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CONTRIBUTIONS ON THE USE OF NEURAL HEADSETS IN THE CONTROL OF ROBOTIC SYSTEMS

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CONTENT

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INTRODUCTION

A brain-computer interface (BCI) is a hardware and software-based communication system that allows a computer or external device to be controlled solely on the basis of brain activity. The main objective of BCI research is to provide a communication pathway for people with disabilities who are totally paralyzed or "blocked" due to neuromuscular neurological disorders, such as: amyotrophic lateral sclerosis, stroke or spinal cord injuries. Here, we review the current state of BCI systems, looking at the different stages that make up a standard BCI system: signal acquisition, signal preprocessing or processing, feature extraction, classification, and control interface. The advantages, disadvantages and latest advances are discussed below, and numerous technologies related to the scientific literature are analyzed in order to design each stage of a BCI system. First, the present research examines the neuroimaging modalities used in the signal acquisition stage, each of which monitors a different functional activity of the brain, such as electrical, magnetic or metabolic activity. Second, the present research analyzes different electrophysiological control signals that determine users' intentions that can be detected in brain activity. Third, the present research looks at some techniques used in the signal processing stage to treat artifacts in control signals and improve performance. Fourthly, a series of mathematical algorithms used in the stages of extraction and classification of features that translate information from control signals into commands used in the operation of a computer or other device are studied. Finally, this research aims to provide an overview of the different applications that use a BCI system to control a wide range of devices.

In chapter 1 we have made an overview that explores the possibilities of using Brain-Computer Interfaces (BCI) technology and that deals with the fundamentals and essential components necessary for the design of such a system, exploring the implications from signal acquisition to the control interface. The types of measurable brain activity are covered in detail, including electrical, magnetic, and metabolic activity, with an emphasis on electroencephalography (EEG) due to functional advantages. Also, a detailed analysis is provided to the main techniques of processing and extraction of the features, as well as the main types of artifacts that contaminate brain signals, with special attention being paid to the main approaches to their elimination.

In chapter 2 we have made a detailed description of some efficient algorithms, used for the classification of motor images and, in particular, for the problem of preprocessing EEG signals, which are based on machine learning, used to be able to efficiently interpret and classify brain signals from various applications. In this regard, the significant expansion of the main BCI applications was also described, covering areas of interest, such as rehabilitation by treating severe communication disabilities, restoration of motor function, device control and use in video games. All these have the role of demonstrating the potential of this technology in improving the quality of life of people with disabilities, but also to open new horizons of interaction for healthy users.

In chapter 3 we conducted a case study meant to analyze and determine the resulting brain model for three subjects for mental training of a relaxation condition, of a mental command, dependent on the user's level of attention, as well as for the intentional operation of the learned command. As a method of acquisition, the electroencephalogram is used, using a neural helmet type device provided with five EEG channels. EEG data is preprocessed and analyzed in MATLAB with the EEGLAB tool, applying independent component analysis to separate useful signals from artifacts, and using a deep learning algorithm to classify brain activity. Each subject goes through a mental training whose intervals are recalculated and displayed by a four-step algorithm written in Python, including neutral state, mental command, intentional action, and validation steps.

In chapter 4 we developed and implemented a control system of a mini drone, based on the brain-computer interface (BCI), combining two related and topical technological fields in a single practical application with practical applicative potential, capable of using only the user's brain signals as inputs, obtaining an intuitive control of the drone. The entire ecosystem of the drone was mathematically modeled, simulated and tested in real flight conditions, in order to validate the efficiency of the BCI system implemented.

In chapter 5 we made and developed a series of applications that use the brain-computer interface to control both video games, robotic platforms and the main couplings that make up the joints of a spider robot, designed and 3D printed. We started from a video game called Mental Pool Game, controlled by the Emotiv Insight neural headset, which uses the motor imagery paradigm and then developed a BCI interface capable of using the electromyography signals detected by the electroencephalogram signals, using an OpenBCI headset with 16 EEG channels, redesigned to control 2 servomotors of the Lego robotic platform. Using a NextMind headset, intended for monitoring the visual cortex, we used the steady-state visual potential (SSVEP) paradigm to drive the spider robot's servo motors.

CHAPTER 1
BRAIN COMPUTER INTERFACES (BCIs)

Introduction

Brain-computer interfaces are advanced command and control technologies that by their nature create a bridge between the human user's brain and the external device whose inputs they operate.

The current chapter aims to address the technology underlying brain-computer interfaces, exploring the fundamentals, conceptual description and implementation of the essential components specific to any BCI system. To begin with, I describe the types of brain activities that can be measured. They also describe the types of approaches specific to a BCI system, in terms of their functional nature. For each of these types of activities that can be measured, I present the main measurement techniques. I also present the main methods of brain signal acquisition, with emphasis on electroencephalography, along with the description of the related advantages, but also on other neuroimaging techniques.

Also in this chapter, I present the techniques for processing and extracting the characteristics present in BCI systems, but also the main types of artifacts that contaminate the useful activity of the brain.

Objectives

The representative objectives of the chapter are:

- Definition and explanation of the concept of brain-computer interface;
- Analysis and presentation of the main types of brain signals that are used in BCI systems;
- Immersion in exploring and describing the main methods of processing brain signals and extracting features that are used in BCI systems;
- Addressing and removing artifacts from BCI systems.

The brain-computer interface (Brain-Computer Interface = BCI), also known as the brain-machine interface (Brain-Machine Interface = BMI), is a hardware and software-based communication system that allows people to interact with the environment solely on the basis of control signals generated from brain activity using the principle of electroencephalogram (EEG).

The idea of successfully deciphering thoughts or intentions based on brain activity using BCI technology has not been sufficiently exploited in previous scientific research. Studies in brain research have usually been limited to analyzing neurological disorders in clinics or exploring brain functions in the laboratory. The design of BCI has long been considered too complex, due to the resolution and reliability of the information that can be detected in the brain, but also because of the high variability.

The BCI research field is a relatively young multidisciplinary field, which integrates researchers from different areas such as: neurology, physiology, psychology, engineering, computer science, rehabilitation and other technical and medical disciplines. As a result, despite notable progress, a common language has not yet emerged and existing BCI technologies vary, making it difficult to compare and harmonize them for standardization.

This overview of the current state of BCI systems is structured as follows: subchapter 1.1 discusses existing neuroimaging approaches to BCI systems, subchapter 1.2 describes the control signals most commonly encountered within BCI systems, subchapter 1.3 briefly explains certain types of BCI systems. Subchapters 1.4, 1.5 and 1.6 cover different signal processing methods used in feature extraction, artifact reduction and feature classification. Subchapter 1.7 provides an overview of the applications using the BCI system, and the main conclusions are presented at the end of the chapter.

Conclusions

Brain-computer interfaces (BCI) are the ones that allow the creation of a bridge between neural activity and external devices, being the main approach in neuroimaging. Electroencephalography remains the cornerstone of these interfaces, especially in the case of the non-invasive approach, both due to the factors related to the excellent temporal resolution offered, but especially due to the versatility of capturing brain activity for the clinical and research environment. However, in addition to these advantages, which make electroencephalography an affordable solution, BCIs using this method of signal capture face numerous challenges, which do not exclude the signal-low noise ratio, a profound susceptibility to the occurrence of internal and external noise phenomena, such as the case of interferences generated by the volume of skull conduction that can cause EEG signal degradation. Also, the presence of biological artifacts of the body located in the brain constitutes another challenge for the preprocessing stage.

Regardless of the type of classification of BCIs, they are user-oriented, in order to give the user, the possibility of controlling devices using brain signals as a means of control, depending only on the user's will and attention, whether it is the presence of predefined choices to train the system or the presence of internal or external stimuli to produce a brain response evoked by them.

CHAPTER 2

BCI ALGORITHMS AND APPLICATIONS

Introduction

The field of BCI interfaces has seen numerous advances in the last two decades, both in relation to the algorithms used and in the case of signal processing and classification, but also in relation to the diversified range of applications to which they apply. Thus, they allowed the classification of motor images that use the electroencephalogram and the evoked visual potentials as a foundation. Algorithms have been developed for vectors of small features. By taking into account the existing instances and relating to their proximity to them in the feature space in order to classify the new instances, the algorithm has become simpler and more computationally efficient. Machine learning has been used as a foundation for the design of most algorithms, being often used by BCI systems in the interpretation and classification of brain signals, for the design of algorithms for classifying brain activity states, in order to translate them into computer commands both in speller applications and in the treatment of models in multiclass systems or for the automatic detection of seizures in the medical field; it was also aimed at treating the spaces of large features, by identifying the optimal of the separation hyperplane through another algorithm to solve the problem of dimensionality; Another algorithm has become useful in recognizing the pattern resulting from the learning data inspired by the way the brain processes information.

As for BCI applications, they are diverse and constantly expanding and cover: the treatment of severe communication disabilities, the restoration of motor function for patients, the control of household devices, the control of a means of transport for people with disabilities and applications in video games.

Objectives

The objectives of this chapter are:

- Understanding and interpreting the role of classification algorithms in BCI systems;
- Presentation and interpretation of the main types of classification algorithms;
- Dealing with the main BCI applications.

BCI is a communication system that does not require any peripheral muscle activity. Indeed, BCI systems allow a subject to send commands to an electronic device only through brain activity. Such interfaces can be considered as the only way of communication for people affected by a number of motor disabilities. To control a BCI, the user must produce different patterns of brain activity that will be identified by the system and translated into commands. In most existing BCIs, this identification is based on a classification algorithm, i.e. an algorithm that aims to automatically estimate the data class as represented by a characteristic vector

The purpose of the classification stage in a BCI system is to recognize the user's intentions based on a characteristic vector that characterizes the brain activity provided by the characteristic stage. Either the regression or classification algorithm can be used to achieve this goal, but classification algorithms are currently the most popular approach in BCI systems. These algorithms are used to recognize users' EEG patterns based on EEG characteristics. Over the years, a great diversity of types of classifiers have been explored to design BCIs, including linear classifiers, neural networks, nonlinear Bayesian classifiers, Nearest Neighbour Classifiers, and classifier combinations.(Lotte, și alții, 2018)

Classification algorithms have traditionally been calibrated by users through supervised learning using a labeled dataset.

For the classification of non-stationary signals, supervised learning is not optimal, but large datasets and long initial calibration sessions are usually required to achieve acceptable accuracy. Semi-supervised learning (SSL) is useful to reduce preparation time and update the classifier in the online session on an ongoing basis.

In a BCI scenario where the signal associated with the subject's intentions is unknown and labels are not available, unsupervised learning and reinforcement learning (RL) can be applied for BCI adaptation. The use of machine learning techniques allowed users, who were unable to obtain successful feedback, to gain significant control over the BCI system.(Abu-Rmileh, Zakkay, Shmuelof, & Shriki, 2019)

Classifiers have to face two main problems related to pattern recognition: the curse of dimensionality and the bias-variance trade-off.

The design of the classification stage involves choosing one or more classification algorithms from several alternatives. Several classification algorithms have been proposed, such as, among others: the k-nearest neighbor classifier (k-NNC), linear classifiers, Support Vector Machine (SVM) and neural networks (ANN).

Currently, patients with LIS and those likely to develop CLIS are the main candidates for BCI. Despite the low rates of information transfer provided by the BCI, the high degree of disability among patients with LIS forces them to use a BCI rather than more reliable conventional interfaces, such as systems based on muscle activity or gaze.

Nowadays, there are a large number of very different BCI applications, such as word processors, adapted web browsers, controlling a wheelchair or neuroprosthesis with the help of the brain and of course games.

As a tool that performs a specific function, BCI's particular specifications correspond to how it performs that function. The following subsections briefly describe the applications of BCI, classified into five main areas: communication, motor restoration, environmental control, locomotion, and entertainment.

Conclusions

This chapter reviewed the state of the art of BCI systems by discussing the fundamental aspects of BCI system design. Some of the most significant objectives that have driven BCI research over the past 25 years were presented. It was noted that many advances have been made in their research. Different neuroimaging approaches have been successfully applied in BCI: (i) EEG, which provides signals of acceptable quality, with high portability being by far the most common modality in BCI; (ii) fMRI and MEG, which are proven and effective methods for locating active regions within the brain; (iii) NIRS which is a very promising neuroimaging method in BCI and (iv) invasive modalities, which have been presented as valuable methods to provide high-quality signals needed in some multidimensional control applications, such as neuroprosthesis control.

A wide variety of signal characteristics and classification algorithms have been tested in the design of the BCI. Although BCI research is relatively young, many advances have been made in less than two decades, as many of these methods are based on previous research into signal processing and pattern recognition. Many studies have demonstrated the accuracy of BCIs and provided an acceptable information transfer speed, despite the major difficulties inherent in brain signal processing. As a result, the training time of users has been significantly reduced, which has led to more widespread BCI applications in the daily lives of people with disabilities, such as, among others, word processing, browsers, email, wheelchair control, environmental control or neuroprosthetics.

Despite recent advances in the field of BCI, some issues still need to be resolved. First, the relative advantages and disadvantages of different signal acquisition methods are still unclear. Clarifying them will require further studies in humans and animals. Second, invasive methods need further investigation to deal with tissue damage, the risk of infection, and long-term stability problems. Electrodes containing neurotropic media that promote neuronal evolution and wireless transmission of recorded neural signals have already been proposed. Third, the electrophysiological and metabolic signals that are best able to encode user intent should be better identified and characterized. Most BCI studies have independently treated the timing, frequency, and spatial dimensions of brain signals. These signal size interdependencies can lead to a significant improvement in BCI performance. Fourth, the speed of information transfer provided by current BCIs is low to ensure efficient human-machine interaction in some applications. BCI based on exogenous signals can provide a much higher yield. Fifth, unsupervised adaptation is a key challenge for the deployment of BCIs outside the laboratory. Some adaptive classification algorithms have already been proposed with moderate success. In addition to low information transfer rates and variable reliability, most current BCI systems are inconvenient because the electrodes need to be moistened, the software may require training, and the electrode contacts need continuous correction. An easy-to-use P300-based BCI with remote monitoring using a high-speed internet connection has already been proposed to reduce reliance on technical experts.

The latest advances in BCI research suggest that innovative developments may occur in the near future. These achievements and the potential for new BCI applications have obviously given a significant boost to BCI research in which scientists from multidisciplinary fields have participated, among others for example, neurologists, engineers, mathematicians and specialists in clinical recovery. Interest in the field of BCI is expected to increase and the design and development of BCI will continue to bring benefits to the daily lives of people with disabilities. Moreover, recent commercial interest within certain companies suggests that BCI systems can find useful applications for the general population and not just for people with severe disabilities. In the near future, BCI systems may therefore become a new way of human-machine interaction with everyday uses, similar to other current interfaces.

CHAPTER 3
BRAINWAVE ANALYSIS

Introduction

In this chapter, in the context of analyzing and determining the brain model resulting from mental training for relaxation, followed by the training of a mental command, but also of the intentional action of the latter, a case study is presented involving a scenario applied to three subjects. The EEG signals were acquired using a commercial neural headset equipped with five EEG channels. The previously recorded EEG data was stored in medical format and analyzed with the EEGLAB toolset in the MATLAB development environment to eliminate noise through a six-step preprocessing algorithm. The algorithm applied independent component analysis to separate useful signals from artifacts. The EEG data was then processed using a classifier, based on deep learning to classify brain activity separately from noise sources.

For each topic, the training was recalculated and displayed using a four-step algorithm written in the Python programming language. Each segment of time was divided for training neutral state and mental command, intentional action, and validation steps. The spectral power density was analyzed to identify alpha and beta waves on each EEG channel, using an algorithm implemented in the C programming language, running in the MATLAB development environment. The results were plotted to determine the amplitude and maximum strength of the EEG signals, as well as their distribution across brain regions.

Objectives

The objectives of this chapter are:

Implementation of an offline preprocessing algorithm of the recorded raw EEG data, related to a case study with 3 subjects;

Evaluation of the impact of artifacts on EEG signals;

Determination of the distribution of dominant brain waves;

Comparative analysis of mental training sessions.

A number of 3 volunteer subjects were chosen to participate in the experiment, aged between 32 and 55 years. All subjects were chosen from the category of people with a good state of health, coming from the same demographic environment and following a training cycle in higher education. The measurements were made by taking the EEG signal from the subjects, over several days, in the same interval of the day, namely in the afternoon, using the same equipment and the same development kit, Emotiv Insight, both for the acquisition and for the processing of EEG signals. Also, all measurements were made in laboratory conditions, without sources of external noise, and the subjects were instructed that throughout the training and imagining the consequence of a mental command not to speak and also not to move so as not to affect the validity of the experiment. The volunteers were trained in advance to familiarize themselves with the BCI interface, each person being allocated a training time of 20 minutes.

The main goal of the experiment was to determine the distribution of the dominant brain waves of all subjects, while following the same pattern and training process for the neutral condition and a single mental command, the Lift. In this regard, we aim to analyze the preprocessed electroencephalogram data, coming from raw data, both during its training and post-training at the time of imagining the trained command.

Thus, all participants were asked to go through two training sessions individually, the first in which to train only the neutral condition in order to be able to analyze the spatial distribution of brain waves for the relaxation period, and in the second to resume its process in order to be able to train the mental command of lifting, both sessions being recorded simultaneously.

To do this, we used the independent Emotiv Xavier TestBench application, which is provided by the company Emotiv Inc. in the standard application package with the purchase of the Emotiv Insight neural headset.

By recording the neutral state and the mental lifting load for each subject, it was possible to perform a comparative analysis of the training sessions using the offline playback facility offered by the Emotiv Xavier TestBench application. Thus, the changes in the electroencephalogram signals for each of the 5 EEG channels analyzed were identified, both during the induction of the state of relaxation and during the training and imagining of the consequence of the imagined mental command, at an implicit sampling rate of 128 samples per second, by applying a first-order top-pass filter on the default signals to eliminate the offset (lag) generated by the direct current produced by the electronic system of the Emotiv Insight headphones, which can only be deactivated if single-channel EEG analysis is chosen.

In the pre-processing stage of the purchased EEG data, I chose to use the open-source EEGLAB toolset that can be integrated into the MATLAB development environment for continuous processing of electroencephalography (EEG), magnetoelectroencephalography (MEG), and other electrophysiological signals.

EEGLAB was also chosen because it is developed around a simple yet intuitive graphical user interface that provides a smooth transition from command-line programming in MATLAB for custom analysis to basic graphs generated through MATLAB

The EEG data are then prepared for further analysis with the aim of discriminating them according to frequency components and cleaning them of noise sources in order to eliminate artifacts.

ICA training was performed at a learning rate originally set to 0.001 (Kittilstved, și alții, 2018). However, during training this rate is adjusted based on a threshold, which relates to a Delta angle that represents the angle between the direction of the vector in the weight space describing the current learning step and the direction describing the previous step. If the Delta angle is greater than or equal to 60°, the learning rate is automatically multiplied by 0,9, with the aim of ensuring the stability of the learning process. By calling the function

pop_runica() the EEGLAB toolkit generates in addition to the ICA weight matrix a data transfer matrix, which achieves a uniform distribution that is used for ICA preprocessing.

In general, the recognition and rejection of ICs obtained from decomposition by applying ICA in the preprocessing of EEG sessions is a difficult step, as it is a process that requires time and experience to correctly understand and evaluate their properties through manual inspection. This is due to the complexity of the CIs, which do not have a clearly defined interpretation or specific order (Asogbon, și alții, 2023).

Thus, for this step, we opted for an ICLabel classifier, which implements a deep learning model for the automatic recognition and removal of independent components from EEG records.

As a first result of the application of the automatic classification of independent components, it was observed that the application of the ICA decomposition produces an efficient separation of the sources that make up the electrical potentials of the brain in the case of the analysis of the EEG data sets related to all the subjects involved in the study.

Thus, five topographic maps, each of which are associated with a result obtained by ICLabel classification, indicating either the type of artifact or the signal source it represents, together with the label related to the percentage of confidence that determines the accuracy of the classification.

Conclusions

The first objective results in obtaining clean EEG datasets, with as many artifacts removed as possible following the application of the preprocessing algorithm, which allow an accurate analysis of individual brain activity for different mental actions, under experimental conditions related to each of the three subjects studied.

The second objective results in ensuring the quality and integrity of the EEG data from each dataset analyzed, in the sense of maintaining a low amplitude of the residual artifacts after processing, in order to obtain optimal results later.

The third objective imprints a way of identifying and comparing the distribution of the dominant brain waves during the state of relaxation, alternating with the installation of attention and concentration during the training of the chosen mental command, which is used as a basis for its intentional action.

The fourth objective results in identifying and understanding the mental patterns per study, the commonalities between entrainment and intentional actuation, and understanding the differences that characterize them through EEG responses between subjects, providing insight into individual variability in the design process of any mental entrainment scenario that is used as a foundation for controlling any BCI application.

CHAPTER 4

DRIVING A DRONE USING NEURAL HEADSETS

Introduction

This chapter presents the way in which two elements that are increasingly present today can be interconnected in order to create a system capable of being led by a wide category of people. On the one hand, drones present and integrated in various fields of activity, both civil and military, extended towards the approach focused on entertainment and the delivery of products and more recently towards the field of the future, that of unmanned air passenger transport. On the other hand, human-machine interfaces, being considered more unconventional, can be considered a niche field that offers generous topics that deserve to be explored both in the present and in the future. Due to these considerations I chose to use and develop a brain-computer interface (BCI) because it offers the advantage of a control that does not involve moving elements. In order to achieve this objective, we developed through mathematical modeling and numerical simulation both the model of a mini drone and the BCI interface used as a control method.

Objectives

The representative objectives of the chapter are:

- Development and implementation of the brain-computer interface;
- Mathematical modeling and simulation of drone dynamics;
- Training and validating mental commands for drone control.

I chose to use BCI technology because it allows the control of electromechanical devices or computers using only brain signals as a means of action. Such a BCI system is able to identify patterns of neural activity that, following processing, can be associated with machine commands. Among BCI systems, in fact, the electroencephalogram (EEG) technique analyzed by the non-invasive method is predominantly used to transform the user's conscious thoughts into command-and-control actions.

The main motivation for the development of BCIs is to improve the quality of life for people suffering from disabilities generated by neuromuscular diseases, stroke, amyotrophic lateral sclerosis (ALS) or severe polyneuropathy . (Moufassih, Tarahi, Hamou, Agounad, & Azami, 2022)

The objective is to create and implement a brain-computer interface, based on the paradigm of motor imagination through which the user is able to control, only using a series of trained mental commands, the position and orientation of a mini drone in space, based on the implementation in the Matlab - Simulink development environment of the results obtained from mathematical modeling and numerical simulation.

The neural headset used, Emotiv Insight is a brain activity tracking device designed in 2015 by an Australian entrepreneur, Tan Le, co-founder of Emotiv Inc., based in San Francisco, California. Emotiv Insight is a wireless, multi-channel, neural headset designed for BCI applications.

On the other hand, the chosen four-rotor mini drone instrument used in the BCI experiment can be seen as a framework for testing and evaluating ideas from multidisciplinary fields, such as: computer science, electrical and mechanical engineering, to solve problems such as: real-time flight control theory, robotics and navigation. The main advantage of this type of device is that it is a versatile test platform, involving a relatively simplistic mechanical design that offers both a low purchase and maintenance cost.

The mini drone is equipped with a Bluetooth Low Energy (BLE) module that gives it an operating range of 20 meters from the operator.

For the design of the brain-computer interface we used as input the successful training of the neutral condition, as the basic mental state of the user. To this end, using the Emotiv Xavier ControlPanel development kit, we trained four classes of mental tasks using our own imagination as a trigger on the kinesthetic movement of the right arm, starting from the assumption that experiencing the same feeling with the real movement of the arm that is based on motor execution and combining it with the observation of an action, can induce a stronger brain response (Miladinović, et al., 2020). We also benefited from visual feedback provided through a series of preset animations that project the movement of a virtual target object represented in 3D, consisting of six merged cubes, each movement being automatically preset according to the mental task to be trained. We have chosen the mental tasks so that they are intuitive and largely correspond to the movement on the axes of the mini drone as follows:

- Mental lift load, shown in Fig. 4.18, used to transmit the take-off command of the Parrot Rolling Spider mini drone at a predetermined altitude of 1.1 m and ascent at a step of 0.2 m/s;
- Mental Drop Load, which controls the reduction of altitude by a step of 0.2 m/s;
- Mental load movement to the right (Right), which controls the turn to the right with a step of 0.05 degrees;
- Mental task Left shift, which controls the turn to the left with a step of 0.05 degrees.

Based on imagining the consequences of the mental command for 8 seconds, the mental patterns are then associated with the command.

Following the processing of the sequences trained through the Emotiv Xavier ControlPanel Interface, they are stored in binary code, they need to be converted into keystroke sequences that serve as inputs for the control of the mini drone in real time.

Only for the reset command, a facial expression was chosen, namely blinking, for which the "occur" trigger condition was set, which will manage the pressing of the "R" key at each activity detection, taking into account the delay established in order to have a double control mechanism, having both the function of canceling previous commands and the safety function in case the user loses concentration.

By implementing a BCI-based solution integrated into the control of a mini drone, the steps involving the interaction between man and machine can be simplified, it is aimed at a large number of people, either healthy, neurological or suffering from amputations, according to the presentation in the section where the motivation for choosing the theme was described.

Conclusions

The first objective was to create a computer-brain interface that uses the motor imagery paradigm as a foundation, through which the user can control the position and orientation of a mini quadcopter drone, only using brain inputs based on trained mental commands. This goal involved using the same Emotiv Insight neural headset, which was used earlier in the case study, to understand the fundamentals of brain models, which underpinned the design of the scenario for training four classes of mental commands.

The second objective aimed to achieve mathematical modeling and numerical simulation of the dynamics of the Parrot Rolling Spider mini drone, being implemented to optimize and validate its control through the BCI interface. This involved testing the validity of the model both in real flight conditions and by simulating the behavior of the mini drone implemented in Simulink 3D Animation.

The third objective consisted of training the user with the aim of learning specific mental commands that were validated in response in controlling the direction and orientation of the drone for validating the effectiveness of the BCI system.

CHAPTER 5

BCI CONTROL APPLICATIONS

Introduction

The brain-computer interface (BCI) allows, in addition to the control of physical devices and virtual instruments, the recognition and transposition in real time of the user's intentions, using as inputs brain models recognized by mapping the user's brain. The continuous advancement of BCI interface technology has made it possible to develop games that involve the direct use of inputs from the brain to the detriment of traditional, established control methods. Thus, using the same BCI interface device, represented by the Emotiv Insight neural headset, we designed and developed a game, entitled Mental Pool Game, based on the user's attention and concentration in controlling the power and speed that he can imprint on a virtual object, in this case a white ball, specific to the game of billiards. The game was developed entirely within the Unity3D cross-platform game engine.

Next is another application that presents the control of a Lego robotic platform, which uses EEG and EMG signals captured using a redesigned OpenBCI headset. Another control method, based on muscle artifacts, is used to control the direction of the Lego Mindstorms robotic platform based on four imposed facial expressions. The section also details the hardware used, along with the software implementation and control interface.

The last application is the one that demonstrates the potential of brain-computer interfaces, by offering new ways of interaction both in games, but especially in robotics, using visual potentials in a state of balance as a foundation, to control and operate the couplings of a 3D printed spider robot. As with the first application presented, the Unity 3D game engine was used for the realization and integration of the BCI interface.

Objectives

The representative objectives of the last chapter are:

- Integration and implementation of the brain-computer interface in a 3D video game;
- Development of a control system of a robotic platform through EEG and EMG signals;
- Control of a spider robot using the SSVEP paradigm.

Designing a BCI-controlled 3D video game

In making this game I chose to implement and use a single neural input, based on the results provided by the case study of the three subjects in terms of the mental command of lifting. Thus, based on the same paradigms of motor imagining, also based on relaxation and concentration levels, we implemented another imagined movement of the human arm. It involves the same degree of kinesthetic awareness, as that produced in the case of flexion movement, generated by the shoulder joint complex, with the elbow and wrist joint fixed, previously used as a general idea of mental training of the lift command. For this purpose, the mental command "push" was chosen as an indicator of the user's power of concentration to control intentional spatial displacement, only through mental control, without involving other muscle groups.

In designing the game we chose Unity, developed by Unity Technologies, because it is an open-source, cross-platform game engine.

This game started from the idea of covering several target groups, both for healthy people and for people with disabilities. Especially in the case of the latter, the use of peripheral PC input devices, such as keyboards, mice or joysticks, could be challenging. Thus, the proposed method, which does not involve these classic commands, but only the analysis and interpretation of commands coming from the brain to control the speed of movement of the white ball in order to hit any of the 15 balls on the pool table, is a solution that aims to provide better results for all these participants.

In order to play the game of billiards, the user must go through 2 stages of mental training, similar in terms of previous activities to the way in which the neutral mental state and the lifting state were trained, through the Emotiv Xavier ControlPanel interface in the case of the quadcopter. Thus, the user initially induces a state of relaxation under the same conditions of maintaining a defocused/unfocused gaze and keeps the head in the same position for ten seconds. As for the training model for the mental command "Push", the user must imagine for 9 seconds the kinesthetic complex of movements mentioned above, but compared to the training of the mental command of lifting, used for navigation along the "z" axis of the quadcopter. Thus, it is the cognitive power that the user allocates to the mental task that determines the variable speed of movement of the white ball on the y-axis of motion.

Lego NXT Mindstorms 2.0 platform controlled by signals considered brain artifacts

I developed an EEG signal capture device to control the actuation of a Lego-type robotic platform, which offers robustness and a low cost. In this sense, the chosen solution offers the advantage of unlimited use of EEG capture electrodes, without requiring the application of a rehydration solution or their periodic replacement, as is the case with those made of semiconductor polymers used by the Emotiv Insight neural helmet in the applications presented above. The first step in the development of the BCI interface was to choose an educational platform, which allows programming in a high-level programming language, such as C# language, but also the integration of a wireless communication protocol via bluetooth. From this point of view, the hardware was also chosen to correspond to an open-source software solution, capable of discriminating between the activity generated by electroencephalogram (EEG) signals and the electrical activity generated by electromyography (EMG) signals. The latter, although they are considered artifacts that contaminate the EEG signal, can be used as a direct method of brain control as in the case of the former, being also the objective pursued to achieve a BCI control of the Lego platform, based on the detection of impulses generated by facial muscles.

To achieve direct control based on neural impulses, we used an OpenBCI headset whose structure was redesigned three-dimensionally based on an open-source license. The main objective was to provide good coverage of the selected EEG locations and a high degree of comfort, together with a quick adjustment of the EEG electrodes on contact with the scalp and providing a quick way of reconfiguration. The OpenBCI helmet thus designed places an array of 16 electroencephalogram electrodes, each of the dry type, which are made of silver chloride (AgCl), being reusable.

To conduct the EEG signal acquisition experiment we used a development board and OpenBCI Cython and an OpenBCI Daisy expansion board, integrated through a PCB provided with gold-plated safety female connectors at , 90˚ made in the Proteus circuit design software.

In order to control the Lego platform, we designed and implemented four facial expressions, obtained as a combined contribution of electromyography and electroencephalogram signals, with the advantage offered by the fact that it does not require time allocated to implement a workout, which uses mental commands as inputs as is the previous case, which involved the paradigm of motor imagery based on relaxation and the previously implemented concentration levels, both in the case of quadcopter control and pool game.

Thus, the four facial expressions followed that produce muscle signals (EMG) are: the lifting of the right eyebrow through its related muscles, the movement generated by the mandible through the intentional movement of its related muscles on the right side, as well as the movement of the other eyebrow and the mandible in the opposite direction. The OpenBCI interface was used to process and interpret muscle signals.

The signal data once interpreted is converted into binary by the OpenBCI interface and is transmitted through the Lab Streaming Layer (LSL) system, in the form of time series to an application implemented with code written in the Python language, called PyCommand.py. This application has the role of classifying each signal obtained and mapping it to keystroke sequences.

In order to receive these keystrokes, we developed and implemented an interface in C#, which would create a bridge between the computer's bluetooth device and that of the Lego platform.

Control of a spider robot based on the BCI SSVEP interface

In this section I propose a BCI system that uses the paradigm of visual evoked potentials in steady state (SSVEP) to control the motion vectors of a spider robot, designed and 3D printed.

The Equilibrium Evoked Visual Potential (SSVEP), in terms of how it can be used as an input into a BCI system, represents the intentional act of a person's will. The potential of SSVEP thus constituted concentrates the spectral energy in a narrow band and depends on attention to modulate this energy voluntarily, which makes it suitable for use in BCI systems.

The control application is based exclusively on the SSVEP paradigm as a way of dealing with the BCI interface, while it is applied to control the movement or action capable of expressing the interaction with the user of a 3D designed spider robot.

From the point of view of the chosen hardware, we used an Arduino Nano V3 development board that integrates an ATmega 328P MCU. In order not to require the design and manufacture of a dedicated PCB board, we used an expansion module designed specifically for this development board to allow PWM control. In order to be able to receive commands remotely, we used another Raspberry Pi Zero W development board as a minicomputer, as it benefits from the integrated WiFi module, making it easy to implement a User Datagram Protocol (UDP) communication protocol for both the client and the server.

The BCI NextMind headset used was developed by NextMind SAS in Paris, France, and was chosen because it offers a number of 9 patented dry type electrodes with preamplifier, placed according to the same International standard 10 - 20, whose locations have been adapted to identify and measure the brain activity produced in the visual cortex. Using as a basis the NextMind SDK developed for Unity3D, we implemented the calibration manager that measures the user's attention as a level in relation to the response of visual stimuli as a reference used in the implementation of an active control.

The resulting GUI interface, integrated in Unity, it augmented with six sphere (primitive) objects in order to represent inputs that generate visual stimuli used as triggers for the SSVEP-BCI system. In each sphere, a NeuroTag component provided by NextMind is then integrated and which gives the object the appearance of a graphic overlay with transparency. In order for the user to be able to validate the action, we have implemented a prefab called TrainagleFeedback that is integrated at the level of each sphere.

As a next step, through a script implemented in the C# programming language, the activations of the NeuroTag trigger are read, which has the role of acting in a similar way to a button that sends through the serial interface the value of the string assigned to the predefined command.

The robot's predefined movements, namely the position: lifting, lowering, steps forward, steps back, turning right, turning left, shaking hands and clapping hands.

In order to validate the accuracy of the BCI-SSVEP system and verify the level of attention required to drive the robot, but also to determine the average time spent by a user to familiarize himself with the mechanics of the application, three subjects were selected for whom mentoring actions were undertaken for 15 minutes each. Each training session was carried out under the same laboratory conditions similar to those brought in the case of training the mental command of lifting through the paradigm based on motor imagining. Thus, the results obtained by each participant throughout the training and the free session of voluntary action of the action were stored in an individual CSV file. It has the role of storing the level of confidence of each user manifested by the level of individual attention generated in response to the presence of visual stimuli. For each stored dataset, an average value of normalized cumulative confidence was then calculated in order to report the percentage of attention obtained as a result of applying a code written in Python whose implementation would provide a graphical representation.

As a first result, the measured time of the first subject **S1** was 157 seconds, in which he obtained a degree of attention expressed in a percentage of 91 %.

And in the case of the **S2** subject, a measured time of 185 seconds was recorded and an increased attention level of 98%.

In the case of the last S3 subject**,** the measured time reached 197 seconds and an attention level reported at 74%.

Conclusions

The first exposed objective of the chapter demonstrates the sustainability and efficiency of using the BCI interface in controlling a 3D video game, which simulates the real behavior of a pool game. It also involves the use of a realistic graphics engine, which provides all the necessary facilities to create an optimized graphical user interface, in order to reduce the time, it takes for them to get used to it. Also, the fact that a brain-computer interface is implemented, which uses an EEG headset to manipulate and control game elements using mental commands as inputs, makes the application available both for recreational purposes for healthy people and for rehabilitation purposes for people with motor impairments.

The second objective focuses on creating a software solution that integrates a link between a hardware solution that has been designed to detect both EEG signals and their muscle artifact (EMG) content, in order to ultimately use them to control the robot's movement. Thus, facial muscle movements in BCI systems based only on EEG should be eliminated so as not to introduce noise sources that alter the quality of the signals, in the current application they are used as control signals.

The last objective integrates the navigation capabilities of a robot, with low cost, equipped with servo motors and controlled by an Arduino development board, with the possibility of neural control based only on focusing on specific visual stimuli.

CHAPTER 6

CONCLUSIONS, CONTRIBUTIONS AND DEVELOPMENT DIRECTIONS

CONCLUSIONS

In chapter 1 we treated brain-computer interfaces (BCI) as a main bridge between external devices and neural activity captured by measuring the user's electrical potentials. Thus, electroencephalography (EEG) is the main method, the most commonly used, for capturing brain signals, due to its excellent temporal resolution. However, most BCI systems that rely solely on EEG present significant challenges that need to be overcome, being susceptible to interference, disturbances and discontinuity, especially in the case of systems using non-invasive capture methods. The presence of biological artifacts are also sources of contamination that can degrade the EEG signal. Regardless of the type of BCI interface chosen, they all have in common the orientation towards the user for controlling the devices, using the interpretation of brain activity, in relation to his intention, attention and will.

In the second chapter I reviewed the current state of the techniques used by BCI systems, in which I sought to point out the significant advances that have been made in recent decades. We have studied various neuroimaging methods, such as EEG, fMRI, MEG and NIRS, which have been successfully applied in the creation of the BCI interface. Compared to non-invasive methods, invasive methods have been shown to provide high-quality signals that are indispensable for complex applications, such as neuroprosthetics control. However, many challenges remain to be overcome in the field of BCI, including clarifying the different methods of signal acquisition in terms of advantages and disadvantages, investigating problems related to non-invasive methods, and improving the speed of information transfer. Recent progress in this area has shown that BCIs will continue to bring significant benefits in the field of rehabilitation for people with disabilities, but useful general-purpose applications will also be found.

In the third chapter we described and implemented the steps necessary to obtain EEG datasets cleaned of artifacts, for which the main objective was to ensure their quality and integrity. In addition to eliminating the artifacts, another objective pursued was to maintain a low amplitude in the case of residual artifacts, but also to compare the distribution of brain waves for various mental states. This chapter highlights the importance of understanding individual variability used in the design process of mental training scenarios as a way of controlling BCI applications.

In chapter 4 I described how to create a BCI interface based on the motor imagery paradigm, which creates a bridge between the user and the keystroke sequences used to control a mini quadcopter drone. To achieve this goal, we integrated the BCI interface technology represented by the Emotiv Insight neural headset with mathematical modeling and numerical simulation of the drone's dynamics. The focus was also on training the user to learn specific mental commands, with the aim of validating the effectiveness of the BCI system.

In chapter 5 we used the BCI interface in controlling a 3D billiards video game, demonstrating the potential of applying this technology in the virtual environment to recreate the real dynamics based on the laws of physics using a graphics engine capable of faithfully reproducing this. We also proposed and integrated an EEG and EMG-based solution to control the direction of movement of a robotic platform through muscle artifacts, demonstrating that physiological artifacts also have the potential to be used as command-and-control inputs for external devices. We have also demonstrated that by integrating a BCI interface created in a graphics game engine, with a neural headset that monitors the visual cortex, it is possible to use a neural control based on focusing on specific visual stimuli that require a short period of user accommodation to control the movement of a robot.

CONTRIBUTIONS

Within the doctoral thesis, a series of contributions were made, of which I would initially mention those related to the current state of the approached theme, which emerge from the bibliographic research.

- We made a comprehensive presentation of the current state of brain-computer interfaces (BCI), through which we covered all the design stages: from the stage of brain signal acquisition to the methods of preprocessing, feature extraction, but also classification and implementation of the control interface. The entire workflow related to the design of BCI was approached in a holistic manner, through which I aimed to create an overview of the current issue of integrating human user intent as a decision factor in the control of external devices;
- We have conducted an in-depth examination of the main modalities used in neuroimaging, in order to identify the main types of control signals that can be used as inputs of BCIs, highlighting both the advantages and disadvantages of each technique;
- We conducted and implemented a multi-subject case study to understand brain models for several mental states and training conditions, to use them as a foundation in designing the most effective BCI design scenarios, to reduce the

complexity and time of learning and the user's accommodation with the environment thus created.

CONTRIBUTIONS DETAILED BY CHAPTERS

Chapter 1:

1. We conducted a study of the main types of brain activities, which constitute existing approaches related to neuroimaging in BCI systems, namely electrophysiological ones, which use as capture methods: electroencephalography, electrocorticography, magnetoencephalography and electrical signal acquisition in single neurons and hemodynamic ones represented by the capture methods: functional magnetic resonance imaging and NIR spectroscopy.
2. We have defined the concept of electroencephalography as a neuroimaging modality, presenting its advantages and disadvantages, especially in non-invasive techniques for capturing brain signals.
3. We have analyzed and described the invasive ways of capturing brain signals, describing the main specific methods in BCI research, and we have described the main problems that arise following microelectrode implantation.
4. We analyzed and described the types of control signals used by BCI systems, including: visual evoked potentials, slow cortical potentials, P300 evoked potentials, and sensorimotor rhythms.
5. We have analyzed and described the types of BCI interfaces, classified as: exogenous or endogenous and respectively synchronous or asynchronous, which are modulated to transmit information, as well as their advantages and disadvantages.
6. We have described and analyzed the main methods of selecting and extracting features from brain signals, used for dimensional reduction, time/frequency analysis methods, and parametric modeling.
7. We have described and dealt with the main physiological and technical artifacts present in BCI systems, as well as the main elimination approaches.

Chapter 2:

8. We have analyzed and described the main classification algorithms for automatic estimation of the data class, generative, linear and nonlinear modeling, used to be able to control a BCI system. They are essential for recognizing patterns of brain activity that once identified by the system are translated into commands.
9. We have identified and analyzed the main current BCI applications used mainly for the medical field, for rehabilitation, but also for the civil sector, such as entertainment and neuromarketing.

Chapter 3:

10. We designed and conducted a case study in which we trained three subjects to use a five-channel EEG neural headset to train a relaxation condition, used as a foundation for training an imposed mental command and intentionally acting it.
11. We created a scenario whereby participants go through two mental training sessions, the first in which they train only the neutral condition in order to analyze the spatial distribution of brain waves for the relaxation period, and in the second to resume the process in order to be able to train the mental command of lifting, both sessions being recorded simultaneously.
12. We proposed and implemented a six-step algorithm for offline preprocessing of EEG data, implemented in the Matlab development environment, using the EEGLAB toolkit, results from each recording for each of the two mental training sessions, in order to obtain statistically independent components to achieve a separation of EEG data, useful for the study, by the artifacts that contaminate them.
13. We have implemented a deep learning-based classifier used for the automatic recognition and removal of independent components from EEG records. We chose this classifier for its ability to predict the signal sources of the brain and the percentage of those of the nature of artifacts.
14. We developed and implemented a four-step represented algorithm, written in the Python programming language, to manage the EEG data recorded after preprocessing and to represent them graphically, in relation to the intervals of training the neutral state, training of the mental command of lifting and intentional action, as well as the intervals of inter-action validation.
15. We developed and implemented a complex spectral power density (PSD) analysis algorithm, written in the C programming language, to evaluate the spatial distribution of brain activity in the alpha and beta wave frequency spectrum for the imposed training scenario.

Chapter 4:

16. We have made a detailed description of the Emotiv Insight Neural Helmet BCI device, according to the patent study, including the technical specifications, the EEG sensors used, the advantages offered and the cortical locations covered.
17. We made a presentation of the Parrot Rolling Spider mini drone used, through which we presented its technical characteristics and the built-in hardware components.
18. We developed the mathematical model of the drone, which contains the equations of motion from the ground to a pole, and determined the dynamic model of the drone to determine the vertical traction force, gyration effect, drift moment, roll effect, traction force, and inertia intervals relative to the axes. These were implemented in a simulation in the Matlab-Simulink development environment

based on which to create an algorithm for driving, estimating and controlling the dynamics of the mini drone in real time.

19. We carried out the implementation process of the BCI interface using as a foundation the process of acquisition and processing of EEG signals based on the Emotive development kits.
20. We implemented the process of training and classifying mental commands, using the Emotive kit as a basis, for four classes of mental tasks (lifting, lowering, left/right movement) using motor imagination. Through another Emotive interface, the result of the mental command training was mapped to the drone's actions.
21. We proposed to extend the functionality of the drone for monitoring hazard areas, by integrating a CC2650 SensorTag kit containing 10 MEMS sensors that can be used for the acquisition of environmental parameters.

Chapter 5:

22. We made and designed a pool game called Mental Pool Game, using the Unity3D game engine. For the acquisition of EEG signals we used the same neural headset used for the control of the quadcopter and in the design of the case study. This game has been developed to be accessible to both healthy and disabled staff. The BCI interface also offers an alternative to traditional peripheral input devices such as keyboard, mouse or joystick.
23. We designed the billiards game in the Unity3D game engine, using mesh components, components that involve elements of physical interaction, rendering components, all of which are used within the game to describe the interactions between virtual objects.
24. For the integration of the BCI interface, we implemented a script in the C# programming language, through which the neutral mental state and the mental command "Push" were trained for nine seconds. A scenario has been implemented whereby the user imagines the movement of a kinesthetic complex performed by the shoulder and elbow joint. Through this imagined action the user can increase the speed of movement of the cue ball in order to hit any of the 15 balls on the pool table.
25. We integrated the reading of the x and y coordinate values coming from the 3-axis gyroscope of the neural headset through a script made in the C# programming language, to control the rotation of the camera using the Emotiv development kit integrated into Unity. This allows the user to control the direction of movement of the cue ball around the table.
26. We implemented the game mechanics of billiards, importing the 3D elements, table, and billiard balls under an open-source license, then added the collision components, along with the physical materials to be able to simulate the realistic interactions between the game objects.

27. In order to be able to configure the BCI system, we created a user interface using UI elements from Unity, to be able to manage the user profile, the buttons for training mental commands and the display of status messages, all of which are included in a main menu panel.
28. We made a BCI command and control application of a Lego NXT Mindstorms 2.0 educational platform, which was programmed using interfaces created in the C# programming language.
29. To make the BCI interface we used an OpenBCI neural headset, based on a Cython development board and a Daisy extension module, whose structure was redesigned and 3D printed to fit the anatomical shape of any user's head.
30. We performed a neural control based on 16 EEG channels, using the OpenBCI interface, to provide feedback related to the EMG signals detected following the recognition of four untrained facial expressions generated by the facial musculature and which control the forward, backward, left and right turn of the robotic platform.
31. To control the Lego platform, we developed an interface in C#, which facilitates Bluetooth communication between the computer and the Lego platform. The interface allows the user to configure the keys for controlling the servo motors, check the battery status, and display the firmware version of the platform.
32. We developed a BCI system that uses the paradigm of finite evoked visual potentials (SSVEP) to control the motion vectors of a spider robot, designed and 3D printed. We used the NextMind neural headset equipped with 9 dry electrodes that allows the measurement of the activity of the visual cortex.
33. We developed a hardware and software architecture of the controlled system, using an Arduino Nano V3 development board, connected through an expansion module designed specifically for this development board, which allows PWM control. We also integrated a Raspberry Pi Zero W board used as a minicomputer for wireless communication and implemented a UDP communication protocol for transmitting commands.
34. We developed a background framework in the computer-aided software SolidWorks, with the aim of improving the appearance of the BCI interface. It has been integrated into the Unity3D game engine, being augmented with six (primitive) sphere-type objects, in order to represent inputs that generate visual stimuli used as triggers for the SSVEP-BCI system.
35. We implemented the BCI interface for robot control in the Unity3D game engine based on a script implemented in the C# programming language, which reads the activations of the NeuroTag trigger integrated in each primitive, which has the role of acting similarly to a button that sends through the serial interface the value of the string assigned to the predefined command.
36. To improve the appearance of the BCI interface, a background frame was created in the SolidWorks computer-aided software (CAD). The resulting GUI interface

will be augmented with six sphere (primitive) objects, in order to represent inputs that generate visual stimuli used as triggers for the SSVEP-BCI system.

37. In order to accommodate the user with the interface and measure the user's attention to the response evoked through visual stimuli, we implemented a calibration manager in Unity3D integrated through the development kit offered by NextMind.
38. We implemented a process of testing the results obtained by each of the three participants throughout the training and the free session of voluntary action, which were stored in an individual CSV file. For each of them, the familiarization time and the level of attention obtained were measured, being represented in graphical form based on a code written in the Python programming language.

DEVELOPMENT DIRECTIONS

As for the future development directions, I can define some main proposals:

- I am considering extending the case study by using the OpenBCI neural headset, equipped with 16 EEG channels, to analyze the distribution of brain waves in locations that are not covered by the Emotiv Insight neural headset. This involves the addition of EEG electrodes in the locations of the primary motor cortex (M1), namely in the C3 and C4 locations that are legislated by means of the international standard 10-20 that provides for the placement of electroencephalogram electrodes. In this way, the results obtained by the proposed scenario of training the mental command of lifting based on the imagination of the kinesthetic movement of the arm can be validated, namely on the basis of the actual implementation of the kinesthetic motor imagery paradigm.
- As a second proposal, I want to extend the BCI applications already proposed to a field of rehabilitation, involving the control of a neuroprosthesis designed and 3D printed, using a non-invasive EEG signal acquisition method. Such a solution can offer an alternative to the expensive prosthesis solutions on the market, which are often uncomfortable and have little functionality due to limited technical characteristics.
- Finally, I am also considering extending the drone control application for outdoor navigation, using another hardware solution, which will benefit from a wider network of sensors, even based on the integration of the kit for monitoring environmental parameters already proposed for the management of hazard situations, using a BCI solution. Also, the availability of a drone that also contains an autonomous navigation module based on GPS technology is another goal, along with finding a remote communication solution between the neural headset and the drone, using a solution based on mobile networks by integrating a GSM module. Thus, the distance covered by the drone can be extended and the possibility of its return to the take-off point, in case the connection between the devices is lost.

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