Mindful Mobility: EEG-Based Brain-Computer Interaction for Elevator Control Using Muse Headset

Devansh Srivastav[1,2], Thomas Kaltbach[2], Ahmer Akhtar Mughal[2], Nischal Giriyan[2,3], Moaz Bin Younus[2], Tobias Jungbluth[1], Jochen Britz[1], Jan Alexandersson[1], and Maurice Rekrut[1]

[1] German Research Center for Artificial Intelligence (DFKI), Saarbrücken, Germany
[2] Universität des Saarlandes, Saarbrücken, Germany
[3] CISPA Helmholtz Center for Information Security, Saarbrücken, Germany
devansh.srivastav@dfki.de, s8thkalt@uni-saarland.de, ahmu00002@uni-saarland.de, nigi00005@uni-saarland.de, mobi00001@uni-saarland.de, tobias.jungbluth@dfki.de, jochen.britz@dfki.de, jan.alexandersson@dfki.de, maurice.rekrut@dfki.de

Abstract. Brain-Computer Interface (BCI) systems represent an innovative approach to human-computer interaction, enabling users to control devices and interact with technology solely through brain activity. This study investigates the feasibility and potential of non-invasive EEG-based BCI for elevator control, addressing two primary research questions: 1) Can a person reliably control an elevator through a BCI system? and 2) What are the usability and user experience outcomes of such a system? We integrated a Muse headset with a remote-controllable elevator system using an iPhone as the interface over a local network. This setup allowed users to operate the elevator using blinking, jaw clenching, and mental focussing as triggers. Performance, accuracy, and user experience were evaluated through experiments involving 50 participants aged 12 to 60. Usability was measured with the System Usability Scale (SUS) questionnaire along with additional feedback questions. Key findings indicate that the system achieved an average SUS score of 80.3, reflecting excellent usability on the adjective rating scale. Moreover, 94% of participants successfully controlled the elevator, performing tasks such as activating and deactivating brain control, calling the elevator, and selecting floors. The user experience questionnaires reveal that most participants found the system easy to use, well-integrated, and perceived the introduction of brain-controlled elevators to positively impact accessibility and inclusivity in buildings.

Keywords: Brain-Computer Interface (BCI) · EEG-based BCI · Non-invasive BCI systems · Elevator control via BCI · Accessibility

1 Introduction

The intersection of neuroscience and technology has led to groundbreaking advancements in the field of Brain-Computer Interface (BCI), revolutionising the way humans interact with machines [11]. BCI systems enable direct communication between the human brain and external devices, bypassing traditional input modalities such as keyboards or touchscreens [29]. This holds promise for enhancing accessibility, improving human-computer interaction, and even restoring lost functionalities for individuals with disabilities [14].

Among various modalities of BCI, electroencephalogram (EEG)-based BCIs have received significant attention due to their non-invasiveness, portability, and affordability [13]. EEG-based BCIs detect and analyse electrical activity in the brain through scalp electrodes, allowing real-time monitoring of neural signals associated with different mental states and intentions [15]. Such systems have demonstrated remarkable potential in enabling users to control external devices solely through their brain activity [23].

Despite the progress made, current BCI-based elevator control studies, as discussed in Section 2, are often hindered by complex setups, limited flexibility, and extensive training requirements. Many existing systems are not intuitive and provide only passive suggestions for floor selection. Addressing these limitations, our work aims to offer a more user-friendly and efficient EEG solution for BCI-based elevator control in a real-world setting. Using Muse headset for its convenience and comfort, we developed a concept that seamlessly integrates into user interaction with minimal interruption and ease of use. The headset captures and interprets EEG data in real-time and transmits the signals to a mobile phone via Bluetooth, where a dedicated application processes them and communicates with the server orchestrating the elevator's operations. By utilising the signals captured by the Muse headset, variations caused by jaw clenching, blinking patterns, and cognitive states such as mental focus are construed to trigger specific actions within the elevator environment, such as calling it and selecting the floor. This setup establishes a seamless interface between the user's brain activity and the elevator's control system, addressing two primary research questions: Can a person reliably control an elevator through a BCI system? and, what are the usability and user experience outcomes of such a system? To answer these questions, we evaluated our developed system in a user study with 50 participants aged 12 to 60, measuring performance, accuracy, and user experience. The results showed an excellent usability and performance, making it, to the best of our knowledge, the first user-friendly and unobtrusive BCI-based elevator control.

2 Related Work

BCIs have seen substantial progress, particularly in smart home scenarios where they are used to control various devices and systems [7]. BCI systems can be categorised into active, reactive, and passive types. Active BCIs rely on deliberate mental tasks, such as motor imagery [17] or speech imagery [22], to generate control signals. Reactive BCIs detect specific brain responses to external stimuli, such as error potentials [2]. Passive BCIs monitor brain activity without requiring volitional modulation, providing insights into cognitive states like attention, mental fatigue, and emotional states [30]. This section reviews existing research on the use of different types of BCIs with a focus on the application of EEG in real-world environments in general and regarding elevator control.

Early research in BCI applications often involved complex clinical EEG setups designed to enable people with mobility impairments to control wheelchairs [21]. These studies demonstrated the feasibility of using EEG-based BCIs to control devices in real-world environments, but also highlighted significant challenges. The setups were typically cumbersome and required extensive calibration and user training, which limited their practical usability [12].

To address these challenges, portable EEG solutions have been developed. Devices such as Emotiv EPOC [27] and Muse headband [16] offer improved usability, although they sacrifice some flexibility and signal quality compared to clinical-grade EEG systems [6]. Despite the limitations, these devices have shown potential in controlling BCI applications. Simar et al. [25] investigated the potential of BCIs to control a small robot using Muse EEG headband. Their study demonstrated successful robot control based on real-time analysis of brain signals, focussing on the modulation of alpha oscillations to determine control commands. Despite the challenges posed by physiological artefacts, their findings suggest the feasibility of using consumer-grade EEG devices for robust BCI applications. Advancements in mobile EEG (mEEG) technology further expanded the application of BCIs in smart home scenarios. Krigolson et al. [10] demonstrated the utility of mEEG in rapidly assessing cognitive performance and neural states. Combining event-related brain potentials (ERPs) and EEG oscillations, their research provided accurate predictions of cognitive states, showcasing the potential of portable mEEG devices for real-world applications in cognitive research.

In the context of smart home environments, Raizer et al. [19] discussed the development of an agent to assist BCI users in controlling smart environments, including elevators. This agent proposed interactions based on various parameters rather than requiring active user control, suggesting relevant actions such as calling an elevator based on predefined goals, state of the environment, and scheduled events. Similarly, Saboor et al. [24] used Steady-State Visual Evoked Potentials (SSVEPs)-based BCIs to control smart devices, including an elevator, through visual stimuli displayed on AR glasses, with QR codes employed to identify the devices to be controlled via BCI. Chatziparasidis et al. [5] focused on residential buildings equipped with BCI functionality, targeting disabled and elderly users. This study used Emotiv EPOC with semi-dry sensors and motor imagery-based BCIs involving imagining pulling a 3D object to control a two-floor elevator. While it provided a proof-of-concept, the study had several limitations, including a small sample size of five participants, long training times, and insufficient reporting on the success rate and usability of interactions.

While existing studies have laid the groundwork for BCI-based elevator control, they face challenges such as complex setups, limited flexibility, and extensive training requirements. Our work seeks to overcome these issues by using more user-friendly and efficient EEG solutions, providing a detailed and comprehensive evaluation of the performance of the BCI elevator in a real-world setting.

3 Methodology

3.1 Design Criteria and Procedure

The primary objective of our study was to design a user-friendly and efficient BCI system for elevator control, emphasising minimal interruption and ease of use. Key design criteria included:

- **Accessibility and Comfort:** Use of a non-invasive, portable EEG device.
- **Simplicity and Intuitiveness:** Ensuring that the control mechanism was straightforward for users of varying ages and abilities.
- **Efficiency:** Reducing the need for extensive training and complex setups.

3.2 EEG Headset

Considering its accessibility and comfort, we decided to use the Muse EEG headset[1], known for its accessibility, portability and versatility. It features an array of strategically positioned electrodes. The headset as shown in Fig. 1, includes two temporal electrodes, TP9 and TP10, situated over the left and right temporal lobes respectively and two frontal electrodes, AF7 and AF8, positioned at the anterior regions of the scalp. Additionally, FPz reference electrodes serve as a stable point for signal comparison, ensuring accuracy in measuring neural oscillations in different regions of the brain.

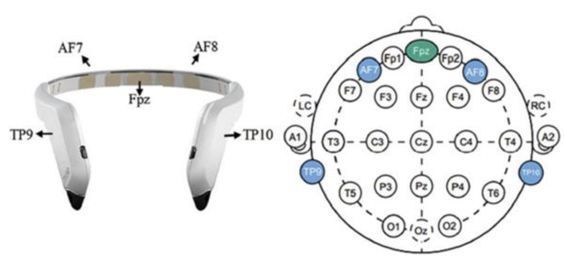

Fig. 1: Electrodes placement in Muse headset [28]

3.3 Elevator Control Procedure

Mental focus to ensure effective modulation of brain activity is a widely recognised criterion in BCI research, providing reliable triggers for control actions. However, artefacts such as jaw clenching and eye blinking pose challenges to signal interpretation and are typically regarded as noise in EEG recordings [20]. Utilisation of these artefacts by repurposing them as meaningful inputs for controlling external systems presents an interesting approach for interaction in BCI

[1] https://choosemuse.com/

applications. We designed our triggers by incorporating mental focus, as well as capitalising on these artefacts, to create a robust and user-friendly BCI control mechanism.

The user interaction with the elevator involves intuitive gestures and cognitive commands. We developed an iOS application that connects to the Muse headset and provides voice instructions to guide the user through each step. To activate brain control, the user performs four blinks to signal readiness and prevent unintended interactions. Subsequently, the user modulates brain activity by mentally focussing on solving a maths problem to call the elevator. For the purpose of the study, the elevator is always called to the ground floor where participants are located. The user then selects one of the 5 destination floors by blinking a specific number of times in the period of 4 seconds to avoid interference with natural blinks. Specifically, no blinks indicate staying on the ground floor, and the number of blinks increases with each subsequent floor. Jaw clenching is further used to deactivate brain control, ensuring a seamless transition between manual and BCI-driven operation. API calls from the application to the server trigger the elevator's actions at each step, facilitating smooth elevator operation.

3.4 EEG Data and Determination of Triggers

To ensure accurate and reliable brain-controlled elevator operation, the system incorporates an intricate process for determining the set triggers based on data acquired from Muse headset. The Muse SDK facilitates the detection of eye blinking and jaw clenching through its built-in functions. Conversely, EEG data, particularly the beta, and gamma bands are used to identify focussed state [20], which is relevant for calling the elevator.

The fact that the beta band dominates during a regular state of mind serves as a foundational understanding for subsequent analysis [18]. Through experimentation, it was observed that when users focus, thereby increasing cognitive engagement, beta band values decrease while gamma band values increase. This shift signifies the transition from the beta state to the gamma state, indicating an increased focus [8]. To operationalise these findings, a calibration process is carried out to determine individual threshold values for beta-band activity. This process involves the following steps:

1. **Baseline Measurement:** Each user undergoes an initial assessment to establish their baseline beta band value in normal state, with minimal cognitive engagement. The mean beta band value during this period is set as the baseline.
2. **Focus State Measurement:** Users are then instructed to engage in a focussing activity, such as performing a mental arithmetic task, during which their beta band values are monitored.
3. **Threshold Setting:** The threshold value is set based on the mean beta band activity observed during the focussed state.

The accuracy and reliability of the system relies on this calibration process. During operation, if beta band values fall below the established threshold by mental focussing, the system initiates the action to call the elevator. Given the distinctive roles of frontal and temporal electrodes, the selection of electrodes for analysis is critical. Frontal electrodes, located on the frontal lobes, are associated with reasoning; however, due to potential interference from eye movements when focussing, temporal electrodes are deemed to be more optimal. Temporal regions, responsible for language, memory, senses, and emotions, offer better reflection of cognitive states and are more robust to muscle artefacts due to their position behind the ears. To induce increased brain activity for focussing, mental maths questions are utilised, leveraging the linguistic processes associated with mathematical reasoning. This task is aligned with the cognitive processes monitored by the temporal electrodes. Comparative analysis of EEG data between the left and right temporal electrodes revealed that the left temporal electrode (TP9) provides more accurate readings. This finding aligns with the understanding that the left hemisphere of the brain, associated with analytical thinking and logical reasoning, is primarily engaged in cognitive tasks requiring focussed attention [9]. Therefore, the signals of TP9 were chosen as input for the elevator control.

3.5 System Configuration

The system comprises interconnected components, as illustrated in Fig. 2. An iPhone running an iOS application serves as the primary interface for the user. The Muse headset connects to the iPhone via Bluetooth BLE, facilitating the transmission of EEG data. Within the local network, the iPhone interfaces with a server hosting a Java-based API developed using the Quarkus framework. This API functions as an intermediary, managing incoming requests and establishing communication with the elevator. It is also possible to remotely monitor elevator actions in real-time via a dedicated device connected to the local network. This device continuously streams and visualises the elevator's movements, facilitating effective system monitoring and interaction.

4 User Study

We conducted a usability study of our BCI-operated elevator control system in a real elevator located in the entrance hall of the German Research Center for Artificial Intelligence. The choice of a real-world environment improves the external validity of our findings, providing realistic insight into practical usability. This method also enables us to capture genuine user behaviour and feedback, ensuring the relevance and applicability of our results to real-life applications.

4.1 Participants

A total of 50 participants were recruited for this study. The demographics of the participants were varied, with a gender ratio of 32 males and 18 females, and ages ranging from 12 to 60 years (mean age = 25.14 years, SD = 9.96). The participants were from various backgrounds, with different levels of familiarity

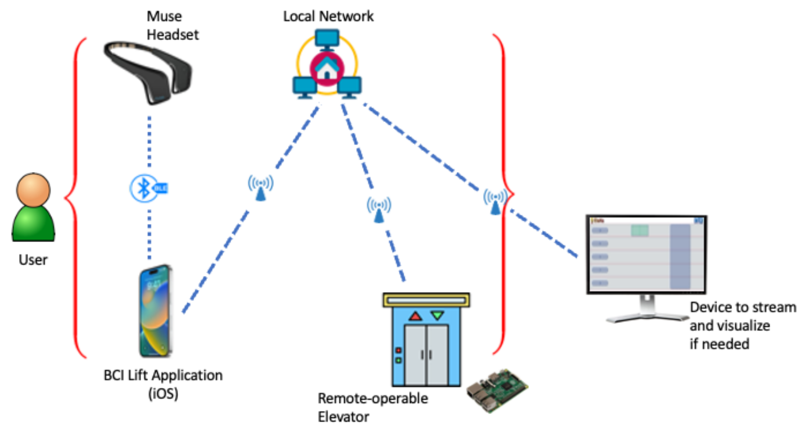

Fig. 2: System configuration of BCI setup for elevator control

with BCI technology. Specifically, 26 participants were familiar with BCI, while 24 participants had no prior knowledge of it. Furthermore, 8 participants had used BCI technology before, while 42 participants were completely inexperienced with BCI systems.

4.2 Procedure

The participants were first given a brief introduction to the study and the BCI technology. They then completed a consent form for participation. Following this, the participants underwent a calibration session with the BCI headset to ensure accurate signal capture. The calibration, which took an average of 45 seconds once the headset was properly worn, involved mental focussing by solving a mental maths problem to observe the variation in the beta signals from the baseline and determining the threshold for the trigger. After calibration, the participants were asked to complete the elevator control procedure as shown in Fig. 3, fill out the System Usability Scale (SUS) questionnaire, and additionally answer custom usability questions regarding the elevator use case. They were also asked to provide qualitative feedback on their experience.

4.3 SUS Questionnaire

The System Usability Scale (SUS) is a ten-item questionnaire that provides an overall evaluation of subjective usability [4]. These ten questions, when applied to systems that exemplify extremes of usability and non-usability, elicit the most extreme positive and negative responses. The individual questions in SUS are not inherently significant on their own and are designed to be broadly applicable across different technologies. The aggregate rating of these ten questions provides

Fig. 3: A participant performing the BCI elevator control task

an overall measure of perceived usability [3]. However, the SUS score should not be used alone to evaluate the system's usability. The success rate and the nature of failures during user testing are also crucial factors in assessing usability [26].

5 Results and Discussion

The data collected from participants included demographic information, previous BCI experience, responses to the SUS, and additional feedback on responsiveness, reliability, comfort, and ergonomics, as well as qualitative feedback. The analysis focussed on evaluating the usability, efficiency, and user satisfaction with the BCI-controlled elevator system.

The average SUS score of the system was evaluated as 80.3, indicating excellent usability on the adjective rating scale [1]. This score signifies that the majority of users found the system easy to use and well-integrated. Despite 84% of the participants having never used a BCI system, 94% were able to successfully complete the elevator control interaction, highlighting the intuitiveness and effectiveness of the system. The distribution of SUS scores among participants is shown in Fig. 4. These scores fall predominantly between 70 and 100, indicating high levels of satisfaction. The peak at 100 indicates that a significant number of users rated the system as extremely user-friendly.

Most of the participants did not experience discomfort or fatigue, reflecting the general comfort and usability of the system. Muse headset received a comfort and ergonomics rating of 4.06 on a scale of 1 to 5, indicating it is well-regarded by users. However, issues were noted, particularly for users who wear glasses or hijab, suggesting a need for design improvements to better accommodate such users. The voice instructions were found helpful by the majority, guiding their interaction with the elevator effectively. Only one participant found the instructions distracting, suggesting that while generally effective, the system should allow customisation of feedback methods to cater to individual preferences.

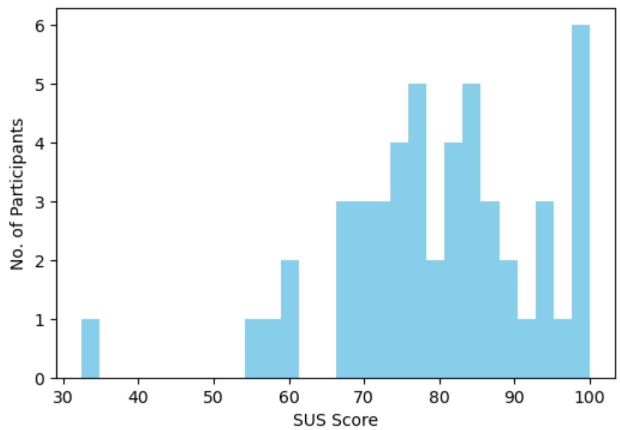

Fig. 4: SUS score distribution for all 50 participants.

The system was perceived reliable and responsive by most participants with a high average rating of 4.2 out of 5. This reliability is crucial for the practical adoption of BCI technology in real-world applications, as it directly impacts user trust and satisfaction. The introduction of brain-controlled elevators was positively rated for improving accessibility and inclusivity, with an average score of 3.96 out of 5. This suggests that participants recognise the potential benefits of such systems in making buildings more accessible to individuals with mobility impairments. However, there remains room for improvement in educating users about these advantages and further enhancing the system's ease of use.

Despite the overall positive feedback, 12% of participants had difficulty deactivating the brain control using jaw clenches. This highlights the need to improve the control mechanisms for more reliable and user-friendly interactions. In addition, participants pointed out discomfort due to sweat accumulation, indicating areas where ergonomic improvements are necessary.

The analysis of the time taken to complete each step in the BCI elevator control process across multiple participants reveal several insights and is illustrated in Fig. 5. Activating brain control generally takes a relatively short amount of time, though there are few outliers indicating some participants took longer, potentially due to initial unfamiliarity with the system. Calling the elevator shows a wider range of time taken, suggesting variability in participants' ability to modulate brain activity to trigger this action. The presence of multiple outliers also suggests that some participants faced challenges in achieving the required mental focus state. The time taken to select a floor is consistently short, with minimal spread and few outliers, indicating the process of selecting a floor by blinking was generally quick and straightforward for most participants. Deactivating brain control shows a larger spread and higher median time, indicating deactivating brain control via jaw clenching was challenging for participants, which aligns with the feedback indicating difficulties with this control mechanism.

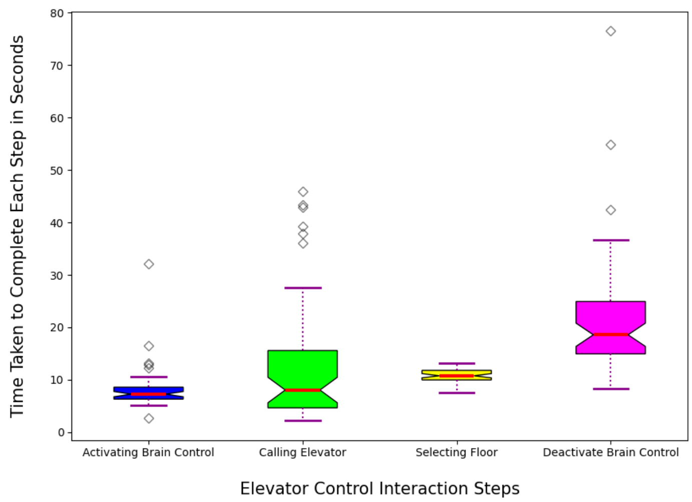

Fig. 5: Analysis of time taken for each step of the BCI elevator control

Participants also provided a range of qualitative feedback, highlighting positive aspects and areas for improvement. Many found the experience exciting, describing it as "fun" and noting the thrill of moving the elevator using BCI. The concept was well-received, with participants recognising its use cases in special areas, even if it might not be practical for everyday life in its current form. There was also a suggestion to ensure affordability to enhance impact on accessibility.

6 Conclusion and Future Work

This study demonstrates the feasibility and effectiveness of EEG-based BCI for controlling elevators. By integrating Muse headset with a remote-controllable elevator, we found that users could reliably control the elevator using brain activity, achieving a 94% success rate among participants, the majority of whom had no prior experience with BCI. Participants positively rated the potential of brain-controlled elevators to enhance building accessibility, highlighting both the novelty of the experience and areas for improvement such as headset comfort and jaw clench detection. Overall, this study highlights the potential of BCI systems in existing infrastructure, suggesting broader adoption possibilities with further refinement.

The current setup assumes the user is always on a specific floor where the elevator is called. Future work includes designing a mechanism to detect the user's location and call the elevator to their current floor using dynamic location detection or a blink-based method. Additionally, we aim to deploy the application on wearable devices like smartwatches for a seamless, hands-free experience. Future research will also explore the long-term usability and acceptance of BCI systems, their sustained use, and their impact on daily life over extended periods. Addressing the factors contributing to occasional failures and user difficulties will be crucial for improving BCI systems and ensuring their practical viability.

References

1. Bangor, A., Kortum, P.T., Miller, J.T.: An empirical evaluation of the system usability scale. Intl. Journal of Human–Computer Interaction **24**(6), 574–594 (2008)
2. Blankertz, B., Curio, G., Müller, K.R.: Classifying single trial eeg: Towards brain computer interfacing. Advances in neural information processing systems **14** (2001)
3. Brooke, J.: Sus: a retrospective. Journal of usability studies **8**(2) (2013)
4. Brooke, J., et al.: Sus-a quick and dirty usability scale. Usability evaluation in industry **189**(194), 4–7 (1996)
5. Chatziparasidis, I., Sfampa, I.K.: Residential buildings with brain-computer interface functionality: An elevator case study. Building Services Engineering Research and Technology **43**(2), 261–272 (2022)
6. Duvinage, M., Castermans, T., Petieau, M., Hoellinger, T., Cheron, G., Dutoit, T.: Performance of the emotiv epoc headset for p300-based applications. Biomedical engineering online **12**, 1–15 (2013)
7. Gao, Q., Zhao, X., Yu, X., Song, Y., Wang, Z.: Controlling of smart home system based on brain-computer interface. Technology and Health Care **26**(5), 769–783 (2018)
8. Halderman, L.K., Finn, B., Lockwood, J., Long, N.M., Kahana, M.J.: Eeg correlates of engagement during assessment. ETS Research Report Series **2021**(1), 1–17 (2021)
9. Hartwigsen, G., Bengio, Y., Bzdok, D.: How does hemispheric specialization contribute to human-defining cognition? Neuron **109**(13), 2075–2090 (2021)
10. Krigolson, O.E., Hammerstrom, M.R., Abimbola, W., Trska, R., Wright, B.W., Hecker, K.G., Binsted, G.: Using muse: Rapid mobile assessment of brain performance. Frontiers in Neuroscience **15**, 634147 (2021)
11. Lebedev, M.A., Nicolelis, M.A.: Brain–machine interfaces: past, present and future. TRENDS in Neurosciences **29**(9), 536–546 (2006)
12. Leeb, R., Lee, F., Keinrath, C., Scherer, R., Bischof, H., Pfurtscheller, G.: Brain–computer communication: motivation, aim, and impact of exploring a virtual apartment. IEEE Transactions on Neural Systems and Rehabilitation Engineering **15**(4), 473–482 (2007)
13. Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., Yger, F.: A review of classification algorithms for eeg-based brain–computer interfaces: a 10 year update. Journal of neural engineering **15**(3), 031005 (2018)
14. Millán, J.d.R., Rupp, R., Mueller-Putz, G., Murray-Smith, R., Giugliemma, C., Tangermann, M., Vidaurre, C., Cincotti, F., Kubler, A., Leeb, R., et al.: Combining brain–computer interfaces and assistive technologies: state-of-the-art and challenges. Frontiers in neuroscience p. 161 (2010)

15. Nicolas-Alonso, L.F., Gomez-Gil, J.: Brain computer interfaces, a review. sensors **12**(2), 1211–1279 (2012)
16. Norton, A., Colino, F., Williams, C., Hassall, C., Krigolson, O.: Finding a muse: Validation of a low-cost, portable system for eeg research. In: PSYCHOPHYSIOLOGY. vol. 54, pp. S172–S172. WILEY 111 RIVER ST, HOBOKEN 07030-5774, NJ USA (2017)
17. Pfurtscheller, G., Neuper, C.: Motor imagery and direct brain-computer communication. Proceedings of the IEEE **89**(7), 1123–1134 (2001)
18. Priyanka, A., Abhang, B., Suresh, M.: Technical aspects of brain rhythms and speech parameters. Introduction to EEG-and Speech-Based Emotion Recognition; Academic Press: Cambridge, MA, USA pp. 16–50 (2016)
19. Raizer, K., Rohmer, E., Paraense, A.L., Gudwin, R.R.: Effects of behavior network as a suggestion system to assist bci users. In: 2013 IEEE Symposium on Computational Intelligence in Rehabilitation and Assistive Technologies (CIRAT). pp. 40–47. IEEE (2013)
20. Rashmi, C., Shantala, C.: Eeg artifacts detection and removal techniques for brain computer interface applications: A systematic review. Int. J. Adv. Technol. Eng. Explor **9**, 354 (2022)
21. Rebsamen, B., Burdet, E., Guan, C., Zhang, H., Teo, C.L., Zeng, Q., Laugier, C., Ang, M.H.: Controlling a wheelchair indoors using thought. IEEE intelligent systems **22**(2), 18–24 (2007)
22. Rekrut, M.: Leveraging EEG-based Speech Imagery Brain-Computer Interfaces. Ph.D. thesis, Saarland University (2023)
23. Rekrut, M., Nadig, M., Jungbluth, T., Ihl, J.: Bison: Bci-based interaction concepts for operating microscopes in neurosurgery. In: 2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE). pp. 393–398. IEEE (2022)
24. Saboor, A., Rezeika, A., Stawicki, P., Gembler, F., Benda, M., Grunenberg, T., Volosyak, I.: Ssvep-based bci in a smart home scenario. In: Advances in Computational Intelligence: 14th International Work-Conference on Artificial Neural Networks, IWANN 2017, Cadiz, Spain, June 14-16, 2017, Proceedings, Part II 14. pp. 474–485. Springer (2017)
25. Simar, C., Petieau, M., Cebolla, A., Leroy, A., Bontempi, G., Cheron, G.: Eeg-based brain-computer interface for alpha speed control of a small robot using the muse headband. In: 2020 International Joint Conference on Neural Networks (IJCNN). pp. 1–4. IEEE (2020)
26. Standard, I.: Ergonomic requirements for office work with visual display terminals (vdts)–part 11: Guidance on usability. iso standard 9241-11: 1998. International Organization for Standardization **55** (1998)
27. Taylor, G.S., Schmidt, C.: Empirical evaluation of the emotiv epoc bci headset for the detection of mental actions. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting. vol. 56, pp. 193–197. SAGE Publications Sage CA: Los Angeles, CA (2012)
28. Teixeira, A., Gomes, A., Brito-Costa, S.: An overview of mindwave applications: Study cases (2023)
29. Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., Vaughan, T.M.: Brain–computer interfaces for communication and control. Clinical neurophysiology **113**(6), 767–791 (2002)
30. Zander, T.O., Kothe, C.: Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. Journal of neural engineering **8**(2), 025005 (2011)