Intelligent Method for Human Concentration Recognition Based on EEG Sensor Data

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***Abstract*— The study examines the applicability of various EEG signal metrics for functional states of concentration and mind-wandering recognition. The metrics were selected based on related work analysis in the topic of human functional states (similar to concentration) recognition. We describe algorithms for calculating the chosen power and entropy metrics across different frequency bands. The study utilizes a dataset containing EEG recordings of functional states, such as concentration on a point in the center of the forehead and a baseline mind-wandering state, including data from 17 participants. The applicability of the metrics was assessed using the point-biserial correlation coefficient between the metric values and functional states, as well as a modified version based on the difference in interquartile ranges of the metric values. We show that the most applicable metrics include power in the α, θ, and SMR frequency bands, as well as signal entropy in the 0.3–30 Hz range. These metrics demonstrate significant but variable changes between functional states for almost all experienced participants in the dataset.**

I. Introduction

Electroencephalogram (EEG) analysis is one of the most widely used methods for recognizing and assessing human functional states. The EEG signal is employed for these purposes both in scientific research and in the operation of devices designed for personal use, such as Muse [1], Emotiv [2], and others. These devices are used in self-regulation practices, concentration, meditation, and other activities to assess their quality and track progress.

At the same time, the neurophysiological foundations of such assessments remain unclear, and various scientific studies related to recognizing concentration states and similar conditions yield inconsistent results (see Section 2). These studies often utilize different, non-overlapping sets of EEG signal metrics, and the obtained values of similar metrics show weak agreement. This inconsistency may be attributed to differences in the functional states being examined, the EEG recording equipment used, or the weak correlation between the selected metrics and the investigated state.

Therefore, it is necessary to evaluate the applicability of various EEG metrics, which will enable the development of an intelligent method for recognizing the state of concentration using a dataset recorded under well-defined functional conditions with high-frequency scientific EEG recording equipment, ensuring sufficiently accurate metric values.

This study consists of four sections. Section 2 provides a review of relevant research on recognizing and assessing concentration and other similar functional states based on EEG signals, examining the metrics used and comparing the results obtained. Section 3 justifies the selection of the most promising metrics for further analysis, describing algorithms for computing these metrics and evaluating their applicability for concentration state recognition. Section 4 describes the dataset used for assessing the applicability of the selected metrics. Section 5 presents the study's results, including the evaluation of the chosen metrics' applicability based on EEG signal analysis from the collected dataset, along with an interpretation of the findings and an assessment of the prospects for using these metrics in concentration state recognition.

II. Related Work

This section presents studies related to the recognition and assessment of human concentration levels or similar processes based on the analysis of EEG signals recorded using gel or dry electrodes on healthy adult participants. Table I provides a list of the reviewed studies, including the number of participants, the investigated state, the comparison object in the study (comparison of different functional states within one group of participants or comparison of the same functional state across different participant groups), the metrics used, and the number of EEG channels.

In study [9], a comparison of three states is conducted: a relaxed state (no concentration), concentration (focused attention on a red dot in the center of the screen), and immersion (playing a MOBA video game). It should be noted that the immersion state, which requires high reaction speed and constant attention to changing external stimuli, is more similar in nature to the concentration state described in most other studies in this review. Meanwhile, the concentration state in this study corresponds closely only to the definition used in study [8].

Nevertheless, both of these states exhibit significant differences in the θ (4-8 Hz), α (8-13 Hz), and β (13-30 Hz) frequency bands compared to the relaxed state. Additionally, the study computed power ratios in specific frequency bands, namely: θ/α, (SMR + Middle β)/θ (where SMR (sensorimotor rhythm) represents the 12–15 Hz range, and Middle β corresponds to 15–20 Hz), and β/θ. These ratios showed different variations across different EEG channels, with θ/α being the most universal in distinguishing between concentration and immersion states. At the same time, study [9] noted that the β/θ ratio does not exhibit stable changes for the immersion state. This partially contradicts the findings of study [3], where significant changes in concentration levels (which largely, though not entirely, correspond to the immersion state in study [9]) were identified using this ratio.

TABLE I. CONCENTRATION METRICS FROM RELATED WORK

Source	Number of participants	States	Object	Metrics	Number of channels
[3]	60	Proofreading (different lighting)	Functional states	θ / β, Cortisol level	2
[4]	12	Concentration game	Functional states	Entropy (MSFEn): Grey relation	1
[5]	14	Logical task / rest	Functional states	δ / β1, α + β + δ + θ + R, Entropy, OCN	63,1
[6]	30	Cognitive tasks (different temperature)	Functional states	(SMR + Middle β) / θ, Prefrontal β, PI	14
[7]	7	Learning (different temperature)	Functional states	Prefrontal (SMR + Middle β) / θ	8
[8]	20	Concentration on a screen (different lighting)	Functional states	δ, α, β1, β2 (relative ratio), KSS, PVT	6
[9]	32	Concentration on a point / rest / videogame	Functional states	θ, α, β, θ / α, (SMR + Middle β) / θ, β / θ	8
[10]	8	Concentration task, watching a video (different lighting)	Functional states	(SMR + Middle β) / θ	2
[11]	71	Mindfulness-meditation	Groups of participants	[α, β, YBOCS, FFMQ]: LDS	4
[12]	22	Mindfulness-meditation / listening to a podcast	Functional states	θ, α, β, FD-analysis, Coherence-analysis	14
[13]	55	Mindfulness- meditation	Groups of participants	Spectral analysis	32
[14]	40	Counting figures (for experienced meditators and a control group)	Groups of participants	(β + γ) / (α + θ), (α + θ - β) / (α + θ), FD-analysis, State transition analysis	32

Studies [7] and [10] share similarities in their topic and methodology. They investigate a process resembling learning (though weakly formalized in both studies), partially based on performing academic tasks from various university disciplines and processing information from electronic sources. The key difference is that study [7] examines the effect of ambient temperature on the learning process, while study [10] focuses on the effect of lighting. Both studies use the same EEG spectral analysis-based concentration metric, namely (SMR + Middle β)/θ, as also employed in studies [6] and [8]. Although study [7] used more EEG channels, only two prefrontal channels were actually used to measure this metric, similar to study [10]. Both studies demonstrated a significant influence of external conditions (temperature and lighting, respectively) on the metric values, which the authors attribute to changes in concentration levels. However, it should be noted that both studies involved only male participants (study [7] justified this by aiming to exclude the potential influence of the female menstrual cycle on experimental results).

The effects of similar external conditions were studied in a significantly larger sample, including female participants, in studies [3], [6], and [8]. The processes examined in these studies are more structured. Study [3] investigates the influence of lighting on the proofreading process, which requires a heightened level of concentration. Study [6] examines the impact of temperature on performing a set of cognitive tests assessing various cognitive abilities, including attention levels. Both studies employ similar EEG spectral analysis-based concentration metrics: (SMR + Middle β) / θ in study [6] (with additional use of prefrontal β power) and a largely inverse metric, θ / β, in study [3] (with slight differences in the frequency ranges used for power calculations). Additionally, these studies incorporate objective concentration level control metrics that are independent of EEG data, such as cortisol levels in study [3] and the accuracy-to-time ratio (PI) in study [6].

Although study [8] investigates the influence of a similar external factor (lighting) on concentration, it significantly differs in both the process under study and the applied metrics. Participants were required to focus their gaze on a screen with different brightness levels. It remains unclear how comparable this process is to other concentration-related processes reviewed in this paper. However, periodically measured subjective (KSS) and objective (PVT) concentration metrics showed significant dynamics, correlating with power fluctuations in the δ, α, β1, and β2 bands (in relative values). Notably, this study did not normalize these power values using the θ band, and the θ band power itself did not show a significant correlation with other concentration metrics. This may confirm the validity of using it as a normalizing factor in the (SMR + Middle β) / θ metric, which is employed as a concentration indicator in other studies.

In all the studies reviewed above, concentration state recognition and its dynamics were assessed exclusively through spectral analysis, involving calculations of absolute EEG signal power values in different frequency bands or their ratios. However, studies [4] and [5] take a fundamentally different approach, incorporating entropy-based metrics in addition to spectral ones (such as δ / β1 and α + β + δ + θ + R, where R = α / β). In study [5], entropy metrics effectively distinguished between a relaxed state and a concentration state while solving a logical task. Study [4] demonstrated a correlation between entropy and real-time concentration levels, as assessed by objective participant performance in a reaction-speed-based game. The entropy metric is based on Shannon entropy theory, which, when applied to EEG signal analysis, reflects its level of predictability and complexity. The authors of studies [4] and [5] propose that this approach may be useful for assessing concentration levels. Study [4] also utilizes grey relation analysis to highlight the advantages of a specific entropy calculation algorithm, MSFEn, over other alternatives. Moreover, study [5] employs an additional non-spectral metric, OCN, developed by the authors. The results obtained using this metric, even with just one EEG channel, were comparable to those obtained using 63 channels. According to the authors of study [4], spectral EEG analysis methods have low accuracy due to the signal's nonlinearity and non-stationarity. For this reason, entropy and other non-spectral methods may hold greater potential for recognizing complex states such as concentration. Study [5] further demonstrates that entropy-based recognition achieves higher accuracy compared to spectral methods.

Studies [11], [12], [13], and [14] examine the effects of mindfulness meditation on brain activity. It is unclear to what extent their findings can be compared with other studies in this review, as mindfulness meditation involves a high degree of concentration on breathing. Additionally, most of these studies differ methodologically, as they compare participants with different levels of meditation experience rather than contrasting concentration with another state (as seen in Table 1). However, they apply similar spectral analysis methods, albeit with slight variations in frequency bands. Furthermore, studies [12] and [14] employ non-spectral analysis techniques such as fractal dimension (FD) analysis, coherence analysis, and EEG state transition clustering. Study [11] uses LDS analysis to demonstrate interdependencies between spectral metrics and subjective psychological scores (YBOCS, FFMQ).

Thus, among the studies reviewed, the most commonly applied metrics for concentration recognition and assessment are those based on EEG spectral analysis. Both absolute power values in different frequency bands (mainly θ, α, and β) and their derivative values (ratios between them) are used. The β band is the most frequently applied, either alone or as part of derivative metrics, appearing in almost all reviewed studies. The θ band is the second most commonly used, although studies [8] and [9] noted a lack of significant correlation between its power (and some derivative characteristics) and concentration levels. The most prevalent derivative spectral metric is (SMR + Middle β) / θ, which is cited in several studies as the one most directly linked to the concentration process.

Despite the widespread use of spectral metrics, studies [4] and [5] highlight the potentially low accuracy of concentration recognition through spectral analysis, attributing this to the EEG signal's nonlinearity and non-stationarity. As an alternative, they propose using various non-spectral metrics, including entropy, coherence analysis, state transition analysis, OCN, FD, and others. Moreover, study [5] demonstrates higher concentration recognition accuracy with entropy metrics compared to spectral characteristics.

It is important to note that not all reviewed studies' results are directly comparable, even when they use the same metrics. This is largely due to the weak formalization of the concept of "concentration," leading to the study of neurophysiologically distinct processes under the same term. Additionally, the baseline states used for comparison in different studies vary significantly (e.g., comparisons with a control group of participants with no deep concentration training or within a single group under different conditions, such as listening to audio messages or resting). Overall, the analysis of these studies supports the existence of significant metric changes during concentration, rather than specific directional trends in those changes. Moreover, EEG signal variations for the same states can differ across different electrode placements. However, several studies indicate that concentration state recognition and assessment are possible even with a minimal number of electrodes. It appears that prefrontal electrodes alone, which are used in all reviewed studies, may be sufficient. Study [5] reports comparable accuracy in concentration recognition using devices with either 63 electrodes or just one prefrontal electrode. Furthermore, one of the most promising metrics, (SMR + Middle β)/θ, appears to be effective when using only prefrontal electrodes, according to study [10].

III. METHOD

Based on the conducted review, the following EEG-based concentration state metrics were selected for further consideration:

- Mean power of the signal in the α-band across channels;
- Mean power of the signal in the lower β-band (up to 20 Hz) across channels;
- Mean power of the signal in the θ-band across channels;
- Mean power of the signal in the SMR-band across channels;
- Mean entropy of the signal in the frequency range from 0.3 to 30 Hz across channels;
- Mean entropy of the signal in the α-band across channels;
- Mean entropy of the signal in the lower β-band (up to 20 Hz) across channels;
- Mean entropy of the signal in the θ-band across channels;
- Mean entropy of the signal in the SMR-band across channels.

Among the listed metrics, two main groups can be distinguished: spectral metrics and entropy-based metrics.

The selected frequency bands for spectral metrics were those used in the largest number of reviewed studies, in which the most consistent results were observed. Although some studies also employed derived spectral values (various ratios and sums), this work considers only their absolute values, as they are the most interpretable concentration state metrics. In addition to the difficulty of directly interpreting derived values from a neurophysiological perspective, it is also important to consider the potential negative impact of weakly correlated individual components on the correlation indicators of summed and/or relative values.

Furthermore, to prevent possible information loss due to edge effects, the chosen frequency bands intentionally overlap to some extent, specifically:

- θ-band: 4 to 8 Hz;
- α-band: 8 to 13 Hz;
- SMR-band: 12 to 15 Hz;
- β-band (lower part): 13 to 20 Hz.

To compute the power spectral density, which is integrated over specific ranges to determine power in the respective frequency bands, Welch's algorithm was used. Welch's method is one of the most widely used approaches for computing the periodogram of a function, which serves as an estimate of the power spectral density and is defined as follows:

$$S_T(\omega) = E\left[\frac{|X_T(i\omega)|^2}{T_r}\right], \quad (1)$$

where $S_T(\omega)$ is the estimate of the power spectral density, and $X_T(i\omega)$ is the amplitude of the Fourier transform for the function $x(t)$ over a finite time interval T_r.

Welch's method defines a practical approach to computing the mathematical expectation presented in Formula 1. It does so by dividing the given interval into overlapping segments, which are determined by parameters specifying the length of these segments and their overlap [15]. Overlapping segments increase their total number, which helps reduce the variance of the power spectral density estimate. To minimize the bias of the estimate for individual segments, a window function is applied to each segment, reducing the effect of side lobes. In this method, the Tukey window is used.

The power of the signal in different frequency bands is a well-interpretable value since these bands correspond to well-studied and defined processes in the human brain [16]. For this reason, although entropy measures in the reviewed studies were calculated over the entire analyzed range, it seems promising to attempt calculating entropy for the same frequency bands used for power estimation. At the same time, in addition to entropy metrics in these specific bands, this study also calculates the overall entropy measure over the entire range from 0.3 to 30 Hz.

A finite impulse response (FIR) filter was used for signal filtering. Before computing all metrics (both spectral and entropy-based), the raw EEG signal was filtered within the 0.3–30 Hz range. After this, an additional filtering step was performed in the corresponding frequency bands before calculating entropy metrics. No other preprocessing methods were applied to maintain the degree of automation in the feature extraction process. Specifically, filtering most signal artifacts is not easily automated [16], and the most easily filterable artifacts, such as those related to blinking, were absent in the original signal due to the experimental conditions. Furthermore, as will be shown later, when evaluating the applicability of the selected metrics, the top and bottom 2.5% of values are excluded from consideration, further reducing the potential influence of artifacts.

Figure 1 illustrates the entropy computation algorithm applied to the filtered signal. The rectangles in the figure represent sequential signal values from an individual EEG channel, with a total count of *N*. At the *i*-th step of the method, a base vector of length *m* is taken, and its distance to all other vectors of length *m* is computed, including those that partially overlap with the base vector and with each other.

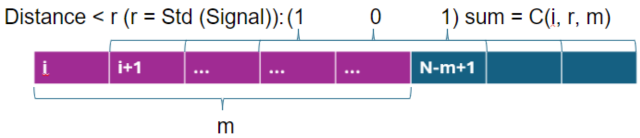

Fig. 1. Entropy calculation ((1 0 1) are three example outcomes of the distance check)

Vectors whose distance is smaller than a predefined threshold *r* are considered similar to the base vector. The value $C(i,r,m)$ represents the total number of such vectors. In this study, the parameter *m* is set to 5, following the recommendations in [17], and the threshold *r*, used for comparison based on the Chebyshev distance, is taken as the standard deviation of the EEG channel signal. The approximate entropy (AppEn) measure is then computed using the following formulas:

$$A(m,r) = AVG[log\,C(i,r,m)], \quad (2)$$

$$AppEn = A(m,r) - A(m+1,r). \quad (3)$$

The general idea behind this entropy estimation method is that when an additional value is added to the vectors, the degree of their similarity in a simple, predictable signal will not change significantly. As a result, the difference given in Formula 3 will, in absolute value, be smaller than the corresponding measure for a more complex and random signal.

At the same time, it should be noted that the entropy estimate obtained in this way is somewhat biased since, when calculating the value of $C(i,r,m)$, the base vector is considered similar to itself. This is necessary to avoid the potential need to take the logarithm of zero in Formula 2.

An improved estimate in this regard is the SampEn (Sample Entropy) metric, which is calculated as follows:

$$A(m,r) = \sum C(i,r,m), \quad (4)$$

$$SampEn = -\log\left(\frac{A(m,r)}{A(m\,+\,1,r)}\right). \quad (5)$$

In Formula 4, the similarity of a vector with itself is not considered when calculating $C(i,r,m)$, and for the computability of Formula 5, it is sufficient to have at least one pair of similar vectors in the signal of a given EEG channel. For this reason, the SampEn (Sample Entropy) estimate is used as the entropy value in this study.

To assess the applicability of the considered metrics for recognizing concentration states, the point-biserial correlation coefficient (PBCC) [18] was used. This coefficient is proportional to the difference in the expected values of a metric for two classes (in this case, the concentration state and the baseline state). However, when analyzing the metric values for individual participants, differences in their distributions were noted for different states, even when the differences in expected values were weakly expressed.

For example, in Fig. 2, the entropy metric values taken over 2-second epochs (selected based on the chosen m parameter value [17] and sufficiently long for the analyzed frequency ranges) show that the concentration state (CN) and the baseline state of mind-wandering (MW) exhibit almost no difference in their mean values (avg). However, they significantly differ in terms of interquartile range (IQR). At the same time, the same entropy metric calculated in the α-band demonstrates greater differences in mean values.

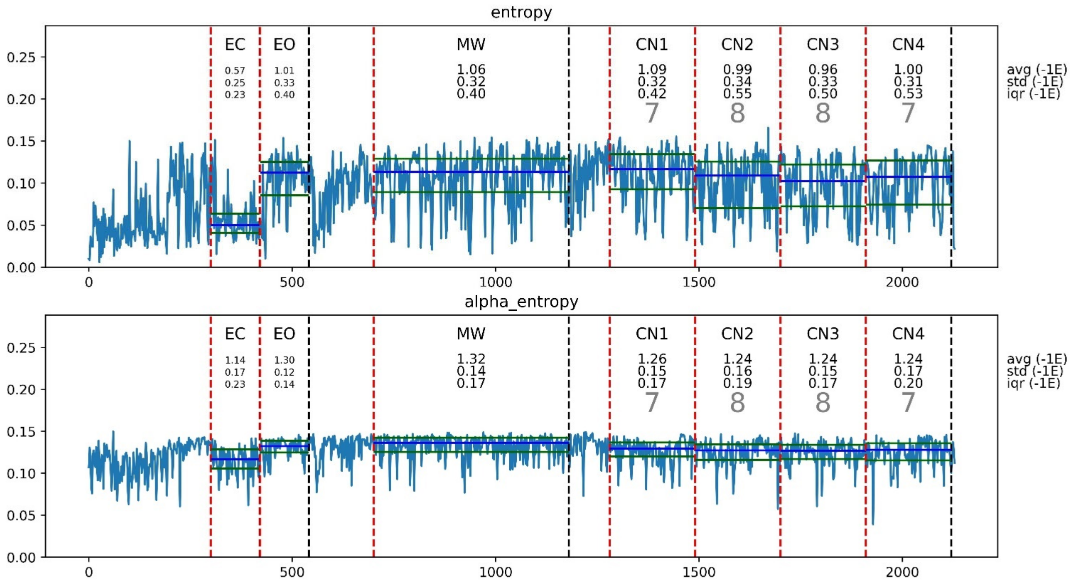

Fig. 2. Example of entropy and α-entropy graphs

Therefore, for further analysis, two indicators were used for each metric: the direct PBCC value and its adaptation for evaluating class differences based on interquartile range, denoted as PBCCIQR, and expressed by the formula:

$$PBCCIQR = \frac{IQR_1 - IQR_0}{s_{n-1}} \sqrt{\frac{n_1 n_0}{n(n-1)}}, \qquad (6)$$

where IQR_1 and IQR_0 are the interquartile range values for the two classes, n_1 and n_0 are their sample sizes, n is the total sample size, and s_{n-1} is the unbiased estimate of the standard deviation for the entire sample.

IV. DATASET

To determine the applicability of concentration state metrics, EEG data were collected from 17 healthy adult participants with at least one year of experience in concentration practice (ranging from 1 to 30 years, with an average of 8 years). The participants were between 20 and 53 years old, with an average age of 36 years (7 men, 10 women). EEG signals were recorded from 63 channels (10-20 system montage) with a sampling rate of 2048 Hz.

Each EEG recording included 15 minutes of a concentration state, during which participants were instructed to focus their attention on the center of their forehead and return to this point whenever their attention wandered. Additionally, there were 10 minutes of a mind-wandering state, where participants were instructed to let their thoughts flow freely. In both conditions, participants sat with their eyes closed under identical external conditions, with the only difference being their internal focus of attention.

For some participants, multiple EEG recordings were obtained, resulting in a total of 23 recordings. After each session, participants completed a survey providing details about their experience with concentration practice and the number of hours they had slept the previous night. They also subjectively assessed the quality of their concentration by mentally dividing the 15-minute period into four quarters and rating the degree of concentration for each quarter on a 10-point scale (1 = complete absence of concentration, 10 = the best concentration they had ever experienced).

V. RESULTS

Using the algorithms described in Section III, we processed the dataset from Section IV and calculated correlations between concentration and mind-wandering states. Figure 3 presents a correlation coefficient matrix for each of the considered metrics across all collected recordings during the mind-wandering state and the second and third quarters of the concentration state. The columns of the matrix are sorted in descending order based on the absolute mean value of the corresponding metrics across all recordings (the mean value is indicated in the AVG row). The rows of the matrix are sorted by participant (the row index corresponds to the participant number). Rows corresponding to multiple recordings of the same participant are grouped together under the same index. The actual recording index is specified in the "rec_id" column.

The columns "exp," "points," and "max_cor" indicate the participant's experience in concentration practice, the average subjective concentration quality score for the second and third quarters (as the most stable ones in terms of concentration quality) of the recording, and the highest absolute correlation coefficient among all metrics for that recording, respectively. A value of 0 in the "points" column indicates that the participant did not provide a concentration quality rating, while a value of -1 denotes recordings where the participant failed to follow the given instructions correctly. Other columns contain correlation coefficient (PBCC) values for entropy and power metrics (denoted as "ent" and "pow," respectively) in the α, β (up to 20 Hz), θ, and SMR frequency bands (labeled as "a," "b20," "th," and "SMR," respectively). Additionally, for each metric, PBCCIQR values (denoted as "iqr") are provided. For example, the column labeled "b20_ent_iqr" represents PBCCIQR for the entropy metric in the β-band up to 20 Hz, while "smr_pow" represents PBCC for power in the SMR band.

From the results, no single metric exhibits consistent and significant changes across states. Even entropy, which shows the most reliable state-dependent changes, has maximum absolute values of 0.62 for participant 12 and -0.62 for participant 5, meaning that relative changes in this metric between concentration and baseline states are completely opposite for these two participants. At the same time, in participant 3's recordings, entropy demonstrates one of the most significant changes for the second recording, while showing almost no variation in the first. However, in the first recording, notable changes appear in the θ-band entropy, which are nearly absent in the second recording. This can be explained by the presence of high-amplitude stationary waves outside the θ-band in the first recording, which are unrelated to the concentration state.

It appears that due to such random brain processes occurring in parallel with the concentration state and exerting a much stronger influence on the EEG signal, it is impossible to identify a universal metric that consistently shows significant unidirectional changes, even within recordings from the same participant. However, for most recordings, at least one of the examined metrics exhibits significant differences between states. In some cases, these differences are more pronounced not in the mean metric values but in the interquartile range—particularly for entropy metrics and power metrics in the α- and θ-bands. For instance, in the second recording of participant 1, the only significant difference is observed in the interquartile range of power in the α-band, despite almost no difference in the mean value of this metric. Differences in mean values are primarily observed for power metrics across different frequency bands, as well as for the entropy metric. However, entropy metrics within specific frequency bands mostly do not show significant changes, with the notable exception of entropy in the θ-band. If we exclude recordings where participants did not correctly follow instructions (they are marked with a value of -1 in the "points" column), had no concentration practice, or rated their concentration quality low (below 6 points or provided no rating), we see that nearly all remaining recordings exhibit significant differences between states in at least one metric. The smallest differences are observed in participant 14's recording and participant 1's second recording.

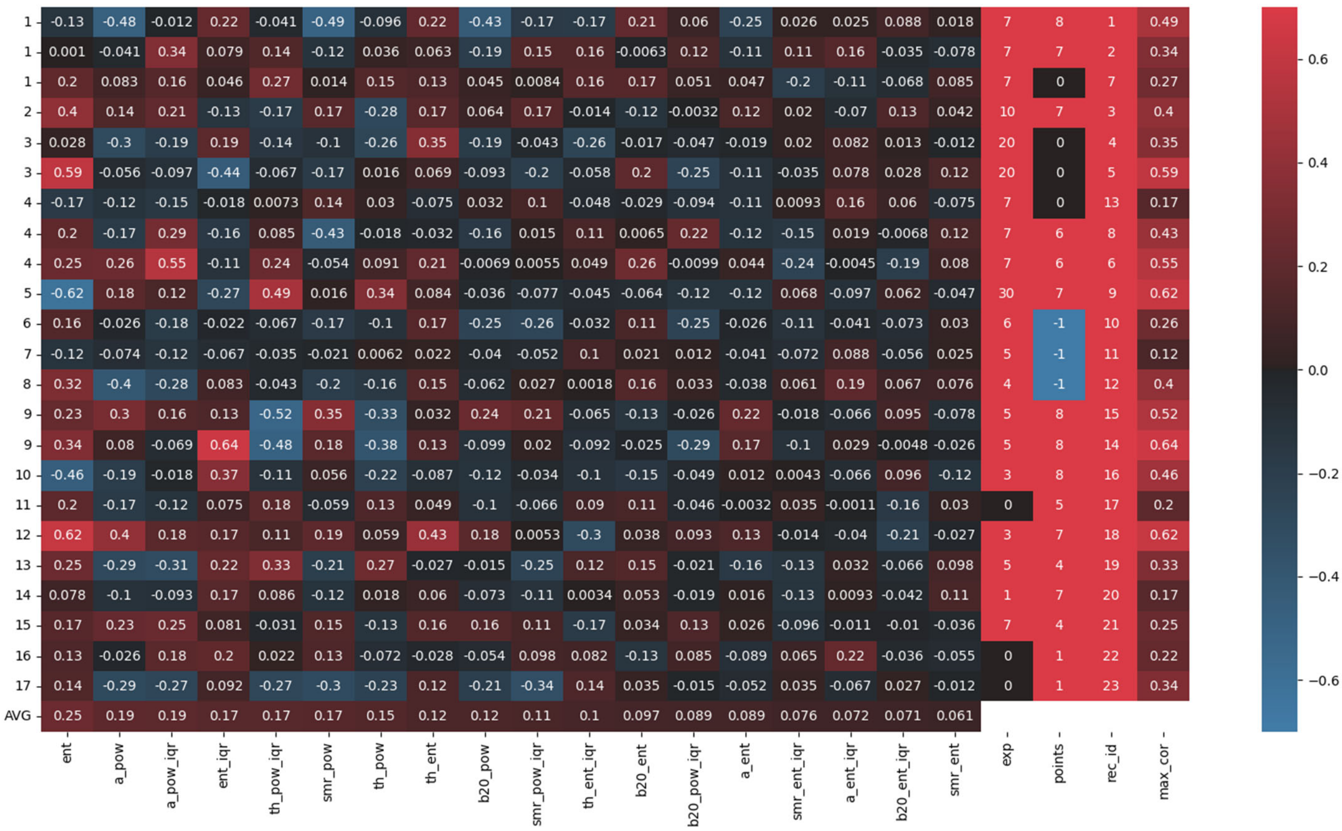

Fig. 3. Correlation matrix

Participant 14 has the least experience in concentration practice (1 year) among all participants. Meanwhile, participant 1, despite providing similar subjective ratings for concentration in the second and third quarters of both recordings, rated their overall concentration quality in the second recording significantly lower than in the first (6, 8, 6, 5 vs. 7, 8, 8, 7, respectively).

For all other recordings, the minimum absolute difference in metric correlation coefficients (max_cor) is no less than 0.4, with this value being higher on average for more experienced participants (over 10 years of practice). Although participant 3, with around 20 years of experience, did not rate their concentration quality in any of their recordings, they also exhibit high max_cor values. Participants who were unable to rate their concentration due to low quality recordings tend to show smaller differences between states. Participants with no experience in concentration practices show some of the smallest differences, with the highest among them (0.34) observed for participant 17. However, this difference primarily appears in the SMR-band power metric, which is largely insignificant for most other participants.

Thus, there is no single metric among the examined ones that can serve as a universal indicator of concentration across different participants and within recordings from the same participant. However, for almost every high-quality recording from experienced participants, there are significant differences in at least one of the considered metrics—something that is not observed in other recordings. This suggests that these metrics can provide some assessment of concentration quality, provided that the baseline state is recorded immediately before evaluating the concentration state.

VI. Conclusion

This study examined the use of EEG signal entropy and power metrics to assess differences between human functional states, based on a review of research on concentration state recognition. The applicability of these metrics was evaluated using 23 recordings of concentration states and mind-wandering baseline states from 17 participants. To assess the applicability of the metrics, the point-biserial correlation coefficient (PBCC) and its modification based on the difference in interquartile ranges (PBCCIQR) were used. We show that the most promising metrics for recognizing the concentration state are power metrics in the α, θ, and SMR frequency bands, as well as the entropy metric of the signal in the 0.3–30 Hz range. Differences from the baseline state can manifest in both the mean values of these metrics and their interquartile ranges. However, none of these metrics exhibit universal changes across all participants. At the same time, for almost all high-quality recordings of experienced participants, at least one of these metrics showed significant changes. Thus, the measurement of these changes can be used as an intelligent method for concentration recognition and assessment only if the baseline state is recorded immediately before the evaluation. Further research is needed to investigate the impact of concentration on these metrics in specific brain regions.

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