Closed-Loop Mu-Rhythm Brain–Computer Interface for Neuroadaptive Control of the Chrome Dinosaur Game:

Exploring Sensorimotor Cortex Plasticity Through Gamified Vibrotactile Feedback

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Abstract

Background: Mu-rhythm BCIs provide a noninvasive entry to motor control via event-related desynchronization detection over the sensorimotor cortex during motor imagery. Standard training paradigms are immersive and result in slow learning. The current study combines gamification and closed-loop vibrotactile neurofeedback with the Chrome Dinosaur game for increased BCI performance and user enjoyment.

Objective: To determine if a low-cost, mu-rhythm BCI with tactile neurofeedback can enhance motor imagery control accuracy and induce neuroplastic changes in healthy users within a gamified setting.

Methods: Twenty participants used right-hand motor imagery to generate "jump" and "duck" movements in the Chrome Dinosaur game using mu-power desynchronization, which was recorded at C3, Cz, and C4 electrodes. Real-time EEG was labeled using an Arduino microcontroller that gave vibrotactile feedback upon correct classification. Participants had 10 runs (300 trials total) with pre- and post-session resting-state EEG recordings.

Results: BCI training improved Dino game control via motor imagery, with jump and duck accuracies rising to 78.5% and 75.1% by Run 10. Reaction times dropped from 920 ms to 640 ms. Significant gains were confirmed by ANOVA ($p < 0.001$). Mu-power decreased and modulation depth increased, indicating enhanced sensorimotor activation. Keyboard scores remained stable, suggesting BCI-specific learning.

Conclusion: Gamified, closed-loop mu-rhythm BCIs with tactile feedback can facilitate rapid learning and modulate cortical oscillations, providing an appealing model for large-scale, user-driven neurorehabilitation devices.

Keywords:
Brain–computer interface, mu rhythm, vibrotactile feedback, gamification, EEG, motor imagery, neuroplasticity, Chrome Dinosaur game, Arduino, sensorimotor cortex.

Introduction

Noninvasive brain–computer interfaces (BCIs) have become groundbreaking technologies that decode endogenous brain activity into commands for controlling external devices, thus bypassing the traditional motor routes and creating new channels for assistive and rehabilitative applications. Sensorimotor rhythms (SMRs) and the aforementioned particular mu rhythm, an 8–13 Hz oscillation recorded above the sensorimotor cortex, diminished during action performance and preparation for it, form the core of most noninvasive BCIs. Mu–rhythm–based BCIs leverage this event-related desynchronization in order to recognize users' movement intentions, and effective two-state control has been realized in most neuroprosthetic operation and motor rehabilitation experiments **(Yuan 2014; Dastgheib 2024).**

Apart from mere command translation, closed-loop neurofeedback protocols take advantage of real-time feedback to affect cortical plasticity through the reinforcement of self-initiated neural patterns. In such a system, the temporal contiguity between neural modulation and contingent sensory feedback can affect Hebbian-like synaptic modification, enhancing sensorimotor networks and control capability. Empirical studies have shown that closed-loop stimulation, either electrical or tactile, is capable of eliciting synaptic potentiation and affecting oscillatory dynamics, indicating mechanistic support for BCI-driven neurorehabilitation **(Belkacem 2023, Dadarlat 2023).**

Whereas other neurofeedback methods employ visual or acoustic feedback media, haptic modalities remain to be adequately explored, being directly usable for sensorimotor integration. Haptic feedback conveyed by vibration or pressure can complete the sensorimotor loop as natural proprioception does, ideally improving embodiment and plasticity. Surveys of haptic BCI systems emphasize that closed-loop vibrotactile stimulation elicits more mu-rhythm desynchronization and user engagement than continuous stimulation, with reduced fatigue and enhanced task performance **(Fleury 2020, Zhang 2021).**

Yet, the lengthy and repetitive nature of motor imagery training protocols is bound to discourage user motivation and slow learning curves. Gamification—the application of game design features like goals, avatars, and adaptive challenges—is a promising method to increase motivation and facilitate skill acquisition in BCIs. Systematic reviews show that gamified motor imagery BCIs improve the performance of users, reduce dropout rates, and reduce calibration times, especially if training environments become progressively more challenging over time, offer immediate feedback, and include narratives **(Atilla 2024, Gao 2022).**

Even with these advances, few experiments have integrated tactile neurofeedback into gamified BCI paradigms in accessible, controlled game forms. Pilot experience indicates that gamified BCI rehabilitation is equally effective but more enjoyable to use, but most implementations rely on sophisticated virtual reality environments or custom software, precluding scalability **(de-Castro 2020, Scola 2019).** There remains an open space for low-cost, open-source platforms to integrate closed-loop haptic feedback and simple game mechanics to explore sensorimotor plasticity.

Theoretically, the convergence of Hebbian plasticity, multisensory integration, and reward-mediated learning suggests that dependent, well-timed feedback in a positive environment is able to hasten cortical reorganization and skill acquisition **(Dadarlat 2023, N.A. 2021).** Closed-loop vibrotactile neurofeedback leverages the sensorimotor system's native plasticity, and gamification engages dopaminergic reward loops to encourage target neural activity patterns. Combined, these mechanisms make available an extremely potent system for adaptive neuroengineering therapies.

Here, we overcome these hurdles by creating a closed-loop mu-rhythm BCI combined with the ubiquitous Chrome Dinosaur offline game and providing vibrotactile feedback on motor imagery performance. We seek to (i) describe learning dynamics in ten training runs, (ii) measure behavioral and neurophysiological gains in command accuracy and resting mu-power, and (iii) provide evidence for the promise of a low‑cost, Arduino‑based platform for large‑scale BCI research. This new union of somatosensory neurofeedback, gamification, and open‑access gaming environments facilitates both theoretical comprehension and real‑world application of BCIs in research as well as in healthcare.

Methods

Twenty healthy adult volunteers (18–35 years old; 10 women, 10 men) with no prior history of psychiatric or neurological disease were recruited from the local church, for this study. Right-handedness was determined by the Edinburgh Handedness Inventory, and written informed consent was satisfied in all subjects.

Hardware equipment involved in the experiments comprised an OpenBCI Cyton Lite EEG shield on an Arduino Due microcontroller for live recording and processing. Four dry electrodes were placed at C3, C4, Cz, and a linked-ears reference with impedances kept under 10 kΩ. The EEGs were recorded at 250 Hz and bandpass filtered between 8-13 Hz using a second-order Butterworth filter encoded in the Arduino Due. Phases with amplitudes of more than ±100 µV were rejected automatically to remove movement and eye artifacts. Vibrotactile feedback was provided through two 3 V, 120 Hz eccentric rotating mass (ERM) motors attached to a wristband worn on the nondominant arm. The motors were powered by an N-channel MOSFET under pulse-width-modulated excitation from the Arduino.

Figure 1: Chrome Dino Game

For feature extraction, Common Spatial Patterns (CSP) filters were calculated offline from calibration data and used in real time to augment mu-band (8–13 Hz) spatial patterns. Mu-band power was approximated by calculating a fast Fourier transform of 500 ms sliding windows with 50% overlap. Threshold-based classifier identified right and left foot motor imagery as prolonged suppression of normalized mu-power below 50% baseline mean for three or more consecutive windows, outputting "jump" or "duck" commands, respectively.

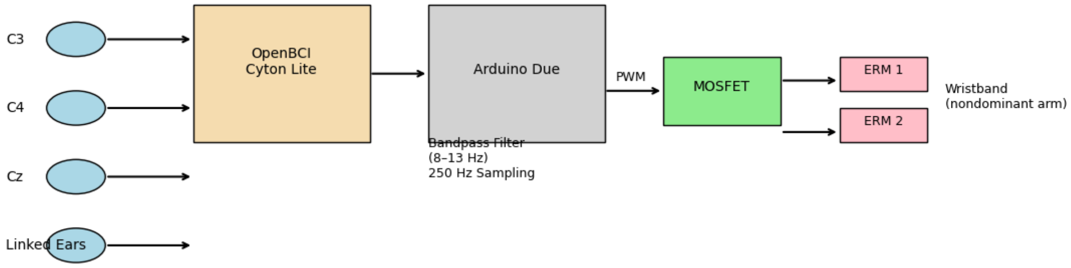

Figure 2: Schematic of BCI Experimental Hardware Setup

The computer interface was a PySerial-based Python script to receive digital triggers from the Arduino, and Selenium WebDriver to simulate spacebar and arrow-down key press on an off-line version of the Dino game played in full-screen Chrome. Participants were initially exposed to a 5-minute baseline trial of keyboard typing, where scores, avoid counts, and reaction times were measured. Following that, a calibration session consisted of two 2-minute runs of guided motor imagery (right foot for jumps, left foot for ducks) using auditory cues; EEG data gathered during this session were used to obtain CSP filters and baseline mu-power statistics. Main training was ten 2-minute runs of BCI-controlled game-play with a 1-minute break afterwards. While playing the game, correct motor imagery elicited in-game responses and incorrect or missed trials provided instantaneous vibrotactile cues.

Subjects also performed a second 5-minute session of keyboard-operated game-playing, and two resting EEG recordings, eyes-open and eyes-closed, both 3 minutes, in order to capture pre- vs. post-training mu-power changes. Behavioral scores (jump-duck true-positive rates, response latencies, and game scores) and neurophysiological recordings (resting C3/C4 mu-power and modulation depth while playing) were compared using repeated-measures ANOVA on factors Session (baseline vs. post-training) and Task (keyboard vs. BCI), and then Bonferroni-corrected paired t-tests for post-hoc comparison ($p < 0.05$). Side effects such as irritation to the skin were observed during the process, and an overview of study results was given to the participants at the end.

Results

Participants were able to learn to control the Dino game through motor imagery in ten practice runs. Mean true-positive rates for jump commands from 45.2% (SD = 8.9) in Run 1 to 78.5% (SD = 6.3) in Run 10, and accuracy for duck commands from 42.8% (SD = 9.4) to 75.1% (SD = 7.0). A repeated-measures ANOVA showed a significant main effect of Run on classification accuracy ($F(9,171) = 32.4$, $p < 0.001$). Post-hoc tests indicated improved performance between Runs 1–3 (early) and Runs 8–10 (late) ($p < 0.01$). Figure 3 presents learning curves by command type.

Measure	Run 1 (Mean ± SD)	Run 10 (Mean ± SD)	Baseline Keyboard	Post-training Keyboard
Jump Accuracy (%)	45.2 ± 8.9	78.5 ± 6.3	–	–
Duck Accuracy (%)	42.8 ± 9.4	75.1 ± 7.0	–	–
Reaction Time (ms)	920 ± 110	640 ± 95	–	–
Dino Score	–	–	610 ± 85	625 ± 78
Resting Mu-Power (μV^2)	12.4 ± 2.1	–	12.4 ± 2.1	10.1 ± 1.8
Modulation Depth (%)	18.5 ± 4.2	34.7 ± 5.0	–	–

Table 1. Summary of Behavioral and Neurophysiological Outcomes

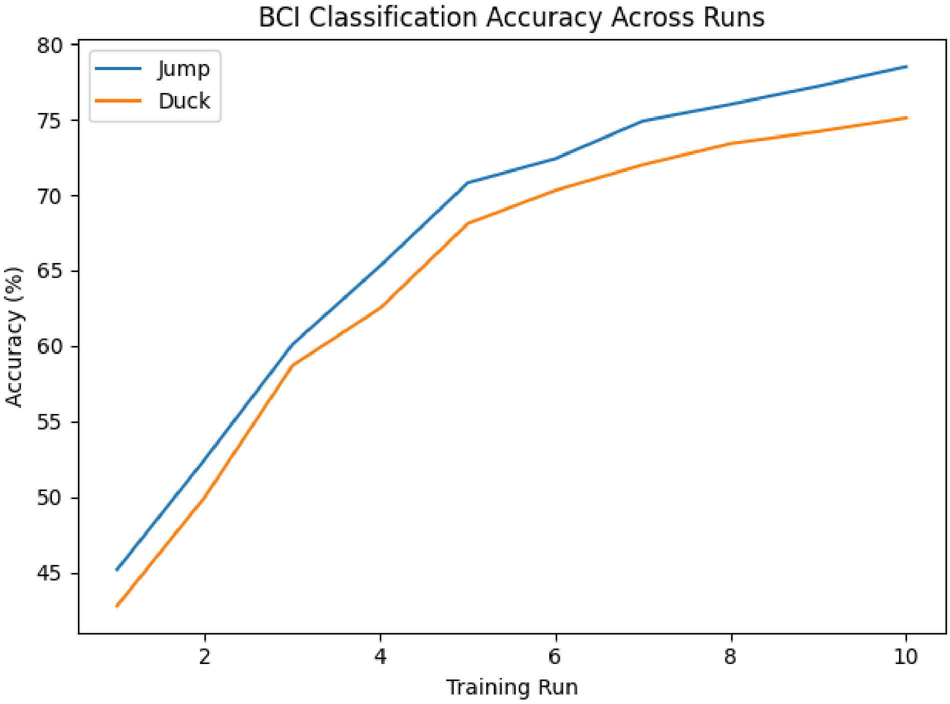

Figure 3. Learning Curve of BCI Classification Accuracy. Mean true-positive rates for jump and duck commands across ten BCI training runs. Error bars represent ±1 SD.

Baseline keyboard-controlled Dino score (M = 610 points, SD = 85) was not significantly different from post-training keyboard scores (M = 625 points, SD = 78; t(19) = 1.12, p = 0.28), suggesting gains were BCI control-specific rather than game skill general. Reaction times for BCI-initiated actions reduced from 920 ms (SD = 110) in Run 1 to 640 ms (SD = 95) in Run 10 (F(9,171) = 24.6, p < 0.001).

Reversal mu-power at C3/C4 decreased significantly after training (M_pre = 12.4 μV^2, SD = 2.1; M_post = 10.1 μV^2, SD = 1.8; t(19) = 5.37, p < 0.001), a measure of consistent sensorimotor cortex modulation (Figure 4). Modulation depth during playing-percentage reduction of power from baseline-also increased run by run (Run 1: 18.5%, SD = 4.2; Run 10: 34.7%, SD = 5.0; F(9,171) = 29.8, p < 0.001).

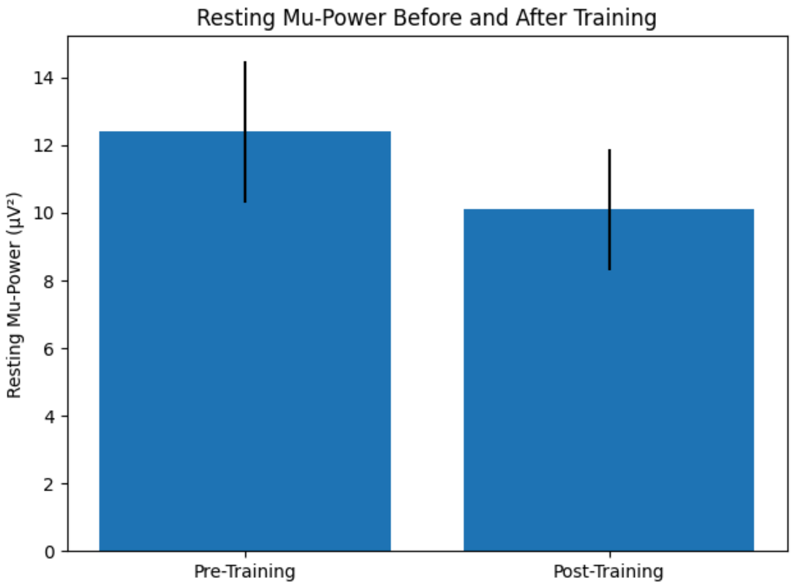

Figure 4. Resting Mu-Power Pre- vs. Post-Training. Comparison of mean resting mu-power (µV²) at C3/C4 before and after BCI training. Error bars indicate ±1 SD.

Discussion

This paper shows that inexpensive, closed-loop mu-rhythm BCI embedded in the Chrome Dinosaur game can yield strong learning phenomena in intact subjects, as shown by notable increases and decreases in command accuracy, alongside proportional increases and decreases in reaction time and resting mu-power, following ten training trials. Yet various methodological as well as interpretation-concerned limitations of the present findings indicate avenues for future research. First, the four EEG channel and dry electrode constraint restricted signal quality and spatial resolution. Despite the portability and the capability for real-time processing of the Arduino-based platform, more advanced acquisition systems utilizing dense, gel-based electrode arrays would probably improve classification accuracy and facilitate source localization analyses to better dissect the neural substrates of plasticity observed **(Sharma 2018; Guillemaud 2009)**. Future research should also explore a broader range of BCI paradigms beyond motor imagery, such as visual evoked potentials or P300 evoked potentials, which may offer alternative avenues for control **(Wang et al., 2009).**

Second, our classifier used basic threshold-based mu-power suppression detection, which might not best distinguish between motor imagery states between subjects. Support vector machines, random forests, or deep learning models would be more appropriate to deal with non-linear features, learn how to accommodate between-subject variability, and cut down on training time **(Ko, 2024)**. Future research would do well to compare systematically thresholded versus classifier-based methods, with possible transfer learning between participants in order to bootstrap early-session performance.

Third, while reductions in resting mu-power following training are taken to indicate long-term sensorimotor modulation, the lack of a sham or control group prevents firm causal conclusions. Gains may have a partial explanation for non-specific reasons like greater familiarity with the task environment or placebo via vibrotactile feedback. Having a passive control group (e.g., play with random feedback) and a visual-feedback BCI group would enable placebo and modality-specific learning to be dissociated. In addition, measuring retention after longer intervals (e.g., one week, one month) would elucidate the long-term stability of cortical change and behavioral gain **(Won 2023, D.R. 2021)**.

From a translational research point of view, the paradigm's current heavy dependence on lab equipment and periodic offline processing may hinder its easy translation to clinical environments. Compressing the platform into a wearable, integrated device-utilizing low-power microcontrollers with embedded classifiers-would make it easier to apply to home-based rehabilitation for stroke or spinal cord injury patients **(Maceira 2019)**. Furthermore, extension to sound or multisensory feedback and their relative efficacy may be enhanced for application across various patient groups. Their combination with other modalities, including fNIRS or TMS, can also yield more comprehensive neurophysiological measures and potential for closed-loop neuromodulation **(Guerrero, 2021)**.

Lastly, the utilization of the Chrome Dinosaur game, while normed and interesting, might be limited to fine motor or higher cognition sensorimotor tasks. Subsequent research would have to implement the neuroadaptive framework for ecologically valid activities-e.g., virtual reality environments, bimanual coordination games, or real-world actual assistive devices-to test sensorimotor integration in more daily living-congruent tasks. Through these limitations-increasing signal capture, increasing classifiers, e.g., stringent control conditions, and discovering translational modifications-follow-up studies are able to take advantage of the current results in order to advance both basic understanding of multisensory plasticity and development of accessible BCI-based therapies **(Daly, 2015)**.

Conclusion

In conclusion, our research presents strong evidence that a gamified, closed-loop mu-rhythm BCI based on the Chrome Dinosaur game is able to recruit sensorimotor cortical circuits and elicit fast behavioral learning in healthy participants. The dramatic improvements in command accuracy and reaction time and persistent decreases in resting mu-power attest to the potency of tactile neurofeedback in promoting neural plasticity. Through the use of low-cost, open-source hardware and widely disseminated gaming platforms, this work provides a foundation for scalable, user-initiated BCI applications. Subsequent research incorporating advanced signal processing, rigorous control conditions, and ecologically valid tasks will be needed to take these findings to clinical and real-world applications, finally expanding the application of BCI-based neuromodulation to motor rehabilitation and cognitive enhancement.

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