Department of Computer Science

VIRTUAL REALITY GAMING BASED ON BRAIN-COMPUTER INTERFACING AND THE ROLE OF COGNITIVE SKILLS

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A Dissertation Submitted to the University of Cyprus in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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VIRTUAL REALITY GAMING BASED ON BRAIN-COMPUTER INTERFACING AND THE ROLE OF COGNITIVE SKILLS

Marios Hadjiaros – University of Cyprus, 2024

Abstract

Electroencephalography (EEG) records the electrical activity of the brain, which can be decoded and processed to understand the physical and psychological state of individuals to improve the quality of life in both healthy and clinical populations. EEG signals are used to detect abnormalities of the brain in routine clinical practice, as well as for neurofeedback, or to control external devices or applications, such as controlling an exoskeleton, as is the case in Brain-Computer Interface (BCI) systems.

Extensive research has been conducted in the field of BCI, with a notable focus on Motor Imagery (MI) in recent years. Despite significant advancements in algorithmic development, the accuracy rates of these systems persistently lag expectations. This discrepancy underscores a notable gap in the literature, wherein insufficient attention has been directed toward elucidating the cognitive mechanisms that underpin effective mental imagery. Hence, there is a clear need for further studies aimed at discerning the cognitive processes associated with enhanced MI performance, thereby addressing this critical shortfall in current research.

To address the aforementioned challenges, the first part of the dissertation explores the most popular approaches and best practices for designing and implementing cognitive gaming interventions that combine BCI systems with Virtual Reality (VR). It focuses on interventions that target cognitive skills related to perception, visuospatial attention, and visuospatial memory. To this purpose, the techniques and algorithms that are commonly used for data pre-processing, feature extraction, and classification in such interventions were reviewed. Issues related to BCI-VR Cognitive Gaming were discussed, including the BCI paradigms, the action tasks and environments, user characteristics, algorithms, channels, accuracy, and the most prominent findings. Furthermore, the current challenges, limitations, future research directions, and potential commercial applications of BCI-VR in cognitive gaming were investigated. The second part of the dissertation introduces a novel BCI framework combined with VR gaming having the potential to advance human-computer interaction by providing immersive and intuitive control mechanisms. This part of the study aimed to evaluate the performance of BCI-VR in a goalkeeper gaming task and explore the influence of cognitive abilities on BCI performance using Motor Imagery. Forty-four healthy volunteers participated in the study who carried out a BCI-VR Goalkeeper task and underwent a left-hand versus right-hand movement imagery task while wearing a VR headset. Twenty-two participants carried out the Flanker task and the Spatial Cueing task and another twenty-two participants carried out the Mental Body Rotation (MBRT) and Spatial Orientation (SOT) tasks. Six classification algorithms were employed for offline and real-time analysis. The Random Forest algorithm exhibited the highest accuracy rates both offline (Mean accuracy rate = 82.4%) and in real-time (Mean accuracy rate = 71.6%). Results from the Flanker task revealed a significant positive correlation between the mean accuracy for the congruent trials of the Flanker task and the mean offline RF classification accuracy in the BCI-VR Goalkeeper task, ($r(22) = .46$, $p = .03$). Additionally, High Achievers in the BCI-VR Goalkeeper task had higher benefits from attentional cues in service of perception than from attentional cues in service of visual working memory (VWM), ($F(1,20) = 9.09$, $p = .007$, $n2 = .07$). These findings suggest the impact of cognitive abilities on BCI-VR performance and emphasize the need to consider cognitive mechanisms and develop cognitive training interventions to enhance humans to produce appropriate EEG patterns while improving BCI accuracy. Further research should explore other cognitive factors and strive to improve the usability and effectiveness of BCI-VR systems for real-world applications. Overall, the current findings contribute to advancing BCI technology and its potential for neurorehabilitation, assistive technologies, and gaming entertainment.

Marios Hadjiaros – University of Cyprus, 2024

VIRTUAL REALITY GAMING BASED ON BRAIN-COMPUTER INTERFACING AND THE ROLE OF COGNITIVE SKILLS

Μάριος Χάτζιαρος – Πανεπιστήμιο Κύπρου, 2024

Περίληψη

Η ηλεκτροεγκεφαλογραφία (EEG) καταγράφει την ηλεκτρική δραστηριότητα του εγκεφάλου, η οποία μπορεί να αποκωδικοποιηθεί και να υποβληθεί σε επεξεργασία για να κατανοηθεί η φυσική και ψυχολογική κατάσταση των ατόμων για τη βελτίωση της ποιότητας ζωής τόσο σε υγιείς όσο και σε κλινικούς πληθυσμούς. Τα σήματα EEG χρησιμοποιούνται για την ανίχνευση ανωμαλιών του εγκεφάλου στη συνήθη κλινική πρακτική, καθώς και για νευροανάδραση ή για τον έλεγχο εξωτερικών συσκευών ή εφαρμογών, όπως ο έλεγχος ενός εξωσκελετού, όπως συμβαίνει στα συστήματα Διεπαφής Εγκεφάλου-Υπολογιστή (Brain Computer Interfacing (BCI)).

Τα τελευταία χρόνια έχει διεξαχθεί εκτενής έρευνα στον τομέα του BCI, με αξιοσημείωτη εστίαση στις Κινητικές Εικόνες (Motor Imagery (MI)). Παρά τις σημαντικές προόδους στην αλγοριθμική ανάπτυξη, τα ποσοστά ακρίβειας αυτών των συστημάτων υστερούν σημαντικά στις προσδοκίες μας. Υπάρχει ένα αξιοσημείωτο κενό στη βιβλιογραφία, όπου δεν έχει δοθεί επαρκής προσοχή στην μελέτη της αποσαφήνισης των γνωστικών μηχανισμών που στηρίζουν την αποτελεσματική νοερή κίνηση. Ως εκ τούτου, υπάρχει σαφής ανάγκη για περαιτέρω μελέτη των γνωστικών διεργασιών που σχετίζονται με την βελτιωμένη απόδοση για MI, αντιμετωπίζοντας έτσι αυτό το κρίσιμο θέμα στην τρέχουσα έρευνα.

Για την αντιμετώπιση των προαναφερθεισών προκλήσεων, το πρώτο μέρος της διατριβής διερευνά τις πιο δημοφιλείς προσεγγίσεις και τις βέλτιστες πρακτικές για το σχεδιασμό και την εφαρμογή γνωστικών παρεμβάσεων με τη χρήση παιχνιδιών (gaming) που συνδυάζουν συστήματα BCI με Εικονική Πραγματικότητα (VR). Το μέρος αυτό επικεντρώνεται σε παρεμβάσεις που στοχεύουν σε γνωστικές δεξιότητες που σχετίζονται με την αντίληψη, την

οπτικοχωρική προσοχή και την οπτικοχωρική μνήμη. Για το σκοπό αυτό, αναθεωρήθηκαν οι τεχνικές και οι αλγόριθμοι που χρησιμοποιούνται συνήθως για την προεπεξεργασία δεδομένων, την εξαγωγή χαρακτηριστικών και την ταξινόμηση σε τέτοιες παρεμβάσεις. Συζητήθηκαν ζητήματα που σχετίζονται με το Γνωστικό Παιχνίδι BCI-VR, συμπεριλαμβανομένων των παραδειγμάτων BCI, των εργασιών και των περιβαλλόντων δράσης, των χαρακτηριστικών των χρηστών, των αλγορίθμων, των καναλιών, της ακρίβειας BCI και των πιο σημαντικών ευρημάτων. Επιπλέον, διερευνήθηκαν οι τρέχουσες προκλήσεις, οι περιορισμοί, οι μελλοντικές ερευνητικές κατευθύνσεις και οι πιθανές εμπορικές εφαρμογές του BCI-VR για γνωστικά παιχνίδια gaming.

Στο δεύτερο μέρος της διατριβής εισάγεται ένα νέο πλαίσιο BCI σε συνδυασμό με παιχνίδια VR που έχουν τη δυνατότητα να προωθήσουν την αλληλεπίδραση ανθρώπου-υπολογιστή παρέχοντας εμβυθιστικούς και διαισθητικούς μηχανισμούς ελέγχου. Αυτό το μέρος της μελέτης είχε ως στόχο να αξιολογήσει την απόδοση του BCI-VR σε μια δραστηριότητα παιχνιδιού τερματοφύλακα και να διερευνήσει την επιρροή των γνωστικών ικανοτήτων στην απόδοση BCI χρησιμοποιώντας MI. Σαράντα τέσσερις υγιείς εθελοντές συμμετείχαν στα πειράματα BCI-VR Goalkeeper και υποβλήθηκαν σε μια δραστηριότητα νοερής κίνησης αριστερού έναντι δεξιού χεριού. Είκοσι δύο συμμετέχοντες πραγματοποίησαν την εργασία Flanker και την εργασία Spatial Cueing και άλλοι είκοσι δύο συμμετέχοντες πραγματοποίησαν τις εργασίες Mental Body Rotation (MBRT) και Spatial Orientation (SOT). Έξι αλγόριθμοι ταξινόμησης χρησιμοποιήθηκαν για ανάλυση σε μη πραγματικό (offline) και σε πραγματικό χρόνο (real-time). Ο αλγόριθμος Random Forest παρουσίασε τα υψηλότερα ποσοστά ακρίβειας τόσο σε μη πραγματικό χρόνο (Μέση ακρίβεια = 82.4%) όσο και σε πραγματικό χρόνο (Μέση ακρίβεια = 71.6%). Τα αποτελέσματα από την εργασία Flanker αποκάλυψαν μια θετική συσχέτιση μεταξύ της μέσης ακρίβειας για τις αντίστοιχες δοκιμές της εργασίας Flanker και της μέσης ακρίβειας ταξινόμησης της εργασίας τερματοφύλακα BCI-VR, σε μη πραγματικό χρόνο, ($r(22) = .46$, $p = .03$). Επιπρόσθετα, τα άτομα με τη μεγαλύτερη απόδοση (High Achievers) στην εργασία τερματοφύλακα BCI-VR είχαν μεγαλύτερα οφέλη από τα σημάδια προσοχής που σχετίζονται με την αντίληψη έναντι των συνθημάτων προσοχής που σχετίζονται με την οπτική μνήμη εργασίας (VWM), ($F(1,20) = 9.09$, $p = .007$, $n2 = .07$). Αυτά τα ευρήματα υποδεικνύουν τον αντίκτυπο των γνωστικών ικανοτήτων στην απόδοση BCI-VR και τονίζουν την ανάγκη να ληφθούν υπόψη γνωστικοί μηχανισμοί και να αναπτυχθούν παρεμβάσεις γνωστικής εκπαίδευσης για να ενισχύσουν τους συμμετέχοντες να παράγουν κατάλληλα μοτίβα EEG βελτιώνοντας παράλληλα την ακρίβεια BCI. Περαιτέρω έρευνα θα πρέπει να διερευνήσει άλλους γνωστικούς παράγοντες με σκοπό να βελτιώσει τη χρηστικότητα και την αποτελεσματικότητα των συστημάτων BCI-VR για εφαρμογές πραγματικού κόσμου. Συνοψίζοντας, τα τρέχοντα ευρήματα συμβάλλουν στην προώθηση της τεχνολογίας BCI και των δυνατοτήτων της για νευροαποκατάσταση, υποστηρικτικές τεχνολογίες και ψυχαγωγία με τη χρήση παιχνιδιών.

VALIDATION PAGE

Doctoral Candidate: Marios Hadjiaros

Doctoral Thesis Title: VIRTUAL REALITY GAMING BASED ON BRAIN-COMPUTER INTERFACING AND THE ROLE OF COGNITIVE SKILLS

The present Doctoral Dissertation was submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy at the **Department of Computer Science** and was approved on the May 24th, 2024 by the members of the **Examination Committee.**

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DECLARATION OF DOCTORAL CANDIDATE

The present doctoral dissertation was submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy of the University of Cyprus. It is a product of original work of my own unless otherwise mentioned through references, notes, or any other statements.

Marios Hadjiaros

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At the culmination of this journey, a profound sense of gratitude fills me, directed particularly towards those whose support and guidance have been instrumental in reaching this milestone.

First, I would to express my sincere thanks to CYENS – CENTER OF EXCELLENCE for the scholarship awarded fully covering my PhD studies. This project has received funding from the European Union's Horizon 2020 Research and Innovation Program under Grant Agreement No 739578 and the Government of the Republic of Cyprus through the Deputy Ministry of Research, Innovation and Digital Policy.

Likewise, I express my deepest appreciation to my supervisor, Prof. Constantinos Pattichis, whose unwavering assistance, invaluable advice, and steadfast guidance have been pivotal in shaping this thesis. His expertise and mentorship have been indispensable throughout this endeavor. I am also indebted to Prof. Marios Avraamides and Dr. Andria Shimi of the Department of Psychology at the University of Cyprus, as well as Dr. Kleanthis Neokleous, the leader of the ITICA team at CYENS-Centre of Excellence. Their tireless contributions and scholarly insights have significantly enriched the research presented in this thesis.

Lastly, I am profoundly grateful to my wife, Georgia, whose unwavering support and love have sustained me through the challenges of this academic journey. Her encouragement and belief in me have been a constant source of strength.

To each of you, I extend my heartfelt gratitude. This thesis stands as a testament to our collective efforts and unwavering commitment. Thank you, from the depths of my heart.

DEDICATION

I dedicate this dissertation to my beloved mother, Photoula Mandritou Hadjiarou, who always fought hard for us to study. Her boundless love, encouragement, and sacrifices have been the guiding light in my academic journey. This work stands as a tribute to her enduring legacy and profound impact on my life.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

GLOSSARY

ANOVA: Analysis of Variance

ACCSP: Adaptive Composite Common Spatial Pattern

ADHD: Attention-Deficit Hyperactivity Disorder

BCI: Brain-Computer Interface

BH: Black Hole

CSP: Common Spatial Pattern

CNN: Convolutional Neural Networks

DBN: Deep Belief Network

DT: Decision Tree

DWT: Discrete Wavelet Transform

DOT: Design Organization Test

EEG: Electroencephalography

EMG: Electromyography

ECG: Electrocardiography

EOG: Electrooculography

ERD: Event-Related Desynchronization

ERS: Event-Related Synchronization

ErrP: Error Potentials

ERP: Evoked-Related Potential

EA: Evolutionary Algorithm

FBCSP: Filter Bank Common Spatial Pattern

GRU: Gated Recurrent Units

HMD: Head-Mounted Display

ICA: Independent Component Analysis

k-NN: k-Nearest Neighbors

LDA: Linear Discriminant Analysis

LED: Light-Emitting Diodes

LH: Left Hemisphere

LSTM: Long Short-Term Networks

MBRT: Mental Body Rotation

MI: Motor Imagery

MLP: Multilayer Perceptron

NN: Neural Networks

PCA: Principal Component Analysis

PD: Parkinson’s Disease

RBM: Restricted Boltzmann Machine

RF: Random Forest

RT: Reaction Time

RNN: Recurrent neural networks

RH: Right Hemisphere

SCP: Slow Cortical Potentials

SACSP: Self-Adaptive Common Spatial Pattern

SMR: Sensorimotor rhythm

SOT: Spatial Orientation

SVM: Support Vector Machine

SSAEP: Steady-state auditory evoked potentials

SSEP: Steady-State Evoked Potentials

SSSEP: Steady-State Somatosensory Evoked Potentials

SSVEP: Steady-State Visual Evoked Potentials

VR: Virtual Reality

VWM: Visual Working Memory

WDP: Wavelet Packet Decomposition

Chapter 1

Introduction

1.1 Problem Statement

Electroencephalography (EEG) records the electrical activity of the brain, which can be decoded and processed to understand the physical and psychological state of individuals to improve the quality of life in both healthy and clinical populations. EEG signals are used to detect abnormalities of the brain in routine clinical practice, as well as for neurofeedback, or to control external devices or applications, such as controlling an exoskeleton [1], as is the case in Brain-Computer Interface (BCI) systems. This sensing and control interaction using brain signals, known as Brain-Computer Interface (BCI), is relevant to critical healthcare applications such as rehabilitation after stroke [2].

A typical BCI system is composed of six basic processing components as shown in Fig. 1: (1) raw EEG signal acquisition, (2) pre-processing of EEG signal for background noise cleaning, (3) extraction of specific application features from the clean data and selection of more discriminative features, (4) classification of the selected features, (5) decision making linked with device and command, and (6) application execution and feedback to the user Fig. 1. These processing components are present in all categories of BCI systems, namely, Active, Reactive, and Passive systems (see TABLE 1).

EEG-based Motor Imagery (MI) signals have been used in various healthcare applications, such as neurological rehabilitation [3], [4] restoration of lost or reduced limb function by controlling an exoskeleton [5], [6] replacement of robotic wheelchair gait function for people who cannot walk [7], [8], [9] and cursor control [10], [11]. MI-EEG signals, however, are complex and have high-dimensional structures. Thus, advanced machine learning algorithms are required to process and decode them. This study aimed to investigate the performance of MI BCI combined with a virtual reality (VR) gaming task.

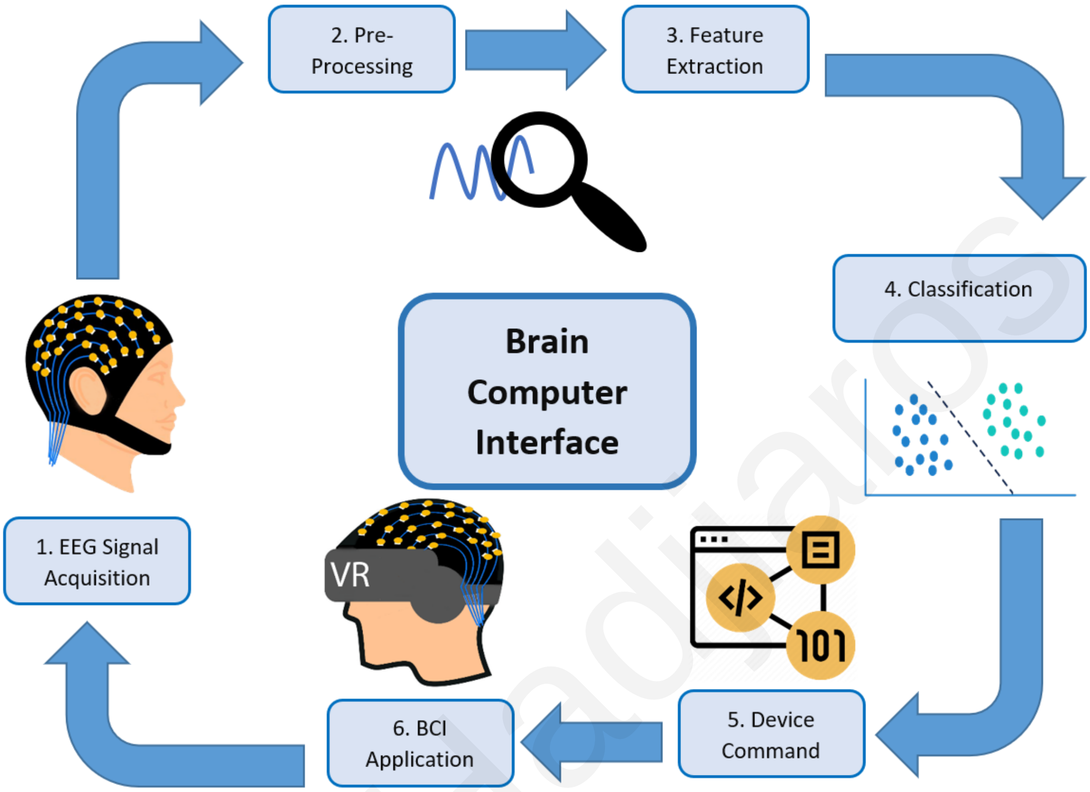

Fig. 1. Main components of a BCI-VR Gaming system. (1) raw EEG signal acquisition, (2) pre-processing of EEG signal for background noise cleaning, (3) extraction of specific application features from the clean data and selection of more discriminative features, (4) classification of the selected features, (5) decision making linked with device and command, and (6) application execution and feedback to the user.

Typical machine learning approaches have been widely used to classify MI-EEG data. These methods usually process the MI-EEG signal in 3 phases: pre-processing, feature extraction, and feature classification. In the pre-processing phase, selected channels related to MI are filtered in the frequency range of interest, and the noise is removed. In feature extraction, various techniques have been proposed to extract task-related MI features from high-dimensional EEG signals. MI features fall into three categories, depending on the domain in which the data are processed: temporal features, spatial features, and spectral features. Temporal features are extracted in the time domain at different time points or during different time blocks, such as mean, variance, etc. [12]. Spatial features aim to identify features from specific electrode locations on the scalp, such as common spatial patterns (CSPs) [13]. CSP and its derivatives (Sparse CSP [14], Stationary CSP [15], divergence CSP [16], probabilistic CSP [17], and filter bank CSP (FBCSP) [18]) are the most common feature extraction methods for MI-EEG data [18], [19], [20], [21], [22]. Spectral features include either frequency domain features or time-frequency features. In the classification phase, several classifiers were used to classify the generated MI features into separate MI tasks [23], such as Support Vector Machine (SVM) [24], Linear Discriminant Analysis (LDA) [22], and the Bayesian classifier [18]. Although there has been significant improvement in conventional MI-EEG signal classification methods, these methods are still plagued by major difficulties. First, EEG signals are easily affected by many noise sources (e.g., computers, sounds, lighting, electricity, internet, etc.). These artifacts, combined with channel correlation, subject dependence, and high dimensionality of EEG signals make the interpretation and classification of brain signals extremely difficult [25]. Therefore, it is critical to develop a more stable and holistic MI-EEG BCI framework that can operate in various scenarios and automatically extract distinct features from challenging MI-EEG data. Additionally, feature extraction relies heavily on human experience in a particular area. For example, basic biological expertise is necessary to analyze the state of MI tasks via EEG signals. Although human experience can help in some respects, in more general cases, it is insufficient. Therefore, an automated approach to feature extraction is required. In recent years, Neural Network methods [2], [6], [67], have been used to address the difficulties associated with EEG classification for MI. Unlike conventional Machine Learning approaches, Neural Networks can automatically learn complex high-level and latent features from raw MI-EEG and eliminate the need for pre-processing and time-consuming feature extraction.

Nevertheless, it seems that the focus on improving the algorithms is not satisfactory. There appears to be a further need to investigate the human characteristics that must govern a person to operate a BCI system with satisfactory accuracy. Moreover, it is no coincidence that one of the many problems preventing BCIs from practical and, by extension, commercial adoption is the variation in performance between the population and the closely related BCI-illiteracy phenomenon, which shows that around 15-30% of the population cannot develop the ability to control BCI systems based on Motor Imagery or Event-Related Potentials, such as the P300 wave [26]. On the other hand, there is evidence against BCI illiteracy, at least in Steady-State Visual Evoked Potentials (SSVEPs), which operate more robustly even after very short training [27]. Most research in the field of BCIs has focused on advances in signal processing, feature extraction, and classification [28]. However, a trend in recent BCI research highlights the importance of the human-facing side of the BCI [29], [30], [31], [32], [33].

TABLE 1
BCI SYSTEMS CATEGORIES [37]

BCI Category	Description
Active	Controlled by the user through a specific mental task performance.
Reactive	Brain activity is modulated in reaction to an external stimulus given by the BCI system.
Passive	Simply monitor brain activity of the user, without requiring the user to perform any mental task or to achieve a certain goal.

1.2 Contribution

The first contribution of the dissertation explores the most popular approaches and best practices for designing and implementing cognitive gaming interventions that combine BCI systems with VR. It focuses on interventions that target cognitive skills related to perception, visuospatial attention, and visuospatial memory. To this purpose, the techniques and algorithms that are commonly used for data pre-processing, feature extraction, and classification in such interventions were reviewed. Issues related to BCI-VR Cognitive Gaming were discussed, including the BCI paradigms, the action tasks and environments, user characteristics, algorithms, channels, accuracy, and the most prominent findings. Furthermore, the current challenges, limitations, future research directions, and potential commercial applications of BCI-VR in cognitive gaming were investigated.

The second contribution of the dissertation introduces a novel BCI framework combined with VR gaming having the potential to advance human-computer interaction by providing immersive and intuitive control mechanisms. Furthermore, the role of cognitive skills in BCI-VR Gaming was investigated aimed to evaluate how it affects BCI-VR performance and explore the influence of cognitive abilities on BCI using Motor Imagery. Forty-four healthy volunteers participated in the study who carried out a BCI-VR Goalkeeper task and underwent a left-hand versus right-hand movement imagery task while wearing a VR headset. Twenty-two participants carried out the Flanker task and the Spatial Cueing task and another twenty-two participants carried out the Mental Body Rotation (MBRT) and Spatial Orientation (SOT) tasks to investigate the impact of cognitive abilities in a BCI-VR control application. Six classification algorithms were employed for offline and real-time analysis. Six classification algorithms were employed for offline and real-time analysis. The Random Forest algorithm exhibited the highest accuracy rates both offline and in real-time. Results from the Flanker task revealed a positive correlation between the mean accuracy for the congruent trials of the Flanker task and the mean offline classification accuracy in the BCI-VR Goalkeeper task. Additionally, High Achievers in the BCI-VR Goalkeeper task had larger benefits from attentional cues in service of perception than from attentional cues in service of visual working memory (VWM). These findings suggest the impact of cognitive abilities on BCI-VR performance and emphasize the need to consider cognitive mechanisms and develop cognitive training interventions to enhance humans to produce appropriate EEG patterns while improving BCI accuracy. Further research should explore other cognitive factors and strive to improve the usability and effectiveness of BCI-VR systems for real-world applications. Overall, the current findings contribute to advancing BCI technology and its potential for neurorehabilitation, assistive technologies, and gaming entertainment.

1.3 Publications

The research work carried out in this dissertation has been published as follows:

Journal Papers

1. M. Hadjiaros, K. Neokleous, A. Shimi, M. N. Avraamides, and C. S. Pattichis, "Virtual reality cognitive gaming based on brain computer interfacing: A narrative review," *IEEE Access*, vol. 11, pp. 18399–18416, 2023.
   DOI: https://doi.org/10.1109/ACCESS.2023.3247133

2. A. Shimi, V. Tsestou, M. Hadjiaros, K. Neokleous, and M. Avraamides, "Attentional skills in soccer: Evaluating the involvement of attention in executing a goalkeeping task in virtual reality," *Appl. Sci. (Basel)*, vol. 11, no. 19, p. 9341, 17 pages, 2021. DOI: https://doi.org/10.3390/app11199341

   M. Hadjiaros, A. Shimi, M. N. Avraamides, K. Neokleous, and C. S. Pattichis, "Virtual Reality Brain-Computer Interfacing and the role of cognitive skills," *IEEE Access*, submitted March 2024.

Conference Papers

1. M. Hadjiaros, K. Neokleous, E. Schiza, M. Matsangidou, M. N. Avraamides, and C. S. Pattichis, "A game-based cognitive assessment for visuospatial tasks: Evaluation in healthy adults," in *2021 IEEE 21st International Conference on Bioinformatics and Bioengineering (BIBE)*, pp. 1–5, 2021.
   DOI: https://doi.org/10.1109/BIBE52308.2021.9635507

Abstracts

1. M. Hadjiaros, S. Sarri, K. Neokleous, A. Shimi, M. N. Avraamides, and C. S. Pattichis, "Preliminary findings on the Virtual Reality Cognitive Gaming based on Brain Computer Interfacing," in *2022 Society of Applied Neurosciences (SAN2022)*, pp. 109–110, 2022.

2. M. Hadjiaros, S. Sarri, K. Neokleous, A. Shimi, M. N. Avraamides, and C. S. Pattichis, "Preliminary findings on the Virtual Reality Brain Computer Interfacing based on Motor Imagery," in *14th Cyprus Workshop on Signal Processing and Informatics (CWSPI)*, 2022.

Additional publications related to this work have been published as follows:

1. M. Matsangidou, F. Frangoudes, M. Hadjiaros, E. C. Schiza, K. Neokleous, "Bring me sunshine, bring me (physical) strength': The case of dementia. Designing and implementing a virtual reality system for physical training during the COVID-19 pandemic," *Int. J. Hum. Comput. Stud.*, vol. 165, no. 102840, p. 102840, 17 pages, 2022.
   DOI: https://doi.org/10.1016/j.ijhcs.2022.102840

2. F. Frangoudes, M. Hadjiaros, E. C. Schiza, M. Matsangidou, O. Tsivitanidou, K. Neokleous, E.Papayianni, M. Avraamides, and C. S. Pattichis , "An overview of the use of chatbots in medical and healthcare education," in *Learning and Collaboration*

Technologies: Games and Virtual Environments for Learning, Cham: Springer International Publishing, pp. 170–184, 2021.
DOI: https://doi.org/10.1007/978-3-030-77943-6_11

3. M. Matsangidou, E. C. Schiza, M. Hadjiaros, K. Neokleous, M. Avraamides, E.Papayianni, F. Frangoudes, and C. S. Pattichis, “Dementia: I am physically fading. Can Virtual Reality help? Physical training for People with dementia in confined mental health units,” in *Lecture Notes in Computer Science*, Cham: Springer International Publishing, pp. 366–382, 2020
DOI: https://doi.org/10.1007/978-3-030-49282-3_26

4. E. C. Schiza, M. Hadjiaros, M. Matsangidou, F. Frangoudes, K. Neokleous, E. Gkougkoudi, S. Konstantinidis, and C. S. Pattichis, “Co-creation of Virtual Reality Re-usable Learning objectives of 360° video scenarios for a Clinical Skills course,” in *2020 IEEE 20th Mediterranean Electrotechnical Conference (MELECON)*, 2020.
DOI: https://doi.org/10.1109/MELECON48756.2020.9140530

1.4 Structure of the dissertation

In Chapter 2, an introduction of the brain anatomy, the main BCI principles, and the state-of the-art techniques and algorithms that are most widely used in BCI-VR systems are presented. Then, in Chapter 3, we review popular EEG-based BCI applications related to BCI-VR Gaming and Cognition, and we summarize the various challenges and discuss future directions related to BCI and VR. In Chapter 4, we delineate the methodology and procedural framework utilized throughout the experimental procedures with participants. Additionally, we elucidate the five tasks administered to the participants. In Chapter 5, we undertake an analysis of the BCI framework based on MI, which was deployed to manage the BCI-VR Goalkeeper task. Furthermore, we evaluate both the merits and drawbacks of the classification algorithms employed in this context. Chapter 6 presents the results of the BCI-VR experimental procedures. Chapter 7 covers the discussion of the results and comparing them with findings from equivalent studies for comprehensive analysis and contextualization. In the final chapter, we summarize the concluding remarks of this study and outline potential future directions.

Chapter 2

BCI Enabling Concepts

2.1 Brain anatomy

2.1.1 Cerebral Cortex

The cerebral cortex, the outer layer of the brain, is a highly intricate structure comprised of four lobes (see Fig. 2) and divided into two hemispheres, as illustrated in Fig. 3. Each lobe is teeming with millions of connections that intricately shape various functions, making the cortex a remarkably complex entity. The two hemispheres of the brain, while sharing certain activities, predominantly govern activities of the opposite side of the body [35], [36].

In the majority of individuals, the left hemisphere (LH) holds dominance, orchestrating activities on the right side of the body. This phenomenon largely accounts for the prevalence of right-handedness. The LH excels in practical domains, displaying prowess in logic, mathematics, and analytical reasoning. Moreover, it spearheads fundamental cognitive processes such as reading, writing, and arithmetic, often referred to as the 3 "R"s. Additionally, the LH plays a pivotal role in linguistic tasks, overseeing spelling, grammar, and verbal memory storage [35] (see Fig. 3).

Conversely, the right hemisphere (RH) showcases its expertise in creativity, perception, and visual-spatial processing. It demonstrates proficiency in tasks requiring non-verbal communication and the recognition of familiar landscapes. Due to the LH's dominance in most individuals, the RH typically assumes the role of the non-dominant hemisphere and tends to govern artistic endeavors [35], [36]. Emotions and musical comprehension predominantly reside within the domain of the LH, while the RH facilitates intuitive insights. However, it is essential to note that logical reasoning primarily pertains to the LH [36].

In instances where the distinction between the dominant LH and non-dominant RH is less clear, certain challenges may arise. Two notable disorders that can manifest under such circumstances are dyslexia and stuttering [35] (see Fig. 3).

Disruptions to the delicate balance of cortical function can have profound clinical ramifications, giving rise to a myriad of neurological disorders. Dysfunctions within the frontal lobe may precipitate deficits in impulse control, emotional regulation, and attentional processing, culminating in conditions such as attention-deficit hyperactivity disorder (ADHD) or frontal lobe epilepsy [35], [36]. Similarly, lesions affecting the temporal lobe can lead to impairments in memory consolidation, language comprehension, and facial recognition, hallmark features of temporal lobe epilepsy and Alzheimer's disease [35], [36]. Understanding the intricate interplay between cortical regions is paramount for elucidating the pathophysiology of these disorders and devising targeted therapeutic interventions [35], [36].

In summary, the cerebral cortex stands as a testament to the brain's remarkable adaptability and complexity. Through its intricate network of specialized regions and hemispheric interactions, the cortex serves as the nexus of human cognition, mediating our perceptions, thoughts, and actions in the ever-unfolding tapestry of consciousness.

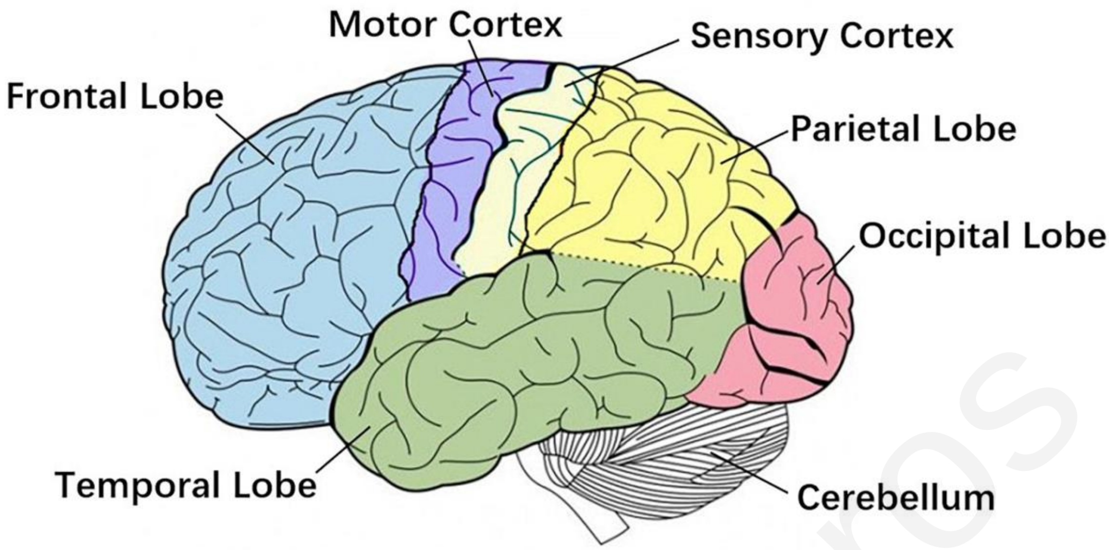

Fig. 2. Major structures of the Cerebral Cortex. The cerebral cortex, an intricate web of neural tissue that envelops the brain's surface, serves as the epicenter for higher cognitive functions and complex behaviors. Comprising four distinct lobes—frontal, parietal, temporal, and occipital—the cortex orchestrates a symphony of neural activity, intricately weaving sensory, motor, and cognitive processes into the fabric of consciousness.

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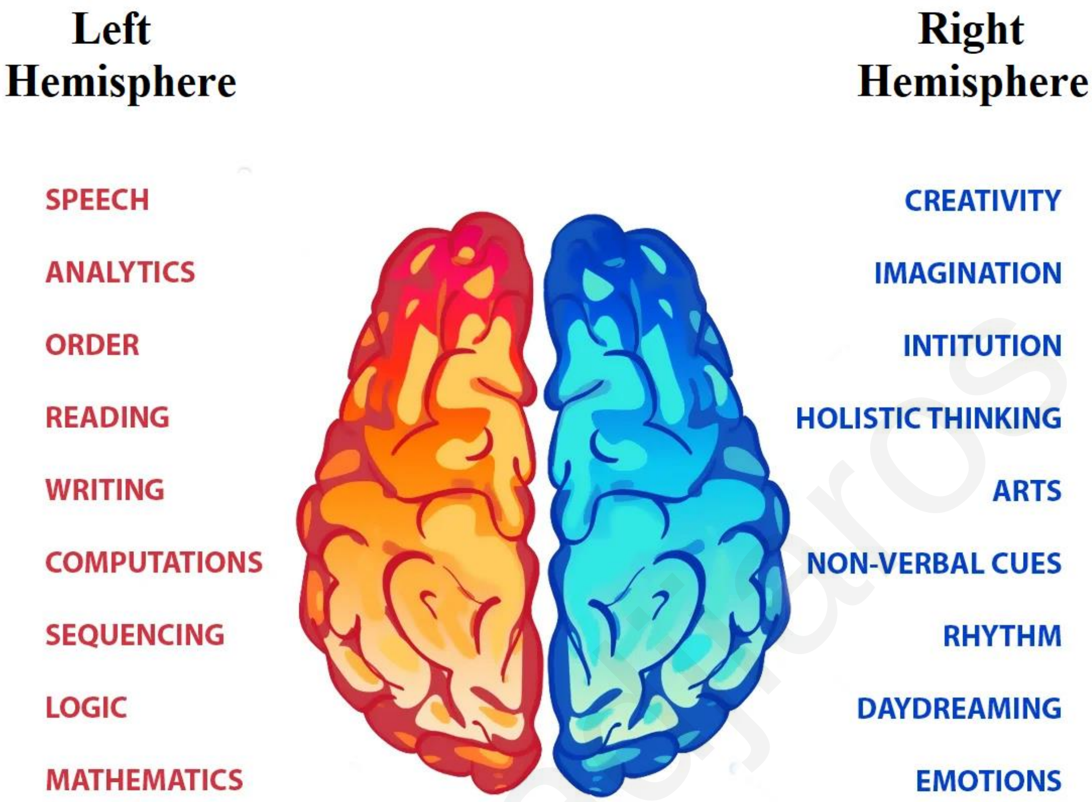

Fig. 3. Cerebral Cortex functions simplified. The left hemisphere serves as the neural hub for speech, analysis, logic, reading, writing and computations. In contrast, the right hemisphere, often relegated to a supporting role, excels in visuospatial processing, emotional perception, creativity, rhythm, imagination, daydreaming, and holistic thinking.
Available on: https://www.centurymedicaldental.com/wp-content/uploads/2022/01/Left-and-Right-Hemisphere-of-the-Brain.jpg.webp

2.1.2 Frontal lobe

The frontal lobe is responsible for immediate and sustained attention, emotional and behavioral control, working memory, social awareness, empathy, time management, organizing, character, executive planning, and motivation [35], [36]. It identifies problems and may send them to other brain regions for a solution [35], [36]. The EEG placement locations of the frontal lobe are the frontal poles – Fp1, Fp2, Fpz, and the frontal – Fz, F3, F4, F7, F8 [35].

2.1.3 Parietal lobe

When the frontal lobe detects a problem, it is likely to send it to the parietal lobe for a solution. Complex grammar, sentence construction, the naming of objects, and mathematical processing can be traced to the left parietal lobe [35]. Spatial recognition, map orientation, and recognition between left and right are all functions of the right parietal lobe. The right parietal lobe is also responsible for analyzing the surroundings and it is involved in attention, body scheme, body image, the physical act of dressing, face recognition, and music [35], [36]. The parietal lobe plays a role in the attentional system and in feeling and displaying emotion. Generally, the parietal lobe is the area of sensory perception and is responsible for spatial processing and for solving mathematical and geometrical problems [35], [36]. The EEG placement locations of the parietal lobe are Pz, P3, P4 [35].

2.1.4 Temporal lobe

The temporal lobe encapsulates the auditory cortex near the amygdala which involves emotions and the hippocampus which involves the memory, as such it’s very crucial to the memory-making process, especially verbal memories [35], [36]. Moreover, the left temporal lobe is associated with word recognition, memory, learning, and a positive mood. The right temporal lobe is associated with facial recognition, stress, and sense of direction, and music. The EEG placement locations of the temporal lobe are T3, T4, T5, and T6 [35].

2.1.5 Occipital Lobe

The occipital lobe is directly connected to the visual cortex and helps to locate objects in the environment. Moreover, it is responsible for the visual field, identification of the objects, and color recognition [35], [36]. It’s also associated with reading, writing, and spelling but the amygdala is necessary as well, to which some connections extend. The EEG placement locations of the occipital lobe are Oz, O1, and O2 [35].

2.1.6 Sensory and Motor (Sensorimotor) Cortex

The sensorimotor cortex is located between the parietal and frontal lobes [36]. The motor cortex is in front of the somatosensory cortex and within the frontal lobe. The somatosensory cortex is behind the motor cortex and within the parietal lobe [35]. The sensory and motor cortex extend deep down to the left and right temporal lobes in the lateral sulcus. It divides the frontal and parietal lobes and coordinates sensory-driven movement [35]. Our character can be translated by the movements of our hands and feet, but also by the wider movement of our body. From the Greek root soma, for the body, the somatosensory system is responsible for the external sensations of touch, pain, temperature, and the internal sensations of joint position [35]. Motor cortex functions have been associated with skilled movements and smooth repetitive operations such as typing, playing musical instruments, writing, fluent speech, and operating complex machinery [35], [36]. It's the connecting node between the voluntary muscles of the brain and the body. The brain wave, sensorimotor rhythm (SMR), is named after this cortex. Additionally, the sensorimotor cortex helps the cerebral cortex to encode both physical and cognitive tasks. The EEG placement locations of the somatosensory motor cortex lobe are C3, C4, and Cz [35].

2.2 EEG Principles

2.2.1 EEG Acquisition

Electrode placement on the scalp is guided by our knowledge of the functions of the four lobes of the cerebral cortex [36]. Most commonly, electrode placement is performed according to the international 10-20 system that labels the electrodes based on positions over the frontal, parietal, temporal, and occipital lobes, indicated by the letters F, P, T, and O respectively (see Fig. 4) [35], [36]. According to the international 10-20 system, each point on the cerebral cortex is assigned a letter and a number. Thus, electrodes with odd numbers represent the positions of the left side of the brain and electrodes with even numbers represent the positions of the right side of the brain [36]. The positions in the midline are indicated by z (zero) instead of a number.

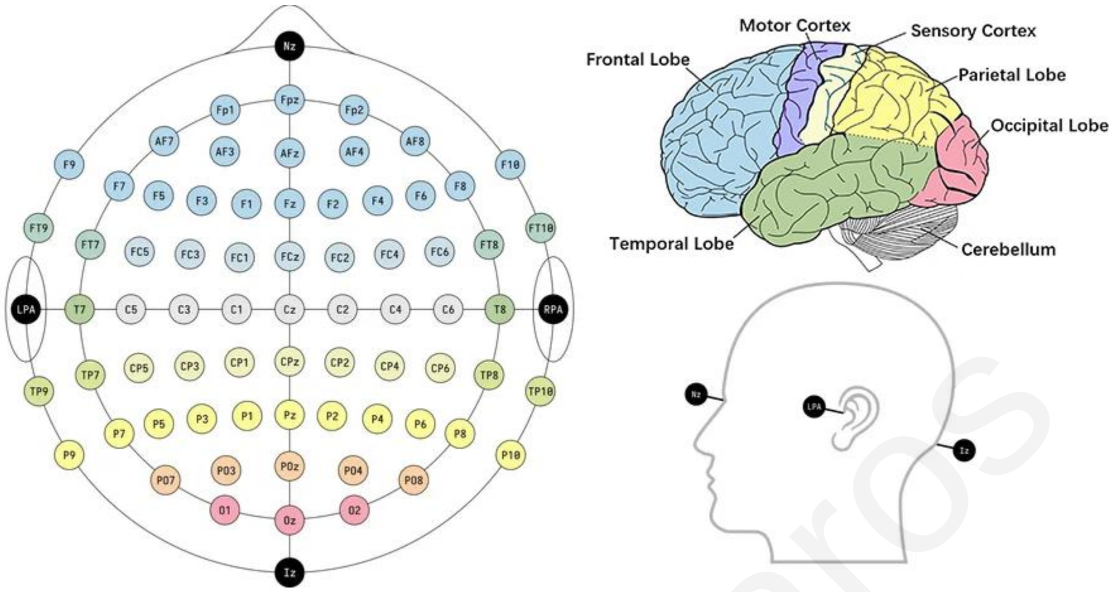

Fig. 4. The international 10-20 system labels the electrodes based on positions over the frontal, parietal, temporal, and occipital lobes, indicated by the letters F, P, T, and O respectively.

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2.2.2 EEG frequency bands

EEG records the electrical brain activity produced from the different structures of the brain. More specifically, it measures voltage fluctuations coming from the ionic flows into the brain neurons [35], [36]. EEG signals recorded from the brain are divided into specific ranges that are more prominent in certain states of the brain [35]. EEG frequency bands are associated with specific brain activity as depicted in TABLE 2.

2.2.2.1 Delta (0.5-4 Hz)

Delta are the slowest, highest amplitude brain waves and are associated with deep sleep and are therefore highly localized in infants [35], [36]. Delta waves are strong brain waves but low frequency waves (see Fig. 5). They are produced during meditation and dreamless sleep. Delta waves are associated with external awareness and are the source of empathy. This deep sleep is necessary for the body to heal and regenerate [35].

2.2.2.2 Theta (4-8 HZ)

Theta waves usually have a sinusoidal or a square top rhythm and may be rhythmic or arrhythmic (see Fig. 5). Theta waves occur most often when we sleep and especially when we are dreaming [35], [36]. Theta is associated with creativity and spontaneity, and also with distractibility inattention, and daydreaming [36]. Theta may reflect depression, anxiety, and other emotional disorders. In theta, the senses are isolated from the external world and focused on signals originating from inner consciousness [35].

2.2.2.3 Alpha (8-12 HZ)

Alpha waves are slower and larger, and they have a sinusoidal rhythm (see Fig. 5). Alpha waves normally range from 9-12 Hz during wakefulness and drop to 8Hz or less, during drowsiness [35]. Sometimes activity between 9-11 Hz is not alpha activity, but it is called "mu" rhythm. It got its name because the waves look like a Greek 'μ' [35]. Alpha rhythm is associated with the inaction of the optical system, increases with closed eyes, and decreases with open eyes. This phenomenon is known as alpha blocking. Alpha blocking refers to the sharp decrease in alpha when the eyes are open [35], [36]. If the amplitude of alpha waves decreases with closed eyes, indicates "drowsiness" of the individual. On the other hand, "mu" waves do not change when eyes are open and can be found only in the sensorimotor cortex or rarely in the parietal lobe [35], [36]. Alpha is prominent in the parietal, temporal and occipital lobes and is associated with meditation and calmness [35].

2.2.3.4 Sensorimotor rhythm (12-15 or 12-16 Hz)

Sensorimotor rhythm (SMR) also called “low beta”, dominates only in the sensorimotor cortex (sensorimotor strip), C3, Cz, or C4 and may reflect a state of being internally oriented [35], [36]. When the brain is in a resting state and the body is not moving SMR increases. In contrast, when the body is moving the amplitude of SMR decreases [35]. During sleep, the EEG becomes more irregular and SMR appears at 12-14 Hz, as a result, the stimulation is more difficult [35].

2.2.2.5 Beta (12-30 Hz)

Beta waves are small but faster brainwaves and are divided into low beta and high beta. Low Beta 12-18 Hz is associated with problem solving, decision making, attention, judgment, analytics, and active thinking [35], [36]. High Beta 18-30 Hz is associated with alertness, mental activity, and agitation [35]. Beta frequency band is higher in adults than in children and increases during drowsiness [35], [36]. However, it does not respond when the eyes are open or closed [35]. Beta bandwidths are defined in several different ranges. For example, some researchers define beta as 13-30 Hz. Others define beta as 12-38 Hz, or 13-21 Hz. Therefore, when referring to beta waves it is important to document the frequency range.

2.2.2.6 Gamma (>30 Hz)

Gamma waves are the fastest and most subtle brainwaves and modulate perception and consciousness [35], [36]. Synchronous bursts of 40 Hz activity have been found in people during problem solving tasks [35]. The 40 Hz rhythm is all over the scalp and not in a specific location [35], [36]. It helps in learning and organizing the brain. It is activated when the brain needs to carry out some tasks and remains dormant when there is no specialized task to carry out [35], [36]. Gamma works during cognitive mechanisms in the individual. Gamma synchronization is related to cognitive processing and appears to be an important coding mechanism in various processes related to brain organization [35]. Additionally, High Gamma is associated with cognitive tasks such as reading, speaking, listening, and memory [35], [36].

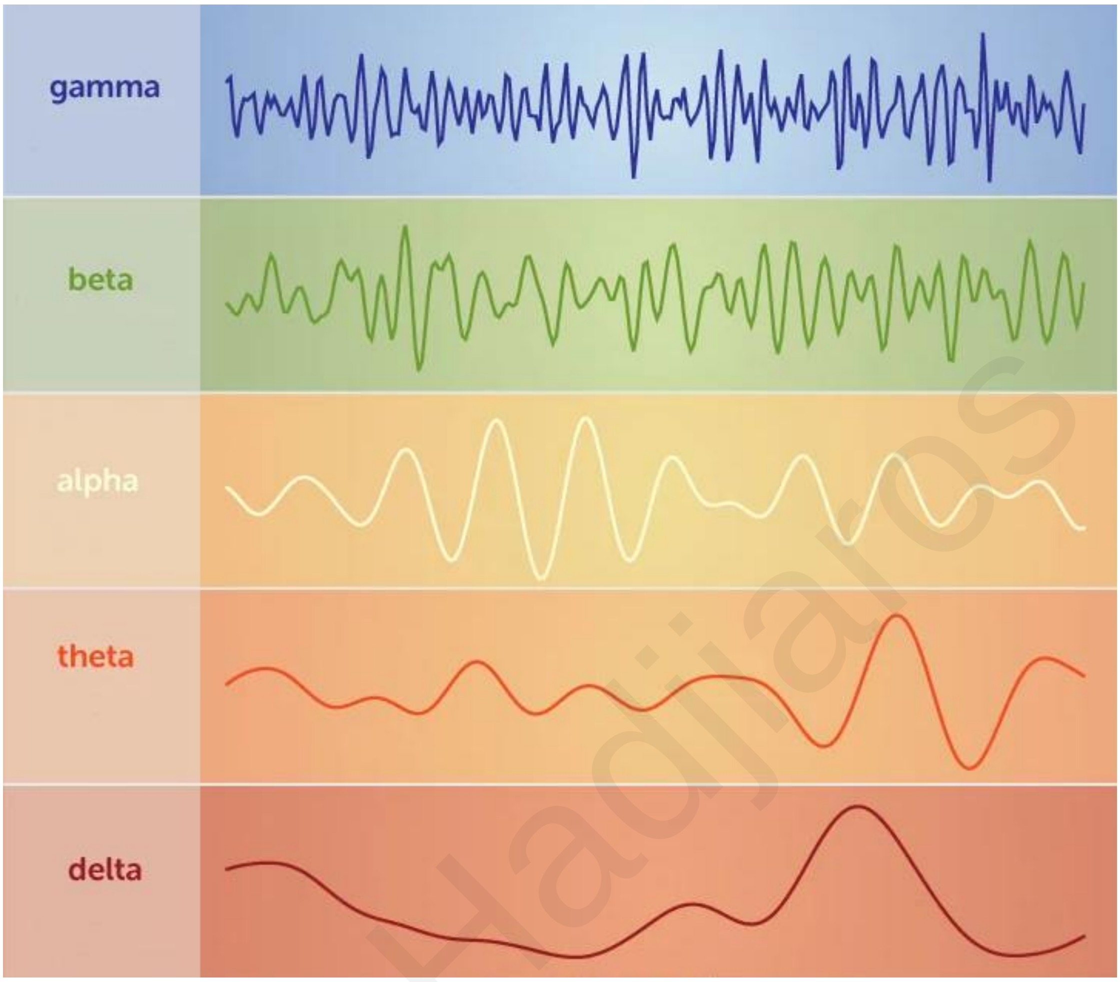

Fig. 5. The 5 main types of brainwave frequencies. Delta are the slowest, highest amplitude brain waves and is associated with deep sleep and is therefore highly localized in infants. Theta waves usually have a sinusoidal or a square top rhythm and may be rhythmic or arrhythmic. Alpha waves are slower and larger, and they have a sinusoidal rhythm. Beta waves are small but faster brainwaves. Gamma waves are the fastest and most subtle brainwaves and modulate perception and consciousness.

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TABLE 2
EEG FREQUENCY BANDS [35], [36]

Band	Frequency (Hz)	Activity
Delta	0.5 - 4 Hz	Deep sleep, no focus, unconscious.
Theta	4 - 8 Hz	Deep relaxation, internal focus, meditation, intuition access to the unconscious. Material such as imaging, fantasy, dreaming.
Low Alpha	8 - 10 Hz	Wakeful relaxation, consciousness, awareness without attention or concentration, good mood, calmness.
High Alpha	10 - 12 Hz	Increased self-awareness and focus, learning of new information.
Low Beta	12 - 18 Hz	Active thinking, active attention, focus towards problem solving, judgment and decision making.
High Beta	18 - 30 Hz	Engagement in mental activity, alertness and agitation.
Low Gamma	30 - 50 Hz	Cognitive processing, senses, intelligence, compassion, self-control.
High Gamma	50 – 70 Hz	Cognitive tasks: memory, hearing, reading and speaking.

2.3 BCI Principles

2.3.1 Categories of BCI Technologies

2.3.1.1 Active BCIs

In active BCIs, the individual voluntarily performs a specific mental task that produces a specific pattern of electrical activity in the brain that can be detected and classified by the system to send a command to an external device [37]. One of the most common mental tasks is hands motor imagery. The person imagines that he is moving his upper body without any physical movement or muscle activation. Imagining the movement of the left versus right hand corresponds to different activations of primary somatosensory and motor cortical areas so that they can be detected and categorized for controlling an application or device.

2.3.1.2 Reactive BCIs

In a reactive BCI, the individual's brain activity is modulated in response to an external stimulus presented to the user [37]. A widely used paradigm of reactive BCI is steady state visual evoked potentials (SSVEP) where external LED light stimuli are flickering at different frequencies [48]. Each external stimulus corresponds to a different command. The users must direct their attention to the stimulus of their choice and the BCI system detects the flickering frequency reflected in the EEG giving the corresponding command.

It is important to note that the distinction between reactive and active BCI in the literature is misleading in that the term "reactive" implies a passive user [35], [37]. In reactive BCIs the user is quite active, for example directing or maintaining attention to the stimuli.

2.3.1.3 Passive BCIs

Passive BCIs are one of the most promising systems in recent years. A passive BCI monitors the user's brain activity without requiring the user to perform any task [36], [37]. Among the most recent developments in the field of passive BCIs are emotional BCIs that detect emotional states [35], [36]. The innovation in these systems is in the support and assistance to the individual in his/her daily life. For example, the system can adjust the room temperature depending on the user's discomfort. Also, such systems can recommend specific movies based on the user's emotions such as a comedy when the person is sad or a telling of a joke. It could also lower the difficulty level in a game when it detects that the user is frustrated or bored and introduces more engaging elements.

2.3.2 Types of BCI in VR Gaming

Depending on the recording method, BCI can be categorized into invasive or non-invasive systems. Invasive BCI requires implanting microelectrode arrays to the brain to record the activity of neurons directly. In contrast, non-invasive BCI records electrical activity with electrodes placed on the scalp. Non-invasive BCI is used more often to detect a variety of control signals, including Slow Cortical Potentials (SCP), Steady-State Evoked Potentials (SSEP), Motor Imagery (MI), Error Potentials (ErrP), and the P300 Evoked-Related Potential (ERP)[38]. In the BCI-VR, the most commonly used control signals are the P300, the MI, and the SSVEP [39].

There are 2 types of BCI systems, dependent and independent. Dependent BCI systems need some form of motor control by the subject. MI-based BCI is a good example of a dependent BCI system that has been used extensively. In contrast, independent BCI systems do not need any form of motor control, which is ideal to use with stroke patients and other patients with severe motor deficits. For example, an SSVEP-based independent BCI system allows the user to produce binary responses (e.g., yes vs. no) without a motor response [40].

Finally, a BCI system can be synchronous or asynchronous. In synchronous BCI, the user is prompted by the system to perform an interaction within a certain time span. Conversely, in the case of asynchronous BCI, the user sends commands through mental thinking throughout the experience to interact with the system. Synchronous BCI is not as user-friendly as asynchronous BCI, but it can be designed more easily [23], [41].

2.3.3 EEG Control signal paradigms

The most widely used EEG-based BCI-VR systems are classified into four basic paradigms according to the procedure the brain waves are extracted. These are: (a) Motor Imagery (MI), (b) Positive 300 (P300), (c) Steady-State Visual Evoked Potentials (SSVEP) and (d) Hybrid signals [23] (see also TABLE 3).

2.3.3.1 Motor Imagery (MI)

In the MI paradigm the user sends a command to an external device by imagining moving a limb without performing any physical activity. This is made possible by detecting EEG activity in the somatosensory motor cortex and generating discriminant patterns in the brain signals. The most detectable activities in the somatosensory motor cortex that are distinguishable in the EEG signal correspond to the left vs. right hand movement, foot movement, and tongue movement [42]. Both the physical and the imagined limb movement generate a unique pattern in the alpha and beta bands, more specifically in the “mu” and “SMR” signals [43], [44]. SMR signals are encapsulated in the alpha (mu) (9 - 11 Hz), beta (13 - 30 Hz), and gamma (> 30 Hz) frequency bands [43], [44]. These patterns are reflected with a power decrease termed “event-related desynchronization” (ERD) that correlates with the preparation of movement [45], or with a power increase termed “event-related synchronization” (ERS) that indexes a resting state [46]. Notably, research has shown that MI generates the same pattern in the motor cortex during the execution and the imagination of the movement [47]. ERD / ERS models are localized because of the somatotopic arrangement that exists in the motor cortex. For example, the representation in the upper limb area is on the mantle of the motor cortex and followed by lateralization [48], which makes spatial discrimination easy among left-hand and right-hand EEG patterns.

The most important electrodes that can detect distinct patterns in the somatosensory motor cortex are C3, C4, and Cz. In the upper limbs, there is an evident contralateral dominance for left-right limb recognition [49], [50]. The presence of contralateral and ipsilateral variations in mu activity are used as distinct signatures in BCI to discriminate left-hand and right-hand movements (see Fig. 6) [51]. In contrast, left and right foot MI discrimination does not rapidly evolve because the locations of the areas of the somatosensory cortex that correspond to the left and right foot are very close to each other. Furthermore, the foot motor area is located deep in the sensorimotor cortex, making it difficult to differentiate the nearly identical EEG activity from the left and the right foot. [48]. Therefore, although studies have used MI-based BCI using feet, they generally did so without discriminating across the left and right sides [52], [53] (see also Fig. 6).

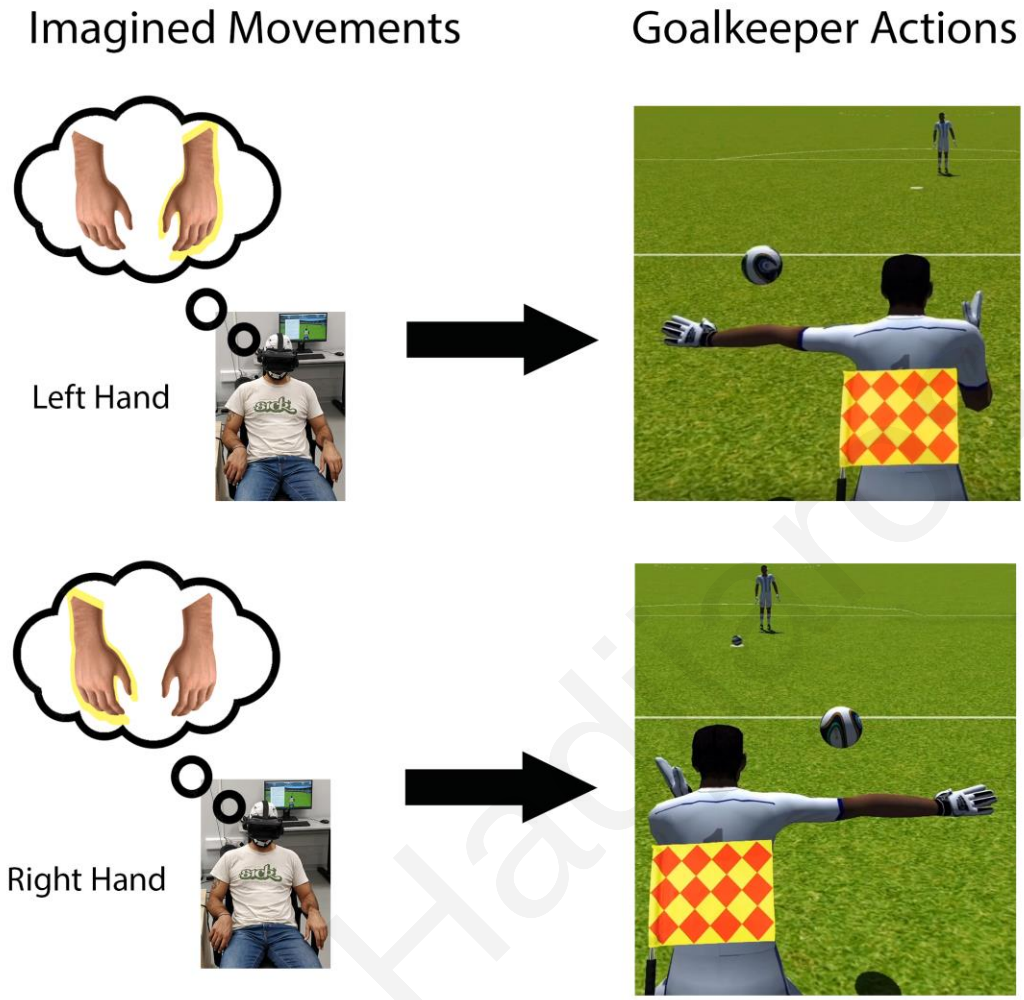

Fig. 6. An example of an MI-based BCI system. The left column shows the movements that the users imagine, without any physical movement or muscle activation to send a command to the VR Goalkeeper avatar, to move his corresponding hand. The right column shows the commands given for the hand movement of the VR Goalkeeper in the game.

2.3.3.2 Positive 300 (P300)

The visual P300 is one of the most popular examples of EEG-based BCI systems, especially in the most modern implementations of BCI-VR gaming. BCI systems with P300 are based on sequential flashing stimuli, such as symbols, letters, or objects. In 1988, Farwell and Donchin pioneered the use of the visual P300-BCI [54] creating what is today known as the P300 Speller. The P300 is obtained by analyzing event-related potentials (ERP). An ERP is generated by averaging the EEG signal, locked to a particular event such as a visual stimulus presented on a screen. The P300 is produced as a response to infrequently presented stimuli that are recognized by the user. It is a positive peak in the EEG ranging from 5 to 10 microvolts in size that appears around 300ms after the onset of the event [55] (see Fig. 7). The most common locations of the recording electrodes for measuring the P300 are in midline electrodes Pz, Cz, and Fz. The most important advantage of using P300-based BCI systems is that most users can generate the P300 with high accuracy and with almost no training. Therefore, the participant can rapidly and easily use the system to handle an application. The disadvantage of P300-based BCI systems is that the tasks they rely on are attentionally demanding and thus elicit fatigue to the users [55]. In addition, given the visual nature of the tasks, users with vision impairments often have difficulties using the system and produce rather poor results [56].

Fig. 7. An example of a 6x6 symbol P300 matrix based BCI system. The user wants to write the letter "O" by focusing on the letter. The system recognizes the correct letter because of the positive peak generated in the EEG signal 300ms after the flash [55].

2.3.3.3 Steady-State Visual Evoked Potentials (SSVEP)

The SSVEP is another popular visual paradigm in BCI [57]. In SSVEP, users direct their gaze to flickering stimulations, a task that requires good attention control as shown in Fig. 8. The most important locations for the recording electrodes are in the occipital lobe and particularly locations O1, O2, and Oz. Focusing on the flickering stimulus generates an EEG pattern whose frequency correlates with that of the stimulus. To produce the stimulus, light-emitting diodes (LED) are often used. Typically, multiple flickering stimuli with distinct flickering frequencies that represent different commands are presented to the user. The stimulus that matches the pattern of EEG activity is then selected and the command associated with it is executed. The SSVEP has many advantages. One notable advantage is that because the stimuli are exogenous, it can be used without user training. Stimuli can flash at many different frequencies, allowing the user to give different commands to the external device. In addition, the SSVEP frequencies can be more reliably classified than the ERP. However, as with the P300, this paradigm causes fatigue to users, especially when using stimuli with low flickering frequencies [58]. This paradigm is also not suitable for the visually impaired as it entails gaze movement. That said, Min et al. [59] have recently proposed a new SSVEP paradigm that uses a grid-shaped line array that is gaze-independent.

Finally, it should be noted that, along with the SSVEP, several similar approaches can be found in the Steady State Evoked Potential (SSEP) family: steady-state somatosensory evoked potentials (SSSEP), steady-state auditory evoked potentials (SSAEP) [60], and hybrid SSSEP-P300 applications [61].

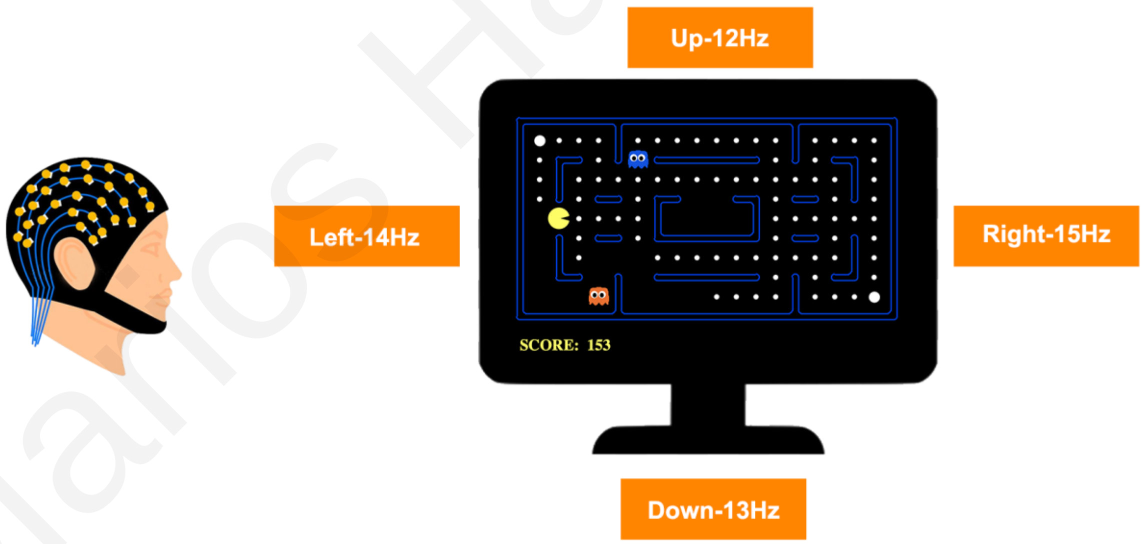

Fig. 8. SSVEP paradigm: The user moves the game character by focusing on the corresponding flickering lights. By focusing on the left flickering light, the EEG signal reflects the 14Hz stimuli and the system triggering a movement to the left [58].

TABLE 3
SUMMARY OF FEATURES OF DIFFERENT NEURAL MECHANISMS

EEG Paradigm	**MI**	**P300**	**SSVEP**
Nature	ERD/ERS	ERPs	SSEP
Advantages	Does not require any external stimulation. Free will operation	Almost no training needed	Almost no training needed
Disadvantages	Requires training	Requires external stimulation. Could provoke tiredness in users.	Requires external stimulation. Could provoke tiredness in users.
Accuracy	65 -70%	6X6 symbol matrix 90%	90%
Training Time	10-30 mins	5 mins	5 mins

2.4 BCI Techniques and Algorithms

2.4.1 Pre-processing strategies

One of the biggest challenges in EEG-based BCI applications is that background noise must be eliminated before performing the analysis. Noise can be caused by both exogenous and endogenous factors. Exogenous factors include televisions, mobile phones, computers, lighting fixtures, etc. Endogenous factors include movement, respiration, skin resistance fluctuations, or other bioelectrical potentials, such as electromyographic (EMG) activity, electrocardiographic (ECG) activity, electrooculographic (EOG) activity, etc. [62]. Therefore, one needs to clean the raw EEG to better suit the requirements. To achieve this, a variety of pre-processing methods can be applied [63], [64], [65], [66], [67], including:

- Notch filtering at 50 or 60Hz (depending on geographic location) to remove power line noise.
- High pass filtering with a low cut-off frequency to erase the drift of the baseline.
- Band pass filtering to pick the appropriate bands.

- Epoching the continuous data to extract segments, time-locked to an event, in specific time-windows.
- EEG amplitude clipping to force the EEG signal into a specific range.
- Cancelling bad trial samples from the EEG.
- Normalizing the data to zero mean and unit variance using z-scores to accelerate convergence and not get stuck in local minimums.
- Down-sampling to accelerate the calculations and reduce the memory.
- Selecting key electrode positions according to the goal of the application.
- Rejecting artifacts using thresholding techniques such as Independent Component Analysis (ICA) [192] or Principal Component Analysis (PCA) [193].

2.4.2 Feature extraction

After the pre-processing that cleans up the signal, the most important features in the EEG signal must be extracted. The most commonly used EEG feature types in BCI systems are statistical, manually-selected, and data-driven adaptive features [68]. The selection of a toolset for dealing with features is a very critical process because of the high complexity and dynamical structure of the EEG signal [69]. There are various ways to achieve feature extraction in the time domain, frequency domain, time-frequency domain, and spatial domain. Extracting features that depend on temporal information only, results in rejecting spectral information. On the other hand, extracting features in the frequency domain only, results in rejecting temporal information.

Two effective techniques for feature extraction are the Discrete Wavelet Transform (DWT) [194] and the Wavelet Packet Decomposition (WPD) [194]. These methods can decompose the EEG signals at multiresolution and multiscale, which is useful as important information in the EEG signal is conveyed in different frequency bands. Moreover, they can extract dynamic features, which is very important given the non-stationary and non-linear nature of the features [70], [71].

Furthermore, time-frequency based methods are highly beneficial when analyzing EEG signals, as they are extremely dynamic. Spatial domain methods and frequency domain methods can be blended to extract more distinct features leading to increased classification accuracy. For better feature extraction, the selection of the most efficient electrode positions, is very important. This can be achieved by setting weights using spatial domain methods [67], [72]. Commonly, high-dimensional features are extracted from the EEG signal. Because of this, statistical transformation methods like PCA and ICA are used for feature selection and dimensionality reduction. However, these methods are computationally expensive and can reduce classification accuracy [67], [73].

To address the problem of high dimensionality, Evolutionary Algorithm (EA) optimization techniques for feature selection from large feature sets are used [74]. Using filter bank approaches, such as the Common Spatial Pattern (CSP), has had a major impact on feature treatment in EEG data [75] and is considered to be one of the most powerful feature extraction techniques widely used in BCI [76]. This method uses a spatial filter that changes the brain signals in a single space where the variation of a feature set is maximized, while lower variation is observed in the rest of the feature set. The CSP approach may not accomplish adequate performance because of the optimal frequency band for each individual. Therefore, selecting an optimized filter band can improve performance. However, selecting the optimal sub-band through pure CSP may take much time [77]. Also, the CSP algorithm has many different variants that are characterized by enhanced performance in BCI systems such as the Adaptive Composite Common Spatial Pattern (ACCSP) and the Self Adaptive Common Spatial Pattern (SACSP) algorithms [78].

Feature extraction methods that are based on Neural Networks (NN) utilize a framework that combines all three phases of feature extraction, selection, and classification in a single pipeline. Despite the long training phase in NN, new invisible data can be analyzed as soon as the network parameters are defined [79]. This results in more effective computations, which in turn extract better features leading to higher classification accuracy.

Finally, it is worth noting that although many researchers skip the feature selection phase, systems using the selection phase seem to achieve greater accuracy [35].

2.4.3 Classification

2.4.3.1 Conventional Machine Learning

The k-Nearest Neighbors (k-NN) algorithm [195] is a well-known non-parametric classification method. In k-NN, the input data corresponding to the different classes create unique groups in the feature space. Adjacent groups are classified together and are defined as neighbors. A distance metric is then used as a measure of similarity of feature vector test among the features of all the classes [79]. The main factors governing the k-NN algorithm are the set of neighbors and the type of distance measurements. k-NN algorithms are not so widespread in the community of BCI because they are very sensitive to the dimensionality of the feature vector [80]. However, when used in low-dimensional feature vectors systems, k-NN can be of great value. Notably, k-NN generates strong outcomes when blended with effective feature selection or feature reduction algorithms.

The Linear Discriminant Analysis (LDA) [98] is another approach that relies on finding the linear patterns of feature vectors that express the corresponding features of the signal. The LDA algorithm separates the classes representing different objects by using hyperplanes. The isolating hyperplane is achieved by searching for the projection that maximizes the distance among the means of the classes and minimizes the interclass variance [81]. The LDA has very low computational requirements and is therefore commonly used. Indeed, it has been applied successfully in many BCI systems that rely on MI, P300, and either multiclass or asynchronous BCI. Nevertheless, while providing good results because of its immunity to non-static issues, due to its extremely linear nature, it downgrades performance in cases of too much non-linear data [82].

Finally, another approach that can be used is the Support-Vector Machine (SVM) [97]. The SVM classification algorithm is a machine learning classification algorithm based on statistical learning theory. The SVM improves generalization, minimizes experience risk and confidence range, solving the problems of overlearning, model selection, dimensionality reduction and nonlinearity in algorithm of pattern recognition under small sample conditions. The algorithm estimates the optimal classification plane that maximizes the classification interval between the two classes [83].

The SVM is a classifier that creates a set of hyperplanes for separating the feature vectors in several classes. SVM picks the hyperplanes that maximize the margins, that is, the distance among the hyperplanes and the nearest training samples [84]. In general, the SVM has been widely accepted by the researchers as one of the simplest algorithms used in the area of BCI. It also proves to be robust with high-dimensional datasets, which means even with high-dimensional feature vectors, a large set of training data is not necessary for a high outcome [85]. Notably, there is no tradeoff with regards to execution speed in real-time BCI integrations. In conclusion, conventional machine learning classification algorithms offer unique advantages and considerations in the field of BCI systems and the selection of an appropriate classification algorithm in BCI design hinges upon the specific requirements of the application.

2.4.3.2 Deep Learning

Deep learning methodologies are increasingly popular in BCI due to their ability to process and analyze complicated patterns in brain signals. In particular, deep learning greatly simplifies the processing of EEG signals as the multiple layers in the network represent and solve a smaller problem, helping the decision-making phase to solve the wider problem by using pre-processing techniques, feature representations, etc. [73]. In addition, there seems to be great success in representing complex patterns with the development of deep learning.

Deep learning algorithms learn hierarchical representations of input data with non-linear transformations techniques [67], [73]. In deep learning, the stacked layers insert a linear transformation to the network and then trigger it through the activation function. The variables of the stacked layers are learned by default with the help of an objective function. Different deep learning architectures have been used, including Convolutional Neural Networks (CNN) [2], [176], [177], Recurrent Neural Networks (RNN) [2], and more.

As their name implies, CNN operate using a linear function called convolution. CNN are widely used for image, video, and EEG analysis. The CNN contain an input layer, where learning data are fed, several hidden layers that process and analyze the input data to create a trained model, and an output layer that predicts the answer to a problem. In the process of network learning, the higher-level features are simplified to lower-level features [67], [86]. The convolution is completed by convolving the signals with multiple 2D filters in order to extract useful complementary features. The connecting weights are changed during the training process to reduce the classification error [87]. Excessive increase in network levels dramatically increases the ability of the neural network to generalize, resulting in overfitting and recognition only in the data it has been trained with. Nevertheless, there are multiple techniques for tackling the problem of overfitting. An effective technique is to use a pooling layer that works as a down-sampling strategy that applies various types of pooling such as max, sum, and average. Pooling layers and convolution layers can decrease the complexity and the feature maps sizes [67].

RNNs include embedded memory cells that store previous network states for later use. The output of these networks results from both the current input and the previous output, and that is why they are referred to as recurrent. By nature, this type of networks is suitable for solving time series related problems such as EEG signal analyses. The memory cells included in the network contain input, output, and forget ports, to determine the output of the cell. The most widely used types of RNNs are the Long Short-Term Networks (LSTM) [2], [68], the Gated Recurrent Units (GRU) [2], and the peephole connection LSTM. By their very nature, these networks have the ability to remember and process complex previous values over a long period of time by subdividing the trials into multiple parts and by extracting temporal-related features as opposed to CNN that process individual trial items to extract spatial features [67].

Finally, the Restricted Boltzmann Machine (RBM) [2],[73] is sometimes used for feature classification. It is a multiplicative unsupervised learning model that contains an input layer, a hidden layer, and two-way connections among the two layers. Each node of the input layer is connected to all the other nodes in the hidden layer. The input data are composed of latent features that are used to reconstruct the data from the input in a backward procedure to create new data points in the hidden layer and vice versa [67], [88]. A Deep Belief Network (DBN) [2], [193] is the total of various layers of RBM. During the learning procedure, the 1st layer in the DBN is the visible and the 2nd layer is the hidden layer. Then, the 2nd layer becomes the visible layer and the 3rd layer the hidden one. The procedure continues in the same pattern until all layers in the network are learned [67].

In conclusion, deep learning techniques, including CNN, RNN, and RBM, offer powerful models for processing and analyzing complex patterns in EEG signals. These methodologies provide efficient means of extracting hierarchical representations and temporal dependencies from brain signals, facilitating advancements in BCI research and applications. By leveraging deep learning architectures, researchers can unlock new insights into brain function and develop innovative solutions for neurorehabilitation, assistive technologies, and cognitive enhancement.

Chapter 3

BCI Applications

3.1 Methodology

The review was conducted in 5 phases based on Bargas-Avila and Hornbaek (2011) and the Cochrane methodology [89]-[91].

PHASE 1: DETAILED PUBLICATIONS EVALUATION

We searched 9 electronic databases, covering a balanced range of disciplines, such as computer science, computer engineering, neuroscience, medical research, and multidisciplinary sources. The databases included in the review were as follows: 1. ACM Digital Library (ACM), 2. Google Scholar, 3. IEEE Xplore (IEEE), 4. MEDLINE, 5. PubMed, 6. Sage, 7. ScienceDirect (SD), 8. Scopus, 9. Web of Science.

Search terms: We applied three queries to each database since we aimed to study the "BCI-VR Gaming technology with Cognitive tasks" fields:

A. BCI-VR Gaming

B. BCI AND Cognitive tasks

C. BCI-VR Gaming AND Cognitive tasks

Search procedure: The search term was used to retrieve the publication's title, abstract and/or keywords.

Search results: The search results and analysis are summarized in Fig. 9.

PHASE 2: PUBLICATIONS RETRIEVED FOR DETAILED EVALUATION

First exclusion: We removed 368 wrong timeframe entries because they included the wrong year. As a result, 1512 articles remain.

Second exclusion: Duplicate studies in the databases (e.g., various terms producing similar result into the same database) and among databases (e.g., different databases producing similar result) were excluded. We excluded 284 duplicate studies. This narrowed down our findings to 1228 different articles.

Third exclusion: We limited the publications to the documents written in English only. We excluded articles that we did not have access to and articles that were not official articles but derived instead to speeches, posters, magazines and in general grey literature without official review. Therefore, we removed 651 articles. The 577 articles that remained include journal articles, conference papers, and book chapters.

PHASE 3: PUBLICATIONS INCLUDED IN THE ANALYSIS

Final exclusion: Since the purpose of this review is to investigate the fields of BCI-VR Gaming and cognitive tasks for Attention, Memory, and Visuospatial skills, we removed publications that used different approaches. We also excluded all studies that used invasive or semi-invasive techniques as well as studies in which BCI was not based on EEG. We also excluded studies that did not use MI, P300, or SSVEP. Finally, we excluded studies that did not mention the methodology or the algorithms they used for pre-processing, feature extraction, classification, and performance, or for which the findings were not clear. Based on these criteria, we removed 513 publications. As a result, we concluded with 32 significant articles (22 studies of BCI-VR Gaming, 8 studies of BCI with Cognitive tasks, and 2 studies that involved both BCI-VR Gaming and cognitive tasks), as presented in Fig. 9. Finally, all articles were grouped to be analyzed.

PHASE 4: DATA GATHERING

In this phase, we extracted all the important information from all the publications to analyze them. We extracted data from all the studies: the BCI paradigm, VR action scene, number of participants, feature extraction algorithm, classification algorithm, EEG electrodes used, and key findings.

PHASE 5: DATA ANALYSIS

We used thematic analysis to classify the selected articles based on the characteristics. The characteristics we used are the BCI paradigms, the BCI pre-processing strategies, feature extraction algorithms, classification algorithms, the BCI-VR challenges, and the BCI-VR gaming future directions.

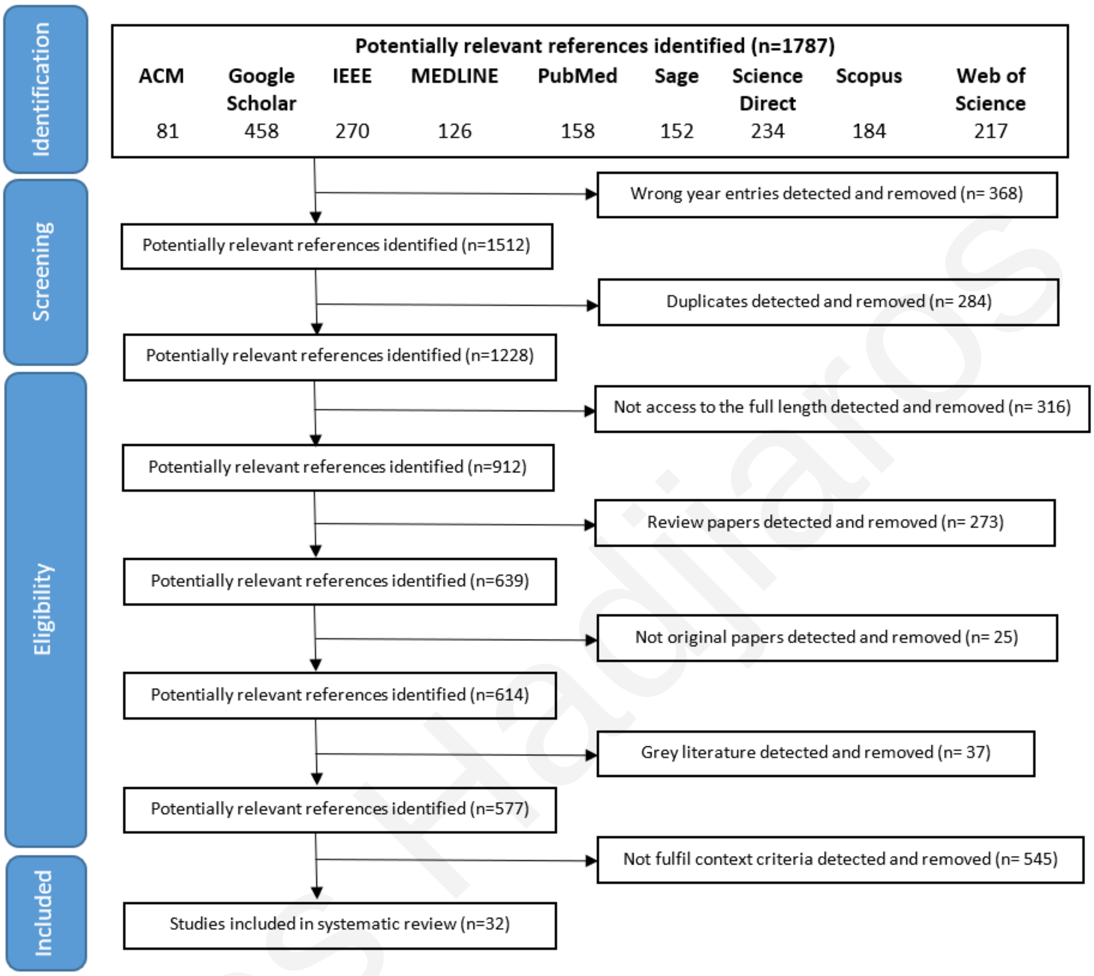

Fig. 9. Summary of search results and analysis for the identification and selection of related studies.

3.2 BCI-VR Gaming

Research on BCI-VR Gaming systems has attracted significant interest for both healthy people and people with motor impairments. VR is a computer technology that uses computer graphics to simulate real environments. Instead of viewing a screen, users are immersed in realistic 3D virtual environments and can interact with the objects as if they were real [92]. This can result in diminished training time and increased efficiency. Also, VR technology makes the training interesting and engaging for the user. Applied in rehabilitation medicine, VR has had documented success, when used for stroke patients with hemiplegia after rehabilitation training [93], Parkinson's Disease rehabilitation [94], upper-limb prosthetics [95], and wheelchair control [96].

The most widely used methods by researchers for BCI-VR Gaming are MI, P300, and SSVEP. TABLE 4 summarizes the most significant BCI-VR games from March 2011 to March 2021.

In one of the studies we reviewed, Xu et al. [97] developed a simulation of a robotic arm in a VR game designed to compare the performance of low-cost devices (OpenBCI) to medical grade BCIs (Neuroscan). The virtual robotic arm was operated using the MI technique and the findings showed that low cost BCIs can produce really good outcomes. The best result of classification accuracy of the robotic arm control was 76.3% with the low-cost device and 79% with the medical quality device [97].

In another study, Vourvopoulos et al. [98] developed the Neu-Row, a novel BCI system that provides multimodal vibrotactile feedback in the VR experience with the use of head-mounted display (HMD) to achieve more distinct activations in the motor cortex areas. The NeuRow system is a holistic BCI approach combining MI, immersive VR environments, and sensory stimulation. During the experimental training, the virtual hands were controlled using only the MI-BCI paradigm in the system. Healthy users were asked to perform a rowing motion with virtual hands using MI. To enhance realism, vibration and tactile feedback were provided. Results showed that the average left-right hand movement accuracy was 70.7%.

In a follow-up study, Vourvopoulos et al. in 2019 [99] used NeuRow with a 60-year-old patient with left hemiparesis caused by a stroke in the right temporal lobe 10 months before. The patient imagined moving his left and right hands to paddle a boat in a virtual environment across 10 sessions carried out over a period of 3 weeks. Electrophysiological data showed increased brain activation, similar to that of healthy individuals. Results showed an improvement in motor function as a result of VR feedback and MI training. This result was also documented in imaging data collected. Overall, the findings of this study extend previous research by showing neuroplastic changes in specific targeted areas of the brain and the effectiveness of BCIs using MI for motor rehabilitation. They also suggest that the systematic training with similar systems that control applications through imagined movement can improve the physical motor ability of individual patients with motor impairments.

Skola et al. [187] investigated how the avatar embodiment in VR influences training for the operation of MI-BCI. This study examined the relationship between BCI performance and subjective levels of embodiment. Online performance from the BCI experiments on the sense of ownership and sense of agency towards the virtual avatar was studied. Using gamification, further increased the performance in the training session. Embodiment in VR mediated by synchrony between mental commands and visual stimulation in VR arose under different conditions than embodiment based on visuo-motor synchrony. Consistency between the perceived sense of ownership and agency played a more important role than the ability to issue MI-BCI commands correctly. The mean accuracy was 70.8%.

Vourvopoulos et al. [188] investigated the role of embodied feedback and how it can help elderly adults increase their BCI performance during MI-BCI training in VR. The elderly population was selected to age-match with the typical stroke age-range demographic, accounting for age-related confounds. Participants received MI-BCI training in two conditions, abstract and embodied feedback. Results showed differences between the two conditions in terms of Event-Related Desynchronization (ERD), lateralization of ERD, and classifier performance in terms of arm discriminability. The mean accuracy with the abstract and embodied feedback was 52.5% and 65% respectively.

Vagaja et al. [189] aimed to examine whether the virtual sense of embodiment (SoE) when induced, as priming of avatar embodiment, and assessed before MI training, could enhance MI-induced EEG patterns. They divided 26 healthy participants into two groups: the embodied group, which experienced SoE with an avatar before undergoing VR-based MI training, and the non-embodied group, which underwent the same MI training without a prior embodiment phase, serving as a control. Although the embodiment phase effectively induced SoE in the embodied group, both groups exhibited similar MI-induced ERD patterns and BCI classification accuracy. This suggests that the induction of SoE prior to MI training may not significantly influence the training outcomes. The mean accuracy of the embodied group and the non-embodied group was 77.4% and 75.2% respectively

In another study, Xu et al. [190] proposed a narrow filter bank CSP (NFBCSP) algorithm, which automatically determined the optimal narrow band for MI by band search tree. The optimal narrow band was combined with the CSP algorithm to extract the dynamic features in the EEG signals. After extracting the features, a Deep Convolutional Neural Network (DCNN) was used for the fusion of band features and classification of multi-class motor imagery. They verified their method using two different motor imagery datasets, the BCI-VR dataset with two classes of motor imagery and the BCI Competition IV dataset 2a with four classes of motor imagery in an offline analysis. The experimental results showed that the proposed method achieved an average classification accuracy of 86.43% for the two-class MI task, and 76.87% for the four-class MI task.

Lakshminarayanan et al. [191] integrated a framework that combined VR-based action observation and kinesthetic motor imagery (KMI), achieving an accuracy of 61.9%.

To explore if P300-BCI VR headsets can achieve similar classification accuracy as 2D monitors, Käthner et al. [100] conducted an experiment in which 18 participants used three different display methods to perform a typical task with a BCI speller. The first display was a 5 X 5 matrix turning the BCI speller into a typical wide screen. The second was an identical 5 X 5 display that was however viewed in immersive VR. The third display was the same as the second one with the exception that only a single letter at a time appeared in the 5 X 5 BCI speller. Results revealed similar spelling accuracy across the three display conditions (96%, 96%, and 94%, respectively), suggesting that VR headsets can accomplish similar accuracy as 2D monitors and that fast P300-BCI communication can be achieved in VR experiences.

In another study, Zeng et al. [101] developed an interface between the brain and a lower robotic limb using the SSVEP paradigm in a virtual environment to help people with ankle movement problems to perform robotic-based rehabilitation tasks. The lowest limb control accuracy was 80% and the highest 100%, documenting the effectiveness of this approach.

In an earlier study, Zhang et al. [102] presented a BCI-based lower-limb rehabilitation training system that merged BCI, VR, and robotics. In the system, a robot and an avatar performed similar movements at the same time while the user could perform various commands such as rotation to the left and to the right, forward movement, etc. Results showed an 85.6% classification accuracy for three participants.

In conclusion, BCI-VR gaming systems offer promising avenues for both healthy individuals and those with motor impairments, leveraging immersive virtual environments to enhance engagement and efficiency in rehabilitation.

TABLE 4
SUMMARY OF EEG-BASED BCI-VR GAMING STUDIES

Author	BCI paradigm	VR action task	No. of subj.	Feature extraction	Classification algorithm	Channels	Accuracy
J. Xu et al. (2020) [97]	MI	Simulation of robotic virtual arm	2	FBCSP	SVM	2 channels: (C3, C4) “mu” and “beta” waves	76.2%
Vourvopoulos et al. (2016) [98]	MI	Virtual rowing with hand movements	13	CSP	LDA	8 channels: (FC5, FC6, C1, C2, C3, C4, CP5, CP6)	70.7%
Vourvopoulos et al. (2019) [99]	MI	Virtual rowing with hand movements	1	CSP	LDA	8 channels: (FC5, FC6, C1, C2, C3, C4, CP5, CP6)	60%
A. Kreilinger et al. (2016) [103]	MI	Car game	10	DP	LDA	32 channels: Important Used: (C3, Cz, C4)	70%
Achanccaray et al. (2017) [104]	MI	Virtual hand control	8	CSP, Log trans.	Adaptive neurofuzzy inference system	16-channels (AF3, AF4, FC3, FCz, FC4, C3, Cz, C4, T7, T8, CP3, CPz, CP4, Pz, PO3, PO4) References: (FZ, A1)	89%
Lupu et al. (2018) [105]	MI	Limb movement control	3	CSP	LDA	12-channels: (FC1, FC2, FC5, FC6, C3, C4, C5, C6, CP1, CP2, CP5, CP6)	85%
Vourvopoulos et al. (2015) [106]	MI	Virtual left and right hand control	9	CSP	LDA	8 channels: (FC3, FC4, C3, C4, C5, C6, CP3, CP4)	65.6%
Munoz et al.(2014) [109]	MI	Virtual left and right hand control	8	CSP	LDA, SVM	8 channels: (F3, F4, FC5, FC6, AF3, AF4, F7 andF8)	96.7%
Badia et al. (2013) [110]	MI	Controlling a virtual arm	9	Bipolar filter (FC3-FC4 and CP3-CP4)	2 dimensional linear classifier	9 channels: F3, C3, P3, T3 ,F4, C4, P4, T4, Cz Ground: FPz Reference: A2	85%
Zheng et al. (2013) [111]	MI	Virtual navigation	1	CSP	LDA	5 channels around the motor cortex	67.5%
Skola et al. (2022) [187]	MI	Virtual left and right hand control	30	CSP	LDA	N/A	70.8%
Vourvopoulos et al. (2022) [188]	MI	Virtual rowing with hand movements	5	CSP	LDA	32 EEG channels	65%
Vagaja et al. (2024) [189]	MI	Virtual left and right hand control	26	CSP	LDA	32 EEG channels	75.2%
Xu et al. (2022) [190]		Virtual hand control	12	FBCSP, CSP	Deep CNN	22 channels: FZ, FC3, FC1, FCz, FC2, FC4, C1, C2, C3, Cz C4, C5, C6, CP3, CP1, CPz, CP2, CP4, P1, Pz, P2, POz	76.9%
Lakshminarayanan et al. (2023) [191]	MI	drinking from a cup, extension of the hand, and grabbing a cup	15	N/A	MLP	20 channels: FP1, FPz, FP2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2	62%
Amaral et al. (2017) [107]	P300	Virtual objects flickering	17	Max-SNR	Naive Bayesian	8 channels: (C3, Cz, C4, CPz, P3, Pz, P4, POz)	80%
Tidoni et al. (2017) [108]	P300	Virtual character control	21	N/A	LDA	8 channels: (Fz, Cz, P3, Pz, P4, PO7, Oz, PO8)	89%
Käthner et al.(2015) [100]	P300	Spelling in virtual scene	18	N/A	Stepwise linear discriminant analysis (SWLDA)	8 channels: (Fz, Cz, P3, P4, PO7, POz, PO8, Oz)	80.5%
Tarnanas et al. (2012) [112]	P300	Virtual navigation in a museum	50	N/A	kNN	N/A	87%
Zeng et al. (2017) [101]	SSVEP	Whack a Mole	5	FFT	N/A	41 channels	90%
Zhang et al. (2015) [102]	SSVEP	Virtual character control	3	N/A	Canonical correlation analysis (CCA)	3 channels: (Oz, O1, O2)	81.4%
Legeny (2011) [113]	SSVEP	Virtual navigation	1	N/A	LDA	3 channels: (CPz, POz, O1, Oz, O2, and Iz)	91%

3.3 BCI for Attention, Memory, and Visuospatial skills

BCI neurofeedback training involves stimulating brain areas with repetitive reward and feedback training, e.g., when the user tries to move a robotic arm through mental imaging strategies [114], [115], [116]. TABLE 5 presents EEG-based BCI studies targeting the cognitive mechanisms of perception, visuospatial attention, and visuospatial memory.

In [117], a BCI neurofeedback game based on MI paradigm was developed to help children with ADHD. The band power results showed that the children improved their attention while playing the game. At the same time, they had fun and were generally in a relaxed state. This is aligned with the result of other studies showing that new approaches that use either 2D or 3D games in combination with BCIs, can implement effective interventions for patients with ADHD, mainly by employing mindfulness training. Techniques such as mindfulness training facilitate brain maturation, improve visual processing, and enhance cognitive skills, by increasing the ability to retain the attention of the user for extensive period of time [86], [87], [118].

In an example study, Qian et al. (2018) [86] showed that a BCI intervention can significantly reduce inattention after 8 weeks of training. Notably, inattention was reduced more in an ADHD intervention group than a control group that included participants without attention difficulties [86]. Of course, additional research may be needed to assess the effects on ADHD patients who have been treated with BCI for extended periods of time, and to develop adaptive systems that can profile and use the users' characteristics to adapt the system [118].

Promsorn et al., in 2017 [119] measured EEG activity while participants performed a spatial ability task. Electrical activity was processed offline and the following frequency bands were analysed: delta (0 - 3 Hz), theta (4 - 7 Hz), alpha (8 - 12 Hz), beta (13 - 30 Hz) and gamma (31 - 47 Hz). The alpha, beta and gamma frequency bands of the participants increased significantly during the execution of the spatial task compared to baseline. BCI studies on video game applications have shown that BCI can offer many advantages when combined with cognitive and gamification techniques. The influence of neurofeedback in classic video games based on BCI is very promising for enhancing the level of attention and cognitive function in both healthy and motor-impaired users [87]. EEG video game control is better suited for BCI because of the portability, affordability, safety, high temporal resolution, and non-invasive access it provides to users with motor impairments, in contrast to other BCI applications such as environmental control, cursor control, robotic arm control, wheelchair control, etc. [120]. BCI neurofeedback gaming has been shown to improve the level of attention and memory, of the users [117].

Mental training and concentration seem to also benefit visuospatial memory and perception in many professional areas, like medical surgery, sports, and music. Thus, BCI applications may help people improve their cognitive skills by using EEG patterns and visualization methods to restore movement and communication [121], [122], [123]. Hammer et al., (2012) [131] conducted an experiment where participants underwent a psychological test-battery before performing an MI task. The psychological test-battery included performance tests, personality tests, clinical tests, and the vividness of movement imagery questionnaire. In the BCI-MI session, participants were instructed to imagine the movement of the left hand, the right hand, and the right foot. Results showed that system recognition accuracy across the three imaginary movements was 74%. In another study carried out by Promsorn et al. [119] participants performed a spatial test with four main common types of spatial abilities which are spatial perception, spatial visualization, mental folding, and mental rotation. Participants demonstrated significantly mean improvement in speed, memory, attention, flexibility, and problem-solving skills when executing an EEG-based spatial task [119].

It should be noted that the operation of BCI devices is based on procedural learning, i.e., learning that mediates the automatic execution of tasks, e.g., learning to ride a bike. An efficient training technique and distinct EEG patterns provide the user with feedback indicating whether she is achieving high BCI control performance and therefore continue with the same strategy or whether she should make more effort to improve performance. This feedback reinforces the procedural training process. There also seems to be a growing number of BCI studies showing movement control generated by the EEG signals using evolutionary algorithms adapted to the user's case to handle BCI systems without moving limbs or muscles [88]. A BCI system that uses a variety of brain mechanisms, like alphabetic ordering, arithmetic, letter synthesis, etc., can train people how to generate the appropriate EEG patterns to rehabilitate their kinetic operations. For example, in one study, participants improved their level of attention by observing signal characteristics generated by more realistic images compared to less realistic images [117].

Despite its promise for improving cognitive skills (a topic we discuss further in the next section), BCI has to overcome a number of challenges. The biggest one is to maintain the user's interest and motivation to engage with the task while using tasks that are difficult enough for each user in order to increase the adaptability of the brain [124]. In addition, some issues still need to be explored, e.g., how EEG-based neurofeedback that improves perception, visuospatial attention and visuospatial memory in healthy individuals could be used with patients, and how such patients can benefit more from the training [116].

3.4 BCI-VR Gaming and cognitive tasks

The application of BCI in games and in education not only leads to fun ways of interaction, improving thus involvement and entertainment, but it can also lead to the improvement of cognitive skills [126]. The P300 BCI is one of the most accurate BCIs available and is associated with a higher level of gaming-specific attention processes. It can also be an index of mental workload and cognitive training [126].

Bulat et al. [126] investigated whether cognitive functions of healthy adults can be improved by playing a P300-BCI-VR based game. A total of 45 healthy participants (25 females and 20 males) between 18 and 37 years old were recruited for the study. Participants were randomly assigned to three groups: the experimental group (P300+VR), the active control group (VR game), and the passive control group (VR movie). The experiment consisted of 5 sessions across a period of 2 weeks. At the beginning, all participants performed a series of cognitive tests, which were then repeated after the 1st, 3rd, and 5th training sessions. Significant changes in cognitive performance were shown after 5 experimental sessions for the experimental group in comparison to both other groups in tasks associated with inhibition and visuospatial attention. Specifically, it was found that the experimental group achieved shorter reaction times than the active control group and the passive control group in a flanker task that requires responding to a stimulus while ignoring distractors and in a visual search task.

In another study, Dey et al. [127] created an adaptive visual search task in VR based on real-time interpretation of the user's EEG. The system adapted to the cognitive load difficulty in real-time based on the effort made by the user. To enable the visual search task adaption participants performed two blocks of n-back trials, first a block with 1-back trials and then a block of 2-back trials, while task load was measured. The n-back task shows a sequence of numbers and asks participants to recall the number that is n positions back from the current number. For example, a 2-back task asked people to recall the 2nd number before the current number was shown. The use of 1-back and 2-back tasks allowed the researchers to obtain an index of the participants' brain activity in relation to an easy and a difficult working memory task respectively, and thereby to calibrate the task difficulty parameters. This was accomplished by taking the mean alpha power induced by these two n-back blocks to calculate a baseline for each user and to use this baseline value to adapt the visual search to their task load. When the task load was above the mean level of the two calibration tasks, the researchers decreased a level and increased it when task load was lower. This process ensured that the adaptation was customized to each individual's cognitive state. This way, the researchers succeeded in creating a system that adjusted the level of difficulty according to the cognitive load [127]. Overall, the results from the studies reviewed indicate that BCI gaming combined with VR can be used for improving cognitive functioning in healthy participants, producing effects that are over and above those achieved by cognitive training.

TABLE 5
SUMMARY OF EEG BASED BCI WITH COGNITIVE TASKS STUDIES

Author	**BCI paradigm**	**Action**	**No. of subj.**	**Feature Extraction**	**Classification algorithm**	**Channels**	**Key Findings / Accuracy**
BCI-based Attention and Spatial studies							
Yang et al., (2018) [117]	MI	Brain controlled game	10	CSP	LDA	27 channels: (F7, FT7, T3, TP7, T5, F3, FC3, C3, CP3, P3, O1, FZ, FCz, Cz, CPz, Pz, O2, P4, CP4, C4, FC4, F4, F8, FT8, T4, TP8, T6)	The analysis of band-power outcomes showed that participants' attention level increased throughout the experiment performing MI tasks.
Promsorn et al., (2017) [119]	MI	Spatial ability test	9	N/A	FFT	1 channel: (FP1)	Participants have shown significantly mean improvement in speed, memory, attention, flexibility and problem solving, respectively.
Jeunet et al., (2015) [125]	MI	Left-hand MI, Mental Rotation, Mental Subtraction	18	CSP	sLDA	30 channels: (F3, Fz, F4, FT7, FC5, FC3, FCz, FC4, FC6, FT8, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8)	Users' profiles can influence their MI-BCI control levels.
BCI-based Attention and Memory studies							
Qian et al., (2018) [86]	N/A	BCI-based attention training game	66	N/A	N/A	2 channels: (FP1, FP2)	The BCI sessions improving the behavioral skills of ADHD children.
Lim et al., (2012) [129]	N/A	BCI-based attention training game.	20	N/A	N/A	N/A	Inattentive and hyperactive-impulsive symptoms improvement in ADHD children.
Nan et al., (2012) [130]	N/A	Short term memory tests	32 total 16 NFT 16 cont. group	N/A	N/A	1 channel: Cz	Significantly higher forward and backward digit span in the neurofeedback training (NFT) group than the control group.
BCI-based Spatial and Visuospatial studies							
Hammer et al., (2012) [131]	MI	Performance, personality and clinical tests and the vividness of movement imagery questionnaire.	83	CSP	LDA	128 channels cap	Predicted accuracy between the classes: 74% (left hand, right hand, right foot).
Hammer et al., (2014) [132]	MI	Performance, personality and clinical tests.	33	N/A	N/A	16 channels: (FP1, FP2, F3, Fz, F4, T7, C3, Cz, C4, T8, CP3, CP4, P3, Pz, P4, Oz)	Predicted accuracy between the classes: 79% (right hand, left hand, both feet).
BCI-based VR Gaming with Cognitive tasks studies							
Bulat et al. (2020) [126]	P300	Controlling machines that shoot monsters.	45	CSP	LDA	16 channels: (Fp1, C3, C1, Cz, C2, C4, CP3, CP1, CP2, CP4, P1, Pz, P2, O1, Oz, O2) References: (A1, A2)	The mean accuracy across all the subjects and all the sessions was 69.3%
Dey et al. (2019) [127]	-	Visual search scene.	14	TFR	Monte Carlo cluster	6 channels: (Oz, O1, O2, Pz, P3, P4) Alpha wave recording	System that adjusts the degree of difficulty according to the performance of the cognitive load of the brain.

3.5 Challenges and Directions

Although BCI has been widely used in the scientific community, it still faces many challenges in attracting commercial interest and being adopted by the general population (see

TABLE 6). These challenges must be addressed by the community of BCI in order to achieve more improvements.

3.5.1 Technological Challenges

Operating an MI-BCI system usually requires a large number of training trials, thus making the training phase required to create a realistic model time consuming. However, when users are taught properly, MI strategies often deliver remarkable results. Thus, efforts should be concentrated on reducing calibration time and promoting effective training. Clever gamification techniques that will keep the user's interest high during the training sessions may help to this purpose. Also, because EEG signals are non-linear, non-stationary, and artifact-prone, the accuracy of multiclass BCI, especially with MI is very low, around 65-70% [75]. Therefore, one may think about using different BCI paradigms like the P300 or the SSVEP.

The P300 has higher average Information Transfer Rates (ITR) and does not require a special training process. However, depending on the severity of the impairment, the P300 may be affected. A large number of studies have found that even people with Amyotrophic Lateral Sclerosis and Locked-In-Syndrome are capable of handling BCI-based P300 for long periods of time. But generally, healthy individuals exhibit higher ITR [128]. Notably, with both healthy users and patients, the experimental procedure requires the assistance of trained personnel. In addition, the need for elaborate instructions in a BCI system using the P300 paradigm lengthens the time of the intervention, which results to reduced total performance. Pairing general models with real-time training can be a good approach to decrease the calibration period and boost P300 accuracy along with user entertainment [133]. Unfortunately, the P300 paradigm requires flashing external stimuli, making it difficult to use in realistic scenarios that mimic everyday life. Furthermore, even after relatively short periods of use, users experience eye strain while people with vision impairments exhibit very low performance.

The SSVEP approach requires almost no training or calibration. Hence, although this BCI paradigm is faster than P300-based systems, due to the inherent flickering, it has the same drawbacks as the P300. That is, it is difficult to use in everyday life, causes eye strain, as well as low performance in people with vision problems. Moreover, some participants produce very poor SSVEP responses.

BCI games are slower and less accurate than conventional interfaces. Therefore, it seems some important issues must be resolved before the general population accepts BCI games. A popular challenge is the use of the most appropriate BCI paradigm depending on the case of the application. Among MI, P300, and SSVEP paradigms, the P300 seems to be preferred by the research community for BCI games. Although the P300 modality is often employed in puzzle games, it needs to be upgraded so that it can be used extensively for other game types too, such as action games with locomotion. The accuracy of real-time BCI systems with moving users seems to be low. When the users are walking, the P300 peak is generated, but the overall system performance decreases dramatically [134], [135]. Therefore, in games where there is movement of a character, controlling the games with MI might be preferable.

In addition, one of the biggest challenges to be faced is BCI illiteracy. In the MI-BCI research, it is widely recognized that there are substantial individual differences in the capability to perform a given MI task. Specifically, individual differences refer to the natural variation in personality traits, cognitive abilities, motivation, and other innate characteristics among individuals [196]. These individual differences can influence MI-BCI performance and level of success in performing MI tasks. For instance, individuals who have low levels of motivation or who have difficulty maintaining attention may struggle with MI-BCI training and may not achieve the desired performance [39], [196]. In the context of MI-BCI research, these aforementioned individuals are considered to have BCI illiteracy, which refers to the lack of knowledge and proficiency in using a BCI system within a standard training period, and around 15–30% of BCI users fail to produce the desired EEG patterns to control a BCI device accurately [196].

Also, physiological factors such as the heart rate can significantly affect the EEG features. In real world, a plethora of sensory stimuli in the environment (e.g., noise, distractions, communication wave flows, etc.), as well as movement, can affect the quality of brain waves. Therefore, when designing a BCI system, developers should take into account the specific environment in which the proposed application will be used. Therefore, at the system design phase, it is important to investigate in depth the nature of the users, basic system criteria, and environmental aspects.

3.5.2 Psychological and Neurological Challenges

Different brain-related factors such as brain anatomy and neuron activity that are associated with mental processes, brain physiology and emotion, also known as neurophysiological factors, have a critical role in BCI performance and cause important variability between individuals [136]. Also, further psychological aspects like memory, attention, cognitive load, tiredness, as well as key individual characteristics such as gender, age and lifestyle, affect the moment-to-moment dynamics of the brain [135], [137]. People with lower empathy for example, are less emotionally involved in a P300 paradigm and may generate better EEG patterns than individuals with higher empathic engagement [138], [139]. In addition, physiological parameters of the resting state (e.g., heart rate and resting state frequency characteristics) affect the performance of BCIs [140]. Furthermore, complexity and variety in the brain, create a highly unstable neural connection over time and variability among participants [141]. An effective BCI system must be robust to such possible physiological oscillations to allow more generalized use [136], [135].

Sensorimotor-based BCI is based on spectral power density and spectral entropy, resulting from resting state EEG recordings that also affect BCI accuracy [142]. Psychological prognostic factors, like motivation, concentration, and attention, are also related with somatosensory motor based BCI performance [131]. About 15-30% of people cannot generate strong brain signals to control a BCI [39], [143].

Examination of neurophysiological factors could decrease BCI illiteracy. The existence of BCI illiteracy is not based solely on the user's ability to generate signals. Sometimes technical constraints may prevent the estimation of key features for a successful BCI operation. For example, scalp EEG measurements may not present distinct patterns in the EEG signals due to the cortex folding, the distance from the scalp to the cortex or bad electrode contacts [135], [144]. Thus, additional case studies are needed for monitoring neurophysiological variants that could contribute to BCI improvement.

Finally, targeted BCI design is required to tackle specific brain lesions such as those found in stroke, where for each specific case, residual brain function for rehabilitative interventions should also be taken into account [145], [146].

3.5.3 Gaming Challenges

Gaming integration into BCI systems is a promising way to increase engagement and promote training with BCI systems. However, various issues still need to be resolved. Although BCI-gaming strongly motivates people to get engaged, nevertheless users have very poor performance and speed compared to classic systems. Also, when the users walk or move their limbs, the overall performance drops dramatically [96], [147]. Since we are interested in games that will motivate and excite users to get more involved, the need for a case-specific BCI game design based on the personal interests of each user becomes imperative.

Cognitive games have been shown to improve certain cognitive functions, not only in healthy individuals but also in many other cases, especially those related to attention, memory, executive control, and generally visuospatial skills [136], [135]. However, it is a great challenge to turn a cognitive task into a serious game while keeping its underlying function intact. VR seems to be a promising approach for cognitive gaming as it allows adapting laboratory tasks as fun and entertaining games.

TABLE 6

SUMMARY OF TECHNOLOGICAL, GAMING, PSYCHOPHYSIOLOGICAL AND NEUROLOGICAL CHALLENGES

Technological Challenges

Motor Imagery	**P300**	**SSVEP**
Calibration period reduction.	The performance over time may be affected.	Flickering external stimuli making it difficult to use in realistic scenarios.
Effective training strategies.	Healthy individuals attribute higher ITR.	After relatively short periods, individual feel pain and fatigue in the eyes.
Clever gamification techniques.	Flashing external stimuli making it difficult to use in realistic scenarios.	People who have vision problems have very low performance results.
Keep the user's interest during training sessions.	After relatively short periods, individual feel pain and fatigue in the eyes.	
Very low accuracy especially in multiclass BCI.	People who have vision problems have very low performance results.	

Gaming Challenges
The accuracy and speed of the games is very low compared to conventional interfaces.
When the users are walking or moving, the overall performance drops.
A case-specific BCI design.
Motivation to engage taking advantage of the gaming.
To keep the interest while performing the cognitive tasks.
Take advantage of virtual reality.
It's difficult to convert a cognitive task into a serious game and keep the nature of the task.

Psychophysiological and Neurological Challenges
Psychological factors such as Attention and Memory Load influence instantaneous brain dynamics.
Fatigue and competing cognitive processes cause EEG signal noise.
Elimination of BCI illiteracy.
Factors such as different levels of cortisol in the body and heart rate variability can significantly affect the features of EEG signals.
Various sensory stimuli exist in the environment outside the laboratory, which can affect the quality of brain waves.
BCI performance may be affected by the features of the frequency domain in resting state and variability of the heart rate.
The Psychological predictors of attention and motivation, are associated with the performane of BCI sensorimotor rhythm.

Chapter 4

Experimental Methodology

4.1 Material and preparatory setup

Forty-four volunteers (20 Men, 24 Women) participated in the study. All participants were between 20 and 43 years of age, with an average of 24.68 years of age, had a normal or corrected-to-normal vision, and reported no health-related issues. Three additional volunteers were excluded after they appeared to have not properly followed the instructions of the experiment. Participants were recruited from introductory undergraduate courses in Computer Science and Psychology as well as from the research and management departments of the CYENS – Centre of Excellence.

All participants carried out the BCI-VR Goalkeeper task, twenty-two participants carried out the computerised Flanker task and the Spatial Cueing task and another twenty-two participants carried out the computerised Mental Body Rotation (MBRT) and Spatial Orientation (SOT) tasks. In the BCI-VR Goalkeeper task, the participant controlled a virtual goalkeeper and repelled the shoots by mental thinking. In the Flanker task, the participants indicated the direction of the target object by pressing the left or the right keyboard arrow. In the Spatial Cueing task, the participants indicated whether a target object was present or absent from a previously presented memory array of 4 objects by pressing the left or the right keyboard arrow accordingly. In the MBRT task, the participants answered whether the target (i.e., a multicolored circle) was on the left-hand or the right-hand of the avatar by pressing the left or the right keyboard arrow. Finally, in the SOT task, the participants indicated the angle between themselves, an object facing them, and a target object in the surroundings, by pressing the left mouse button. The accuracy of the BCI-VR Goalkeeper task, the reaction time (RT) and accuracy of the Flanker task, the RT and d' of the Spatial cueing task, the accuracy and the RT of the MBRT, and the Angular Error of the SOT were used in four separate mixed-design ANOVAs. In all ANOVAs, the "Group" variable (Low Achievers and High Achievers in the BCI-VR Goalkeeper task) was used as the between-subject variable. In the Flanker task, "congruency" (congruent vs incongruent) was the within-subject variable. In the Spatial Cueing task, "cue type" (pre-cue, retro-cue, neutral) was the within-subject variable. In the MBRT, "angle" was the within-subject variable. Finally, in the SOT, "angle" was the within-subject variable. We expected the scores from the four tasks to correlate with performance in the BCI-VR Goalkeeper task. All other variables were included as exploratory variables in the analyses. Before completing the tasks, participants read a short description of the study. Then, the experimenter explained the procedure to be followed in the experiment and clarified any ambiguities. Before each task, participants performed practice trials to familiarize themselves with the tasks and the setup. Participants were tested individually in a quiet lab at the CYENS-Centre of Excellence premises. Upon arrival at the laboratory, each participant read and signed an informative consent form.

4.2 BCI-VR Goalkeeper Gaming Task

4.2.1 Task Description

In MI the user tries to imagine limb movement (i.e. left hand vs. right hand) in order to give a command in an external device or application. This is made possible by detecting EEG activity in the somatosensory motor cortex and generating discriminant patterns of the brain signals. The Goalkeeper task was chosen because in this study we wanted to investigate attention and spatial perception abilities, that by definition professional goalkeepers must possess in order to be able to successfully respond to their duties.

The main objective of this task was to initially train a classifier that will predict the movement of the left hand or right hand through the EEG activity produced by the participant (calibration phase), and then repel as many shoots as possible by controlling the virtual goalkeeper through Motor Imagery (real-time scenario). The task consisted of two scenarios, firstly, the calibration scenario for the training of the algorithms and secondly, the real-time trial scenario.

The user was immersed in the virtual stadium behind the virtual goalkeeper avatar. The calibration phase, illustrated in Fig. 10, consisted of the following steps: (a) each trial began with the flag onset (3000 msec), signaling the start of a new trial, (b) followed by a random hand highlight that remained visible for 1250 msec, signaling that when the highlight disappeared, the participant should start imagining the corresponding hand movement, without any physical movement or muscle activation; (c) as soon as the hand highlight disappeared, and only while the flag remained visible, the participant imagined the hand movement for 3750 msec; (d) the trial ended with the flag offset and the participant rested for 1500-3500msec until the next trial began. The following process was repeated 40 times (20 trials for the left hand and 20 trials for the right hand) and the EEG signals were recorded and saved for classification training.

The real-time phase, illustrated in Fig. 11, consisted of the following steps: (a) each trial began with the flag onset (3000 msec), signaling the start of a new trial, (b) followed by a random hand highlight that remained visible for 1250 msec, signaling that when the highlight disappeared, the participant should start imagining the corresponding hand movement, without any physical movement or muscle activation; (c) as soon as the hand highlight disappeared, an avatar of a player across the field shot the ball in the indicated direction (same direction as the goalkeeper's avatar hand highlight from the previous step b) and the participant started imagining the corresponding hand movement, without any physical movement or muscle activation. In case the participant produced the appropriate EEG pattern from the hand imagination, then the VR goalkeeper avatar was controlled accurately (through the prediction of the BCI-VR goalkeeper framework) and repelled the ball. If the participant failed to produce the appropriate EEG pattern from the hand imagination, then the VR goalkeeper avatar failed to repel the ball (3750 msec); d) the trial ended with the flag offset and the participant rested for 1500-3500msec until the next trial began. The following process was repeated 40 times (20 trials for the left hand and 20 trials for the right hand) and the EEG signals were recorded and saved for further analysis.

This framework could be applied to any BCI application with two classes. First, calibration is necessary to create a model that distinguishes between the two imagined movement classes (left hand and right hand). Once this calibration is complete, these movements can then be translated into any desired commands, such as 'turn left' or 'turn right of a robotic limb or a wheelchair. The user's effort to issue commands would once again involve imagining left or right-hand movements and the mapping of commands can be customized to suit specific needs.

4.2.2 Experimental Setup

For the BCI-VR Goalkeeper task, participants wore an OpenBCI EEG cap of 16 wet electrodes (C3, C4, Cz, O1, O2, P3, P4, Pz, T3, T4, F3, F4, F7, F8, T5, and T6 according to the 10-20 system) and an electro gel was placed on each electrode. They also wore a Valve Index HMD that immersed them in a virtual football stadium. No HMD controllers were used in this task. The OpenBCI Cyton + Daisy Biosensing Board 16-channel device was used in participant sessions. The aforementioned board has a sampling rate = 125 Hz and the sample count per sent block is 32 blocks.

In the calibration phase, 40 trials were performed, of which in 20 trials, the participant imagined moving their left hand, and in 20 trials the participant imagined moving their right hand, in a randomized order. Depending on the displayed cue (hand highlight), the user imagined movement of the corresponding hand without any physical movement or muscle activation to train a classifier with the electrical brain activity (see Fig. 10). In the real-time phase, 40 trials were similarly performed, of which 20 trials for the imagination of left-hand movement and 20 trials for the imagination of right-hand movement in random order. The difference in this phase, was the extra feedback given by the virtual goalkeeper, who moved the hand that the participant imagined moving, to repel as many shoots as possible (see Fig. 11). In both phases, calibration and real-time, the participants performed 10 practice trials before the start of the experimental session. At the end of the BCI-VR Goalkeeper session, all the equipment was carefully removed to continue with the next tasks.

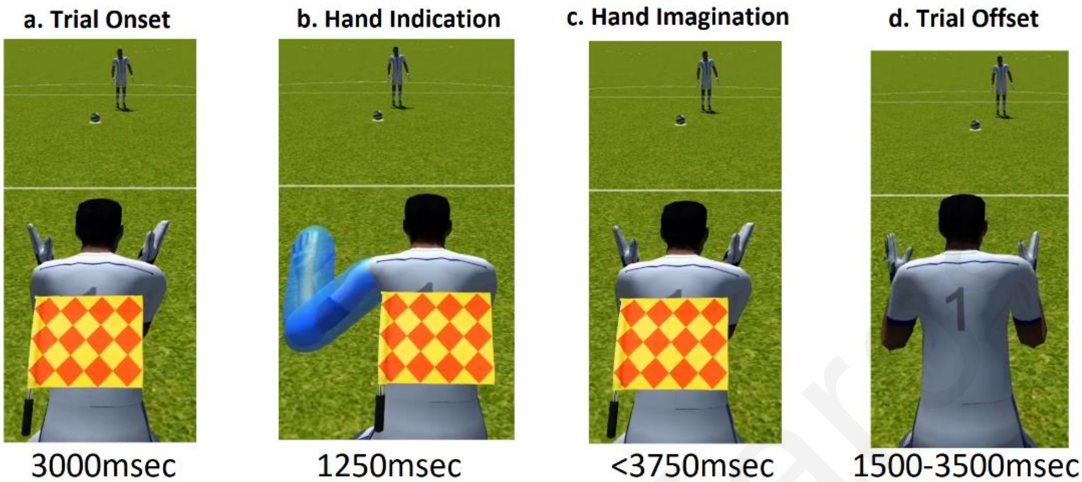

Fig. 10. Schematic illustration of the calibration of BCI-VR Goalkeeper task: a. The flag onset signaled the start of a new trial; b. the highlighted hand onset alerted (state of alertness) the participant that when prompted (by the hand highlight offset) they will need to start imagining the corresponding hand movement (here left-hand imagery); c. with the highlighted hand offset, the participant began imagining the corresponding hand movement; d. the trial ended with the flag onset.

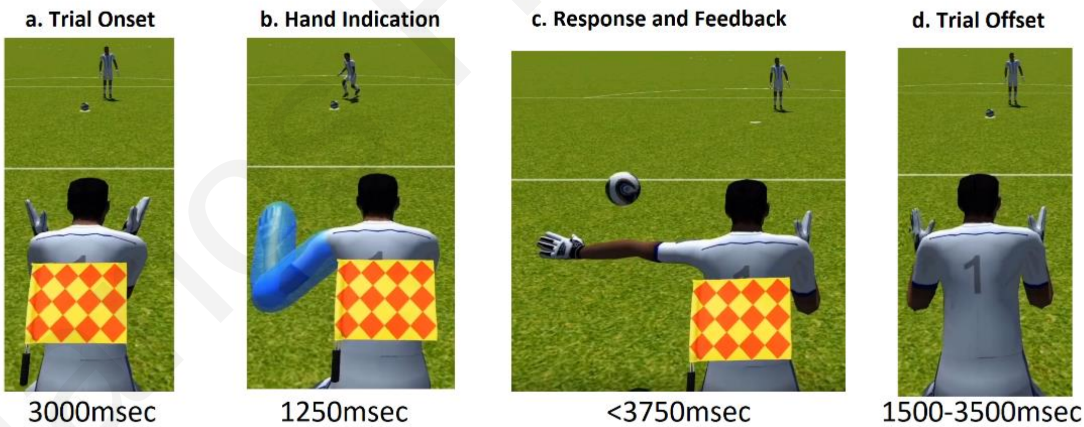

Fig. 11. Schematic illustration of the real-time BCI-VR Goalkeeper task: a. The flag onset signaled the start of a new trial; b. the highlighted hand onset alerted (state of alertness) the participant that when prompted (by the hand highlight offset) they will need to start imagining the corresponding hand movement (here left-hand imagery); c. with the highlighted hand offset, the participant began imagining the corresponding hand movement and received real-time feedback from the goalkeeper; d. the trial ended with the flag offset.

4.3 Flanker Gaming Task

4.3.1 Task Description

In cognitive psychology, the Eriksen flanker task [148] is designed to tap into cognitive processes related to executive functions, such as inhibitory/executive control and the ability to manage conflicting information. In this task, the participants were required to indicate as fast as possible the direction of a central target, by pressing the left or right arrow key on the keyboard, while ignoring “congruent” (i.e., same facing direction) or “incongruent” (i.e., opposite facing direction) flanker stimuli. The interference caused by the conflicting information from the “incongruent” flankers measures the individual's inability to inhibit irrelevant information and maintain focus on the target stimulus.

Typically, participants exhibit faster RTs and higher accuracy on congruent trials, compared to incongruent trials, because there is no conflicting information in this condition. On the other hand, in incongruent trials, participants often show slower RTs and decreased accuracy due to the interference caused by the conflicting flanker information. The difference in performance between congruent and incongruent trials is known as the "flanker effect." A larger flanker effect, reflected in increased RTs and reduced accuracy on incongruent trials, suggests greater difficulty in inhibiting irrelevant information and maintaining focus on the target [148], [149]. This effect is caused by the fact that the flanker stimuli, though task-irrelevant, often receive a considerable amount of processing even up to the level of the primary motor cortex [150], resulting in a processing conflict on incongruent trials [149].

To arouse the interest and increase the motivation of the participants, instead of arrows that are typically used in computerized flanker tasks, we used different animals (e.g., cats, ducks, penguins, etc.) to make the task more enjoyable and gamified (see Fig. 12.).

4.3.2 Experimental setup

For the Flanker task, a computer and keyboard were used, without the use of an HMD or EEG cap. In this task (Fig. 12.), participants saw an array of 5 items on the screen and were asked to indicate the direction of the central target item by pressing the left and right arrows on the keyboard for left-facing and right-facing targets, respectively. The 5 items were colored drawings of identical animals in each trial. Each participant performed 100 trials, 50 of which were congruent (i.e., the direction of the target matched the direction of the other 4 items) and 50 were incongruent (i.e., the target faced the opposite direction to the other 4 items). Before the experimental task, participants were shown the 4 different types of animals (cats, ducks, penguins, sheep) and were given instructions on how to respond.

Fig. 12. Schematic illustration of the Flanker task: a. In the congruent trials, the target direction was the same as with all the other items; b. In the incongruent trials, the target direction was the opposite to all the other items.

4.4 Spatial Cueing Gaming Task

4.4.1 Task Description

This task measures the effects of visuospatial selective attention in service of visual working memory (VWM) and it was programmed after Shimi et al., 2014a [151] and Shimi et al., 2014b [152]. In this task, participants were required to memorize a memory array of 4 items (e.g., cats, ducks, penguins, etc.), and subsequently indicate whether a probe item was one of the 4 previously presented memory items, by pressing the mouse buttons. Before and after the memory array, attentional cues were presented to examine the effects of attention in encoding and/or maintaining information in VWM. Specifically, there were three different types of trials: in pre-cue trials, we used arrows as informative spatial cues that were presented before the memory array and guided participants' attention to one of the four to-be encoded items in VWM (measuring encoding). In retro-cue trials, we used arrows as informative spatial cues that were presented after the memory array and guided participants' attention to one of the already encoded items in VWM (measuring maintenance). In neutral trials, we used filled squares as uninformative spatial cues that were presented before and after the memory array and required participants to encode and maintain in VWM all 4 items until the probe test. Fig. 13. illustrates the sequence of the types of trials along with the stimulus timings.

Typically, this task yields a pre-cue and a retro-cue benefit, in which participants demonstrate higher accuracy and faster RTs in pre-cue compared to neutral trials, and higher accuracy and faster RTs in retro-cue compared to neutral trials, respectively [151], [152], [153], [154].

4.4.2 Experimental Setup

For the Spatial Cueing task, a computer and mouse were used, without the use of an HMD or EEG cap. In this task (Fig. 13), participants saw an array of 4 items, followed by a probe item and were asked to answer if the probe was present or absent in the memory array. Pre-cues, retro-cues, and/or neutral cues were presented before and after the memory array, depending on the type of trial. Each participant performed 144 trials, 96 of which were present and 48 were absent. Of the 96 present trials, 24 trials were pre-cue, 24 trials were retro-cue and 48 trials were neutral. Of the 48 absent trials, 12 trials were pre-cue, 12 trials were retro-cue and 24 trials were neutral. Before the experimental task, participants were shown the 5 different animals (targets), were informed about the 3 different types of trials (pre-cue, retro-cue, neutral) and received instructions on how to respond.

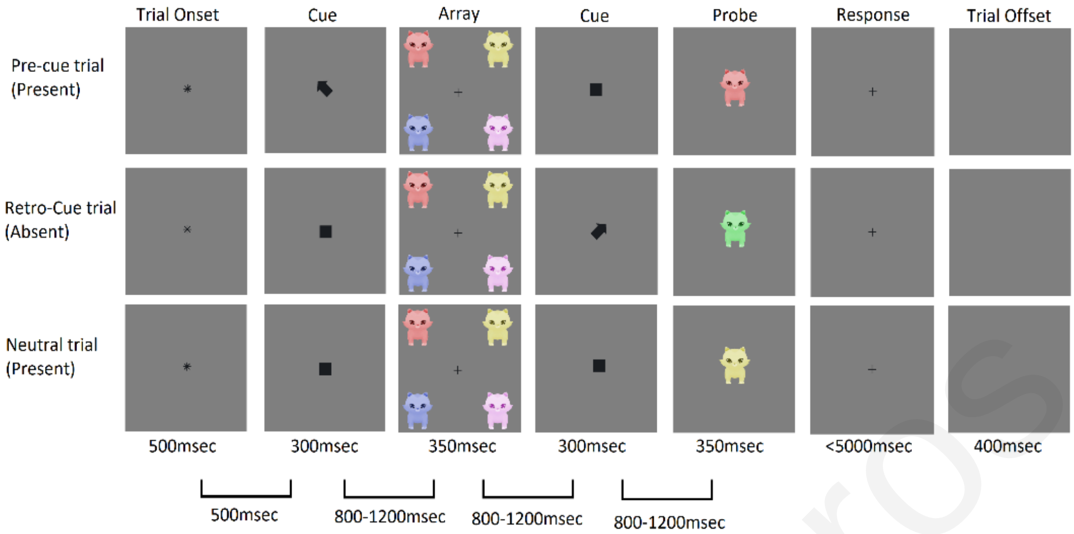

Fig. 13. Schematic illustration of the Spatial cueing task: The 3 different types of trials (pre-cue, retro-cue, neutral), and the duration of each successive symbol that has been used are presented.

4.5 Mental Body Rotation Task

4.5.1 Task Description

In this task, three types of transformations can be distinguished based on an environmental reference frame, an egocentric reference frame, and an object-based reference frame. The environmental reference frame is defined relative to a fixed point of the environment, locating things relative to axes concerning a fixed space. In contrast, the egocentric reference frame is defined relative to the self. Humans use this egocentric reference frame with the axes up-down, front-back, and left-right. The object-based reference frame is the third type of spatial reference frame, which is defined relative to external objects. The object-based reference frame can be used either for characterizing the relationship between the parts of an object independent of the object's location in the environment or to locate an object relative to another object.

Here, a human male figure was posed in 12 different ways by varying the position of his shoulders, elbows, waist, knees, and ankles (see Fig. 14). Human figures were marked on the left or right hand by superimposing a multi-colored circle onto the picture. Each human figure spanned approximately 8° of visual angle and was presented on a light grey background. Rotated versions of each unique stimulus were created by rotating the original picture in the picture plane in 30° increments. Horizontally mirrored versions of each rotated stimulus were then created by flipping each image along the vertical axis. The human male figures used in this task are from [155]. Each participant performed 296 trials. At the beginning of each trial, a fixation cross was presented for 500 ms, and then replaced with a pseudo-randomly selected stimulus item. Participants judged whether the left or right hand (relative to the figure's egocentric perspective) of a centrally presented stimulus figure was marked with a circle. Participants responded by pressing the left arrow button on the keyboard if the colorful circle was on the figure's left hand, and the right arrow button if the colorful circle was on the figure's right hand.

4.5.2 Experimental Setup

For the Mental Body Rotation task (MBRT) [155], a computer and keyboard were used, without the use of an HMD or EEG cap. Before the experimental task, participants were shown example images (see Fig. 14) and were instructed to press the left arrow on the keyboard on the occasions when the colorful circle was present on the left hand of the avatar or to press the right arrow on the keyboard on the occasions when the colorful circle was present on the right hand of the avatar. The stimuli were taken from [155].

Fig. 14. Examples of stimuli used in the Mental Body Rotation task. Participants are asked to identify which side of the figure is marked, from the figure's point of view.

4.6 Spatial Orientation Task

4.6.1 Task Description

In each trial of the SOT, a series of objects was displayed with the following instruction: "Imagine you are standing at object A (traffic light) and facing object B (tree). Point to object C (barrel)"(see Fig. 15). Therefore, participants had to imagine being located at the first object, while facing the second object (the orienting cue) and indicate the direction of the third object (the target object), by drawing a line from the center of the circle in the direction believed to be correct.

4.6.2 Experimental Setup

For the Spatial Orientation task (SOT) [156], a computer and a mouse were used, without the use of an HMD or EEG cap. Participants had 5 minutes to execute 12 different trials as described in the description above, and the performance measure was the angular error. Before the experimental task, participants were shown example images and were instructed how to point the angle (see Fig. 15). The task was taken from [156].

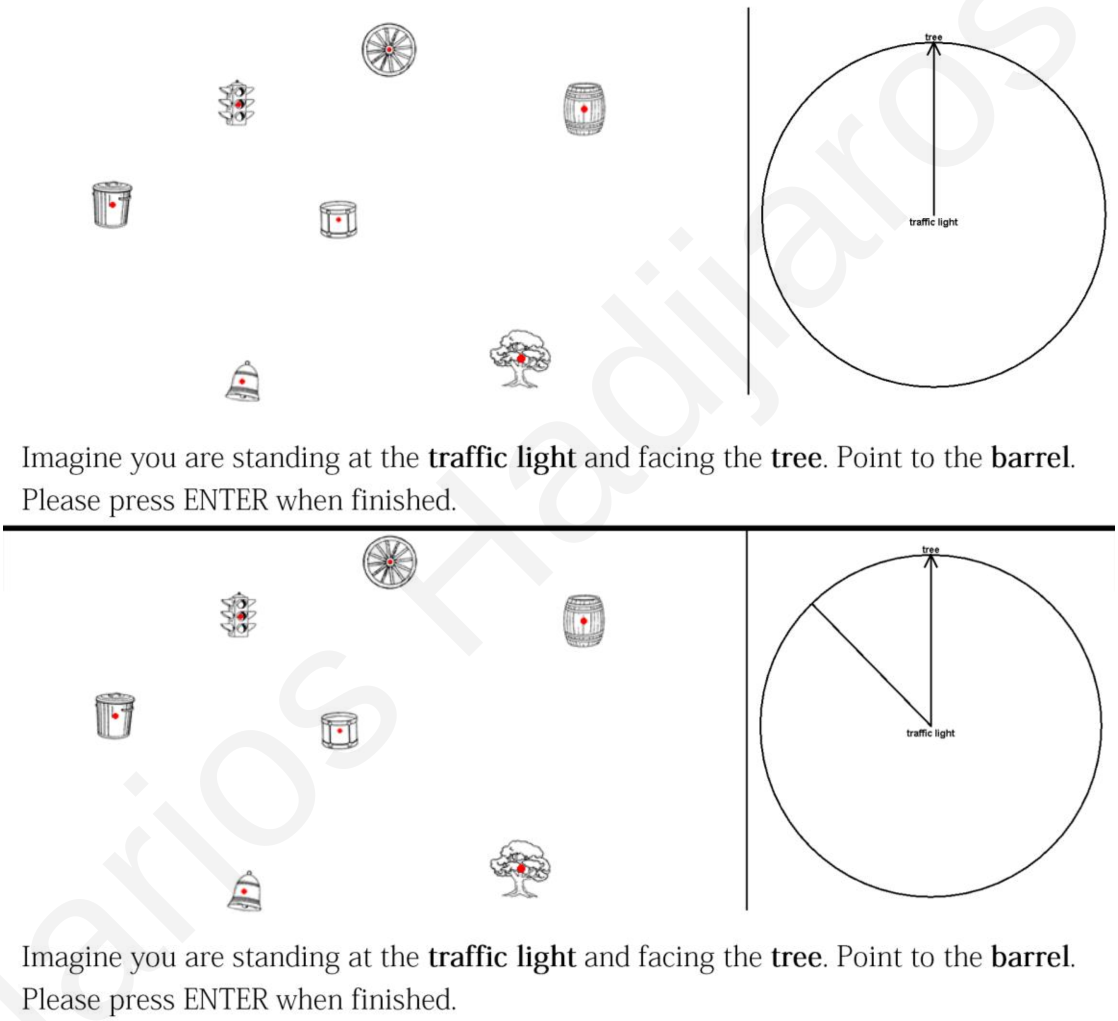

Fig. 15. A sample item (trial) with the exact correct answer in the Spatial Orientation Test.

Chapter 5

BCI-VR Data Analysis

5.1 Pre-Processing: Common Spatial Pattern (CSP) Algorithm

In the pre-processing phase, the Common Spatial Pattern (CSP) algorithm plays a crucial role in our study, particularly in the context of MI tasks for left-hand versus right-hand movement imagination in BCI using EEG signals. The CSP algorithm is instrumental in optimizing spatial filters to enhance the discriminative power of EEG signals between left-hand and right-hand motor imagery tasks. By maximizing the variance of the filtered EEG signal for one class (e.g., left-hand MI) and minimizing it for another class (e.g., right-hand MI), CSP facilitates the extraction of band power features that are highly discriminant between the two classes [76], [77]. This feature is particularly beneficial for BCIs relying on oscillatory activity, such as MI tasks, where band power features are essential for accurate classification [76], [77]. Typically, in our study, EEG signals are filtered within the 8–30 Hz band (μ and β rhythms) before undergoing spatial filtering by CSP. The resultant CSP features represent the band power of the signal spatially filtered with CSP filters [77]. Three pairs of CSP filters are used (6 in total), which correspond to the three largest and three smallest eigenvalues (see Fig. 16). The utilization of CSP in our study offers several advantages. Firstly, it enables relatively high classification performance for distinguishing between left-hand and right-hand MI tasks. Additionally, CSP is a flexible algorithm suitable for various BCI paradigms utilizing MI tasks [76], [77]. Moreover, it is computationally efficient and straightforward to implement, making it a popular choice for designing BCIs based on oscillatory activity. Overall, the integration of the CSP algorithm in our pre-processing pipeline enhances the robustness and efficacy of our BCI system, enabling accurate and efficient control of the virtual goalkeeper through MI tasks.

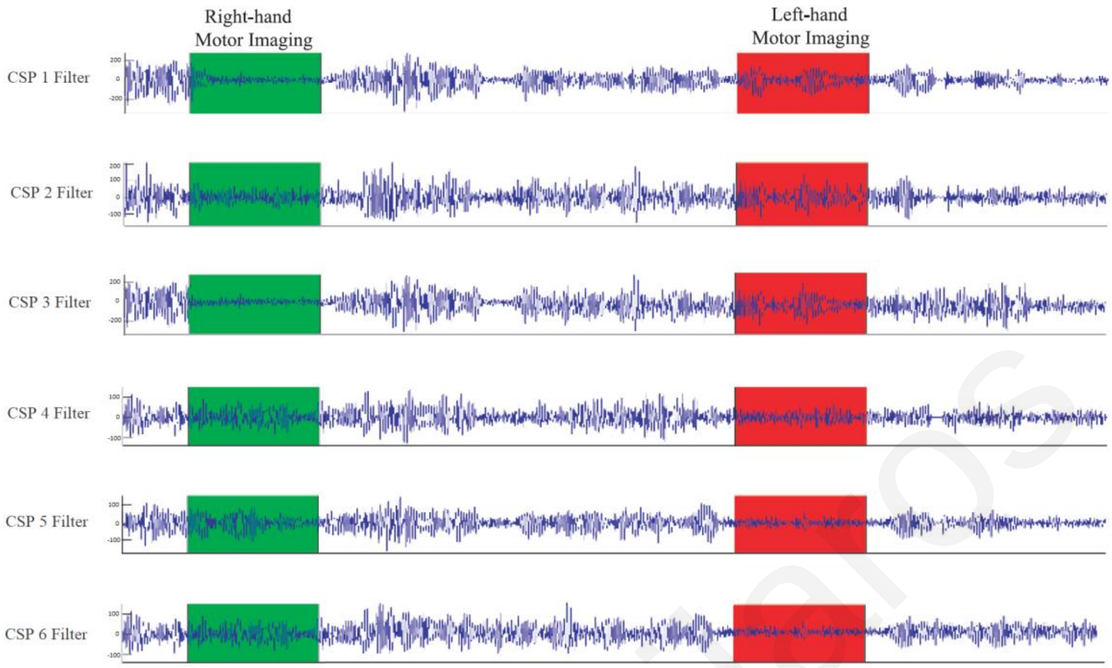

Fig. 16. EEG signals spatially filtered with the common spatial patterns (CSPs) algorithm. CSP1, CSP2, and CSP3 maximize the variance of the signals in the “imagined movement of the left hand” class (in red) while minimizing those of the “imagined movement of the right hand” class (in green). CSP4, CSP5, and CSP6 do the opposite, they maximize the variance of the “imagined movement of the right hand” class, while minimizing the variance of the “imagined movement of the left hand” class.

5.2 Machine Learning Algorithms

5.2.1 Decision Tree (DT)

Decision Tree (DT) is a widely used algorithm in machine learning, particularly suitable for classification and regression tasks [160]. It operates by partitioning the dataset into subsets based on the values of input features, creating a tree-like structure where each internal node represents a feature, each branch represents a decision based on that feature, and each leaf node represents a class label or a numerical value [160]. Decision trees are constructed through a recursive process where, at each node, the algorithm selects the feature that best splits the data into homogenous subsets, typically aiming to maximize information gain or minimize impurity [160]. This process continues until a stopping criterion is met, such as reaching a maximum tree depth, having a minimum number of samples in a node, or when no further improvement in purity can be achieved.

In the context of EEG Motor Imagery, where the objective is to classify left versus right hand movements, Decision Trees offer an intuitive and interpretable approach. By examining the decision path from the root to a leaf node, it's possible to understand the reasoning behind the classification, which can be beneficial for gaining insights into the underlying EEG patterns associated with different motor imagery tasks. However, Decision Trees are prone to overfitting, especially when the dataset is complex or noisy. Therefore, techniques like pruning or using ensemble methods, such as Random Forests, can be employed to enhance the generalization ability of Decision Trees in EEG Motor Imagery classification tasks. Despite this limitation, Decision Trees remains a valuable tool for initial exploration and understanding of the data, providing a foundation for more sophisticated machine learning approaches in BCI applications.

5.2.2 Random Forest (RF)

Random Forest (RF) is a widely recognized and powerful machine learning technique. It belongs to the supervised learning category and can be applied to both Classification and Regression problems in the field of machine learning. The strength of Random Forest lies in its utilization of ensemble learning, which involves combining multiple classifiers to tackle complex problems and enhance the model's performance [161]. Random Forest functions by employing several decision trees, each operating on different subsets of the provided dataset [161]. By averaging the predictions of these individual trees, the algorithm improves the overall predictive accuracy [161]. Unlike relying solely on a single decision tree, Random Forest considers the majority votes from each tree to determine the final output (see Fig. 17). This approach results in higher accuracy and mitigates the risk of overfitting, particularly advantageous for dynamic data such as EEG signals. Therefore, Random Forest proves to be an ideal algorithm for BCI applications. Considering the context of EEG Motor Imagery, where the objective is to accurately classify left versus right hand movements, Random Forest emerges as an effective solution. The algorithm's ability to generate multiple decision trees using random subsets of training data and features enables it to maximize the difference between the classes during the splitting process. The construction of decision trees continues recursively until specific stopping criteria are met, such as reaching a maximum tree depth or a minimum number of samples in a leaf node.

In the specific context of EEG Motor Imagery, where the discrimination of left versus right hand movements is of interest, Random Forest proves to be a powerful tool. By leveraging ensemble learning and the construction of multiple decision trees, this algorithm demonstrates its capability to effectively process dynamic EEG data, providing accurate classification results.

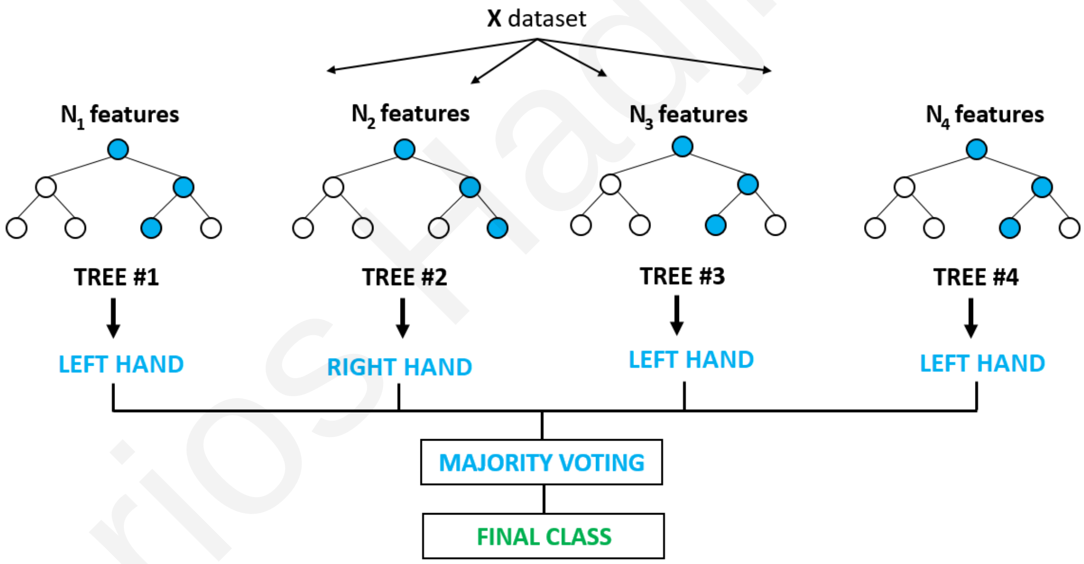

Fig. 17. The Random Forest classifier divides the dataset into subsets that are used to train the corresponding decision trees. Each decision tree produces its specific output. For example, the prediction for trees 1, 3, and 4 is left hand, whereas the prediction of the 2nd tree is right hand. The majority of the decision trees voted for left hand, which is the classifier final prediction.

5.2.3 Linear Discriminant Analysis (LDA)

LDA is a Bayesian approach that assumes that the positive (and negative) datapoints follow normal distributions. Also relies on finding the linear patterns of feature vectors that express the corresponding features of the signal and separates the classes representing different objects, by using hyperplanes [81]. The isolating hyperplane is achieved by searching for the projection that maximizes the distance among the means of the classes and minimizes the interclass variance (see Fig. 18) [81].

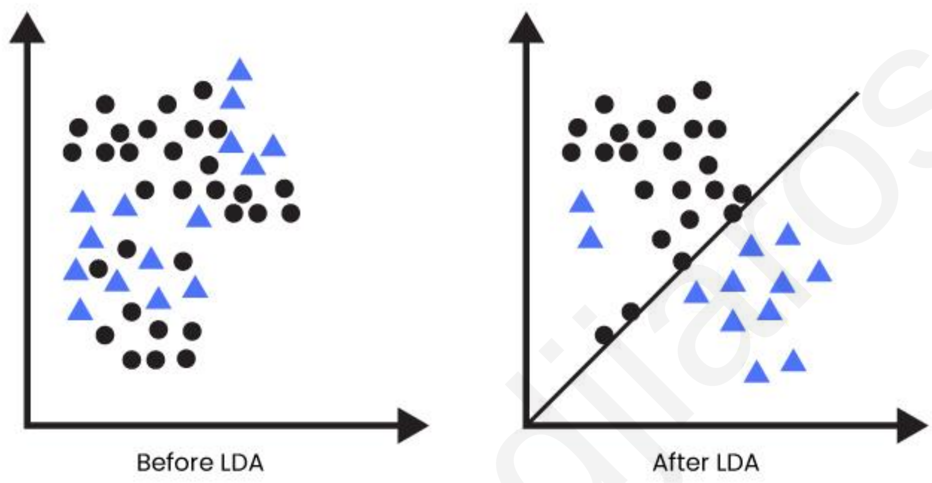

Fig. 18. On the left side of the image, the data depicting left-hand versus right-hand classification before LDA is presented. On the right side of the image, the data illustrating left versus right hand classification after applying LDA. Here, LDA maximizes the distance between the means of the classes while minimizing the interclass variance. In the center is the dividing line between the 2 classes.

5.2.4 Support Vector Machines (SVM)

Support Vector Machine (SVM) is one of the most popular Supervised Learning algorithms, which is used for Classification as well as for Regression problems [83]. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data points in the correct class in the future [83]. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called support vectors, and hence the algorithm is termed as Support Vector Machine (see Fig. 19)

SVM stands out due to its ability to effectively handle complex classification problems by constructing optimal decision boundaries. It accomplishes this by transforming the original input data into a higher-dimensional feature space, where a hyperplane is created to separate different classes [83]. This hyperplane aims to maximize the margin or the distance between the closest data points of different classes, allowing for better generalization and improved predictive accuracy [83]. In SVM, the selected hyperplane is defined by support vectors, which are a subset of training data points that lie closest to the decision boundary. These support vectors play a crucial role in determining the optimal separation between classes and classifying new, unseen data points [83]. SVM also employs a kernel function that enables nonlinear transformations of the input data, allowing for the effective handling of complex and nonlinear relationships between features. Moreover, SVM is known for its ability to prevent overfitting by finding the best decision boundary that generalizes well to unseen data. By optimizing the margin and effectively separating classes, SVM minimizes the risk of misclassifying new instances.

In the EEG Motor Imagery area, where the objective is to accurately classify left versus right hand movements, SVM can be a valuable tool. By utilizing the distinctive features extracted from EEG signals and creating an optimal decision boundary, SVM demonstrates its capability to discriminate between imagined left versus right hand movement classes with high accuracy. The algorithm's ability to handle nonlinear relationships and prevent overfitting makes it well-suited for analyzing dynamic EEG data. Overall, SVM is a versatile algorithm that excels in complex classification tasks. In the context of EEG Motor Imagery, SVM offers a robust solution for accurately discriminating between left versus right hand movements by leveraging optimal decision boundaries and support vectors derived from EEG signals.

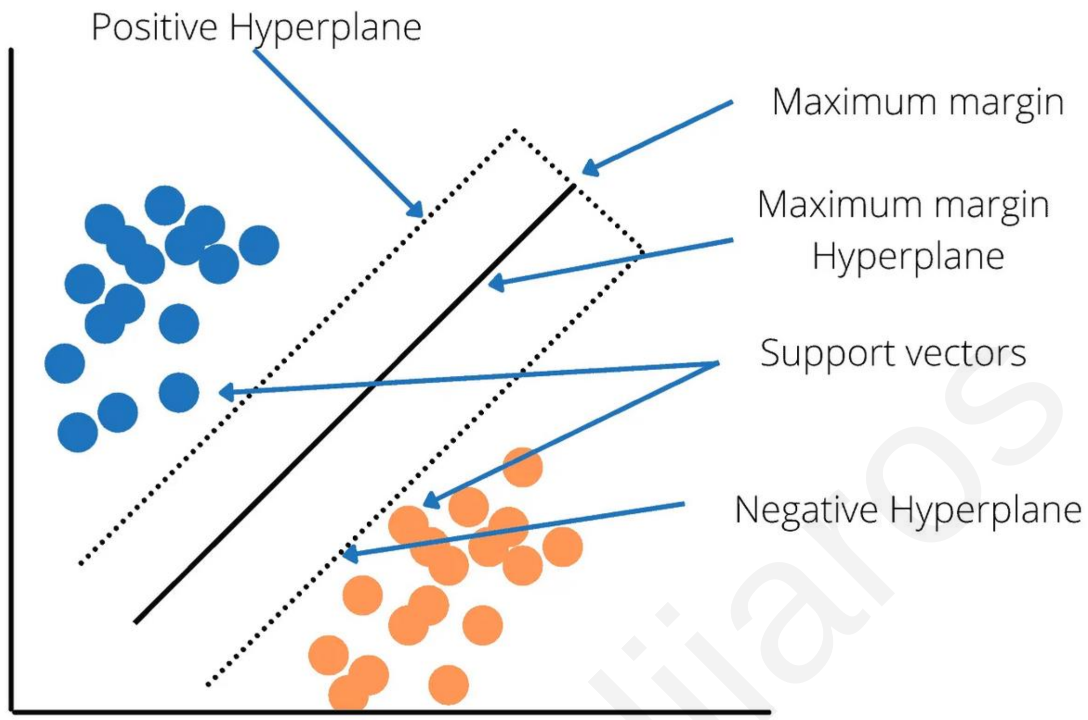

Fig. 19. Maximum-margin hyperplane and margins for an SVM trained with samples from two classes (left versus right hand movement). Samples on the margin are called the support vectors that are data points closest to the hyperplane. These points define the separating line better by calculating margins that are more relevant to the construction of the classifier.

5.2.5 Multilayer Perceptron (MLP)

A multilayer perceptron (MLP) is a fully connected class of feedforward artificial neural network. An MLP consists of at least three layers of nodes: an input layer, a hidden layer, and an output layer [162]. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron and can distinguish data that is not linearly separable [162].

5.2.6 Black Hole (BH)

The Black Hole algorithm is a meta-heuristic algorithm based on Newton's laws of gravity [163]. This algorithm can find an optimal solution to a search problem in an n dimensional space. The main idea is to create several solutions (known as stars) that approach the optimal solution through the laws of motion. During the iterations of the algorithm, various solutions approach the solution that gives the best result (known as a black hole). This algorithm has been used in various problems [163] and has even been used for feature selection in EEG problems [164]. The Black Hole algorithm is based on three main concepts: the stars, which are possible solutions to the problem and are uniformly distributed throughout the search space, the Black Hole, which is the star with the best fitness value (a possible solution) and the motion of the stars, which is the equation that expresses the updating of the solutions as the algorithm is repeated. The basic idea is that the space near a black hole is a space where the best solutions can be found. So, once we have a black hole, it creates a gravitational field that pulls the various stars towards the nearest space. As the stars move, the solutions are resolved in the search space, but a star can fall into the black hole. This star then disappears, and a new star is created at a random location within the search space. This prevents the algorithm from falling into a local minimum or local maximum and the full search space can be explored [165]. The Black Hole Algorithm is randomly generated by generating an initial population of n stars, each representing a possible solution to the problem within the search space. Once the stars are created, the fitness value of each star is calculated and the star with the best fitness value is the one assigned as the black hole. After the fitness is calculated and the black hole is assigned, we update the star positions. A star that falls into the event horizon of the black hole disappears and a new star is randomly created. The algorithm is repeated until an optimal solution is found or a certain number of iterations are completed [165].

5.3 BCI-VR Goalkeeper Data Analysis Framework using Motor Imagery

Fig. 20 summarizes the feature extraction and classification steps followed. The protocol used for the BCI-VR Goalkeeper task was designed based on the Graz-BCI protocol [157]. The session for each participant lasted 430592 secs. The sampling frequency of the OpenBCI EEG cap used in this study was 125 Hz with 32 sample count per block.

A. EEG acquisition: A total of 1280 samples per trial of raw EEG data for each channel were recorded (10.24 secs * 125Hz = 1280 samples) which consist of 40 epochs (1280 samples /32 blocks = 40 epochs), (see Fig. 20).

The raw EEG data were recorded throughout the training session of the BCI-VR Goalkeeper task from 16 scalp locations (C3, C4, Cz, O1, O2, P3, P4, Pz, T3, T4, F3, F4, F7, F8, T5, T6, Ref: CPz, Gnd: AFz). The participant had to perform mental imagery of the corresponding hand, based on the presented stimuli. The calibration phase was configured to acquire data in 20 trials (epochs) per class (left-hand vs right-hand) in a randomized order.

B. Pre-processing: Raw EEG data were filtered offline with a 5-order band pass Butterworth filter between 8-30 Hz, to extract only the alpha and beta frequency bands which are reactive in MI [98]. More specifically, the alpha frequency band is usually more reactive [98]. The purpose was to compare the resting state (trial onset) segment with the motor action segment for alpha and beta frequency bands. The reason for the comparison arises from the knowledge we have of the literature [157] of ERD/ERS where the power of alpha and beta frequency bands falls during MI imagination in relation to the resting state. Subsequently, stimulation-based epoching was performed for left-hand or right-hand stimulus. The EEG signals were split into 4 sec segments during movement imagination. So, the epoch duration was 4 sec with an epoch offset of 0.5 sec. This gives us 500 new samples for each trial (4sec * 125Hz = 500), 10000 samples/channel for the left-hand trials, and 10000 samples/channel for the right-hand trials (500 samples * 20 trials).

Then, we used the Common Spatial Pattern (CSP) filter to reduce the EEG signal dimensions from 16 channels to 6 CSPs, where each output channel is a linear combination of the input channels (see Fig. 20). The CSP algorithm optimizes spatial filters such that the variance of the filtered EEG signal is maximum for one class and minimal for another class. Since the variance of a filtered signal is equal to the power of the signal, this means that CSP optimizes the spatial filters to obtain the band power features that are optimally discriminant because their value is maximally different between the two classes. CSP is commonly used for BCI applications. Three pairs of CSP filters were used (6 in total), which correspond to the three largest and three smallest eigenvalues (see Fig. 21).

Fig. 22 illustrates the data before applying the CSP filter whereas Fig. 23 illustrates the data after applying the CSP filter.

C. Feature Extraction: Re-epoching of the left- and the right-hand signals was performed (see Fig. 20). The signal was split into sliding segments of 1 second (125 samples) every 0.056 sec (0.056 sec * 53 segments + 1st segment = 4 sec → 54 segments per trial). Following that, the logarithm of average power was computed per segment. The input to the classifier was 54 feature vectors per trial (20 trials per class) for each of the six dimensions. This procedure is based on the Graz protocol [158].

D. Classification: The input feature vectors that include the band power for the left hand or the right hand were used as input to the classifier (see Fig. 20).

Six different classification algorithms from the scikit-learn library [159] were used to predict the imagination of left-hand versus right-hand movement based on EEG. The classifiers employed were the Linear Discriminant Analysis (LDA), Black Hole (BH), Multilayer Perceptron (MLP), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF).

For parameter tuning, we conducted an extensive search using the RandomizedSearchCV function from the scikit-learn library [159]. This approach allowed us to efficiently explore a wide range of hyperparameter combinations and identify the settings that yielded optimal performance for each classifier. For LDA [159], the optimized parameter settings were determined as follows: a learning decay of 0.9, solver set to "eigen," and the number of topics set to 10. The BH [159] classifier, inspired by gravitational force, utilized the following optimized parameters: a maximum of 10 layers, 15 iterations, and 8 stars. In the case of MLP [159], the optimized parameter values were determined as follows: an activation function of ReLU, an alpha value of 0.0001, a single hidden layer with 20 neurons, a constant learning rate, and the Adam solver. For SVM [159], the optimized parameters consisted of a regularization parameter (C) of 10, a gamma value of 0.0001, and a radial basis function (RBF) kernel. The DT classifier [159] employed the following optimized parameters: entropy as the criterion, a maximum depth of 7, a minimum of 20 samples per leaf, and a minimum of 8 samples per split. Lastly, the RF classifier [159] utilized the following optimized parameters: bootstrap set to True, a maximum depth of 80, a maximum of 6 features considered for splitting at each node, a minimum of 5 samples per leaf, a minimum of 12 samples per split, and a total of 100 estimators.

E. Device Command and BCI Application: To give correct feedback, the VR Goalkeeper system expects a negative value for one class and a positive value for the other class and according to this value the VR Goalkeeper avatar moves the corresponding hand (see Fig. 20).

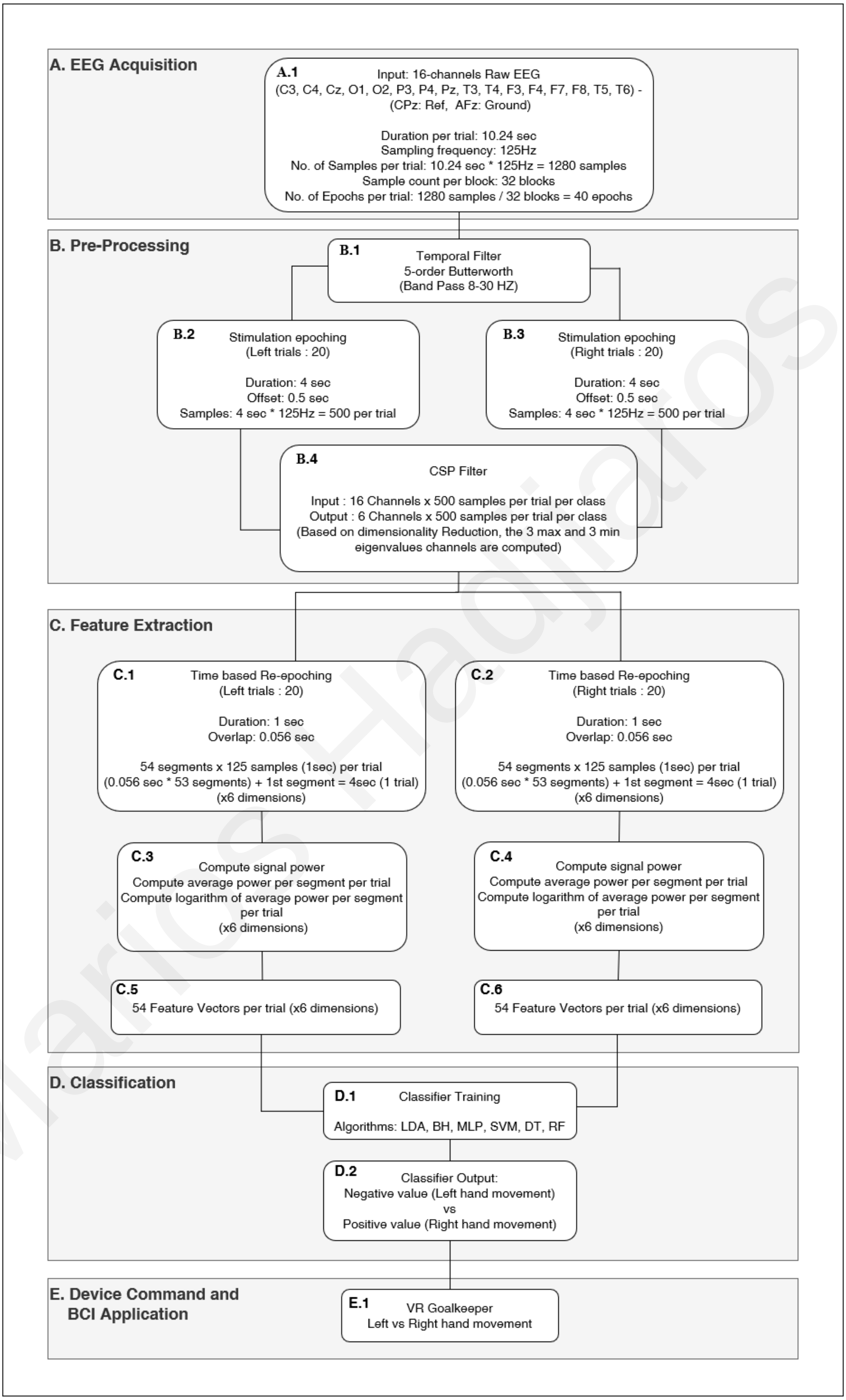

Fig. 20. BCI-VR Goalkeeper Data Analysis Framework using Motor Imagery.

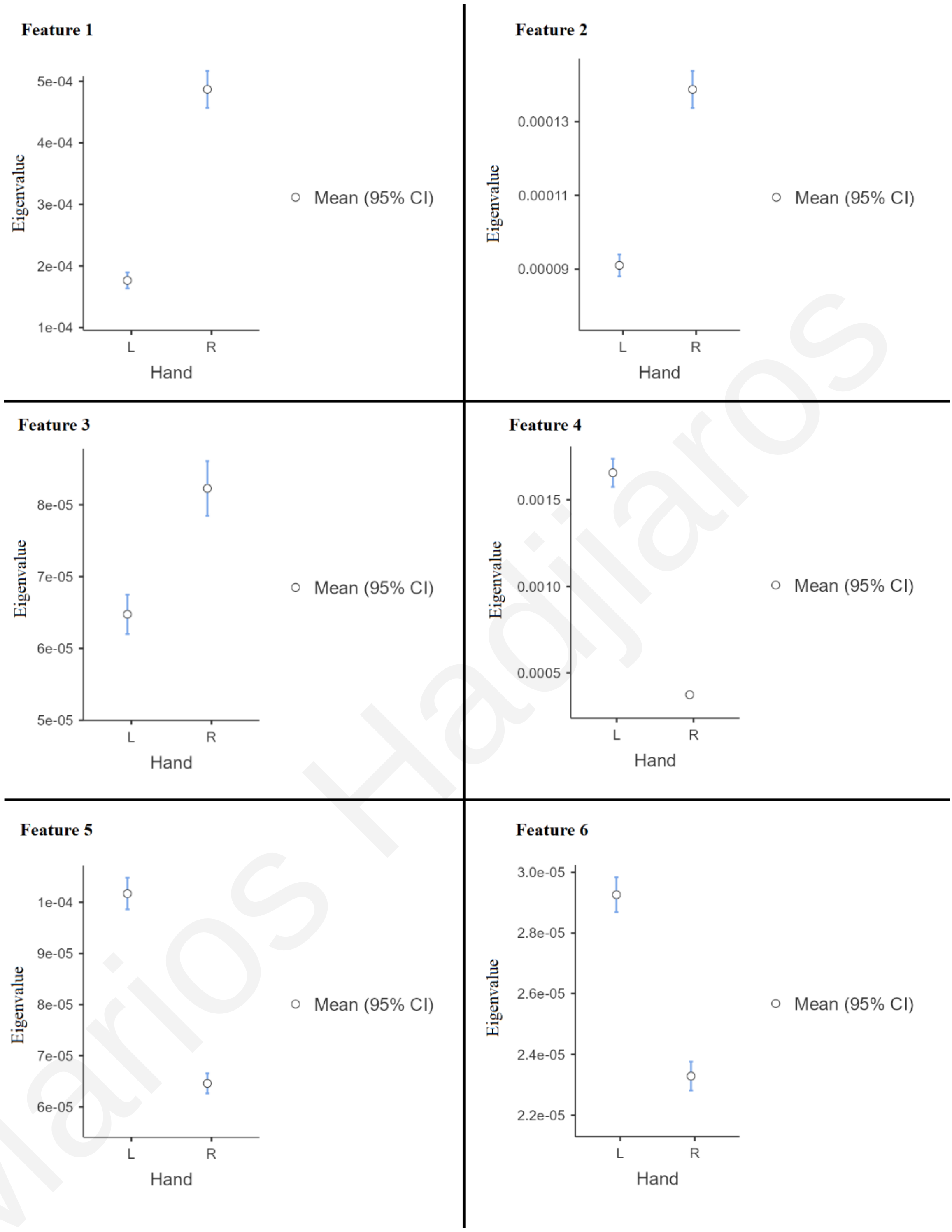

Fig. 21. The variance of the mean feature vectors of the filtered EEG signal, which is maximum for one class and minimum for the other class (Left vs Right MI) as presented in the BCI-VR Goalkeeper framework step D.2 in Fig. 20. The mean is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines.

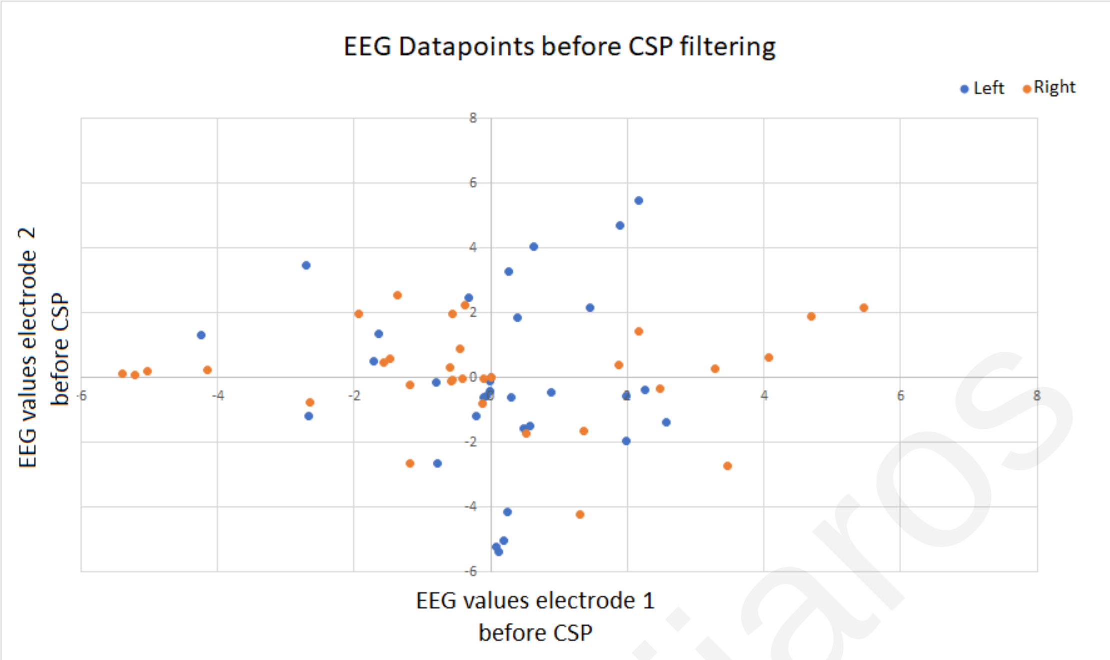

Fig. 22. The scatter plot of example data points of an EEG segment for left-hand and right-hand motor imagery before CSP spatial filtering as presented in the BCI-VR Goalkeeper framework of step B.2 and B.3 in Fig. 20.

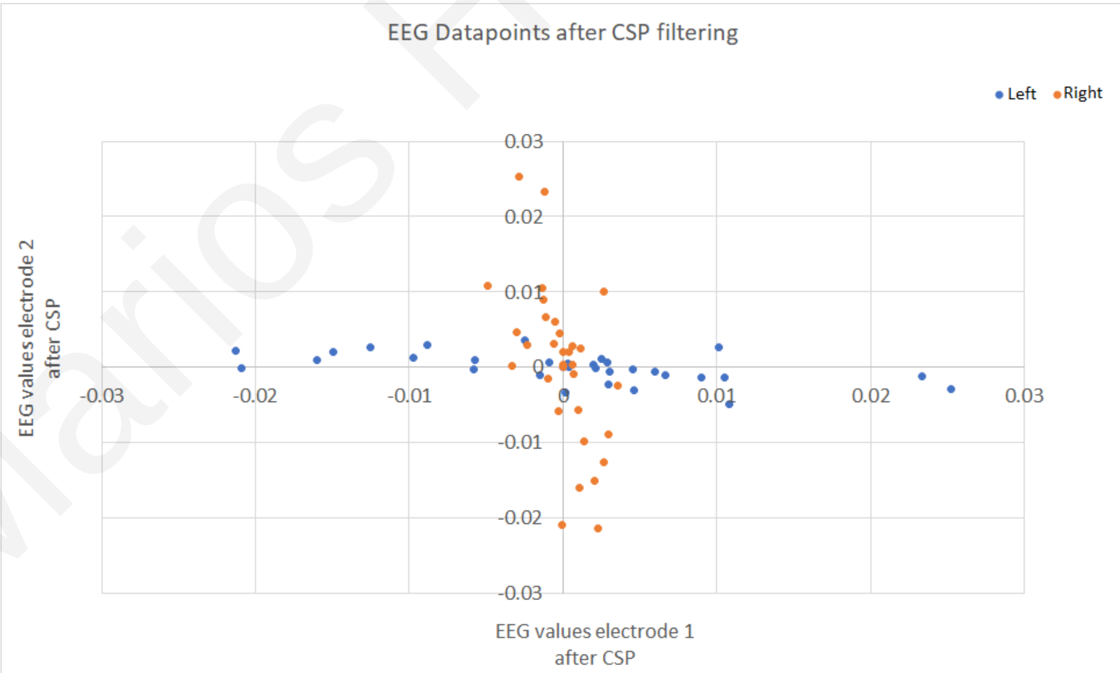

Fig. 23. The scatter plot of example data points of an EEG segment for left-hand and right-hand motor imagery after CSP spatial filtering as presented in the BCI-VR Goalkeeper framework of step B.4 in Fig. 20.

Chapter 6

Experimental Results

6.1 BCI VR Goalkeeper Results

In this section, we present the performance metrics results of six different classification algorithms (LDA, BH, MLP, SVM, DT, RF) used to detect left-hand versus right-hand movement imagery in 44 healthy participants. The models developed were trained offline and tested in real time. The Offline Mean Accuracy of the 6 algorithms were LDA (M = 78.5%), BH (M = 78.6%), MLP (M = 74.0%), SVM (M = 77.1%), DT (M = 77.2%), and RF (M = 82.4%) as depicted in TABLE 7 and Fig. 24. The Online Mean Accuracy of the 6 algorithms were LDA (M = 68.5%), BH (M = 69.5%), MLP (M = 66.9%), SVM (M = 68.0%), DT (M = 68.1%), and RF (M = 71.6%), as shown in TABLE 8 and Fig. 25. Notably, the Random Forest (RF) algorithm demonstrated higher accuracy both offline and in real-time compared to the other algorithms. The mean accuracy for offline RF was 82.4% whereas the mean accuracy for real-time RF was 71.6%.

To analyze the accuracy results, we conducted two repeated-measures ANOVAs comparing the performance of the six algorithms in offline and real-time scenarios separately. The dependent variables in both ANOVAs were the accuracy of the six algorithms. The analyses revealed statistically significant main effects for offline classification accuracy ($F(5,215) = 17.5$, $p < .001$, n2 = .08) and real-time classification accuracy ($F(5,215) = 7.12$, $p = .001$, n2 = .02). This indicates a consistent discrimination between left-hand and right-hand movement imagination across all algorithms. Notably, the highest-performing participant achieved the highest accuracy across all six algorithms, while the lowest-performing participant exhibited the lowest accuracy among the same set of algorithms. This uniformity suggests that all algorithms effectively differentiated between participants in a similar manner.

TABLE 7
PERFORMANCE METRICS CALCULATED OVER THE OFFLINE SESSION

Offline					
Algorithms in Offline	**Accuracy**	**Sensitivity**	**Specificity**	**Precision - Positive predictive value (PPV)**	**Negative predictive value (NPV)**
LDA	78.5 %	78.3 %	78.8%	78.7 %	78.4 %
BH	78.6 %	78 .4%	78.6 %	78.8 %	78.8 %
MLP	74.0 %	73.2 %	73.7 %	73.3 %	73.8 %
SVM	77.1 %	76.1 %	75.9 %	76.2 %	75.3 %
DT	77.2 %	76.1 %	76.9 %	76.8 %	76.9 %
RF	82.4 %	82.2 %	82.7 %	83.0 %	82.5 %

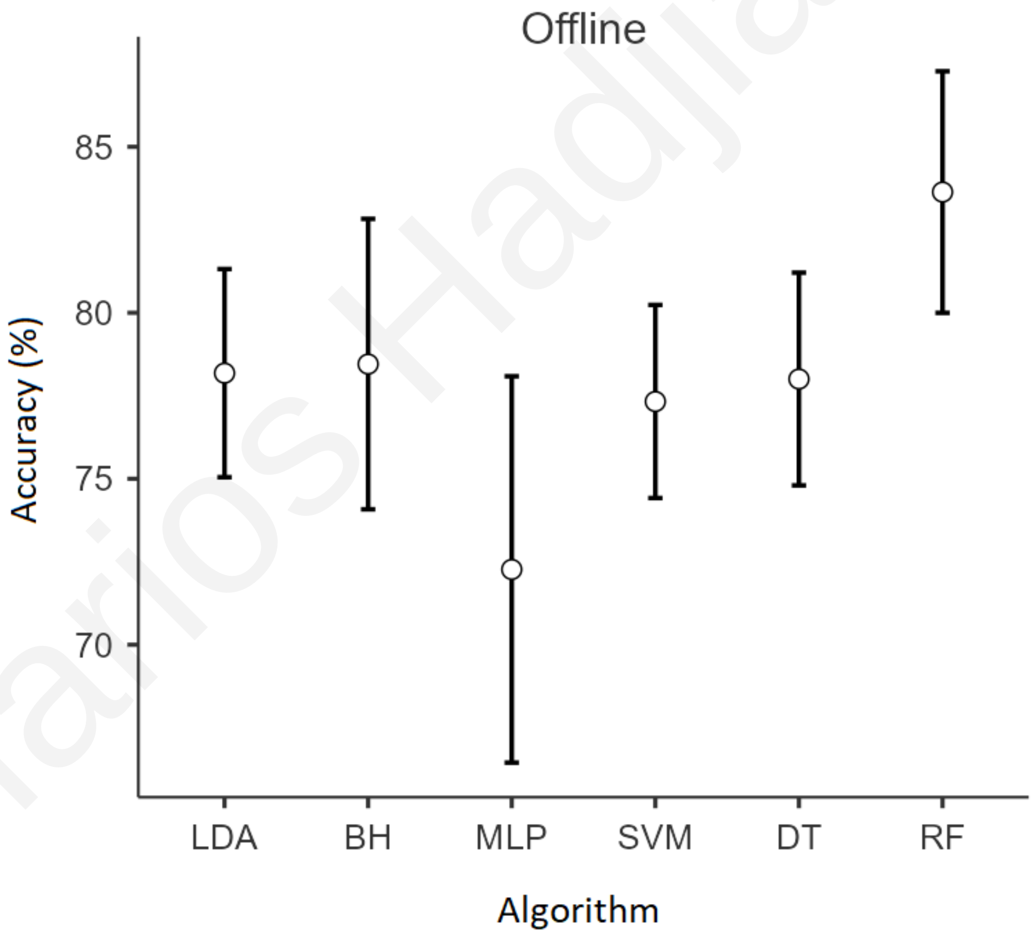

Fig. 24. The mean accuracy of the offline BCI-VR Goalkeeper Gaming task is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines. The Random Forest (RF) algorithm demonstrated a higher mean accuracy of 82.4% across all 44 participants.

TABLE 8
PERFORMANCE METRICS CALCULATED OVER THE REAL-TIME SESSION

		Real-time			
Algorithms in Real-time	**Accuracy**	**Sensitivity**	**Specificity**	**Precision - Positive predictive value (PPV)**	**Negative predictive value (NPV)**
LDA	68.5 %	67.8 %	68.8 %	68.9 %	68.2 %
BH	69.5 %	69 1%	69.1 %	67.8 %	67.9 %
MLP	66.9 %	66.1 %	65.5 %	65.4 %	65.3 %
SVM	68.0 %	67.9 %	69.1 %	67.9 %	68.3 %
DT	68.1 %	68.1 %	67.5 %	67.2 %	66.4 %
RF	71.6 %	71.3 %	71.9 %	72.1 %	71.8 %

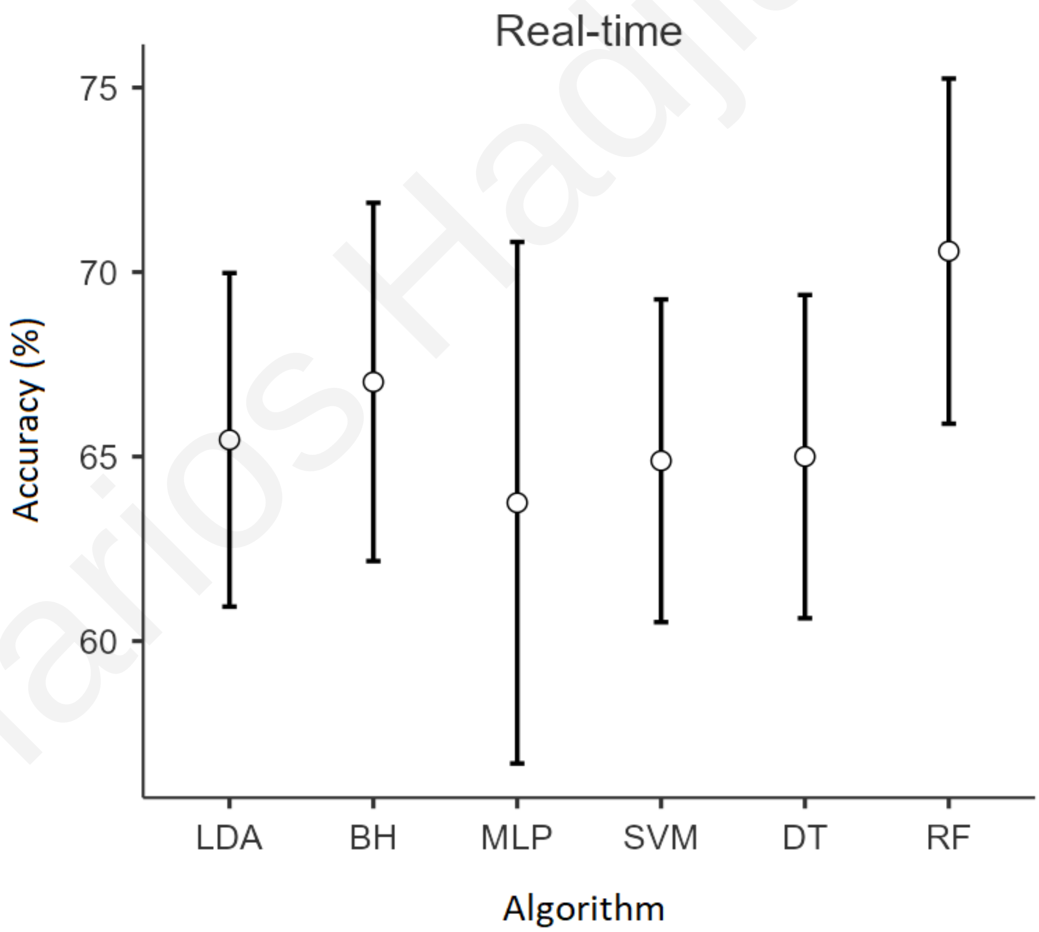

Fig. 25. The mean accuracy of the real-time BCI-VR Goalkeeper Gaming task is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines. The Random Forest (RF) algorithm demonstrated a higher mean accuracy of 71.6% across all 44 participants.

6.2 Flanker Gaming Task Results

Due to the modification of the Flanker task to make it more gamified, we first examined whether our task yielded the expected pattern of results similar to the traditional Flanker task. As shown in Fig. 26, there was a statistically significant difference between congruent and incongruent accuracy, $t(25) = 4.45$, $p < .001$, with participants having higher accuracy in congruent than incongruent trials. Also as shown in Fig. 27, there was a statistically significant difference between congruent and incongruent Mean RT, $t(25) = -6.14$, $p < .001$, with participants responding faster in congruent than incongruent trials. These results are consistent with previous findings, suggesting that the gamified versions of the task successfully replicated the expected performance levels, as reported in the existing literature [149], [150].

To explore a potential relation between inhibitory/executive control and BCI-VR performance, we computed a flanker interference variable for both accuracy and RT in the Flanker gaming task. For accuracy, we subtracted the accuracy for incongruent trials from that of congruent trials. For RT, we subtracted the RT for congruent trials from the RT for incongruent trials. We also computed a group variable on the RF algorithm accuracy by performing a median split to the BCI-VR Goalkeeper accuracy data (11 Low Achievers, 11 High Achievers). We then carried out separate One-Way ANOVAs for flanker interference on accuracy and on RT with Group as the independent variable. No significant effects of Group were found in either analysis, $F(1,19.8) = .10$, $p = .75$ for accuracy and $F(1,14) = 1.84$, $p = .20$ for RT. However, a significant positive correlation was found between the mean accuracy for the congruent trials of the Flanker task and the mean offline classification accuracy in the BCI-VR Goalkeeper task, $r(22) = .46$, $p = .03$ (see Fig. 28). No significant correlation was found between the accuracy for incongruent trials and the offline classification accuracy in the BCI-VR Goalkeeper task. The positive correlation between congruent trial accuracy and offline classification accuracy suggests a potential relationship between inhibitory/executive control and BCI-VR performance.

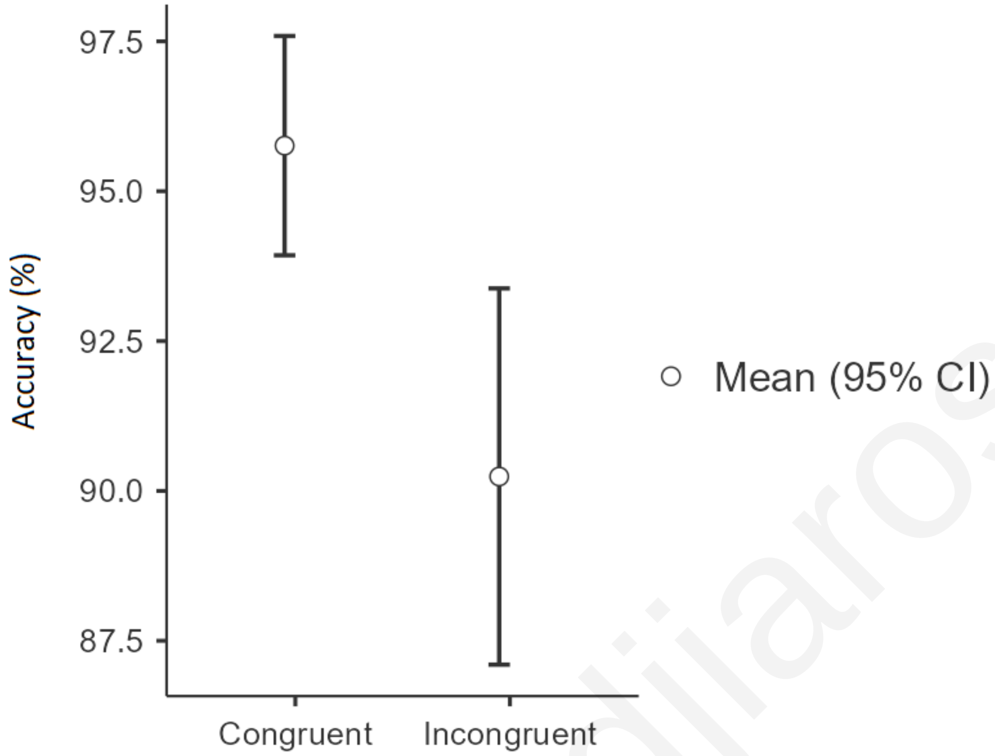

Fig. 26. The mean accuracy for congruent and incongruent trials in the Flanker Gaming task is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines.

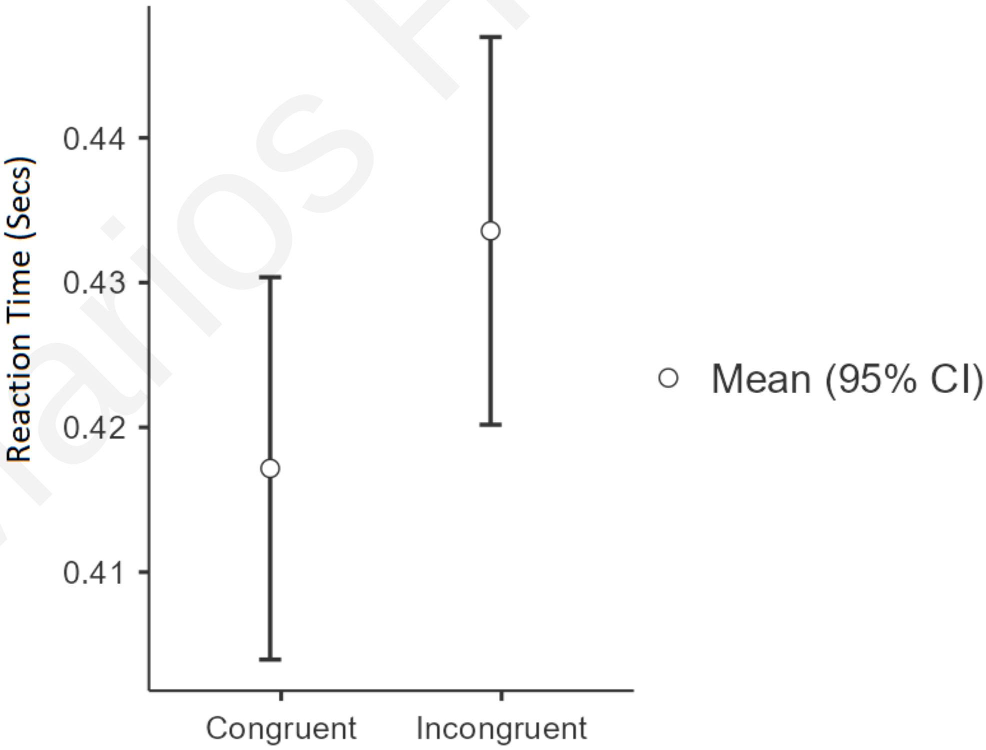

Fig. 27. The mean Reaction Time (RT) for congruent and incongruent trials in the Flanker Gaming task is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines.

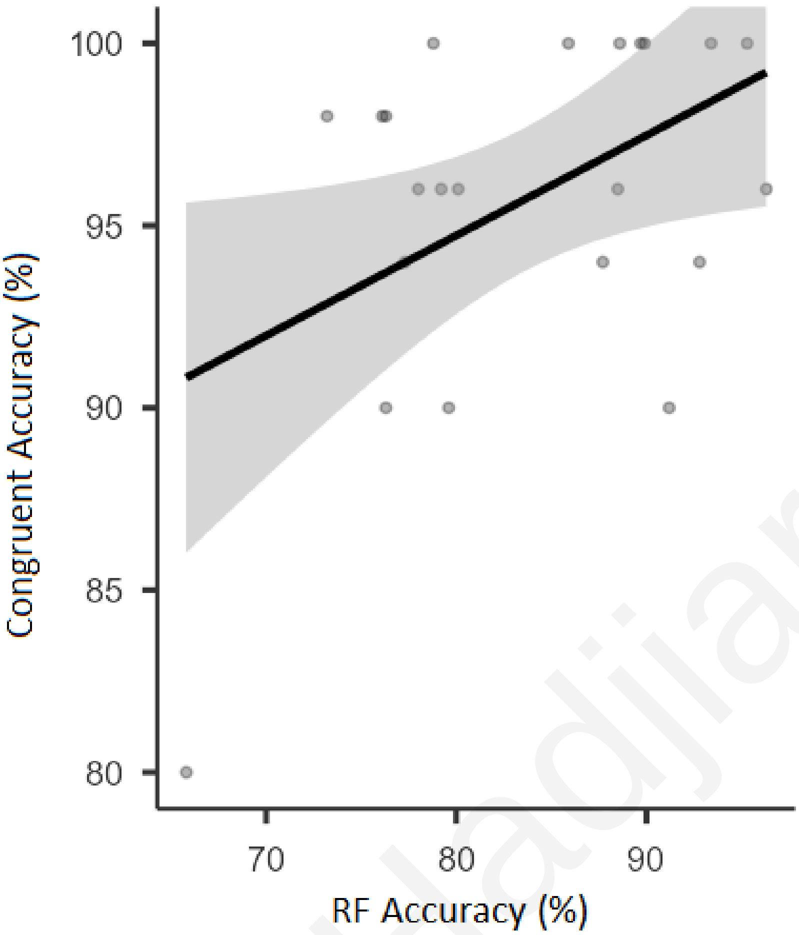

Fig. 28. Scatter plot and a significant positive correlation (r(22) = .46, p = .03) between accuracy with the congruent trials of the flanker task and BCI-VR Goalkeeper task accuracy, across the 22 participants who executed both tasks. Participants demonstrating higher accuracy with the congruent trials also exhibited increased accuracy in the BCI-VR Goalkeeper task.

6.3 Spatial Cueing Gaming Task Results

Due to the modification of the Spatial cueing task to make it more gamified, we need to demonstrate first that it exhibits the correct patterns with the traditional Spatial cueing task. A repeated-measures ANOVA on d' revealed a statistically significant main effect for the cue type (neutral, pre-cue, retro-cue) $F(2,48) = 38.4$, $p < .001$, $\eta^2 = .47$. The d' is a sensitive discrimination measure that reflects the degree to which participants accurately report the presence or absence of the probe in the preceding memory array. The d' was calculated using the formula: d' = z (hit rate) − z (false alarm rate).

As shown in Fig. 29, participants had higher d' in pre-cue trials than in retro-cue and neutral trials, and higher d' in retro-cue trials than in neutral trials indicating attentional cueing benefits in service of encoding information into VWM and in service of maintenance in VWM. A repeated-measures ANOVA on mean RT revealed a statistically significant main effect for the cue type (neutral, pre-cue, retro-cue) $F(2,48) = 29.3$, $p < .001$, $n2 = .25$. The analysis of simple main effects revealed that participants exhibited faster RT in pre-cue and retro-cue trials compared to neutral trials (see Fig. 30) indicating attentional cueing benefits in service of VWM in terms of speed. Additionally, there was no statistically significant difference in RT between pre-cue and retro-cue trials. These results are consistent with previous findings, suggesting that the gamified versions of the task successfully replicated the expected performance levels, as reported in the existing literature involving adult participants [151]. By aligning with the established effects, our study further supports the validity and effectiveness of the gamified approach.

To examine whether the RF algorithm accuracy mediated performance in the Spatial Cueing task, we first computed benefit scores for pre-cues and retro-cues. For the pre-cue benefit score, we subtracted the d' for neutral trials from the d' for pre-cues. Similarly, to compute the retro-cue benefit, we subtracted the d' for neutral trials from the d' for retro-cues. We then carried out a mixed-design ANOVA with the cue benefit (pre-cue, retro-cue) as the within-subject variable and the Group (High Achievers vs Low Achievers in the BCI-VR Goalkeeper task) as the between-subject variable. The benefit score was the dependent variable. The analysis revealed a statistically significant main effect for cue benefit, with the pre-cue benefit being larger than the retro-cue benefit, $F(1,20) = 15.58$, $p < .001$, $n2 = .01$. More importantly, a significant interaction between Group and cue benefit was found, $F(1,20) = 9.09$, $p = .007$, $n2 = .07$. The interaction was caused by the presence of a larger pre-cue than retro-cue benefit for High Achievers, $p<.001$ (see Fig. 31). No difference was observed in Low Achievers (see Fig. 31).

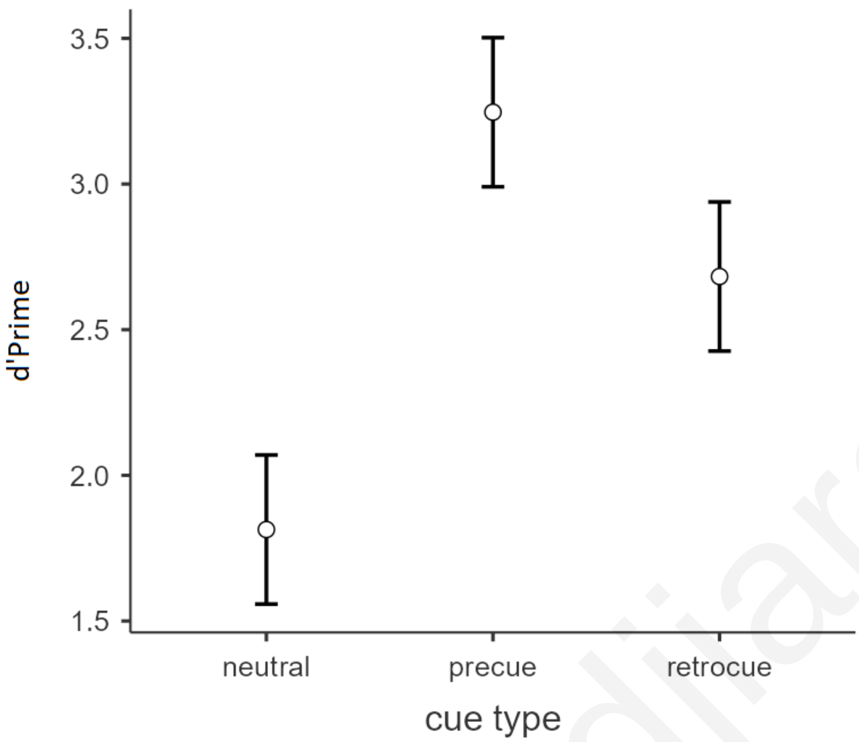

Fig. 29. The mean d' for pre-cue, retro-cue, and neutral trials in the spatial cueing task is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines.

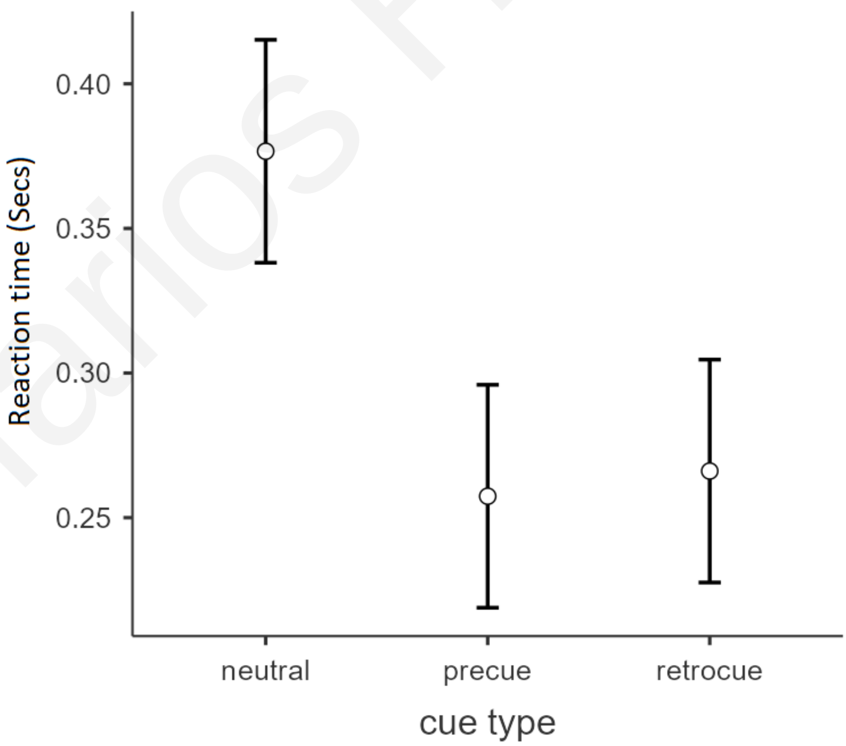

Fig. 30. The mean RT for pre-cue, retro-cue, and neutral trials in the spatial cueing task is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines.

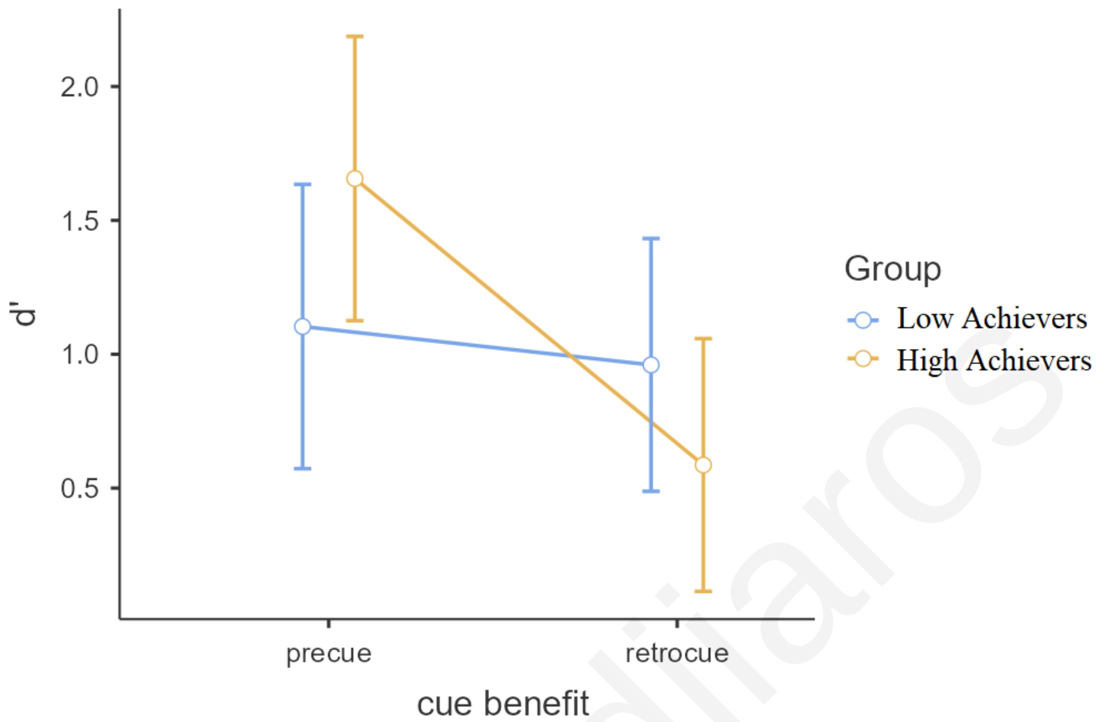

Fig. 31. The pre-cue benefit is larger than the retro-cue benefit and is denoted by the circle. The interaction was caused by the presence of a larger pre-cue than retro-cue benefit for High Achievers (11 participants). No difference was observed in Low Achievers (11 participants). The confidence interval 95% error bars are depicted by the lines.

6.4 Spatial Orientation Task Results

A repeated-measures ANOVA on Angular error revealed a statistically significant main effect for the angles (25°, 41°, 93°, 143°, 151°, 165°, 249°, 250°, 266°, 268°, 318°, 333°) $F(11, 220)=3.56$, $p<.001$, $n2 = .11$. In Fig. 32, it is evident that obtuse angles, occurring in both the left and right sectors (angles 93°, 143°, 249°, 250°, 266°), i.e., those situated in the 2nd and 3rd quadrants, exhibited a noticeably higher angular error compared to acute angles. Additionally, for angles nearing 180 degrees, the angular error remained minimal due to their alignment along a nearly straight line. Also, the overall angular error was 30.35. This result is consistent with previous findings where the overall angular error was 33.73, suggesting that the task we used successfully reproduced the expected performance levels as reported in the existing literature [156].

To test whether the angular error in the Spatial Orientation Task could be differentiated between High Achievers and Low Achievers in the BCI-VR Goalkeeper task, we carried out an independent samples t-test. Results revealed no difference, t(20) = 1.36, p = .19.

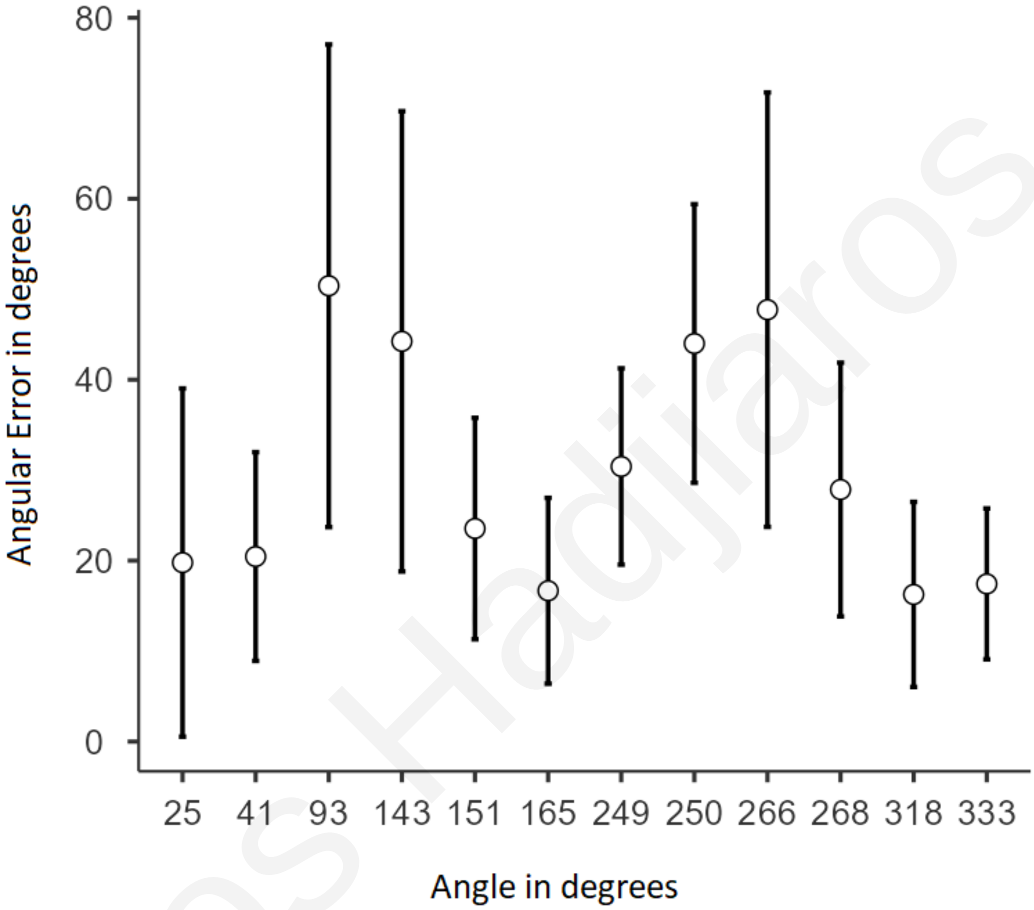

Fig. 32. Participants' mean angular error per angle is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines.

6.5 Mental Body Rotation Task Results

A repeated-measures Analysis of Variance (ANOVA) revealed no statistically significant main effect in RT for angles F(11, 231) = 1.12, p = .35, n2 = .02 (see Fig. 33). To test whether RT in the Mental Body Rotation task could be differentiated between High Achievers and Low Achievers in the BCI-VR Goalkeeper task, we carried out an independent samples t-test. Results revealed no difference, t(20) = 0.94, p = .36. Upon closer examination, it became evident that the cognitive differences between the two tasks played a more prominent role in the lack of correlation.

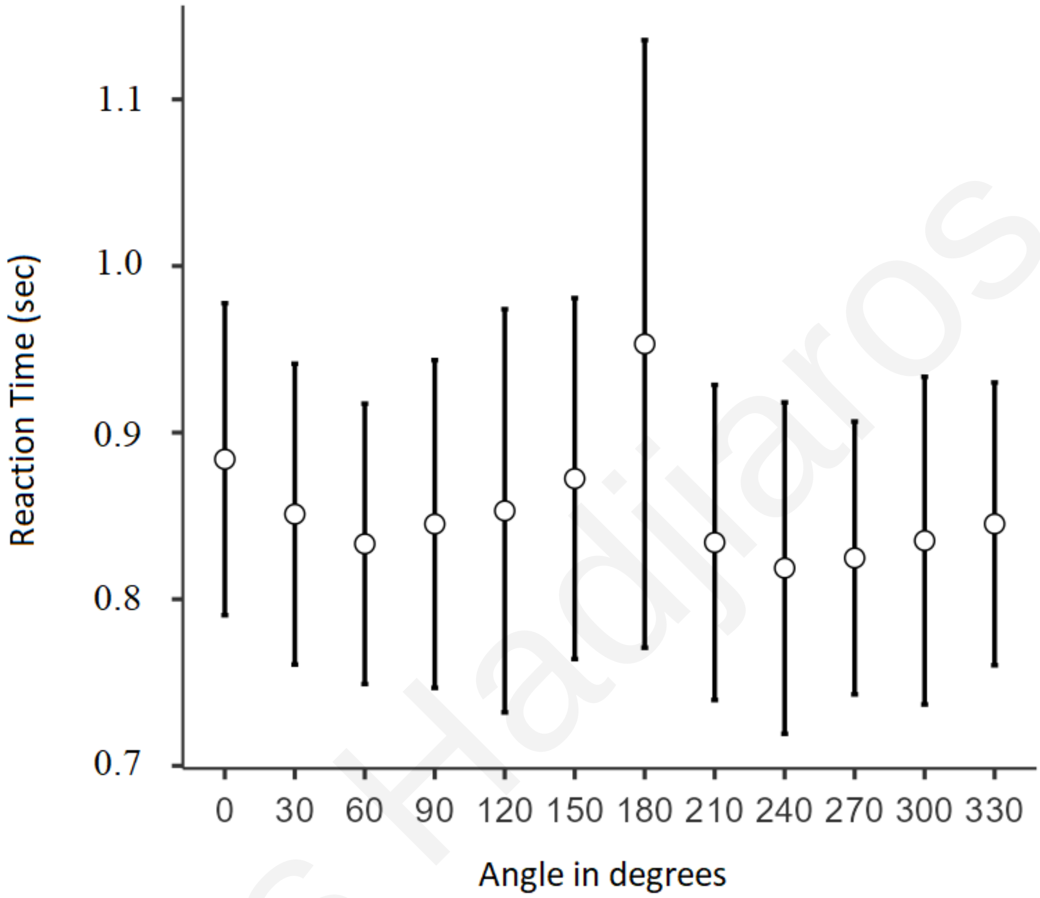

Fig. 33. Participants' mean RT per angle is denoted by the circle, and the confidence interval 95% error bars are depicted by the lines.

Chapter 7

Discussion

7.1 BCI VR Goalkeeper Task

The BCI-VR Goalkeeper gaming framework presented in this study demonstrated promising results in terms of detecting left-hand versus right-hand movement imagery using brain-computer interface technology combined with VR. The findings shed light on important aspects of Motor Imagery BCI-VR algorithms, i.e., performance and the corresponding BCI-VR cognitive abilities.

The objective of this study was twofold: firstly, to assess and compare the accuracy of Motor Imagery based on Brain-Computer Interface tasks utilizing VR across six distinct algorithms, aiming to draw insightful conclusions regarding their performance. Secondly, the study aimed to establish the cognitive abilities that significantly influence MI-BCI performance in novice users, by exploring inhibitory/executive and attentional control, spatial orientation, and mental body rotation. The BCI-VR Goalkeeper task, developed in the context of this study, performed best using the RF algorithm among 44 participants, achieving a mean accuracy of 82.4% offline and 71.6% in real-time. The results obtained from all six algorithms used in the BCI-VR Goalkeeper gaming yielded accuracies that are comparable to those reported in the literature [166], [168], [169], [170], [98], [171] (see TABLE 9). These findings are consistent with prior research that has demonstrated the effectiveness of RF in various BCI applications [172], [173].

A previous study by Skola et al. [166] developed a similar BCI-VR system to increase engagement, attention, and motivation using gamification and VR. Like our BCI-VR Goalkeeper task, users were trying to pull a left lever versus a right lever to destroy asteroids using MI. The average classification accuracy of all 19 participants was 72.8%.

In another study, Choi et al. [168] investigated the difference between MI-BCI tasks when run in an immersive VR headset and a monitor display. From 18 healthy participants experimented, the average accuracy in the session with the monitor was 58% and the average accuracy in the session with the VR headset was 68%. In both of the aforementioned studies that were similar to our BCI-VR Goalkeeper task, the accuracy performance of the BCI-VR Goalkeeper was very close or better (see TABLE 9).

Furthermore, Lupu et al. [169] developed a therapy system for stroke rehabilitation based on VR and BCI, and functional electrical stimulators. The system immersed the participant into a virtual scenario where a virtual therapist coordinated the exercises aimed at restoring brain function. The electrical stimulator helped the participant to perform rehabilitation exercises and the BCI system and an EEG device were used to determine if the exercises were executed properly. The average accuracy of the three participants in 7 sessions was 85%. In that study, three main differences could justify the high accuracy of the system over our BCI-VR Goalkeeper. Firstly, the sample of three participants was very small and therefore not representative at all. In our work, extensive experimentation was done with forty-four participants performing the task without any prior knowledge. Also, an electrical stimulator helped the participant to perform the exercises, something that could significantly improve the performance of the participants compared to others who had no help. Finally, the same participants performed 7 sessions which gave them prior knowledge, which clearly could increase the performance significantly.

In another study, H. Ziadeh et al. [170] developed a BCI-VR application using the MI paradigm. This study aimed to understand whether the embodiment of a hand depicted in VR can enhance performance accuracy. Twenty-two healthy participants participated in a within-subject study where their accuracy was compared in two different embodiment experiences: 1) avatar hand (with the body), or 2) abstract blocks. The accuracy of both conditions was similar with the avatar hand accuracy 53% and abstract blocks accuracy 54%.

Finally, Vourvopoulos et al. [98] developed a novel BCI-VR system that provided auditory, haptic, and visual feedback in the VR experience with the use of head-mounted display (HMD), integrated with a BCI MI training task for left-hand and right-hand MI to achieve more distinct activations in the motor cortex areas and enhance realism. More specifically, they integrated a holistic BCI approach combining MI, immersive VR environments, and sensory stimulation. During the experimental training, the virtual hands were controlled using only the MI-BCI paradigm in the system. Healthy users were asked to perform a rowing motion in a boat with virtual hands using MI. Results showed that the average left-right hand movement accuracy of 13 healthy participants was 70.7%. Both in the study by Ziadeh et al. [170] as well as in the study by Vourvopoulos et al. [98] the BCI-VR Goalkeeper task had better results even when haptic feedback was used.

Although we have found that in our study the RF algorithm had the best results, it is important to note that the effectiveness of the RF algorithm in BCI applications may vary depending on factors like the specific dataset, the preprocessing methods used, and the feature engineering techniques applied. The outcome confirms that the RF algorithm can be effective in BCI applications for several reasons. RF is an ensemble learning method that combines multiple decision trees to make predictions. In the context of EEG-based BCI, this ensemble approach can help reduce the risk of overfitting and improve generalization to unseen data. EEG data can be noisy and affected by various artifacts, and the ensemble nature of RF can help moderate these issues [172], [173]. EEG data can be noisy due to various factors, such as eye movement, breathing, and environmental interference. RF is known for its robustness to noisy data. RF can handle noisy features and still provide accurate predictions, making them suitable for EEG data, where noise is a common challenge.

Also, Fig. 34 illustrates that our study's RF algorithm achieved the fourth highest average accuracy among seven studies, surpassing the overall average. Moreover, as depicted in the same figure, it is noteworthy that all other studies included a significantly smaller number of participants compared to our study, which may potentially skew the presented results, particularly for studies with fewer than 10 participants.

7.2 Mental Body Rotation

Beyond the performance accuracy investigation, we explored the influence of cognitive abilities on MI-BCI performance. In the MBRT, we did not observe a statistically significant correlation, which was somewhat unexpected considering the seeming similarities with the BCI-VR Goalkeeper task. However, upon closer examination, it became evident that the cognitive differences between the two tasks played a more prominent role in the lack of correlation. The MBRT measures mental rotation that is not required for the successful execution of the VR task, which instead relies on attentionally selecting the highlighted hand of the goalkeeper avatar and then imagining a movement on the selected lateral side. In the MBRT, the human figure appeared in various postures and rotations, with participants viewing its front side. In contrast, in the BCI-VR Goalkeeper task, the avatar remained static without rotating. Additionally, participants could only view the avatar's backside, eliminating the need for mental rotation to distinguish left-hand from right-hand cues. We believe these fundamental cognitive differences significantly contributed to the absence of a correlation between these two tasks. Similarly in a previous study, Leeuwis et al. [171] investigated the impact of spatial abilities and visuospatial memory on MI-BCI performance. Fifty-four novice users participated in an MI-BCI task and carried out two cognitive tests namely the Mental Rotation Test (MRT) and the Design Organization Test (DOT). The impact of spatial abilities and visuospatial memory on BCI task error rate in three feedback sessions was measured. Their results showed that spatial abilities, as assessed by the Mental Rotation Test, were not related to MI-BCI performance.

7.3 Spatial Orientation

As with the MBRT, we did not observe a statistically significant correlation between the SOT and the BCI-VR Goalkeeper task either. The SOT utilizes egocentric perspective-taking as a context for mental rotation and these abilities do not seem to be employed in a similar cognitive fashion in the BCI-VR Goalkeeper task. Regarding the SOT behavioral results alone, the mean angular error for all 22 participants was 28.85°, which is similar to the mean angular error of 35.35° found by Friedman et al. [156]. Furthermore, in our SOT task, participants exhibited a greater angular error when the angle under consideration was larger, whether on the left or right side. Conversely, as the angle decreased in size, the error rate reduced accordingly. Moreover, the error rate was notably reduced in cases where the angle approached 180°, essentially representing an almost straight line. These findings underscore the fact that larger angles have a more pronounced impact on human accuracy in calculations compared to smaller angles, except when the angles approach a size resembling a straight line.

7.4 Flanker Task

Our proposal of differential cognitive abilities between these two tasks (the MBRT and the SOT) and the BCI-VR Goalkeeper task is further supported by the significant correlation we observed between the flanker task and the BCI-VR Goalkeeper task. Executive/inhibitory control is thought to underlie the flanker task and a recent study using a similar VR goalkeeping task to the one we used here, demonstrated that the ability to orient attention and resolve the conflict amongst competing stimuli predicted performance in the VR goalkeeping task [174].

Furthermore, our study's behavioral results regarding the Flanker Gaming task align with previous literature, particularly with the findings from McDermott et al. [167]. We observed a statistically significant main effect of congruency on RT, where incongruent trials elicited slower responses compared to congruent trials, consistent with the typical outcomes of this task. In McDermott et al.'s study, which involved 20 adult participants, the RT differences between congruent and incongruent conditions were statistically significant. Similarly, in our Flanker Gaming task with 22 participants, we also found statistically significant RT differences between congruent and incongruent trials. Importantly, we found statistically significant positive correlations between congruent accuracy in the Flanker task and the offline classification accuracy in the BCI-VR Goalkeeper task, highlighting the importance of individual differences in understanding BCI classification. Overall, our current results suggest a relation between executive/inhibitory control and BCI-VR performance. Individuals with better executive/inhibitory control abilities exhibit higher accuracy in controlling the virtual goalkeeper using motor imagery.

7.5 Spatial Cueing

Similarly, when dividing participants based on performance in the BCI-VR Goalkeeper task, we found that High Achievers had larger pre-cue than retro-cue benefits in the Spatial Cueing Gaming Task, demonstrating that those participants that scored the highest in the BCI-VR Goalkeeper task benefited more from attentional cues in service of perception (i.e., external attention) than from attentional cues in service of VWM (i.e., internal attention). Given that in the BCI-VR Goalkeeper task participants must orient their attention spatially to the side highlighted by the hand of the goalkeeper avatar, in order to imagine a movement on the selected lateral side, our findings suggest that external attentional orienting (rather than internal attentional orienting) is implicated in efficient performance in the BCI-VR Goalkeeper task. In contrast, we observed no difference between pre-cue and retro-cue benefits in Low Achievers in the BCI-VR Goalkeeper task, corroborating that a poorer ability to employ external attention before movement imagination results in lower accuracy in controlling the virtual goalkeeper using motor imagery.

In the Spatial Cueing Gaming task, pre-cues measure the ability to orient attention to perceptual stimuli while retro-cues measure the ability to orient attention to stimuli held in memory. Our behavioral results for the Spatial Cueing Gaming task align with the findings of Shimi et al. [151], [152], [153] and Nobre et al. [154]. An analysis of variance (ANOVA) revealed a statistically significant main effect (d') for the cue type (neutral, pre-cue, retro-cue). These findings affirm that our task yielded similar outcomes to their traditional counterparts, thus demonstrating their appropriateness.

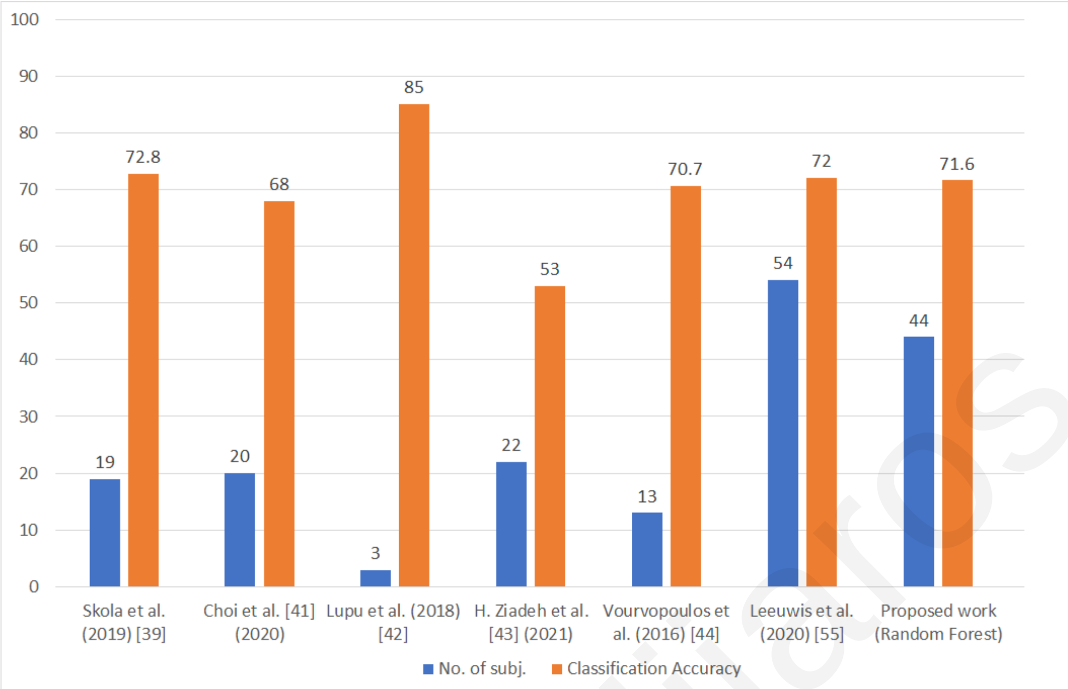

Fig. 34. Comparison of accuracy and number of participants with studies related to the BCI VR Gaming task.

TABLE 9
STUDIES RELATED TO THE BCI VR GAMING TASK

Author	BCI paradigm	VR action task	No. of subj.	Feature extraction	Classification algorithm	Channels	Classification Accuracy
Skola et al. (2019) [166]	MI	pulling left and right levers	19	CSP	LDA	10 channels: C1, C2, C3, C4, C5, C6, CP3, CP4, FC3, FC4	72.8%
Choi et al. (2020) [168]	MI	Virtual left and right hand movement	20	CSP	LDA	20 channels: FC5, C5, CP5, FC3, C3, CP3, FC1, C1, CP1, Cz, CPz, FC2, C2, CP2, FC4, C4, CP4, FC6, C6, CP6	68%
Lupu et al. (2018) [169]	MI	Limb movement control	3	CSP	LDA	12-channels: (FC1, FC2, FC5, FC6, C3, C4, C5, C6, CP1, CP2, CP5, CP6)	85%
H. Ziadeh et al. (2021) [170]	MI	pop balloons with left and right hand	22	CSP	LDA	7 channels: F3, F4, C3, Cz, C4, P3, P4 Reference: CPz, Ground: AFz	53%
Vourvopoulos et al. (2016) [98]	MI	Virtual rowing with hand movements	13	CSP	LDA	8 channels: (FC5, FC6, C1, C2, C3, C4, CP5, CP6)	70.7%
Leeuwis et al. (2020) [171]	MI	Feedback bar showing the direction of the participant's performance.	54	CSP	LDA	16 electrodes: (F3, Fz, F4, FC1, FC5, FC2, FC6, C3, Cz, C4, CP1, CP5, CP2, CP6, T7, T8) Ground AFz	72%
Proposed work (Random Forest)	MI	Virtual goalkeeper hand control	44	CSP	RF	16-channels (C3, C4, Cz, FP1, FP2, P3, P4, Pz, T3, T4, F3, F4, F7, F8, T5, T6) Reference: CPz, Ground: AFz	71.6%

7.6 Study Limitations

Despite the promising potential of BCI technology, several limitations inherent in the experimental sessions must be acknowledged (see TABLE 10). These limitations encompass both technical constraints and challenges in participant engagement and performance.

The device used to record EEG signals, specifically the OpenBCI EEG cap, poses challenges due to its limited electrode coverage, particularly over areas proximal to the motor cortex (CP3, C1, C5, CP4, C2, C6). This inadequate spatial resolution can impede the accurate classification of left-hand versus right-hand motor imagery tasks. Moreover, the OpenBCI device's classification as a non-medical device raises some concerns about the quality of the recorded signals which may have led to reduced performance.

Conducting experimental sessions in non-specifically configured laboratories introduces the risk of environmental noise pollution from sources such as electrical interference, ambient light, screens, and computers. These extraneous stimuli can interfere with high quality EEG signal acquisition, compromising the quality and reliability of recorded data.

Furthermore, communicating instructions to participants on how to perform motor imagery tasks, particularly the visualization of upper limb movements without physical execution or muscle activation, presents inherent difficulties. The abstract nature of motor imagery makes it challenging for participants to grasp and execute accurately, leading to variability in task performance across individuals.

The experimenter faces challenges in gauging the level of participant engagement and effort during experimental sessions. Without real-time feedback on participant performance or subjective measures of effort, it is difficult to ascertain whether participants are genuinely exerting effort or simply waiting for the session to conclude, potentially skewing experimental outcomes.

Hemispheric dominance, particularly the left hemisphere's superiority in right-handed individuals, poses challenges in generating precise motor imagery for non-dominant hand movements [35]. This asymmetry in motor control may contribute to discrepancies in BCI performance between left-hand and right-hand motor imagery tasks.

Inter-individual variability in the neural mechanisms underlying motor imagery introduces further complexity to BCI experiments. Variations in cortical excitability, interhemispheric connectivity, and the organization of motor-related brain regions can influence the ease and accuracy of generating motor imagery for each hand, contributing to inconsistencies in BCI performance across participants [35].

Motor imagery abilities vary among individuals, with some participants finding it more challenging to generate vivid and accurate mental representations of movements for one hand compared to the other. These individual differences can manifest as discrepancies in BCI performance between left versus right hand motor imagery tasks, complicating data interpretation and generalization [35].

Addressing these limitations necessitates innovative methodological approaches. By addressing these challenges, researchers can enhance the robustness and reliability of BCI experimental sessions, paving the way for advancements in BCI neurotechnology and clinical applications.

TABLE 10
THE MAJOR STUDY LIMITATIONS

#	Limitations
1	Limited electrode coverage by the OpenBCI device, in the motor cortex (CP3, C1, C5, CP4, C2, C6).
2	Conducting experimental sessions in non-specifically configured laboratories introduces the risk of environmental noise pollution.
3	Communicating instructions to participants on how to perform motor imagery tasks, without physical execution or muscle activation, presents inherent difficulties.
4	Hemispheric dominance, poses challenges in generating precise motor imagery for non-dominant hand movements.
5	Inter-individual variability in the neural mechanisms underlying motor imagery introduces further complexity to BCI experiments.

Chapter 8

Concluding Remarks and Future Work

8.1 Concluding Remarks

In conclusion, this study demonstrated the feasibility and effectiveness of the BCI-VR Goalkeeper gaming task for detecting left-hand versus right-hand movement imagery. The findings contribute to the field of brain-computer interfaces and virtual reality gaming by showcasing the potential for immersive and interactive experiences.

The RF algorithm emerged as the top-performing classifier, exhibiting high accuracy both offline and in real-time scenarios. This reinforces the suitability of RF for accurate movement imagery detection in BCI-VR applications. The statistically significant interaction between high achievers and pre-cues and the positive correlations observed between response inhibition accuracy and offline classification accuracy further emphasize the impact of cognitive abilities on BCI-VR performance and shows that external attention has an important role in BCI performance. Our findings suggest that external attentional orienting is implicated in efficient performance of tasks using MI. Moving forward, it is important to continue exploring additional cognitive mechanisms and incorporating cognitive training interventions to enhance BCI performance. By advancing both algorithm development and cognitive training, we can work towards improving the accuracy, reliability, and practicality of MI-based BCI systems for various applications, including neurorehabilitation, assistive technologies, and gaming entertainment.

Overall, this study provides valuable insights into the potential of BCI-VR systems and lays the foundation for further research in the field. Continued efforts in algorithm refinement and cognitive training interventions will pave the way for the development of more robust and effective BCI-VR technologies that can significantly benefit individuals in their daily lives.

8.2 Future work

Although significant progress has been made in enhancing classification algorithms and employing effective feature extraction strategies, the accuracy of MI-based BCI systems still falls short of practical and commercial viability in people's daily lives. This emphasizes the ongoing need for research and development in both algorithmic improvements and cognitive training interventions. By addressing these aspects, we can strive to enhance the usability and effectiveness of BCI-VR systems for real-world applications.

Furthermore, the results of this study highlight the importance of considering cognitive factors when designing BCI-VR systems and cognitive training intervention development to enhance BCI performance. While the current study focused only on executive/inhibitory control, visuospatial selective attention, mental body rotation, and spatial orientation, it is crucial to explore other cognitive mechanisms that could potentially improve humans to produce appropriate EEG patterns while improving BCI performance. Incorporating training in these cognitive mechanisms could potentially lead to further improvements in the control of BCI-VR systems.

8.2.1 Pre-Processing and Feature extraction

In this study, we utilized CSP filtering and the variance of the logarithm of the average power of the EEG signal segments as features for the classification. However, alternative approaches exist that could potentially enhance our understanding and classification accuracy in motor imagery tasks. For instance, T. Shi et al. [175] proposed the calculation of autoregressive coefficients from EEG signals, which capture temporal dependencies and offer valuable insights for motor imagery classification. Furthermore, T. Shi et al. [175] introduced a novel EEG feature extraction algorithm incorporating CSP and adaptive autoregressive (AAR) techniques. Their work highlights the feasibility of utilizing band energy, sample entropy, and order accumulation as distinguishing characteristics for motor imagery classification. Another promising alternative, proposed by B. Xu et al. [176], involves a wavelet transform-based approach. By combining time-frequency features from specific EEG channels (C3, Cz, and C4), this method aims to extract informative features from motor imagery EEG signals.

Moreover, to tackle challenges such as suboptimal feature extraction and limited cross-subject performance in MI classification tasks, the adoption of a Multi-Scale Adaptive Transformer Network (MSATNet) [197] presents a promising solution. The MSATNet framework integrates innovative components designed to enhance feature extraction, capture temporal dependencies adaptively, and facilitate efficient transfer learning. MSATNet framework facilitates efficient transfer learning by leveraging the Subject Adapter module where the model can fine-tune target subject data while preserving the knowledge learned from source domains. This enables seamless adaptation to individual subject characteristics, thereby enhancing classification performance and generalization across diverse user populations. This study uses the BCI Competition IV 2a and 2b dataset in an offline analysis to evaluate the validity of the MSATNet model. The MSATNet has a similar accuracy of 81.75% to our RF accuracy of 82.4% in the BCI Competition IV 2a and outperforms our accuracy in the BCI Competition IV 2b with 89.34% accuracy. Therefore, this alternative methodology offers a promising avenue for improving the accuracy of BCI systems.

These alternative methodologies offer promising avenues for improving the accuracy of BCI systems. Further investigation and comparative analysis are needed to assess their effectiveness and potential contributions to MI classification tasks.

8.2.2 Classification

Liu et al. [177] in 2023 proposed an end-to-end Filter-Bank Multiscale Convolutional Neural Network (FBMSNet) for MI classification. A filter bank was first used to extract a multi-faceted spectral representation of the EEG data. A mixed depth convolution was then applied to extract temporal features at multiple scales, followed by spatial filtering to mitigate volume conductivity. Finally, with the joint supervision of cross-entropy and center loss, FBMSNet obtained features that maximize the dispersion between classes and compact interclass. They compared FBMSNet with several state-of-the-art EEG decoding methods on two MI datasets: the BCI Competition IV 2a dataset and the OpenBMI dataset, in offline analysis. FBMSNet showed the highest classification accuracy of 79.17%. Although FBMSNet had the highest performance it has not surpassed the accuracy of the RF algorithm in our study, which showed 82.4% in offline analysis.

In this research we have not used deep learning for the BCI-VR Goalkeeper MI classification, taking into account that our dataset was quite small comprised of only 42 subjects with 20 left-hand trials and 20 right-hand trials only. However, this is something that needs to be further investigated.

Recently, Explainable Artificial Intelligence (XAI) has gained significant attention, focusing on developing methods that can explain and interpret machine learning models [178]. In this context, our research group has proposed two different methodologies for rule extraction based on machine learning and argumentation theory [179] – [183]. The derived BCI-VR Random Forest classification models can be used to extract rules using the TE2rules algorithm [184] that converts a tree ensemble (TE) to a rule list (RL). Then, rule selection could be performed selecting the models with high training accuracy and a minimum sample of rules. Then, argumentation-based reasoning can be applied using Gorgias' theory [185], [186], which involves constructing arguments using a basic argument scheme, connecting a set of premises to the claim of the argument. The extracted rules can be modified as object-level arguments that can support contradictory claims, leading to arguments attacking one another. Moreover, the use of priority on object-level arguments can express a local preference between arguments and establish relative strength, tightening the attack relation between them. It is expected that the rules will demonstrate the CSP EEG channel segments contributing to the discrimination between left-hand versus right-hand motor imagery. This explainability rule set concept might be used as feedback to the user to generate more discriminatory patterns.

Furthermore, in conventional BCI classification, the models are trained and evaluated on data from the same subject. Deep Neural Networks, while powerful, often entail a large number of trainable parameters compared to classical models. Such complexity demands substantial amounts of data and time for training. Although various publicly available BCI datasets exist [202], [203], individual subject data remains limited in quantity. Furthermore, extensive data collection for a new subject is time-consuming and may induce mental fatigue during prolonged recording sessions, potentially compromising data quality. To overcome the scarcity of subject-specific data, transfer-based approaches utilizing pre-existing data from other subjects have been explored as conducted by Zhang et al. [198]. In this study [198], 54 participants performed binary class MI task and the average classification accuracy for subject-specific was 63.54%, and for the subject-independent was 84.19%. These strategies are crucial for advancing the efficacy and applicability of BCI systems in diverse user populations.

8.2.3 Virtual Reality

In this study, we chose not to use embodiment techniques at all because it is a very demanding process to convince a person that a foreign virtual body is their own body, especially without the use of special haptic equipment. However, it is a process that, if performed with utmost care, may improve the performance of the participants since there will be an increase in motivation and engagement. Vourvopoulos et al. [98] developed a BCI-VR system that provided auditory, haptic, and visual feedback in the VR experience, integrated with a MI-BCI training task for left-hand or right-hand MI to achieve more distinct activations in the motor cortex areas and enhance realism. They integrated a holistic BCI approach combining MI, immersive VR environments, and sensory stimulation. During the experimental training, the virtual hands were controlled using only the MI-BCI paradigm in the system. Healthy users were asked to perform a rowing motion in a boat with virtual hands using MI. Results showed that the average accuracy of the LDA algorithm of the 13 healthy participants was 70.7% in real time.

Nevertheless, we believe that haptic technologies, more realistic graphics, and generally more realistic experiences can help increase the performance of BCI systems. Similarly, Škola et al. [166] developed a gamified immersive VR MI-BCI system. The aim of the proposed system was to increase engagement, attention, and motivation in co-adaptive event-driven MI-BCI training. This was achieved using gamification, progressive increase of the training pace, and VR design reinforcing body ownership transfer (embodiment) into the avatar. After repeated training, the average accuracy in real time was 72.8%.

It should be noted that the results of both Vourvopoulos et al. [98] and Škola et al. [166] are very close to the average accuracy of our experiments of 71.6% derived with the RF classification algorithm.

8.2.4 Cognitive tasks

Our investigation into the relationship between cognitive abilities, as assessed by tasks such as the Flanker Task and the Spatial Cueing Task, and performance in the BCI-VR Goalkeeper task has provided valuable insights into the potential impact of executive functions and attentional processes on BCI accuracy. The observed significant correlations between performance in these cognitive tasks and offline classification accuracy in the BCI-VR Goalkeeper task suggest that individual differences in cognitive skills may influence one's ability to control virtual avatars through MI.

To further explore this relationship, future research could consider conducting longitudinal studies to evaluate whether participants who undergo cognitive skills training demonstrate subsequent improvements in BCI accuracy. By implementing targeted interventions aimed at enhancing executive functions, inhibitory control, and attentional processes, researchers can investigate whether enhancements in these cognitive domains translate into improved performance in BCI tasks. Moreover, exploring the neural mechanisms underlying such improvements, such as through EEG analysis, can provide valuable insights into the neural plasticity associated with cognitive skill acquisition and its impact on BCI performance.

Furthermore, future studies could investigate the influence of variables such as occupational status, hobbies, and educational background on BCI performance accuracy. Understanding how individual characteristics shape the cognitive mechanisms underlying BCI control can inform the development of personalized BCI training protocols tailored to individual needs.

In addition, professionals such as goalkeepers, formula drivers, etc. can investigat e similar strategies that might improve their cognitive abilities related to their professional orientation.

In conclusion, future research endeavors should aim to elucidate the causal relationship between cognitive skills and BCI accuracy through longitudinal interventions and training. By unraveling the intricate interplay between cognition and BCI performance, we can pave the way for more effective and personalized BCI interventions, ultimately advancing the field of BCI towards its full potential.

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