EegCNR: A Novel Feature for Attention Estimation from EEG

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Abstract—**Attention is one of the most crucial cognitive factors for a high-quality living and survival for a person. Electroencephalogram (EEG)-based attention estimation has been explored by researchers as a promising approach for non-invasive monitoring of a person's mental focus and vigilance. In this paper, we present a novel approach for EEG-based attention quantification using an image contrast feature, generalized Contrast-to-Noise Ratio (gCNR) adopted from the domain of biomedical ultrasound. The work validates the effectiveness of gCNR in attention quantification, using the EEG data collected from 14 healthy subjects using the proposed experimental paradigm. The performance of the gCNR feature is further tested on Healthy-Brain Network (HBN)-R1, a larger open-source dataset of 136 subjects. The results confirm the effectiveness of gCNR in quantifying EEG attention, aligning with other established EEG attention metrics. To the best of our knowledge, this is the first work that derives image contrast features to quantify attention from EEG, as a promising novel feature for attention decoding.**

I. INTRODUCTION

Attention is one of the most essential cognitive skills for humans to maintain a high-quality living. From simple tasks like clicking a button on a computer to complex tasks like driving a car through heavy traffic, the majority of daily-life tasks require attention. Maintaining a higher level of attention is essential for learning and processing new information, staying focused on tasks and responding effectively to environmental changes, making it a crucial cognitive function, the lapse of which can lead to fatal outcomes [1]. The Brain plays a central role in controlling the level of attention we maintain.

Electroencephalogram (EEG) is a non-invasive, cost-effective and portable modality for capturing electrical activity of the brain with high temporal resolution. EEG-based measurement of human attention [2] has gained significant research interest, as it can provide non-invasive and real-time insights into the cognitive process. A variety of EEG band power ratio-based features, such as beta-to-(alpha+ theta) ratio (BATR), Theta-to-beta ratio (TBR) [3], [4] etc., have been used to quantify attention from EEG in literature. In addition to these band power features, signal complexity-based features such as sample entropy [5], [6] and fractal dimensions [7] have also been proven to quantify attention effectively. Hjorth complexity and mobility are other popular features that are reported to quantify attention [8] and have been employed in several attention studies in the recent past [9].

In this work, we reframe EEG attention quantification as an image contrast measurement problem. We introduce a novel attention feature, EEG generalized Contrast-to-Noise Ratio (EegCNR), inspired from the popular image contrast measure from biomedical ultrasound, generalized Contrast-to-Noise ratio (gCNR) [10], to quantify attention from EEG. To the best of our knowledge, this is the first work towards employing an image contrast feature in EEG attention estimation, which opens up new possibilities to enhance attention decoding from EEG. The rest of the paper is organized as follows. Section II describes the experimental paradigm, data collection and the proposed novel attention feature. Section III presents the results and analysis, and Section IV concludes the paper.

II. MATERIALS AND METHODS

A. *CognoBoost Racer Traffic Light Setup*

The EEG data recorded during a simulated car navigation task is used for analysis in this work. The experimental paradigm is designed in the form of real-time EEG Neurofeedback game named 'CognoBoost Racer' in three dimensions using 'Unity3D' software. The CognoBoost Racer is a simulated car navigation game in which the navigation of the car is driven by the attention level of the player, measured from real-time EEG. This work is limited to the calibration session of CognoBoost Racer. The calibration session begins with the car running at a preprogrammed speed on the road, where the subject is asked to relax ('Relax' phase). The 'Relax' phase lasts for five seconds duration after which the car stops at a 'red' color traffic light signal as shown in Fig. 1 a). At this time, the subject is given a focus cue (text display: "turn the signal green by focusing on the car") which instructs that the traffic light will turn 'green' only if the subject focuses on the car sufficiently ('Focus' phase). This instruction is designed to induce a focused attention state in the subject. Irrespective of the attention score during the ‘Focus’ phase, the traffic light is preprogrammed to turn ‘green’ after five seconds of the focus cue. The attention score computed during the ‘Focus’ phase is used as a baseline for fixing the attention threshold in the latter part of the game. Real-time EEG is recorded during both the ‘Relax’ and ‘Focus’ phases using a consumer-grade wireless headset, Muse 2 [11] that has only four electrodes AF7, AF8, TP9 and TP10 with a minimal setup time and user convenience. The experimental setup with a subject wearing Muse 2 is shown in Fig. 1 b).

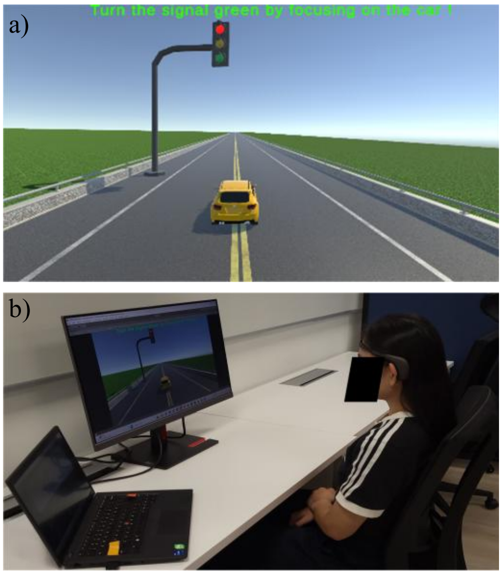

Fig. 1. a) The CognoBoost Racer traffic-light based calibration session. b) A player wearing Muse 2 EEG headset attending the traffic light-based calibration session.

B. *Data Collection*

14 healthy adults (8 male and 6 female) aged 22-30 (25.21±2.48; mean ± standard deviation) with good English literacy participated in the experiment. The experiment received ethical approval from the Singapore Institute of Technology-Institutional Review Board (SIT-IRB). All the participants signed the Informed Consent Form and were fully explained the details of the experiment before the start of the study. The participants were compensated monetarily for their participation in the experiment, as per the approved IRB norms. Subjects with any known neuropsychiatric disorders (such as epilepsy or mental retardation), gross hearing, visual or speech impairment that are uncorrected, or taking medications for any mental disorders were excluded from participating. Each subject attended two trials per session for a total of three sessions, with each session being on a separate day, with an average session interval of 8 days. For 14 subjects, we have 84 trials each for ‘Relax phase’ and ‘Focus phase’ with each trial of 5-second duration.

C. *Data Preprocessing*

The real-time EEG data during ‘Relax’ and ‘Focus’ phases is streamed to a laptop via Bluetooth using Lab Streaming Layer (LSL) at a sampling rate (F_s) of 256 Hz. The pre-processing involved bandpass filtering between [4, 40] Hz using a Finite Impulse Response (FIR) filter of order 300 that also rejected the powerline noise at 50 Hz. All the pre-processing and analysis are done in MATLAB R2024a.

D. *Proposed EegCNR for Attention quantification from EEG*

One of the proven EEG attention metrics, sample entropy [5], measures the complexity of the signal. Signal complexity becomes high when the person is focused, thereby enabling discrimination between attentive and inattentive states. A higher signal complexity suggests that adjacent signal segments are less likely to be similar, whereas they are more likely to be similar when signal complexity is low. This notion of similarity is intuitively the same as the contrast in the image domain. Thus, a higher contrast between signal subsegments reflects greater dissimilarity among them, which in turn suggests higher attention and vice versa.

We aim to leverage this analogy between signal complexity and image contrast to derive a novel metric for attention quantification. Generalized Contrast-to-Noise Ratio (gCNR) [10] is one of the established image contrast features in the domain of biomedical ultrasound. For an ultrasound image containing a cyst, it is estimated to quantify the contrast by finding the overlap area of probability density functions inside and outside the cyst regions as given by (1).

$$gCNR = 1 - \int \min\left(f_{CY}, f_{BG}\right) \tag{1}$$

where, f_{CY} and f_{BG} are respectively the probability density functions of the signals from the cyst and the background regions.

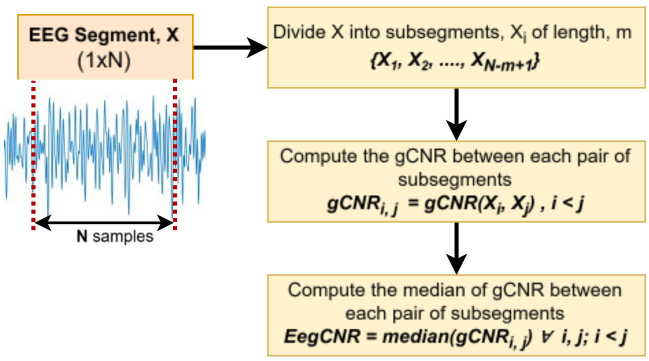

Fig. 2. The proposed EegCNR for attention quantification from an EEG segment.

The proposed EegCNR (EEG generalized Contrast-to-Noise Ratio) is computed on EEG as follows. Given an EEG segment X of N samples (Fig. 2), create a new set of sub-segments each of length m $\{X_1, X_2, X_3, X_4, \ldots, X_{N-m+1}\}$. X_i is a sub-segment of EEG X, starting from i^{th} sample with a length of m samples. gCNR is calculated for all unordered pairs of

EEG subsegments X_i, X_j as per (1), where one segment acts as a region of interest (similar to cyst) and the other one acts as the reference (the background). gCNR between the same segments are avoided. The EegCNR for input EEG X is calculated as the median of all the pairwise gCNR values according to (2).

$$EegCNR = median\{\text{gCNR}(X_i, X_j)\ \forall\, i, j,\ i < j\} \qquad (2)$$

To quantify the attention level for the 'Relax' and 'Focus' phases from EEG, the pre-processed 5 sec. data is split into non-overlapping epochs of length 1 sec. and EegCNR is computed for each resulting 1 sec. epoch. The attention level for 'Relax' and 'Focus' phases EEG is evaluated as the mean of EegCNR of the constituent 1 sec. epochs.

The following hyperparameters are used in this work for EegCNR. The segment length, m is chosen as half of the sampling rate ($F_s/2$). Histogram is used for obtaining the probability distribution function. The histogram minimum bin and maximum bin are chosen as -150 and +150 with the number of bins being 300. This assumes the preprocessed EEG values fall in the range of -150 µV to +150 µV.

III. RESULTS AND DISCUSSION

EEG attention levels corresponding to 'Relax' and 'Focus' phases were computed using the proposed EegCNR for all the 84 trials of 'CognoBoost Racer' traffic lights paradigm. Additionally, the attention levels were also quantified using two established EEG attention features namely sample entropy and beta-to-(alpha+theta) ratio (BATR), for comparison and validation.

As attention is predominantly controlled by the frontal part of the brain [12], only the two anteriofrontal electrodes of Muse 2 (AF7 and AF8) are considered for attention discrimination analysis. The mean attention levels during 'Relax' and 'Focus' quantified using state-of-the-art EEG attention metrics and the proposed EegCNR are shown in Fig. 3. Fig. 3 a) shows the mean Sample Entropy corresponding to 'Relax' and 'Focus' trials evaluated for the EEG data of AF7 and AF8 electrodes. From Fig. 3 a), it is evident that the Sample Entropy feature can clearly discriminate between 'Relax' and 'Focus' phases. Fig. 3 b) depicts the mean BATR corresponding to 'Relax' and 'Focus' phases, which also confirms discrimination between the two states. The mean attention values for the 'Relax' and 'Focus' states quantified using the proposed EegCNR feature is shown in Fig. 3 c). It can be observed that the proposed EegCNR metric is able to effectively discriminate between the 'Relax' and 'Focus' phases and the mean EegCNR values exhibit the same trend as that of established EEG attention features, sample entropy and BATR.

A statistical significance test was performed to test the significant differences in the features between 'Relax' and 'Focus' phase. Wilcoxon's Signed Rank-test, a non-parametric test, was used with a confidence interval of α=0.05. The resulting p-values are given in Table I. The p-values confirm that the EEG attention levels associated with 'Relax' and 'Focus' phases exhibited statistically significant differences when quantified using the EEG metrics, Sample entropy and BATR. It can be observed that the proposed EegCNR feature also offered significant difference between the 'Relax' and 'Focus' phases for both AF7 and AF8 electrodes. This confirms the effectiveness of EegCNR as an EEG attention feature and validates its concordance with existing EEG attention metrics.

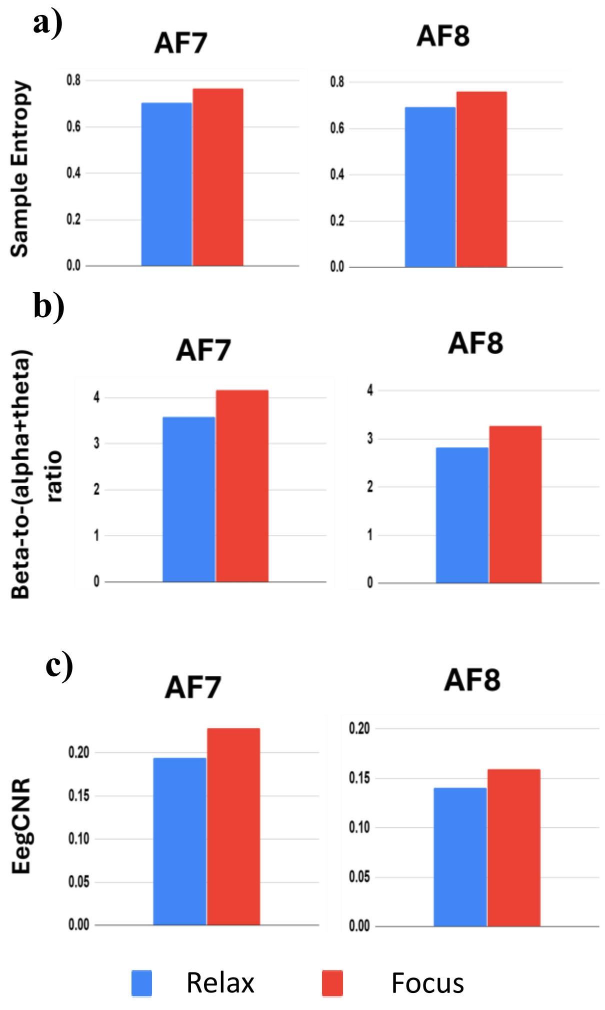

Fig. 3. Comparison of attention scores from EEG using a) Sample entropy, b) beta-to-(alpha+theta) ratio (BATR), and c) the proposed EegCNR for 'Relax' and 'Focus' phases for CognoBoost Racer traffic light-based calibration session.

TABLE I.

p-VALUES FOR THE PROPOSED EegCNR AND OTHER EEG FEATURES FOR THE COGNOBOOST RACER TRAFFIC LIGHT BASED CALIBRATION SESSION 'RELAX' AND 'FOCUS' PHASE.

EEG Feature	*p*-value	
	AF7	***AF8***
Sample entropy	1.56E-10	4.36E-13
BATR	0.05	0.003
EegCNR	4.48E-13	2.85E-10

To further validate the potential of EegCNR in quantifying EEG attention, we analyzed an open-source EEG dataset, Healthy Brain Network -Release 1 (HBN-R1) [13]. The HBN-R1 dataset contains high resolution EEG data (128 channels, GSN 200) for 136 subjects doing various tasks. For this work, EEG data during Resting State (RS) and Contrast Change Detection (CCD) tasks alone are considered. During Resting State, the subjects remained at rest with their eyes open and closed. During the CCD task, participants looked at two flickering patterns and had to quickly select the pattern that had a greater contrast. As the nature of the RS task does not demand any attention from the participants, RS EEG is considered as 'Relax' phase data and EEG during CCD task as the 'Focus' phase data, owing to the higher attention that may be naturally induced while attending the CCD task. Only 102 subjects out of 136 had both RS and CCD data available for analysis. We also excluded one subject from analysis due to highly noisy EEG data. Thus, the analysis is conducted on 101 subjects.

The GSN 200 has electrodes labelled as E1, E2, …, E128 [14] and does not follow the standard naming conventions as that of 10-20 system for electrode placement. Hence, we derived the electrodes in close proximity to AF7 and AF8 electrodes of 10-20 system based on the Euclidean distance and the resulting electrodes are considered for analysis. The GSN electrodes E26, E22, E23 and E27 are found to be nearest to AF7 whereas electrodes E2, E9, E3 and E123 are close to AF8. The selected electrodes for analysis (colored red) can be visualized from Fig. 4., and these electrodes taken have symmetry across the left and right hemispheres.

The Raw EEG data from these electrodes were preprocessed using a Bandpass FIR filter of order 300 between 4 and 40 Hz. The EEG attention levels during RS and CCD ('Rest'/'Relax' phase and 'Focus' phase) are quantified using the metrics, sample entropy, BATR and EegCNR separately for all the selected 8 electrodes. The mean attention levels during 'Rest' and 'Focus' measured using sample entropy, BATR and proposed EegCNR are shown in Fig. 5. From Fig. 5 a) and 5 b), it can be observed that sample entropy gives clear discrimination between the 'Focus' and 'Relax' phases across

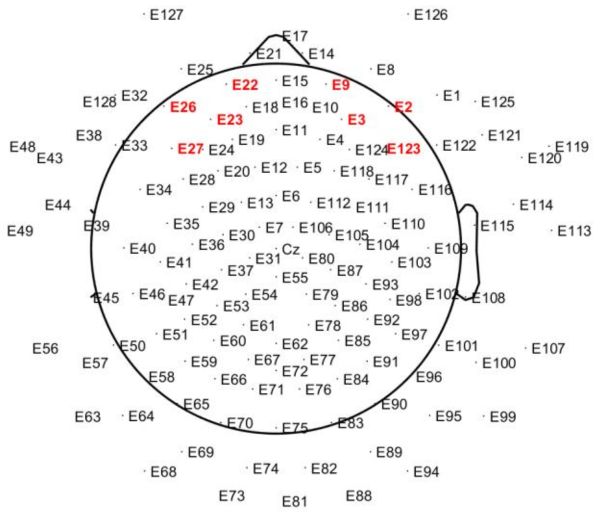

Fig. 4. The GSN 200 electrode configuration. The 8 electrodes labelled with red colour fonts are the electrodes selected for our study.

all the selected electrodes. This validates our choice of the RS data for 'Relax' phase and the CCD data for the 'Focus' phase from the HBN dataset. BATR also gives a similar observation as depicted in Fig. 5 c) and d). As observed from Fig. 5 e) and f), the proposed EegCNR also clearly discriminates between the 'Relax' and 'Focus' phases across all the electrodes, which validates the ability of the proposed feature to quantify attention.

The statistical significance of these results is tested using Wilcoxon's signed rank-test, which showed that there is a significant difference as depicted by the *p*-values in Table II. The proposed EegCNR also offered a significant difference between the 'Relax' and 'Focus' states.

TABLE II.

p-VALUES FOR THE PROPOSED EegCNR AND OTHER EEG FEATURES FOR THE HBN DATASET 'RELAX' AND 'FOCUS' PHASES.

Electrode Number	*p*-value		
	Sample Entropy	***BATR***	***EegCNR***
E26	1.19E-08	1.47E-13	0.0095
E22	2.75E-05	2.37E-08	7.63E-10
E23	2.23E-08	1.03E-11	0.0019
E27	2.73E-09	1.60E-14	0.0122
E2	6.36E-09	8.76E-14	6.48E-06
E9	7.87E-08	1.68E-12	3.04E-05
E3	2.04E-09	6.98E-15	0.0012
E123	5.00E-08	7.18E-16	0.0052

From Table I and Table II, it can be noted that the *p*-values for sample entropy and BATR are generally more significant than that of the proposed EegCNR. However, tuning

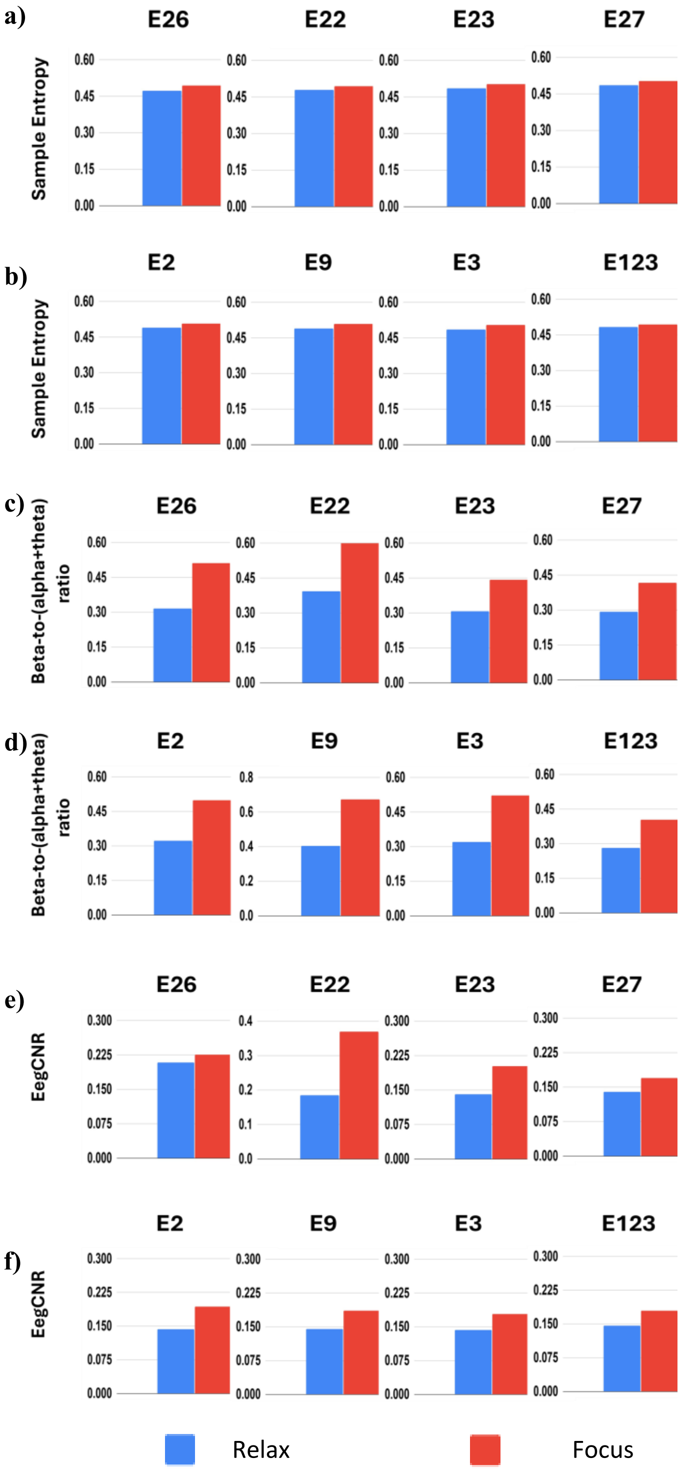

Fig. 5. a) Sample entropy of AF7 nearby electrodes, b) Sample entropy of AF8 nearby electrodes, c) BATR of AF7 nearby electrodes, d) BATR of AF8 nearby electrodes, e) the proposed EegCNR of AF7 nearby electrodes, f) the proposed EegCNR of AF8 nearby electrodes comparison for 'Relax' and 'Focus' phases for HBN.

the hyperparameters, such as the histogram bin size and the segment lengths could improve the p-value significance of EegCNR, which is our future work. The results highlight the potential of image contrast feature in quantifying EEG attention and hence open possible future research directions.

IV. Conclusions

In this work, we proposed a novel EEG feature for attention, EegCNR, inspired by an image contrast feature, gCNR. The feature is tested on 14 healthy subjects collected using CognoBoost Racer traffic light-based calibration and is found to show the same trend as that of the state-of-the-art attention features, such as sample entropy and beta-to-(alpha+theta) ratio (BATR). The efficacy of the proposed EegCNR is further validated on an open-source dataset, Healthy Brain Network (HBN)-R1, consisting of a larger number of subjects. The EegCNR demonstrated significant statistical difference between attention (RS) and inattention (CCD), exhibiting a similar trend as sample entropy and BATR. Thus, the results highlight the potential of image contrast features derived from the image domain for EEG-based attention quantification, which is a new research direction opened by this work.

V. Acknowledgment

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References

[1] P. R. Davidson, R. D. Jones, and M. T. R. Peiris, "EEG-Based Lapse Detection With High Temporal Resolution," *IEEE Trans Biomed Eng*, vol. 54, no. 5, pp. 832–839, 2007, doi: 10.1109/TBME.2007.893452.

[2] R. H. C. e Souza and E. L. M. Naves, "Attention Detection in Virtual Environments Using EEG Signals: A Scoping Review," *Front Physiol*, vol. Volume 12-2021, 2021, doi: 10.3389/fphys.2021.727840.

[3] R. J. Barry, A. R. Clarke, and S. J. Johnstone, "A review of electrophysiology in attention-deficit/hyperactivity disorder: I. Qualitative and quantitative electroencephalography," *Clinical Neurophysiology*, vol. 114, no. 2, pp. 171–183, 2003, doi: https://doi.org/10.1016/S1388-2457(02)00362-0.

[4] M. Arns, C. K. Conners, and H. C. Kraemer, "A Decade of EEG Theta/Beta Ratio Research in ADHD: A Meta-Analysis," *J Atten Disord*, vol. 17, no. 5, pp. 374–383, 2013, doi: 10.1177/1087054712460087.

[5] J. S. Richman and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy," *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 278, no. 6, pp. H2039–H2049, 2000, doi: 10.1152/ajpheart.2000.278.6.H2039.

[6] K. P. Thomas, A. P. Vinod, and C. Guan, "Design of an online EEG based neurofeedback game for enhancing attention and memory," in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2013, pp. 433–436. doi: 10.1109/EMBC.2013.6609529.

[7] Q. Wang, O. Sourina, and M. K. Nguyen, “Fractal dimension based neurofeedback in serious games,” *Vis Comput*, vol. 27, no. 4, pp. 299–309, 2011, doi: 10.1007/s00371-011-0551-5.

[8] M. Vourkas, S. Micheloyannis, and G. Papadourakis, “Use of ANN and Hjorth parameters in mental-task discrimination,” in *2000 First International Conference Advances in Medical Signal and Information Processing (IEE Conf. Publ. No. 476)*, 2000, pp. 327–332. doi: 10.1049/cp:20000356.

[9] T. A. Suhail and A. P. Vinod, “Enhancing Overt and Covert Attention Using a Real-Time Neurofeedback Game With Consumer-Grade EEG,” *IEEE Trans Cogn Dev Syst*, vol. 16, no. 1, pp. 223–231, 2024, doi: 10.1109/TCDS.2023.3260441.

[10] A. Rodriguez-Molares *et al.*, “The Generalized Contrast-to-Noise Ratio: A Formal Definition for Lesion Detectability,” *IEEE Trans Ultrason Ferroelectr Freq Control*, vol. 67, no. 4, pp. 745–759, 2020, doi: 10.1109/TUFFC.2019.2956855.

[11] “Muse-InteraXon. “Accessed: April. 16, 2025. [Online].Available:https://choosemuse.com/products/muse-2.”

[12] A. F. Rossi, L. Pessoa, R. Desimone, and L. G. Ungerleider, “The prefrontal cortex and the executive control of attention,” *Exp Brain Res*, vol. 192, no. 3, pp. 489–497, 2009, doi: 10.1007/s00221-008-1642-z.

[13] S. Y. Shirazi *et al.*, “HBN-EEG: The FAIR implementation of the Healthy Brain Network (HBN) electroencephalography dataset,” *bioRxiv*, 2024, doi: 10.1101/2024.10.03.615261.

[14] I. Electrical Geodesics, “Geodesic sensor net technical manual. Electrical Geodesics,” 2007, *Inc*. Available: https://med.stanford.edu/content/dam/sm/lucasmri/documents/16_0824_EGI_geodesic_sensor_net.pdf