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RESTING-STATE BRAIN CRITICALITY AND PERFORMANCE WITH P300-BASED BCIS

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ABSTRACT: Here we present correlations between criticality-related measures calculated from resting-state electroencephalography (EEG) recordings and subsequent performance with a visual P300-based brain-computer interface (BCI) in healthy participants. Results suggest a positive relationship between resting-state brain criticality and subsequent BCI performance using P300-based BCIs.

INTRODUCTION

The P300-based brain-computer interface (BCI) speller is the most widely used BCI application, and P300-based BCIs are generally described as being convenient, reliable, and easy to use [1] – see also a direct comparison between sensorimotor rhythm-based and event-related potential (ERP)-based BCI applications such as the P300-based BCI speller in Kübler et al. [2]. However, attempts to predict the future performance of a P300-based BCI based on neural brain activity have been rare[1]. Halder et al. [3] and Won et al. [1] showed that in healthy participants[2], elicited ERPs in a preceding oddball or rapid serial visual presentation (RSVP) task were related to subsequent performance with a P300-based BCI. In the Won et al. [1] sample, the P300 amplitude elicited during the RSVP was positively correlated with subsequent P300 speller performance. The sample of Halder et al. [3] showed that the amplitude of the N2 ERP elicited in the preceding oddball paradigm was related to subsequent performance with a visual P300-based BCI. The latter result was subsequently replicated in patients with amyotrophic lateral sclerosis (ALS) [6]. Nonetheless, these attempts were based on task-related activity and would not allow for performance prediction based on spontaneous brain activity. To establish relationships between spontaneous brain activity and performance with a P300-based BCI that may be useful for predicting performance in the future, it seems fruitful to investigate correlations between performance with P300-based BCIs and preceding resting-state electroencephalography (EEG) recordings.

While attempts have been made to detect relationships between resting-state brain activity and the subsequent performance achieved with motor imagery BCIs [8, 9, 10, 11], to our knowledge there is only one available study that has attempted to predict BCI performance for the use of a P300-based BCI from resting-state brain activity in healthy participants. Shin et al. [12] found a negative correlation between delta-frequency band power in the resting-state EEG and the subsequently achieved performance with a P300-based BCI. They also reported negative correlations between delta- and alpha-frequency band connectivity at rest and subsequent BCI performance, and a positive correlation between gamma-frequency band connectivity at rest and subsequent BCI performance. Recently, we also investigated the relationship between resting-state brain activity and the subsequently achieved performance with a P300-based BCI [13]. Aiming to establish a relationship between BCI performance and the level of consciousness, we examined the correlations between two theoretically supported measures of consciousness, i.e., the power-law exponent (PLE) and the Lempel-Ziv complexity (LZC), at rest and the subsequently achieved performance with a P300-based BCI. We showed strong and significant correlations between both PLE and LZC at rest and the performance of a locked-in ALS-patient during the subsequent use of a tactile P300-based BCI.

The PLE[3] provides information about the non-periodic, arrhythmic, and scale-free activity of the brain [14, 15, 16] by means of the 1/f aperiodic scaling [17], i.e. the slope of the EEG power spectrum, also called spectral

[1] We have limited our review here to neurophysiological predictors of P300-based BCI performance because of our interest in the relationship between spontaneous brain activity and BCI performance. Research on the influence of psychological factors, e.g., Kleih et al. [4], is not included.

[2] We specifically focus on healthy participants here because many studies investigating the predictability of upcoming performance for the use of a P300-based BCI have examined patients with amyotrophic lateral sclerosis (ALS) (e.g., [5, 6]). However, we have recently suggested that the brain activity of ALS-patients shows alterations in brain criticality, making the relationship between their spontaneous brain activity and the use of a P300-based BCI a special case [7].

[3] We will use PLE as a catch-all abbreviation throughout this paper, although the cited literature may have referred to this phenomenon as *1/f*, *aperiodic*, or *scale-free activity*, *1/f slope*, *1/f* or *aperiodic scaling*, *spectral slope*, or *power-law distribution*.

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slope [18, 19]. This means that with increasing power in lower frequencies and decreasing power in higher frequencies, the slope of the power spectrum becomes steeper and the PLE value increases. Conversely, with decreasing power in lower frequencies and increasing power in higher frequencies, the slope becomes flatter and the PLE decreases. The LZC applied to neural brain activity provides information about the complexity of a neural signal according to its compressibility [20]. The more easily the brain activity can be compressed, the less complex the corresponding brain activity is. This complexity has been interpreted as reflecting the amount of information content in conscious experience [21], most clearly formulated in the *Entropic Brain Hypothesis* [22]. The PLE plays a prominent role in the *Temporo-Spatial Theory of Consciousness*, where it shows how neural activity of different temporal and spatial scales are nested within a single conscious experience [23]. Both PLE and LZC have recently received empirical support for their ability to discriminate between different states of consciousness [14, 18, 24] or brain states [25, 19]. In addition, recent results have provided evidence for their reactivity to sensory processing [24, 26] as a function of the participants' states of consciousness [24] and the ongoing task demands [26]. Finally, both PLE and LZC are considered to be closely related to the so-called brain criticality, making them *criticality-related measures* that indicate increasing brain criticality with increasing LZC and decreasing PLE, and decreasing brain criticality with decreasing LZC and increasing PLE [18].[4]

Since brain activity at the point of criticality is considered to express remarkable information processing capabilities, with maximal sensitivity to perturbations, an enriched repertoire of system states, and a high capacity to store and transfer information [17], brain criticality may be an interesting concept to be explored in the context of BCI use. Therefore, we have recently discussed the relevance of brain criticality for the use of P300-based BCIs [7]. Based on the available literature, we have argued that an increase in resting-state brain criticality appears to be beneficial for reorganizing brain activity to meet upcoming task demands, such as the use of a P300-based BCI. Central to our argument, Irrmischer et al. [27] showed that while a measure of brain criticality during a sustained attention task was negatively related to the performance in that task, the same measure showed a positive relationship with task performance when derived from the preceding resting-state EEG recording. Thus, Irrmischer et al. [27] hypothesized that two distinct processes are at work when it comes to criticality and task performance in attention-demanding tasks. While increased brain criticality at rest is indicative of the brain's ability to adapt to upcoming task demands, the execution of an attention-demanding task appears to favor less critical brain activity. This favorable reduction in brain criticality was also demonstrated by the only study, other than our own [17], that examined a relationship between brain criticality and the use of a P300-based BCI [28]. The authors showed that when using a P300-based BCI, decreasing brain criticality[5] was associated with increased P300 amplitudes. In contrast, Herzog et al. [30] showed that, consistent with Irrmischer et al. [27], resting-state brain criticality was positively associated with the P300 amplitude in a subsequent Go/Nogo task. Investigations of the relationship between functional connectivity and the P300 further support the proposed relationship between resting-state brain criticality and performance on an attentionally demanding task. Functional connectivity and brain criticality have been shown to be positively related (see, e.g., [31,32]). Given this, Li et al.'s [33] finding of a positive relationship between increased functional connectivity at rest and the P300 amplitude in a subsequent task, as well as Li et al.'s [34] finding of a positive relationship between decreased functional connectivity during the task and the P300 amplitude, suggest that while the P300 amplitude appears to be positively related with resting-state brain criticality, it appears to be negatively associated with on-task brain criticality.

These results suggest that resting-state brain criticality is likely to be related to subsequent performance with a P300-based BCI, and that increased criticality at rest is related to better performance during the subsequent use of a P300-based BCI. The latter hypothesis was tested in this paper using two selected criticality-related measures, LZC and PLE, and the open-access dataset of Won et al. [35]. In our first study [13], in which we looked for correlations between these variables and BCI performance in a locked-in ALS-patient, we already tried to find similar correlations for healthy participants from the Won et al. [35] dataset. Problematically, the online BCI performance of the participants in this dataset showed a pronounced ceiling effect, which prevented meaningful correlation analyses. To circumvent this ceiling effect in this re-analysis of these data, we here use BCI offline performance as a measure of BCI performance, calculated on the basis of the letter

[4] Note that the *spectral slope*, as calculated by Maschke et al. [18], is positively correlated with brain criticality. However, in contrast to our calculation (see Materials & Methods), they do not use the absolute value of the spectral slope. Accordingly, the PLE, as calculated here, can be expected to be negatively correlated with brain criticality. This difference in calculation also explains the observed strong correlation between the spectral slope and LZC in Maschke et al. [18], which contrasts with our observed anticorrelation between PLE and LZC (see Results).

[5] Bojorges-Valdez and Yanez-Suarez [28] did not use the word *criticality*, only a measure of brain criticality. This is a more common phenomenon. A recent review highlighted the inconsistent use of *criticality* in the brain criticality literature [29]. Although authors may use concepts or measures that are part of the brain criticality concept, they do not necessarily refer to the concept or use the word.

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detection accuracy after only two repetitions of the stimulus sequence (see Materials and Methods for details). We show correlations between our criticality-related measures calculated from resting-state EEG and the subsequent BCI offline performance using a visual P300-based BCI. The positive correlation between LZC at rest and subsequent BCI offline performance, and the negative correlation between PLE at rest and subsequent BCI offline performance, suggest that increased resting-state brain criticality is associated with better subsequent BCI performance when using a P300-based BCI.

MATERIALS AND METHODS

Dataset: The dataset we used is part of the publicly available BCI dataset by Won et al. [35]. The data analyzed here include the BCI performance of 55 participants using a visual P300-based BCI speller, as well as their open-eyes resting-state EEG recordings that were taken prior to the BCI use and that were the closest to the BCI use (see Procedure).

Participants: 55 participants took part in the study of Won et al. [35]. 14 of the participants were female and their mean age was 22.91 years (± 2.87). None of the participants were excluded for this analysis.

Procedure: The data analyzed here, i.e., BCI performance achieved with a visual P300-based speller and a preceding open-eyes resting-state EEG recording, were obtained as part of a larger experimental procedure consisting of 3 blocks of resting-state EEG recordings, each with an open-eyes and closed-eyes condition, a RSVP task, and the use of a visual P300-based BCI speller (for details, see [35]). The entire experiment was presented and recorded using BCI2000 [36]. The EEG data was recorded at a sampling rate of 512 Hz using a Biosemi Active Two system with 32 AG/AgCl active electrodes placed according to the international 10-20 system (Fp1, AF3, F7, F3, Fc1, Fc5, T7, C3, Cp1, Cp5, P7, P3, Pz, Po3, O1, Oz, O2, Po4, P4, P8, Cp6, Cp2, C4, T8, Fc6, Fc2, F4, F8,, AF4, Fp2, Fz, Cz). To investigate possible correlations between preceding resting-state EEG recordings and the performances reached with the visual P300-based BCI, which may have predictive value, we used the resting-state EEG recording that was taken before and closest to the BCI use. The resting-state EEG recordings analyzed here were recorded with opened eyes. The resting-state EEG was recorded for approximately 139 seconds, and the participants were instructed to fixate a cross on the screen in front of them, to remain relaxed, and to minimize movement. The subsequent BCI use consisted of two calibration runs and four test runs. In each of the two calibration runs, the participants were instructed to copy spell a word without visual feedback. In each of the test runs, the participants were instructed to copy spell a word with visual feedback. The visual P300-based BCI speller was based on a 6x6 matrix speller with six columns and six rows and included the letters of the alphabet, digits, and a space. Each of the 12 stimuli – six columns and six rows – of a stimulus sequence was flashed for 125 ms followed by a 62.5 ms inter-stimulus interval before the next stimulus of the sequence was flashed. For the selection of a single letter, the stimulus sequence was presented 15 times, resulting in a total of 180 stimuli with 30 stimulus flashes comprising the target and 150 non-target stimulus flashes.

BCI Offline Performance: BCI offline performance was calculated from the letter detection accuracy provided with the dataset [35]. Letter detection accuracy was calculated as the number of correctly selected letters of the word to be copied in a single test run as a function of the number of repetitions of the stimulus sequence. Provided for each of the 55 participants, consisting of 4 test runs with one word to be copied per run, and 15 repetitions of the stimulus sequence per letter selection, the letter detection accuracy was provided as a matrix with dimensions of 55x4x15. We first calculated a mean letter detection accuracy for each participant as the average of the letter detection accuracies of the four words which had to be copied. As shown in Settgast et al. [13], the letter detection accuracies after 15 repetitions of the stimulus sequence showed a pronounced ceiling effect, with 25 out of 55 participants having reached 100 percent accuracy and 51 out of 55 participants having reached the 70 percent benchmark for successful BCI performance [37]. To avoid problems related to this ceiling effect, we decided to use the letter detection accuracy whose distribution was closely centered around 50 percent and did not show a violation to normal distribution. We tested the normal distribution for each of the letter detection accuracies across participants as a function of the number of repetitions of the stimulus sequence. We chose the letter detection accuracy after two repetitions of the stimulus sequence as BCI offline performance. This cross-participant letter detection accuracy after two stimulus sequences showed a mean of 0.52 (0.2), showed no significant skewness and kurtosis, and showed no violation of normality according to the Shapiro-Wilk test.

EEG Pre-Processing (Resting-State): Resting-state EEG data was pre-processed with EEGLAB [38]. First, the data was band-pass filtered from 1-40 Hz. The 1-Hz low cutoff was applied according to the recommendations of Winkler et al. [39] to ensure good results in the later performed independent component analysis (ICA). The EEGLAB built-in clean_artifacts function was used to remove flatline, highly correlated, and noisy channels as well as short time bursts and otherwise bad data periods. Deleted channels were then spherically interpolated. The EEG data was re-referenced to the common average because the used EEG recording device does not provide a hardware-based reference [35]. An ICA was performed, and artifact components were automatically flagged and removed using MARA [40].

Data Analyses: Both PLE and LZC values were obtained using custom MATLAB scripts. Each of the variables was computed using a sliding-window method with 1-second windows and 50% overlap between windows (for computation details, see [14]) for each of the 32 EEG channels. To account for differences in EEG

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recording length due to bad data period rejection in the previous pre-processing step, we took 130 s of EEG data for each participant, starting 5 s after the start of the recording, for further analysis. To calculate the PLE, the power spectral density (for computation details, see [14]) was logarithmically transformed in both frequency and power spectrum domain. The slope of the PSD was then calculated by linear least squares regression. The PLE was then obtained as the absolute value of this slope. For further analysis, we took the average of these values across channels and time windows for each participant. LZC values were computed largely according to the algorithm of Zhang and Roy [41], using the median as the threshold for binarization due to its robustness to outliers [42]. To reflect the number of accruing pattern in the sequence, the LZC was normalized [43]. As for the PLE, the LZC values were averaged across time windows and channels for further analysis. LZC and PLE were tested for normality. None of the variables showed significant kurtosis, skewness, and/or a violation of normality according to the Shapiro-Wilk test. Therefore, the following correlation analysis was performed using parametric Pearson's product-moment correlation (two-tailed). To adjust for multiple comparisons, we report Bonferroni-corrected p-values.

RESULTS

The results of the correlation analysis are shown in Tab. 1.

Table 1: Correlation Matrix

Variables	LZC	PLE	BCI offline performance
LZC	-		
PLE	-.99** [-.99, -.98]	-	
BCI offline performance	.38* [.13, .59]	-.34* [-.55, -.08]	-

Table 1: Pearson's product-moment correlation (two-tailed) between the selected criticality-related measures, PLE and LZC, and BCI offline performance. * indicates p<.05, and ** indicates p<.001 after Bonferroni correction for multiple comparison. Confidence interval for the according correlations provided in square brackets.

There was a very high and significant anticorrelation between PLE and LZC (r=-.99, p<.001). We also observed significant moderate correlations between both PLE and LZC and the BCI offline performance (see Fig. 1). PLE and BCI offline performance showed a negative correlation (r=-.34, p<.05), whereas LZC and BCI offline performance showed a positive correlation (r=.38, p<.05). This supports our hypothesis that brain criticality calculated from resting-state brain activity is related to the subsequent BCI performance – as indicated by BCI offline performance – when using a P300-based BCI.

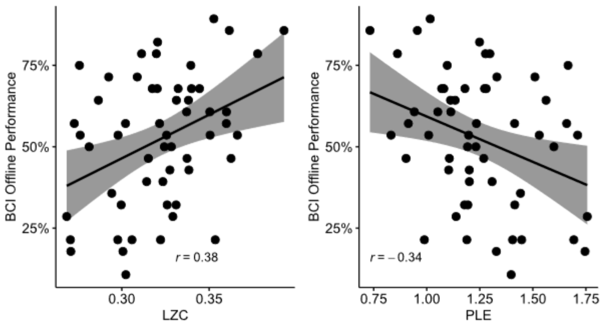

Figure 1: Correlations between the selected criticality-related measures, LZC and PLE, and BCI offline performance (Pearson's product-moment correlation (two-tailed)).

DISCUSSION

We present here, to our knowledge, the first results indicating a relationship between brain criticality calculated from a preceding resting-state EEG recording and the subsequently achieved performance with a P300-based BCI in healthy participants. The presented correlations between two criticality-related measures, PLE and LZC, at rest and subsequent BCI offline performance suggest that increased resting-state brain criticality appears to be positively related to BCI performance when using a P300-based BCI. This finding is consistent with our hypothesis based on the proposed relationship between resting-state brain criticality and BCI performance with P300-based BCI, which we recently outlined [7]. Increases in EEG-derived measures of brain criticality at rest seem to improve the performance during the subsequent use of a P300-based BCI. This is sound with the idea that brain activity at the point of criticality expresses remarkable information processing capacities [17] and, as shown by Herzog et al. [30], the resting-state brain criticality may even interact with the P300 amplitude itself.

The only other available study that examined the relationship between resting-state brain activity and subsequent performance with a P300-based BCI [12] may support our findings. Shin et al. [12] showed a negative correlation between resting-state delta-frequency band power and subsequent BCI performance with a P300-based BCI. Given that significant increases in low-frequency oscillatory activity in the EEG power spectrum may reflect, or at least be confounded by, a steepened spectral slope [26], i.e., an increased PLE, the results of Shin et al. [12] would suggest that BCI performance with a P300-based BCI decreases with an increasing PLE value, i.e., decreasing criticality. Therefore, their result suggests a positive relationship between resting-state brain criticality and BCI performance with a P300-based BCI, as we have shown here.

The investigation of BCI performance based on brain criticality from preceding brain activity has also been performed with motor imagery (MI) BCI [44]. Samek and colleagues showed that brain criticality during a training session with a MI BCI was positively associated

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with the subsequent performance in the test session. Although they did not use resting-state brain activity, this finding further suggests the importance of state-dependent brain criticality for the upcoming task, such as BCI use.

We speculate that one of the classical target groups for P300-based BCIs, i.e., complete locked-in (CLIS) ALS-patients, could benefit from the demonstrated relationship between resting-state brain criticality and subsequent BCI performance with a P300-based BCI. Limiting BCI communication attempts to periods of increased brain criticality might eventually improve their often inadequate performances with non-invasive BCIs (see e.g., Bettencourt et al. [45] for a recent overview). This would be a first attempt to detect the so-called *Windows of Consciousness* postulated by Kübler [46]. The potential increase in resting-state brain criticality may be even more relevant, as CLIS patients appear to show a general decrease in brain criticality, as indicated by changes in our selected criticality-related measures [14].

CONCLUSION

We present here results indicating a relationship between resting-state brain criticality and subsequent performance with a visual P300-based BCI. Increasing brain criticality in resting-state brain activity, as indicated by criticality-related measures, appears to be beneficial for the subsequent use of a P300-based BCI in healthy participants.

REFERENCES

[1] Won K, Kwon M, Jang S, Ahn M, & Jun SC. P300 speller performance predictor based on RSVP multi-feature. Frontiers in human neuroscience. 2019; 13: 261

[2] Kübler A, Holz EM, Riccio A, Zickler C, Kaufmann T, Kleih SC, et al. The user-centered design as novel perspective for evaluating the usability of BCI-controlled applications. PloS one. 2014; 9(12): e112392

[3] Halder S, Hammer EM, Kleih SC, Bogdan M, Rosenstiel W, Birbaumer N, et al. Prediction of auditory and visual p300 brain-computer interface aptitude. PloS one. 2013; 8(2): e53513

[4] Kleih SC, Nijboer F, Halder S, Kübler AJCN. Motivation modulates the P300 amplitude during brain–computer interface use. Clinical Neurophysiology. 2010; 121(7): 1023-1031

[5] Mak JN, McFarland DJ, Vaughan TM, McCane LM, Tsui PZ, Zeitlin DJ, et al. EEG correlates of P300-based brain–computer interface (BCI) performance in people with amyotrophic lateral sclerosis. Journal of neural engineering. 2012; 9(2): 026014

[6] Halder S, Ruf CA, Furdea A, Pasqualotto E, De Massari D, van der Heiden L, et al. Prediction of P300 BCI aptitude in severe motor impairment. PloS one. 2013; 8(10): e76148

[7] Settgast T, Kübler A. Brain Criticality and Its Relation to BCI Operation, in 2024 12th International Winter Conference on Brain Computer Interface (BCI), IEEE, in press

[8] Ahn M, Cho H, Ahn S, Jun SC. High theta and low alpha powers may be indicative of BCI-illiteracy in motor imagery. PloS one. 2013; 8(11): e80886

[9] Lee M, Yoon JG, Lee SW. Predicting motor imagery performance from resting-state EEG using dynamic causal modeling. Frontiers in human neuroscience. 2020; 14: 321

[10] Wang K, Tian F, Xu M, Zhang S, Xu L, Ming D. Resting-State EEG in Alpha Rhythm May Be Indicative of the Performance of Motor Imagery-Based Brain–Computer Interface. Entropy. 2022; 24(11): 1556

[11] Zhang R, Xu P, Chen R, Li F, Guo L, Li P, et al. Predicting inter-session performance of SMR-based brain–computer interface using the spectral entropy of resting-state EEG. Brain topography. 2015; 28: 680-690

[12] Shin GH, Lee M, Kim HJ, Lee SW. Prediction of event related potential speller performance using resting-state EEG, in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), IEEE, 2020, 2973-2976

[13] Settgast T, Zilio F, Kübler A, Northoff G. Correlation between Neurophysiological Measures of Consciousness and BCI Performance in a Locked-in Patient, in 2023 11th International Winter Conference on Brain-Computer Interface (BCI), IEEE, 2023, 1-6

[14] Zilio F, Gomez-Pilar J, Chaudhary U, Fogel S, Fomina T, Synofzik M, et al. Altered brain dynamics index levels of arousal in complete locked-in syndrome. Communications Biology. 2023; 6(1): 757

[15] Northoff G, Huang Z. How do the brain’s time and space mediate consciousness and its different dimensions? Temporo-spatial theory of consciousness (TTC). Neuroscience & Biobehavioral Reviews. 2017; 80: 630-645

[16] He BJ, Zempel JM, Snyder AZ, Raichle ME. The temporal structures and functional significance of scale-free brain activity. Neuron. 2010; 66(3): 353-369

[17] O’Byrne J, Jerbi K. How critical is brain criticality?. Trends in Neurosciences. 2022; 45(11): 820-837

[18] Maschke C, O’Byrne J, Colombo MA, Boly M, Gosseries O, Laureys S, et al. Critical dynamics in spontaneous EEG predicts anesthetic-induced loss of consciousness and perturbational complexity. Communications Biology. 2024; 7(1): 946

[19] Höhn C, Hahn MA, Lendner JD, Hoedlmoser K. Spectral slope and Lempel-Ziv complexity as robust markers of brain states during sleep and wakefulness. bioRxiv. 2022

[20] Schartner M, Seth A, Noirhomme Q, Boly M, Bruno MA, Laureys S, et al. Complexity of multi-dimensional spontaneous EEG decreases during propofol induced general anaesthesia. PloS one.

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10.3217/978-3-99161-014-4-029

2015; 10(8): e0133532

[21] Mateos DM, Guevara Erra R, Wennberg R, Perez Velazquez JL. Measures of entropy and complexity in altered states of consciousness. Cognitive neurodynamics. 2018; 12: 73-84

[22] Carhart-Harris RL. The entropic brain-revisited. Neuropharmacology. 2018; 142: 167-178

[23] Northoff G, Zilio F. Temporo-spatial Theory of Consciousness (TTC)–Bridging the gap of neuronal activity and phenomenal states. Behavioural brain research. 2022; 424: 113788

[24] Alnes SL, Bächlin LZ, Schindler K, Tzovara A. Neural complexity and the spectral slope characterise auditory processing in wakefulness and sleep. European Journal of Neuroscience. 2023: 1-20

[25] Medel V, Irani M, Crossley N, Ossandón T, Boncompte G. Complexity and 1/f slope jointly reflect brain states. Scientific Reports. 2023; 13(1): 21700

[26] Gyurkovics M, Clements GM, Low KA, Fabiani M, Gratton G. Stimulus-induced changes in 1/f-like background activity in EEG. Journal of Neuroscience. 2022; 42(37): 7144-7151

[27] Irrmischer M, Poil SS, Mansvelder HD, Intra FS, Linkenkaer-Hansen K. Strong long-range temporal correlations of beta/gamma oscillations are associated with poor sustained visual attention performance. European Journal of Neuroscience. 2018; 48(8): 2674-2683

[28] Bojorges-Valdez E, Yanez-Suarez O. Association between EEG spectral power dynamics and event related potential amplitude on a P300 speller. Biomedical Physics & Engineering Express. 2018; 4(2): 025028

[29] Gervais C, Boucher LP, Villar GM, Lee U, Duclos C. A scoping review for building a criticality-based conceptual framework of altered states of consciousness. Frontiers in Systems Neuroscience. 2023; 17: 1085902

[30] Herzog ND, Steinfath TP, Tarrasch R. Critical dynamics in spontaneous resting-state oscillations are associated with the attention-related P300 ERP in a Go/Nogo task. Frontiers in neuroscience. 2021; 15: 632922

[31] Lee H, Golkowski D, Jordan D, Berger S, Ilg R, Lee J, et al. Relationship of critical dynamics, functional connectivity, and states of consciousness in large-scale human brain networks. Neuroimage. 2019; 188: 228-238

[32] Heiney K, Huse Ramstad O, Fiskum V, Christiansen N, Sandvig A, Nichele S, et al. Criticality, connectivity, and neural disorder: a multifaceted approach to neural computation. Frontiers in computational neuroscience. 2021; 15: 611183

[33] Li F, Liu T, Wang F, Li H, Gong D, Zhang R, et al. Relationships between the resting-state network and the P3: Evidence from a scalp EEG study. Scientific Reports. 2015; 5(1): 15129

[34] Li F, Tao Q, Peng W, Zhang T, Si Y, Zhang Y, et al. Inter-subject P300 variability relates to the efficiency of brain networks reconfigured from resting-to task-state: evidence from a simultaneous event-related EEG-fMRI study. NeuroImage. 2020; 205: 116285

[35] Won K, Kwon M, Ahn M, Jun SC. EEG dataset for RSVP and P300 speller brain-computer interfaces. Scientific Data. 2022; 9(1): 388

[36] Schalk G, McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. BCI2000: a general-purpose brain-computer interface (BCI) system. IEEE Transactions on biomedical engineering. 2004; 51(6): 1034-1043

[37] Kübler A, Neumann N, Wilhelm B, Hinterberger T, Birbaumer N. Predictability of brain-computer communication. Journal of Psychophysiology. 2004; 18(2/3): 121-129

[38] Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of neuroscience methods. 2004; 134(1): 9-21

[39] Winkler I, Debener S, Müller KR, Tangermann, M. On the influence of high-pass filtering on ICA-based artifact reduction in EEG-ERP, in 2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC), 2015, 4101-4105

[40] Winkler I, Haufe S, Tangermann M. Automatic classification of artifactual ICA-components for artifact removal in EEG signals. Behavioral and brain functions. 2011; 7: 1-15

[41] Zhang XS, Roy RJ. Derived fuzzy knowledge model for estimating the depth of anesthesia. IEEE Transactions on Biomedical Engineering. 2001; 48(3): 312-323

[42] Nagarajan R. Quantifying physiological data with Lempel-Ziv complexity-certain issues. IEEE Transactions on Biomedical Engineering. 2002; 49(11): 1371-1373

[43] Aboy M, Hornero R, Abásolo D, Álvarez D. Interpretation of the Lempel-Ziv complexity measure in the context of biomedical signal analysis. IEEE transactions on biomedical engineering. 2006; 53(11): 2282-2288

[44] Samek W, Blythe DA, Curio G, Müller KR, Blankertz B, Nikulin VV. Multiscale temporal neural dynamics predict performance in a complex sensorimotor task. Neuroimage. 2016; 141: 291-303

[45] Bettencourt R, Castelo-Branco M, Gonçalves E, Nunes UJ, Pires G. Comparing Several P300-Based Visuo-Auditory Brain-Computer Interfaces for a Completely Locked-in ALS Patient: A Longitudinal Case Study. Applied Sciences. 2024; 14(8), 3464

[46] Kübler A. The history of BCI: From a vision for the future to real support for personhood in people with locked-in syndrome. Neuroethics. 2020; 13(2), 163-180

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