponent was lower for partial repetitions than for complete repetitions or alternations. This indicates more cortical noise, greater excitatory dominance of the *E*/*I* ratio, and noisier decision-making. The scalp distribution of this effect also fits with its sensorimotor nature. Our findings align with previous studies indicating that tasks requiring response conflict (such as Go/No-go or Flanker tasks) trigger adjustments in cognitive control, evidenced by an increase in the aperiodic exponent [18–20]. This is not surprising, as both code conflict and response conflict engage cognitive control mechanisms, whereby the brain must allocate resources to reconcile competing information and maintain focus on the task at hand. The necessity for resolution in both scenarios can lead to an elevated aperiodic exponent, reflecting the inefficiencies that emerge when the cognitive system processes multiple pieces of information. To conclude, we consider the current findings as the first, encouraging evidence that the aperiodic exponent might represent a useful neural indicator of code conflict which extends previous findings on the association between the aperiodic exponent and attentional processes [15], sensory integration [16], and task switching [21].

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Conflicts of interest

There are no conflicts of interest.

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