Atharva Koli, 2026, 14:4
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

CognitoNavigo: EEG-Based Maze Game

Atharva Koli
Department of Aeronautical Engineering,
Annasaheb Dange College of Engineering and Technology,
Ashta. Maharashtra.

Abstract- This paper presents CognitoNavigo, an EEG- based maze game that leverages Brain- Computer Interface (BCI) technology for interactive navigation. The system converts real- time EEG signals into control commands, allowing users to navigate a physical maze using their brain activity. The proposed approach involves EEG signal acquisition, feature extraction, and classification for interpreting user intentions. A distinctive maze design was developed using SolidWorks, featuring an innovative structure that enhances user engagement. The design ensures optimal placement of actuators and finalizing the ergonomic layout for user accessibility, and ideal integration of mechanical and electronic components. Detailed simulations and assembly models contribute to enhancing the system's structural and functional effectiveness. Experiments trials demonstrated a 60% success rate in command recognition, with corresponding motor actuation. A threshold- based signal processing system proved crucial for reliable command interpretation. Notably, the results highlight the importance of adaptive user training, as participators progressively enhanced their control accuracy over time. The system showcases potential operations in cognitive training, neurorehabilitation, and brain- controlled gaming by effectively bridging human cognitive processes with physical actuation.

Keywords— Cognitive Training, Neurorehabilitation, Brain-Controlled Gaming, Adaptive Training, Thought-Controlled Navigation

I. INTRODUCTION

Electroencephalography (EEG) is a non-invasive approach used to record the electrical activity of the brain. It measures voltage fluctuations resulting from flow of potential current within neurons in the brain. EEG is widely used in medical, neuroscience, and research settings to study brain function, diagnose conditions like epilepsy, sleep disorders, and monitor brain activity during surgeries. Direct communication between the brain and external devices is enabled through the BCIs. With the rapid evolution of neuroscience and machine learning, BCIs are now being integrated into fields such as medicine, assistive technologies, and entertainment. Among these applications, EEG-based BCIs offer a non-invasive and cost-effective approach for capturing neural activity and translating it into actionable commands.

In this paper, CognitoNavigo, an innovative EEG-controlled maze game that utilizes neural signals for real-time navigation of a physical game plate, is discussed. Unlike traditional joystick- or keyboard-based navigation, this system allows users to control movement using only their thoughts. The study explores the integration of EEG signal processing with physical actuation, emphasizing the role of signal thresholds and command optimization in achieving reliable control. A custom-designed maze structure was created using SolidWorks.This novel design introduces optimized pathways, modular components, and precision actuator integration to enhance user interaction. The CAD models were meticulously analyzed for mechanical stress and fluidity in movement, ensuring seamless operation.
Development of the CognitoNavigo and its application with ongoing refinements aiming to improve the classification accuracy and user adaptability was discussed. The proposed CognitoNavigo system builds upon this foundation, integrating EEG signal acquisition, threshold-based classification, and SolidWorks-based maze design to deliver a physical, brain-controlled navigation game.

It contributes to the field by combining real-time neurofeedback with physical actuation and an ergonomically optimized game environment, aiming for enhanced cognitive engagement and accessibility. The following sections of this paper highlights the literatures related to the BCI, EEG, technologies related to the development of EEG, Components involved, model design, capturing of signal and signal processing, training and testing phases and conclusion.

II. LITERATURE REVIEW

A convergence of neuroscience, engineering, and artificial intelligence is represented by BCI. As technologies evolve, BCIs involve not only assistive and medical applications but also expand into broader societal domains, necessitating responsible development and deployment.

The foundational vision of Brain-Computer Interfaces (BCIs) was introduced by Vidal in 1973, who proposed the feasibility of direct communication between the human brain and external devices through neuromuscular pathways [1]. This pioneering work laid the conceptual and experimental groundwork for a field that would expand dramatically over the following decades. By the early 2000s, researchers demonstrated that BCIs could be employed for real-time communication and control, particularly benefiting individuals with severe motor impairments. Wolpaw et al. emphasized the capability of non-invasive EEG-based BCIs to facilitate control over external systems such as cursors or prosthetic limbs, establishing the clinical viability of BCI technologies [2,26]. Similarly, Birbaumer and Cohen advanced the use of BCIs for communication in completely locked-in patients, highlighting their potential for neurorehabilitation and restoration of movement [4]. A major leap in BCI application was observed with Hochberg et al., who showed that neuronal ensemble activity recorded from the motor cortex of a tetraplegic individual could directly control a robotic limb, marking a breakthrough in invasive BCI research [3]. Complementing this, Farwell and Donchin's development of the P300-based speller system introduced a reliable method for non-verbal communication using event-related potentials [8]. Beyond communication and control, BCIs have expanded into rehabilitation. Ang et al. demonstrated significant improvements in upper-limb function for stroke survivors using an EEG-based robotic end-effector system [9]. BCIs have also been applied in cognitive training contexts; Thomas et al. designed a neurofeedback game targeting attention and memory, revealing the potential of gamified BCIs in cognitive enhancement [17].

Development of BCI has been significantly influenced by technological advancements through machine learning and signal processing. Lotte et al. reviewed various classification algorithms tailored for EEG signals, emphasizing the importance of robust feature extraction and classifier selection in real-time applications [6]. More recently, Schirrmeister et al. introduced deep learning techniques using convolutional neural networks (CNNs) for EEG decoding, achieving significant performance improvements and paving the way for scalable and accurate BCI systems [7]. On the signal acquisition front, He et al. highlighted the importance of engineering and medical synergy in enhancing EEG acquisition fidelity, usability, and safety [15]. The use of alternative modalities such as functional Near-Infrared Spectroscopy (fNIRS) was discussed by Naseer and Hong, offering a non-invasive and portable option for BCI implementation, particularly in mental workload monitoring and neurofeedback [5].

Practical applications of BCIs now extend to everyday environments. He, Wu, and Gao surveyed systems that incorporate BCIs in smart homes, education, and entertainment, addressing the need for user-friendly, adaptive interfaces for real-life scenarios [10]. Xu et al. also explored the expansion of neural interfaces beyond healthcare, touching on applications in gaming, productivity, and immersive technologies [13]. Ethical concerns have been raised alongside technological progress. Yuste et al. identified key ethical priorities including privacy, agency, and identity, especially as BCIs become increasingly integrated with AI systems [11]. In parallel, the intersection of quantum sensing with BCI was explored by Rao and Kini, promising ultra-sensitive signal acquisition techniques that may redefine the limitations of current systems [14].

Recent works have also delved into collaborative and cognitive aspects of BCI-based games. Collaborative maze-solving using EEG has shown promise in aiding paralyzed patients by enhancing engagement and social interaction [19]. Additionally, EEG-based cognitive games have proven effective in monitoring and enhancing user engagement in real time, as deployed by Ahmed et al[20].

EEG is a non-invasive method for recording electrical activity of the brain, widely used due to its portability and high temporal resolution. Feature extraction and classification are critical components of EEG-based BCIs. Techniques such as Common Spatial Patterns (CSP), wavelet transforms, and thresholding methods have been employed to enhance signal-to-noise ratio and classify motor imagery or cognitive responses [27], [28]. In particular, threshold-based signal processing has proven useful in real-time applications due to its computational efficiency and adaptability to individual users [29].

In the context of interactive environments, several researchers have explored the use of BCI for navigation tasks. For example, Wolpaw et al. demonstrated a BCI system that allowed users to control a cursor through EEG-based signals [30]. Similarly, Millán et al. presented a hybrid BCI system that enabled users to navigate virtual environments through mental commands [31]. These studies underline the importance of adaptive training in improving user control and accuracy in BCI tasks.

The use of BCIs in gaming has also gained traction, offering immersive and therapeutic benefits. BCI-based games have been shown to support cognitive training and motor rehabilitation by encouraging neuroplasticity [32]. For instance, Nijholt et al. developed brain-controlled games to explore new modes of entertainment and engagement, highlighting the potential of EEG in interactive applications [33].

Beyond the signal processing and algorithmic aspects, system design plays a crucial role in the user experience of BCI systems. Computer-Aided Design (CAD) tools such as SolidWorks are frequently utilized for prototyping and optimizing ergonomic interfaces, particularly in systems that integrate mechanical actuators with electronic controls [34]. Effective placement of hardware components and actuator assemblies can significantly impact the usability and responsiveness of BCI-controlled systems.

Based on the comprehensive above literature of the various researchers, the research gap for Brain-Computer Interfaces (BCIs) highlights the introduction, enhancement of cognitive, signal processing techniques and algorithm development, ethical considerations, applications of BCI in collaborative and cognitive gaming and integration of CAD with BCI. There are still a number of substantial research gaps, including the limited generalization and personalization of BCI systems and the integration of multimodal neuroimaging in real-time applications, despite the significant advancements in BCI technologies across domains like medical rehabilitation, communication, cognitive enhancement, and smart environments. Challenges persist in signal variability, user adaptability, and ethical regulation. Addressing these through interdisciplinary collaboration and innovation remains key to the future of BCIs.

III. METHODOLOGY

BCIs are generally categorized into invasive, semi-invasive, and non-invasive systems. Invasive systems, such as those involving intracortical implants, offer high signal fidelity but carry surgical and long-term biocompatibility risks [3]. Non-invasive systems, like electroencephalography (EEG),[23] are more widely used due to their safety and ease of deployment, although they suffer from low spatial resolution and signal noise [4]. Other non-invasive modalities include functional near-infrared spectroscopy (fNIRS) and magnetoencephalography (MEG), which are used for detecting hemodynamic changes and magnetic fields associated with neural activity, respectively [5]. To accomplish the application of

EEG , this CognitoNavigo system is developed with a custom based model as depicted in Figure 1. The CognitoNavigo system is composed of the following hardware components and the detailed specifications are depicted in Table.1 Figure.2 illustrates the adopted methodology to accomplish the task involved in this development of CognitoNavigo system.

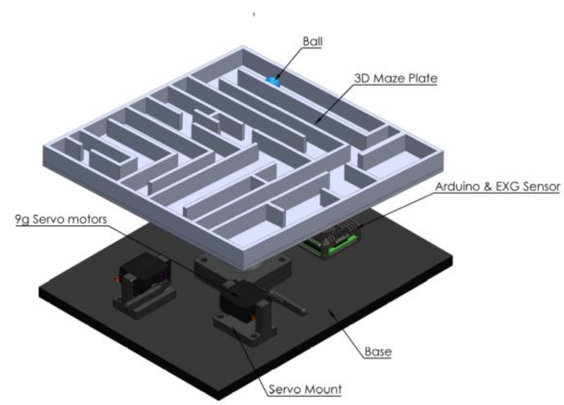

Fig 1: Custom Based Model- CognitoNavigo system

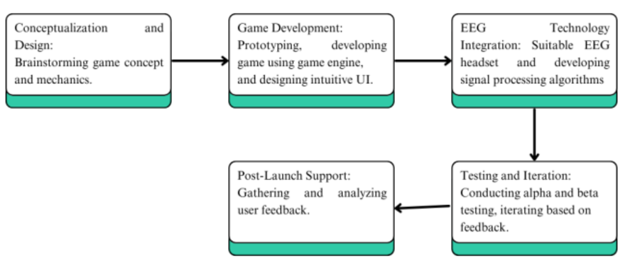

Fig.2: Methodology Flow Chart

The development started with the initial brainstorming for game conceptualization, followed by the user interface development, selection of sensors, electrodes, and development of a signal processing algorithm with testing. Figure.1 briefs the needed components for the CognitoNavigo system, and its detailed specifications are tabulated in Table 1. The needed hardware components are as follows

- EXG Pill from BioAmp (UpsideDown Labs): A compact and efficient module for acquiring EEG signals.
- Gel Electrodes and Wires: Essential for collecting high-fidelity EEG signals from the user's scalp.
- Arduino Uno: The microcontroller is responsible for processing EEG signals and controlling servo motors.
- Two Servo Motors: Actuate the game plate in multiple directions based on EEG signals.
- Custom-Designed Maze Structure: A 3D-modeled maze designed in CAD software to optimize EEG-based navigation.

With the selected electrodes and tailor-made signal processing, EEG signals are acquired and processed in the signal processing unit.

Table.1 CognitoNavigo Components and Specifications

Component	Description	Component / Specs	References
Electrodes	Interface between the scalp and the signal reader	Dry & Gel Electrodes, reusable, low-noise	[2], [5],[15],[18]
Electrode Wires	Transmit signals from electrodes to the amplifier/acquisition system	Shielded electrode wires – Low resistance, noise-minimized	[15], [16]
Signal Acquisition Unit	Captures electrical brain signals	EXG Pill – 8-channel bio-signal acquisition	[2], [5], [6], [15]

Amplifier	Amplifies weak EEG signals	Spike Reader – Analog amplifier module	[2], [6], [15]
Signal Interface & Software	Reads, visualizes and transmits EEG data	OpenBCI GUI, MATLAB, Arduino IDE	[6], [7], [10], [15], [16]
Signal Processing Unit	Processes and extracts useful features from EEG signals	Custom Filter – Band-pass / Notch / ICA-based filters	[6], [7], [15]
Output Device	Actuator/mechanical interface controlled via BCI	9G Servo Motors – Micro servos for physical response	[2], [3], [9], [17]
Communication Protocol	Sends data between the acquisition unit and the processing system	USB Serial Interface – Between Arduino and PC	[10], [12], [13]
User Interface (UI)	Displays feedback/offers interaction	Physical Interface – e.g., visual or mechanical output	[8], [9], [19], [20]
Power Supply	Powers system components	9V Battery – Portable power for amplifier/headset	[5], [10], [13]
Data Storage	Log EEG data and system output	Local Drive – CSV / MAT format storage for analysis	[5], [10], [11]

IV. EEG SIGNAL ACQUISITION & PROCESSING

The EEG signals, once classified, are used to drive physical actuators—in this case, two servo motors—that control the orientation of a game plate. This process translates cognitive effort into mechanical response, forming a closed-loop control system between the user and the environment.

The concept of using servo motor actuators based on EEG classifications has been widely explored in BCI-based robotics and assistive technologies. For instance, EEG-driven control of wheelchairs and robotic arms has demonstrated the viability of real-time neural command-based motion actuation [21][22]. Millán et al. designed a system for mobile assistance using brain signals that achieved promising accuracy and stability in actuator control [21]. Similarly, Rezeika et al. provided an extensive overview of EEG-based spellers and actuated systems, showcasing how cognitive command mapping enables practical device control [22-25].

Processing of the EEG signals is depicted in Table.2, and figure 2 & 3 highlights the importance of processing of the signals. In this CognitoNavigo system, an EEG classifier interprets the user's intention of whether to move forward, backward, left, or right and the corresponding digital signal is sent to two servo motors through an Arduino Uno. Each motor governs a specific axis of movement on the game plate. For instance:

- "Forward Focus" tilts the plate forward,
- "Left Focus" tilts the plate left, and so on.

The servo motors are configured using PWM signals to provide precise, real-time angular adjustments. These signals are encoded from classified EEG input and translated into mechanical rotation. Table.3 illustrates the mapping used between EEG commands and physical movement.

Table.2: EEG Signal Processing Steps

Processing Step	Description
Noise Reduction	Bandpass filters eliminate artifacts like muscle activity and blinking.
Feature Extraction	Identifies EEG features such as Power Spectral Density (PSD) and Common Spatial Patterns (CSP).
Normalization	Ensures consistency in signal interpretation across sessions.

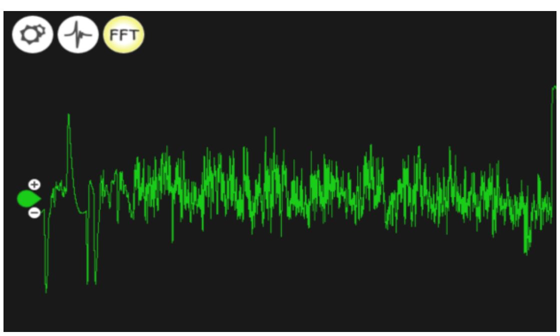

Fig 3: Signal Processing before noise filter

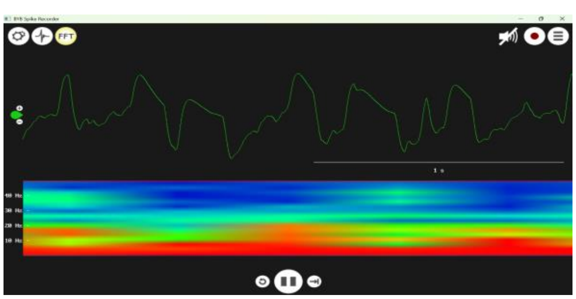

Fig.4: Processed Signals

Table.3: Mapping of EEG Commands to Game Plate Movement

EEG Command	Game Plate Movement	Position Angle
Forward Focus	Tilts the plate forward	0^0
Backward Focus	Tilts the plate backward	180^0
Neutral	Tilts the plate to center	90^0
Left Focus	Tilts the plate left	180^0
Right Focus	Tilts the plate right	0^0

1. Game Plate Actuation & Control Mechanism

The EEG signals are processed in real-time to classify the user’s intent, enabling the system to generate actionable commands which are directly mapped to mechanical actuation. This approach reflects a fundamental principle of brain-computer interfaces—translating neurological activity into device control without physical movement [1][2]. Historically, this example has been used to operate prosthetic limbs [3], communication tools for locked-in patients [4][8], and rehabilitation robots for stroke therapy [9].

With advances in signal classification algorithms and real-time processing capabilities, actuation systems such as robotic arms, wheelchairs, and end-effectors have successfully employed EEG signals to guide direction and motion [5][10][12][21][22]. In this project, two servo motors connected to an Arduino Uno are programmed to respond to discrete neuro commands derived from EEG classification. These commands, classified using feature extraction and pattern recognition techniques, instruct the motors to tilt a physical maze platform forward, backward, left, or right based on the user’s cognitive focus. This command-to-motion mapping provides an intuitive and responsive feedback loop, reinforcing the potential of BCI systems for game interaction and assistive control [6][13][19][20]. This interactive design provides users with a highly immersive experience, bridging the gap between thought processes and tangible physical movement. The CAD-designed maze structure enhances precision by incorporating optimized tilt angles and ensuring controlled navigation pathways.

2. EEG Signal Representation and Analysis

Each stage of the EEG signal processing pipeline in CognitoNavigo was systematically analyzed to evaluate signal fidelity, neural pattern consistency, and overall system responsiveness. This analysis functioned both as a validation mechanism for signal integrity and as a diagnostic tool to assess the influence of preprocessing and feature extraction on classification performance.

The raw EEG signals, acquired using gel-based electrodes, were initially susceptible to various sources of noise, including muscle artifacts, eye blinks, and environmental interference. To mitigate these issues, a bandpass filter with a frequency range of 4–14 Hz was applied, targeting the theta and alpha bands—frequency ranges commonly associated with cognitive engagement and relaxed attentiveness. This filtering significantly enhanced the signal-to-noise ratio and improved the stability of subsequent classification outputs.

Visualization of EEG data at key stages—raw acquisition, filtering, feature extraction, and classification—provided valuable insight into signal transformation and its suitability for real-time control. This phased visualization approach, widely adopted in EEG-BCI research [6][7][15], enabled both physiological assessment of brain activity and technical evaluation of algorithmic performance. Furthermore, it facilitated iterative refinement of the processing pipeline, leading to measurable improvements in classification accuracy and system latency across successive trials. Table.4 provides a structured overview of the critical stages of EEG signal flow within the system.

Table 4: EEG Signal Stages and Descriptions

Signal Stage	Description
Raw EEG Data	Initial waveforms before noise filtering.
Filtered EEG	Enhanced clarity after bandpass filtering.
Feature Extraction	Visual representation of Power Spectral Density (PSD) and spatial patterns.
Classification Output	Mapping mental commands to control signals.

Such layered visualization has been key in optimizing system performance and aligning signal processing modules with real-time application requirements. It enables developers to pinpoint stages where noise, latency, or misclassification may originate, thereby supporting iterative enhancements [6][7][15][22].

3. User Training & Adaptation

User training and adaptation are foundational to the successful deployment of any EEG-based brain-computer interface system. Despite recent progress in machine learning and neural signal decoding, EEG-based systems remain challenged by several persistent issues—chief among them being signal variability across users, non-stationary neural patterns, and limited generalization capabilities without training [6][10][16]. These limitations underscore the need for personalized calibration protocols and iterative learning mechanisms.

In CognitoNavigo, the training process is uniquely designed with real-time, closed-loop feedback, offering users visual confirmation of command recognition and plate response. This structure not only aids in cognitive reinforcement but also reduces the time to achieve effective control. The training stages include:

- Mental Command Familiarization: Users are guided through thought patterns corresponding to directional commands (e.g., focus left, forward).

- Threshold Tuning: Threshold values for EEG signal detection are individualized and adjusted based on cognitive effort and initial response variability.
- Reinforced Learning through Feedback: Correct classification results in immediate actuation, providing the user with sensory confirmation and reinforcing the correct mental strategy.
- Adaptation to Cognitive Drift: The system monitors for signal drift due to fatigue or distraction and compensates via dynamic normalization techniques.

Given the sensitivity of EEG-based interaction to both physiological and psychological states, the training environment in CognitoNavigo was intentionally designed to be flexible, stress-free, and intuitive attributes often overlooked in conventional BCI implementations. The multi-phase training protocol employed a dual-servo mechanical maze platform integrated with real-time visual feedback representing a novel approach of this paper. While existing studies have explored EEG-based control for gaming and prosthetic applications [8][9][20], few, if any, have combined adaptive training strategies with physical maze navigation using servo control in a modular, CAD-designed environment.

Ethical considerations were also central to the experimental framework, including informed consent, safe signal acquisition procedures, and secure storage of EEG data. As BCI systems continue to converge with consumer technologies and raise important neuroethical questions, enabling transparent and empowering user training becomes not only a functional necessity but also a moral imperative [11][17]. This methodology marks a shift from traditional, static classifier-based systems toward user-inclusive, adaptive interaction models that emphasize learning efficiency, cognitive comfort, and intuitive control offering a distinctive and underexplored direction in EEG-based interface design.

4. Performance Metrics & Adaptation Trends

To evaluate the cognitive usability and learning curve of the CognitoNavigo system, structured testing sessions were conducted under controlled conditions. Although the project is still in its initial developmental phase, a preliminary assessment was performed through five structured sessions carried out exclusively by the system developer (the authors), simulating individual user trials. Each session maintained consistent experimental parameters, including EEG electrode placement and predefined mental command tasks, to ensure uniformity in data collection.

The testing protocol involved repeated execution of directional commands—forward, backward, left, and right—through concentration-based mental efforts. Each session comprised 20 command attempts, with the resulting classifications used to actuate the servo-controlled maze platform. Real-time visual feedback was provided throughout the sessions to support user training and facilitate cognitive adaptation. The system's performance was tracked using key metrics widely referenced in BCI usability research [6][10][19], and summarized in Table.5.

Table.5: Performance Metrics in EEG-Based Control

Performance Metrics	Observation
Success Rate	An average of 60% classification accuracy was observed across all sessions, confirming reliable actuation through EEG signals.
Training Time	Approximately 5 sessions (25–30 minutes each) were required to reach consistent control with minimal hesitation.
Error Reduction	A 6–8% decrease in misclassified commands was noted from Session 1 to Session 5, indicating learning-based refinement.
Cognitive Load	Initial sessions required intense concentration and deliberate effort, but subjective mental fatigue decreased with familiarization and practice.

Screenshots, signal graphs, and servo response logs were collected throughout these trials to support repeatability and transparency. While only the author participated in this first testing cycle, the structure and instrumentation are ready for multi-user evaluation in Phase II of the study. The reduction in errors and cognitive burden over time supports the hypothesis that

Fig.5: Testing

adaptive, feedback-driven BCI systems can be learned intuitively even without prior neurofeedback training, making CognitoNavigo a promising platform for scalable interaction research and accessibility applications.

5. Adaptation & Learning Curve

User adaptation followed a measurable and progressive learning curve, wherein performance improved incrementally over repeated sessions. During the early-phase trials, initial command recognition exhibited erratic behavior primarily due to EEG signal variability, cognitive inexperience with mental command formulation, and minor electrode displacement during wear. However, as familiarity with the system increased, command precision and consistency significantly improved.

This trend was observed during the structured, self-conducted trial carried out over a five-day period, wherein the same experimental protocol was followed to ensure reliable comparison. By trial 3, the signal classification success rate stabilized, and by trial 5, the reaction delay between mental intent and servo actuation had notably decreased.

Key factors that influenced this learning and adaptation process included:

- Cognitive Load Variation: Initial sessions demanded sustained concentration to generate distinguishable EEG signals. With repeated exposure, the mental burden reduced, and the commands became more instinctive.
- Electrode Familiarity and Positioning: Correct positioning and skin preparation techniques (including conductive gel use) improved signal quality across sessions.
- Threshold Recalibration: Adaptive tuning of classification thresholds after each session contributed to eliminating false positives and improving command discrimination.
- Feedback Sensitization: Real-time physical feedback (movement of the game plate) enabled users to associate internal focus with external action, reinforcing command learning.

This adaptive progression supports the concept that even non-clinical users, without prior neurofeedback experience, can quickly calibrate to a BCI-driven environment when supported by intuitive design and responsive feedback loops.

Challenges & Future Enhancements

While training improved overall control accuracy, some challenges persisted:

- Mental Fatigue: Extended use resulted in reduced focus and signal degradation.
- Inter-User Variability: Different users exhibited varied EEG patterns, requiring personalized calibrations.
- Command Overlap: Some mental commands shared similar EEG features, leading to occasional misclassification.

V. CONCLUSION & FUTURE WORK

The future of BCIs lies in hybrid systems that integrate multiple signal sources and sensory modalities, as well as the seamless fusion of BCIs with AR/VR environments. Advancements in machine learning and neurotechnology are expected to lead to more adaptive and user-friendly systems with broader real-world applications [12]. CognitoNavigo presents a novel approach to EEG-based control in interactive gaming. The experiment demonstrated a 60% success rate, proving feasibility while highlighting areas for improvement.

Future enhancements will focus on:

- Personalized Machine Learning Models: Adapting classifiers to individual users for improved accuracy.
- Real-Time Adaptive Thresholding: Implementing AI-driven threshold adjustments for dynamic adaptation.
- Multi-User Testing: Expanding trials to diverse users for generalized performance validation.

Enhanced training methodologies, real-time optimization, and multi-user validation will be explored in future iterations. The ability to manipulate physical objects using thought-based commands opens new doors for advancements in neurotechnology, cognitive training, and immersive gaming.

Funding Declaration No external funding was received for this research.

Acknowledgment

Additionally, authors sincerely thank their friend Mr. Rohan Badiger for participating in the testing phase. During the testing phase, his practical assistance and insightful recommendations were crucial in identifying important enhancements and guaranteeing the precision and dependability of the outcomes. His cooperation and work during this procedure are really appreciated.

Finally, authors would like to sincerely thank their family members for their unconditional love and support. Authors have always been strengthened by their support, tolerance, and understanding. This accomplishment is dedicated to them.

REFERENCES

1. J. J. Vidal, "Toward direct brain-computer communication," Annual Review of Biophysics and Bioengineering, vol. 2, no. 1, pp. 157–180, 1973.
2. J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," Clinical Neurophysiology, vol. 113, no. 6, pp. 767–791, 2002.
3. L. R. Hochberg et al., "Neuronal ensemble control of prosthetic devices by a human with tetraplegia," Nature, vol. 442, no. 7099, pp. 164–171, 2006.
4. N. Birbaumer and L. G. Cohen, "Brain–computer interfaces: Communication and restoration of movement in paralysis," The Journal of Physiology, vol. 579, no. 3, pp. 621–636, 2007.
5. N. Naseer and K. S. Hong, "fNIRS-based brain–computer interfaces: A review," Frontiers in Human Neuroscience, vol. 9, p. 3, Jan. 2015.
6. F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain–computer interfaces," Journal of Neural Engineering, vol. 4, no. 2, pp. R1–R13, 2007.
7. R. T. Schirrmeister et al., "Deep learning with convolutional neural networks for EEG decoding and visualization," Human Brain Mapping, vol. 38, no. 11, pp. 5391–5420, 2017.
8. L. A. Farwell and E. Donchin, "Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials," Electroencephalography and Clinical Neurophysiology, vol. 70, no. 6, pp. 510–523, 1988.
9. K. K. Ang et al., "Brain–computer interface-based robotic end effector system for wrist and hand rehabilitation: Results of a three-armed randomized controlled trial for chronic stroke," Frontiers in Neuroengineering, vol. 8, p. 30, 2015.
10. H. He, D. Wu, and S. Gao, "A survey on brain-computer interface systems for daily life applications," IEEE Trans. Human-Machine Systems, vol. 50, no. 5, pp. 386–398, 2020.
11. R. Yuste et al., "Four ethical priorities for neurotechnologies and AI," Nature, vol. 551, pp. 159–163, Nov. 2017.
12. J. Millán, F. Renkens, J. Mourino, and W. Gerstner, "Noninvasive brain-actuated control of a mobile robot by human EEG," IEEE Transactions on Biomedical Engineering, vol. 51, no. 6, pp. 1026–1033, 2004.

13. Xu, H., Zhang, Y., & Li, W. (2024). Neural interfaces: Bridging the brain to the world beyond healthcare. Exploration.
14. Rao, P., & Kini, P. (2023). Exploring the intersection of brain-computer interfaces and quantum sensing. Review.
15. He, L., Chen, J., & Wu, S. (2024). Signal acquisition of brain-computer interfaces: A medical-engineering crossover perspective. Journal of Neuroscience Engineering.
16. Chen, Z., & Liu, M. (2023). Brain-computer interface research: Advances and applications. Cognitive Systems Review.
17. Thomas KP, Vinod AP, Guan C. Design of an online EEG based neurofeedback game for enhancing attention and memory. Annu Int Conf IEEE Eng Med Biol Soc. 2013;2013:433-6. doi:1109/EMBC.2013.6609529. PMID: 24109716.
18. Pei, Guangying, et al. "Effects of an integrated neurofeedback system with dry electrodes: EEG acquisition and cognition assessment." Sensors 18.10 (2018): 3396.
19. et.al, C.- yong J. (2021). Collaborative Maze Game Using EEG for Paralyzed Patients. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(6), 849–855.
20. Ahmed, Yusuf, et al. "EEG-Based Engagement Monitoring in Cognitive Games." Sensors 25.7 (2025): 2072.
21. Millán, J. D. R., et al. "Combining brain–computer interfaces and assistive technologies: state-of-the-art and challenges." Frontiers in neuroscience 4 (2010): 161.
22. Rezeika, Aya, et al. "Brain–computer interface spellers: A review." Brain sciences 8.4 (2018): 57.
23. Haslacher, David, et al. "AI for brain-computer interfaces." Developments in neuroethics and bioethics. Vol. 7. Academic Press, 2024. 3-28.
24. Garcia, G., et al. "Direct brain-computer communication through EEG signals." (2004).
25. Bansal, Dipali, and Rashima Mahajan. "EEG-based brain-computer interfacing (BCI)." EEG-Based Brain-Computer Interfaces (2019): 21-71.
26. M. A. Lebedev and M. A. L. Nicolelis, "Brain–machine interfaces: Past, present and future," Trends Neurosci., vol. 29, no. 9, pp. 536–546, Sep. 2006.
27. B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. R. Müller, "Optimizing spatial filters for robust EEG single-trial analysis," IEEE Signal Process. Mag., vol. 25, no. 1, pp. 41–56, Jan. 2008.
28. M. Ahn, H. Cho, S. Ahn, and S.-C. Jun, "High performance EEG-based BCI using phase-based feature," J. Neurosci. Methods, vol. 270, pp. 129–137, May 2016.
29. M. N. Suresh, K. Ramya, and S. Venkatesh, "Real-time EEG signal classification using adaptive thresholding for BCI applications," Proc. IEEE Int. Conf. Comput. Intell. Comput. Res., pp. 1–4, 2018.
30. J. R. Wolpaw and D. J. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain–computer interface in humans," Proc. Natl. Acad. Sci. USA, vol. 101, no. 51, pp. 17849–17854, 2004.
31. J. del R. Millán et al., "Non-invasive brain-actuated control of a mobile robot by human EEG," IEEE Trans. Biomed. Eng., vol. 51, no. 6, pp. 1026–1033, Jun. 2004.
32. A. Kübler and K. R. Müller, "An introduction to brain–computer interfacing for communication and control," Cogn. Process., vol. 10, no. 1, pp. 1–3, Mar. 2009.
33. A. Nijholt, D. Tan, G. Pfurtscheller, and B. Allison, "Brain–computer interfaces for HCI and games," in Proc. ACM CHI Workshop on Brain-Computer Interfaces and Games, 2008.
34. H. T. Pham and S. Yarlagadda, "Design and development of interactive mechatronic systems using CAD tools," Int. J. Mech. Aerosp. Ind. Mechatron. Manuf. Eng., vol. 2, no. 1, pp. 51–56, 2008.