A Low-Cost EEG-Based Neurofeedback Game Using a Social Robot for Attention Training in ADHD

Ignacio Pla Penalba[1], Mostafa Haghi[2][0000−0001−8966−0176], and Nima TaheriNejad[1,2][0000−0002−1295−0332]

[1] Institute of Computer Technology, TU Wien, Vienna, Austria
[2] EclectX Team, Institute for Computer Engineering, Heidelberg University, Heidelberg, Germany
{mostafa.haghi, nima.taherinejad}@ziti.uni-heidelberg.de

Abstract. Attention-Deficit Hyperactivity Disorder (ADHD) is a prevalent neurodevelopmental condition characterized by inattention, impulsivity, and hyperactivity, often persisting into adulthood and substantially affecting academic and social functioning. While pharmacological treatments are effective for many individuals, non-pharmacological approaches such as neurofeedback have gained increasing attention as complementary interventions. However, existing neurofeedback systems are typically expensive, stationary, and dependent on expert supervision, limiting scalability and use in everyday environments. This work presents the design and preliminary evaluation of a low-cost, portable neurofeedback system that supports attention training through socially embodied interaction. The system integrates a consumer-grade, single-channel Electroencephalogram (EEG) headset with a custom-developed soft social robot (TUK) that provides intuitive real-time feedback based on EEG-derived attention metrics. EEG signals are acquired at the Fp1 position and processed via an Arduino-based brain–computer interface that verifies signal quality and wirelessly transmits attention values to the robot. A fuzzy-logic–based control algorithm maps continuous attention values to five discrete expressive states. The user's attention level directly modulates the robot's facial expressions, forming an embodied neurofeedback loop consistent with operant conditioning principles. We conducted a preliminary study with six healthy participants, each completing four 2-minute sessions. Four of six participants reached the highest concentration state during their initial trial, and all participants improved or maintained performance across subsequent sessions. We observed reduced performance during evening sessions in four participants, suggesting an effect of mental fatigue. These results demonstrate the feasibility of robot-based neurofeedback using affordable hardware, which supports future deployment in home or other similarly low-barrier settings.

Keywords: ADHD · EEG Neurofeedback · Socially Assistive Robotics.

1 Introduction

Difficulties in sustaining and regulating attention represent a major challenge in both educational and everyday contexts, particularly when such difficulties persist across developmental stages [1]. In neurodevelopmental conditions such as Attention-Deficit Hyperactivity Disorder (ADHD), impairments in attentional control can significantly affect learning, social interaction, and daily functioning, often extending beyond childhood into adolescence and adulthood [2]. While pharmacological treatments are widely used, there is a growing demand for complementary, non-pharmacological approaches that support attention regulation in an objective, repeatable, and context-independent manner [3].

A major challenge in attention-focused interventions is the objective measurement and monitoring of attentional states. Electroencephalography (EEG) has long been used as a noninvasive method to capture neural activity associated with cognitive processes, including attention and executive control, due to its high temporal resolution and sensitivity to cortical dynamics [4]. In particular, frontal EEG activity has been consistently linked to attentional control and executive function, reflecting the involvement of prefrontal networks in sustained attention [5]. Prior studies have reported systematic relationships between attention and spectral characteristics of EEG signals, including increased β-band activity during focused cognitive engagement, modulations of α-band power related to attentional suppression, and elevated theta activity associated with reduced attentional control. Alterations in the θ–β ratio have been widely reported in individuals with attention deficits, including ADHD populations, establishing EEG-derived features from frontal regions as physiologically meaningful proxies for attention [6–8].

EEG-based neurofeedback builds on these correlations by transforming ongoing neural activity into real-time feedback, enabling users to learn self-regulation of attentional states through operant conditioning. In research-grade neurofeedback systems, this process typically involves explicit computation of band-specific features, such as θ, α, or β power (see Fig. 1). In contrast, consumer-grade EEG devices often provide derived attention indices based on proprietary signal processing pipelines. Although such indices offer limited transparency with respect to underlying neural mechanisms, prior work has shown that they can provide sufficiently stable control variables for real-time neurofeedback and interactive attention-training applications [9, 10].

Despite this promise, most existing neurofeedback systems rely on screen-based interfaces, abstract visualizations, and stationary clinical setups [11]. These characteristics can increase cognitive load, compete with attentional resources, and limit scalability and applicability in everyday environments such as homes or schools. As a result, there remains a gap between EEG-based attention sensing and feedback modalities that are intuitive, interpretable, and suitable for short, frequent training sessions outside specialized settings.

Recent advances in socially interactive robotics suggest an alternative approach to delivering neurofeedback through embodied, non-screen-based interaction. Social robots can convey information through expressive movement and

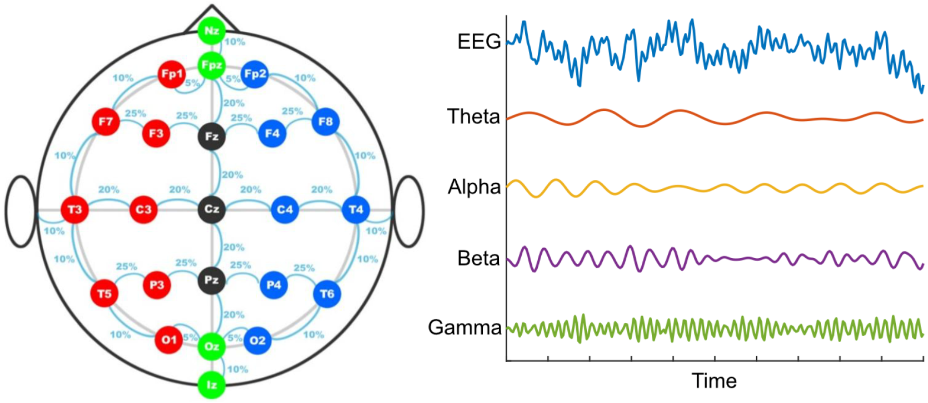

Fig. 1. EEG frequency bands and frontal electrode placement. (Left) Conceptual illustration of EEG rhythms θ, α, β, γ over time. (Right) International 10–20 system highlighting frontal electrode locations; EEG data in this work were recorded from Fp1.

facial cues, potentially reducing cognitive load and supporting more naturalistic interaction [12]. However, existing work rarely integrates EEG-based neurofeedback with expressive robotic embodiment in a manner that is lightweight, discrete, and reproducible. In particular, there is a lack of systems that map attention-related neural signals to stable, interpretable robot behaviors designed specifically for attention regulation contexts.

In this paper, we present a robot-based neurofeedback system for attention training centered on a custom-developed social robot, TUK. The main contributions are as follows:

– We present TUK, a custom-developed, soft and expressive robotic platform that integrates embedded EEG processing and real-time facial actuation, enabling socially embodied neurofeedback in short, standalone interaction sessions.
– We propose a discrete, state-based neurofeedback paradigm in which EEG-derived attention levels are communicated through interpretable expressive states of a social robot, rather than continuous visual or numerical feedback.

The remainder of this paper is organized as follows. Section 2 presents the materials and methods, including the design of the TUK robot, the neurofeedback pipeline, and the experimental protocol. Section 3 reports the results, Section 4 discusses the findings and limitations, and Section 5 concludes the work.

2 Materials and Methods

2.1 System Overview

We proposed and designed a portable neurofeedback platform integrating EEG acquisition, real-time signal processing, and an expressive social robot to form a closed-loop brain–computer interaction system.

EEG signals are acquired using a consumer-grade, single-channel EEG headset, MindWave Mobile (NeuroSky Inc., San Jose, CA, USA) and transmitted wirelessly via Bluetooth to an embedded processing unit based on an Arduino Uno Rev3 (Arduino S.r.l., Somerville, MA, USA). The incoming data stream is parsed, validated based on signal quality, and transformed into an attention-related control variable. This variable is subsequently mapped to five discrete expressive states of the robot, each representing a predefined attention level. The expressive states range from a fully alert state (eyes open) to a target "asleep" state (eyes fully closed), with three intermediate states characterized by graded eyelid closure and reduced facial motion, and transmitted to the TUK robot in real time. The robot provides immediate visual and social feedback through facial expressions and head movements, enabling the user to modulate their attention state through operant conditioning.

2.2 TUK Robot Design

Mechanical Structure and Actuation The mechanical structure of TUK consists of a modular body and head assembly mounted on a rigid internal frame. We padded and covered the outer shell with soft textile materials to provide a plush, animal-like appearance and ensure safe physical interaction.

The robot employs a total of 11 servo motors to actuate facial features and head movement. Four servo motors control horizontal and vertical eye movements using micro servo motors (Mikro-4 Miniservo, mikromodellbau.de) to accommodate space constraints within the eyeball assembly. Four additional servo motors actuate eyelid rotation and blinking, two motors provide bidirectional nose movement, and one high-torque servo motor enables rotational movement of the neck. A dedicated Arduino Uno Rev3, responsible for motion control, controls all servo motors. For each actuator, predefined motion ranges and initial positions were specified in degrees to ensure consistent and repeatable expressive behavior.

We integrated a ball-bearing mechanism into the neck assembly to ensure smooth and reliable head rotation, reducing mechanical friction and strain on the neck servo motor. All mechanically active components were housed within the robot's internal structure, while externally accessible surfaces remain soft and compliant.

Expressive Facial Mechanisms We implemented the facial expressiveness of TUK through coordinated actuation of the eyes, eyelids, and nose. Each eye provides two degrees of freedom, enabling independent horizontal and vertical motion. Eyelids are actuated using separate servo motors to support both rotational movement and blinking.

The nose was actuated with two degrees of freedom (up–down and left–right) and incorporated a capacitive touch electrode connected to the sensing subsystem. Facial components, including eyes, eyelids, and nose mechanisms, were primarily fabricated using 3D-printed parts, allowing precise definition of geometry and mechanical alignment.

We grouped the facial configurations into five discrete expressive states, each defined by a predefined combination of eye position, eyelid closure, and head posture. These states were ordered according to increasing levels of EEG-derived attention. Fully open eyes and raised eyelids represented the lowest attention state, while intermediate states were characterized by progressively reduced eye openness and partial eyelid closure. The highest attention state corresponded to an “asleep” configuration, in which the eyes were fully closed and facial motion was minimized (see Fig. 2).

Transitions between expressive states were driven by the EEG-derived attention value provided by the eSense algorithm, with higher attention values selecting higher expressive states.

Embedded Electronics and Sensing TUK’s control architecture is based on a dual-microcontroller setup implemented using two Arduino Uno Rev3. One microcontroller was dedicated to motion control and expression rendering, generating servo control signals for all facial and head actuators. The second microcontroller was responsible for sensor input acquisition, Bluetooth communication, and EEG data parsing, including reception of EEG-derived attention values from the EEG headset and touch input from the capacitive sensing subsystem.

Capacitive touch sensing was implemented using an MPR121 capacitive touch controller (NXP Semiconductors, Eindhoven, The Netherlands). The MPR121 provided up to 12 independent capacitive sensing channels and communicated with the embedded processing unit via the Inter-Intergrated Circuit (IIC) interface. In the TUK robot, the controller was connected to the sensor microcontroller and configured with predefined touch and release thresholds to detect gentle contact events. Capacitive electrodes were distributed across the robot’s head, nose, and body to enable detection of touch interactions. In this study, we did not use touch sensing as an input modality for neurofeedback control and it was not included in the experimental protocol.

Fig. 2. Expressive states of the TUK robot used for neurofeedback. From left to right, the figure illustrates the five discrete expressive states corresponding to increasing EEG-derived attention levels: Angry (weak or poor signal), Sad (low attention), Neutral (neck and nose movement), Tired (slightly elevated attention), and Asleep (elevated attention). Each state is defined by a specific combination of eye position, eyelid closure, and nose orientation and is rendered through coordinated facial actuation.

2.3 EEG Acquisition and Signal Processing

EEG signals were acquired using a single-channel consumer-grade EEG headset, MindWave Mobile. The device recorded frontal EEG activity via a dry electrode positioned at the Fp1 location according to the international 10–20 system, with an ear-lobe reference electrode. Raw EEG signals are internally sampled by the device at 512 Hz and processed onboard.

The headset applied proprietary preprocessing and feature extraction through the NeuroSky eSense algorithm, which provides real-time cognitive state indices, including attention, meditation, blink strength, and signal quality indicators. We only used the attention index for neurofeedback control. The Attention index is reported as an integer value ranging from 1 to 100 and updated at a rate of 1 Hz. According to the manufacturer's specification, values between 40 and 60 correspond to a neutral baseline, while higher values indicate increased attentional engagement.

EEG-derived data packets were transmitted wirelessly via Bluetooth to the Arduino Uno microcontroller. Data parsing was performed according to the ThinkGear communication protocol, which encapsulates EEG-derived features into structured data packets. The embedded system extracted attention values and signal quality information from each packet.

We continuously monitored signal integrity using the POOR_SIGNAL indicator provided by the device, which ranges from 0 to 255. A value of 0 indicates acceptable electrode contact, whereas higher values indicate increasing signal contamination or loss of contact. Attention values were processed and forwarded to the neurofeedback control logic only when the POOR_SIGNAL value indicated acceptable signal quality; we discarded data segments associated with poor signal conditions.

2.4 Neurofeedback Interaction and Control Strategy

We implemented the neurofeedback paradigm as a closed-loop control process in which we continuously receive EEG-derived attention values and used them to modulate the robot's expressive state in real time (see Fig. 3). We defined five discrete attention states, ordered from low to high concentration, with the highest state corresponding to the robot's predefined "asleep" configuration.

We applied a fuzzy-logic–based state selection strategy with hysteresis to map continuous attention values to discrete expressive states. We associated each expressive state with an overlapping membership function and updated the selected state only when the attention value remained within the corresponding region for a sustained period. This hysteresis mechanism suppresses rapid state switching caused by short-term fluctuations in the EEG-derived attention signal.

Based on the selected expressive state, we generated deterministic motor commands and transmitted them to the motion control microcontroller, which actuates eye position, eyelid angle, and head posture according to predefined configurations.

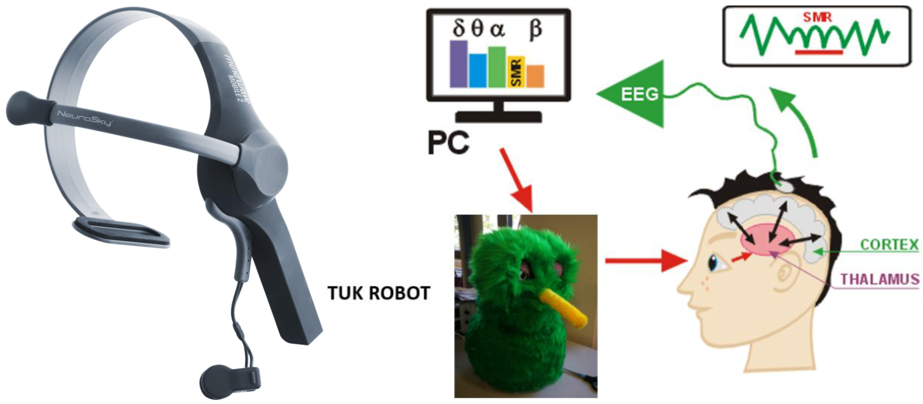

Fig. 3. Overview of the neurofeedback setup: (right) schematic illustration of the EEG headset components, and (left) the NeuroSky MindWave Mobile headset used in this study.

2.5 Experimental Evaluation

Participants We recruited six healthy adult participants (three female, three male; aged 22–25 years). All participants reported no history of neurological or psychiatric disorders and had normal or corrected-to-normal vision. The study did not involve clinical populations. All participants provided informed consent prior to participation.

Experimental Protocol Each participant completed four neurofeedback sessions, with each session lasting 2 min. Two sessions were conducted during the morning hours and two sessions during the afternoon or evening. Participants were seated in front of the TUK robot at a close interaction distance and were instructed to observe TUK's facial expressions throughout each session.

During the first session, we provided only minimal instructions, asking participants to focus on the robot and attempt to influence its behavior. Before subsequent sessions, we explained the general purpose of the system and suggested simple cognitive strategies such as focusing on a visual target, performing mental arithmetic, or maintaining mental imagery. No explicit performance feedback was provided outside the robot's expressive behavior.

Study Design and Procedure We employed a within-subject exploratory study design without a control condition. Each participant completed all sessions using the same hardware and system configuration. The order of sessions was fixed, with morning sessions preceding afternoon or evening sessions for each participant.

At the start of each session, we verified EEG signal quality and ensured acceptable electrode contact. Sessions were initiated only when valid EEG-derived attention values were available. Between sessions, participants were allowed to rest briefly to minimize carry-over effects.

Recorded Variables During each session, we recorded the EEG-derived attention values provided by the eSense algorithm, the corresponding expressive state selected by the control logic, and session timing information. No additional physiological signals or behavioral performance measures were collected. The analysis focused on descriptive assessment of expressive state transitions and attention-level dynamics across sessions.

3 Results

All six participants completed the four neurofeedback sessions. Across participants, we observed successful modulation of the robot's expressive states during the sessions. During the initial session, four out of six participants (66.7%) reached the highest expressive state corresponding to the robot's "asleep" configuration at least once. The remaining two participants reached intermediate expressive states but did not attain the highest state during their first session.

Across subsequent sessions, all participants either improved their performance or maintained their previously achieved highest expressive state. No participant exhibited a consistent decrease in maximum expressive state across sessions when comparing early and later trials conducted under similar conditions.

During each session, we recorded transitions between the five predefined expressive states selected by the neurofeedback control logic. Participants exhibited varying numbers of state transitions within and across sessions. Sessions in which participants reached higher expressive states were characterized by sustained occupancy of intermediate or high states rather than frequent oscillations between adjacent states. The control logic prevented rapid switching between expressive states, and expressive configurations were rendered consistently throughout all sessions.

When comparing sessions conducted at different times of day, we observed reduced neurofeedback performance during afternoon or evening sessions for four out of six participants (66.7%). Two participants showed comparable performance across all sessions regardless of session timing. No participant reported technical issues or interruptions related to EEG acquisition or robot operation.

4 Discussion

We demonstrated the feasibility of integrating a consumer-grade EEG device with a custom-developed expressive social robot to deliver real-time neurofeedback for attention training. The results showed that all participants were able to modulate the robot's expressive states within short interaction sessions, and that a majority reached the highest expressive state even during their initial exposure to the system. These observations indicate that the proposed closed-loop interaction can produce observable and repeatable behavioral effects without extensive training or expert supervision.

Performance differences observed across sessions suggest that contextual factors influence neurofeedback outcomes. In particular, reduced performance during afternoon or evening sessions for several participants is consistent with known effects of mental fatigue and diurnal variation in attentional capacity [13]. Although the present study was not designed to systematically investigate timing effects, these observations highlight the importance of contextual consistency when deploying attention-training systems in everyday settings.

The use of a discrete, state-based representation for neurofeedback was significant in stabilizing interaction dynamics. By mapping continuous EEG-derived attention values to a finite set of expressive states, the system avoided rapid oscillations and maintained consistent feedback behavior despite signal variability inherent to consumer-grade EEG. This design choice supports interpretability and robustness, which are particularly important for applications outside controlled laboratory environments.

Beyond the experimental setting, we could also show that the proposed system has applicability for attention support in everyday environments such as homes and classrooms. The short-session design, standalone operation, and absence of screens or complex user interfaces make the system compatible with frequent, low-burden training sessions that could be embedded into daily routines. In home settings, the system could support individualized attention exercises under parental supervision, while in school environments it could serve as a complementary tool during structured breaks or supervised focus activities. Although we did not explicitly evaluate these deployment scenarios, they require dedicated investigation in future work.

The physical embodiment of the TUK robot and the use of soft materials may further shape interaction quality, particularly for users with attention regulation difficulties. By relying exclusively on facial expressions and head movements, the system minimizes sensory load and avoids competing visual or auditory stimuli. The soft, padded exterior supports safe close-range interaction and reduces the risk of overstimulation. While we did not isolate the effect of embodiment or material choice on neurofeedback performance, these characteristics represent intentional design decisions that warrant systematic evaluation.

An additional strength of our approach is in its reproducibility and accessibility. The system is constructed using widely available electronic components, open microcontroller platforms, and consumer-grade fabrication methods. Structural components can be fabricated using standard 3D printing (as we did), and the control logic is implemented entirely on embedded hardware. These design choices lower the barrier for replication and extension by other researchers and support transparent evaluation and comparison.

Several limitations still exist. The evaluation involved a small number of healthy adult participants and did not include individuals diagnosed with ADHD. The system relied on a single-channel consumer-grade EEG device and a proprietary attention metric, limiting physiological interpretability and precluding analysis of underlying neural mechanisms. In addition, the study focused on short-term interaction and did not assess long-term learning effects or transfer to functional attention outcomes. Future work will address these limitations through controlled studies with ADHD populations, extended training protocols, and the integration of additional sensing modalities or learning-based control strategies. Systematic evaluation of embodiment, material properties, and deployment context in home and school environments will further clarify the applicability and impact of robot-based neurofeedback.

5 Conclusion

We presented a robot-based neurofeedback system for attention training centered on TUK, a custom-developed soft and expressive social robot. The proposed approach targeted attention regulation, a core challenge in ADHD, by communicating EEG-derived attention levels through five discrete sets of interpretable expressive robot states. By integrating a consumer-grade EEG device with fully embedded signal processing and real-time robotic actuation, the system operated as a standalone closed-loop platform suitable for short, non-screen-based interaction sessions. Results from a preliminary exploratory study with healthy participants demonstrated that users were able to modulate the robot's expressive states within brief sessions, indicating the feasibility of the proposed neurofeedback paradigm for attention-related applications. The discrete, state-based feedback representation contributed to stable interaction dynamics and mitigated the impact of short-term fluctuations in EEG-derived attention measures. Observed performance variations across sessions further highlighted the influence of contextual factors, such as mental fatigue, on attention regulation. While the present work does not claim therapeutic efficacy and does not include clinical ADHD populations, it establishes a technical and conceptual foundation for socially embodied neurofeedback as a complementary approach to attention training.

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