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PHD THESIS
SUMMARY

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PHD THESIS

TITLE (english): **RESEARCH ON THE USE OF BRAIN-COMPUTER INTERFACES IN EXTENDING THE FUNCTIONALITY OF BIO-MECHATRONIC SYSTEMS**

Doctoral domain: Mechanical Engineering

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LIST OF ABBREVIATIONS

ANNs = Artificial Neural Networks

BCI = Brain-Computer Interface = Interfața Creier-Computer

BMI = Brain-Machine Interface = Interfața Creier-Mașină

LIS = Locked-In Syndrome

SSVEPs = Steady-State Visual Evoked Potentials = Potențiale Evocate de Stare Staționară / Regim Permanent

EEG = Electroencephalography = Electroencefalografie

MEG = Magnetoencephalography = Magnetoencefalografie

ECoG = Electrocorticography = Electrocorticografia

fNIRS = Functional Near-Infrared Spectroscopy = Spectroscopie în Infraroșu Apropiat

fMRI = Functional Magnetic Resonance Imaging = Imagistică prin Rezonanță Magnetică Funcțională

PET = Positron Emission Tomography = Tomografie cu Emisie de Pozitron

SPECT = Single Photon Emission Computed Tomography

SCP = Slow Cortical Potentials = Potențiale Corticale Lente

MI = Motor Imagery = Imaginare Motorie

ERD = Event-Related Desynchronization

ERS = Event-Related Synchronization

SMRs = Sensorimotor rhythms

ERPs = Event Related Potentials

SVM = Supported Vector Machines

LDA = Linear Discriminant Analysis

CHAPTER 1

INTRODUCTION

The brain-computer interface (official term BCI = Brain-Computer Interface) is a multidisciplinary research field providing applications for medical engineering by extending the functionality of bio-mechatronic systems aimed at the assistance of people with neuromotor disabilities. By leveraging theoretical and experimental knowledge from various fields (neuroscience, psychology, signal processing, machine learning, artificial intelligence, computer science, mechatronics, electronic engineering, virtual reality), the brain-computer interface proves its potential for developing both non-clinical applications for the entertainment areas such as digital video games, marketing/advertising, meditation, and cognitive skill enhancement, and especially medical applications designed to support people who have suffered a stroke, spinal cord injuries, or have been diagnosed with amyotrophic lateral sclerosis, Locked-In syndrome (Lou Gehrig's disease), tetraplegia, or paralysis, which prevent them from moving their upper and lower limbs using normal control methods such as muscles and peripheral nerves. These subjects, who require permanent assistance from a caregiver, constitute the ideal beneficiaries of brain-computer interface technology, as it is the only solution able to provide them with independence and autonomy in performing all daily activities.

BCI systems are based on hardware and software innovations developed alongside the evolution of information technology, through the design of compact, mobile, portable devices and discoveries in computer science, the performance determined by processing large volumes of data, increased computing speed, and the implementation of complex artificial intelligence algorithms, compatible with real-time execution to classify cognitive tasks associated with the mental intentions of persons with neuromotor disabilities. Consequently, the brain-computer interface can translate thoughts into actions on bio-mechatronic assistive devices such as a robotic arm, a multifunctional mobile robot, a robotic hand, an exoskeleton, an augmentative communication system, or a virtual simulation application. Thoughts or mental intentions underlying the generated actions or commands, transmitted by subjects, can be interpreted or analysed to a certain extent at well-defined time intervals or continuously, by applying processing techniques, extracting specific features, and classifying the neuronal signals acquired from the brain. Thus, the researchers used both invasive methods (electrodes implanted inside or outside the cerebral cortex - electrocorticography) and non-invasive clinical techniques (electroencephalography, magnetoencephalography, near-infrared spectroscopy, functional magnetic resonance imaging, positron emission tomography) for the detection of neuronal biopotentials. The electroencephalography is characterized by high temporal resolution, portability, non-invasive character, and simple working principle, by highlighting the development of commercial versions of headsets and kits for acquiring electroencephalographic signals. The current popular and portable EEG headsets (NeuroSky Mindwave, Emotiv Insight, Emotiv Epoc, Muse, GTEC Unicorn) are cost-effective, attractive, and efficient for achieving simple or advanced brain-computer interface applications.

The first investigations at the human brain level using the electroencephalography technique were accomplished by the researcher Hans Berger in 1929. The first brain-computer interface systems, tested on monkeys, were developed in the 1969-1970s. The brain-computer interface experiments on human subjects were conducted in the early 1990s, and the BCI definition was established by the researcher Wolpaw in 2000. Although BCI systems have seen upward evolution over the past two decades, there are still numerous significant challenges facing researchers, so a reliable, portable, efficient, attractive system capable of functioning in real-time and adapting to a wide range of BCI users has not yet been achieved. Challenges to be overcome by multidisciplinary research include the high degree of difficulty regarding the ability to perform cognitive tasks (e.g., focusing attention on light stimuli, imagining the movement of lower or upper limbs, mentally reproducing words, sounds, or actions projected to three-dimensional objects), variability of brain physiology and anatomical structures specific to each person, discontinuity of random signals detected by electroencephalography, selection of optimal signal processing and classification methods (e.g., algorithms based on artificial neural networks, linear discriminant analysis - LDA, wavelet transform analysis or machine learning using SVM), the requirements addressed to computing systems regarding high hardware and software performance, increased speeds, and large memory capacity for real-time processing and storage of extensive data volumes, along with the versatility of commands and the complexity of the controlled mechatronic systems.

Considering the aforementioned challenges, according to the scientific literature, remarkable results regarding the successful development, experimentation, and optimization of a brain-computer interface by people with neuromotor disabilities could only be achieved within multidisciplinary research university institutes, where there are controlled environmental conditions, massive and expensive equipment, the possibility of performing invasive techniques for acquiring brain signals, as well as the availability of multifunctional systems that can be controlled. Therefore, it is currently observed that brain-computer interface systems are not widely commercialized and do not offer a sufficiently high degree of reliability, they do not present a generalized character, are not portable, do not provide a compact design, and have not proved optimal precision or accuracy alongside a rapid response time in detecting and interpreting mental intentions. Therefore, referring to the scientific activity of novice researchers or those with limited experience in the BCI field, or considering the situation of doctoral or master's students, there is a noticeable and justified preference for developing, testing, and optimizing experimental prototypes of brain-computer interfaces for controlling mechatronic devices using portable electroencephalographic signal acquisition headsets and multifunctional platforms with microcontrollers such as Arduino and Raspberry Pi. Thus, the endeavours related to creating simple and efficient brain-computer interface devices, extending the fields of applicability, are accepted and encouraged. Portable technology for non-invasive electroencephalographic signal acquisition, compact biomechatronic devices that can be controlled, and the energy, passion, and intrinsic motivation shown by novice researchers regarding brain-computer interfaces stimulate the development of simple, low-cost, professional-looking devices that allow mental training, demonstration of BCI functionality principles, and experimentation with BCI systems, gradually leading to advanced evolution in the brain-computer interface field.

This doctoral thesis was based on the use of portable, compact, ergonomic, low-cost equipment, providing increased reliability, attractiveness, and high precision, with the final goal being the achievement of simple brain-computer interface systems intended for experimentation, testing, and use at the persons' home. Therefore, according to the proposed thesis title, brain-computer interfaces were used to extend the functionality of bio-mechatronic systems such as a mobile robot, a robotic arm, a robotic hand, a miniature motorcycle, or three-dimensional models, virtual simulations, a hologram control system, a virtual keyboard for writing and communication applications, or virtual systems for displaying graphical effects or text messages, respectively accessing Internet resources or addressing questions to the Chat GPT assistant. Moreover, concerning a highly original contribution, the doctoral thesis presents a LabVIEW software tool with complex and flexible functionalities intended for various brain-computer interface applications, through the acquisition of raw electroencephalographic signals from the integrated biosensor of the portable NeuroSky Mindwave headset, EEG data processing, selection and extraction of characteristic features, and statistical measurements calculation and classification, based on artificial intelligence, performed both offline and online (in real-time) of neuronal biopotential variations, ultimately resulting in the necessary commands for controlling bio-mechatronic systems.

Considering the need to use the portable NeuroSky headset, the simplest to recognize, quantify, and precise control signal is represented by voluntary eye blinking, which was used to define different commands in a brain-computer interface system intended for people with neuromotor disabilities. Analysing the scientific literature in the field of brain-computer interfaces, it is observed that there are a limited number of EEG datasets including voluntary eye blinking of different types, used for determining control signals in a BCI system. Therefore, to accomplish to such a requirement, this doctoral thesis includes exhaustive EEG datasets generated by performing simple, double, or triple eye blinks for training and testing classification models based on artificial neural networks.

Overall, the current thesis proposes a variety of original software (programs implemented in LabVIEW, Matlab, Python, Arduino) and hardware (mechatronic systems controlled with NI myRIO, Arduino – various versions, Raspberry Pi, Micro:Bit) applications associated with simple, portable, attractive, efficient brain-computer interfaces, based on control signals determined by voluntary eye blinking or P300 evoked biopotentials, resulting in the simulation, experimentation, and testing of the functionality principle of such innovative, complex, and challenging technology aimed at people with neuromotor disabilities. The significant contributions of the doctoral thesis are represented by the general-purpose BCI application facilitating the acquisition, processing, extraction of characteristic features, and classification of raw EEG signals detected by the NeuroSky biosensor, numerous EEG datasets including voluntary eye blinking (simple, double, triple), and the variety of controlled applications by extending the functionality of experimental bio-mechatronic systems, real or virtual models (mobile robots, robotic arm, robotic hand, miniature motorcycle, hologram control system) and communication systems using the virtual keyboard, virtual display systems, or an Android application for transferring chat messages between laptop and smartphone.

BRIEF PRESENTATION OF THE THESIS CHAPTERS

Chapter 1 – Introduction – presents general aspects regarding brain-computer interfaces, the challenges faced by researchers in this field, possible developments, implementations, and solutions that can be realized at the doctoral study level, all of which also constitute the foundation for conducting experimental activities and designing original applications within this doctoral thesis.

Chapter 2 encompasses the Current State of Research in the Field of Brain-Computer Interface Systems. It presents aspects related to the analogy between the nervous system and the computer. Additionally, a subchapter is introduced containing a series of theoretical notions describing the concept of a brain-computer interface. Thereafter, conclusions are drawn that also generate the research directions focused on in the doctoral thesis.

Chapter 3 presents the motivation for addressing the research theme – Brain-Computer Interface in the doctoral thesis, stating the main and secondary objectives.

Chapter 4 includes the theoretical elements necessary for understanding, developing, experimenting, testing, and optimizing brain-computer interface systems. Consequently, it describes certain general notions regarding the evolution of brain-computer interfaces. The classification of BCI systems is also introduced. Thereafter, methods for acquiring and recording cerebral biopotentials used in a BCI system are presented. Additionally, the types of electroencephalographic signals necessary for BCI systems are shown.

Chapter 5 comprises the methodology of the experimental research conducted by the doctoral candidate and highlighted in this thesis, through the development, testing, and optimization of software and hardware applications to extend the functionality of bio-mechatronic systems using brain-computer interfaces. Therefore, Chapter 5 provides an overview of the operating principles and working methods designed and applied by the doctoral candidate in experimental activities, which involved subjects represented by third and fourth-year students. Additionally, the portable headsets (NeuroSky, Emotiv, GTEC) used by the doctoral candidate for acquiring neural signals, the hardware platforms (Raspberry Pi, Arduino, NI myRIO) necessary for controlling mechatronic systems, and the controlled devices (mobile robots) using a brain-computer interface are mentioned and describerd.

Chapter 6 presents the original contributions brought by the author of this doctoral thesis, highlighting the original software implementations, namely the programming sequences in multiple languages (Python, Arduino) or environments (LabVIEW, Matlab, NodeRED, MIT App Inventor), based on various algorithms for analysing electroencephalographic data detected by the integrated sensors of portable headsets. The algorithms refer to the operating principles underlying the software applications proposed by the doctoral candidate, whom she developed and experimented with students during the doctoral studies. Consequently, there resulted the commands determined by counting voluntary eye blinks or detecting P300 evoked biopotentials. The counting of eye blinks can be achieved through techniques based on classifying the raw EEG signal using artificial neural network models or determining the amplitude of a blink, or the Divide and Conquer method, or other modalities represented by transitions and selections or Fuzzy Logic techniques.

Moreover, the identified methods for the efficient integration between the software technologies associated with portable electroencephalography headsets and the developed applications, as well as the hardware platforms, are briefly highlighted and explained.

Chapter 7 describes the results obtained by volunteer subjects involved in experimenting with brain-computer interface applications to achieve the thesis's objectives related to the development, testing, and optimization of simple, portable, efficient, attractive, and useful BCI systems. These systems allowed: optimal integration between EEG headsets – hardware platforms – software environments; communication and Chat message transmission; Artificial Intelligence-based BCI research; control of robotic systems and cognitive training by generating commands for 3D models. Thus, the subjects used portable EEG headsets, performed mental tasks determined by focusing attention and looking at light flashes, and voluntary eye blinks to control robotic systems – real or virtual 3D prototypes (mobile robots, robotic hand, robotic arm, miniature motorcycle, RGB lighting in a mini smart home, wheelchair, scooter guided by a humanoid robot, juice vending machine), to communicate using a virtual keyboard, to send chat messages to an Android smartphone, to create and address questions to the Chat GPT assistant, to access Internet resources, to display holograms of Master Yoda, and to run graphical effects or move text messages on LED systems.

Chapter 8 comprises the final conclusions of the doctoral thesis and, at the same time, presents specific original contributions according to the initially established objectives. The results obtained through the research conducted during the doctoral studies are also stated, and the published scientific papers leveraging the experimental activities are mentioned.

At the end of the thesis, there is an exhaustive section for Bibliographic References and a detailed section for Appendices based on obtaining experimental data and implementing source code for various procedural programming languages (Python, Arduino, Matlab) and block diagrams for graphical/visual programming environments (LabVIEW and MIT App Inventor).

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CHAPTER 2

CURRENT STATE OF RESEARCH ON BRAIN-COMPUTER INTERFACE SYSTEMS

2.1. ASPECTS REGARDING THE ANALOGY BETWEEN THE NERVOUS SYSTEM AND THE COMPUTER

2.1.1. The Correlation between the Brain and a Computer Processor

The brain, a component of the nervous system, is the command and control center of the human body, determining the functioning of all vital, voluntary, and involuntary processes. The computer is an indispensable tool for managing, organizing, and coordinating activities in most professional fields.

Both the human brain and a computer processor, when functioning under normal parameters, fulfill fundamental roles in the integration, cohesion, and adaptation of other subsystems to the external environment.

Thus, the brain receives information from sensory organs (e.g., the sensation produced by a burn on the skin), processes the received data, and promptly sends the expected response, manifested through glands, muscles (immediate withdrawal of the affected limb), or peripheral nerves.

Similarly, the hardware and software structure of a computer includes devices dedicated to input data entry (e.g., mouse, keyboard, microphone, touch screen, trackpad, and scanner), software programs for decoding generated codes, and systems necessary for displaying output data (e.g., monitor, printer, video projector, LED indicating low battery level).

The brain, as the most representative component of the nervous system, monitors, integrates, regulates, and determines the actions performed by internal organs to fulfill, automatically and without conscious intervention from the human, the functions of the respiratory, cardiac, lymphatic, digestive, and excretory systems. The brain's superiority is revealed by its ability to coordinate and synchronize the activity of all cells, organs, and anatomical systems contributing to the physiology of the human body, ensuring adaptability to external conditions (heat, cold, dangers) provided by the living environment.

The processor, as the main component of a computer, manages and allocates memory resources based on the priority or complexity of processes executed independently of the user's will, i.e., in the absence of concrete intentions. Examples include the recurrent execution of an automatic data-saving process after waiting for a certain time interval or performing calculations or mathematical operations for resizing, scaling, or moving virtual three-dimensional objects. The computer processor integrates information received from peripheral components, allows parallel data processing, and elaborates commands adapted to the user's desires. For example, pressing the volume control key or selecting the corresponding virtual icon will result in decreasing or increasing the sound perceived by the user.

2.1.2. Brain-Computer Interaction

Regarding the similarity between the nervous system and the computer, science has noted that the electric signal is the medium that facilitates the reception of stimuli or data acquisition, as well as the processing and transfer of information in both involved components.

At the brain level, neuronal biopotentials are generated, which can be detected using headsets equipped with sensors and electrodes, advanced technology for amplifying and filtering low voltage levels, and compact high-performance processors. Thus, the raw signal obtained is amplified, filtered, measured, processed, graphically displayed, subjected to feature extraction processes, and the classification of specific patterns to associate them with certain thoughts, desires, or mental intentions manifested by the investigated person.

Therefore, there is an evident symbiosis between the physiology of the human brain and the functioning of a personal computer. Every clinically healthy person has certain cognitive abilities, managing to maintain focused attention, continuously learn, evolve, and adapt to new situations by generating creative ideas. The human brain's ability to develop intelligent processes is closely correlated with the hardware and software specifications characterizing a computer's performance.

Therefore, in a brain-computer interface, it is important for the human subject to acquire the mental skills necessary to generate individualized, consistent, or consistent (repeatable, recurrent), intelligible brainwave patterns so that the computer's software component (the necessary software programs for applying signal processing methods and artificial intelligence techniques [465], [499]) can efficiently decode or classify the received information in real-time (which implies high hardware performance). Mental tasks executed by a person include performing mathematical calculations or mental counting [256], imagining operations [502] (rotation, translation, resizing, movement) attributed to 3D geometric figures, mentally enunciating words, humming a song in the mind, focusing attention on a single idea, and intending to execute a movement (motor imagery [171], [3], [192], [246], [283], [310] of a limb – hand or foot). The decoding or classification tasks performed by the computer processor involve extracting characteristic features of brainwave patterns (which can be statistical or determined by mathematical algorithms such as the Wavelet transform [473]) and applying artificial intelligence techniques [278], [499] (using artificial neural networks [183], [257], [298], [10], [453], SVM algorithms [104], LR algorithms [279], [512]) to delineate categories of signals necessary for individualizing commands fulfilled by the brain-computer interface.

2.2. DESCRIPTION OF THE BRAIN-COMPUTER INTERFACE CONCEPT

2.2.1. Brain-Computer Interface – Definitions and Functions

A brain-computer interface (BCI) is a system that records the activity of the central nervous system (CNS) and translates it into artificial output signals to replace, restore, or enhance the natural output modalities of the CNS (Figure 2.2.1.1). A BCI system requires recording brain signals that originate from electrophysiological, neurochemical, and metabolic phenomena constantly manifested within the central nervous system. The most frequently used method for monitoring neural activity is electroencephalography (EEG). EEG signals can be recorded through non-invasive techniques with sensors located on the scalp [157], or invasive techniques with electrodes placed on the cortical surface or inside the brain.

BCI systems have vast areas of applicability, being useful for controlling motorized devices necessary for paralyzed individuals [251], expressing thoughts through speech synthesizers, enhancing recovery in stroke (CVA) patients, and improving the ability to concentrate attention.

Depending on their reliance on the normal output pathways/signals (neuromuscular) of the central nervous system, brain-computer interfaces can be dependent or independent. Dependent BCI systems utilize visually evoked potentials [136], involving the muscles that control eye movement. Independent BCI systems use sensorimotor rhythms, where muscular activity is not involved.

Hybrid brain-computer interface systems [168], [536] use two distinct types of brain signals (visual evoked potentials and sensorimotor rhythms), with the possibility of generating commands based on muscle activity as well.

BCI systems can be considered adaptive neurotechnologies [41], which act directly on the CNS, stimulating cortical or subcortical sensory areas [251], supporting individuals diagnosed with Parkinson's disease.

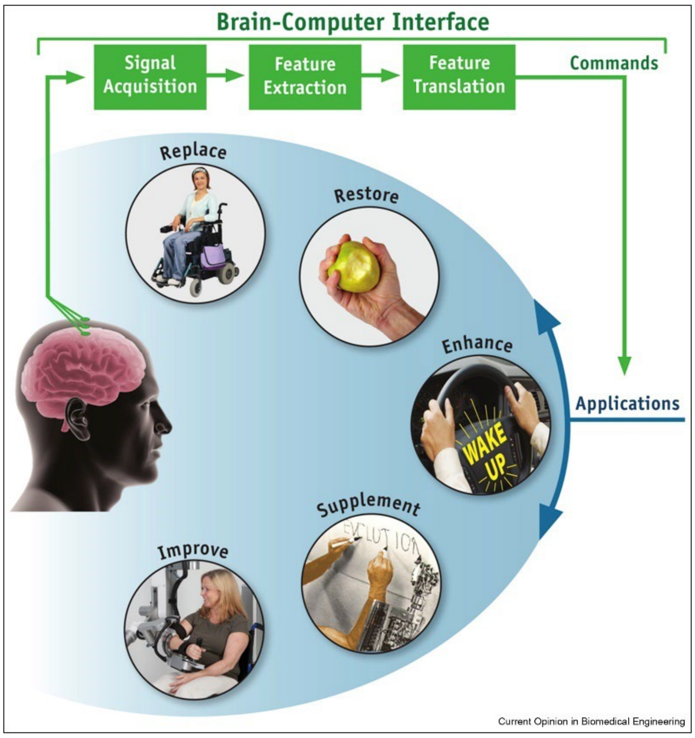


Figure 2.2.1.1. The 5 functions of a Brain-Computer Interface – Romanian Translation [251].

CONCLUSIONS

2.3.1. The Utility of a Generalized Brain-Computer Interface System

A generalized brain-computer interface (BCI) system is useful for conducting scientific research activities on medical rehabilitation and developing cost-accessible applications. A generalized BCI system will facilitate research and experimentation of various applications in the early stages of design and development. Unfortunately, the limited number of research centers specialized in the BCI field

[179], along with the technical and financial difficulties faced by scientists in countries lacking optimal intellectual and financial resources, can negatively influence, delay, or halt the development of BCI systems. The difficulties refer to the high costs of brain signal acquisition equipment, the absence of adequate facilities in experimental research laboratories, reduced collaboration between multidisciplinary groups, and lack of resources for intellectual training and the organization of practical and theoretical knowledge-sharing sessions. These issues can result in the discouragement of novice researchers and hinder the development of innovative brain-computer interfaces to assist individuals with neuromotor disabilities.

According to the specialized literature [441], [342], [98], the following brain-computer interface systems have been identified, which are based on generalized functionality and structure: BCI2000, OpenViBE, and EEGLAB. These BCI systems involve specific limitations: BCI2000 is no longer updated for the integration of recent portable EEG headsets (e.g., NeuroSky Mindwave Mobile), OpenViBE is more complex and less accessible to novice researchers without experience, and EEGLAB does not include machine learning methods for raw EEG data classification.

The fundamental elements necessary for developing a tool for BCI research are:

- Acquisition of EEG signals;
- Processing of EEG signals;
- Preparation of temporal sequences necessary for the EEG dataset;
- Generation of the EEG dataset for training and testing processes;
- Training of machine learning models resulting from the classification of EEG data;
- Testing the machine learning models obtained through the training process to measure classification accuracy and precision values;
- Deploying machine learning models in a real-time running BCI application.

2.3.2. The Necessity of EEG Datasets for Blink Recognition

Recording EEG datasets is necessary for recognizing brain patterns indicating multiple ocular blinks used as control signals in a brain-computer interface system. A simple and accessible application, tested with the help of a virtual tool proposed in this doctoral thesis, involves the classification of multiple ocular blinks to determine precise control signals. Voluntary ocular blinking generates a distinct pattern in the EEG signal, being simple to detect. By identifying this pattern and counting its occurrences, control commands can be generated for devices and assistive systems for people with disabilities: an electric wheelchair, a mobile robot [413], [411], a robotic hand [412], a robotic arm [531], household objects [32], various experimental prototypes [422], and communication systems [414], [397].

The specialized BCI scientific literature contains numerous studies investigating the use of voluntary ocular blinks in the development of brain-computer interfaces. Researchers have targeted various techniques, such as measuring the amplitude of ocular blinks necessary for setting a threshold value [341], [446], applying statistical calculations to implement an algorithm for counting voluntary ocular blinks [526], [513], [321], and developing experimental BCI prototypes [144], [474], classification of blinks based on artificial neural networks [347], [69], [159], [437], wavelet methods [273], [473], or support vector machines [8].

2.3.3. The BCI Field – Applicability, Performance, Novelty, Challenges, Opportunities

2.3.3.1. Conclusions on the Concept of Brain-Computer Interface

The initial impression focuses on transcending our cognitive abilities, achieving impressive results in this research field, partly anticipated by science fiction movies and partly as a precursor to the digital revolution and cutting-edge technology. The brain-computer interface stands out through the contrast between the simplicity of its operating principle and the complexity of the processes involving the acquisition of neuronal biopotentials, processing them to extract relevant features, classifying and translating them into control commands for biomechatronic devices: a motorized wheelchair, a robotic hand, a robotic arm [531], or a multifunctional mobile robot [187]. The main goal of the brain-computer interface (BCI) is to assist individuals with neuromotor disabilities in performing daily activities to regain their independence. This aim involves augmenting and extending the functionality of biomechatronic systems to provide optimal and safe conditions for performing tasks interacting with the surrounding environment, also ensuring a communication and locomotor control tool for individuals diagnosed with neurological conditions (such as ataxia, amyotrophic lateral sclerosis, locked-in syndrome, stroke, spinal cord injuries).

2.3.3.2. Conclusions on the Applicability of BCI Systems

The conduct and deepening of research on brain-computer interfaces are justified by the diversity of usage domains, including applications intended for clinically healthy individuals to obtain an alternative or supplementary communication and control channel and through the aspiration to explore a fascinating area, the power of thought, which piques our curiosity considering that the mysteries of the human brain have not yet been fully elucidated. There are also so-called brain-machine interface systems intended for automotive transport, mechatronic systems, and industrial robots. Other application branches of brain-computer interface systems include developing video games for computers, interactive applications to improve the level of concentration, and the depth of meditation, or monitoring parameters correlated with different psychological states: stress, relaxation, interest, delight, and engagement.

2.3.3.3. Conclusions on the Performance Factors of BCI Operation

The performance of these systems is influenced by a variety of factors, such as:

- Methods for acquiring neuronal biopotentials, invasive (implantation of a sensor matrix at the intracortical level and electrocorticography), which offer high spatial resolution, or non-invasive (electroencephalography, magnetoencephalography, functional magnetic resonance imaging, and near-infrared spectroscopy), which provide increased temporal resolution;
- Hardware and software techniques for signal filtering to reduce noise (e.g., from the electrical network or vibrations), eliminate artifacts (caused by unintentional gestures such as head movements or ocular blinking), and delimit useful components (patterns particularized by graphical representation amplification or diminution);

- Mathematical algorithms (involving certain statistical measures: mean, median, standard deviation, Kurtosis coefficient, and others) necessary for extracting relevant features for a cognitive task;
- Techniques based on artificial intelligence and machine learning algorithms for classifying acquired signals and extracted features;
- The reliable, compact mechanical structure, mobility, degrees of freedom, versatility, and optimal functioning of devices controlled through cognitive commands;
- Paradigms presented to users and tasks they need to perform: light stimuli of evoked potentials like P300, SSVEP, N200; motor imagery; sensorimotor rhythms to measure the level of attention.

2.3.3.4. Conclusions on the Novelty Degree of Brain-Computer Interface

The previously mentioned factors confer the novelty degree of brain-computer interface systems, thus highlighting the multidisciplinary nature of this research field, requiring knowledge and skills from various areas such as mechanical engineering, electronics, computer science, neurology, or psychology. Additionally, through the possibility of implementing non-clinical applications, the interaction between humans and computers is redefined, with the latter representing the data processing center in a mechatronic system used in assistance and rehabilitation programs. Therefore, there is a transition from standard/ordinary tools (keyboard, mouse, touch screen, gestures [225], [226], [227], voice) to devices based on the power of thoughts or mental command transmission, which currently represent both a novelty for most people, regardless of age, gender, religion, social status, or intellectual preparation, and a strong curiosity for specialists and enthusiasts of future technologies, video games, and other interactive applications based on artificial intelligence [438].

The novelty degree characteristic of brain-computer interfaces is also reflected by the fact that progress in this field has gained momentum with the development of machine learning techniques and the evolution of transistors and processors, according to Moore's Law. This observation is explained by the fact that such interfaces achieve optimal functionality and fully fulfill their role when they allow continuous acquisition of signals from the brain and permanent monitoring of users' cognitive states to identify real-time variations of neuronal potential, determining the instantaneous execution of a command by an assistive mechatronic device. Therefore, in the mentioned processes, an enormous amount of information is handled, an extensive volume of data is processed, requiring an exorbitant computing power provided by a very high-performance computer.

2.3.3.5. Conclusions on the Current Challenges of Brain-Computer Interface

Currently, the field of brain-computer interfaces faces numerous challenges: costly, robust, and powerful computing systems are required, offering a high information transfer rate and allowing rapid data processing. Research laboratories are the primary locations where high-accuracy EEG signal acquisition systems are available in a favorable environment for technical configurations and experimentation to avoid incidents during user familiarization and training with BCI technology.

Furthermore, within specialized laboratories, high-performance software programs based on advanced artificial intelligence techniques are available, so various scenarios are created for system testing and user training, but all these come at costs exceeding an individual's financial power. Due to the bulky equipment, high effort, and long training intervals, users experience psychological discomfort, impatience, and frustration. This results in the variability of brain connections, constantly evolving based on each person's experiences and cognitive abilities determining the success rate in performing mental tasks: motor imagery of limb movement, performing mathematical calculations or reciting poems in mind, focusing on a single aspect, or the ability to clear the mind of any thoughts.

An alternative to these inconveniences is the use of tasks correlated with evoked potentials, which individualize through a specific pattern in the EEG signal. However, costly, versatile software programs based on advanced artificial intelligence techniques are needed to ensure the processing of acquired signals, identification of characteristic features, and classification to delimit the moment when the user intentionally transmitted a command.

2.3.3.6. Conclusions on the Perspectives of Brain-Computer Interfaces

Considering the aforementioned disadvantages, it is necessary to design, create, and develop a brain-computer interface prototype that allows users to test and conduct experiments at their own home or in another familiar environment where research laboratory conditions are not ensured. Such a future perspective is explored in this doctoral thesis, considering the following criteria for implementing a viable solution:

- Simple and quick acquisition of EEG signals using portable headset sets;
- Elimination of inherent EEG signal artifacts with filters built into portable headsets;
- Comfort during use and simplicity of initial setup/installation, ergonomic design;
- Avoidance of additional chemical solutions to improve accuracy values;
- Control of assistive mechatronic devices (robotic arm [531], robotic hand, mobile robot [187]) with development platforms such as Arduino, Raspberry Pi, NI myRIO, Micro;
- High performance at an affordable price, allowing use at home;
- Possibility of developing various applications in the field of mechatronics/medical engineering;
- Availability on the Internet of numerous simple programs ensuring basic functionalities;
- Implementation of software programs in different programming languages (C, Python, or Javascript) or development environments (LabVIEW or Node-RED) to ensure communication between the previously mentioned hardware components;
- LabVIEW offers various kits of predefined functions, being an intuitive and attractive development environment, considering it is based on graphical programming methods specific to the G language;
- LabVIEW [451] facilitates simple and rapid design of user graphical interfaces, having a friendly and attractive appearance;
- LabVIEW facilitates the acquisition, processing, and classification of EEG signals [472];
- Node-RED is an online programming environment that offers numerous packages of predefined functions and allows coding in Javascript for applications in the Internet of Things domain, specifically home automation;
- Python is a very popular programming language necessary for implementing applications covering various usage domains;
- C is a fundamental programming language required for implementing applications developed with the Arduino platform.

CHAPTER 3

MOTIVATION FOR ADDRESSING THE TOPIC AND OBJECTIVES OF THE THESIS

3.1. MOTIVATION FOR ADDRESSING THE TOPIC AND OBJECTIVES OF THE THESIS

The brain-computer interface (BCI) is a challenging and attractive research field, considered captivating due to the diversity and utility of its applications, as well as complex due to the inter/multidisciplinarity of the involved sub-domains. The brain-computer interface allows the control of external assistive or communication devices by translating mental intentions into commands fulfilled by mobile robots, neuroprostheses, or the movement of wheelchairs. Therefore, due to advanced techniques for processing and classifying neuronal signals, commands are generated for controlling external systems (bionic arm, exoskeleton, multimedia platforms) necessary for achieving independence for people with neuromotor disabilities.

Regarding the motivation for addressing such a scientific topic within the doctoral studies, the author of this thesis has demonstrated passion, exceptional interest, active involvement, deep dedication, compatibility, and enthusiasm since her undergraduate studies in Medical Engineering and later during her Master's studies in Mechatronic Systems for Industry and Medicine. Since 2014, the doctoral candidate has conceived, developed, implemented, and realized a variety of brain-computer interface applications, ranging from simple to complex, based on simulations in the LabVIEW graphical programming environment, control of virtual 3D models (the video demonstration is available on YouTube [354]), and command of mobile robots using the portable electroencephalography set NeuroSky Mindwave Mobile. Consequently, the projects, works, and presentations created between 2014 – 2017 were recognized through awards at various scientific events: communication sessions, student achievement contests, and national conferences. The intrinsic motivation, inner attraction towards science fiction innovations in advanced technology, genuine passion for brain-computer interfaces, and successful results achieved with implemented BCI applications formed the solid foundation and premises for deciding on the main topic – Brain-Computer Interface – around which the doctoral activities were focused from 2017 to 2024.

In the past two decades, numerous research teams, internationally renowned for their elaborated scientific activity, have invested considerable time and intellectual effort to achieve high performance in the brain-computer interface field, enabling the valorization of promising results obtained in laboratories equipped with state-of-the-art, massive, and costly equipment based on various medical investigation techniques (nuclear magnetic resonance, near-infrared spectroscopy, electroencephalography, electrooculography, electrocorticography, and others) to conduct experiments under optimal conditions.

Although there has been rapid experimental progress and overwhelming evolution, currently, there is no optimal solution or portable/mobile brain-computer interface system that allows efficient use at the home of a person with neuromotor disabilities, enabling them to regain independence, interact with the external environment as a person with intact physical capacities, and communicate naturally with those who can offer support, understand their desires, concerns, or other needs.

Therefore, gradually, numerous researchers from multidisciplinary scientific fields (computer science, mechatronics, medical engineering, artificial intelligence, signal acquisition and processing, neuroscience, psychology) have contributed to developing a portable brain-computer interface system compatible with home use for those diagnosed with neuromotor disorders (Locked-In syndrome, amyotrophic lateral sclerosis, and tetraplegia) or who have suffered a stroke or severe spinal cord injuries, thus facing tetraplegia or various forms of paralysis.

Considering the aforementioned aspects, it is evident that the field of brain-computer interface systems is still insufficiently explored. Its ascent is also influenced by the performance achieved in related technical-scientific areas, which allowed, for example, the development of portable microcontroller platforms (Arduino and Raspberry Pi) or FPGA technology (NI myRIO) or portable EEG signal acquisition sets (NeuroSky, Muse, Emotiv, GTEC Unicorn, and others). Thus, it is highlighted that electroencephalography is the only medical investigation technique that allows simple and rapid monitoring of neuronal biopotentials at the home of a person with disabilities.

Therefore, not only are solid discoveries needed both theoretically/analytically and experimentally, but more than that, initial contributions are welcome through the identification and implementation of integration solutions for the aforementioned hardware subsystems with various software development environments or programming languages (LabVIEW, Matlab, Python, and others) and later through experimenting, testing, and optimizing these systems. From the perspective of the applicability domain of brain-computer interface systems, the possibility of deepening research is evident, both from the necessity of designing versatile devices with a robust, reliable, and compact mechanical structure and from the utility of creating experimental models such as a robotic arm, robotic hand, or mobile robot, which appropriately meet the requirements of people in need.

The previously mentioned aspects also reflect the direction of theoretical and experimental research within this doctoral thesis, which aims as its primary objective: designing, creating, and implementing a portable brain-computer interface system to extend the functionality of bio-mechatronic systems.

To achieve the primary objective, the following specific objectives have been established:

1. Designing, creating, and implementing efficient interfacing solutions between hardware platforms (NI myRIO, Arduino, Raspberry Pi, Micro), software development environments (LabVIEW, Matlab, Arduino, Python, NodeRED), and portable sets (NeuroSky, Emotiv Insight, GTEC Unicorn) for EEG signal acquisition;
2. Designing, creating, and implementing software tools for the acquisition, processing, and classification of EEG signals, both online (in real-time) and offline, using techniques based on artificial neural networks and Fuzzy Logic methods;
3. Designing, creating, and implementing software tools for writing and communication applications, enabling text writing from a virtual keyboard, virtual LED display systems,

chat message transfer to an Android application or the ChatGPT platform based on generative artificial intelligence, and internet information search, using control signals determined by voluntary ocular blinks or visual evoked potentials of type P300;

4. Designing, creating, and implementing efficient control solutions for experimental devices such as a robotic hand, robotic arm, and mobile robot;
5. Designing, creating, and implementing software tools to demonstrate the brain-computer interface's operating principle and creating simulation applications or training environments for controlling virtual models, such as a robotic arm, robotic hand, and humanoid-like mini-robots.

3.2. GENERAL PERSPECTIVE ON DEVELOPED APPLICATIONS

Chapter 7 focuses on experimental research and briefly presents the results obtained from testing the brain-computer interface applications developed to achieve the previously mentioned specific objectives. These applications involved creating integrated components (hardware and software), with the research methodology described in Chapter 5, and the doctoral candidate's implementations represented by original programming algorithms and sequences presented in Chapter 6, considering the following aspects: the proposed goal, hardware and software components, operating principle, usage mode, degree of novelty, previously considered possibilities, and highlighting the optimal solution for supporting people with disabilities.

On the one hand, the applications developed within this doctoral thesis provided the necessary environment to demonstrate the operating principle of a brain-computer interface system and to experiment with its use at the personal home of such a portable device.

On the other hand, the applications developed within this doctoral thesis ensured the conditions for conducting research activities, which involved studying the achievements in this field up to the present, identifying challenges that need to be overcome, stating hypotheses, confirming or rejecting them, developing and optimizing tools necessary for experiments, analyzing and interpreting the obtained results, and formulating conclusions.

Achieving the first specific objective, previously stated, encompasses the following integrated (software and hardware) brain-computer interface applications developed within the doctoral thesis:

1. BCI application based on integration in LabVIEW between NeuroSky and NI myRIO;
2. BCI application based on integration in Matlab between NeuroSky and Arduino Nano 33 IoT;
3. BCI application based on integration in Python between NeuroSky and Raspberry Pi;
4. BCI application based on integration in NodeRED between Emotiv and Micro;
5. BCI application based on integration in Python between Emotiv and Arduino;
6. BCI application based on integration in LabVIEW between Unicorn and Arduino.

Achieving the second specific objective, previously stated, encompasses the following integrated (software and hardware) brain-computer interface applications developed within the doctoral thesis:

1. LabVIEW application for monitoring and analyzing EEG data from NeuroSky;
2. Python application for monitoring and analyzing EEG data from NeuroSky;
3. BCI LabVIEW application based on Fuzzy Logic.

Achieving the third specific objective, previously stated, encompasses the following integrated (software and hardware) brain-computer interface applications developed within the doctoral thesis:

1. BCI application for controlling a virtual keyboard;
2. BCI applications for chat message transfer to an Android smartphone;
3. BCI applications for displaying text messages on LED systems;
4. BCI application for communication with ChatGPT using P300 Speller;
5. BCI application for accessing internet resources using P300 Speller.

Achieving the fourth specific objective, previously stated, encompasses the following integrated (software and hardware) brain-computer interface applications developed within the thesis:

1. BCI application for controlling a robotic hand using NeuroSky and Arduino;
2. BCI application for controlling a robotic arm using NeuroSky;
3. BCI application for controlling a mobile robot using NeuroSky and Arduino;
4. BCI application for controlling a mechatronic system using P300 Speller.

Achieving the fifth specific objective, previously stated, encompasses the following integrated (software and hardware) brain-computer interface applications developed within the thesis:

1. BCI application for controlling a 3D robotic hand using NeuroSky;
2. BCI application for controlling Yoda holograms using NeuroSky;
3. BCI application for controlling a 3D robotic arm using P300 Speller;
4. BCI application for controlling a 3D wheelchair using P300 Speller;
5. BCI application for controlling a 3D scooter using P300 Speller;
6. BCI application for simulating a Juice Vending Machine using P300 Speller.

CHAPTER 4

THEORETICAL CONSIDERATIONS REGARDING BRAIN-COMPUTER INTERFACE SYSTEMS

4.4. TYPES OF ELECTROENCEPHALOGRAPHIC SIGNALS USED IN BRAIN-COMPUTER INTERFACES

Brain-computer interface (BCI) systems rely on control signals originating from the brain. Some of these types of signals have features that can be easily recognized and extracted. However, other EEG rhythms, which have more challenging-to-identify characteristics, require additional preprocessing techniques. The control signals intended for a BCI system are classified into three categories: evoked signals, spontaneous signals, and hybrid signals (Figure 4.4.1).

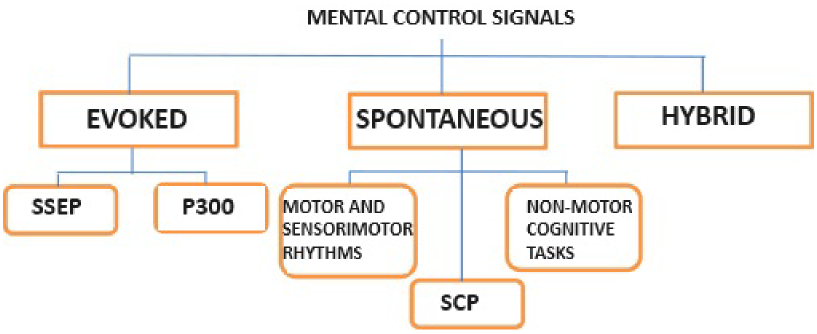


Figure 4.4.1. Classification of Cognitive Control Signals Used in a Brain-Computer Interface. Translation - [331].

Evoked Signals in Brain-Computer Interfaces

Evoked signals, also known as Visual Evoked Potentials (VEP), are generated unconsciously when the subject receives external stimuli. The most well-known types of evoked signals are Steady State Evoked Potentials (SSEP) and P300. Evoked signals are triggered by external stimuli, which can sometimes cause the subject to feel exhaustion, irritability, and high psychological demand.

SSEP Signals:

SSEP signals are generated when users of a brain-computer interface perceive a periodic stimulus [331], which can be caused by the flickering display of an image, a frequency-modulated sound, or a specific vibration. In the brain, a specific response manifests when the subject detects a certain change or variation, characterized by a particular frequency. The level of cortical signals will amplify in accordance with the stimulus frequency.

Depending on the brain region reacting to the stimulus perceived by the user, the following types of evoked potentials are distinguished: visual, somatosensory, and auditory. Steady-State Visual Evoked Potentials (SSVEPs), generated in the visual cortex, are the most common control methods in

BCI applications. The SSVEP rhythm (Figure 4.4.2) triggered is characterized by frequency values (between 6–30 Hz) similar to the flickering effect frequency of the displayed image.

Transfer Frequencies of SSVEP Signals:

The transfer frequency of SSVEP signals can vary:

- Low, with values around 30 bits/minute in t-VEP (time-modulated visual evoked potentials).
- Moderate, with values between 30–60 bits/minute in f-VEP (frequency-modulated visual evoked potentials).
- High, exceeding 100 bits/minute in c-VEP (pseudo-random code-modulated visual evoked potentials).

Before experimenting with BCI systems based on SSVEP, users participate in a low-difficulty mental training session to familiarize themselves with the control method. SSVEP-specific applications rely on selecting a single option from multiple virtual buttons associated with various commands. Each button or option is illuminated at a specific frequency (e.g., 7 Hz, 10 Hz, 14 Hz, 21 Hz), and the user focuses on the desired response area, causing the corresponding oscillation to be generated in their visual cortex [100]. SSVEP potentials enable multiple control options within a BCI system and can be used in applications involving numerous degrees of freedom.

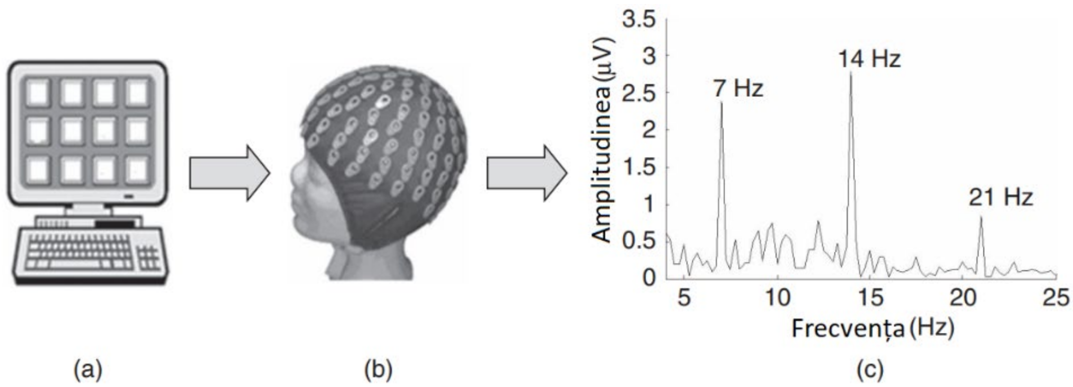


Figure 4.4.2. SSVEP Potential Based on Frequency Encoding: (a) Visual stimulation involves target elements with different flickering frequencies; (b) The Subject focuses on the flickering target item; (c) The SSVEP potential, triggered by stimulation at 7 Hz, shows characteristic frequency components with peaks determined by values of fundamental and harmonic frequencies obtained from the electrode placed at position O2 [496].

P300 Evoked Potential in Brain-Computer Interfaces

The P300 evoked potential is generated in the parietal cortical region approximately 300 milliseconds after the subject is exposed to an infrequent task within the "oddball" paradigm, often represented as a virtual keyboard [331], [100]. The P300 response is activated by the subject's focused attention [100] on a specific stimulus (the target letter) within the entire set of stimuli (the character set). When this stimulus (considered "rare") becomes relevant to the subject, the P300 evoked potential is triggered (Figure 4.4.3).

The most commonly used paradigm for generating the P300 evoked response [100] in a brain-computer interface system is the spelling matrix designed by Farwell and Donchin in 1988. This matrix contains the letters of the alphabet, and the subject must focus attention on a specific letter. The P300 response is generated when the row and column corresponding to the target letter are repeatedly illuminated.

BCI systems based on P300 evoked signals do not require an intense mental training program, except for the initial calibration session of the P300 response characteristic to each user, which is generated when they focus on an irregularly flashing light stimulus. However, the BCI control method based on triggering P300 evoked potentials involves repetitive stimuli, which can lead to fatigue or decreased interest from the subject. Numerous research groups have investigated and experimented with optimal solutions for stimulus presentation, achieving superior accuracy values for a P300-based BCI system. Research in this field is directed towards obtaining the P300 response recognition with as few light flashes as possible, in a brief time frame.

CHAPTER 5

RESEARCH METHODOLOGY

5.1. OVERVIEW – THEORETICAL AND EXPERIMENTAL RESEARCH

The author of this doctoral thesis conducted theoretical research by evaluating the current state of achievements, developments, and the evolution of brain-computer interfaces (BCI). This culminated in the implementation of original algorithms and new methods for analyzing EEG signals and specialized control techniques using voluntary ocular blinks or P300 evoked potentials. Additionally, the doctoral candidate carried out experimental research by designing innovative BCI applications, which were subsequently optimized and tested by subjects through tasks aimed at evaluating performance in use.

The development of these BCI applications required the complete integration of functionalities through programming sequences (LabVIEW, Python, Matlab, NodeRED) to facilitate the full stages of acquiring and processing signals from EEG sensor kits and generating commands on development platforms (Arduino, NI myRIO, Raspberry Pi, Micro) to control systems (mechatronic prototypes, virtual simulations, 3D models) conceived during the doctoral period from 2017 to 2024.

According to the table in Figure 5.1.1, the author of this doctoral thesis designed, developed, implemented, tested, and optimized 25 BCI applications for controlling various systems (experimental devices, 3D virtual models, interactive multimedia simulations) using different hardware development platforms with microcontrollers or FPGA technology, software platforms for programming integral functionalities, and EEG headset kits (NeuroSky, Emotiv, GTEC Unicorn).

Nr.	Controlled Brain-Computer Interface System	Control Technique by Brain-Computer Interface	Hardware Platform	Software Platform	EEG Headset	Paper - Conference/Journal	Publication	Author Type
1	Mobile Robot	Voluntary Eye-Blinks - Counting	NI myRIO	LabVIEW	NeuroSky - 1 Sensor	CEMD China, 2017 ACME Iași, 2018	BDI - ASME Press Web of Science	Co-Author First-Author
2	Virtual Keyboard	Voluntary Eye-Blinks - Divide et Impera	Arduino Uno	LabVIEW - Arduino	NeuroSky - 1 Sensor	PRASIC Brașov, 2018	BDI - IOP Science	First-Author
3	3D Robotic Arm	Evoked Biopotentials P300 EEG Rhythms - Delta, Theta, Alpha, Beta, Gamma	It is not necessary.	LabVIEW	GTEC Unicorn - 8 Senzori	PRASIC Brașov, 2018 ICNBME Chișinău, 2023 *Hackathon GTEC BR41N.IO April 2023*	BDI - IOP Science BDI - Springer	First-Author Single-Author
4	Robotic Hand	Voluntary Eye-Blinks - Switch & Select	Arduino Uno	LabVIEW - Arduino	NeuroSky - 1 Sensor	EHB Iași, 2019	Web of Science	First-Author
5	Robotic Hand - 3D Model	Voluntary Eye-Blinks - Switch & Select	It is not necessary.	LabVIEW	NeuroSky - 1 Sensor	EHB Iași, 2019	Web of Science	First-Author
6	Mobile Robot	Voluntary Eye-Blinks - Switch & Select	Arduino Uno	LabVIEW - Arduino	NeuroSky - 1 Sensor	ACME Iași, 2020	BDI - IOP Science	First-Author
7	Chat - Messages Transfer	Voluntary Eye-Blinks - Switch & Select	Android Smartphone	LabVIEW - MIT App Inventor	NeuroSky - 1 Sensor	EHB Iași, 2020	Web of Science	First-Author
8	Miniature Motorcycle	Voluntary Eye-Blinks - Counting	Arduino Uno 33 IoT	Matlab	NeuroSky - 1 Sensor	ICISIL Brașov, 2020	SCIENDO	First-Author
9	EEG Data Monitoring	EEG Raw Signal - Acquisition, Processing, Classification Artificial Neural Networks	It is not necessary.	LabVIEW	NeuroSky - 1 Sensor	Jurnal IJOE, AUSTRIA, 2023 Preprint - 2 Versiuni	Web of Science FI = 1.3	Single-Author
10	Robotic Arm	Voluntary Eye-Blinks - Switch & Select	NI myRIO	LabVIEW	NeuroSky - 1 Sensor	EHB Iași, 2021	Web of Science	Single-Author
11	Mobile Robot	Voluntary Eye-Blinks - Fuzzy Logic	Arduino Uno	LabVIEW	NeuroSky - 1 Sensor	INTER-ENG Târgu Mureș, 2021	Web of Science	Single-Author
12	EEG Data Monitoring	EEG Raw Signal - Acquisition, Processing, Classification Artificial Neural Networks	It is not necessary.	Python	NeuroSky - 1 Sensor	ICNBME Chișinău, 2021	BDI - Springer	Single-Author
13	Mobile Robot	Voluntary Eye-Blinks - Optimized Algorithm Analysis of Raw EEG Signal	Raspberry Pi	Python	NeuroSky - 1 Sensor	ICNBME Chișinău, 2021	BDI - Springer	Single-Author
14	Humanoid Robot - 3D Model	EEG Data Simulation	It is not necessary.	LabVIEW	It is not necessary.	REV EGIPT, 2022	BDI - Springer	First-Author
15	Display Systems Matrix 8x8 LEDs - LCD TEXT 2x16	Voluntary Eye-Blinks - Switch & Select	Arduino Uno	LabVIEW	NeuroSky - 1 Sensor	ACME Iași, 2022	BDI - IOP Science	Single-Author
16	Yoda Holograms	Voluntary Eye-Blinks - Binary Codes	Android Smartphone	LabVIEW - MIT App Inventor	NeuroSky - 1 Sensor	ICL AUSTRIA, 2022	BDI - Springer	First-Author
17	Juice Vending Machine - Simulation	Evoked Biopotentials P300	It is not necessary.	LabVIEW - Unicorn P300 Speller	GTEC Unicorn - 8 Sensors	INTER-ENG Târgu Mureș, 2022	BDI - Springer	Single-Author
18	Smart House - LED RGB	Voluntary Eye-Blinks - Counting	Arduino Mega	Python	Emotiv Insight - 5 Senzori	EHB Iași, 2022	BDI - IEEE Xplore	Single-Author
19	Display Systems - Matrix 5x5 LEDs	Opening & Closing Eyes EEG Alpha Rhythm	Micro:Bit - Raspberry Pi	Python - NODE-Red	Emotiv Insight - 5 Sensors	REV GRECIA, 2023	BDI - Springer	Single-Author
20	Accessing Internet Resources	Evoked Biopotentials P300	It is not necessary.	LabVIEW - Unicorn P300 Speller	GTEC Unicorn - 8 Sensors	ICL SPANIA, 2023	BDI - Springer	Single-Author
21	Chat GPT - Messages Transfer	Evoked Biopotentials P300	It is not necessary.	LabVIEW - Python - Unicorn P300 Speller	GTEC Unicorn - 8 Sensors	IMCL GRECIA, 2023	BDI - Springer	Single-Author
22	Juice Vending Machine - Real Prototype	Evoked Biopotentials P300	Arduino Mega	LabVIEW - Arduino - Unicorn P300 Speller	GTEC Unicorn - 8 Sensors	INTER-ENG Târgu Mureș, 2023	BDI - Springer	Single-Author
23	Robotic Arm & Mobile Robot	Evoked Biopotentials P300	Arduino - Wifi	LabVIEW - Arduino - Unicorn P300 Speller	GTEC Unicorn - 8 Sensors	EHB București, 2023 *Hackathon GTEC BR41N.IO October 2023*	BDI - Springer	Single-Author
24	Wheelchair - 3D Model	Evoked Biopotentials P300	It is not necessary.	LabVIEW - Unicorn P300 Speller	GTEC Unicorn - 8 Sensors	STE FINLANDA, 2024	BDI - Springer	Single-Author
25	Scooter Driver - 3D Model (Game)	Evoked Biopotentials P300	It is not necessary.	LabVIEW - Unicorn P300 Speller	NeuroSky - 1 Sensor	*Hackathon GTEC BR41N.IO April 2024 & ICUSI Constanța 1014*	Not Yet	Single-Author

Figure 5.1.1. Overview of Theoretical and Experimental Research.

The doctoral candidate implemented original algorithms for controlling brain-computer interfaces (BCI), resulting in the elaboration of 28 scientific papers, which were presented and published at conferences and in journals. Consequently, the systems controlled by the thesis author using brain-computer interfaces include:

- Mobile robots
- Robotic arms
- Miniature motorcycle
- Display systems (8x8 LED matrix and 2x16 LCD TEXT)
- Smart house (RGB LED lighting)
- Programmable drink vending machine
- Simulations based on 3D models (robotic arm, robotic hand, humanoid robot, wheelchair)
- Multimedia applications (virtual keyboard, Chat message transfer on Android, Chat GPT, internet resource access, Yoda hologram playback)

The commands for controlling the aforementioned systems were executed on the following platforms: Arduino (Uno, Mega, Nano 33 IoT), NI myRIO, Raspberry Pi, and Micro. Additionally, EEG signals were acquired from multiple headset kits, including: NeuroSky (Mindwave, Mindwave Mobile, Force Trainer) with a single sensor, Emotiv Insight with 5 sensors, and GTEC Unicorn with 8 sensors. The algorithms implemented by the doctoral candidate for controlling brain-computer interfaces were based on:

- Detecting voluntary ocular blinks using predefined functions
- Identifying voluntary ocular blinks through optimized implementations
- Counting voluntary ocular blinks
- Transitions and selections (Switch & Select) among commands using voluntary ocular blinks
- Divide and Conquer technique for multiple selections determined by voluntary ocular blinks
- Determining blink amplitude using Fuzzy Logic-based methods
- Acquiring, processing, and classifying raw EEG signals using Artificial Neural Networks
- Generating binary codes using voluntary ocular blinks
- Detecting and utilizing P300 evoked potentials
- Monitoring the Alpha EEG rhythm during eye closure and opening

Furthermore, the doctoral candidate utilized the following development and programming environments for implementing the aforementioned algorithms for controlling brain-computer interfaces: LabVIEW, Matlab, Python, Node-RED, Arduino, and MIT App Inventor.

CHAPTER 6

ORIGINAL IMPLEMENTATIONS. ALGORITHMS. PROGRAMMING SEQUENCES. BCI APPLICATIONS.

6.1. THE USE OF VOLUNTARY EYE-BLINKS AS BCI CONTROL SIGNAL

Voluntary ocular blinks represent a prominent artifact detected in raw electroencephalographic (EEG) signals. While most neuroscience research aims to eliminate artifacts generated by ocular blinks, brain-computer interface (BCI) applications can efficiently use the precise control signal obtained from voluntary ocular blinks [476], [484], [527], [532]. This doctoral thesis leverages the potential of the simple facial gesture of intentional blinks by users with neuromotor disabilities who cannot move their upper and lower limbs. According to previous studies, including the renowned case of researcher Stephen Hawking, who suffered from amyotrophic lateral sclerosis, the voluntary control of ocular blinks remains intact for a long period after losing other neuromotor abilities.

Figure 6.1.1 presents the EEG signal pattern corresponding to voluntary ocular blinks, an image included by the doctoral candidate in a paper published at the ICNBME Conference in Chișinău, 2021: [401].

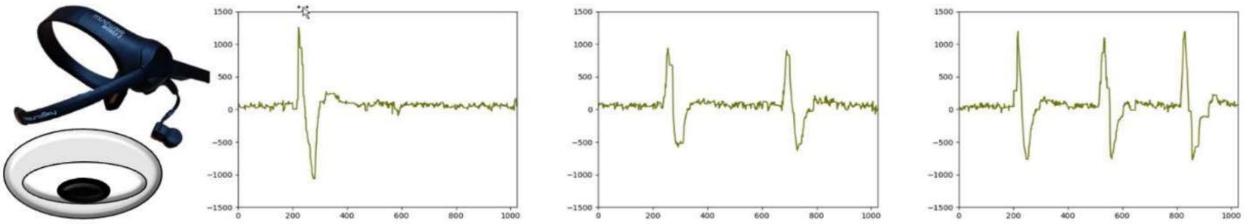


Figure 6.1.1. Reprezentarea grafică a formelor de undă pentru diferitele tipuri de clipire – simplă, dublă, triplă detectate la nivelul biosenzorului căștii EEG NeuroSky Mindwave.

Considering the argument that voluntary eye blinking represents a precise, efficient, simple, and easily detectable control signal, the research in this doctoral thesis has focused on the study, exploration, implementation, experimentation, testing, and optimization of techniques for detecting and quantifying or counting voluntary eye blinks, serving as commands in brain-computer interface systems. Thus, the following 10 interactive applications, developed within this thesis, were based on utilizing the control signal determined by detecting voluntary eye blinks, by leveraging a function offered by the ThinkGear toolkit of the NeuroSky EEG headset:

- Subchapter 7.3.2. LabVIEW Brain-Computer Interface application based on the integration of the NI myRIO development system and the NeuroSky headset for controlling a mobile robot;
- Subchapter 7.3.3. Matlab Brain-Computer Interface application based on the integration of the NeuroSky EEG headset and the Arduino Nano 33 IoT platform for controlling a motorcycle;
- Subchapter 7.5.2. LabVIEW Brain-Computer Interface application for controlling a virtual keyboard that facilitates communication for individuals with disabilities;

- Subchapter 7.5.3. Integrated LabVIEW – Android applications designed for chat message communication based on a brain-computer interface controlled with the NeuroSky EEG headset;
- Subchapter 7.5.4. LabVIEW Brain-Computer Interface applications based on simulating graphic animations and transmitting text messages to virtual LED display systems and devices connected to the Arduino Uno platform;
- Subchapter 7.6.2. LabVIEW Brain-Computer Interface application for controlling an experimental physical model of a robotic hand using the NeuroSky EEG headset;
- Subchapter 7.6.3. LabVIEW Brain-Computer Interface application for controlling a robotic arm and a mobile system for movement in different directions;
- Subchapter 7.6.4. LabVIEW Brain-Computer Interface application for controlling a mobile robot using the Arduino Mega platform and the NeuroSky Mindwave EEG headset;
- Subchapter 7.7.2. LabVIEW Brain-Computer Interface application for controlling a virtual 3D robotic hand model;
- Subchapter 7.7.3. LabVIEW Brain-Computer Interface application for cognitive training activities by controlling Yoda holograms according to a digital game-based paradigm using binary codes.

6.2. DETECTION AND QUANTIFICATION OF VOLUNTARY EYE BLINKS

6.2.1. Detection of Voluntary Eye Blinks with the ThinkGear Function

The algorithm for detecting voluntary eye blinks involved several stages where the amplitude or intensity of an eye blink was assessed using the ThinkGear function dedicated to the NeuroSky Mindwave EEG headset.

The first stage consisted of acquiring the EEG signal from the biosensor integrated into the portable NeuroSky headset by invoking the LabVIEW subprograms offered by the NeuroSky instrument driver package [289]. This .dll ThinkGear function library [108] allowed for: the initial configuration of the wireless communication between the NeuroSky set and the computer, the assessment of EEG signal quality, the activation or deactivation of the eye blink amplitude detection function, reading the blink amplitude value, acquiring the raw EEG signal, or classifying it into specific EEG rhythms (Figure 6.2.1.1).

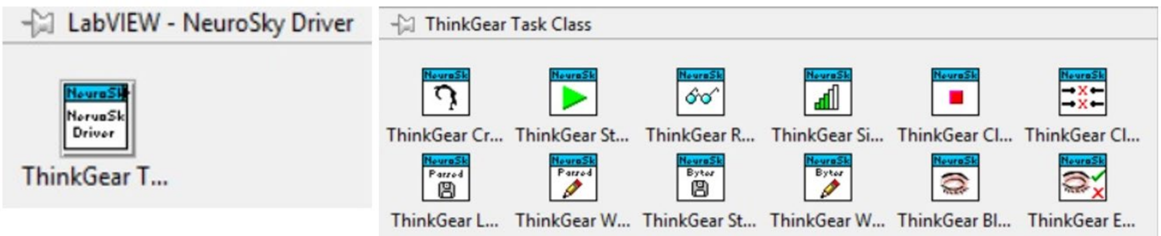


Figure 6.2.1.1. NeuroSky function palette corresponding to the ThinkGear toolkit dedicated to LabVIEW.

The second stage involved a comparison operation between the detected eye blink amplitudes and a threshold value defined for each user. The purpose of such an algorithm implemented in LabVIEW, Python, or Matlab is to evaluate this condition to determine if the eye blink amplitude has exceeded the established threshold. If affirmative, a voluntary eye blink is detected. If negative, it is considered an involuntary eye blink or a reflex action.

6.2.3. Transitions and Selections at the Command Level Based on Voluntary Eye Blinks

In this doctoral thesis, the counting or quantification of voluntary eye blinks is implemented using a state-machine algorithm. Intentionally executed eye blinks are characterized by amplitudes exceeding the threshold value initially set in the LabVIEW graphical interface. The threshold value can also be adjusted during the LabVIEW application's execution, accommodating each user's varying ability to perform voluntary eye blinks with lower (softer blinks) or higher intensity (stronger blinks).

The doctoral candidate implemented an algorithm in LabVIEW to facilitate transitions and selections at the command level generated by performing the voluntary eye blinks necessary for the original brain-computer interface applications developed in this thesis to control various systems: virtual keyboard, chat message transfer application, LED display systems, robotic hand (real and virtual), robotic arm, and mobile robot.

The implemented algorithm consists of four states: Init, Transition (Switch), Selection (Select), and Ready. Each of the four states includes a similar sequence of instructions, except for an alternative instruction (by invoking a causal structure in the LabVIEW programming environment) to evaluate the condition of whether an eye blink characterized by an amplitude exceeding the preset threshold value has been performed.

The Transition (Switch) state is equivalent to detecting a single voluntary eye blink, while the Selection (Select) state represents the counting of two intentionally executed eye blinks. Thus, performing a single eye blink results in a transition, movement, or shift at the command level represented by virtual buttons or other options (emoticons). Additionally, performing two eye blinks accomplishes the selection and transmission of the desired command, at which point the user stops the transition process.

Further information on the LabVIEW programming sequences for implementing the algorithm that determines transitions and selections at the command level based on voluntary eye blinks in brain-computer interfaces can be found in the Appendices – Section 6.2.3.

6.2.4. The Divide and Conquer Algorithm Using Multiple Voluntary Eye Blinks

The author of this doctoral thesis developed a brain-computer interface application to facilitate communication for individuals with neuromotor disabilities. Therefore, the doctoral candidate implemented the Divide and Conquer algorithm in the LabVIEW environment to generate the multiple commands necessary to control a virtual keyboard using voluntary eye blinks. This approach also served as the starting point for designing similar virtual keyboards based on the brain-computer interface [247], [103]. According to the literature [330], [68], researchers have rarely used the LabVIEW environment to create a logical algorithm for such brain-computer interfaces.

The implementation of the Divide and Conquer algorithm was based on the state-machine paradigm, characterized by the following features:

- Counting voluntary eye blinks characterized by an amplitude exceeding the threshold value;
- Activating the Switch command for transitioning at the level of rows, half-rows, or characters (keys) when a single voluntary eye blink is performed;
- Activating the Select command to select a specific row, half-row, or particular character (key) when two voluntary eye blinks are performed;
- The HIGHLIGHT option to indicate/highlight/color the current row, half-row, or selected key at the current moment, followed by inserting the corresponding character into the text box;
- Activating the Cancel command associated with performing three voluntary eye blinks to cancel the current selection. It is then possible to select a specific row of keys;
- The Delete command triggered when four voluntary eye blinks are recorded;
- The Space command determined by performing five voluntary eye blinks.

Further information on the LabVIEW programming sequences for implementing each stage of the Divide and Conquer algorithm for controlling the virtual keyboard using voluntary eye blinks can be found in the Appendices – Section 6.2.4.

6.3. ACQUISITION, ANALYSIS, AND CLASSIFICATION OF EEG SIGNALS USING ARTIFICIAL NEURAL NETWORK METHODS IN LABVIEW AND PYTHON

6.3.1. General Aspects

During her doctoral studies, the author of this thesis designed, developed, tested, and optimized certain LabVIEW and Python applications for the acquisition, processing, and classification of raw electroencephalographic (EEG) signals from the NeuroSky headset biosensor to identify voluntary eye blinks, which serve as control signals for brain-computer interface systems. The doctoral candidate applied simple methods based on artificial neural networks in LabVIEW and Python, presenting complete information and specifics regarding the stages covered in [357], which she published as the sole author in the Web of Science-indexed IJOE Journal, with an impact factor FI = 1.3, and at the ICNBME Conference held in Chișinău in 2021. Extended versions describing the BCI applications based on artificial intelligence techniques applied in LabVIEW were also published as Preprint papers [356].

6.3.6. Generating EEG Data for Training and Testing ANN

The classification of voluntary eye blinks is achieved by training and testing models based on artificial neural networks using EEG data sets composed of multiple combinations of selected EEG signals and extracted features. Each of the 12 two-dimensional vectors comprises 40 rows and 1024 columns, containing a total of 40,960 raw EEG values. The 12 two-dimensional vectors were equally divided (6 in the Time domain and 6 in the Frequency domain) and used in the graphical representations of Raw, Delta, Theta, Alpha, Beta, and Gamma EEG rhythms.

The LabVIEW application in this section was based on implementing three subprograms for generating the EEG data set.

The first LabVIEW subprogram transforms the 12 two-dimensional vectors into a single three-dimensional vector. This vector includes 12 pages corresponding to EEG signals, 40 rows associated with temporal sequences, and 1024 columns corresponding to EEG values.

The second subprogram extracts the two-dimensional vectors corresponding to the previously selected signals. The resulting 3D vector includes a number of pages equal to the number of selected signals, 40 rows, and 1024 EEG values.

The third subprogram calculates the specified statistical features for the selected signals and creates a 4D vector containing detailed information about features and signals.

The fourth and fifth LabVIEW subprograms are intended for reorganizing and reducing the dimensions of the obtained data. These programs transform the data into 3D and 2D vectors, respectively, to facilitate storage and subsequent analysis. Finally, a 2D vector representing the EEG data set is generated, which is saved in a .csv file to be used for training and testing classification models based on artificial neural networks.

Further information on the four LabVIEW subprograms for generating EEG data sets can be found in the Appendices – Section 6.3.6.

6.3.7. Training ANN Classification Models by Setting Parameters

This stage involves using the EEG data set generated in the previous steps. Classification based on artificial neural networks (ANN) is performed using standardized virtual instruments included in the LabVIEW AML - 'Analytics and Machine Learning' function package [185].

The virtual instrument 'Aml_Read CSV File.vi' is required for opening the CSV file and reading the training data set. 'Load Training Data (2D Array).vi' is then used to load the EEG data set for training the ANN classification model.

'Normalize.vi' allows for the normalization of the training data set using methods such as 2-Score or Min-Max, so the values fall within a certain range.

'Initialize Classification Model (NN).vi' initializes the parameters of the classification algorithm based on NN - Neural Networks. The user can set parameters such as the number of hidden neurons, the type of hidden layer (Sigmoid, Tanh, or Rectified Linear Unit), and the output layer (Sigmoid or Softmax), the cost function (Quadratic or Cross-Entropy), tolerance, and the maximum number of iterations.

Additionally, the user can set the option for cross-validation configuration, specifying the number of sections into which the training data will be divided and configuring metrics (by setting mediation methods: micro, macro, weighted, binary).

'Train Classification Model.vi' is used for training the classification model, and 'Aml_save Model to JSON.vi' is required for saving the model in JSON format.

Further information on the LabVIEW programming sequences for training classification models based on artificial neural networks by setting specific parameters can be found in the Appendices – Section 6.3.7.

6.3.8. Training ANN Classification Models by Generating Optimal Parameters

In the classification process based on searching for optimal parameters, the same tools and principles are used as in the classification process based on setting specific parameters, presented earlier. However, there is one important exception regarding how the parameters for initializing the classification model are set. Therefore, the user must specify multiple values for each parameter in the virtual instrument 'Initialize Classification Model (NN).vi' to allow the 'Train Classification Model.vi' instrument to perform a grid search and identify the optimal parameter set.

This optimal parameter search strategy is used in the current thesis research because it provides a higher degree of confidence and is more efficient. The exhaustive search option determines metrics (accuracy, precision, recall, and F1 score) for all possible combinations of specified parameters. In the case of activating the random search, a limited number of possible combinations among the specified parameters is tested.

In the research study of this doctoral thesis, 50 classification models based on artificial neural networks generated with the presented LabVIEW application were analyzed. The training duration for each model ranged from 1 to 3 hours. In total, it took between 50 and 150 hours to train all models.

Further information on LabVIEW programming for the stages of training classification models based on ANN by generating optimal parameters can be found in the Appendices – Section 6.3.8.

CHAPTER 7

EXPERIMENTAL RESEARCH. RESULTS AND DISCUSSIONS.

7.1. GENERAL ASPECTS OF BCI EXPERIMENTATION

7.1.1. Sample of Volunteer Subjects for BCI Experimentation

Information regarding the sample of volunteer subjects participating in the BCI applications experimentation

The testing of brain-computer interface (BCI) applications in this doctoral thesis was conducted with a total of 129 subjects who provided written consent and voluntarily signed up to participate in the experimental activities. The gender distribution of the 129 subjects was as follows: 39 females and 90 males. Among the 129 volunteers, there were 3 young adults aged between 28-31 years, working in the fields of software testing, financial management, and instrumental music. Additionally, the 129 subjects included 79 young adults aged 21-22 years, who were third-year students in the Computer Science program, and 42 young adults aged approximately 23 years, representing fourth-year students in the Bachelor's program in Information Technology within the Faculty of Electrical Engineering and Computer Science (IESC) at Transilvania University of Brașov (UnitBV). An essential aspect was the increased motivation of the 121 students for their active involvement in experimenting with the brain-computer interface applications by rewarding them with bonus points for their laboratory work in the Virtual Instrumentation (LabVIEW) course.

Figure 7.1.1.1. The first experimental session organized in December 2022, attended by third-year Computer Science students from the Faculty of Electrical Engineering and Computer Science (IESC), Transilvania University of Brașov (UnitBV).

Figure 7.1.1.2. The second experimental session organized in January 2023, attended by third-year Computer Science students from the Faculty of Electrical Engineering and Computer Science (IESC), Transilvania University of Brașov (UnitBV).

The first two series of experimental sessions (Figure 7.1.1.1 and Figure 7.1.1.2) regarding brain-computer interface (BCI) applications for communication through written message transmission and virtual simulations based on 3D models, which involved 39 Computer Science students, were organized in December 2022 and January 2023. The third and fourth series of experimental sessions (Figure 7.1.3.1 and Figure 7.1.3.2) on BCI applications for controlling mechatronic systems (mobile robots, miniature motorcycle, robotic hand), which involved another 40 Computer Science students, were organized in December 2023 and January 2024. The fifth and sixth series of experimental sessions (Figure 7.1.3.3 and Figure 7.1.3.4) on BCI applications based on specialized techniques (P300 evoked potentials or the classification of voluntary eye blinks using artificial neural network models), involving 42 Information Technology students, were conducted in April 2024. Additionally, throughout the doctoral stage, between 2017 and 2024, the BCI applications developed by the doctoral candidate were also experimented with by the other 7 subjects, who included her family members aged approximately 58-59 and 82-83 years. Furthermore, the applications implemented and proposed in this doctoral thesis were initially tested and experimented with by the doctoral candidate.

7.1.2. EEG-HW-SW Stands Used in BCI Experimentation

Description of the experimental stand for brain-computer interface applications:

The experimental stands provided by the thesis author to the subjects during the sessions organized at the University included the following hardware and software systems:

- 6 laptops with acceptable performance (Windows 7/8.1/10 Home/Professional 64-Bit, Intel Core i5/i7/i9 Processor, 8/16/32 GB RAM, 512 SSD or 1 TB Hard Disk);

- 6 portable headsets with a single EEG sensor (various versions: Mindwave, Mindwave Mobile, Force Trainer) based on NeuroSky technology, with an integrated ThinkGear chip;
- 2 Emotiv Insight portable headsets with 5 EEG sensors;
- 1 GTEC Unicorn headset with 8 EEG sensors;
- 10 mechatronic systems - experimental prototypes: mobile robots, robotic arm, robotic hand, miniature house, based on mechanical and electronic components (servomotors, DC motors, Bluetooth module, motor driver, WiFi module);
- 7 development platforms - Arduino (Uno, Nano 33 IoT, Mega, ESP8266), Raspberry Pi, NI myRIO, Micro;
- Lenovo Yoga 10 Tablet – running the Android application for displaying Yoda holograms;
- Samsung Smartphone – running the Android application for sending Chat messages;
- Software applications/programs based on LabVIEW, Python, Matlab, NodeRED, MIT App Inventor, Arduino programming environments/languages.

7.1.3. Preliminary Stages of BCI Experimentation

Preliminary preparation of subjects for experimenting with brain-computer interfaces:

Before performing the experimental tasks with the proposed brain-computer interface applications, the subjects underwent a preliminary stage aimed at familiarizing them with attaching, adjusting, connecting, using, or wearing the NeuroSky, Emotiv Insight, and GTEC Unicorn EEG headsets and learning how to perform voluntary eye blinks and the technique of focusing attention on light symbols to generate P300 evoked potentials, considered as commands for controlling mechatronic systems based on Arduino, Raspberry Pi, Micro, NI myRIO platforms or interacting with virtual simulations based on 3D models.

Therefore, the thesis author was involved in coordinating and guiding the subjects, showing them how to properly fix each portable headset so that the EEG sensors were correctly positioned according to the International 10-20 System to accurately capture the raw EEG signal generated when the eye muscles contract for eye blinking or the P300 evoked potentials transmitted when the person focuses attention and looks at a light symbol that appears at an irregular frequency. It is also important to correctly position the reference or ground elements at the ear level to close the EEG signal measurement circuit. Fixed components of the headset structure should be arranged at the skull level according to official documentation. Flexible elements, including the EEG sensors, are adjusted based on each subject’s anatomical skull structure. Additionally, most portable EEG headsets can be adjusted to fit the circumference of the skull.

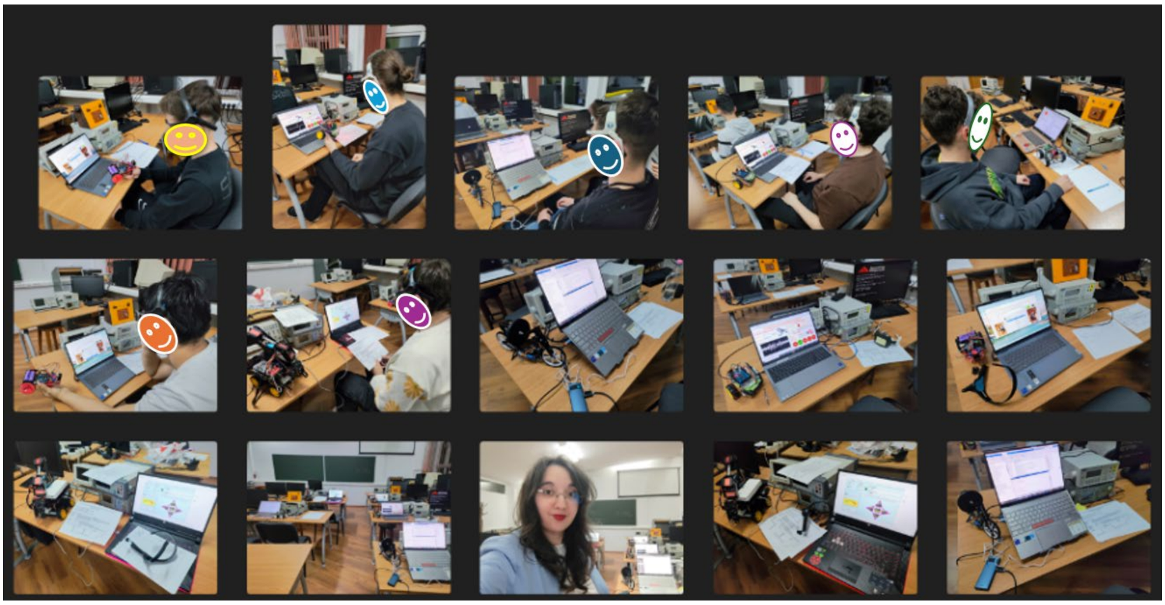


Figure 7.1.3.1. The third experimental session organized in December 2023, attended by third-year Computer Science students from the Faculty of Electrical Engineering and Computer Science, UnitBV.

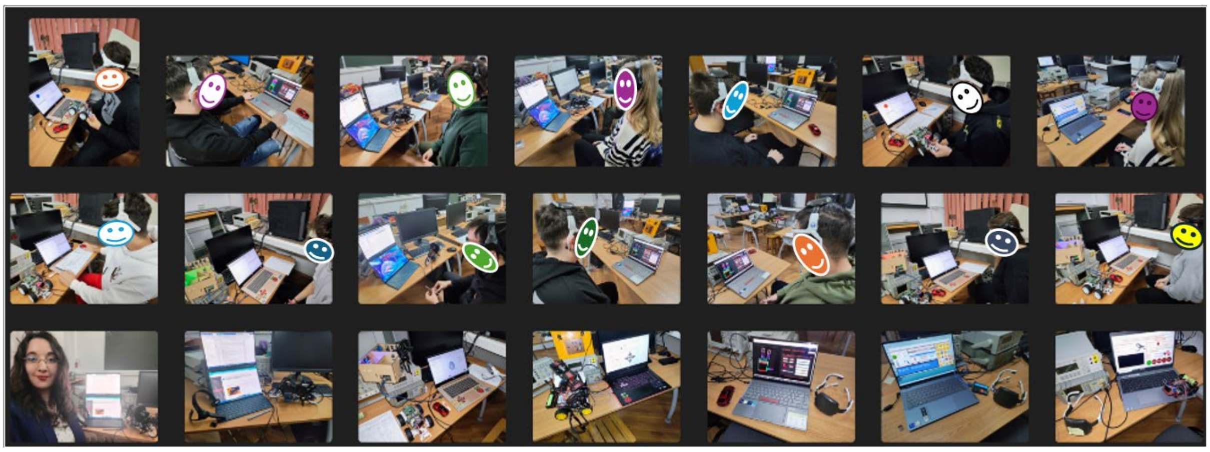


Figure 7.1.3.2. The fourth experimental session organized in January 2024, attended by third-year Computer Science students from the Faculty of Electrical Engineering and Computer Science, UnitBV.

Moreover, the thesis author contributed to the subjects' training by clearly explaining and additionally providing a practical demonstration presented in real-time, encompassing all the stages of experimenting with the brain-computer interface applications. Initially, the doctoral candidate, alongside the students, went through the stages intended for the wireless connection between the laptop and the development platforms, as well as the Bluetooth connection between the laptop and the headset. Thus, aside from their role as subjects, the students had the opportunity to learn new general aspects regarding the efficient interfacing of these hardware systems. Subsequently, the doctoral candidate assisted the subjects in attaching and adjusting the headset on their heads in a proper position. Afterward, the doctoral candidate succinctly explained and practically demonstrated to the subjects the steps necessary to launch all software applications, running on a Windows 10 PC and on a Raspberry Pi with Linux.

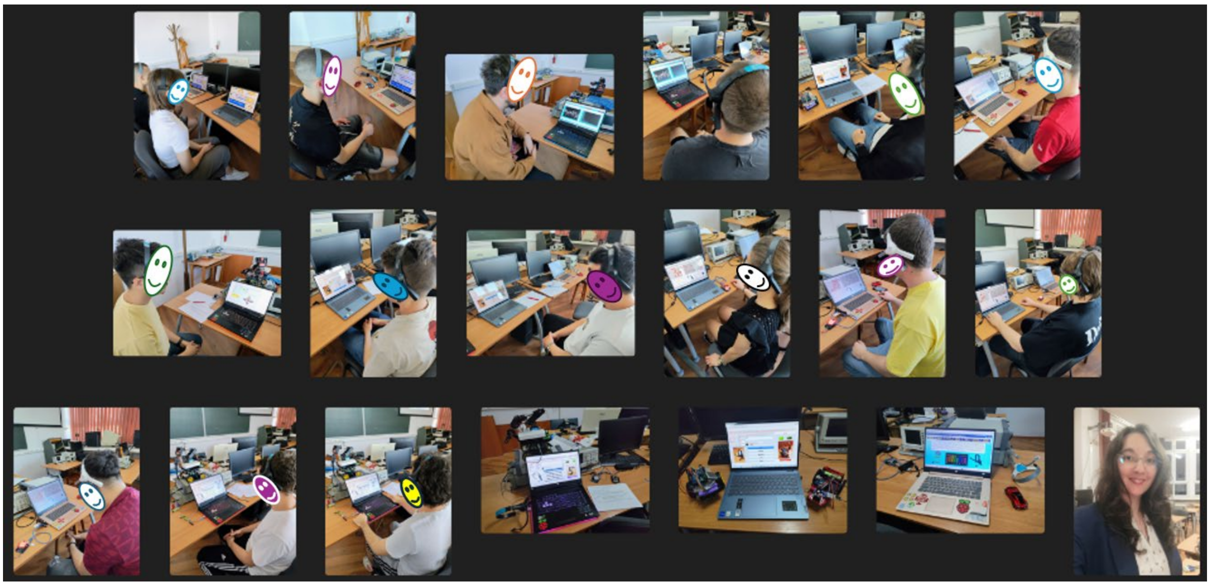


Figure 7.1.3.3. The fifth experimental session organized in April 2024, attended by fourth-year Information Technology students from the Faculty of Electrical Engineering and Computer Science, UnitBV.

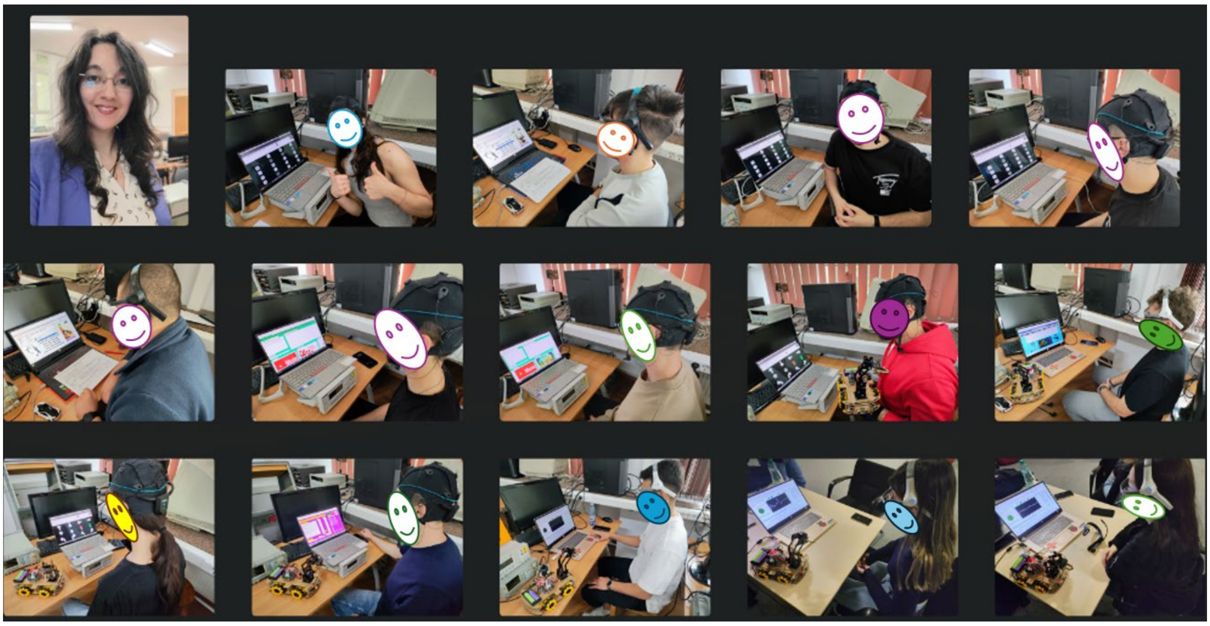


Figure 7.1.3.4. The sixth experimental session organized in April 2024, attended by fourth-year Information Technology students from the Faculty of Electrical Engineering and Computer Science, UnitBV.

Furthermore, the doctoral candidate and the students jointly verified that the Bluetooth communication between the EEG headset and the laptop was successfully established, and the EEG data were acquired in real-time, which is necessary for the algorithm to detect voluntary eye blinks and recognize P300 evoked potentials. Initially, the doctoral candidate individually executed a sequence of commands to control the proposed experimental prototypes. Subsequently, she assisted the subjects in a familiarization session on performing voluntary eye blinks and generating commands based on P300 evoked potentials, both variants accompanied by visual feedback. This initiation session, pertaining to the use of the brain-computer interface application, lasted approximately 5 minutes, aiming to build the subjects' self-confidence, acquaint them with wearing the NeuroSky EEG headset, monitor the controlled systems, develop the ability to perform voluntary eye blinks, acquire the capacity to focus attention and gaze to generate P300 potentials, and observe the specific mode of visual feedback.

Presentation of Work Tasks for Experimenting with Brain-Computer Interfaces

The thesis author created experiment sheets (Appendices – Section 7.1.3) containing essential information about the proposed work tasks, which she distributed, presented, and exemplified to the subjects. Therefore, in the experiments using the NeuroSky EEG headset, the respective sheet included the following main aspects: a description of the two types of voluntary eye blinks (strong or soft), enumeration and explanation of individual commands, and exemplification of the three progressive levels (beginner, intermediate, advanced) for sequences composed of multiple commands.

For example, the experiment sheet clearly specifies the difference between a strong voluntary eye blink and a soft voluntary eye blink by fulfilling the condition determined by comparing the intensity of the eye blink performed by the user with the threshold intensity or limit defined inherently in the LabVIEW, Matlab, or Python program, based on the analysis of the raw EEG signal acquired from the NeuroSky EEG headset sensor. If the subject voluntarily performs an eye blink with an intensity exceeding the limit value, it is considered a strong voluntary eye blink. If the subject voluntarily performs an eye blink characterized by an intensity below the threshold value, it is considered a soft voluntary eye blink. The commands necessary for brain-computer interface applications to control experimental prototypes using the NeuroSky EEG headset are represented by successively executed strong voluntary eye blinks.

NOTE: The threshold intensity or limit value was determined automatically, customized for each subject. Therefore, an application was implemented in the LabVIEW graphical programming environment to detect a total of 20 blink intensity values based on 20 strong voluntary eye blink executions by each subject. The role of the LabVIEW program was to generate the threshold intensity value by applying a mathematical calculation formula, based on determining the arithmetic mean and standard deviation of the 20 values, stored in a numerical vector.

7.1.5. Experimentation Stages and BCI Performance Parameters

BCI Experimentation Stages Using Voluntary Eye Blinks

BCI Applications for Robotic System Control - Mobile Robot (Arduino, Raspberry Pi, NI myRIO) and Miniature Motorcycle - Through Counting Voluntary Eye Blinks

This section describes the stages (proposed commands, methods for quantifying voluntary eye blinks, calculation of performance evaluation metrics for using the brain-computer interface) undertaken during the experimentation of the BCI application for controlling a mobile robot based on Arduino Uno, using the NeuroSky Mindwave EEG headset. The particularity of this BCI application lies in determining the blink amplitude using techniques based on Fuzzy Logic. All information presented in the following sections is also applicable to the experimentation of the BCI application for controlling the mobile robot commanded with voluntary eye blinks, using the NI myRIO system and NeuroSky EEG headset. Furthermore, the described stages are also applicable to the experimentation of the BCI application for controlling the mobile robot using a custom algorithm for detecting and counting voluntary eye blinks, utilizing the Raspberry Pi system and the NeuroSky Mindwave EEG headset. Similarly, the same stages and a similar performance evaluation algorithm, but considering a different number of commands, apply to the experimentation of the BCI application for controlling the movement of the miniature motorcycle using the Arduino 33 IoT platform and the NeuroSky Mindwave EEG headset.

The first significant aspect, specified in the experimental protocol, refers to the conditions for performing a strong voluntary eye blink and a soft voluntary eye blink. Thus, fulfilling the condition "Detected Blink Amplitude > Initial Threshold Intensity" signifies a strong voluntary eye blink. Conversely, fulfilling the condition "Detected Blink Amplitude < Initial Threshold Intensity" signifies a soft voluntary eye blink. The ways in which a user can perform a strong voluntary eye blink include: vigorous, sudden, and rapid eyelid movement or a more forceful contraction of the ocular muscles. The ways to perform a soft voluntary eye blink include: slow, light, and gentle eyelid movement or shifting the gaze direction, or a certain distraction of attention.

The threshold intensity for detecting a strong or soft voluntary eye blink is user-specific and automatically set by running a LabVIEW program. This threshold intensity varies depending on the user's individual capability, personal preference, natural blinking habit (stronger or softer), which correlates with psychological state (emotions, inner calm, agitation, alertness, safety, relaxation), time of day (morning, evening), or energy level.

An important observation from the experimental protocol, supplementing the information in Tables 7.1.5.1 and 7.1.5.2 regarding the description of individual commands, is that for transmitting the command after executing the number of strong voluntary eye blinks, an additional soft voluntary eye blink is performed. Therefore, for the description of the experimentation stages in the following sections, this observation will be considered, and for simplicity, the term "voluntary eye blink" will be preferred, omitting the additional word "strong."

For example, the experimental protocol includes Table 7.1.5.1, which lists and presents the 5 individual commands (stop, forward, backward, left, right). The first command (stop or halt) involves executing a single voluntary eye blink. The second command (move forward) refers to executing two successive voluntary eye blinks. Continuing, the third command (move backward) is equivalent to performing three successive voluntary eye blinks. For the fourth command (turn left), four voluntary eye blinks are required. The fifth command (turn right) is determined by executing five successive voluntary eye blinks. Therefore, the subject must try to execute each of the 5 commands and then fill in the table with: OK, if the subject managed to perform the correct number of blinks, and NOK, if the user did not generate the command by executing the corresponding number of blinks.

Table 7.1.5.1 Description of commands required for experimenting with brain-computer interface applications based on counting voluntary eye blinks for controlling robotic systems.

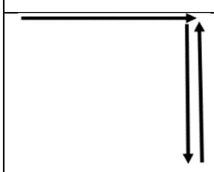
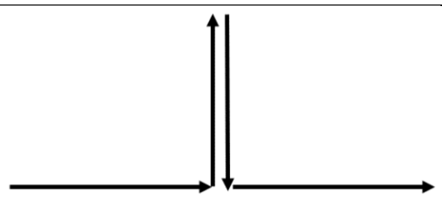
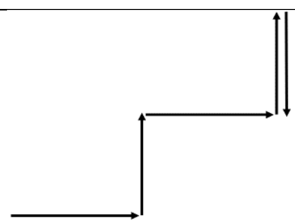
INDIVIDUAL COMMANDS	DESCRIPTION
STOP	1 voluntary eye blink
Move - FORWARD	2 voluntary eye blinks
Move - BACKWARD	3 voluntary eye blinks
Turn - LEFT	4 voluntary eye blinks
Turn - RIGHT	5 voluntary eye blinks

For example, the experimental protocol presents Table 7.1.5.2, which outlines the three levels - beginner, intermediate, advanced - and specifies the number of commands (6, 9, 13) and describes the corresponding sequence of multiple commands. By completing the Beginner level, the subject is required to correctly execute, in the established order, the following sequence consisting of 6 commands to control the mobile robot in different movement directions: Forward, Stop, Right, Forward, Stop, Backward. Continuing, by completing the Intermediate level, the subject must correctly execute, in the given order, the following sequence consisting of 9 commands to control the mobile robot in different movement directions: Forward, Stop, Left, Forward, Stop, Backward, Left, Forward, Stop. Finally, by completing the Advanced level, the subject has the task of transmitting the following 13 commands regarding the control of the mobile robot in different movement directions: Forward, Stop, Left, Forward, Stop, Right, Forward, Stop, Left, Forward, Stop, Backward, Stop.

Table 7.1.5.2 Presentation of difficulty levels for experimenting with the brain-computer interface.

LEVEL	NUMBER OF COMMANDS	SEQUENCE OF MULTIPLE COMMANDS
BEGINNER	6	Forward – Stop – Right – Forward – Stop - Backward
INTERMEDIATE	9	Forward – Stop – Left – Forward – Stop – Backward – Left – Forward – Stop
ADVANCED	13	Forward – Stop – Left – Forward – Stop – Right – Forward – Stop – Left – Forward – Stop – Backward – Stop

Table 7.1.5.3 Trajectories corresponding to the movement directions of the mobile robot according to the command sequence.

BEGINNER	INTERMEDIATE	ADVANCED
		

Additionally, regarding the three experimentation levels – beginner, intermediate, advanced – of the proposed brain-computer interfaces, the experimental protocol illustrates Table 7.1.5.3 with schematic trajectories, based on the sequences of multiple commands determined by the previously mentioned movement directions.

In terms of completing the results on the experimental protocol, the subject writes the number of commands correctly detected by the brain-computer interface, according to their intention and the tasks included at each difficulty level (beginner, intermediate, advanced). Also, an essential aspect of experimenting with the proposed applications for controlling mechatronic systems is that the subject had the opportunity to perform certain command sequences repeatedly, resulting in up to 3 attempts for each level. If the subject achieves maximum performance by correctly completing all 9 commands on the first attempt to transmit the intermediate level sequence, then the subject will continue with executing the commands for the final level – advanced. Otherwise, if the subject does not achieve maximum performance on the first attempt, they are given the opportunity to repeat the entire sequence of commands, and the table will specify both the fact that there were 2 execution attempts for that level and the number of correctly detected commands on the attempt with superior performance. According to their own preference, the subject can make up to 3 attempts to complete the commands for each difficulty level.

Main Parameters Measured During the Experimentation of Brain-Computer Interface Applications

During the experimentation of the proposed brain-computer interface applications for controlling mechatronic systems and virtual simulations based on 3D models using the NeuroSky EEG headset, subjects were monitored, and the number of voluntary eye blinks executed according to the work tasks specified in the protocol for each difficulty level was determined. As shown in Figure 7.1.5.1, initially, the optimal number of successive voluntary eye blinks needed to execute each control command for the experimental hardware prototype or 3D model was defined according to the sequence for each level – beginner, intermediate, and advanced. Additionally, the optimal number of non-blinks, representing the absence of voluntary eye blinks, was considered to avoid incorrect transmission of control commands for physical or virtual systems.

By determining the number of correctly (in reality) or incorrectly executed voluntary eye blinks by each subject, according to the work task in the experimental protocol, the number of true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) cases was generated. Based on the values of the TP – TN – FP – FN cases, the sensitivity, specificity, accuracy, and precision metrics necessary for evaluating the efficacy and performance of the brain-computer interface application were calculated. Table 7.1.5.4 details the TP – TN – FP – FN cases, and Table 7.1.5.5 presents the mathematical formulas for calculating these metrics.

BEGINNER			
No.	Command	Eye-Blinks	Non Eye-Blinks
1	Forward	2	1
2	Stop	1	1
3	Right	5	1
4	Forward	2	1
5	Stop	1	1
6	Backward	3	1
	TOTAL	14	6
		eye-blinks	non eye-blinks

INTERMEDIATE			
No.	Command	Eye-Blinks	Non Eye-Blinks
1	Forward	2	1
2	Stop	1	1
3	Left	4	1
4	Forward	2	1
5	Stop	1	1
6	Backward	3	1
7	Left	4	1
8	Forward	2	1
9	Stop	1	1
	TOTAL	20	9
		eye-blinks	non eye-blinks

ADVANCED			
No.	Command	Eye-Blinks	Non Eye-Blinks
1	Forward	2	1
2	Stop	1	1
3	Left	4	1
4	Forward	2	1
5	Stop	1	1
6	Right	5	1
7	Forward	2	1
8	Stop	1	1
9	Left	4	1
10	Forward	2	1
11	Stop	1	1
12	Backward	3	1
13	Stop	1	1
	TOTAL	29	13
		eye-blinks	non eye-blinks

Figure 7.1.5.1. Determining the optimal number of successive voluntary eye blinks and the optimal number of non-blinks needed for completing the multiple command sequences for each difficulty level.

Table 7.1.5.4 Description of cases based on voluntary eye blinks executed by the subject.

CASES	DESCRIPTION
True-Positive (TP)	The subject performed a strong voluntary eye blink. The brain-computer interface correctly detected the blink.
True-Negative (TN)	The subject did not perform a strong voluntary eye blink. The brain-computer interface did not detect the blink in reality.
False-Positive (FP)	The subject did not perform a strong voluntary eye blink. The brain-computer interface incorrectly detected the blink.
Fals-Negative (FN)	The subject performed a strong voluntary eye blink. The brain-computer interface incorrectly did not detect the blink.

Table 7.1.5.5 Presentation of mathematical formulas for calculating metrics for evaluating brain-computer interface applications.

Metric	Mathematical Formula	Description
Sensitivity	$\frac{TP}{TP+FN}$	Sensitivity determines the proportion of correctly identified voluntary eye blinks by the BCI application. Sensitivity of the BCI application increases if the number of FN cases is reduced.
Specificity	$\frac{TN}{TN+FP}$	Specificity determines the proportion of correctly identified non-blinks by the BCI application.
Precision	$\frac{TP}{TP+FP}$	Precision measures the BCI application's ability to correctly classify voluntary eye blinks. Precision of the BCI application increases if the number of FP cases is reduced.
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Accuracy determines the overall correctness of the results returned by the BCI application.

Calculation of TP – TN – FP – FN Cases for Determining Sensitivity-Specificity-Precision-Accuracy Metrics Regarding Performance Evaluation of Brain-Computer Interfaces

For example, consider a voluntary subject participating in the experimentation of the brain-computer interface for controlling the mobile robot through commands based on voluntary eye blinks, who achieved the following results:

- Beginner level (including a total of 6 commands):
    - 4 successful commands and 2 failed commands on the first attempt;
    - successful commands on the second attempt;
- Intermediate level (including a total of 9 commands):
    - 5 successful commands and 4 failed commands on the first attempt;
    - successful commands and 3 failed commands on the second attempt;
    - successful commands and 2 failed commands on the third attempt;
- Advanced level (including a total of 13 commands):
    - 7 successful commands and 6 failed commands on the first attempt;
    - 9 successful commands and 4 failed commands on the second attempt;
    - 11 successful commands and 2 failed commands on the third attempt.

Given the information in the table illustrated in Figure 7.1.5.1, the optimal number of TP and TN cases will be calculated by applying the mathematical formula:

Sum of TP Cases (Optimal) = No. of Blinks for Beginner Level x No. of Attempts for Beginner Level + No. of Blinks for Intermediate Level x No. of Attempts for Intermediate Level + No. of Blinks for Advanced Level x No. of Attempts for Advanced Level = 14 x 2 + 20 x 3 + 29 x 3 = 175 voluntary blinks, correctly detected.

Sum of TN Cases (Optimal) = No. of Non-Blinks for Beginner Level x No. of Attempts for Beginner Level + No. of Non-Blinks for Intermediate Level x No. of Attempts for Intermediate Level + No. of Non-Blinks for Advanced Level x No. of Attempts for Advanced Level = 6 x 2 + 9 x 3 + 13 x 3 = 78 voluntary non-blinks, correctly detected.

To obtain the FP and FN cases, the total number of failed commands for each difficulty level performed by the subject during the experiment will be determined:

- Beginner level: 2 failed commands
- Intermediate level: 9 failed commands
- Advanced level: 12 failed commands

By monitoring the subject, it can be observed that the execution of a command failed due to two possible causes:

1. In reality, the subject did not perform a strong voluntary eye blink, but the brain-computer interface erroneously detected the blink.
    - In this case, the number of false-positive (FP) cases will increase.

2. In reality, the subject performed a strong voluntary eye blink, but the brain-computer interface incorrectly did not detect the blink.
    - In this case, the number of false-negative (FN) cases will increase.

Therefore, the following mathematical formulas will be applied to calculate the FP and FN cases based on the two causes mentioned above:

Sum of FP Cases = No. of Blinks for Failed Commands at Beginner Level + No. of Blinks for Failed Commands at Intermediate Level + No. of Blinks for Failed Commands at Advanced Level.

Sum of FN Cases = No. of Non-Blinks for Failed Commands at Beginner Level + No. of Non-Blinks for Failed Commands at Intermediate Level + No. of Non-Blinks for Failed Commands at Advanced Level.

Hence, the failed commands for each level must be specified:

- Beginner: Forward, Backward
- Intermediate: Left, Forward, Backward, Left, Stop, Left, Forward, Stop, Backward
- Advanced: Forward, Stop, Left, Right, Forward, Backward, Stop, Left, Forward, Stop, Left, Backward

Applying the above mathematical formulas, based on the two causes that led to failed commands in practice, results in the sum of FP and FN cases:

Sum of FP Cases = 2 (for Beginner Level) + 4 + 3 + 4 + 2 + 1 (for Intermediate Level) + 4 + 5 + 2 + 1 + 2 + 1 + 4 (for Advanced Level) = 35

Sum of FN Cases = 1 (for Beginner Level) + 1 + 1 + 1 + 1 (for Intermediate Level) + 1 + 1 + 1 + 1 + 1 (for Advanced Level) = 10

Finally, the number of TP and TN cases will be updated by subtracting the FP and FN cases:

Sum of TP Cases = Sum of TP Cases (Optimal) – Sum of FP Cases = 175 – 35 = 140

Sum of TN Cases = Sum of TN Cases (Optimal) – Sum of FN Cases = 78 – 10 = 68

Thus, the following values were obtained: TP = 140; FP = 35; TN = 68; FN = 10.

By applying the mathematical formulas from Table 7.1.5.5, the four evaluation metrics regarding the performance of a brain-computer interface application are calculated:

- Sensitivity: TP/(TP+FN) = 140/(140+10) = 0.93 = 93%
- Specificity: TN/(TN+FP) = 68/(68+35) = 0.66 = 66%
- Precision: TP/(TP+FP) = 140/(140+35) = 0.80 = 80%
- Accuracy: (TP+TN)/(TP+ TN+FP+FN) = (140+68)/(140+68+35+10) = 0.82 = 82%

Therefore, for evaluating all the original brain-computer interface applications developed and experimented within this doctoral thesis, the calculation algorithm described above was considered to identify the number of TP – FP – TN – FN cases and determine the corresponding metrics (sensitivity, specificity, precision) for each of the 129 subjects.

The stages described above regarding defining the command sequences for the three difficulty levels (beginner, intermediate, advanced), and the calculation algorithm of the Sensitivity – Specificity – Precision – Accuracy metrics for evaluating the performance of brain-computer interfaces, based on determining the number of TP – TN – FP – FN cases, apply similarly to the experimentation of other applications implemented by the doctoral candidate for controlling the following robotic systems: mobile robots, robotic arm, robotic hand (real prototype and virtual model), miniature motorcycle. However, the only differences are represented by the number, order, and type of commands (movement or positioning) established for each difficulty level.

Applications of BCI for the control of robotic systems (Robotic Hand, Robotic Arm), 3D models (Robotic Hand), and communication systems (Android Chat) via transition and selection commands using voluntary eye blinks

Alternatively, the experimental sheet for BCI applications controlling various robotic systems (mobile robot, robotic hand, robotic arm), 3D models (robotic hand), or communication platforms (Android Chat), developed and tested by the doctoral candidate in this dissertation, includes Table 7.1.5.6, which describes individual transition commands executed by a single voluntary eye blink and selection commands executed by two voluntary eye blinks. The number of blinks corresponding to the selection of a command is counted according to the position of the command that the user needs to select. For example, if the user needs to select the "Turn Left" command, located in the fourth position (the fourth button in the application's graphical interface), the user should ideally perform four voluntary blinks.

Table 7.1.5.6 Description of the commands necessary for experimenting with brain-computer interface applications based on selections and transitions using voluntary eye blinks.

INDIVIDUAL COMMANDS	DESCRIPTION
TRANSITION	1 voluntary eye blink
SELECTION	2 voluntary eye blinks

Determining the number of commands for controlling the robotic hand

Figure 7.1.5.2 presents specific commands for controlling the robotic hand (prototype based on Arduino Uno) by executing the optimal number of voluntary eye blinks, detected using the NeuroSky Mindwave EEG headset. A particular feature of the BCI application for controlling the robotic hand is the multiple commands determined by the flexion (contraction)/extension actions of each segment/finger. For beginners, performing the main hand closing/contraction command (excluding thumb contraction) involves four secondary commands for flexing each finger: index, ring, middle, and little finger.

BEGINNER				
No.	Command	Eye-Blinks		Total - TP
		Selection	Switch	
1	Closed Hand - Thumb Finger 4 Commands	8	4	12
2	Open Hand 4 Commands	8	4	12
	Total Commands: 8			24
16 non eye-blinks (true-negative) - TN				

INTERMEDIATE				
No.	Command	Eye-Blinks		Total - TP
		Selection	Switch	
1	Thumb and Index Fingers 3 Commands	6	4	10
2	Thumb-Index-Ring Fingers 2 Commands	4	4	8
3	Thumb-Index-Ring-Middle Fingers 1 Command	2	4	6
4	Pinky-Thumb Fingers 3 Commands	6	4	10
	Total Commands: 9			34
25 non eye-blinks (true negative) - TN				

ADVANCED				
No.	Command	Eye-Blinks		Total - TP
		Selection	Switch	
1	Index Finger 3 Commands	6	4	10
2	Thumb and Middle Fingers 2 Commands	4	4	8
3	Thumb, Index and Pinky Fingers 2 Commands	4	4	8
4	Thumb Finger 4 Commands	8	4	12
5	Index-Middle-Ring Fingers 1 Command	2	4	6
	Total Commands: 12			44
32 non eye-blinks (true negative) - TN				

Figure 7.1.5.2. Type, number, and order of commands based on the optimal counting of voluntary eye blinks when experimenting with the BCI application for controlling the robotic hand using NeuroSky and Arduino.

For the intermediate level, the general command for raising (extending) or opening the thumb and index fingers involves performing three secondary commands for lowering (contracting) or closing the other three fingers: middle, index, and little fingers. For the advanced level, the general command for raising/extending the thumb, index, and little fingers is executed through two secondary commands: contraction of the middle finger and flexion of the ring finger.

Determining TP – TN – FP – FN cases in experimenting with the control of the robotic hand

The optimal number of voluntary eye blinks representing true-positive (TP) cases, according to the table in Figure 7.1.5.2, is calculated using the following formula for each difficulty level (beginner, intermediate, advanced):

Number of Blinks (True-Positive Cases) = Sum of Secondary Commands x 2 Blinks (Selections) + Sum of General Commands x 4 Blinks (Transitions).

For the optimal number of non-blinks representing true-negative (TN) cases, according to the table in Figure 7.1.5.2, the calculation is: for the first general command—hand closing—through the execution of the four secondary commands for contracting the four fingers at the beginner level, after each of the four selections, the user should no longer blink, resulting in 4 non-blinks, and after each of the four transitions, the user will not blink, resulting in another 4 non-blinks. A similar calculation applies to other commands using the following formula:

Number of Non-Blinks (True-Negative Cases) = Sum of Blinks (Transitions) + Sum of Blinks (Selections)/2.

Additionally, the following conditions are considered: for selecting a command (flexion or extension of a finger), two voluntary eye blinks are executed, while transition/movement among options/commands is performed through a single voluntary eye blink. The number of blinks executed for the transition depends on the positioning and distance between buttons in the BCI application's graphical interface developed in LabVIEW.

The number of FP (false-positive) cases increases when the user mistakenly, unintentionally selects a flexion/extension command for a finger different from the received task or the initially set goal. Also, from the TP cases, 2 blinks (corresponding to a selection) x the number of erroneous commands are subtracted.

The number of FN (false-negative) cases increases when the user unintentionally, incorrectly omits to select a specific flexion/extension command for a finger, which does not coincide with the received task or the initially set goal. Thus, from the TN cases, 1 blink (corresponding to a transition) x the number of erroneously omitted commands is subtracted.

Figure 7.1.5.3. Intermediate positions constituting the necessary commands for experimenting with the BCI application for controlling the 3D robotic hand using the NeuroSky EEG headset.

Figure 7.1.5.3. Intermediate positions constituting the necessary commands for experimenting with the BCI application for controlling the robotic hand using the NeuroSky EEG headset and Arduino.

Figures 7.1.5.3 and 7.1.5.4 present both the real/virtual robotic fingers and the gestures obtained or the positioning of the hand by fulfilling commands based on voluntary eye blinks.

Similarly, the commands and counting of voluntary eye blinks are determined based on the difficulty level when experimenting with the BCI application for controlling the 3D robotic hand, considering a single difference: the beginner level includes 10 secondary commands: 5 contractions/flexions for closing the hand (the thumb is mobile in the 3D model) and 5 extensions for opening the hand. For example, for the first general command at the intermediate level, referring to the extension of the thumb (mobile) and index fingers and the flexion of the other three fingers, 3 selection commands equivalent to 3 x 2 voluntary eye blinks and 4 transition commands corresponding to the 4 fingers for which the transition/movement is made.

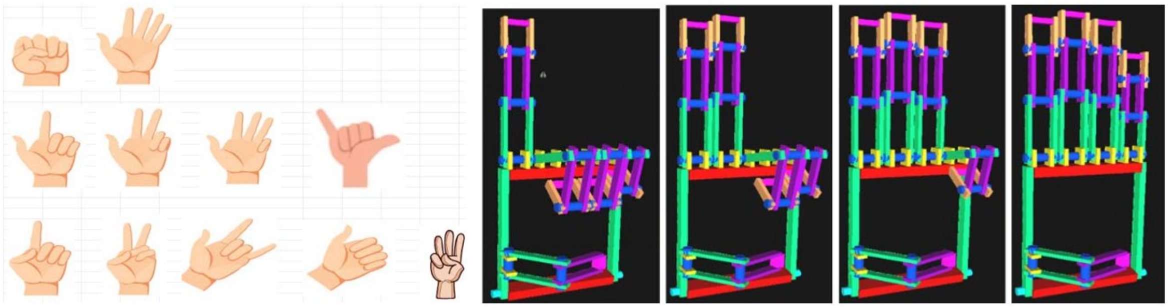


Figure 7.1.5.4. Pozițiile intermediare care constituie comenzile necesare la experimentarea aplicației BCI pentru controlul mâinii robotice 3D utilizând casca EEG NeuroSky.

BCI applications for controlling communication systems – virtual keyboard – through the Divide et Impera method using voluntary eye blinks

The commands implemented in the LabVIEW brain-computer interface application, based on the Divide et Impera method for facilitating communication by transferring messages using a virtual keyboard through voluntary eye blinks, are described in Table 7.1.5.7.

Table 7.1.5.7 Description of the commands necessary for experimenting with brain-computer interface applications based on the Divide et Impera method using voluntary eye blinks.

INDIVIDUAL COMMANDS	DESCRIPTION
TRANSITION between rows, halves/portions of a row, and keys	1 voluntary eye-blink
SELECTION of a row, half of a row, or key	2 voluntary eye-blink
CANCELING the selection of a row, half of a row, or key	3 voluntary eye-blink
DELETING the last entered character	4 voluntary eye-blink
SPACE – entering a space character	5 voluntary eye-blink

The BCI communication application experiment using the virtual keyboard was performed by completing the following three tasks, based on entering the following three words: EYE, BRAIN, and COMPUTER. Figures 7.1.5.6, 7.1.5.7, 7.1.5.8, and 7.1.5.9 present the optimal number of voluntary eye blinks that a subject should ideally perform to efficiently write each of the three requested words, considering the placement of all necessary characters on the virtual keyboard in the user interface – Figure 7.1.5.5. Information, explanations, and additional details regarding the determination of the number of blinks for each word can be found in the ANNEXES – Section 7.1.5.

The total number of voluntary eye blinks correctly detected by the LabVIEW BCI communication application constitutes the sum of all true-positive (TP) cases, while the total number of correctly identified non-blinks by the LabVIEW tool for controlling the virtual keyboard represents the sum of all true-negative (TN) cases.

Moreover, voluntary eye blinks that are incorrectly undetected by the LabVIEW application result in an increased number of false-negative (FN) cases. This increase occurs when the user performs blinks for transitions or selections, but these are not recognized, and consequently, the corresponding actions are not observed on the virtual keyboard. The number of FN cases increases when the threshold amplitude for detecting voluntary eye blinks is very high, making it unattainable for the user during the actual experiment.

Additionally, non-blink events (muscle artifacts, vibrations, noise) that are incorrectly identified as voluntary eye blinks by the LabVIEW application contribute to an increased number of false-positive (FP) cases. This increase occurs when the user does not intentionally blink to perform transitions or selections, yet the corresponding actions erroneously appear on the virtual keyboard. The number of FP cases increases when the threshold amplitude for detecting voluntary eye blinks is very low, causing the user to unintentionally exceed it during the real experiment.

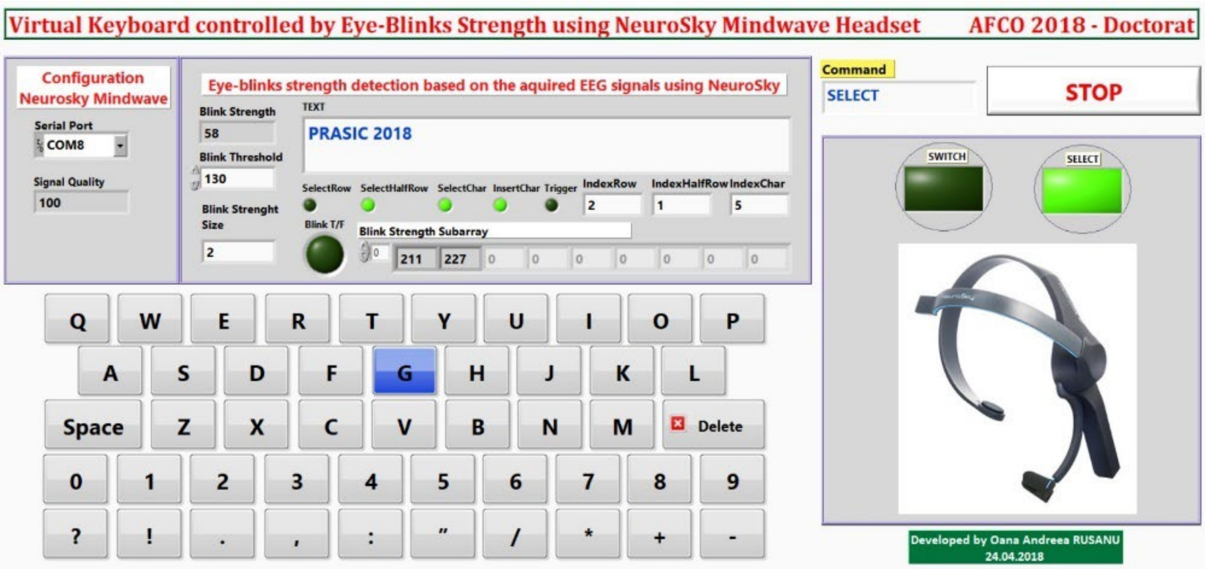


Figure 7.1.5.5. The Front Panel (User Graphical Interface) of the LabVIEW application for controlling the virtual keyboard using voluntary eye blinks detected from the NeuroSky EEG signal.

EYE	2 eye-blinks select row 1	3 eye-blinks - CANCEL	3 eye-blinks - CANCEL	1+1+1+1 eye-blinks - SPACE - Insert Character SPACE	
	2 eye-blinks select first half-row	2 eye-blinks select row	2 eye-blinks select row		
	1+1 eye-blinks switch until E	1 clipire - switch to second half-row	1 clipire - switch to first half-row		
	2 eye-blinks select E	2 eye-blinks select second half-row	2 eye-blinks select first half-row		
		2 eye-blinks select Y	1+1 eye-blinks switch to E		
			2 eye-blinks select E		
	total: 4 non eye-blinks	total: 5 non eye-blinks	total: 6 non eye-blinks	total: 1 non eye-blinks	TOTAL: 16 Non Eye-Blinks
	total: 8 eye-blinks - Character E	total: 10 eye-blinks - Character Y	total: 12 eye-blinks - Character E	total: 4 eye-blinks - Space Character	
	TOTAL: 8 + 10 + 12 + 4 = 34 Eye-Blinks for EYE				

Figure 7.1.5.6 Typing the word "EYE" on the virtual keyboard using voluntary eye blinks.

BRAIN	3 eye-blinks - CANCEL row 1	3 eye-blinks - CANCEL / anutore row 3	3 eye-blinks - CANCEL row 1	3 eye-blinks - CANCEL row 2	3 eye-blinks - CANCEL row 1	1+1+1+1 eye-blinks - insert SPACE
	1+1 eye-blinks switch to row 3	1+1+1 switch/return to row 1	1 eye-blink - switch to row 2	1+1+1+1 eye-blinks - switch to row 1	1+1 eye-blinks - switch to row 2	
	2 eye-blinks - select row 3	2 eye-blinks - select row 1	2 eye-blinks - select row 2	2 eye-blinks - select row 1	2 eye-blinks - select row 3	
	1 eye-blink = switch to second half-row	2 eye-blinks - select first half-row	2 eye-blinks - select first half-row	1 eye-blink - switch to second half-row	1 eye-blink - switch to second half-row	
	2 eye-blinks - select second half-row	1+1+1 eye-blinks - switch Character R	2 eye-blinks - select Character A	2 eye-blinks - select select second half-row	2 eye-blinks - select second half-row	
	2 eye-blinks - select Character B	2 eye-blinks - select Character R		1+1 eye-blinks - switch to Character I	1 eye-blink - switch to Character N	
				2 eye-blinks - select Character I	2 eye-blinks - select Character N	
	total: 6 non-eye-blinks	total: 6 non-eye-blinks	total: 5 non-eye-blinks	total: 7 non-eye-blinks	total: 7 non-eye-blinks	TOTAL: 32 non-eye-blinks
	total: 12 eye-blinks - Character B	total: 15 eye-blinks - Character R	total: 10 eye-blinks - Character A	total: 16 eye-blinks - Character I	total: 13 eye-blinks - Character N	
			TOTAL: 12 + 15 + 10 + 16 + 13 + 4 = 70 eye-blinks pt. BRAIN			

Figure 7.1.5.7. Typing the word "BRAIN" on the virtual keyboard using voluntary eye blinks.

COMPUTER	3 eye-blinks - CANCEL the previous command	3 eye-blinks - CANCEL row 3	3 eye-blinks - CANCEL row 1	3 eye-blinks - CANCEL row 3	3 eye-blinks - CANCEL the previous command
	2 eye-blinks - select row 3	1+1+1+1 switch/return to row 1	1+1 eye-blinks - switch to row 3	1+1+1 eye-blinks - switch to row 1	2 eye-blinks - select row 1
	1 eye-blink - switch to first half-row	2 eye-blinks - select row 1	2 eye-blinks - select row 3	2 eye-blinks - select row 1	1+1 eye-blinks - switch to Character U
	2 eye-blinks - select first half-row	1 eye-blink - switch to second half-row	1 eye-blink - switch to second half-row	1 eye-blink - switch to second half-row	2 eye-blinks - select Character U
	1+1 eye-blinks - switch to Character C	2 eye-blinks - select second half-row	1+1 eye-blinks - switch to Character M	1+1+1+1 eye-blinks - switch to Character P	
	2 eye-blinks - select Character C	1+1+1 eye-blinks - switch to Character O	2 eye-blinks - select Character M	2 eye-blinks - select Character P	
		2 eye-blinks - select Character O			
	total: 6 non-eye-blinks	total: 7 non-eye-blinks	total: 6 non-eye-blinks	total: 6 non-eye-blinks	total: 4 non-eye-blinks
	total: 12 eye-blinks - Character C	total: 17 eye-blinks - Character O	total: 12 eye-blinks - Character M	total: 15 eye-blinks - Character P	total: 9 eye-blinks - Character U
				TOTAL: 12 + 17 + 12 + 15 + 9 + 14 + 10 + 8 = 97 eye-blinks pt. COMPUTER	

Figure 7.1.5.8. Typing the word "COMPUTER" (first characters up to "U") on the virtual keyboard.

3 eye-blinks - CANCEL the previous command	3 eye-blinks - CANCEL the previous command	3 eye-blinks - CANCEL the previous command	
2 eye-blinks - select row 1	2 eye-blinks - select row 1	2 eye-blinks - select row 1	
1 eye-blink - switch to first half-row	1+1+1 - switch to Character E	1 eye-blink - switch to Character R	
2 eye-blinks - select first half-row	2 eye-blinks - select Character E	2 eye-blinks - select Character R	
1+1+1+1 eye-blinks - switch to Character T			
2 eye-blinks - select Character T			
total: 6 non-eye-blinks	total: 4 non-eye-blinks	total: 4 non-eye-blinks	TOTAL: 43 non-eye-blinks
total: 14 eye-blinks - Character T	total: 10 eye-blinks - Character E	total: 8 eye-blinks - Character R	

Figure 7.1.5.9. Typing the word "COMPUTER" (characters starting from "T") on the virtual keyboard.

Figure 7.1.5.10 presents the information previously revealed in Figures 7.1.5.6, 7.1.5.7, 7.1.5.8, and 7.1.5.9, summarized in three tables corresponding to the difficulty levels (beginner, intermediate, advanced). It shows the total optimal number of true-positive (TP) cases (voluntary eye blinks) and the total optimal number of true-negative (TN) cases (non-blinks) determined for completing each task: entering a specific character from the words EYE – BRAIN – COMPUTER.

BEGINNER			
No.	Command	Eye-Blinks	Non Eye-Blinks
1	E	8	4
2	Y	10	5
3	E	12	6
4	SPAȚIU	4	1
	TOTAL	34	16

INTERMEDIATE			
No.	Command	Eye-Blinks	Non Eye-Blinks
1	B	12	6
2	R	15	6
3	A	10	5
4	I	16	7
5	N	13	7
6	SPACE	4	1
	TOTAL	70	32

ADVANCED			
No.	Command	Eye-Blinks	Non Eye-Blinks
1	C	12	6
2	O	17	7
3	M	12	6
4	P	15	6
5	U	9	4
6	T	14	6
7	E	10	4
8	R	8	4
9	SPACE	4	1
	TOTAL	101	44

Figure 7.1.5.10. The type, number, and order of commands based on the optimal quantification of voluntary eye blinks when experimenting with the BCI application for controlling the virtual keyboard using the NeuroSky EEG headset.

BCI Applications for Display Systems Control (Yoda Holograms and 8x8 LED Matrix) Using Binary Codes Generated by Voluntary Eye Blinks

The experimental stages for BCI applications controlling display systems, which include rendering animations on 8x8 LED matrices connected to the Arduino platform and transitioning through Yoda holograms displayed on a tablet running an Android application, involved executing commands determined by strong or soft voluntary eye blinks to generate binary codes. Therefore, based on setting a threshold value for the amplitude or intensity of voluntary eye blinks, strong blinks (with an amplitude above the threshold) and soft blinks (with an amplitude below the threshold) were categorized. A binary value of 1 represents a strong voluntary eye blink, while a binary value of 0 represents a soft voluntary eye blink. Thus, the cases TP – FP – TN – FN were determined as described below:

- TP (True-Positive) Cases: correctly detected strong voluntary eye blinks;
- FP (False-Positive) Cases: incorrectly detected strong voluntary eye blinks;
- TN (True-Negative) Cases: correctly detected soft voluntary eye blinks;
- FN (False-Negative) Cases: incorrectly detected soft voluntary eye blinks.

The number of FP cases increases when the blink threshold amplitude is low, erroneously recording additional strong voluntary eye blinks beyond those actually performed. Similarly, FP cases increment when the user generates a binary value of 1 (strong voluntary eye blink) instead of a binary value of 0 (soft voluntary eye blink) during experimentation. The number of FN cases increases when the blink threshold amplitude is high, erroneously resulting in additional soft voluntary eye blinks beyond those actually performed. FN cases also increment when the user generates a binary value of 0 (soft voluntary eye blink) instead of a binary value of 1 (strong voluntary eye blink) during experimentation.

Figure 7.1.5.11 illustrates three tables containing the optimal total number of TP cases (strong voluntary eye blinks) and the optimal total number of TN cases (soft voluntary eye blinks) for the proposed tasks at each difficulty level (beginner, intermediate, advanced), achieved by generating 16 binary codes during the experimentation of the BCI application for controlling the Yoda hologram display system using the NeuroSky EEG headset and an Android application.

BEGINNER			
No.	Binary Code	Strong Eye-Blinks	Mild Eye-Blinks
0	0000	0	4
1	0001	1	3
2	0010	1	3
	TOTAL	2	10

INTERMEDIATE			
No.	Binary Code	Strong Eye-Blinks	Mild Eye-Blinks
3	0011	2	2
4	0100	1	3
5	0101	2	2
6	0110	2	2
7	0111	3	1
	TOTAL	10	10

ADVANCED			
No.	Binary Code	Strong Eye-Blinks	Mild Eye-Blinks
8	1000	1	3
9	1001	2	2
10	1010	2	2
11	1011	3	1
12	1100	2	2
13	1101	3	1
14	1110	3	1
15	1111	4	0
	TOTAL	20	12

Figure 7.1.5.11. Type, number, and order of commands based on optimal quantification of voluntary eye blinks during the experimentation of the BCI application for the Yoda Hologram display system with NeuroSky EEG headset.

BEGINNER			
No.	Binary Code	Strong Eye-Blinks	Mild Eye-Blinks
0	00000001	1	7
	TOTAL	1	7

INTERMEDIATE			
No.	Binary Code	Strong Eye-Blinks	Mild Eye-Blinks
3	00000011	2	6
4	00000111	3	5
5	00001111	4	4
	TOTAL	9	15

ADVANCED			
No.	Binary Code	Strong Eye-Blinks	Mild Eye-Blinks
8	00011111	5	3
9	00111111	6	2
10	01111111	7	1
11	11111111	8	0
	TOTAL	26	6

Figure 7.1.5.12. Type, number, and order of commands based on optimal quantification of voluntary eye blinks during the experimentation of the BCI application for the 8x8 LED matrix display system with NeuroSky EEG headset and Arduino development platform.

Figure 7.1.5.12 presents the optimal results based on generating 12 codes, each consisting of 8 binary values, to generate the commands needed to control the BCI application for rendering graphical animations on 8x8 LED matrices connected to the Arduino platform. The three tables present the optimal number of TP cases (strong voluntary eye blinks) and TN cases (soft voluntary eye blinks) calculated for each task/binary code and difficulty level (beginner, intermediate, advanced).

Experimental Stages for BCI Using P300 Evoked Potentials

The experimentation stage of BCI applications for controlling various assistive systems involves transmitting commands by correctly identifying symbols covered by light flashes to detect P300 evoked potentials. During the BCI testing or experimentation stage, a specific number of P300 commands or symbols are projected with 16 flashes each. Within approximately 10 seconds after displaying the 16 flashes, a single symbol can be selected, resulting in the corresponding command based on the subject's attention depth and gaze direction. The P300 Speller software application cannot generate two simultaneous selections.

Therefore, if the user's intention (according to the initially established command) is correctly generated by the Unicorn P300 Speller tool, the number of TP (true-positive) and TN (true-negative) cases will increment. TP cases refer to the correct detection of desired target symbols. TN cases refer to the correct detection of undesired non-target symbols. TN cases are incremented because an undesired non-target symbol was not erroneously selected. Considering that multiple symbols cannot be selected simultaneously, for simplicity, the increment of TN cases involves adding a single unit (+1) in most BCI applications based on P300 evoked potential detection developed and experimented with in this doctoral thesis.

If the user's intention (determined by the proposed BCI experiment command) is not correctly generated by the Unicorn P300 Speller application, the number of FP (false-positive) and FN (false-negative) cases will increment. An erroneously selected alternative symbol represents a false-positive result because it was incorrectly chosen (unintentionally). The target symbol remained erroneously unselected, resulting in a false-negative outcome. Obviously, TP and TN cases do not increment, remaining unchanged.

7.1.6. Feedback Questionnaire Addressed to Volunteer Subjects After BCI Experimentation

Secondary Parameters Measured During the Experimentation of BCI Applications

Additionally, the experimentation with the proposed brain-computer interface applications for controlling mechatronic systems or communication tasks, using commands determined by voluntary eye blinks or P300 biopotentials (attention and gaze focus), involved monitoring the subjects to determine the following secondary parameters:

- The total number of attempts made to achieve maximum performance;
- The time allocated for the experimentation session;
- The intrinsic or extrinsic motivation level of the subjects regarding their participation in the testing activities of the proposed BCI application;
- The time of day when the subject performed the experiment;
- The degree of understanding of the explained instructions and exemplified steps;
- The clarity level of the received tasks;
- The perceived difficulty level by the subjects regarding the execution of voluntary eye blinks or focusing attention/gaze on light flashes;
- The degree of subjects' accommodation with the use of EEG headsets;

- The stress level experienced by each subject during the BCI experiment.

At the end of the brain-computer interface experimentation session, the thesis author asked the participants to complete a questionnaire (ANNEXES – Section 7.1.6) consisting of 28 questions: 11 mandatory questions requiring a response from the subjects, one optional question, and out of the remaining 14 questions, the subject needed to answer only those referring to the applications they tested. The questionnaire was uploaded to the educational platform – Moodle Elearning of the Transilvania University of Brașov, allowing students to complete the form electronically.

7.2. GENERAL ANALYSIS OF RESULTS OBTAINED IN BCI EXPERIMENTATION

7.2.1. Descriptive-Qualitative Analysis

The 129 volunteer subjects, comprising 121 students from the Computer Science program, third year (two cohorts – 79 young people aged 21-22 years) and Information Technology, fourth year (42 young people aged 23-24 years), as well as one doctoral candidate (female – 31 years old) along with 7 non-academic individuals (one male – 28 years old; one female – 30 years old; two men – 58 and 83 years old; three women – 58, 80, and 83 years old), experimented with at least one of the 25 brain-computer interface (BCI) applications. These applications were based on the use of NeuroSky EEG headsets (1 sensor), Emotiv Insight (5 sensors), or GTEC Unicorn (8 sensors), controlled with Arduino, Raspberry Pi, Micro, NI myRIO platforms, and implemented by the thesis author in LabVIEW, Python, Matlab, NodeRED during the doctoral program. Of the 129 subjects involved in the BCI experiments, 110 used the NeuroSky EEG headset, 4 participants wore the Emotiv EEG headset, performing voluntary eye blinks to control the applications, and 15 volunteers used the GTEC Unicorn EEG headset, focusing their gaze and attention on the P300 Speller.

This section describes and qualitatively analyzes all experimental results obtained by the 129 subjects, with specific details based on the headset used and highlights the perceptions of those involved in testing the BCI applications regarding the understanding of received instructions, performance achieved, difficulty of executing the BCI control method, EEG signal accuracy, accommodation with the EEG data acquisition device, task completion level, and internal state.

The annexes – Section 7.2.1 present the favorable and constructive feedback given by students on why they chose to participate in the BCI experimentation. They expressed interest and curiosity about the proposed activities.

Figure 7.2.1.1 shows the responses of the subjects regarding the extent to which the doctoral candidate presented the general instructions necessary for experimenting with the BCI application.

A percentage of 91% or 117 out of the 129 subjects involved confirmed that they received ample information, details that facilitated correct BCI experimentation. A number of 12 students (9%) understood the instructions reasonably well. Regarding the clarity of the tasks, 96% or 124 out of the 129 volunteer subjects reported that everything was clear, knowing from the beginning what results they needed to achieve by the end of the experiment, while 4% or 5 of the 129 participants noted that they almost completely understood the tasks, with some uncertainties remaining.

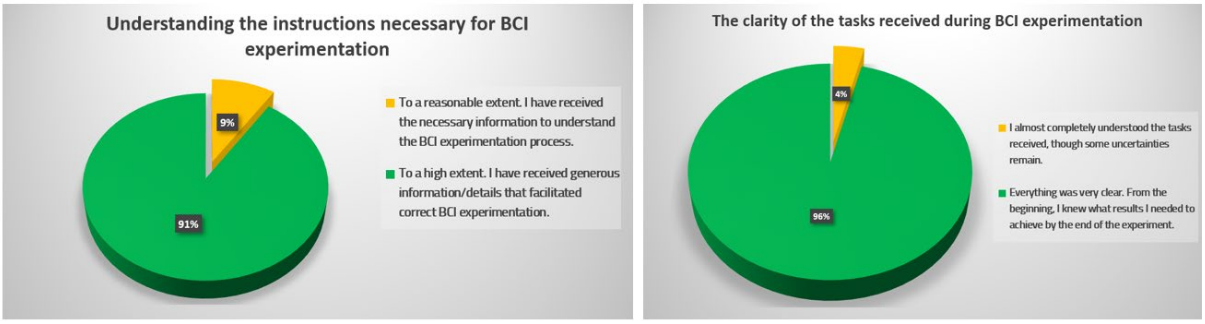


Figure 7.2.1.1. Subjects' responses regarding the level of understanding of the instructions and the clarity of the received tasks during BCI experimentation.

Figure 7.2.1.2 shows the subjects' responses regarding the difficulty level of the control method by performing voluntary eye blinks to control the BCI applications using NeuroSky headsets with a single EEG sensor and Emotiv Insight with 5 EEG sensors. The questionnaire completed by the subjects reported the following results regarding performance: low – 3% (3 subjects); medium – 54% (62 subjects); high – 43% (49 subjects). According to Figure 7.2.1.2, in the case of the control method by focusing attention and gaze on light flashes for detecting P300 evoked biopotentials necessary for BCI application control using the Unicorn headset with 8 EEG sensors, the performance was: high – 86% (13 subjects), medium – 7% (1 subject); low – 7% (1 subject).

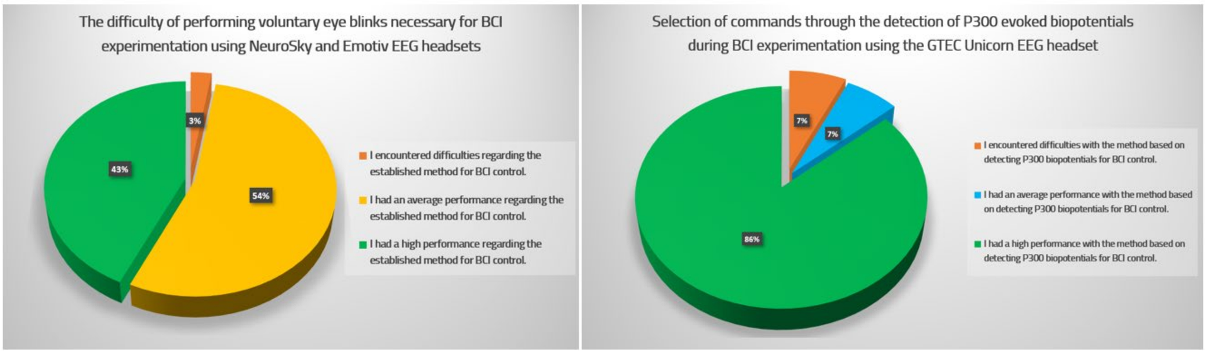


Figure 7.2.1.2. Subjects' responses regarding the difficulty level of the control method (eye blinks or looking at light flashes) during BCI experimentation.

Figure 7.2.1.3 shows the students' responses regarding their internal perception or how they felt during the BCI application experimentation, resulting in: 38% (49 subjects) had fun, were delighted, and fully dedicated to the experimental activity; 36% (47 subjects) felt relaxed, calm, with no constraints, worries, or fears; 12% (15 subjects) were more cautious/attentive/focused on fulfilling the received task; 9% (12 subjects) were slightly emotional but curious about the BCI control method; 3% (4 subjects) felt quite pressured due to the need to correctly perform the task; 2% (2 subjects) had predominantly positive personal experiences.

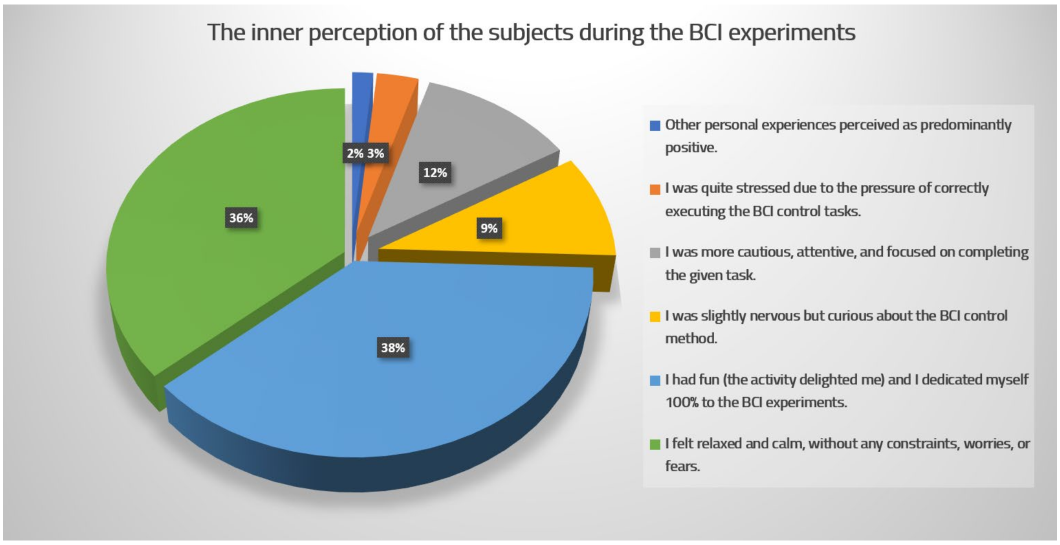


Figure 7.2.1.3. Subjects' responses regarding how they felt during the BCI application experimentation.

According to Figure 7.2.1.4, regarding the question about accommodation with the NeuroSky and Emotiv EEG sets (for detecting eye blinks) during BCI experiments, the subjects reported the following results: 78% (90 subjects) – everything was fine, accommodation took approximately 5 minutes; 17% (19 subjects) – encountered minor technical issues (quickly resolved), but did not perceive discomfort; 4% (4 subjects) – had difficulties, requiring more time to mount the EEG headset on the scalp; 1% (1 subject) – did not accommodate to wearing the headset, feeling discomfort. Concerning accommodation with the GTEC Unicorn EEG set (for detecting P300 evoked biopotentials) during BCI experiments, the subjects reported the following results: 73% (11 subjects) – the EEG signal quality was maximum during configuration and 27% (4 subjects) – the EEG signal quality was medium during configuration.

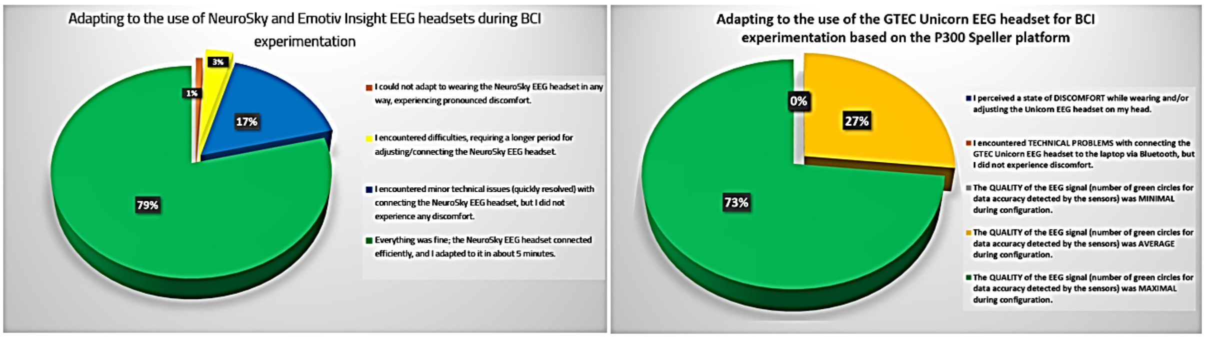


Figure 7.2.1.4. Subjects' responses regarding using the EEG headsets during BCI experimentation.

According to Figure 7.2.1.5, regarding the question about the performance achieved in testing BCI applications using the NeuroSky and Emotiv Insight EEG headsets, the subjects reported the following results: advanced level – 67% (103 subjects); intermediate level – 26% (40 subjects); beginner level – 7% (10 subjects). Regarding the performance of subjects in testing BCI applications using the GTEC Unicorn EEG headset, the results were: advanced level – 72% (21 subjects); intermediate level – 21% (6 subjects); beginner level – 7% (2 subjects). The results obtained are justified by the following observation: the graphs in Figure 7.2.1.5 were designed by accumulating data from the 182 multiple subjects or the 182 experimental observations, indicating that a subject tested, experimented, or evaluated multiple BCI applications.

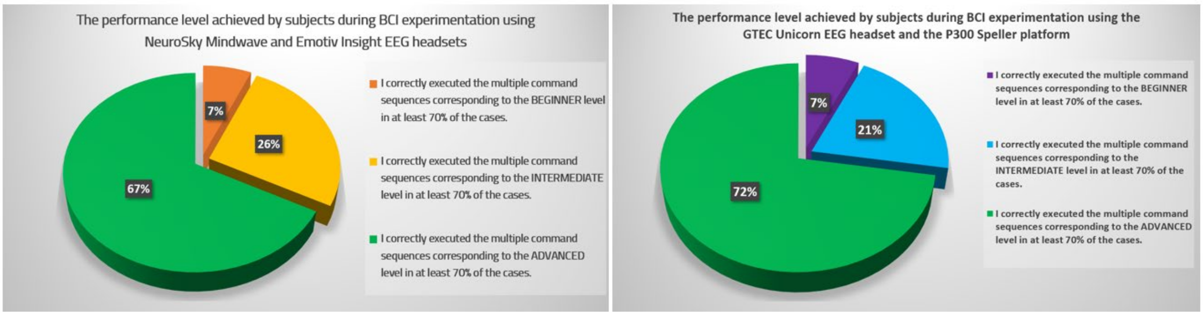


Figure 7.2.1.5. Subjects' responses regarding the performance level achieved in BCI experimentation using NeuroSky, Emotiv Insight, and GTEC Unicorn EEG headsets integrated with P300 Speller.

7.2.2. Descriptive-Quantitative Analysis

The experimentation of the 25 brain-computer interface (BCI) applications was conducted by 182 multiple subjects, of whom 129 represented unique subjects. Therefore, multiple subjects experimented with 2-3 BCI applications, while unique subjects tested a single BCI application.

The graph in Figure 7.2.2.1 shows the number of subjects who experimented with each of the BCI applications developed during the doctoral program. Thus, the minimum number – 2 subjects tested the BCI applications that involved monitoring EEG data in Python using the NeuroSky EEG headset, respectively controlling a 3D wheelchair model using the GTEC Unicorn headset. Also, a maximum number of 13 subjects explored the BCI application that involved transferring Android chat messages using the NeuroSky EEG headset.

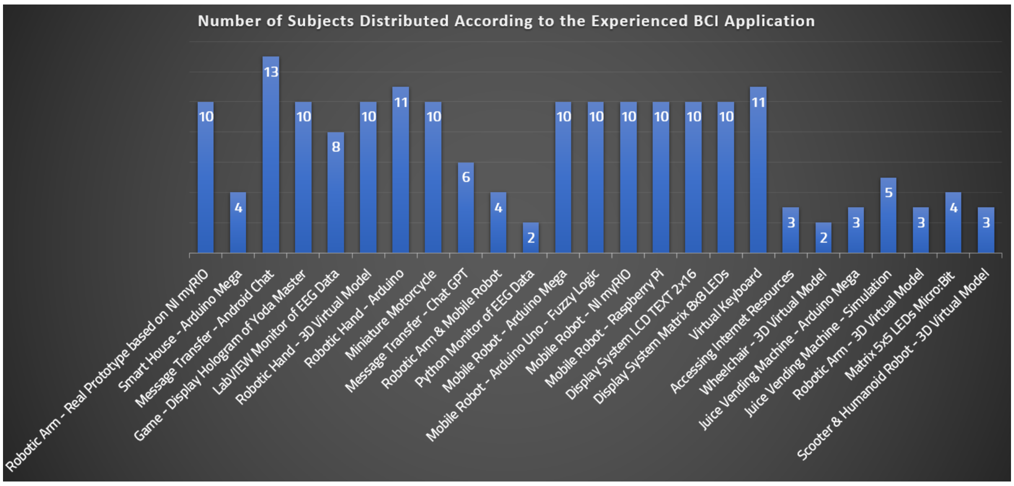


Figure 7.2.2.1. Determining the number of subjects who experimented with each of the 25 BCI applications.

The graph in Figure 7.2.2.2 shows the percentage of BCI applications that required a specific EEG headset (NeuroSky Mindwave, Emotiv Insight, GTEC Unicorn) during experimentation. Thus, 60% representing 15 BCI applications were tested with the NeuroSky Mindwave EEG headset. Also, 32% representing 8 BCI applications were experimented with the GTEC Unicorn EEG headset. The percentage of 8% determined by 2 BCI applications were explored using the Emotiv EEG headset.

The graph in Figure 7.2.2.2 shows the number of subjects who used a specific EEG headset during BCI experimental activities. The following percentages resulted: 80% or 145 multiple subjects wore the NeuroSky headset, 16% or 29 subjects used the GTEC Unicorn headset, and 4% or 8 subjects used the Emotiv headset during BCI experiments. In other words, there were: 145 uses or 80% for the NeuroSky headset, 29 uses or 16% for the GTEC headset, and 8 uses or 4% for Emotiv.

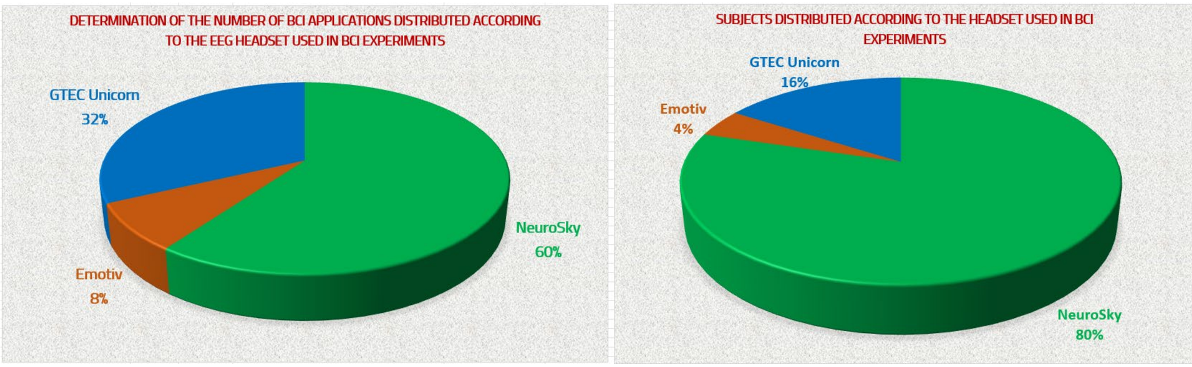


Figure 7.2.2.2. Distribution of the number of BCI applications and subjects based on the EEG headset used.

The graph in Figure 7.2.2.3 shows the distribution of BCI applications according to the three main control methods during experimentation by subjects: 64% or 16 BCI applications involved performing voluntary eye blinks, 32% or 8 BCI applications required focusing attention and gaze on light flashes, and 4% or a single BCI application was based on closing and opening the eyeballs.

The graph in Figure 7.2.2.4 shows the distribution of BCI applications based on the specific control method during experimentation, resulting in the following classification: 8 BCI applications based on detecting P300 evoked biopotentials, 6 BCI applications based on transition and selection commands determined by voluntary eye blinks; 3 BCI applications based on a blink counting algorithm; 2 BCI applications each involving generating binary codes by performing blinks and analyzing raw EEG signals; one BCI application each integrating different techniques – a custom blink counting algorithm or determining blink amplitude by analyzing EEG data using Fuzzy Logic; Divide et Impera algorithm applied to blinks; Alpha EEG rhythm analysis.

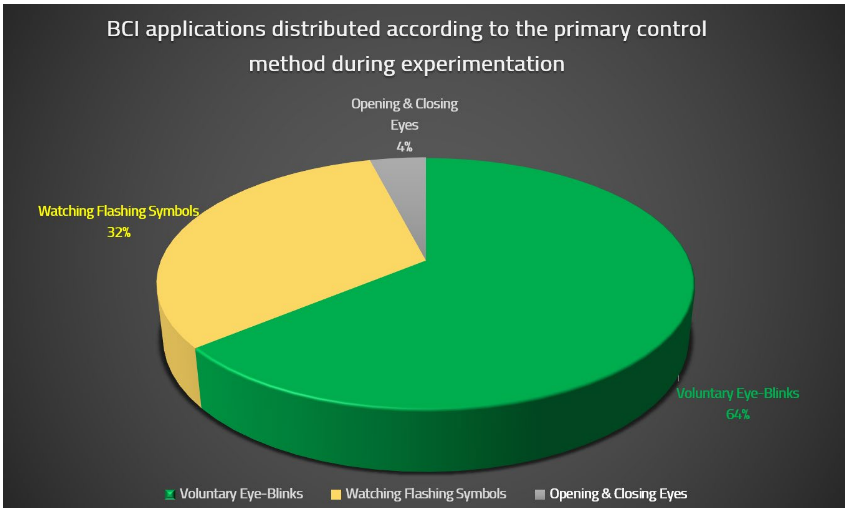


Figure 7.2.2.3. Distribution of BCI applications according to the main control method during experimentation.

The graph in Figure 7.2.2.5 shows the distribution of BCI applications according to the purpose fulfilled during experimentation and the software environment in which they were developed by the author of this doctoral thesis. Based on the primary purpose or final utility, the results were: 8 BCI applications each for controlling robotic systems and 3D models or virtual simulations, 4 BCI applications each for communication or message transfer and implementing EEG – SW – HW interfacing solutions, and 2 BCI applications created for educational purposes, for scientific research through EEG data acquisition, processing, and classification. According to the software environment in which they were developed, the results were: 6 BCI applications in LabVIEW; 5 BCI applications in LabVIEW and Arduino; 2 BCI applications – Python; LabVIEW and MIT App Inventor; one BCI application each integrating – LabVIEW, Arduino or Python, Unicorn P300 Speller; Matlab; NodeRED; Python and Arduino.

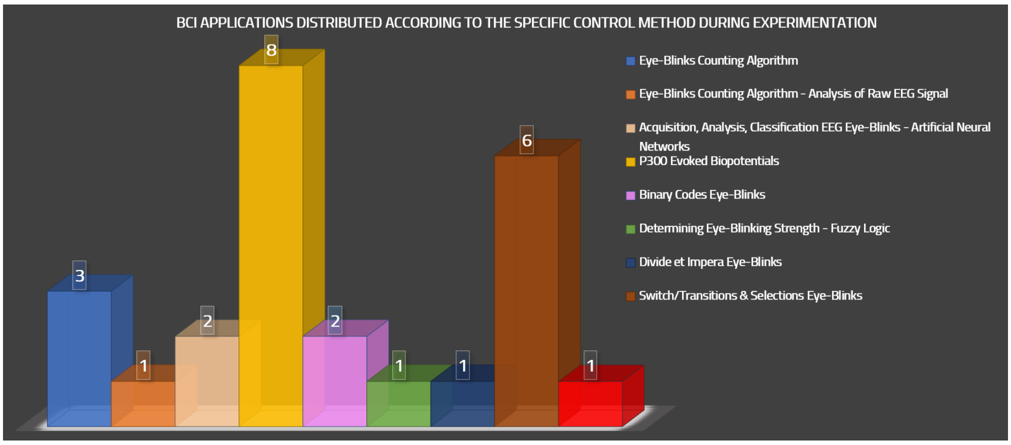


Figure 7.2.2.4. Distribution of BCI applications based on the specific control method during experimentation.

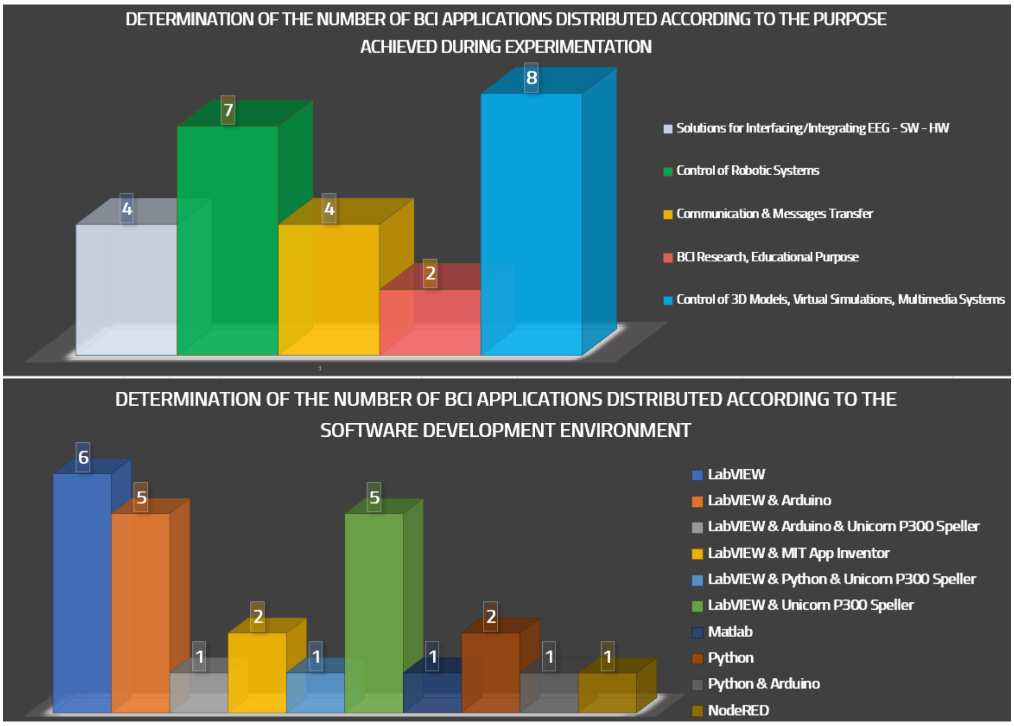


Figure 7.2.2.5. Distribution of BCI applications according to the purpose fulfilled and the software environment used for development.

The graph in Figure 7.2.2.6 shows the distribution of BCI applications according to the hardware platform used for control by the author of this doctoral thesis. The results were: 4 BCI applications each developed with Arduino Mega and Arduino Uno; 2 BCI applications programmed with NI myRIO; one application each implemented with Arduino Nano 33 IoT, Raspberry Pi, and Micro. The remaining 12 BCI applications involved controlling 3D models, virtual simulations, or multimedia systems, so they did not require a development platform.

The graph in Figure 7.2.2.7 shows the minimum – average – maximum values for Sensitivity, calculated based on the overall results obtained by the 182 multiple subjects in experimenting with the 25 BCI applications to evaluate performance. The following general results for Sensitivity were determined: minimum value = 56%, average value = 90%, and maximum value = 100%.

The graph in Figure 7.2.2.8 shows the minimum – average – maximum values for Specificity, calculated based on the overall results obtained by the 182 multiple subjects in experimenting with the 25 BCI applications to evaluate performance. The following general results for Specificity were determined: minimum value = 51%, average value = 88%, and maximum value = 100%.

The graph in Figure 7.2.2.9 shows the minimum – average – maximum values for Precision, calculated based on the overall results obtained by the 182 multiple subjects in experimenting with the 25 BCI applications to evaluate performance. The following general results for Precision were determined: minimum value = 56%, average value = 90%, and maximum value = 100%.

The graph in Figure 7.2.2.10 shows the minimum – average – maximum values for Accuracy, calculated based on the overall results obtained by the 182 multiple subjects in experimenting with the 25 BCI applications to evaluate performance. The following general results for Accuracy were determined: minimum value = 56%, average value = 90%, and maximum value = 100%.

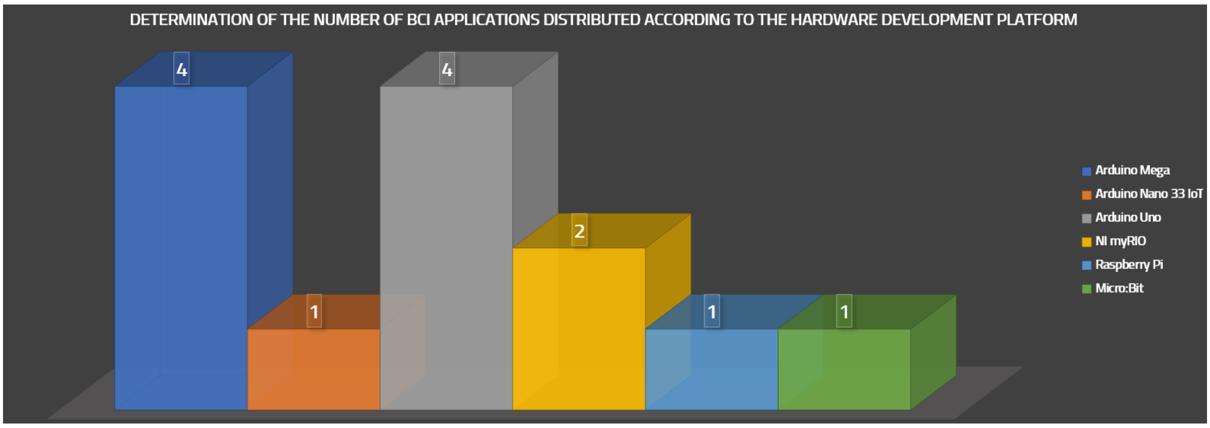


Figure 7.2.2.6. Distribution of BCI applications according to the hardware platform used for development.

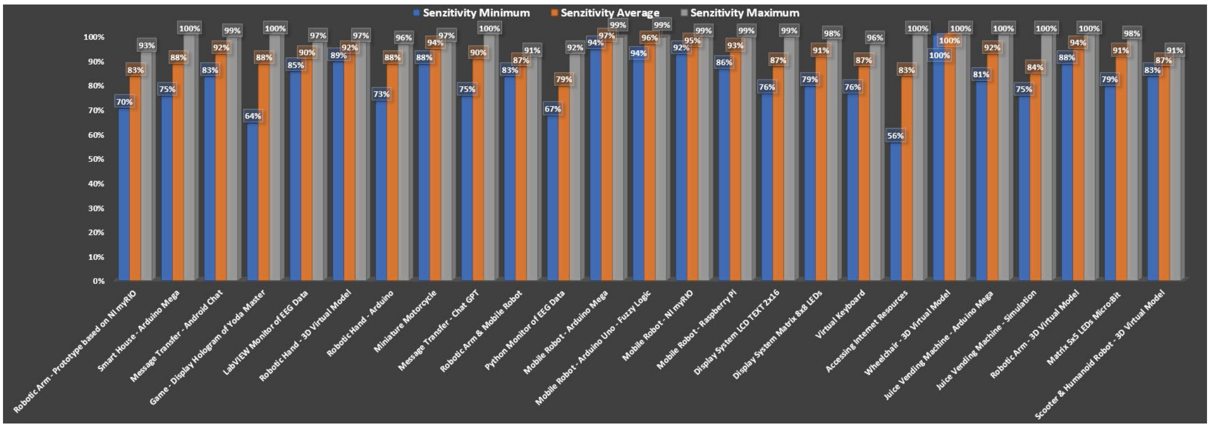


Figure 7.2.2.7. Minimum – average – maximum values for Sensitivity calculated based on all results obtained by subjects in experimenting with the 25 BCI applications.

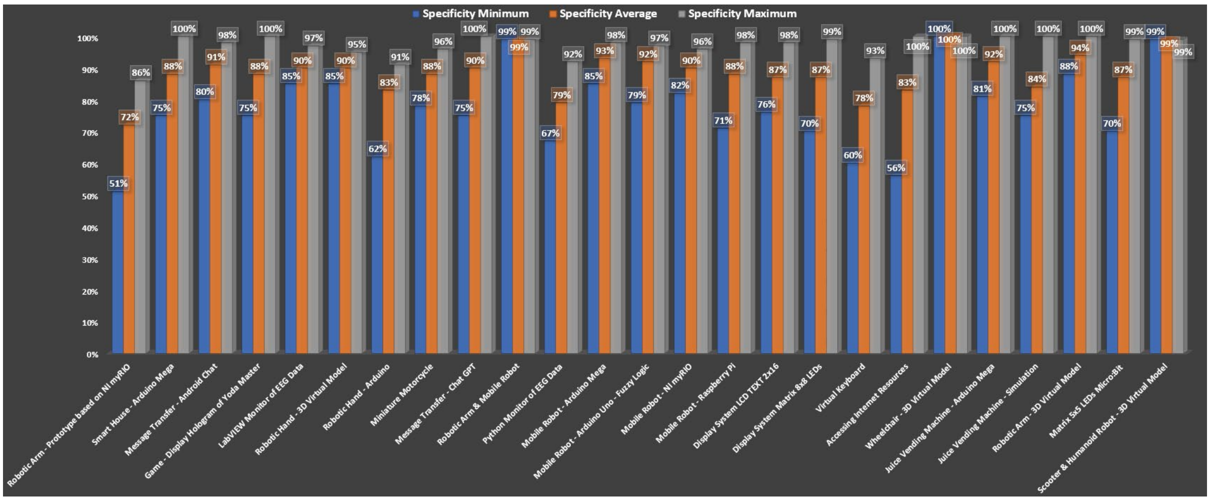


Figure 7.2.2.8. Values for Specificity calculated based on the experimentation of the 25 BCI applications.

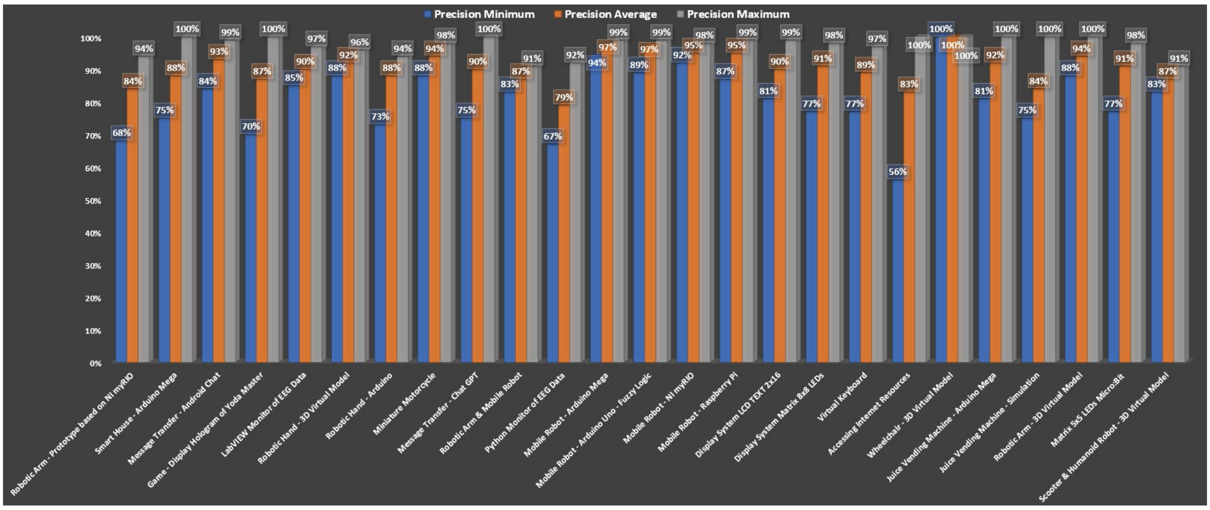


Figure 7.2.2.9. Minimum – average – maximum values for Precision calculated based on all results obtained by students in experimenting with the 25 BCI applications.

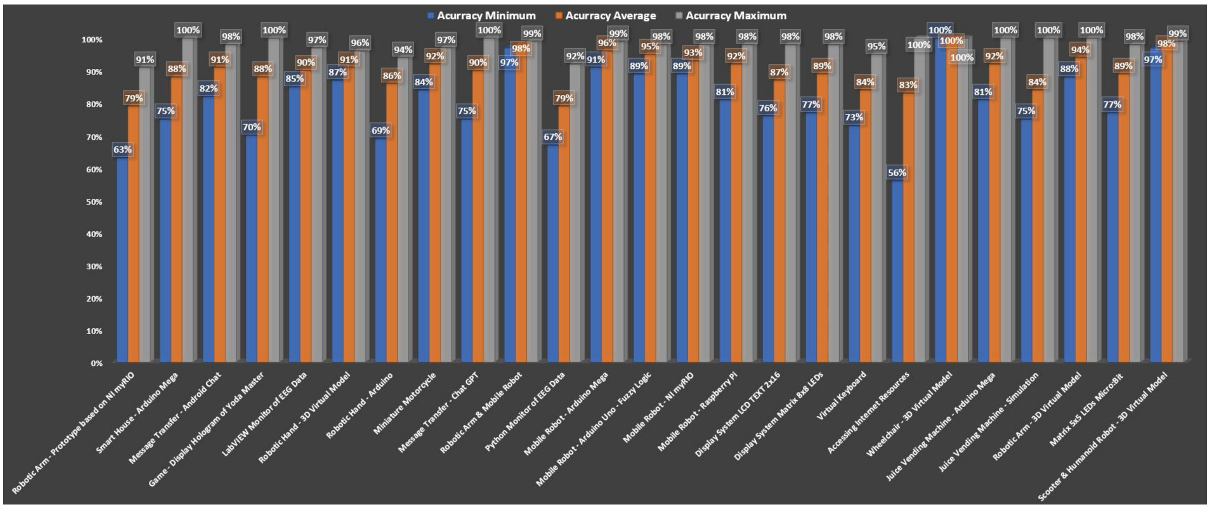


Figure 7.2.2.10. Minimum – average – maximum values for Accuracy calculated based on all results obtained by students in experimenting with the 25 BCI applications.

7.2.5. SWOT Analysis

This section presents three SWOT analyses to highlight the strengths, weaknesses, opportunities, and threats regarding the evaluation of the proposed, designed, implemented, and experimented Brain-Computer Interface (BCI) applications within the doctoral thesis. These are classified/grouped as follows:

- SWOT Analysis for the evaluation of BCI applications controlled by voluntary eye blinks or P300 evoked biopotentials from the user's perspective – Figure 7.2.5.1;
- SWOT Analysis for the evaluation of BCI applications controlled by voluntary eye blinks or P300 evoked biopotentials from the developer's perspective – Figure 7.2.5.2;
- SWOT Analysis for the evaluation of BCI applications controlled by voluntary eye blinks or P300 evoked biopotentials from the researcher's perspective – Figure 7.2.5.3.

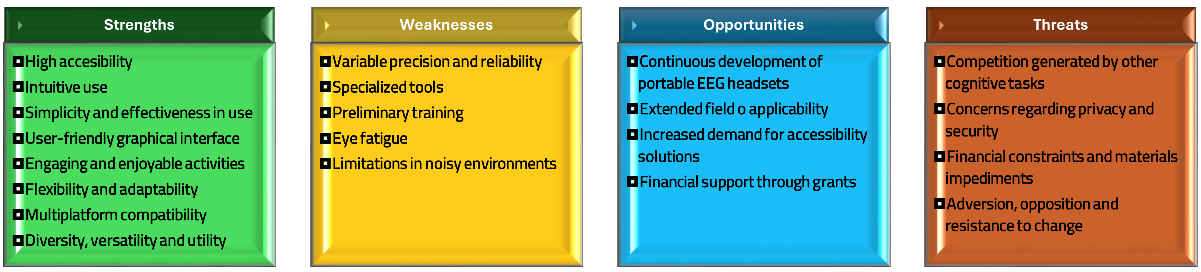


Figure 7.2.5.1 SWOT Analysis for the evaluation of BCI applications controlled by voluntary eye blinks or P300 evoked biopotentials from the user's perspective.

Figure 7.2.5.2 SWOT Analysis for the evaluation of BCI applications controlled by voluntary eye blinks or P300 evoked biopotentials from the developer's perspective.

Figure 7.2.5.3 SWOT Analysis for the evaluation of BCI applications controlled by voluntary eye blinks or P300 evoked biopotentials from the researcher's perspective.

7.3. BCI APPLICATIONS BASED ON THE INTEGRATION OF EEG - HARDWARE - SOFTWARE

7.3.1. Essential Aspects of the Developed and Experimented BCI Applications

This subchapter presents the results of experimental research based on a series of original software and hardware brain-computer interface (BCI) applications, implemented in various programming languages and environments, with the integral contribution of the author of this doctoral thesis. Thus, the results obtained by integrating EEG data acquisition solutions, software development environments, and hardware systems have fulfilled the first specific objective: Designing, creating, and implementing efficient interfacing solutions between hardware platforms (NI myRIO, Arduino, Raspberry Pi, Micro), software development environments (LabVIEW, Matlab, Arduino, Python, NodeRED), and portable sets (NeuroSky, Emotiv Insight, GTEC Unicorn) for the acquisition of electroencephalographic signals.

BCI Application Based on the Integration in LabVIEW between NeuroSky and NI myRIO

Regarding the BCI application experimented in section 7.3.2, the doctoral candidate has published several pieces of information in the form of a scientific paper, indexed ISI (Web of

Science), in the IOP Science database. Since 2018, the paper [411] has been accessible at the DOI link: 10.1088/1757-899X/444/4/042014. Additionally, the paper titled "A brain-computer interface based on the integration of NI myRIO development device and NeuroSky Mindwave headset" was presented at the ACME 2018 Conference (The 8th International Conference on Advanced Concepts in Mechanical Engineering), held in Iași, Romania, on June 7-8, 2018.

Furthermore, utilizing the specific information regarding the BCI application experimented in section 6.3.2, the doctoral candidate, as a co-author, included a section in the scientific article [92], indexed BDI (ASME Press), presented at the CEMD 2017 Conference (International Conference on Control Engineering and Mechanical Design), held in China. Since 2018, the paper [92] has been accessible at the DOI link: https://doi.org/10.1115/1.861677_ch23.

Moreover, the LabVIEW tools of the brain-computer interface (BCI) type, experimented in section 7.3.2, were initially developed and presented in the Dissertation Work [398], conceived by the author of this thesis in 2017, to complete the Master's studies – Mechatronic Systems for Industry and Medicine. The Dissertation Work laid the groundwork for publishing two scientific articles during the doctoral stage and formed the basis on which the doctoral candidate designed the more complex BCI application, presented in section 7.6.3 of this thesis, for controlling a robotic arm using NI myRIO and the NeuroSky EEG headset to detect voluntary eye blinks.

Additionally, the LabVIEW BCI applications, experimented in section 7.3.2, enjoyed high success in 2017, reflected both by the significant awards received by the doctoral candidate in student project competitions held at events such as AFCO (Graduates in Front of Companies – organized at Transilvania University of Brașov) and ZEM (Mechatronics Education Days – with the participation of mechatronics students from faculties across the country), as well as through local media coverage, including presentations at scientific events like Researchers' Night.

BCI Application Based on the Integration in Matlab between NeuroSky and Arduino Nano 33 IoT

Regarding the BCI application experimented in section 7.3.3, the doctoral candidate has published additional information in the form of a scientific paper, indexed in the SCIENDO database. Since December 2021, the paper [422] has been accessible at the DOI link: https://doi.org/10.2478/9788395815065-033. Additionally, this paper was presented at the ICISIL 2021 Conference (The 11th International Conference on Information Science and Information Literacy), held in Brașov, Romania, on March 11-12, 2021. A video clip demonstrating the partial use of this BCI application is available on YouTube at address [391].

BCI Application for Integration in Python between NeuroSky and Raspberry Pi

Regarding the BCI application experimented in section 7.3.4, the doctoral candidate has published additional information in the form of a scientific paper, indexed in the BDI – Springer database. Since January 1, 2022, the paper [399] has been accessible at the DOI link: https://doi.org/10.1007/978-3-030-92328-0_31. This paper was also presented at the ICNBME 2021 Conference (The 5th International Conference on Nanotechnologies and Biomedical Engineering), held in Chișinău, Moldova, on November 3-5, 2021. The live presentation recording from the conference can be viewed at this YouTube link: [353] (uploaded by IDSI TV).

Real-time demonstration videos of the proposed Python application's functionality and usage principles can be viewed on YouTube at the following addresses: [358], [359], and [537].

BCI Application Based on the Integration in NodeRED between Emotiv and Micro

Regarding the BCI application experimented in section 7.3.5, the doctoral candidate has published additional information in the form of a scientific paper [409], indexed in the BDI – Springer database. Since January 1, 2024, the paper [409], [410] has been accessible at the DOI link: https://doi.org/10.1007/978-3-031-42467-0_82. This paper was presented at the REV 2023 Conference (The 20th International Conference on Remote Engineering and Virtual Instrumentation), held in Thessaloniki, Greece, on March 1-3, 2023.

Real-time demonstration videos of the proposed Python, NodeRED, and LabVIEW applications' functionality and usage principles can be viewed on YouTube at the following addresses: [306], [369], [370], [373], and [362].

BCI Application Based on the Integration in Python between Emotiv and Arduino

Regarding the BCI application experimented in section 7.3.6, the doctoral candidate has published additional information in the form of a scientific paper [383], indexed in the BDI – Springer database. Since January 2, 2023, the paper [383] has been accessible at the DOI link: https://doi.org/10.1007/978-3-031-42467-0_82. This paper was presented at the EHB 2022 Conference (The 10th edition of the E-Health and Bioengineering Conference), held in Iași, Romania, on November 17-18, 2022.

The real-time demonstration video of the proposed Python and Arduino applications' functionality and usage principles can be viewed on YouTube at the address: [360].

BCI Application Based on the Integration in LabVIEW between Unicorn and Arduino

Regarding the BCI application experimented in section 7.3.7, the doctoral candidate has published additional information in the form of a scientific paper [355], indexed in the BDI – Springer database. Since April 2, 2024, the paper [355] has been accessible at the DOI link: https://doi.org/10.1007/978-3-031-42467-0_82. This paper was also presented at the ICL 2023 Conference (The 26th International Conference on Interactive Collaborative Learning), held in Madrid, Spain, on September 26-29, 2023.

Real-time demonstration videos of the proposed Python, NodeRED, and LabVIEW applications' functionality and usage principles can be viewed on YouTube at the following addresses: [388], [384], [386].

7.4. BCI APPLICATIONS FOR RESEARCH BASED ON ARTIFICIAL INTELLIGENCE

7.4.1 Essential Aspects of the Developed and Experimented BCI Applications

This chapter presents the results of experimental research based on a series of original software and hardware brain-computer interface (BCI) applications, implemented in LabVIEW and

Python, with the integral contribution of the author of this doctoral thesis. The applications proposed in the following sections allow for the acquisition, processing, and classification of electroencephalographic signals, both online (in real-time) and offline, using techniques based on artificial neural networks. Additionally, by methods based on Fuzzy Logic, the amplitude of voluntary eye blinks was determined, which subsequently represented commands for controlling a mobile robot.

Thus, the results obtained in this subchapter have fulfilled the second specific objective: Designing, creating, and implementing software tools for the acquisition, processing, and classification of electroencephalographic signals, both online (in real-time) and offline, using techniques based on artificial neural networks and Fuzzy Logic methods.

LabVIEW Application for Monitoring and Analyzing EEG Data

The aspects presented in section 7.4.2 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, indexed in the ISI – Web of Science database. Since April 27, 2023, the paper [401] has been accessible at the DOI link: https://doi.org/10.3991/ijoe.v19i05.37857. Therefore, the mentioned paper was published in the International Journal of Online and Biomedical Engineering, volume 19, issue 5, year 2023.

Previously, the doctoral candidate published two initial Preprint versions (shortened, with 33 pages, and extended, with 44 pages), which can be accessed at this link: https://www.preprints.org/manuscript/202106.0016/v2.

The demonstration videos showing the proposed LabVIEW application's functionality can be viewed on YouTube at the following links: [367] and [376].

Python Application for Monitoring and Analyzing EEG Data

The aspects presented in section 7.4.3 regarding the description of the developed Python application are based on information published by the author of this thesis in the form of a scientific paper, indexed in the BDI - Springer database. Since January 1, 2022, the paper [401] has been accessible at the DOI link: https://doi.org/10.1007/978-3-030-92328-0_84. This paper was also presented at the ICNBME 2021 Conference (The 5th International Conf. on Nanotechnologies and Biomedical Engineering), held in Chișinău, Moldova, on November 3-5, 2021. The live presentation recording from the conference can be viewed at this YouTube link: [400] (uploaded by IDSI TV).

Real-time demonstration videos of the proposed Python application's functionality and usage principles can be viewed on YouTube at the following addresses: [371], [372] (uploaded by the author of this thesis).

LabVIEW Application for BCI Based on Fuzzy Logic

The aspects presented in section 7.4.4 regarding the description of the LabVIEW application for detecting blink amplitude through Fuzzy Logic are based on information published by the author of this thesis in the form of a scientific paper, indexed in the ISI (Web of Science) – Springer database. Since February 2022, the paper [415] has been accessible at the DOI link: https://doi.org/10.1007/978-3-030-93817-8_66. This paper was presented at the INTER-ENG

2021 Conference (The 15th International Conference – Interdisciplinarity in Engineering), held in Târgu Mureș, Romania, on October 7-8, 2021.

Additionally, the real-time demonstration video of the LabVIEW application's usage principles, presented in this chapter, can be found at the YouTube link: [361].

7.5. BCI APPLICATIONS FOR COMMUNICATION AND MESSAGE TRANSFER

7.5.1 Essential Aspects of the Developed and Experimented BCI Applications

This subchapter presents the results of experimental research based on a series of original software and hardware brain-computer interface (BCI) applications, implemented in LabVIEW, with the integral contribution of the author of this doctoral thesis. The applications proposed in the following sections are intended for communication and information tasks, by transferring chat messages to a smartphone, using spelling platforms, displaying texts on real or virtual LED systems, searching the Internet, and addressing questions to Chat GPT, using techniques based on detecting P300 visual evoked biopotentials from the GTEC Unicorn EEG headset and the blink-counting algorithm with the NeuroSky Mindwave headset.

Thus, the results obtained in this subchapter have fulfilled the third specific objective: Designing, creating, and implementing software tools for writing and communication applications, allowing for the drafting of texts from a virtual keyboard, virtual LED display systems, transferring chat messages on an Android application or the ChatGPT platform based on generative artificial intelligence, and searching for information on the Internet, using control signals determined by voluntary eye blinks or P300 visual evoked biopotentials.

BCI Application for Controlling a Virtual Keyboard

The aspects presented in section 7.5.2 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, indexed in the IOP Science database. Since 2019, the paper [397] has been accessible at the DOI link: http://dx.doi.org/10.1088/1757-899X/514/1/012020. Additionally, the paper titled "Virtual keyboard based on brain-computer interface" was presented at the PRASIC 2018 Conference (Product Design, Robotics, Advanced Mechanical & Mechatronic Systems and Innovation Conference), held in Brașov, Romania, on November 9-10, 2018.

The video demonstration partially showing the functionality of the proposed LabVIEW application, presented in this chapter, can be viewed on YouTube at the following address: [379].

BCI Applications for Transferring Chat Messages to an Android Smartphone

The aspects presented in section 7.5.3 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, indexed in the ISI (Web of Science) - IEEE Xplore database. Since December 10, 2020, the paper [414] has been accessible at the DOI link: https://doi.org/10.1109/EHB50910.2020.9280193. Additionally, the paper titled "LabVIEW and

Android BCI Chat App Controlled By Voluntary Eye-Blinks Using NeuroSky Mindwave Mobile EEG Headset" was presented at the EHB 2020 Conference (International Conference on e-Health and Bioengineering), held in Iași, Romania, on October 28-30, 2020.

Additionally, the real-time demonstration video of the proposed brain-computer interface application, presented in this chapter, can be found on YouTube and can be viewed at the following address: [365].

BCI Applications for Displaying Text Messages on LED Systems

The aspects presented in section 7.5.4 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, accepted for publication and indexing in the ISI/BDI – IOP Science database. Therefore, the paper titled "LabVIEW Instruments for Creating Brain-Computer Interface Applications by Simulating Graphical Animations and Sending Text Messages to Virtual and Physical LEDs Based Display Systems Connected to Arduino Board" was presented at the ACME 2022 Conference (The 10th International Conference on Advanced Concepts in Mechanical Engineering), held in Iași, Romania, on June 8-9, 2022.

The author of this thesis has uploaded various YouTube videos presenting the functionality and usage principles of the original LabVIEW applications presented in this chapter: [363], [364], [404], [405], [406], [407], [408], [416], [417], [418], [419], [425], [426], [427], [428].

BCI Application for Communicating with Chat GPT using P300 Speller

The aspects presented in section 7.5.5 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, accepted for publication and indexing in the ISI/BDI – Springer Link database. Therefore, the paper titled "A Brain-Computer Interface Application based on P300 Evoked EEG Potentials for Enabling the Communication between Users and Chat GPT" was presented at the IMCL 2023 Conference (The International Conference on Interactive Mobile Communication, Technologies, and Learning), held in Thessaloniki, Greece, on November 9-10, 2023.

The author of this thesis has uploaded a video on YouTube, presenting the functionality, usage, and real-time experiments on which the original BCI application is based, included in this chapter: [380].

BCI Application for Accessing Internet Resources Using P300 Speller

The aspects presented in section 7.5.6 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, accepted for publication and indexing in the ISI/BDI – Springer Link database. Therefore, the paper titled "A LabVIEW Based Brain-Computer Interface for Accessing the Internet Resources by Using the Unicorn EEG Headset and the P300 Speller board" was presented at the ICL 2023 Conference (The 26th International Conference on Interactive Collaborative Learning), held in Madrid, Spain, on September 26-29, 2023. The author of this thesis has uploaded various YouTube videos presenting the functionality, usage, and real-time experiments on which the original BCI application is based, included in this chapter: [382], [385].

7.6. BCI APPLICATIONS FOR CONTROLLING ROBOTIC SYSTEMS

7.6.1 Essential Aspects of the Developed and Experimented BCI Applications

This subchapter presents the results of experimental research based on a series of original software and hardware brain-computer interface (BCI) applications, implemented in LabVIEW, with the integral contribution of the author of this doctoral thesis. The applications proposed in the following sections are intended for controlling mechatronic systems, such as a mobile robot, a robotic hand, a robotic arm using commands determined by voluntary eye blinks detected in the EEG signal acquired from the ThinkGear chip of the NeuroSky headset.

Thus, the results obtained in this subchapter have fulfilled the fourth specific objective: Designing, creating, and implementing efficient command and control solutions for experimental devices such as a robotic hand, robotic arm, and mobile robot.

BCI Application for Controlling a Robotic Hand Using NeuroSky and Arduino

The aspects presented in section 7.6.2 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, indexed ISI (Web of Science), in the IEEE Xplore database. Since 2019, the paper [420] has been accessible at the DOI link: https://doi.org/10.1109/EHB47216.2019.8970050. Additionally, the paper titled "Experimental Model of a Robotic Hand Controlled by Using NeuroSky Mindwave Mobile Headset" was presented at the EHB 2019 Conference (International Conference on e-Health and Bioengineering), held in Iași, Romania, on November 21-23, 2019.

The preliminary demonstration video of the functionality of the proposed LabVIEW application, presented in this chapter, can be viewed on YouTube at the following address: [390].

BCI Application for Controlling a Robotic Arm and a Mobile System

The aspects presented in section 7.6.3 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, indexed in the ISI (Web of Science) - IEEE Xplore database. Since December 30, 2021, the paper [402] has been accessible at the DOI link: https://doi.org/10.1109/EHB52898.2021.9657549. Additionally, this paper was presented at the EHB 2021 Conference (International Conference on e-Health and Bioengineering), held in Iași, Romania, on November 18-19, 2021.

Additionally, several YouTube videos uploaded by the author of this thesis present the real-time usage and functionality of the proposed brain-computer interface application, included in this chapter. To view the video demonstrations, the following addresses can be accessed: [366], [374], [375], [377].

BCI Application for Controlling a Mobile Robot Using NeuroSky and Arduino

The aspects presented in section 7.6.4 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, indexed BDI, in the IOP Science database. Since 2020, the paper [413] has been accessible at the DOI link: http://dx.doi.org/10.1088/1757-899X/997/1/012059. Additionally, the paper titled "Arduino based mobile robot controlled by voluntary eye-blinks using LabVIEW GUI & NeuroSky Mindwave Mobile Headset" was presented at the ACME 2020 Conference (The 9th International Conference on Advanced Concepts in Mechanical Engineering), held in Iași, Romania, on June 4-5, 2020.

BCI Application for Controlling a Mechatronic System Using P300 Speller

The aspects presented in section 7.6.5 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, which is to be published by Springer and indexed BDI. Therefore, the paper titled "A LabVIEW and P300 Speller based Brain-Computer Interface for Controlling a Robotic Arm and a Mobile Robot by Using the GTEC Unicorn Headset" was presented at the EHB 2023 Conference (International Conf. on e-Health and Bioengineering), held in Bucharest, Romania, on November 9-10, 2023.

7.7. BCI APPLICATIONS FOR SIMULATION AND TRAINING BASED ON 3D MODELS

7.7.1. Essential Aspects of the Developed and Experimented BCI Applications

This subchapter presents the results of experimental research based on a series of original software and hardware brain-computer interface (BCI) applications, implemented in LabVIEW, with the integral contribution of the author of this doctoral thesis. The applications proposed in the following sections are intended for controlling 3D models, representing a robotic hand, a robotic arm, a wheelchair, a scooter using commands determined by voluntary eye blinks detected in the EEG signal acquired from the ThinkGear chip of the NeuroSky headset.

Thus, the results obtained in this subchapter have fulfilled the fifth specific objective: Designing, creating, and implementing software tools to demonstrate the functionality principle of the brain-computer interface and create simulation applications or training environments for controlling virtual models, such as a robotic arm, a robotic hand, and mini humanoid robots.

BCI Application for Controlling a 3D Robotic Hand Using the NeuroSky EEG Headset

The aspects presented in section 7.7.2 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, indexed ISI (Web of Science), in the IEEE Xplore database. Since 2019, the paper [412] has been accessible at the DOI link: https://doi.org/10.1109/EHB47216.2019.8969941. Additionally, the paper titled "Simulation of a BCI System Based on the Control of a Robotic Hand by Using Eye-blinks Strength" was presented by the doctoral candidate at the EHB 2019 Conference (International Conference on e-Health and Bioengineering), held in Iași, Romania, on November 21-23, 2019.

The real-time demonstration videos of the functionality and usage principles of the proposed LabVIEW brain-computer interface application can be viewed on YouTube at the following addresses: [368] and [378].

BCI Application for Controlling Yoda Holograms Using NeuroSky

The aspects presented in section 7.7.3 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, published and indexed in the BDI/ISI – Springer database. Therefore, the paper titled "A LabVIEW Based Brain-Computer Interface Training Environment by Controlling Yoda Holograms Using Eye-Blinks according to an Interactive Game Framework" was included and presented at the ICL 2022 Conference (The 25th International Conference on Interactive Collaborative Learning), held in Vienna, Austria, on September 27-30, 2022.

The real-time demonstration video of the usage principles of this LabVIEW brain-computer interface application, presented in this chapter, can be found on YouTube and can be viewed at the following address: [403].

BCI Application for Controlling a 3D Robotic Arm Using P300 Speller

The aspects presented in section 7.7.4 regarding the experimentation of the developed LabVIEW application are based on information published by the author of this thesis in the form of two scientific papers, published and indexed in the ISI/BDI – Springer database. Since September 14, 2023, the paper [381] has been accessible at the DOI link: https://doi.org/10.1007/978-3-031-42782-4_12. Additionally, the paper titled [381] was presented at the ICNBME 2023 Conference (The 6th International Conference on Nanotechnologies and Biomedical Engineering), held in Chișinău, Republic of Moldova, on September 20-23, 2023. In 2019, the doctoral candidate published the first paper [421], based on the design and realization of the 3D model of the robotic arm, having a simple structure. The paper titled "Virtual robot arm controlled by hand gestures via Leap Motion Sensor" was presented at the PRASIC 2018 Conference (Product Design, Robotics, Advanced Mechanical & Mechatronic Systems and Innovation Conference), held in Brașov, on November 9-10, 2018.

Additionally, the author of this thesis has uploaded a YouTube video presenting the usage principles and real-time implementation of the brain-computer interface experiments included in this subchapter: [387].

BCI Application for Controlling a 3D Wheelchair Using P300 Speller

The aspects presented in section 7.7.5 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, which is to be published and indexed in the ISI/BDI – Springer database. Therefore, the paper titled "A Brain-Computer Interface for Controlling a Wheelchair based Virtual Simulation Using the Unicorn EEG Headset and the P300 Speller Board" was presented at the STE 2024 Conference (The 21st International Conference on Smart Technologies & Education), held in Helsinki, Finland, on

March 6-8, 2024. The online presentation of the paper, given by the doctoral candidate, can be viewed on YouTube at the address: [395].

Additionally, the author of this thesis has uploaded a YouTube video presenting the usage principles and real-time implementation of the brain-computer interface experiments: [381], [389], and [392].

BCI Application for Controlling a 3D Scooter Using P300 Speller

During an international hackathon – BR41N.IO [396], organized by GTEC Medical Engineering Austria in April 2024, the author of this thesis fully developed the LabVIEW brain-computer interface application, experimented in section 7.7.6, which ensures the control of a 3D scooter guided by a humanoid robot, using commands based on P300 evoked biopotentials detected in the EEG signals acquired from the Unicorn headset. The online presentation of the project, given by the doctoral candidate, can be viewed on YouTube at the address: [394].

BCI Application for Simulating a Juice Vending Machine Using P300 Speller

The aspects presented in section 7.7.7 regarding the description of the developed LabVIEW application are based on information published by the author of this thesis in the form of a scientific paper, published and indexed in the ISI/BDI – Springer database. Since December 16, 2022, the paper (Rusanu O. A., 2023) has been accessible at the DOI link: https://doi.org/10.1007/978-3-031-22375-4_68. Additionally, the paper titled "A Brain-Computer Interface-Based Simulation of Vending Machine by the Integration Between Gtec Unicorn EEG Headset and LabVIEW Programming Environment Using P300 Speller and UDP Communication" was presented at the INTER-ENG 2022 Conference (The 16th International Conference Interdisciplinarity in Engineering), held in Târgu Mureș, Romania, on October 6-7, 2022.

Additionally, the author of this thesis has uploaded a YouTube video presenting the usage principles and real-time implementation of the brain-computer interface experiments included in this subchapter: [387].

CHAPTER 8

FINAL CONCLUSIONS. ORIGINAL CONTRIBUTIONS, UTILIZATION OF RESULTS, AND FUTURE RESEARCH DIRECTIONS

8.1. FINAL CONCLUSIONS

The doctoral thesis titled "RESEARCH ON THE USE OF BRAIN-COMPUTER INTERFACES IN EXTENDING THE FUNCTIONALITY OF BIO-MECHATRONIC SYSTEMS" was founded on the significant importance of the innovative brain-computer interface (BCI) technology, both software and hardware, in optimizing bio-mechatronic systems to assist individuals with neuromotor disabilities.

This thesis focused on developing portable, mobile systems with low costs, offering a simple mode of operation and a user-friendly graphical interface, intended to demonstrate and experiment with the operating principle of BCIs, and to train and test cognitive control tasks.

The final conclusions regarding the approaches and conduct of theoretical research, and the implementation and development of original BCI applications, carried out during the doctoral studies and presented in this work, concentrated on achieving the objectives of the doctoral thesis.

Each application included in the thesis illustrated the original contribution of the doctoral candidate by identifying, documenting, and implementing reliable, practical, fully functional, attractive, portable, and simple solutions to diversify BCI applications by integrating this scientific field with the extension of the functionality of bio-mechatronic systems. This is crucial as the multidisciplinary field of BCIs faces significant challenges internationally, due to the high costs of hardware components, the complexity of computer algorithms, and the advanced computational technology required to analyze and classify the unique cerebral dynamics and each individual's capacity to perform recognized mental activities as standardized cortical signal patterns.

Thus, internationally, researchers in the BCI field have achieved remarkable results primarily under controlled conditions in specialized laboratories, equipped with advanced, large, and costly equipment, by conducting experiments on subjects diagnosed with severe neuromotor disorders who had undergone surgery to insert sensors at the inter/intra-cortical level to obtain a high-accuracy signal.

The first stage of the doctoral thesis comprises theoretical research, materialized in the second chapter - The Current State of Developments and Achievements in the BCI Field, and the fourth chapter - Theoretical Considerations, providing a complete, in-depth description of the elements necessary for understanding and implementing a BCI system.

The theoretical study and comparative analysis of all methods, software, and hardware components used to achieve BCI systems concluded that currently, researchers can benefit from the opportunity to launch and expand portable headsets incorporating advanced technology to facilitate the acquisition and processing of EEG signals, albeit at high costs. With these EEG headsets, it is necessary to develop varied, versatile, creative, efficient, and attractive BCI applications capable of offering support and hope for an independent lifestyle, especially for individuals with neuromotor disabilities.

Therefore, this thesis provides a series of diverse applications for extending the functionality of bio-mechatronic systems (mobile robots, robotic arms, robotic hands, miniature motorcycles, correlated with virtual simulations based on 3D models) using BCIs. Moreover, the current work presents original software tools with complex functionalities implemented in LabVIEW and Python, for developing a generalized BCI system intended for the NeuroSky Mindwave EEG headset. This is the simplest, most compact, portable, and cost-effective option compared to other headsets.

Additionally, considering that the software tools developed during the doctoral research, based on artificial intelligence techniques, were tested on the task of recognizing the simplest and most precise EEG patterns, namely voluntary eye blinks, extensive EEG datasets for training artificial neural networks for detecting multiple voluntary eye blinks (single, double, triple) were produced. According to the theoretical analysis of the specialized literature conducted in the aforementioned chapters, there is an absence of EEG datasets containing specific patterns of voluntarily executed eye blinks for use as control signals in a BCI.

Furthermore, an additional benefit of the LabVIEW applications created for developing a generalized BCI system using the portable NeuroSky EEG headset, which does not target a specific application, lies in providing an accessible, simple, fast, efficient, and versatile software environment for demonstrating, experimenting with, and implementing a BCI system by researchers in the early stages of BCI exploration from various scientific fields, without requiring exceptional technical skills. This benefit is also justified by the multidisciplinary nature of BCI applications.

The second stage of the doctoral thesis comprises experimental research, materialized in the seventh chapter with subchapters related to BCI applications, which ensured the achievement of the specific objectives of this doctoral thesis.

The first specific objective of this doctoral thesis was to design, create, and implement efficient interfacing solutions between hardware platforms (NI myRIO, Arduino, Raspberry Pi, Micro

), software development environments (LabVIEW, Matlab, Arduino, Python, NodeRED), and portable sets (NeuroSky, Emotiv Insight, GTEC Unicorn) for acquiring EEG signals. The fulfillment of the first specific objective of the thesis was achieved by the doctoral candidate through the experimentation of original BCI applications in subchapters 7.3.2, 7.3.3, 7.3.4, 7.3.5, 7.3.6, and 7.3.7.

In this context, **subchapter 7.3.2** presented the experimentation of a LabVIEW BCI application for controlling a mobile robot using the NeuroSky EEG headset and the NI myRIO platform with FPGA technology. The efficient real-time integration of the three programming levels was notable: the graphical interface on the computer providing visual feedback to the user and facilitating EEG signal processing, the FPGA level for controlling the components/actuators connected to the NI myRIO, and the Real-Time level for correlating the computer and FPGA through the association between commands determined by voluntary eye blinks and the coding of movement commands for the mobile robot.

Additionally, **subchapter 7.3.3** presented the experimentation of a Matlab BCI application based on integrating EEG signal acquisition from the portable NeuroSky headset and transmitting control commands to an experimental prototype of a miniature motorcycle programmed with the Arduino Nano 33 IoT development platform. The uniqueness or high novelty degree of such an interfacing approach or strategy in the Matlab environment, between the two hardware components, NeuroSky EEG headset, and Arduino Nano 33 IoT board, was notable in the context of previous achievements in the BCI field. Moreover, the efficacy and attractiveness of the presented application were enhanced by the algorithm for counting voluntary eye blinks, used as precise control signals for generating commands to change the motorcycle's direction.

Subchapter 7.3.4 presented the experimentation of a Python BCI application based on integrating raw EEG signal acquisition from the biosensor incorporated in the NeuroSky headset and developing control commands for the movement of a mobile robot programmed with the Raspberry Pi platform. The novelty elements regarding the implementation of this application consisted of creating code sequences to facilitate wireless communication between the computer and the Raspberry Pi board using the WebSockets protocol for command transfer. Additionally, the originality of the application was highlighted by implementing an optimized algorithm for analyzing the raw EEG signal from the biosensor of the portable NeuroSky headset to determine the time when a voluntary eye blink was recorded and to record the EEG data from that moment.

Subchapter 7.3.5 presented the experimentation of a NodeRED BCI application based on integrating the Alpha EEG rhythm acquisition from the biosensor incorporated in the Emotiv Insight headset and developing control commands for a 5x5 LED matrix programmed with the Micro platform. By monitoring the Alpha EEG rhythm, commands were identified as determined by closing the eyes and opening the eyes. The amplitude of the Alpha EEG rhythm increases when the person closes their eyes and decreases when the user opens their eyes, resulting in two binary commands necessary in a BCI. The integration between the Emotiv Insight EEG headset and the NodeRED online development platform is currently insufficiently explored in the specialized BCI scientific literature, constituting a significant novelty element. Additionally, identifying research articles presenting the integration between the Micro platform and the NodeRED environment is difficult. Furthermore, the solution implemented by the doctoral candidate is adapted to the latest version of the Cortex V2 technology integrated into the Emotiv Insight EEG headset. The advantage of this BCI application developed by the author of the thesis lies in its compatibility with remote experimentation and the possibility of creating a remote research laboratory, considering that EEG data is acquired in the Emotiv Cloud. Additionally, the Micro mini-computer offers the opportunity for distance learning using the Microsoft MakeCode-based virtual development environment. In the published scientific work [409], [410], the doctoral candidate presented two original BCI applications implemented in NodeRED and Python for monitoring the Alpha rhythm from the biosensors of the Emotiv Insight EEG headset to control the 5x5 LED matrix incorporated in the Micro platform and the mobile robot based on the Raspberry Pi system using commands determined by closing and opening the eyes.

Subchapter 7.3.6 presented the experimentation of a Python BCI application based on detecting voluntary eye blinks in the EEG signal detected by the biosensors of the portable Emotiv Insight headset to transmit control commands to the RGB lighting in a mini smart home based on Arduino Mega, to which an expansion board with the ESP-12s/ESP8266 WiFi chip was connected.

EEG signal acquisition from the Emotiv Server and the algorithm for detecting and counting voluntary eye blinks were implemented in the Python application. The primary original contribution made by the doctoral candidate to developing this BCI application lies in avoiding the debouncing effect regarding detecting and quantifying multiple eye blinks. The lighting of the RGB LED in different colors and turning it off in the mini smart home was possible by programming the application dedicated to the Arduino Mega 2560 development platform. Additionally, the doctoral candidate implemented a WebSockets communication protocol-based code sequence in both the Python program and the Arduino script. The BCI application proposed in subchapter 7.3.6 represents a simple prototype for demonstrating, experimenting, understanding, and testing the operating principle of a BCI. Furthermore, individuals with disabilities can enjoy the opportunity to train at home using a portable EEG headset and performing voluntary eye blinks to control the lighting in the smart home.

Subchapter 7.3.7 presented the experimentation of a LabVIEW BCI application integrated with the official Unicorn P300 Speller software platform and the Arduino Mega development platform for detecting and using P300 evoked potentials to control an experimental prototype for the automated delivery of juices using mental commands transmitted through the Unicorn headset with eight EEG sensors. The official Unicorn Speller application identifies the symbol selected by the user based on the individualized impact through triggering P300 evoked potentials. The UDP communication protocol allows data transfer between the Unicorn Speller and the LabVIEW application, where the UDP packets are acquired and processed to correctly extract the BCI command transmitted by the user. The original LabVIEW application developed by the doctoral candidate facilitates transferring commands via Bluetooth to the Arduino Mega platform, where a program runs to activate and deactivate the DC motors, such as air pumps, ensuring the delivery of selected juices. Traversing, selecting, and transferring commands for delivering the desired juices are managed by the state-machine algorithm implemented by the doctoral candidate in the LabVIEW application. The original contribution of this BCI application consists of the software implementation by the author of the thesis for integrating EEG signal acquisition, processing, and classification solutions (Unicorn headset and Unicorn P300 Speller application), the LabVIEW tool for simulating the juice vending machine, and the experimental control prototype for juice delivery based on Arduino [355].

The second specific objective of this doctoral thesis was to design, create, and implement software tools for acquiring, processing, and classifying, online (in real-time) and offline, EEG signals using artificial neural network techniques and Fuzzy Logic methods. The fulfillment of the second specific objective of the thesis was achieved by the doctoral candidate through the experimentation of original BCI applications in subchapters 7.4.2, 7.4.3, and 7.4.4.

In this context, **subchapter 7.4.2** presented a series of LabVIEW tools offering various complex functionalities for acquiring, processing, and classifying the raw EEG signal detected by the NeuroSky biosensor in real-time by training and testing artificial neural network models on EEG datasets to recognize multiple voluntary eye blinks (single, double, triple) used as precise control signals in BCI applications. The LabVIEW implementation presented in subchapter 7.4.2 reflects a high degree of originality and complexity by completing the following stages: manual and automatic acquisition of the raw EEG signal, EEG data processing, feature extraction, training set generation based on multiple combinations of 10 EEG rhythms and 10 statistical measures, training classification models based on artificial neural networks (ANN), and testing these ANN models considering new EEG data sets different from those used for training the ANN models. Additionally, a supplementary LabVIEW application was implemented for running and evaluating the resulting ANN models in real-time. Furthermore, subchapter 7.4.2 includes extensive experimental data that can be subsequently reused in equivalent research in the BCI field. Therefore, 4 x 25 = 100 EEG datasets for ANN model training, comprising 4 x 25 x 40 = 4000 recordings, i.e., 4000 voluntary eye blinks (1000 of each type: non-blinks, single, double, triple) and 4 x 5 = 20 EEG datasets for ANN model testing, comprising 4 x 5 x 40 = 800 recordings, i.e., 800 multiple voluntary eye blinks (200 of each type).

Continuing within the theme of the second specific objective, **subchapter 7.4.3** presented the experimentation of Python applications required for acquiring, processing, and classifying the EEG signal detected by the NeuroSky biosensor using artificial neural networks to detect multiple voluntary eye blinks (single, double, triple) used as fast and precise control signals in a BCI system. In contrast to the LabVIEW applications based on ANN models previously presented in subchapter 7.4.2, Python applications are characterized by a simpler implementation method, not offering the functionality for generating multiple combinations of EEG rhythms and characteristic features (statistical measures) for generating EEG training sets for ANN models. Therefore, the raw EEG signal was strictly analyzed, and 7 characteristic features were extracted/calculated, resulting in 3 x 25 = 75 training sets containing 3 x 25 x 40 = 3000 recordings for multiple voluntary eye blinks (1000 of each type: single, double, and triple). The proposed solution in subchapter 7.4.3 stands out for the universality and extensibility of the Python programming language, which is open-source (no license purchase required) and thus adopted and preferred by many developers and users.

Finally, **subchapter 7.4.4** contributed to achieving the second objective by presenting the development of a LabVIEW application based on classifying the EEG signal detected by the NeuroSky biosensor using the Fuzzy Logic method for implementing a BCI to control a mobile robot programmed with the Arduino Uno platform. The originality of the LabVIEW application presented in subchapter 7.4.4 lies in eliminating the need to use the default function provided by the LabVIEW toolkit dedicated to the NeuroSky EEG set for determining or measuring the amplitude of voluntary eye blinks. In the context of analyzing the raw EEG signal and configuring the Fuzzy Logic system with the corresponding variables based on statistical measures, it becomes possible to display the amplitude of eye blinks in real-time and simultaneously process the EEG data to obtain different metrics (e.g., measuring attention concentration level or meditation depth). The novelty element of using Fuzzy Logic algorithms implemented in LabVIEW to determine the amplitude of eye blinks based on the raw EEG signal extends and diversifies the field of BCI applications using the portable NeuroSky headset.

The third specific objective of this doctoral thesis was to design, create, and implement software tools for writing and communication applications to allow the drafting of texts from a virtual keyboard, virtual LED display systems, transferring chat messages to an Android application or the ChatGPT platform based on generative artificial intelligence, and searching for information on the Internet using control signals determined by voluntary eye blinks or P300 evoked visual potentials. The fulfillment of the third specific objective of the thesis was achieved by the doctoral candidate through the experimentation of original BCI applications in subchapters 7.5.2, 7.5.3, 7.5.4, 7.5.5, and 7.5.6.

In this context, **subchapter 7.5.2** presented the development of a LabVIEW software tool to facilitate writing applications by drafting messages/texts for people with neuromotor disabilities. The LabVIEW application presented in chapter 7.5.2 stands out for its versatility, user-friendly graphical interface, effectiveness, and simplicity, implemented based on the Divide et Impera principle and using selection and transition commands on virtual buttons/keys by performing voluntary eye blinks. The originality of this BCI application lies in the LabVIEW implementation of control methods, and the novelty element is the elimination of the limitation regarding the time interval within which the user should perform a voluntary eye blink to allow either the transition between keys or the selection of a specific key to enter a character and draft a text message.

Furthermore, **subchapter 7.5.3** contributed to achieving the third specific objective of this doctoral thesis by presenting the development of integrated LabVIEW and Android BCI applications for transferring chat messages using the Bluetooth communication protocol between the computer and the smartphone. The LabVIEW application presented in chapter 14 is addressed to people with neuromotor disabilities who can perform voluntary eye blinks to generate selection and transition commands on virtual buttons representing attractive emoticons associated with specific messages. The novelty of the LabVIEW application lies in the additional functionality regarding the augmentative and alternative communication system due to incorporating the set of emoticons represented by buttons with suggestive images for each transmitted message. The originality of subchapter 7.5.3 lies in the LabVIEW and Android programming methods of the writing application based on the brain-computer interface and the design of graphical interfaces that offer versatility, ease of use, and an innovative control strategy using voluntary eye blinks.

Subchapter 7.5.4 presented the experimentation of BCI applications based on using voluntary eye blinks to control real and virtual display systems with 8x8 LED matrices and LCD TEXT for rendering graphic animations and moving text messages. Additionally, the doctoral candidate published results based on developing a series of BCI applications for controlling these display systems, including an additional 7-segment and 8-digit display for designing a virtual timer to measure a time interval, and binary to hexadecimal or hexadecimal to binary conversion systems based on the 8x8 LED matrix. Interactive virtual display systems can be useful for various educational applications, distance learning, communication, entertainment, or especially for studying and experimenting with brain-computer interfaces by implementing different light frequencies on LED matrices. The originality of the implementations brought by the doctoral candidate in subchapter 7.5.4 lies in extending the applicability of BCI and facilitating new scientific contributions through the experimentation, exploration, or testing of new interactive and easy-to-use applications. Research on the integration of BCI and display systems is currently insufficiently explored, and the specialized literature provides general ideas about virtual keyboards triggered by P300 evoked potentials for communication applications. The novelty elements introduced by the doctoral candidate through developing display systems refer to the advantage of designing personalized animations and creating messages in a fast and user-friendly manner.

Subchapter 7.5.5 presented the experimentation of a LabVIEW BCI application to facilitate communication with the Chat GPT [393] assistant based on generative artificial intelligence using commands determined by P300 evoked potentials. Therefore, in the LabVIEW application, UDP data packets related to the selection of a symbol from the official P300 Speller software platform were acquired and processed, where the user focused their attention by looking at a single character representing a part of the question addressed to Chat GPT. Additionally, the LabVIEW application allowed calling a Python function to access the Open AI API package to benefit from real-time communication with Chat GPT by connecting the input (the asked question) and the output (the received answer). The novelty element lies in integrating the two attractive communication methods by detecting P300 evoked potentials and transferring messages between the user and Chat GPT, resulting in an interactive learning tool for the operating principle and use of a BCI. Real-time communication in a natural language generated by artificial intelligence amplifies the motivation of the person with disabilities who benefits from the opportunity to develop the ability to perform cognitive tasks for controlling the BCI.

Subchapter 7.5.6 presented the experimentation of a LabVIEW BCI application to facilitate access to Internet resources using commands determined by P300 evoked potentials. The original LabVIEW application developed by the doctoral candidate in this thesis offers people with disabilities the possibility of performing cognitive commands to search for information on the Internet, such as a video clip on YouTube, a person on Facebook, or significant information on Google. These tasks can be performed by users wearing a GTEC Unicorn EEG headset and focusing their attention on a P300 Speller platform based on projecting light flashes on all symbols representing possible selections for Internet searches. Therefore, the novelty element of leveraging the BCI technology for web resource accessibility, demonstrated in the user-friendly graphical interface application developed by the doctoral candidate at a low cost, contributed to increasing the independence of people with neuromotor disabilities. Thus, these people can enjoy a pleasant and modern way of quickly and easily accessing Internet resources and quality multimedia content while also experiencing natural interaction with a computer. Additionally, the LabVIEW application implemented by the doctoral candidate in subchapter 7.5.6 constitutes an educational tool that can be used to familiarize engineering students with the general concepts underlying BCI technology.

The fourth specific objective of this doctoral thesis was to design, create, and implement efficient control solutions for experimental devices such as a robotic hand, a robotic arm, and a mobile robot. The fulfillment of the fourth specific objective of the thesis was achieved by the doctoral candidate through the experimentation of original BCI applications in subchapters 7.6.2, 7.6.3, 7.6.4, and 7.6.5.

In this context, **subchapter 7.6.2** presented the experimentation of a LabVIEW application to implement a portable BCI system based on controlling an experimental robotic hand model (real hardware prototype) programmed with the Arduino Uno development platform and controlled using selection and transition commands based on voluntary eye blinks detected in the EEG signal from the NeuroSky portable headset biosensor. The LabVIEW application presented in subchapter

7.6.2 offers versatility, efficacy, and attractiveness with a user-friendly graphical interface, providing visual feedback and involving low costs, considering that the experimental robotic hand prototype was designed from a miniature hand model intended for games. The originality of the application experimented in subchapter 7.6.2 lies in the LabVIEW programming sequences for simultaneous and individual control of the segments/fingers in the robotic hand structure. This application presents a novelty degree, considering that the specialized literature offers very limited evidence regarding the control of robotic hands using BCIs.

Furthermore, **subchapter 7.6.3** contributed to achieving the fourth specific objective of this doctoral thesis by presenting the experimentation of a LabVIEW application for controlling a robotic arm programmed with the NI myRIO system and commanded using voluntary eye blinks detected in the EEG signal from the NeuroSky portable headset. The challenges to be overcome by the BCI application presented in subchapter 7.6.3 relate to the mechanical assembly and electronic structure of the robotic arm to obtain a functional and reliable experimental prototype. Additionally, the obstacles encountered in implementing the BCI application in subchapter 7.6.3 consisted of determining and implementing manual and automatic control methods regarding simultaneous or individual commands of the joints/components in the robotic arm construction to enable the implementation of real-life applications. Considering the novelty element represented by interfacing the NI myRIO platform, NeuroSky portable headset, and LabVIEW software environment for developing the BCI application controlled using multiple voluntary eye blinks, subchapter 7.6.3 is equivalent to subchapter 7.3.2, with differences determined by the mechatronic system controlled (robotic arm in subchapter 7.6.3 and mobile robot in subchapter 7.3.2) and the control strategies based on eye blinks (selection and transition commands in subchapter 7.6.3 and blink counting algorithm in subchapter 7.3.2). The originality of the BCI application presented in subchapter 7.6.3 lies in the LabVIEW implementation of manual and automatic control of the robotic arm and the integration of the NI myRIO system and the NeuroSky headset.

Among the applications developed to achieve the fourth specific objective, **subchapter 7.6.4** presented the development of a LabVIEW BCI application for controlling a mobile robot programmed with the Arduino Mega platform and commanded based on voluntary eye blinks detected in the EEG signal from the NeuroSky portable headset biosensor. The LabVIEW application presented in subchapter 7.6.4 is equivalent to the LabVIEW application presented in subchapter 7.3.2, both being intended for controlling the mobile robot according to different movement directions, with differences in software implementation and hardware components used. Therefore, from a hardware perspective, the BCI application in subchapter 7.3.2 controlled the mobile robot based on the NI myRIO system, providing performance in operation, the possibility of programming in the LabVIEW environment, and wireless communication integration. In contrast, the BCI application in subchapter 7.6.4 controlled the mobile robot based on the Arduino Mega platform, which is open-source, has a compact appearance, offers simplicity in use and programming, and facilitates connecting an additional Bluetooth communication module. Additionally, from a software perspective, the BCI application in subchapter 7.3.2 was implemented by counting voluntary eye blinks, with movement commands determined by the total number of blinks, while the BCI application in subchapter 7.6.4 was implemented considering two selection and transition options on virtual buttons/keys constituting various movement commands for the mobile robot. In conclusion, the application in subchapter 7.6.4, categorized under the fourth specific objective of the doctoral thesis, provided a portable, efficient, and attractive system for simple and quick experimentation with BCI technology.

Subchapter 7.6.5 presented the experimentation of a BCI application for controlling a mechatronic system to assist people with disabilities using a 3-DOF robotic arm and a mobile robot with omnidirectional wheels, with moving components actuated by 12 commands determined by P300 evoked potentials detected by the EEG sensors integrated into the GTEC Unicorn headset. The original contributions made by the doctoral candidate to developing this BCI system are represented by implementing a fully functional and interactive LabVIEW application that allowed integrating the official Unicorn P300 Speller software platform and the Arduino Mega hardware platform. The transfer of P300 evoked potential-based selections between the P300 Speller application and the LabVIEW tool was achieved using the UDP communication protocol. The proposed BCI system, tested by volunteer subjects and evaluated in subchapter 7.6.5, can be considered an experimental prototype integrating all stages of EEG signal acquisition, processing, and decision-making for controlling external assistive devices for people with neuromotor disabilities. Additionally, the BCI system implemented by the doctoral candidate constitutes a significant and useful educational resource for familiarizing students with general concepts underlying BCI technology. The novelty of the BCI application in subchapter 7.6.5 lies in extending and diversifying experimentation possibilities based on using P300 evoked potentials, especially in controlling mechatronic systems or robotic devices with commands transmitted from the EEG Unicorn headset, which is less frequently encountered in the specialized literature, despite offering significant benefits regarding BCI accessibility even at the homes of people with disabilities.

The fifth specific objective of this doctoral thesis was to design, create, and implement software tools to demonstrate the operating principle of BCIs and create simulation applications or training environments for controlling virtual models such as a robotic arm, a robotic hand, and miniature humanoid robots. The fulfillment of the fifth specific objective of the thesis was achieved by the doctoral candidate through the experimentation of original BCI applications in subchapters 7.7.2, 7.7.3, 7.7.4, 7.7.5, 7.7.6, and 7.7.7.

In this context, **subchapter 7.7.2** presented the experimentation of a LabVIEW simulation of a BCI application based on controlling a 3D robotic hand using voluntary eye blinks detected in the EEG signal obtained from the biosensor incorporated into the portable NeuroSky headset. Similar to the real experimental prototype (hardware model) of the robotic hand presented in subchapter 7.6.2 and controlled by integrating the Arduino Uno platform and the NeuroSky EEG headset, the control based on voluntary eye blinks determining the selection and transition functions on virtual buttons constituting control commands for both simultaneous and individual control of the segments/fingers in the structure of the virtual robotic hand was implemented.

The originality of the application evaluated in subchapter 7.7.2 lay in the software implementation in LabVIEW of the construction and control of the 3D model of the virtual robotic hand, composed of five fingers/segments, each having an anthropomorphic structure. The novelty elements were represented by the LabVIEW environment interfacing of the BCI technology using the NeuroSky EEG headset and the simple and precise control method based on voluntary eye blinks with animating and modeling the 3D virtual robotic hand.

Additionally, **subchapters 7.7.4, 7.7.5, and 7.7.6** presented LabVIEW BCI applications based on 3D design and manual and automatic control of simple virtual models illustrating a robotic arm with six degrees of freedom constructed as a mobile telepresence device, a mobile wheelchair, and a scooter driven by a humanoid robot. These virtual simulation applications allowed the implementation of interactive cognitive training environments for individuals with neuromotor disabilities by practicing control over 3D characters using P300 evoked potential-based commands in safe conditions. The originality of the LabVIEW tools lay in the novelty of integrating all high-complexity stages (3D design, automatic control of virtual models, integration with the official Unicorn P300 Speller software platform, and UDP data packet acquisition and processing incorporating P300 evoked potentials) necessary to demonstrate the operating principle of a BCI, resulting in innovative and interactive software applications with a user-friendly graphical interface, having an educational and practical utility for cognitive training of BCI system users.

Moreover, **subchapters 7.7.7 and 7.7.3** presented LabVIEW tools integrated with Android and Arduino applications, based on designing a system for displaying Yoda character holograms or a virtual simulation for automated juice delivery to assist and train individuals with neuromotor disabilities by providing interactive visual feedback based on 8x8 LED matrices for rendering graphic animations or LCD screens for displaying text messages to amplify the success of performing voluntary eye blinks or focusing attention to correctly detect P300 evoked potentials. The originality of these BCI applications lay in the attractiveness of cognitive control paradigms based on the idea of a motivating digital game, innovative visual feedback, and graphic elements meant to capture users' attention. A novelty element was implementing the strategy in the LabVIEW programming environment to correlate voluntary eye blink execution with generating binary codes. Additionally, originality was determined by implementing the algorithm for acquiring and processing UDP data from the official Unicorn P300 Speller software platform, resulting in extracting P300 commands in LabVIEW and using them in the state-machine programming paradigm to alternately display the selected juice image. Furthermore, the originality of integrating hardware systems (NeuroSky EEG headset, Android smartphone, Arduino Mega platform) and software environments (LabVIEW, MIT App Inventor, Arduino IDE, official Unicorn P300 Speller platform) to create simple BCI applications for virtual simulations or training environments for individuals with neuromotor disabilities was notable.

8.2. ORIGINAL CONTRIBUTIONS

The doctoral thesis titled "RESEARCH ON THE USE OF BRAIN-COMPUTER INTERFACES IN EXTENDING THE FUNCTIONALITY OF BIO-MECHATRONIC SYSTEMS" includes the following original contributions, innovative elements, and additional personal aspects developed by the author during the theoretical and experimental research stages:

- Conducting an exhaustive bibliographic study (536 references) on the analogy between the nervous system and computers, describing brain-computer interface (BCI) systems, and theoretical considerations necessary for implementing such technology.

- Systematizing the theoretical and experimental content of current information on the description, classification, limitations, general structure, methods of cortical signal acquisition, types of evoked EEG potentials, control tasks, and BCI-based applications.
- Supporting the viewpoint on current issues/challenges in the scientific field of BCIs, which formed the basis for the research directions of the doctoral thesis.
- Designing, developing, implementing, and experimenting with portable BCI systems using NeuroSky, Emotiv Insight, and GTEC Unicorn EEG headsets, which are compact, reliable, technologically advanced, and cost-effective, to extend the functionality of bio-mechatronic systems. These systems include experimental prototypes (mobile robots, robotic hand, robotic arm, miniature smart house, and miniature motorcycle, automated juice delivery system) and training environments through virtual simulations controlling 3D models (mobile robots, robotic hand, robotic arm, wheelchair, scooter driven by a humanoid robot) and Yoda holograms at the level of an optical pyramid.
- Creating, implementing, successfully executing in real-time, and experimenting with a state-machine algorithm for counting voluntary eye blinks as commands in BCIs through original programming sequences in the LabVIEW virtual instrumentation environment.
- Creating, implementing, successfully executing in real-time, and experimenting with an algorithm based on defining custom functions in Matlab for counting voluntary eye blinks as commands in a BCI used to generate control commands for the miniature motorcycle.
- Creating, implementing, successfully executing in real-time, and experimenting with a Fuzzy Logic-based algorithm in LabVIEW for measuring or determining the amplitude or intensity of eye blinks detected by analyzing the raw EEG signal acquired from the NeuroSky portable headset biosensor.
- Creating, implementing, successfully executing in real-time, and experimenting with an optimized algorithm based on Python analysis of the raw EEG signal detected by the NeuroSky biosensor to recognize voluntary eye blinks.
- Creating, implementing, successfully executing in real-time, and experimenting with a state-machine algorithm in LabVIEW to use simple and double voluntary eye blinks to obtain transition, selection, and highlighting commands of keys representing various commands in a BCI system and in applications that allowed control of the following devices: robotic hand (real model), robotic hand (virtual model), robotic arm, mobile robot, emoji palette for chat message transfer, and virtual keyboard for text writing.
- Creating, implementing, successfully executing in real-time, and experimenting with a Divide et Impera algorithm in LabVIEW for controlling a virtual keyboard, enabling the transition, selection, and gradual highlighting of intermediate levels, first covering rows of keys, then halves of each row, and finally reaching a specific key associated with a particular character, allowing the user to form the desired word.
- Creating, implementing, successfully executing in real-time, and experimenting with a generalized LabVIEW BCI application through the following stages: manual and automatic acquisition of raw EEG signal detected by the NeuroSky biosensor, processing the raw EEG signal to obtain EEG rhythms in time and frequency domains, graphically representing EEG

signal variations in time and frequency, extracting characteristic features by calculating statistical measures, generating 50 multiple combinations between the 10 selected EEG signals and the 10 extracted features, generating 50 EEG datasets, training, testing, and evaluating/running (in real-time through an additional LabVIEW application) classification models based on artificial neural networks (ANNs) to detect multiple voluntary eye blinks (simple, double, and triple).

- Creating, implementing, successfully executing in real-time, and experimenting with a generalized Python BCI application through the following stages: acquiring the raw EEG signal from the NeuroSky headset, processing the EEG signal, extracting characteristic features by calculating a set of statistical measures, generating the EEG dataset, training, and testing an ANN-based model.
- Creating, implementing, successfully executing in real-time, and experimenting with a LabVIEW application for acquiring and processing data packets based on the UDP communication protocol incorporating responses based on detecting P300 evoked potentials in the official GTEC Unicorn P300 Speller software platform to extract P300-based commands for controlling mechatronic systems (robotic arm, mobile robot, automated juice delivery system) to assist people with neuromotor disabilities, 3D models (robotic arm, wheelchair, scooter driven by a humanoid robot) in virtual simulations for cognitive training or multimedia communication systems (asking questions to Chat GPT assistant and accessing Internet resources).
- Creating, implementing, successfully executing in real-time, and experimenting with Python and Arduino programming sequences based on the WebSockets communication protocol for transferring commands between BCI applications running on a Windows computer and mobile robots controlled by Raspberry Pi and Arduino Mega platforms.
- Creating, implementing, successfully executing in real-time, and experimenting with a NodeRED programming sequence for transferring commands to the BCI application controlled by the Micro:Bit development platform.
- Creating, implementing, successfully executing in real-time, and experimenting with fully functional BCI systems based on integrating portable EEG headsets (NeuroSky, Emotiv Insight, GTEC Unicorn), software development environments or programming languages (LabVIEW, Matlab, NodeRED, MIT App Inventor, Arduino IDE, Python), and hardware platforms (NI myRIO, Arduino Uno, Mega, Nano 33 IoT, ESP8266, Raspberry Pi, Micro).
- Designing sheets with essential information, fundamental stages, tasks required for progressing through three levels of difficulty (beginner, intermediate, advanced), and tables for completing results obtained from experimenting with original BCI applications designed, developed, and implemented in the thesis.
- Presenting general objectives, describing the operating principle, conducting practical demonstrations of the original BCI applications proposed in the thesis, recruiting, instructing, and coordinating subjects who voluntarily participated to experiments.

- Establishing conditions and preliminary preparation for conducting experimental sessions based on testing original BCI applications for communication, mechatronic systems control, 3D model command, or using virtual simulations.
- Designing, applying, and interpreting a feedback questionnaire addressed to all participants in experimental sessions based on testing the performance of BCI applications and evaluating subjective factors regarding the participants' inner perceptions during unconventional control of proposed systems through voluntary eye blinks or focusing attention on light stimuli.
- Conducting descriptive qualitative statistical analysis of all results obtained from experimenting with original BCIs by volunteer subjects.
- Conducting descriptive quantitative statistical analysis of all results obtained from experimenting with original BCIs by volunteer subjects.
- Conducting inferential statistical analysis of all results obtained from experimenting with original BCIs by volunteer subjects.
- Conducting multi-criteria analysis for classifying and evaluating three proposed BCI solutions for control through voluntary eye blinks and detecting evoked potentials of mechatronic systems, 3D models, virtual simulations, and enabling communication, information display, and text message transfer.
- Conducting a SWOT analysis for evaluating BCI applications controlled by voluntary eye blinks or P300 evoked potentials from the perspectives of the user, developer, and researcher.

8.3. DISSEMINATION OF RESEARCH RESULTS

The scientific, theoretical, and experimental research on the main doctoral thesis topic, Brain-Computer Interface (BCI) and its emerging fields, during the doctoral studies and thesis elaboration, materialized in the following results, valorized through **29 publications**:

- 1 paper in an ISI/WOS (Web of Science) indexed journal, impact factor = 1.7;
- 6 papers in ISI/WOS (Web of Science) indexed proceedings, non-rated;
- 18 papers in BDI indexed proceedings (up to the current moment);
- 1 paper accepted for publication in BDI/ISI (WOS) indexed proceedings;
- 2 Preprint papers (published on the Preprints.org website, supported by MDPI), based on a published ISI indexed and rated journal paper;
- 1 paper submitted for publication in BDI/ISI (WOS) indexed proceedings.

Considering these articles, the PhD candidate is: **single author** on **18 papers**, **first author** on **10 articles**, and **co-author** on 1 publication**.**

Below are the scientific papers published/accepted for publication:

- ***ISI – Web of Science Indexed (the PhD student achieved a Web of Science H-Index of 2)***

1. **O. A. Rușanu**, L. Cristea, M. C. Luculescu și P. A. Cotfas, "A brain-computer interface based on the integration of NI myRIO development device and NeuroSky Mindwave headset,"

2018 IOP Conference Series: Materials Science and Engineering, 444 042014, DOI: 10.1088/1757-899X/444/4/042014.

2. **O. A. Ruşanu**, L. Cristea, M. C. Luculescu și S. C. Zamfira, "Experimental Model of a Robotic Hand Controlled by Using NeuroSky Mindwave Mobile Headset," 2019 E-Health and Bioengineering Conference (EHB), 2019, pp. 1-4, DOI: 10.1109/EHB47216.2019.8970050.
3. **O. A. Ruşanu**, L. Cristea și M. C. Luculescu, "Simulation of a BCI System Based on the Control of a Robotic Hand by Using Eye-blinks Strength," 2019 E-Health and Bioengineering Conference (EHB), 2019, pp. 1-4, DOI: 10.1109/EHB47216.2019.8969941.
4. **O. A. Rușanu**, L. Cristea și M. C. Luculescu, "LabVIEW and Android BCI Chat App Controlled By Voluntary Eye-Blinks Using NeuroSky Mindwave Mobile EEG Headset," 2020 International Conference on e-Health and Bioengineering (EHB), 2020, pp. 1-4, DOI: 10.1109/EHB50910.2020.9280193.
5. **O. A. Rușanu**, "The Development of a Brain-Computer Interface for Controlling a Robotic Arm and a Mobile Device by Using the Voluntary Eye Blinking," 2021 International Conference on e-Health and Bioengineering (EHB), 2021, pp. 1-4, DOI: 10.1109/EHB52898.2021.9657549.
6. **O.A.Rușanu,** (2022). A Fuzzy Logic-Based LabVIEW Implementation Aimed for the Detection of the Eye-Blinking Strength Used as a Control Signal in a Brain-Computer Interface Application. In: Moldovan, L., Gligor, A. (eds) The 15th International Conference Interdisciplinarity in Engineering. Inter-Eng 2021. Lecture Notes in Networks and Systems, vol 386. Springer, Cham. https://doi.org/10.1007/978-3-030-93817-8_66.
7. **Rușanu, O. A.** (2023). A LabVIEW Instrument Aimed for the Research on Brain-Computer Interface by Enabling the Acquisition, Processing, and the Neural Networks based Classification of the Raw EEG Signal Detected by the Embedded NeuroSky Biosensor. International Journal of Online and Biomedical Engineering (iJOE), 19(05), pp. 57–81. **https://doi.org/10.3991/ijoe.v19i05.37857 cotat F.I. = 1.7.**

- *BDI Indexed – Considered for future Web of Science Indexing*

8. **O.A.Rușanu** (2022). Python Implementation for Brain-Computer Interface Research by Acquiring and Processing the NeuroSky EEG Data for Classifying Multiple Voluntary Eye-Blinks. In: Tiginyanu, I., Sontea, V., Railean, S. (eds) 5th International Conference on Nanotechnologies and Biomedical Engineering. ICNBME 2021. IFMBE Proceedings, vol 87. Springer, Cham. https://doi.org/10.1007/978-3-030-92328-0_84.
9. **O.A. Rușanu** (2022). A Brain-Computer Interface for Controlling a Mobile Assistive Device by Using the NeuroSky EEG Headset and Raspberry Pi. In: Tiginyanu, I., Sontea, V., Railean, S. (eds) 5th International Conference on Nanotechnologies and Biomedical Engineering. ICNBME 2021. IFMBE Proceedings, vol 87. Springer, Cham. https://doi.org/10.1007/978-3-030-92328-0_31.

10. ***Rusanu, O.A., Rosca, I.C.*** (2023). A LabVIEW Application Implemented for Simulating the Working Principle of the Brain-Computer Interface. In: Auer, M.E., El-Seoud, S.A., Karam, O.H. (eds) Artificial Intelligence and Online Engineering. REV 2022. Lecture Notes in Networks and Systems, vol 524. Springer, Cham. https://doi.org/10.1007/978-3-031-17091-1_63
11. **O.A. Rușanu**, "LabVIEW Instruments for Creating Brain-Computer Interface Applications by Simulating Graphical Animations and Sending Text Messages to Virtual and Physical LEDs Based Display Systems Connected to Arduino Board," The 10th International Conference on Advanced Concepts in Mechanical Engineering (ACME 2022), Iași, România, DOI: 10.1088/1757-899X/1262/1/012037
12. ***Rușanu, O.A., Roșca, I.C.*** (2023). A LabVIEW Based Brain-Computer Interface Training Environment by Controlling Yoda Holograms Using Eye-Blinks According to an Interactive Game Framework. In: Auer, M.E., Pachatz, W., Rüütmann, T. (eds) Learning in the Age of Digital and Green Transition. ICL 2022. Lecture Notes in Networks and Systems, vol 634. Springer, Cham. https://link.springer.com/chapter/10.1007/978-3-031-26190-9_107
13. **O. A. Ruşanu**, "A Python-based Brain-Computer Interface Application for Controlling An Intelligent Houseby Using Emotiv Insight EEG Headset and Arduino Mega Development Board," 2022 E-Health and Bioengineering Conference (EHB), Iasi, Romania, 2022, pp. 1-4, DOI: http://dx.doi.org/10.1109/EHB55594.2022.9991302.
14. **Rusanu, O.A.** (2024). A LabVIEW Based Brain-Computer Interface Application for Controlling a Virtual Robotic Arm Using the P300 Evoked Biopotentials and the EEG Bandpower Rhythms Acquired from the GTEC Unicorn Headset. In: Sontea, V., Tiginyanu, I., Railean, S. (eds) 6th International Conference on Nanotechnologies and Biomedical Engineering. ICNBME 2023. IFMBE Proceedings, vol 92. Springer, Cham. https://doi.org/10.1007/978-3-031-42782-4_12.
15. **Rușanu, O.A.** (2023). A Brain-Computer Interface-Based Simulation of Vending Machine by the Integration Between Gtec Unicorn EEG Headset and LabVIEW Programming Environment Using P300 Speller and UDP Communication. In: Moldovan, L., Gligor, A. (eds) The 16th International Conference Interdisciplinarity in Engineering. Inter-Eng 2022. Lecture Notes in Networks and Systems, vol 605. Springer, Cham. https://doi.org/10.1007/978-3-031-22375-4_68.

- ***BDI Indexed (the PhD student achieved Scopus H-Index = 4 and Google Scholar H-Index = 5)***

16. P.A. Cotfas, D.T. Cotfas. **O.A. Rușanu**, M.C. Luculescu, "Energy and Mechatronics Applications based on NI myRIO," 2017International Conference on Control Engineering andMechanical Design (CEMD), ASME Press, 2018, DOI: https://doi.org/10.1115/1.861677_ch23.
17. **O.A. Rușanu**, L. Cristea, M.C. Luculescu, P.A. Cotfas și D.T. Cotfas, "Virtual robot arm controlled by hand gestures via Leap Motion Sensor," 2019 IOP Conference Series:

Materials Science and Engineering, 514 012021, DOI: 10.1088/1757-899X/514/1/012021.

18. **O.A. Rușanu**, L. Cristea, M.C. Luculescu, P.A. Cotfas și D.T. Cotfas, "Virtual keyboard based on a brain-computer interface, " 2019 IOP Conference Series: Materials Science and Engineering, 514 012020, DOI: 10.1088/1757-899X/514/1/012020.
19. **O.A. Rușanu**, L. Cristea și M.C. Luculescu, "Arduino based mobile robot controlled by voluntary eye-blinks using LabVIEW GUI & NeuroSky Mindwave Mobile Headset," 2020 IOP Conference Series: Materials Science and Engineering, 997 012059, DOI: 10.1088/1757-899X/997/1/012059.
20. **Rusanu, O.A.** (2024). A LabVIEW Based Brain-Computer Interface for Accessing the Internet Resources by Using the Unicorn EEG Headset and the P300 Speller Board. In: Auer, M.E., Cukierman, U.R., Vendrell Vidal, E., Tovar Caro, E. (eds) Towards a Hybrid, Flexible and Socially Engaged Higher Education. ICL 2023. Lecture Notes in Networks and Systems, vol 911. Springer, Cham. https://doi.org/10.1007/978-3-031-53382-2_49
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22. **Rusanu, O.A.** (2024). A Brain-Computer Interface Application Based on P300 Evoked EEG Potentials for Enabling the Communication Between Users and Chat GPT. In: Auer, M.E., Tsiatsos, T. (eds) Smart Mobile Communication& Artificial Intelligence. IMCL 2023. Lecture Notes in Networks and Systems, vol 937. Springer, Cham. https://doi.org/10.1007/978-3-031-56075-0_22.
23. **Rușanu, O.A.** (2024). A P300 Based Brain-Computer Interface LabVIEW Instrument for Controlling an Experimental Prototype of Juices Vending Machine Using the Unicorn EEG Headset. In: Moldovan, L., Gligor, A. (eds) The 17th International Conference Interdisciplinarity in Engineering. Inter-ENG 2023. Lecture Notes in Networks and Systems, vol 929. Springer, Cham. https://doi.org/10.1007/978-3-031-54674-7_31.
24. **Rusanu, O.A.** (2024). A Brain-Computer Interface for Controlling a Wheelchair Based Virtual Simulation Using the Unicorn EEG Headset and the P300 Speller Board. In: Auer, M.E., Langmann, R., May, D., Roos, K. (eds) Smart Technologies for a Sustainable Future. STE 2024. Lecture Notes in Networks and Systems, vol 1028. Springer, Cham. https://doi.org/10.1007/978-3-031-61905-2_41.

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25. **O. A. Rușanu**, L. Cristea și M. C. Luculescu. "The development of a BCI prototype based on the integration between NeuroSky Mindwave Mobile EEG headset, Matlab software environment and Arduino Nano 33 IoT board for controlling the movement of an experimental motorcycle". 11th International Conference on Information Science and

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26. **Rusanu, O.A.,** A LabVIEW and P300 Speller based Brain-Computer Interface for Controlling a Robotic Arm and a Mobile Robot by Using the GTEC Unicorn Headset, The 11th International Conference on e-Health and Bioengineering. EHB 2023. https://www.ehbconference.ro/Portals/0/EHB%202023_Detailed_Program.pdf

- *Preprint Publications*

27. **O.A. Rușanu**, "Advanced LabVIEW Applications Aimed for theAcquisition, Processing and Classification of the Electroencephalographic Signals Used in a Brain-Computer Interface System". Preprints 2021, 2021060016 (doi: 10.20944/preprints202106.0016.v1).
28. **O.A. Rușanu**, "A LabVIEW Instrument Aimed for the Research on Brain-Computer Interface by Enabling the Acquisition, Processing, and the Neural Networks based Classification of the Raw EEG Signal Detected by the Embedded NeuroSky Biosensor". Preprints 2021, 2021060016 (doi: 10.20944/preprints202106.0016.v2).

- *Submitted for Publications – BDI/ISI Indexed Proceedings*

29. **O.A. Rușanu,** "A P300-based Brain-Computer Interface to Control a 3D LabVIEW Simulation using GTEC Unicorn P300 Speller Aimed at Cognitive Training", International Conference on User-System Interaction, 19-20 Septembrie, Constanța, România.

8.4. FUTURE RESEARCH DIRECTIONS

The theoretical and experimental results obtained in this doctoral thesis lay the foundation and premises for developing new research directions concerning the extension of the functionality of bio-mechatronic systems through the implementation, use, testing, and optimization of brain-computer interface (BCI) systems. Therefore, the future research directions in the domain of this doctoral thesis, described and enumerated below, will be pursued during the subsequent stages of the academic career that the doctoral candidate aspires to:

- Theoretical study and comparative experimental analysis of various portable headsets (Emotiv Insight, Emotiv EpochX, GTEC Unicorn, Muse, NeuroSky) for acquiring EEG data used as control signals in a BCI;
- Theoretical study, implementation, and experimentation of advanced methods for processing and classifying raw EEG signals to recognize various types of voluntary eye blinks:
  - Performed with both eyes or separately with one eye;
  - Of shorter or longer duration;
  - Voluntary or involuntary;
  - Characterized by different amplitudes (soft, medium, strong);

- Implementation of machine learning methods (SVM = supported vector machines and LR = logistic regression) in the LabVIEW application, aimed at generalized classification of various mental tasks;
- Expanding the types of specific features by adding new feature extraction methods in the generalized LabVIEW application for classifying a variety of mental tasks;
- Optimization of the mechanical and electronic structure of bio-mechatronic systems for experimental prototype systems such as the robotic arm, robotic hand, mobile robot, mini motorcycle, smart house, and juice delivery machine;
- Diversification of control methods (manual, automatic, hybrid) for bio-mechatronic systems for experimental prototypes such as the robotic arm, robotic hand, mobile robot, mini motorcycle, smart house, and juice machine;
- Development of a motor imagery-based BCI for controlling a bio-mechatronic system aimed at post-stroke rehabilitation of upper or lower limb movements;
- Optimization of control strategies based on evoked biopotentials (P300 or SSVEP) for implementing commands in a BCI;
- Integration and experimentation of control methods based on motor imagery or attention focus for implementing commands in a simple experimental prototype BCI;
- Development of an interactive, versatile, and high-performance simulation based on augmented reality or virtual reality using the Unity programming environment for cognitive training necessary for experimenting with a BCI;
- Development of BCI applications for improving, therapy, or reorganization of cortical structures through the development of neurofeedback techniques to nullify the negative effects caused by affective disorders.

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