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Electroencephalogram-Based Effective Features for Sustained Attention Assessment in Conversation

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***Abstract*—Sustained attention, or concentration, is the ability to focus on a task for a long time. Evaluation methods include subjective assessments using questionnaires and objective measures such as electroencephalogram (EEG). The EEG method offers promising concentration level insights, but it is a challenge to fully leverage the multi-channel nature of EEG at the same time. In this study, we conducted a button press task using the go/no-go paradigm to measure concentration during the simulated conversational scene while addressing the EEG multi-channel complexity. We measured response times and recorded EEG, simultaneously. The extracted features such as frequency band characteristics and information-theoretical features like entropy were used to evaluate the concentration level. We employed group Lasso and cross-correlation analysis to expose the explainable EEG feature for sustained attention relevant to the variance time course (VTC). As a result, we found that EEG power ratios were strongly related to concentration. Combining these several power ratios could open up the possibility of quantifying the concentration.**

***Index Terms*—sustained attention, electroencephalogram, sparse model, power, entropy**

I. Introduction

Sustained attention, also known as concentration, is the cognitive ability to maintain focus on a specific task over an extended period. In the workplace, this ability engages in work productivity and achievement. Besides the professional field, concentration enhances the performance of various activities from academic studies to hobbies. This ability is essential for our daily lives and closely related to life success. Consequently, demand is growing for precise and reliable methods to quantify concentration.

Both subjective reports and objective measures have been used to assess one's concentration levels. Subjective evaluations often rely on self-report questionnaires designed for various purposes. The cognitive failures questionnaire (CFQ) is a widely trusted subjective measure for assessing concentration [1], [2]. While questionnaire-based subjective evaluations are simple and less burdensome for individuals, they can lack consistency due to variations in interpretation and the possibility of false responses. Moreover, the responses can be biased by personal perception and social desirability.

In addition to subjective measures, behavioral experiments, and physiological signal-based indicators have been proposed. A typical example of behavioral experiments involves tasks where participants respond to image stimuli by pressing buttons and measuring response times and accuracy. The go/no-go task [3] is particularly notable, being used in research and clinical settings across a wide range of areas, from children to adults, including the assessment of higher brain dysfunction in brain injuries and epilepsy, and evaluating the effects of drug therapies [4]. During the task, the participant responds with a button press when the go stimuli are presented and refrains to press the button when other (no-go) stimuli are presented. The continuous performance test [5] and the sustained attention to response task [6] are examples of concentration measurements using the go/no-go paradigm.

Electroencephalogram (EEG) is a prominent physiological signal-based method for assessing concentration. It is closely linked to concentration and may capture potential neural activities of focus that are not apparent in behavior [7]. Furthermore, EEG has the potential to monitor temporal fluctuations in concentration due to its high temporal resolution [8]. Studies on EEG indicated that multiple oscillatory components of EEG are correlated with various states of concentration. During go/no-go tasks, theta and alpha band power in EEG at midline electrodes (Fz, Cz, Pz) are related to concentration levels, as compared with eyes-closed and eyes-open resting state[9]. Coelli et al. demonstrated a negative correlation between the beta-to-alpha power ratio and mean response time across electrode groups, suggesting that higher concentration is associated with greater beta power and lower alpha power [10]. Besides the spectral features, information-theoretic measures such as entropy have proven effective in characterizing EEG signals [11]. Despite advancements in the understanding of the relationship between concentration and EEG, most studies have focused on single-channel EEG analysis, neglecting the inherently multi-channel nature of EEG data. This gap in the literature limits our understanding of how different brain regions interact during sustained attention tasks. Therefore, this study aims to identify features that can represent concentration while accounting for the multi-channel characteristics of EEG.

These previous findings suggests that frequency power and information-theoretic (entropy) features [12] can represent concentration levels, we hypothesize that a small number of features and brain regions can effectively explain concentration. Our novel approach combines multi-channel EEG analysis with advanced machine learning techniques, specifically group Lasso [13]. This method aims to identify the most relevant EEG features across different brain regions that can explain behavioral indicators of concentration. While there are several feature selection techniques [14], we chose group Lasso because it can handle the two-dimensional nature (feature $\times$ location) of multi-channel EEG data, where we set up groups for each feature across all electrodes. Moreover, we designed a go/no-go task to collect our data on behavioral indicators and EEG. Frequency and entropy features were extracted from the recorded EEG, and their importance ($\ell_{2,1}$-norm) was evaluated using group Lasso. Additionally, we identified brain regions associated with concentration based on the spatial distribution of features selected by group Lasso.

II. Methods

A. Participants

Sixteen volunteers (mean age 24.0 ± 4.92 years, two females) participated in this study. Before the experiment, informed consent was obtained from all participants based on the approval of the Tokyo University of Agriculture and Technology Research Ethics Committee (231104-0555). None of the student participants were encouraged by their professors to participate, nor did they receive any academic credits for their involvement.

B. Experimental Task

The go/no-go task was designed using two facial stimuli as shown in Figure 1, considering the focus on concentration during human conversations. These faces were extracted from the publicly available racially diverse affective expression (RADIATE) face stimulus set [15]. One face had an open mouth (visible teeth), while the other had a closed mouth (no visible teeth). Participants were instructed to respond by clicking the left mouse button as quickly as possible to the go stimulus (the face with the open mouth) and to withhold response to the no-go stimulus (the face with the closed mouth). Stimuli were presented for 3000 milliseconds with an inter-stimulus interval of 2000 milliseconds. A total of 360 stimuli were presented throughout the task, including 288 go stimuli, which constituted 80% of the total. The task was created using Tobii Pro Lab version 1.232 (Tobii AB, Stockholm, Sweden).

C. Data Acquisition

EEG was recorded using 30 electrodes placed according to the international 10-10 system, as shown in Figure 2. The ground electrode was placed at AFz and the reference was the average of A1 and A2 electrodes placed on the earlobes. To monitor eye movements, an electrooculogram (EOG) was recorded using four electrodes placed as shown in Figure 3. These electrodes were connected to an AC amplifier, Polymate AP5148 (Miyuki Giken, Tokyo, Japan), and recorded using the

(a) Go stimulus with mouth opened.

(b) No-go stimulus with mouth closed.

Fig. 1: Two facial stimuli from the RADIATE Face Stimulus Set were used in the experiment [15].

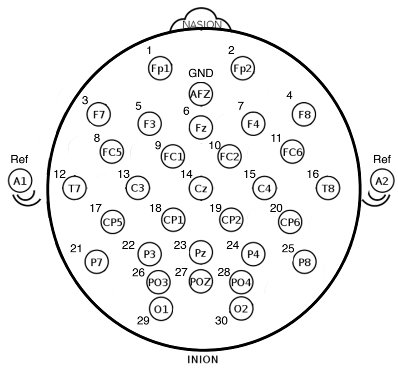


Fig. 2: Thirty EEG electrode placement based on the international 10-10 system.

accompanying software, AP Monitor. The sampling frequency was set to 1,000 Hz. In addition to EEG, we recorded the behavioral responses including button press (mouse clicking) and the response time.

D. Analysis Methods

The analysis pipeline consisted of several steps: defining a concentration index based on behavioral responses, preprocessing the EEG data, extracting relevant features, selecting features using sparse modeling, and performing cross-correlation analysis. Each stage is described in detail below.

1) Definition of Concentration Index Based on Response: Response time was defined as the duration from stimulus onset to the participant's button press, which was calculated for each trial. For trials without a response, linear interpolation using adjacent response times was applied. Based on response times, the variance time course (VTC) [16], a metric derived from the temporal dynamic of the response time, was used as an index of concentration. The VTC was computed by the moving average of standardized response times across all trials A Gaussian smoothing kernel with a full width at half maximum (FWHM) of 4 trials was used for the moving average. The window was applied to 7 trials before and after each point, resulting in the span of 15 trials in a window. Thus, we could achieve

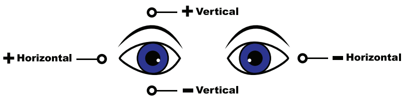


Fig. 3: EOG electrode placement.

the weight averaging that can balance between preserving the temporal dynamic of the central trial and reducing random variability in time responses. The obtained VTC then underwent the log transformation.

2) EEG Preprocessing: The preprocessing was performed using MNE-Python [17]. First, a 1–30 Hz FIR bandpass filter was applied to the raw EEG data. Next, the fast independent component analysis (FastICA) algorithm [18] was used to transform the EEG into 30 independent components, equal to the number of electrodes. The `find_bad_eog` function from MNE-Python was used to remove independent components highly correlated with EOG[1]. The data was then epoched from -200 to 300 milliseconds relative to the stimulus onset. Epochs with the peak-to-peak EEG amplitudes exceeding 100 μV were rejected. Two participants who had more than 20% of their epochs rejected were excluded from the further analysis in the next steps.

3) Feature Extraction:

a) Frequency Power Features: For each epoch, the power spectral density $P(f)$ of the EEG was calculated using Welch's method [19]. From $P(f)$, the relative power feature for the theta band (4–8 Hz) was defined as:

$$\theta = \frac{\int_4^8 P(f)df}{\int_4^{30} P(f)df} \tag{1}$$

The denominator 4–30 Hz represents the band extracted by the preprocessing bandpass filter. Similarly, relative power features α and β were defined for the alpha (8–13 Hz) and beta (13–30 Hz) bands, respectively. Power ratios $\frac{\theta}{\alpha}$, $\frac{\theta}{\beta}$, and $\frac{\alpha}{\beta}$ were also calculated. All relative powers and power ratios were expressed in decibels (dB).

b) Information Theoretic (Entropy) Features: The EEG was decomposed into theta, alpha, and beta bands using FIR bandpass filters for each epoch. Approximate entropy, sample entropy, permutation entropy, and spectral entropy were extracted from each EEG oscillation band. The Python library EntropyHub [20] was used for entropy calculations.

4) Feature Selection Using Sparse Modeling: Group Lasso [13], a sparse modeling technique, was used to select EEG features that best explain the VTC. It is a linear regression method that can shrink all parameters within a group to zero. This method was for feature selection by rejecting features with zero coefficients and selecting those that were left with non-zero coefficients. The regression coefficients (weight coefficients) $w \in \mathbb{R}^{p\times 1}$ was divided corresponding to different G features. Each group were represented as $w_g \in \mathbb{R}^{p_g\times 1}$, where p_g was the number of electrodes for feature g. Given the VTC $y^{(n)} \in \mathbb{R}^{l\times 1}$, where l represents the number or trials in the task for participant, and explanatory variables $X_g^{(n)} \in \mathbb{R}^{l\times p_g}$ for each feature of participant n, group Lasso estimates the regression coefficients as:

$$\widehat{w}_\lambda = \arg\min_w \left(\sum_{n=1}^{N} \left\| y^{(n)} - \sum_{g=1}^{G} X_g^{(n)} w_g \right\|_2^2 + \lambda \sum_{g=1}^{G} \sqrt{p_g}\, \|w_g\|_2 \right) \tag{2}$$

where $\|\cdot\|_2$ is the ℓ_2-norm. The term $\sum_{g=1}^{G} \sqrt{p_g}\|w_g\|_2$ is the $\ell_{2,1}$-norm, which promotes sparsity across entire groups of coefficients. The regularization parameter λ was set to 0.001.

For each selected feature g, the $\ell_{2,1}$ norm term $\|w_g\|_2$ was compared, and the weights for each electrode of the top three features with the largest $\|w_g\|_2$ were examined.

5) Cross-correlation Analysis between Features and VTC: For each of these top three features, the electrode that provided the largest weight $\|w_g\|_2$, representing the most effective spatial location for that feature, was selected. The cross-correlation functions were calculated between the time course of the feature at the selected electrode and the VTC time course. Considering potential time lags between EEG features and VTC, t-tests were conducted on the maximum cross-correlation coefficients. The null hypothesis was that the cross-correlation coefficient is zero, with a significance level of 0.05.

III. Results

This section presents the outcomes of our analysis, focusing on two main aspects: the comparison of weights in selected features from the group Lasso analysis, and the cross-correlation between these features and the VTC. Our findings reveal patterns in EEG features that were associated with sustained attention during the go/no-go task.

A. Comparison of Weights in Selected Features

Application of group Lasso to EEG of all participants ($N = 14$) resulted in the selection of 10 features as shown in Figure 4. The top three features in terms of weight were the power ratios $\frac{\theta}{\alpha}$, $\frac{\alpha}{\beta}$, and $\frac{\theta}{\beta}$, where the top two features included α. Additionally, the spectral entropy of the beta band and the relative power of the alpha band were above-average weights. On the other hand, other selected features included sample entropy and approximate entropy of the beta band, which represent the temporal complexity of the beta band, had the weights below the average.

Figures 5a, 5b, and 5c show bar graphs of the weights for each electrode for the top three features. Electrodes were colored and plotted in blue for the left hemisphere, green for the midline, and orange for the right hemisphere. As shown in Figures 5a and 5c, $\frac{\theta}{\alpha}$ and $\frac{\theta}{\beta}$ both had positive weights for the midline electrodes Fz, Cz, and Pz. Figure 5b shows that for $\frac{\alpha}{\beta}$, electrodes in the frontal, temporal, and occipital regions had weights greater than 0.01. Moreover, we also observed a tendency for weights that were greater than 0.01 to be more distributed in the left hemisphere compared to the right hemisphere.

[1]Specifically, independent components with absolute z-scores greater than 3 for their Pearson correlation coefficients with EOG were removed.

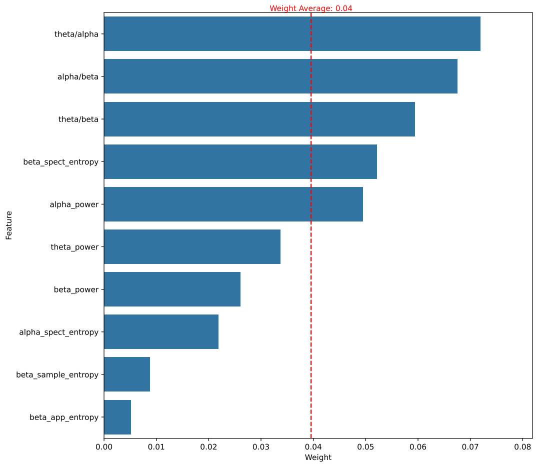


Fig. 4: $\|w_g\|_2$ values for the 10 selected features, shown in descending order. The vertical axis shows the features. The red dotted line indicates the mean $\|w_g\|_2$ value of the 10 features.

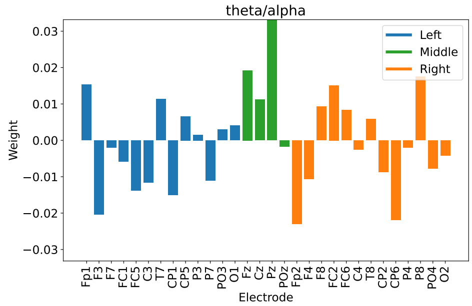
B. *Comparison of Cross-correlation Coefficients between Features and VTC*

Figures 6 shows examples of the line graphs overlaying the features and VTC for a participant for the features that have the largest (Figure 6a) and the lowest (Figure 6b) maximum cross-correlation at the electrodes with the largest weights. In the figures, blue lines represent the features and red lines represent the VTC. The maximum cross-correlation coefficient between the feature and VTC is shown in the top left of each figure. The highest maximum cross-correlation coefficient between the feature and VTC was 0.412, observed for $\frac{\theta}{\alpha}$ feature at the Pz electrode, while the lowest coefficient was 0.139 for $\frac{\alpha}{\beta}$ feature at the F3 location. Figure 7 shows the box plots of the maximum cross-correlation coefficients for each participant across the three features. T-tests were conducted under the null hypothesis that the cross-correlation coefficient is zero. As a result, the null hypothesis was rejected for all three features ($t(13) = 12.421, p < .001, d = 3.320$; $t(13) = 11.949, p < .001, d = 3.194$; $t(13) = 3.17, p < .001, d = 3.166$).

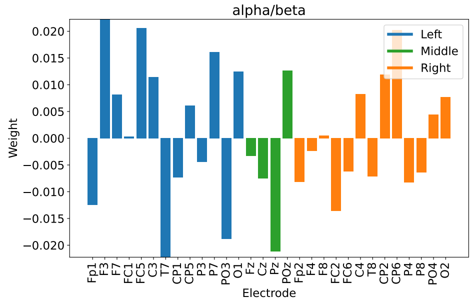
IV. Discussion

This study aimed to identify EEG features that effectively represent concentration levels during the go/no-go task, with a focus on the multi-channel nature of EEG data. Our analysis, using group Lasso for feature selection, revealed several key findings that provide insights into the neurophysiological correlates of sustained attention. In this section, we discuss the significance of our results, their relationship to existing literature, and their potential implications for understanding and measuring concentration.

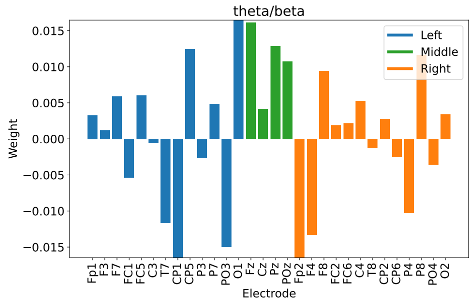
The feature selection results from group Lasso revealed that power ratios had the highest weights. This suggests that power ratios are more sensitive to fluctuations in concentration levels than features from single-frequency bands. As mentioned in Section I, it is known that as concentration decreases, power



(a) Electrode-wise weights for $\frac{\theta}{\alpha}$



(b) Electrode-wise weights for $\frac{\alpha}{\beta}$



(c) Electrode-wise weights for $\frac{\theta}{\beta}$

Fig. 5: Electrode-wise weights for the top three features with the largest $\|w_g\|_2$ among the 10 selected features. The horizontal axis shows the 30 electrodes, and the vertical axis shows the weight of each electrode. Electrodes are color-coded: blue for the left hemisphere, green for the midline, and orange for the right hemisphere.

in the theta and alpha bands increases while power in the beta band decreases [10]. This inverse relationship between low and high frequencies may be strongly reflected in the power ratios. Regarding the electrode-specific weights of the power ratios, $\frac{\theta}{\alpha}$ and $\frac{\theta}{\beta}$ both showed positive weights for the midline electrode. This could be attributed to the influence of theta band power, which is common to both ratios. Theta waves are known to primarily appear during sleep [21]. In our experiment, which required sustained concentration over an extended period, participants may have temporarily entered a near-sleep state, resulting in increased theta band power. It is known that such temporary near-sleep states reduce concentration and activate theta band signals in the frontal and parietal regions along

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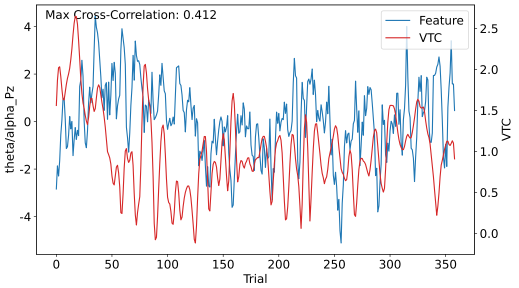
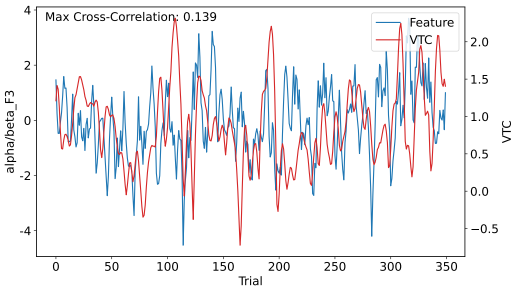


(a) The highest maximum cross-correlation for $\frac{\theta}{\alpha}$ at Pz.



(b) The lowest maximum cross-correlation for $\frac{\alpha}{\beta}$ at F3.

Fig. 6: Example of the time course of feature and VTC at the most effective electrode for a participant. The horizontal axis shows the trial number, the left vertical axis shows the feature value and the right vertical axis shows VTC.

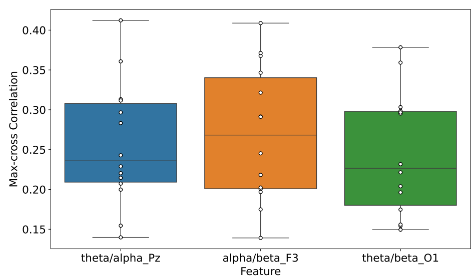


Fig. 7: Box plots of the maximum cross-correlation coefficients between VTC and the three features with the largest $\|\beta_g\|_2$ ($\frac{\theta}{\alpha}$, $\frac{\alpha}{\beta}$, $\frac{\theta}{\beta}$) at the electrodes with maximum weight coefficients. Circles indicate the maximum cross-correlation coefficients for each participant.

the midline [22]. Indeed, participants reported experiencing temporary drowsiness during the experiment. These findings suggest that power ratios including theta band activity from frontal and parietal midline regions may capture fluctuations in concentration levels. Moreover, Behzania et al. also observed that the theta power when the participant during a sustained attention task increases to a similar level as the closed-eye resting state [9]. This suggests that performing a long task, even without entering a near-sleep state, can increase theta power and potentially lower concentration. Therefore, the power ratio that included theta power can be promising for sustained attention assessment.

Focusing on $\frac{\beta}{\alpha}$, electrodes in the frontal, temporal, and occipital regions of the left hemisphere show large weights. The activation of frontal and occipital regions may be related to the default mode network (DMN) [23]. Activation of the frontal and occipital cortices and an active DMN are associated with states where individuals are relaxed and not focusing on external stimuli [24]. In our analysis, the relatively large weights for frontal, temporal, and occipital electrodes might imply that the DMN has been strengthened and resulted in enhancement of the alpha band activity in these regions [25]. The larger weights in the left hemisphere could be due to hemispheric dominance, as all except one of the analyzed participants were right-handed. It might also be noted that concentration has also been reported to be related to EEG asymmetry in the frontal region [26], suggesting that this hemispheric bias might reflect concentration levels as well.

When we compared the time course of the features and VTC, we found the high maximum cross-correlation coefficient between them was 0.412. Although the lowest coefficient was as low as 0.139, we could still observe a similar trend plotted for time course comparison, indicating that the features can capture the general trends of VTC. Furthermore, the cross-correlation coefficient tests demonstrated that these three features effectively evaluate individual concentration levels. Combining these features may enable the estimation of concentration levels from EEG characteristics.

V. Conclusion

This study aimed to identify EEG features that effectively represent concentration levels during a go/no-go task, addressing the multi-channel nature of EEG data. Our group Lasso analysis demonstrated that power ratios of theta, alpha, and beta bands in EEG are superior to the power itself in explaining the concentration levels relative to VTC. The ratios including the theta band showed relatively large weights in midline electrodes, while the $\frac{\beta}{\alpha}$ ratio showed prominence in frontal, temporal, and occipital electrodes. These findings align with established literature on attention networks and the default mode network, providing a neurophysiological basis for our results. We conclude that combining these EEG features could potentially estimate concentration from EEG data, addressing our initial research question.

While this study provides valuable insights into the EEG correlates of concentration, it is important to note limitations such as the small sample size and the specific task context. Moreover, the gap between static stimuli and conversational dynamics issues should be considered in the experimental design for the development of more accurate sustained attention assessment tools. Future research could explore the generalizability of these findings to other cognitive tasks and investigate how these EEG features relate to different measures of attention and cognitive performance.

Acknowledgment

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