Environment. Technology. Resources. Rezekne, Latvia
Proceedings of the 15th International Scientific and Practical Conference. Volume II, 202-207

An Implementation of Brain-Computer Interface in Research Activities

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Abstract. **The paper provides brief overview of Brain-Computer Interface (BCI), highlighting BCI-based assisting technologies for disabled persons in healthcare applications as one of the key priorities. A proposed solution for implementation OpenBCI-based hardware and software in research on computer typing assistance system described, including general view of experimental test bench and software approach description. An experimental verification of a possible computer typing assistance system is presented, as well as basic test results obtained along with their interpretation and discussion.**

Keywords: BCI, ANN, EEG, signal analysis.

I. INTRODUCTION

Brain-Computer Interface (BCI) technology is a cutting-edge field at the intersection of neuroscience, engineering, and computer science. It aims to establish direct communication pathways between the brain and external devices, bypassing traditional peripheral nerves and muscles. The fundamental principle behind BCI is to interpret neural signals, typically extracted non-invasively using electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), or invasive methods like electrocorticography (ECoG) and intracortical electrodes [1].

The concept of BCI dates back to the late 1960s when researchers first demonstrated the feasibility of translating brain signals into control commands for external devices. Since then, significant advancements in signal processing algorithms, machine learning techniques, and hardware technology have propelled the development of more sophisticated and reliable BCI systems.

BCI technology holds immense promise for various applications, ranging from medical rehabilitation to assistive technologies, neuroprosthetics, gaming, and beyond. In the medical domain, BCI offers new possibilities for individuals with severe motor disabilities, such as spinal cord injuries or amyotrophic lateral sclerosis (ALS), enabling them to control assistive devices, communicate, and even regain some degree of autonomy.

Moreover, BCI research has expanded beyond clinical applications to explore cognitive neuroscience, human-computer interaction, and neuroergonomics. By studying brain activity patterns during different tasks or cognitive states, researchers gain insights into neural mechanisms underlying human behavior, perception, and cognition.

Despite remarkable progress, several challenges remain in the field of BCI technology. These include signal processing artifacts, low signal-to-noise ratios, limited spatial resolution, user training requirements, and ethical considerations surrounding invasive BCI approaches. Addressing these challenges requires interdisciplinary collaboration, innovative research approaches, and continuous improvement in hardware and software technologies.

In general, BCI technology represents a transformative approach to interfacing with the human brain, with the potential to revolutionize healthcare, communication, and human-computer interaction. Continued research and development efforts are essential to unlock the full capabilities of BCI and translate them into practical applications that benefit individuals and society as a whole.

II. MATERIALS AND METHODS

A. Overview of existing BCI applications in research

A literature overview of existing BCI applications in research reveals a wide range of domains where BCI technology has been employed to address various scientific

Print ISSN 1691-5402
Online ISSN 2256-070X
https://doi.org/10.17770/etr2024vol2.8055

questions and practical challenges. Here's a glimpse into some key areas of BCI research applications [1–5].

Neuroscience and Cognitive Psychology. BCI technology allows researchers to study brain activity associated with cognitive processes such as attention, memory, decision-making, and language comprehension. For instance, studies have used BCI to investigate neural correlates of attentional control by decoding attentional states from EEG signals. Similarly, BCI paradigms have been employed to explore neural mechanisms underlying motor imagery, mental rotation, and spatial navigation tasks, providing insights into brain-behavior relationships.

Motor Rehabilitation and Neurorehabilitation. BCI-based rehabilitation approaches offer promising strategies for restoring motor function and facilitating neuroplasticity in individuals with motor disabilities. Research in this area focuses on using BCI systems to provide real-time feedback for motor imagery-based training, functional electrical stimulation, or robotic-assisted therapy. These studies demonstrate the potential of BCI technology to enhance motor learning, promote neural recovery, and improve functional outcomes in patients with stroke, spinal cord injury, or motor impairments.

Assistive Technology and Augmented Communication. BCI systems have been developed as assistive devices to facilitate communication and control for individuals with severe motor disabilities. These applications range from spelling and typing interfaces based on EEG signals to more sophisticated control systems for robotic prosthetics or smart home devices. BCI research in assistive technology aims to improve the accuracy, speed, and reliability of communication channels, enabling individuals to express their intentions, navigate their environment, and interact with external devices using brain signals alone.

Human-Computer Interaction and Gaming. BCI technology is increasingly integrated into interactive systems and gaming platforms to create immersive experiences and adaptive interfaces. Studies explore the use of BCI for controlling virtual avatars, playing neurofeedback-based games, or enhancing user engagement in virtual reality environments. BCI research in human-computer interaction seeks to optimize user interfaces, design intuitive interaction paradigms, and personalize user experiences based on real-time brain activity patterns.

Clinical Diagnosis and Monitoring. BCI methods hold potential for diagnosing and monitoring neurological disorders, such as epilepsy, attention-deficit/hyperactivity disorder (ADHD), or Alzheimer's disease. Researchers investigate the utility of BCI-based biomarkers for early detection, differential diagnosis, and disease progression tracking. BCI research in clinical applications aims to develop reliable diagnostic tools, identify neurophysiological signatures of pathology, and facilitate personalized interventions for patients with neurological and psychiatric conditions.

Brain-Computer Interface Technology Development. Beyond specific applications, BCI research contributes to advancing the fundamental principles and technological capabilities of BCI systems. Studies focus on developing novel signal processing algorithms, improving feature extraction methods, enhancing machine learning techniques for brain signal decoding, and exploring innovative neuroimaging modalities or electrode technologies. These advancements drive the evolution of BCI technology, making it more robust, versatile, and accessible for research and practical applications.

Overall, the literature on BCI applications in research highlights the multifaceted nature of BCI technology, its potential to address diverse scientific questions and societal needs, and the ongoing efforts to harness its capabilities for improving human health, cognition, and interaction with technology.

Basing on provided overview, main benefits and challenges of BCI methods were summarized in table 1.

TABLE 1 PROS AND CONS FOR GREEN STRATEGIES IMPLEMENTATION

Pros	***Challenges***
Insights into Brain Function: BCI offers a unique window into the workings of the human brain, allowing researchers to directly observe and manipulate neural activity. By decoding brain signals associated with specific tasks or cognitive processes, BCI facilitates a deeper understanding of brain function, organization, and plasticity.	Signal Quality and Variability: BCI performance is influenced by the quality and variability of brain signals, which can be affected by factors such as electrode placement, participant movement, environmental noise, and individual differences in brain anatomy or physiology. Ensuring robust signal acquisition and processing remains a significant challenge in BCI research, requiring advanced signal processing techniques and artifact removal methods.
Precise Control and Measurement: BCI provides precise control over experimental variables and enables real-time measurement of neural activity with high temporal resolution. This level of control allows researchers to design experiments with fine-grained manipulation of stimuli, tasks, or feedback modalities, enhancing the reliability and reproducibility of research findings.	User Training and Adaptation: Effective BCI operation often requires user training and adaptation to learn new control strategies or mental tasks. This training process can be time-consuming, challenging, and subject to individual variability in cognitive abilities, attentional control, or motor imagery proficiency. Developing user-friendly training protocols and enhancing user engagement are essential for improving BCI usability and user experience.
Non-invasive Exploration: Non-invasive BCI modalities, such as EEG or fMRI, enable researchers to investigate brain function in human participants without the need for invasive procedures. This approach enhances the ethical	Limited Spatial and Temporal Resolution: Non-invasive BCI modalities, such as EEG or fMRI, have inherent limitations in spatial and temporal resolution compared to invasive techniques like ECoG or intracortical recording.

Pros	***Challenges***
acceptability and accessibility of neuroscientific research, allowing for the study of diverse populations and longitudinal assessments.	These limitations constrain the spatial specificity and temporal precision of neural measurements, posing challenges for deciphering fine-grained neural dynamics and distinguishing between closely related brain processes.
Interdisciplinary Collaboration: BCI research fosters interdisciplinary collaboration among neuroscientists, psychologists, engineers, clinicians, and computer scientists. This collaborative approach leverages diverse expertise to tackle complex research questions, develop innovative methodologies, and translate scientific discoveries into practical applications for healthcare, rehabilitation, and human-computer interaction.	Ethical and Privacy Considerations: BCI research raises ethical and privacy concerns related to the collection, storage, and use of sensitive neural data. Ensuring participant confidentiality, informed consent, and data security is crucial for protecting individual privacy and maintaining trust in BCI research. Ethical guidelines and regulatory frameworks are needed to address these concerns and uphold ethical standards in BCI research.
Clinical Translation and Therapeutic Potential: BCI research holds promise for translating scientific discoveries into clinical applications and therapeutic interventions. BCI-based rehabilitation protocols, assistive devices, and diagnostic tools offer new avenues for improving patient outcomes, enhancing quality of life, and promoting neurorecovery in individuals with neurological disorders or disabilities.	Generalization and Transferability: BCI-trained skills and neural patterns may not always generalize or transfer effectively to real-world contexts or novel tasks. Achieving robust generalization requires understanding the underlying neural mechanisms, identifying task-relevant features, and optimizing training protocols to promote adaptive learning and transfer of BCI skills across domains.

In general, while BCI offers numerous benefits for advancing neuroscience research and technological innovation, it also presents challenges related to signal quality, user training, ethical considerations, and generalization of findings. Addressing these challenges requires interdisciplinary collaboration, methodological innovation, and ethical stewardship to harness the full potential of BCI in research activities.

B. Review of relevant studies on BCI implementation

The seminal review [6] provides an overview of the principles, techniques, and applications of BCI technology, focusing on its potential for communication and control in individuals with severe motor disabilities. The authors discuss various BCI paradigms, signal acquisition methods, and decoding algorithms, highlighting key challenges and future directions for BCI research and clinical translation.

Another review article [7] examines the historical development, current state, and future prospects of brain-machine interfaces (BMIs), including BCI systems. The authors discuss the evolution of BMI technology, from early experimental demonstrations to contemporary applications in neuroscience, prosthetics, and neurorehabilitation. They also explore emerging trends in BMI research, such as closed-loop systems, neuroprosthetic devices, and neuroethics considerations.

In [8] authors explore the expanding scope of BCI technology beyond medical applications, highlighting its potential in non-medical domains such as gaming, neurofeedback, and human augmentation. The authors discuss recent advancements in BCI hardware, software, and signal processing techniques that have enabled new applications and enhanced user experience. They also address challenges and opportunities for future BCI development, including ethical considerations and interdisciplinary collaboration.

Study [9] investigates the feasibility of using a P300-based BCI for communication and control in patients with amyotrophic lateral sclerosis (ALS). The authors demonstrate that individuals with severe motor disabilities can learn to use the BCI system to spell words and phrases using only their brain signals. The study highlights the potential of BCI technology to improve communication and quality of life for individuals with neurodegenerative diseases.

Review article [10] discusses future directions and challenges in brain-machine interface (BMI) research, with a focus on BCI applications. The authors explore emerging technologies, such as optogenetics, nanotechnology, and neural prosthetics, that hold promise for advancing BMI capabilities and addressing current limitations. They also emphasize the importance of interdisciplinary collaboration, ethical considerations, and translational efforts to realize the full potential of BMI technology for research and clinical applications.

These studies provide valuable insights into the principles, applications, and challenges of BCI implementation, contributing to the advancement of neuroscience research, clinical practice, and technological innovation in the field of brain-computer interfaces.

C. Methodology

Current study deals with development of experimental setup, both hardware and software, capable to be employed for research activities with the use of BCI technology. As a target area of implementation, it was chosen computer typing assistant for patients with motion disabilities. As a hardware component it was chosen OpenBCI solutions, which is an easy-to-use system and good choice for initial experiments with BCI technology.

Designing an experimental setup for research on computer typing assistance using an OpenBCI set involves several components and considerations to ensure reliable data acquisition, user comfort, and experimental control.

OpenBCI hardware used for acquiring EEG signals from the user's scalp. These devices offer flexibility, portability, and open-source compatibility, making them suitable for research applications.

The system uses EEG electrodes, such as Ag/AgCl electrodes, attached to the user's scalp using a 3D-printed helmet. The International 10-20 system for electrode placement is used to ensure standardized positioning across participants.

OpenBCI USB Dongle is used to connect the OpenBCI device to a computer for real-time data streaming and communication with the EEG acquisition software.

Software Setup. OpenBCI GUI software is utilized for configuring the OpenBCI device, visualizing EEG signals in real-time, and recording data during experiments. Software could be customized to display relevant channels, filter settings, and experimental markers.

Collected signals are postprocessed at preparations stage using signal processing libraries, such as MNE-Python and EEGLAB for offline analysis of EEG data. Preprocessing steps such as filtering, artifact removal, and feature extraction to prepare data for classification algorithms are implemented.

Experimental Paradigm was designed in the following way. Typing task paradigm assumes that participants should "type" alphabet characters using a visual stimuli interface. GUI presents visual stimuli corresponding to alphanumeric characters or symbols on the screen, and participants are instructed to select characters using cognitive tasks.

Calibration Phase assumes conducting a calibration where participants perform motor imagery tasks (e.g., imagining left-hand or right-hand movements) while EEG data is recorded. This data is used to train a classifier for decoding motor imagery patterns associated with different characters.

Real-time feedback provided to participants based on decoded EEG signals. Selected characters are displayed on the screen to indicate successful or incorrect character selection.

Control Conditions Include a random selection or no-feedback conditions, to compare performance and make it possible to validate the effectiveness of the BCI typing system.

Participant Setup includes comfortable environment: a quiet and comfortable room to minimize distractions and promote relaxation during EEG recording sessions.

Participants are instructed to wash their hair to remove oils and debris before electrode placement. Electrode gel is applied to ensure good conductivity and minimize skin impedance.

Participant are provided with clear instructions to regarding the typing task, motor imagery instructions, and feedback mechanisms. Participants are instructed to understand the experimental protocol and task requirements before data collection.

By implementing this experimental setup, researchers can investigate the feasibility and effectiveness of BCI-based typing assistance systems using OpenBCI technology, contributing to advancements in assistive technology and human-computer interaction research.

Participant selection criteria are essential to ensure the validity and generalizability of study findings. However, this particular research is limited to university students chosen for experiment verification.

Data collection methods. EEG data is recorded during the typing task using the OpenBCI device and EEG acquisition software. Collected data is saved to files in a standardized format (e.g., EDF or HDF5) for offline analysis.

EEG data is analysed offline during preparations stage using signal processing and machine learning algorithms. Then a classifier is trained to decode motor imagery patterns associated with different characters or commands. Finally, classifier performance is evaluated using cross-validation techniques and assess typing accuracy.

III. Results and Discussion

A. Implementation of BCI in Research Activities

Basing on provided analysis and described findings, an experimental setup for research on computer typing assistant was built. The setup is based on OpenBCI hardware and software solutions used for data collection, and machine learning algorithms for signals analysis and data classification. General view of experimental setup operation is shown in fig. 1.

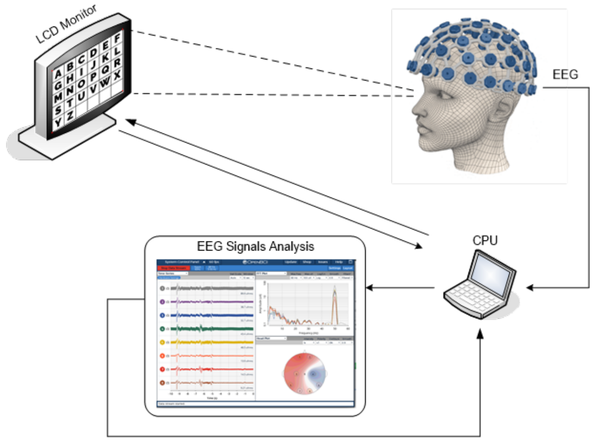


Fig. 1 General view of experimental setup

Developed experimental bench consist of OpenBCI EEG sensors set enclosed with 3D-printed helmets, laptop with OpenBCI native software for EEG data collection, separate LCD monitor used to demonstrate visual stimuli for tested persons, and own software for EEG signals analysis and classification.

B. Experiment description

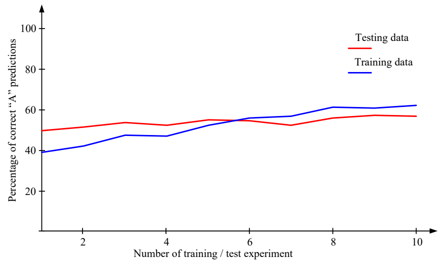
To experimentally verify the BCI typing assistant, both qualitative and quantitative data were collected to assess its performance and usability. Experiment was conducted for a test group of 25 participants, consisting of 20 males and 5 females, aged between 18 and 25 years old. In this particular research tested persons should recognize one out of four possible characters: "A", "B", "C" and "D". Characters were demonstrated on a separate LCD Monitor, while tested persons should imagine desired character for input.

During preparation stage it was detected characteristic features in EEG signals correspondent to brain reaction on highlighted character demonstrated thru LCD monitor for each tested person.

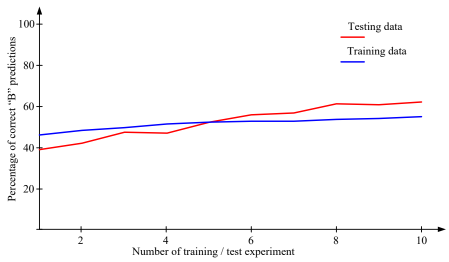
During training stage, a supervised Artificial Neural Network was trained for character recognition based on previously detected features for each signal for each tested person separately. System should recognize each imagined character during 10 attempts per each character demonstrated in random sequence (in total – 40 attempts).

Finally, during verification stage, system should use trained ANN for character recognition [11]. This stage also employed 10 attempts per each character demonstrated in random sequence.

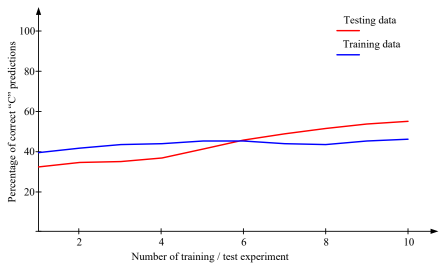
Averaged results for each tested character detection are presented in fig. 2.



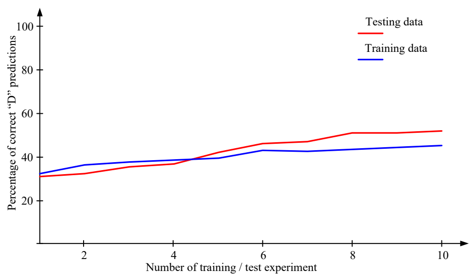
a)



b)



c)



d)

Fig. 2 Test and experiment results on imagined character recognition: a) for letter "A", b) for letter "B", c) for letter "C" and d) for letter "D"

Experimental results demonstrated average character recognition accuracy at 57.8% with slight decrease in testing experiments accuracy over training.

In general, signal processing and feature classification algorithms implemented in this research should be improved and extended for all character set. However, main result of current study is implementation of experimental test bench along with developed software solutions which could be further used in research activities on BCI investigations on university premises.

IV. Conclusion

The paper presents results on possible solution for BCI implementation in research activities. Analysis of existing trends in the area confirms importance of BCI research on possibilities of its implementation in real-life solutions, especially in healthcare, particularly, in development assistant systems for motion disabled patients.

A possible solution for computer typing assistance, based on OpenBCI hardware and software, was proposed and described in the paper. Main features and attributes of proposed system are highlighted.

A research experiment plan with the use of proposed system, was designed, and implemented within current research. Experiment results revealed lower character recognition accuracy than expected, but important outcome of this research is the developed experimental test bench for BCI research.

Future work will be related to improvement signal processing and feature classification algorithms, extending experimental character set for all alphabet, numbers and special characters used in computer typing.

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