BCI-Based Drawing Interface: SSVEP to Select Pre-defined Shapes and Visual Attention to Control the Size of the Shapes

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***Abstract*—This study introduces a brain–computer interface (BCI) drawing system that combines Steady-State Visually Evoked Potentials (SSVEP) for discrete shape selection with EEG-based attention signals for continuous size modulation. Users select one of four flickering visual stimuli—circle, rectangle, triangle, or "do nothing"—tagged at 6 Hz, 10 Hz, 12 Hz, or 15 Hz, eliciting an SSVEP response. After the selection, a moving-ball task engages the user's visual attention, measured in real time using the beta/alpha power ratio. A higher ratio indicates increased attention, resulting in larger shapes being drawn. The system enables intuitive, hands-free drawing with two degrees of control—what to draw and how large—using only EEG input. Offline testing confirmed feasibility, achieving 44% accuracy in size modulation, although SSVEP classification requires further improvement. This lightweight design, implemented with a simple 8-channel EEG headset, demonstrates the potential for expressive graphical interaction without the need for complex or multi-modal input.**

***Index Terms*—Brain-Computer Interface (BCI), Electroencephalography (EEG), Steady-State Visually Evoked Potential (SSVEP), Visual Attention, Dual-Parameter Control, Real-time Systems.**

I. Introduction

Brain-computer interfaces (BCIs) enable direct communication between the brain and external devices, bypassing peripheral neural and muscular pathways [1]. By interpreting neural signals—typically via EEG—they allow users to control computers, prostheses, and other machines through thought alone [2], offering promise for restoring communication to individuals with severe motor impairments [1], [2]. Beyond clinical and rehabilitation uses, BCIs are increasingly explored for creative and expressive tasks. Recent work has shown that brain signals can even be used to generate artistic output; for example, hybrid SSVEP/P300 BCIs have enabled users to "paint" on a digital canvas through EEG [3]. These advances highlight the transformative potential of BCIs not only for assistive technology but also for expanding the boundaries of human-computer interaction and digital creativity.

Despite these advances, providing simple yet expressive multi-dimensional control via BCI remains challenging. Existing BCI painting or drawing systems often rely on complex multi-modal signals or multi-step interfaces to achieve even basic functionality [3]. Such approaches can impose high cognitive load and limited throughput. In other words, offering intuitive control of both "what" (shape) and "how much" (size or intensity) through only neural signals is an open challenge in current BCI research.

This work addresses the following research question: Can an EEG-based BCI provide intuitive dual-parameter control for simple drawing tasks by combining discrete shape selection with a continuous attention-based signal? In particular, we ask whether a user can select basic geometric shapes and simultaneously adjust their size using two independent EEG mechanisms (SSVEP and attention-related rhythms), thereby enabling simple graphical creation without muscle input.

To address this, we propose a novel BCI drawing interface with dual control dimensions. Users view flickering stimuli representing geometric shapes (circle, rectangle, triangle) and a "do nothing" option. Focusing on a target evokes a steady-state visually evoked potential (SSVEP) at the corresponding frequency, allowing discrete shape selection. Simultaneously, the user's visual attention is monitored by computing the ratio of EEG beta to alpha band power in real time; higher attention (higher beta/alpha ratio) results in the selected shape being drawn large, otherwise small.This design uses just two EEG signals and well-established brain activation paradigms (SSVEP and attention) to provide two degrees of control—discrete shape selection and continuous size modulation. Prior work has shown that SSVEP can reliably drive simple painting tasks [4], and that the beta/alpha EEG ratio is a well-established index of engagement or attention [5]. By integrating these signals, our system enables users to create basic drawings with selectable shapes and sizes using only their thoughts.

The rest of this report is organized as follows: Section II reviews related work on SSVEP-based BCIs, EEG-based attention detection, and BCI-driven graphics. Section III covers the theoretical background of SSVEP and attention-related EEG rhythms. Section IV describes the system architecture, signal processing, and implementation. Section V presents user testing results and system evaluation. Finally, Section VI concludes with findings and future directions.

II. Related Work

Brain–computer interfaces (BCIs) based on Steady-State Visually Evoked Potentials (SSVEP) have been widely applied in communication and control systems due to their high information transfer rates, minimal user training requirements, and robustness to noise [2], [6]. Classic applications include spellers, wheelchair control, and menu selection interfaces, where each visual option flickers at a unique frequency and user intent is decoded based on the frequency of the strongest SSVEP response. However, these systems typically offer only discrete control (e.g., selection among predefined items), limiting their expressiveness.

In recent years, BCIs have been extended to artistic applications. Hybrid paradigms combining SSVEP with P300 signals have enabled users to paint or draw using EEG input. Tang et al. [4] proposed a BCI painting system where users selected tools and shapes from flickering menus and used P300 responses for confirmation. While effective, the system relied on multiple interaction stages and frequent gaze shifts, increasing cognitive load and limiting real-time fluidity.

In terms of continuous control, attention-based EEG features such as the beta/alpha power ratio have been explored to estimate cognitive engagement [7], [8]. These features have been used in neurofeedback training, workload assessment, and simple binary classification tasks in BCI systems. However, their integration into creative or drawing applications remains limited.

To date, few systems have combined discrete SSVEP-based control with continuous attention-based modulation. Those that do often rely on complex multimodal setups, require extensive calibration, or do not operate in real time. Existing approaches also tend to prioritize classification accuracy over intuitive interaction, overlooking the cognitive demands of users during extended tasks such as drawing.

In contrast, our work proposes a lightweight, dual-channel EEG interface that uses SSVEP for shape selection and beta/alpha power ratios for real-time size modulation. This design bridges the gap between robust signal decoding and intuitive user experience, offering a new framework for expressive, real-time BCI-driven graphical interaction using only neural signals.

III. Theoretical Background

A. Steady-State Visually Evoked Potentials (SSVEP)

Steady-State Visually Evoked Potentials (SSVEPs) are regular, rhythmic EEG responses that arise primarily from the visual cortex when someone gazes at a light flickering at a consistent rate [9]. This phenomenon results from neurons aligning their activity with the flicker—a process called neural entrainment. The visual signal is first captured by the retina, then transmitted through the lateral geniculate nucleus (LGN) in the thalamus, before reaching the primary visual cortex (V1) located in the occipital lobe [10], [11]. As this entrainment occurs, coupled oscillations emerge in these brain regions—which can be measured non-invasively on the scalp as SSVEPs.

An important feature of SSVEPs is that the brain's oscillatory response not only matches the stimulus's fundamental flicker frequency but also shows strong activity at integer multiples of that frequency, known as harmonics [9], [12]. For example, an 8 Hz flicker may evoke peaks at 8 Hz, 16 Hz, and 24 Hz. Moreover, when attention is focused on the flickering source, the amplitude of these frequency-locked responses grows substantially. In the spectral domain, this appears as distinct peaks at the driving frequency and its harmonics [13]. Because these signals are both strong and sensitive to where attention is directed, SSVEPs are particularly effective for brain-computer interface (BCI) implementations [6], [11].

B. Canonical Correlation Analysis

Canonical Correlation Analysis (CCA) is a statistical technique employed to identify linear relationships between two multivariate datasets by finding projections that maximize their correlation. In the context of SSVEP-based Brain-Computer Interfaces (BCIs), one dataset comprises multi-channel EEG signals, while the other consists of reference signals, typically sine and cosine waves corresponding to potential stimulus frequencies. Mathematically, CCA aims to maximize the correlation between the weighted EEG data and the reference signals, expressed as:

$$\rho = \max_{\mathbf{w}_x, \mathbf{w}_y} \operatorname{corr}(\mathbf{w}_x^T \mathbf{X}, \mathbf{w}_y^T \mathbf{Y}), \tag{1}$$

where $\mathbf{X}$ is the EEG data matrix, $\mathbf{Y}$ contains reference sinusoids, and $\mathbf{w}_x$, $\mathbf{w}_y$ are spatial filters applied to each dataset [14].

In practice, CCA computes spatial filters that enhance the alignment between the EEG signals and the reference frequencies. The resulting canonical correlation coefficient ρ, reaches its peak when the reference frequency aligns with the actual SSVEP frequency. By evaluating CCA across various candidate frequencies, the one yielding the highest correlation is inferred as the target stimulus frequency [14]. This approach effectively integrates information across multiple EEG channels, making it particularly suitable for SSVEP detection in BCI applications.

C. Visual Attention

Visual attention is a core cognitive function that allows individuals to focus on particular elements within their visual surroundings while disregarding unrelated information [15]. This selective mechanism is essential for effectively navigating and interacting with complex, stimulus-rich surroundings.

Visual attention is typically categorized into two main forms: overt attention, which involves observable eye movements that direct the fovea toward a target, and covert attention, wherein attention is internally shifted without corresponding ocular motion, allowing focus on peripheral visual stimuli [16]. In the context of our project, which involves tracking a randomly moving ball, overt attention is directly engaged, as participants are instructed to visually follow the moving object, requiring continuous eye movements and sustained focus.

The neural mechanisms underlying visual attention involve a distributed network of cortical and subcortical regions. Notable structures include the frontal eye fields (located in the frontal lobe), which are involved in voluntary eye movements and goal-directed attention; the intraparietal sulcus and superior parietal lobule (located in the parietal lobe), which play key roles in directing spatial attention and selecting relevant targets; along with visual regions in the occipital lobe that amplify the processing of focused visual input [17]. These regions operate together as part of dynamic attentional networks that modulate perceptual sensitivity and cognitive resource allocation.

Maintaining attention and putting in mental effort also affect electrical activity in the brain, which can be recorded using electroencephalography (EEG) [8]. Electroencephalography (EEG) signals are categorized into distinct frequency bands, each associated with different cognitive and mental states:

- **Alpha rhythms (8–13 Hz)**are mostly seen in the back areas of the brain (parietal and occipital lobes). Higher alpha power is often related to a calm, restful state, inward focus, or active blocking of outside distractions [18]. When alpha power decreases, it usually signals that the brain is more alert and actively engaged with a task.
- **Beta rhythms (13–30 Hz)** are commonly found in the front and middle parts of the brain and are connected to active thinking, attention, and ongoing mental work [19]. Greater beta power generally reflects stronger focus and cognitive involvement.
- **Beta/Alpha power ratio**: The beta/alpha power ratio—which compares the power of beta and alpha EEG bands—has become a widely used neural marker for estimating attention and mental effort [7]; a higher ratio typically reflects greater cognitive engagement and focused attention, and in this study, it is used to evaluate participant attentiveness during the ball-tracking task, offering real-time insights into attentional states in brain-computer interface (BCI) applications.

IV. System Architecture and Implementation

A. System Overview

The BCI-based drawing interface combines Steady-State Visually Evoked Potentials (SSVEP) generation and visual attention modulation to enable intuitive graphical control. The system operates in real-time, allowing users to select predefined shapes and concurrently control their size. Fig. 1 illustrates the overarching architecture of the system.

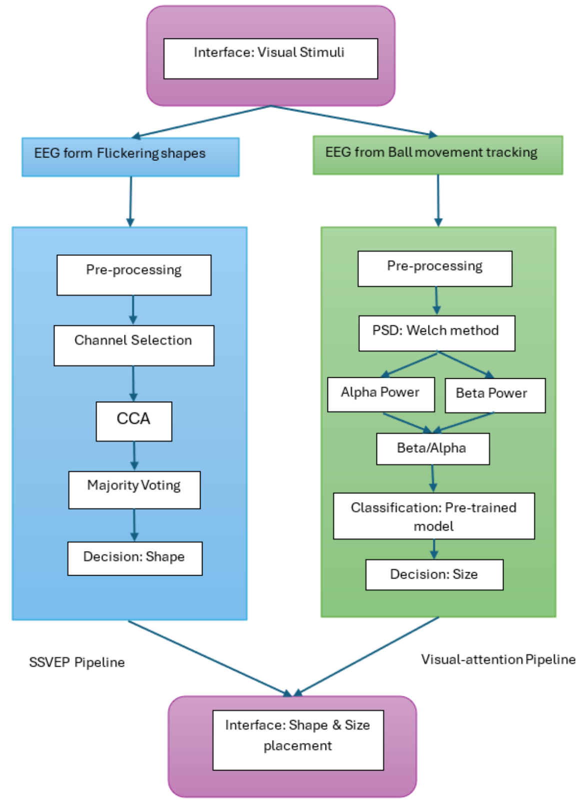

Fig. 1. Overarching architecture of the system.

The workflow begins with EEG signal acquisition from the user's scalp during two phases: the shape selection phase and the attention detection phase. Two separate processing pipelines are implemented—one for SSVEP detection and another for attention level classification. In the SSVEP pipeline, raw EEG signals elicited by flickering visual stimuli are preprocessed to remove noise and artifacts, followed by the shape selection step. In parallel, the visual attention module processes EEG signals collected during a ball-tracking task, which are similarly preprocessed and then used to classify the user's level of attention. Finally, the outputs from both modules—the selected shape and its determined size—are forwarded to the Drawing Interface, which renders the shape on the screen in accordance with the user's brain commands during the placement phase.

B. Hardware Setup

The system comprises three core components essential for EEG signal acquisition, visual stimulus presentation, and real-time processing:

1) EEG Headset: EEG signals are recorded using a g.tec Unicorn Hybrid Black headset with 8 channels. Electrodes are positioned according to the international 10/20 system at Fz, Cz, P3, Pz, P4, PO7, PO8, and Oz—covering frontal, central, parietal, and occipito-parietal regions to effectively capture SSVEP and attention-related signals. Data is sampled at 250 Hz and transmitted wirelessly via Bluetooth.Fig. 2 illustrates the g.tec Unicorn Hybrid Black EEG headset used in this system.

Fig. 2. g.tec Unicorn Hybrid Black EEG headset. Adapted from [20].

2) Display Monitor: Visual stimuli, including flickering targets and a moving ball, are presented on the user's laptop screen (approximately 17 inches) with a 60 Hz refresh rate, sufficient for reliable SSVEP generation.

3) Processing Unit: A high-performance laptop equipped with an Intel Core Ultra 7 processor, 32 GB RAM, and a 6 GB GPU is used to perform real-time EEG signal processing, classification, and interface rendering. The hardware ensures minimal latency and supports smooth execution of the dual pipelines for signal decoding and feedback display.

C. Software Environment

1) Programming Language: We used Python to develop all core BCI functions, including EEG data processing and the graphical interface. The visual interface—comprising interactive elements such as flickering targets and the drawing canvas—was built using the Pygame library.

2) Unicorn Hybrid Black Software: We used the Unicorn Suite, which includes the Unicorn Recorder for device setup and data logging, the Unicorn LSL Application for real-time EEG data streaming via the Lab Streaming Layer (LSL), and the Unicorn Python API, enabling seamless integration with Python applications for EEG data acquisition and processing.

D. System Implementation

1) Interface Design: The user interface of the BCI-based simple drawing system is designed for clarity and intuitive control, presenting the visual stimuli necessary for both SSVEP generation and the visual attention task. The interface occupies a standard display screen and is divided into distinct interactive regions. Fig. 3 and 4 demonstrate the interface in its inactive mode and during the data acquisition phase when the shapes begin to flicker, respectively.

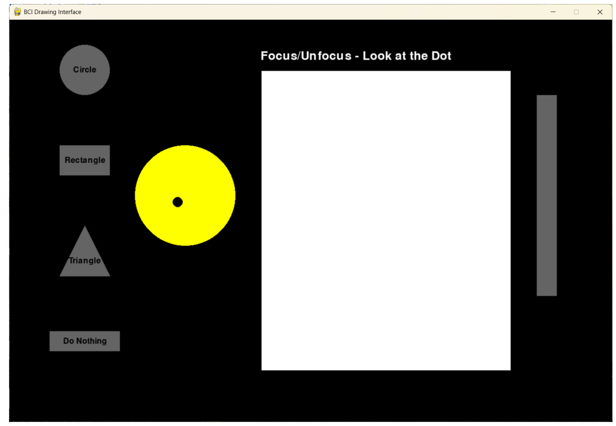

Fig. 3. The BCI Drawing Interface in inactive mode, with all shape targets displayed in gray.

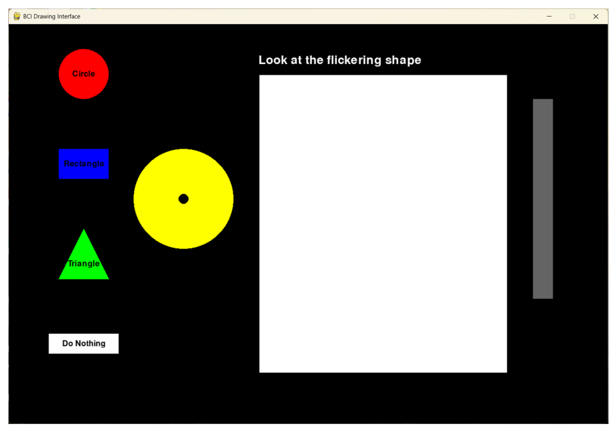

Fig. 4. The BCI Drawing Interface during the 5-second data acquisition phase for SSVEP, showing shapes flickering with their active colors.

a) Shape Selection Stimuli (SSVEP): Four static visual targets are strategically positioned along the left side of the screen, corresponding to the pre-defined shapes: Circle, Rectangle, Triangle, and a 'Do Nothing' option. Each target is displayed in gray and remains inactive when not in a selection phase. During a real-time data acquisition window (specifically, for 5 seconds), all four targets simultaneously begin to flicker at their unique, designated frequencies, and their color changes to their specific active hue (e.g., Red for Circle). The user is required to direct their gaze and sustained attention towards one of these flickering shapes within this 5-second window to register a selection. After this 5-second flickering period, all shapes immediately transition to an inactive (gray color) state. The assigned frequencies and active colors are as follows:

- **Do Nothing**: 6 Hz (Active Color: White)

- **Circle**:10 Hz (Active Color: Red)
- **Rectangle**:12 Hz (Active Color: Blue)
- **Triangle**:15 Hz (Active Color: Green)

These frequencies are carefully selected to be distinct, avoid harmonics of the display refresh rate, and minimize visual fatigue.

b) Attention Control Stimulus (Ball Tracking): The central drawing canvas area also serves as the host for the attention control stimulus. This stimulus consists of a static large circle in yellow color with a smaller, randomly moving black ball (or dot) inside it. During the dedicated phase for data acquisition for focus level selection (a 5-second window), the smaller ball within the yellow circle begins to move randomly. At all other times, the small black ball remains static. The user's primary task during the movement period is to continuously track the movement of this inner ball with their eyes and maintain sustained visual focus on it. The speed and trajectory of the inner ball's movement are designed to elicit a consistent level of visual engagement necessary for modulating the size control mechanism.

c) Drawing Canvas: A large white rectangular area to the right of the attention stimulus serves as the primary drawing canvas, where the selected shapes are rendered according to the user's BCI commands.

d) Focus Meter: On the far right edge of the screen, a vertical gray bar functions as a real-time Focus Meter. This meter provides immediate visual feedback on the user's attentional state, becoming active only when the system successfully detects a focus level. It dynamically changes color: green indicates a high level of user focus/attention, signifying a "Large" size selection, while red represents a low level of focus/attention, indicating a "Small" size selection.

e) Instruction and Decision Display: Positioned centrally above the white drawing canvas, this dynamic text area is utilized to display all system instructions, user prompts, and real-time decision feedback. Examples include "Look at the flickering shape," "Focus on the ball for large size," "Relax for small size," or confirmation messages about selected shapes and sizes.

2) EEG Data Acquisition:

a) Offline Data Acquisition for Model Training: Prior to real-time system operation, EEG data were collected in controlled offline sessions to train and validate the visual attention classification models. During this phase, participants were exposed to the moving ball stimulus while their EEG responses were recorded and saved.

The EEG data for model training were collected from one participant over a total duration of 40 minutes. This collection was divided into sessions designed to capture both high and low focus states. High-focus data consisted of 10 sessions, each lasting 2 minutes, where the participant actively tracked the moving ball within the static circle. Low-focus data included 5 sessions where the participant's eyes were closed and 5 additional sessions where their eyes were open but not focused on any particular stimulus.

We extracted power spectral density (PSD) features from the alpha (8–13 Hz) and beta (13–30 Hz) frequency bands, with the beta-to-alpha power ratio used as the primary feature for classification, as it is commonly associated with variations in attention levels. A Random Forest classifier was chosen for its robustness in handling complex, noisy EEG data and its minimal need for parameter tuning [21]. It is particularly effective for classification tasks involving high-dimensional feature spaces and helps reduce overfitting through ensemble learning [21]. Furthermore, Random Forests demonstrate strong performance even with relatively small datasets like our case, making them a practical choice for the offline training phase of our system [22].

After training, the model was saved for use during the real-time attention classification phase.

b) Real-time Data Acquisition: For real-time system control, EEG signals are continuously acquired from the Unicorn Hybrid Black headset and streamed via the Lab Streaming Layer (LSL) protocol using the Unicorn LSL Application. The Brain-Computer Interface (BCI) operation follows a predefined session plan that outlines the sequence and duration of different functional phases. This plan is essential for synchronizing visual stimulus presentation with the precise timing of EEG signal acquisition and subsequent processing required for specific control commands. Fig. 5 illustrates the session planning used for real-time implementation.

Throughout the session, event markers are automatically embedded in the EEG data stream at the start and end of each distinct phase. These markers are used for segmenting the continuous EEG stream to isolate and process only the relevant data required for real-time classification. Data outside these marked phases can be temporarily buffered and discarded if not immediately relevant to the ongoing task.

During active classification periods:

- **SSVEP detection** is performed during the *"Look at the flickering shape"* phase. During this phase, shape flickering occurs so the user can focus on a particular shape, and EEG data is streamed in real-time. The EEG is processed in the backend using non-overlapping 0.5-second windows.
- **Visual attention detection** occurs during the *"Focus/Unfocus—Look at the Dot"* phase. In this phase, the small black ball inside the yellow circle starts to move randomly, and the user attempts to track its movement. EEG data is streamed during this interaction and is processed in real-time using non-overlapping 1-second windows.

Although 0.5-second and 1-second windows are processed in real-time in the backend for SSVEP and attention classifi-

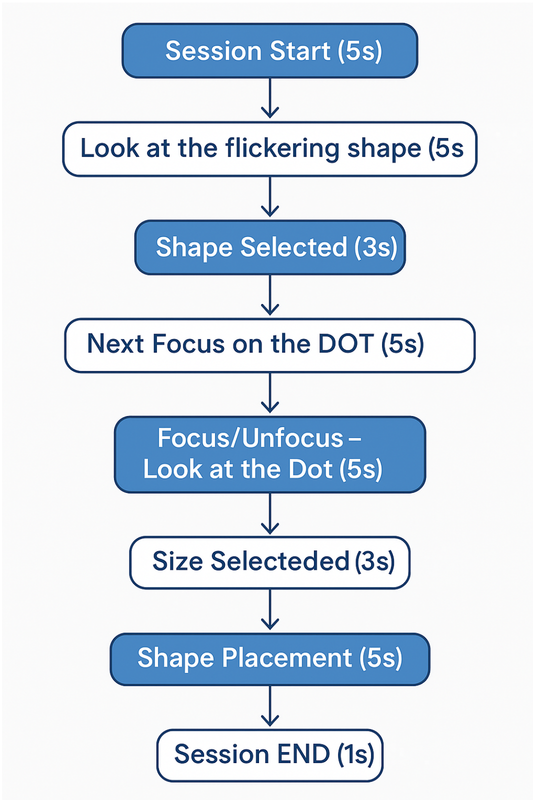

Fig. 5. Session planning used for real-time implementation

cation respectively, the total duration for each flickering task and ball tracking phase is 5 seconds. As EEG segments of 0.5 or 1 second are received, they are immediately processed by the corresponding SSVEP or visual attention pipeline. The classification output from each window is stored and later aggregated to produce the final decision at the end of the 5-second interval.

3) SSVEP Pipeline: After the EEG data collection corresponding to the user's interaction with the flickering shapes, the acquired data is fed into the SSVEP pipeline (see Fig 6 for an overview of the pipeline). The pipeline for SSVEP detection operates as follows:

a) Pre-processing: The raw EEG signals undergo a comprehensive pre-processing stage to remove artifacts and noise. A notch filter and OSCAR (Online Source Component Artifact Removal) were used to eliminate power line noise and artifacts caused by body movements. Additionally, a band-pass filter (5–30 Hz) was applied to retain the relevant frequency components for SSVEP analysis.

b) Channel Selection: The following EEG channels—Pz, PO7, Oz, and PO8—were selected as they are positioned over the visual cortex (occipital lobe), where SSVEP responses are most prominent.

c) Canonical Correlation Analysis (CCA): CCA was computed over each 0.5-second window, comparing the col-

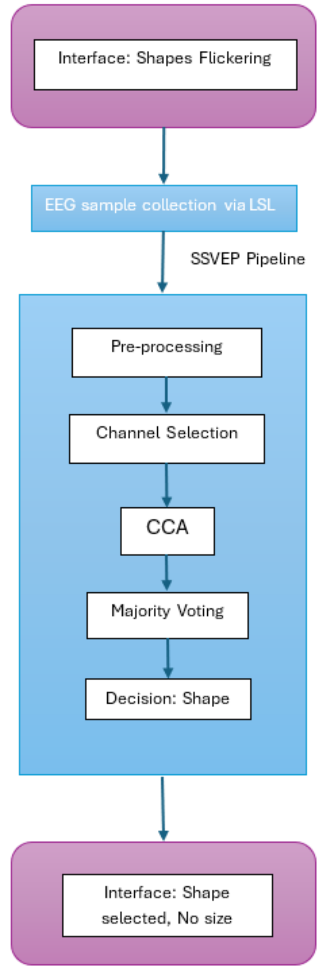

Fig. 6. Overview of the SSVEP-shape selection pipeline.

lected EEG data against reference signals at 6 Hz, 10 Hz, 12 Hz, and 15 Hz, including their harmonics. Based on the highest CCA correlation scores, an intermediate classification decision was made for each window. Each such decision was then saved for final aggregation.

d) Majority Voting: To enhance the robustness and accuracy of the final selection, the individual intermediate decisions from all 0.5-second CCA windows within the 5-second "Look at the flickering shape" phase are aggregated using a majority voting scheme. This method counts the occurrences of each predicted frequency across all windows and prioritizes the frequency with the longest consecutive streak of predictions. In the event of a tie—where multiple frequencies have the same maximum streak length—the system selects the frequency from the most recent longest streak to ensure a timely and definitive decision.

e) Decision: Shape—based on the final decision about the chosen frequency from the majority voting, this chosen frequency is then mapped back to its corresponding graphical shape, and a message is displayed to the user confirming which shape was detected.

4) Visual Attention Pipeline: Following the selection of a shape via the SSVEP pipeline, the system transitions to the visual attention pipeline, which is responsible for controlling the size of the selected shape. This pipeline (see Fig 7 for an overview of the attention pipeline) processes EEG data acquired while the user focuses or unfocuses on a moving central dot, modulating their attention to determine the desired size. The pipeline for visual attention detection operates as follows:

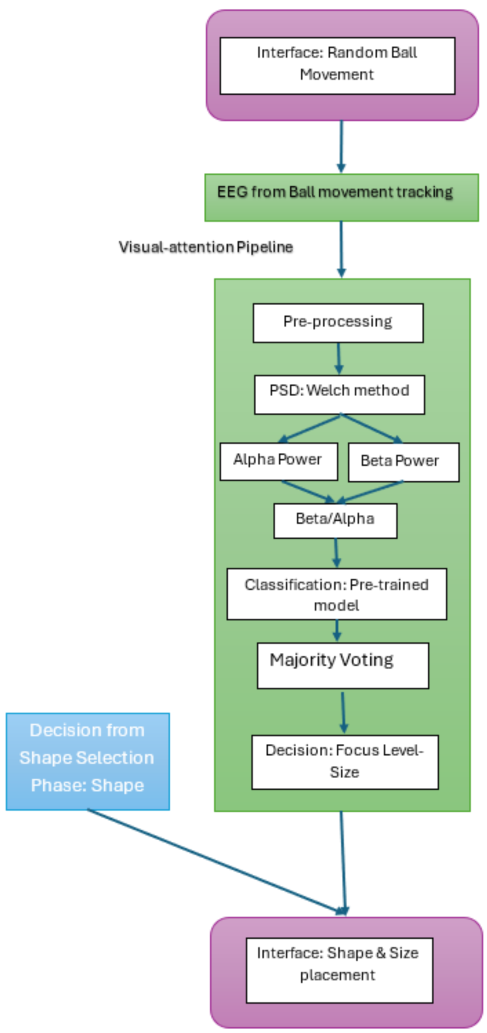

Fig. 7. Overview of the visual attention detection and size control pipeline.

a) Pre-processing: The raw EEG signals undergo a comprehensive pre-processing stage to remove artifacts and noise. A notch filter is applied to eliminate power line interference, while OSCAR (Online Source Component Artifact Removal) is used to remove artifacts caused by body movements. Additionally, a band-pass filter (1–30 Hz) is employed to retain frequency components relevant to attention. For this pipeline, all available EEG channels were utilized for analysis.

b) Power Spectral Density (PSD) Calculation: After preprocessing, the power spectral density (PSD) of the EEG signals is calculated using the Welch method, which estimates the power distribution across frequency bands by dividing the signal into overlapping segments and averaging their periodograms.

c) Feature Extraction (Alpha and Beta Power): From the PSD, specific features related to attention modulation are extracted. A band-pass filtering approach is used to isolate the Alpha band (8–13 Hz) and Beta band (13–30 Hz) frequencies. The average band power is computed for each, and the Beta/Alpha power ratio is then derived. This ratio serves as a key indicator of the user's attentional state, with higher values generally corresponding to greater levels of cognitive focus.

d) Classification: The extracted features are then fed into a pre-trained Random Forest classifier, which was trained using offline EEG data. This classifier outputs a real-time prediction of the user's current attentional level. Each classification decision is made over a 1-second window of EEG data, and each such intermediate decision is saved.

e) Majority Voting: We used similar logic as the SSVEP for the decision-making of the final attention level from 1-second window decisions over a 5-second period. This approach ensures that transient fluctuations are smoothed out, leading to a more stable and accurate assessment of the user's attentional state.

f) Decision: Size—Based on the final classification decision from the majority voting regarding the user's attentional state, the system determines the size of the selected shape. A "focused" state typically corresponds to a "Large" size, while a "not-focused" state corresponds to a "Small" size.

5) Placement: After the user successfully selects a shape via the SSVEP pipeline and determines its size through the visual attention pipeline, the system moves to the placement phase, which is the final step of the BCI control sequence for each object. During this phase, the system takes the confirmed shape and size and displays the corresponding graphical object at a predetermined location on the interface drawing canvas, along with a confirmation message. If the user intends to "Do Nothing," no shape will be placed, and an appropriate message will be shown. Currently, we have implemented the real-time system for a single session where only one shape and size can be selected per session, which will then end the current session.

V. Results & Discussion

The developed EEG-based BCI system was evaluated for its ability to enable intuitive dual-parameter control (shape selection and size adjustment) for simple drawing tasks. A total of 50 trials were conducted in the real-time setup to assess the system's performance. The system's performance in accurately interpreting user intent across different control dimensions is summarized in Table I.

From Table I, we can see that the system demonstrates the fundamental feasibility of dual-parameter control through distinct EEG mechanisms; however, there is significant room for improvement in overall accuracy. The 16% success rate for SSVEP-based shape selection is considerably low, suggesting substantial challenges in reliably distinguishing between target flickering frequencies. Additionally, during the trial, we noticed the system most often selected the Circle (10Hz) more times than other shapes, even when the decision was incorrect. Similarly, the 44% accuracy for attention-based size determination, while performing above chance level for a binary classification task, suggests that the underlying attentional signal was not consistently strong enough for robust real-time control. We also observed a tendency for the system to detect the "Focused" level more than the "Unfocused" level, particularly during incorrect decisions.

A. SSVEP Classification Performance

The very low SSVEP accuracy (16%) highlights a major challenge in correctly detecting the user's intended brain response. Feedback from participants helped explain this issue: they reported that because the shapes were placed too close together, they could still notice flickering from nearby shapes even when trying to focus on just one. This effect, known as visual interference or the spatial proximity effect, occurs when closely spaced flickering stimuli cause the brain to unintentionally process unwanted signals. As a result, the EEG recordings contain mixed frequency information, making it difficult for the CCA classifier to identify the correct target frequency. To verify this, we plotted the power spectrum to check whether a peak appeared at the target frequency (15 Hz), as shown in Fig. 8. We observed that there was no clear peak at 15 Hz—the peaks in the power spectrum were not distinct or significantly higher than the surrounding frequencies. The line remained relatively flat, suggesting a weak or absent SSVEP response, and the system incorrectly predicted 6 Hz as the attended frequency.

Additionally, the system often wrongly selected the circle (10 Hz). One possible explanation is that 10 Hz overlaps with the brain's natural alpha rhythm, which is present when people are awake but relaxed. If a 10 Hz flickering stimulus is used, and the brain already has ongoing 10 Hz alpha activity, the SSVEP signal may blend with this spontaneous rhythm [23]. This makes it difficult to tell whether the signal is from true visual focus or background brain activity. As a result, the system may falsely detect the 10 Hz frequency as dominant, even when the user was attending to a different flicker. These observations highlight the importance of selecting flicker frequencies that are less likely to overlap with natural brain rhythms, and optimizing spatial and frequency separation to improve classification accuracy.

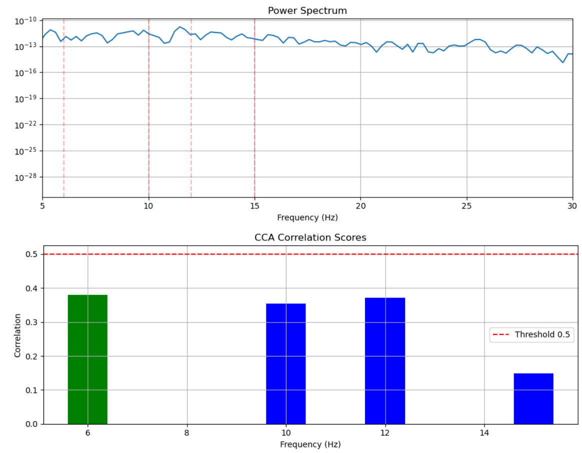

Fig. 8. Power Spectrum and CCA scores for 15-Hz frequency flickering

B. Visual Attention Classification Performance

The visual attention classification component, responsible for determining the shape's size, achieved a 44% accuracy rate, as shown in Table I. This performance indicates only limited success in classifying between "focused" and "unfocused" attentional states. Since random guessing in a balanced binary classification task would yield an expected accuracy of 50%, the observed 44% accuracy suggests the classifier performed slightly worse than chance, raising concerns about the robustness of the attention detection pipeline.

To explore this further, Fig. 9 presents the detailed classification report for the pre-trained Random Forest model trained using offline EEG data. The trained classifier achieved an overall accuracy of approximately 55.21% on the test set, indicating better performance during offline evaluation than in the real-time condition. However, even this result is only marginally better than chance, suggesting potential limitations in the current feature extraction or classification strategy.

```
✅ Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.59      0.57        49
           1       0.55      0.51      0.53        47

    accuracy                           0.55        96
   macro avg       0.55      0.55      0.55        96
weighted avg       0.55      0.55      0.55        96

✅ Accuracy: 0.5520833333333334
```

Fig. 9. Classification report for the Random Forest Classifier

An additional observation was the model's tendency to more frequently classify attentional states as "Focused," even when incorrect. This may indicate a bias toward the "Focused" class within the classifier or suggest that participants generally maintained a higher level of cognitive engagement throughout the task—even during trials labeled as "Unfocused." One contributing factor could be the way we labeled the fo-

TABLE I
TABLE 1: SYSTEM ACCURACY RATES FOR DUAL-PARAMETER BCI CONTROL

Control Dimension	**Correct Trials**	**Incorrect Trials**	**Accuracy Rate (%)**
Shape Selection (SSVEP)	8	42	16%
Size Determination (Attention)	22	28	44%
Total Trials	**50**	**-**	**-**

cused and unfocused data. During the EEG recording session, we observed that signal strength was not always strong or consistent for either class. However, we did not reject any samples with weak signal strength and still labeled them as ”Focused” or ”Unfocused,” which may have introduced noisy or ambiguous training data. This could have further degraded classifier reliability. The current feature set (Beta/Alpha ratio alone) may also be too simplistic to fully capture the nuances of attentional shifts in EEG, especially given the inter-subject variability and subtle nature of cognitive engagement.

VI. CONCLUSION

A. Conclusion

This work set out to answer the fundamental research question mentioned in the I: Can an EEG-based brain-computer interface (BCI) enable intuitive, simultaneous dual-parameter control for simple drawing tasks by combining discrete shape selection with continuous size modulation? Specifically, we investigated whether users could select geometric shapes using steady-state visual evoked potentials (SSVEP) while concurrently adjusting the size of those shapes through attention-related EEG rhythms—thereby allowing simple graphical creation without any muscle involvement. Our results confirm the feasibility of this approach, demonstrating that dual-parameter control via independent EEG mechanisms is achievable, though several challenges remain to be addressed.

This project's key achievements include the real-time integration of SSVEP-based shape selection with an attention-derived EEG signal for size modulation, offering users two degrees of freedom through a simple and intuitive interface. As a proof-of-concept, we developed a functional BCI painting application that enabled users to draw multiple shapes on a canvas using EEG commands, demonstrating the practical potential of this approach.

While the core system functionality, including interface smoothness and data pipeline reliability, was established, the accuracy rates of 16% for SSVEP-based shape selection and 44% for attention-based size adjustment highlight areas requiring substantial improvement. Challenges identified included visual interference between closely spaced flickering stimuli and overlaps between SSVEP frequencies and natural brain rhythms. For attention-based control, consistently extracting robust signals and mitigating bias toward detecting a 'focused' state proved difficult.

Despite these limitations, this project provides valuable proof-of-concept evidence supporting integrated EEG-based BCI systems for intuitive dual-parameter control. The insights gained emphasize the complexities involved in translating brain signals into reliable commands and identify critical areas that must be improved to enhance accuracy and usability in future developments.

B. Future Work

Future improvements to the proposed BCI drawing interface should focus primarily on two areas: enhancing interface components and layout design to address SSVEP performance issues, and collecting a larger, more diverse EEG dataset to improve the accuracy of the attention-based size modulation model. Optimizing stimulus placement and reducing visual overlap could improve SSVEP classification, while training personalized machine learning models on richer EEG data can make attention detection more consistent across users. Additionally, gaze tracking can be integrated to assist with shape positioning or to disambiguate SSVEP target selection by confirming where the user is looking, thereby reducing false positives. A P300 speller module could be used to enable color selection through visual oddball paradigms, while motor imagery could control orientation or toggle between drawing and selection modes to enhance functionality. The system could also benefit from a more immersive and naturalistic user interface; for example, using augmented reality (AR) or virtual reality (VR) displays may improve engagement and spatial interaction while reducing visual fatigue from prolonged exposure to screen-based flickering stimuli. Finally, structured usability studies involving individuals with motor impairments should be conducted to evaluate the system's accessibility, performance, and adaptability in real-world assistive scenarios.

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Appendix

A. Reflection: What We Learned from This Project

Throughout the course of this BCI project, we learned the critical importance of resilience and adaptability in research and development. Initially, our proposal focused on building a complex system for "Detecting and Adjusting Attention Level Through a BCI-Controlled Painting System with Neurofeedback," inspired by the Unicorn Painting application. However, due to licensing constraints, we had to pivot our project direction toward designing a simpler, more focused interface. This change required us to quickly adapt our goals and rethink our approach.

We also learned that the EEG data collection process—selecting appropriate tasks and applying correct preprocessing steps—is crucial for the accuracy of the model and overall system performance. Proper handling of this data can significantly impact the effectiveness of classification and system reliability.

During implementation, we experimented with different components, layouts, visual attention tasks, and classification models. Although our final model did not achieve the desired accuracy, the system architecture, data handling, and pipeline ran smoothly. This iterative process highlighted the need for flexibility and persistence when working with emerging technologies like BCI, teaching us to view challenges as opportunities for growth.

B. Use of AI Assistance and Tools

During the preparation of this work, the authors used AI assistance such as ChatGPT and DeepSeek in order to debug and fix errors in code and provide tips on implementations. Overleaf was used to write this document, with assistance from DeepSeek. Grammarly was also used to check the grammar within this document. After using these tools, the authors reviewed and edited the content as needed.