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Review on Brain computer Interface (BCI)

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Aflah and hassen

ملخص

واجهة الدماغ والحاسوب هي من التطورات والتقنيات التواصل بين الدماغ والآلة، فعلى عكس أدوات الإدخال التقليدية (لوحة المفاتيح، الفأرة، الطابعة..). تقوم واجهة الدماغ والآلة بقراءة إشارات الدماغ من مناطق مختلفة من رأس الانسان وتترجم هذه الإشارات إلى أوامر تستطيع التحكم بالآلة أو أي جهاز إلكتروني ممكن أن تكون (كرسي متحرك .أطراف اصطناعية...) , فهي تعتبر الطريقة الوحيدة للتواصل بالنسبة لكثير من الأشخاص الذين يعانون على عدم القدرة على الحركة. وتكمن أهميتها في الكثير من التطبيقات مثل التطبيقات الطبية, فهي خاصة لمساعدة الأشخاص الذين لديهم إعاقة أو مساعدة الأشخاص المصابين بمتلازمة المنحبس, فهي تساعدهم على التواصل مع العالم الخارجي وتساعدتهم على التعامل مع أجهزة الحاسوب. ومع تطور التكنولوجيا والبحوث فى هذا المجال لم تعد موجهة فقط للذين يعانون من مشاكل الحركة, بل أصبحت أيضا موجهة للمجالات الغير الطبية مثل المستخدم العادي من أجل تحسين إستخدام الحاسوب أو مجال الألعاب.

والهدف منه إيجاد الحلول للمشاكل التي تواجهها واجهات التواصل بين الدماغ والآلة الطرق المستخدمة من التقاط إشارات الدماغ إلى تصنيفها ومعالجتها وتصفيتها وأخيرا تطبيق هذه الأفعال.

الكلمات المفتاحية

واجهة الكمبيوتر والدماغ، واجهة الكمبيوتر والآلة، تخطيط كهربائية الدماغ، تحويل فورييه السريع، تحويل فورييه المنفصل.

Résumé

L'interface du cerveau et de l'ordinateur fait partie des développements et technologies de communication entre le cerveau et la machine, contrairement aux outils de saisie traditionnels (clavier, souris, imprimante ...). L'interface cerveau-machine lit les signaux cérébraux de différentes zones de la tête humaine et traduit ces signaux en commandes permettant de contrôler la machine ou tout appareil électronique qui pourrait l'être (fauteuil roulant, membres artificiels ...). C'est le seul moyen de communiquer pour de nombreuses personnes qui ont du mal avec Incapacité à se déplacer. Son importance réside dans de nombreuses applications telles que les applications médicales, il s'agit notamment d'aider les personnes handicapées ou les personnes atteintes du syndrome de confinement, il les aide à communiquer avec le monde extérieur et les aide à faire face à l'informatique. Avec le développement de la technologie et la recherche dans ce domaine Il ne s'adresse plus uniquement aux personnes souffrant de problèmes de mouvement, mais s'adresse également à des domaines non médicaux tels que l'utilisateur moyen afin d'améliorer l'utilisation des ordinateurs ou le domaine des jeux. Son objectif est de trouver des solutions aux problèmes rencontrés par les interfaces de communication entre le cerveau et la machine, les méthodes utilisées depuis la capture des signaux cérébraux jusqu'à la catégorisation, le traitement, le filtrage et enfin l'application de ces actions.

Mot clé :

Interface cerveau ordinateur, Interface cerveau machine, Transformée de Fourier Rapide., Électroencéphalographie, Transformée de Fourier discrète.

summary

The interface of the brain and the computer is one of the developments and technologies of communication between the brain and the machine, unlike traditional input tools (keyboard, mouse, printer ...). The brain-machine interface reads brain signals from different areas of the human head and translates these signals into commands that can control the machine or any electronic device that could be (wheelchair, artificial limbs ...). It is the only way to communicate for many people who struggle with Inability to move. Its importance lies in many applications such as medical applications, it is specially to help people who have a disability or help people with confinement syndrome, it helps them communicate with the outside world and helps them to deal with computers. With the development of technology and research in this field It is no longer intended only for those suffering from movement problems, but also directed to non-medical fields such as the average user in order to improve the use of computers or the field of games. Its aim is to find solutions to the problems encountered by the communication interfaces between the brain and the machine, the methods used from capturing brain signals to classifying, processing, filtering and finally applying these actions.

Keywords:

Brain Computer Interface, Brain Computer Interface, Fast Fourier Transform.**,** Electroencephalography, Discrete Fourier Transform.

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List of abbreviations

AEF: Auditory Evoked Field

BCI: Brain Computer Interface

BMI: Brain Machine Interface

BOLD: Oxygen-Dependent Blood Leve

CAR: Common Average Reference

CKC: CorticoKinematic Coherence

CMC: Coherence of Cortex-Musc

DFT: Discrete Fourier Transform

DCM: Complex Causal Modeling

EEG: Electroencephalography or Electroencephalogram

EMG: electromyogram

ECG: electrocardiogram

EOG: electrooculogram

ERP: event-related potentials

ECD: Equal Current Dipole

ECoG: electrocorticograp

FIR: Finite Impulse Response

FFT: Fast Fourier Transform

FNIR: functional near infrared imaging

FMRI: Functional Magnetism Resonance Imaging

IIR : Infinite Impulse Response

ISI: Inter Stimulus Interval

LFP: local field potentials

MEG: Magnetoencephalography

MNE: Minimal Standard Estimate

MRI: Magnetic Resonance Imaging

MUSIC: Multiple Signal Classificatio

NIRS: Near Infrared Spectroscopy

PSP: Post-Synaptic Potentials

PET: Positron Emission Tomography

RF: Radio Frequency

SL: Surface Laplacian

SLA: Sclerosis Literate Amyotrophique

SNR: Signal-to-Noise Ratio

SQUID: Superconducting Quantum Interference Device

SSS: Separation of Signal Space

STN: SubThalamic Nucleus

TMS: Magnetic Transcranial Stimulation

TSSS: Separation of Temporo-Spatial Signal Space

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General Introduction

General Introduction

Man has used resources and capabilities to meet his simple and daily needs since its inception and its conception to build the tools necessary for his existence.

After many years, people made them think about how to create tools to help them solve their problems, such as hearing loss and paralysis of some organs [1], due to the nature of the brain which is so diverse and adaptable in a different and terrible way, to the point that it can be learned to control devices that are radically different from Our bodies. This interaction between the brain and the computer is considered, and this topic is relatively new due to its rapid development and is a very interesting topic by taking advantage of recent developments in neuroscience, signal processing [2], machine learning and information technology, including what has been created the so-called computer-brain interface (BCI).

But here, several problems or questions are raised, what is the meaning of BCI? How did this science develop or its history and what aspects of neuroscience research made these developments possible? What are the machine learning techniques that allow brains to control machines? What are the applications of technology in brain computer interfaces (BCIs) [3]. These are some of the questions covered in this work.

The primary motivation of this note is to serve as an introduction to the field of communication between the brain and the computer and its ability to restore lost sensory and motor function. In the first chapter, , a general introduction is examined to the brain from the central nervous system, which consists of structure and function in addition to its functions, and the biological neural network with how the nervous system communicates and how the communication between neurons.

In the second chapter, the signal is linked to the brain and the general structure of the brain, how it is linked, and the brain and computer engineering, starting from the signal extraction To apply it in reality, was delved into the pre-treatment stage in which the temporal and spatial filtering takes place.

In the last chapter, general applications in human life is dealt, such as medical and non-medical devices, and this is what will be answered in terms of solutions and applications to solve brain problems, the aim of which is to translate brain activity into orders for devices. Restore nerve function.

Chapter I
Stat of the art

1.1. Introduction

The brain-computer interface (BCI) acquires neural signals that correspond to an imagined command, and then processes these signals and decodes them to produce linguistic output in the form of signals, sounds, or sentences. Recent research has demonstrated the ability of neurolinguistics to enhance decoding approaches to visualized commands while including semantics in experimental procedures. As the results of neurolinguistics research begin to be incorporated into the scope of BCI research, it is our view that a comprehensive understanding of imagined commands and its relationship to explicit commands should be considered an integral feature of research in this area. Focusing on visualized commands, this part presents a review of the most important neurolinguistics research informing the field of BCI and suggest how this research can be used to improve current experimental protocols and decoding techniques for those commands. The concepts and methods of neurolinguistics are used to help develop a natural pattern of communication. Hence, it presents the development histories of BCI [4].

1.2. Statistical study of BCI

This section presents some developments in BCI throughout history:

In the 1970s, research on BCIs started at the University of California, which led to the emergence of the expression brain-computer interface. The focus of BCI research and development continues to be primarily on neuro prosthetics applications that can help restore damaged sight, hearing, and movement. The mid-1990s marked the appearance of the first neuro prosthetic devices for humans. BCI doesn't read the mind accurately but detects the smallest of changes in the energy radiated by the brain when you think in a certain way. A BCI recognizes specific energy/ frequency patterns in the brain.

June 2004 marked a significant development in the field when Matthew Nagle became the first human to be implanted with a BCI, Cyber kinetics' Brain Gate™.

In December 2004, Jonathan Wolpaw and researchers at the New York State Department of Health's Wadsworth Center came up with a research report that demonstrated the ability to control a computer using a BCI. In the study, patients were asked to wear a cap that contained electrodes to capture EEG signals from the motor cortex — part of the cerebrum governing movement.

BCI has had a long history centered on control applications: cursors, paralyzed body parts, robotic arms, phone dialing, etc.

Recently Elon Musk entered the industry, announcing a $27 million investment in Neural link, a venture with the mission to develop a BCI that improves human communication in light of AI. And Regina Dugan presented Facebook's plans for a game-changing BCI technology that would allow for more efficient digital communication. [5].

1.3. Brain Signals for Brain–Computer Interfaces

1.3.1. Key Principles

For generations, humans have dreamed of communicating with the machine through the activities of the brain. The imagination of scientists and others was in films science fiction and creativity about signal activities in the human brain, and this dream seemed to be fulfilled at the present time by capturing brain impulses and monitoring real-life equipment with electronic devices Sophisticated. Sure, some limitations and obstacles still exist, but it was concluded that there will be a lot more to do with brain signals and effective solutions to many of the current scientific issues in the next few years.

The Brain Machine Interface (BCI) is a complete structure of software and hardware that manages computers and various communication devices by controlling human signals [6].

1.3.2. The Origin of Brain Signals Used in BCIs

In theory, a BCI might use brain signals recorded by a variety of methodologies. These include: recording of electric or magnetic fields, functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and functional near infrared (fNIR) imaging. In reality, however, most of these methods are at present not practical for clinical use due to their intricate technical demands, prohibitive expense, limited real-time capabilities. Electric field recordings measure changes in membrane potentials of CNS synapses, neurons, and axons as they receive and transmit information. Neurons receive and integrate synaptic inputs and then transmit the results down their axons in the form of action potentials. Synaptic potentials and action potentials reflect changes in the flow of ions across the neuronal membranes. The electric fields produced by this activity can be recorded as voltage changes on the scalp (EEG), on the cortical surface (electrocorticographic activity (ECoG)), or within the brain (local field potentials (LFPs) or neuronal action potentials (spikes) [7].

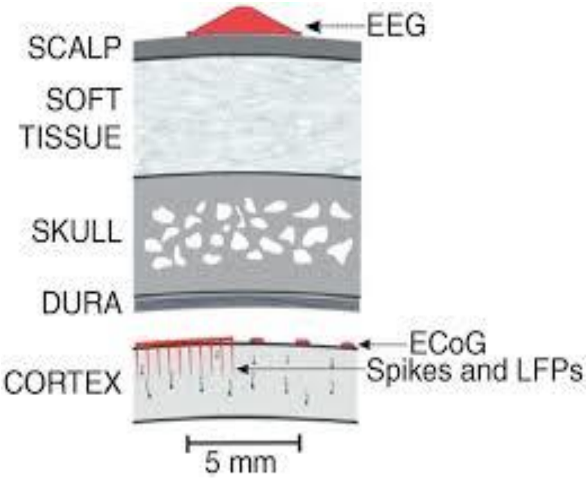


Figure1. 1 : Recording sites for electrophysiological signals used by BCI systems.

(a): Electroencephalographic activity (EEG) is recorded by electrodes on the scalp.
(b): Electrocorticographic activity (ECoG) is recorded by electrodes on the cortical surface.
(c): Neuronal action potentials (spikes) or local field potentials (LFPs) are recorded by electrode arrays inserted into the cortex (modified from Wolpaw and Birbaumer) [8].

The EEG recorded on the scalp provides the most convenient non-invasive access to brain activity. The EEG is traditionally analyzed in the time domain or in the frequency domain. In the time domain, EEG is measured as voltage levels at particular times relative to an event or stimulus. When voltage changes are time locked to a particular event or stimulus, they are called "event-related potentials" (ERP). In the frequency domain, EEG is measured as voltage oscillations at particular frequencies (eg, 8-12 Hz mu). EEG characteristics measured in the time and frequency domains have been shown to be useful for BCIs [9].

1.3.3. Brain Signal Features Measured from the Cortical Surface

Short-term experiments of hospitalized patients briefly implanted on the cortical surface with electrode clusters prior to epilepsy surgery showed highly oriented ECoG movement correlated with motion or touch, or motor imaging. This ECoG activity has greater amplitude, higher topographical accuracy, broader frequency spectrum, and much less sensitivity to artifacts such as EMG activity, relative to scalp-recorded EEG. Therefore, with EEG, ECoG could be able to provide BCI-based connectivity and control superior to that feasible or probably even necessary [10].

1.4. The central nervous system

1.4.1. Structure and function

The central nervous system is that part of the nervous system that consists of the brain and spinal cord. And it is a place where the received information is processed and integrated for the action or response by effectors.

The nervous system consists of two main parts: the central nervous system (CNS) and the peripheral nervous system (PNS). It is also the body's internal communication system. The central system (CNS) is the body's primary command center, and it consists of the brain and spinal cord. The peripheral nervous system (PNS) consists of a network of nerves that connect the rest of the body to the central nervous system (Figure 1.2).

The two systems work together to gather information from inside the body and from the environment outside it. Nerve cells receive information through the body's senses: touch, taste, smell, sight, and sound. The brain interprets these sensory signals to understand what is happening outside and inside the body. This allows a person to use their bodies to interact with their surroundings and control body functions [11].

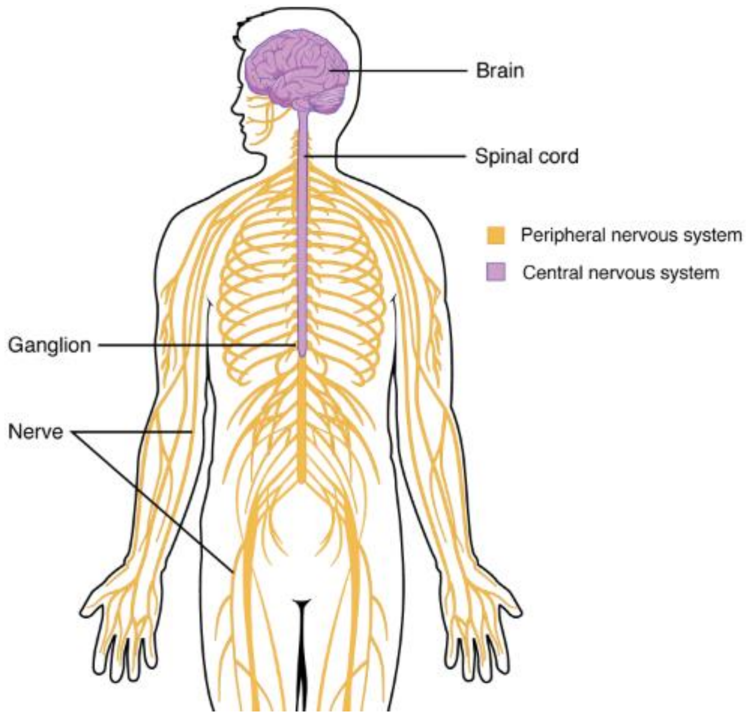


Figure1. 2 : Central and Peripheral Nervous System: The CNS contains the brain and spinal cord, the PNS includes nerves.

The PNS is divided into two types based on the organs/tissue it transmits the nerve impulse to. These are:

Somatic nervous system: The somatic involves parts of the body a person can command at will and Impulse is transmitted from CNS to skeletal muscles.

Autonomic nervous system: Impulse is transmitted from CNS to smooth muscles and involuntary organs of the body. helps run involuntary functions such as pumping blood. [12]

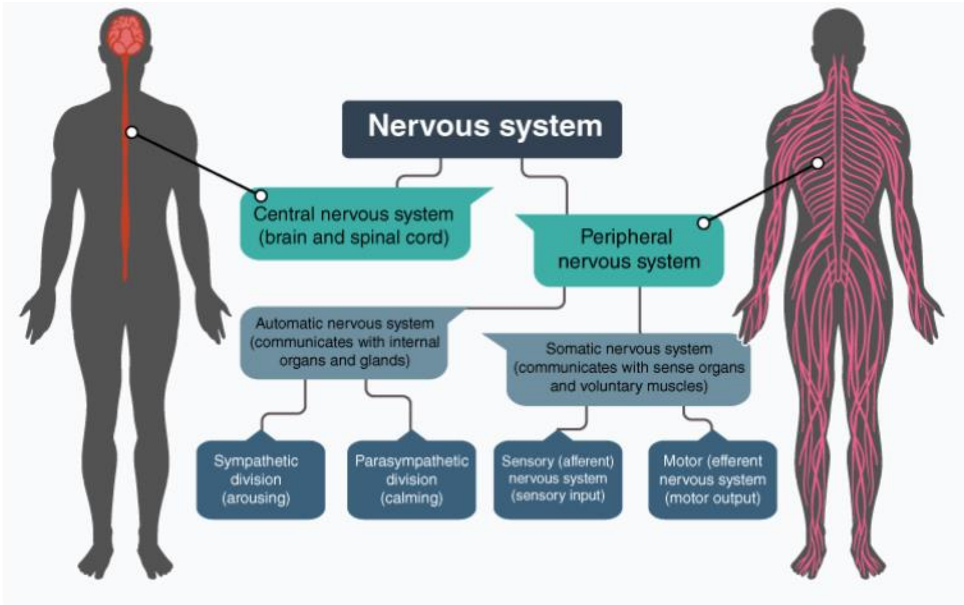


Figure1. 3 : Divisions of the Nervous System.

1.4.2. Functions of the Nervous System

1. Take all information from both inside and outside the body - Sensory Function (Sensation). Sensation refers to receiving information about the environment, either what is happening outside (heat from the sun) or inside th35e body (heat from muscle activity). These sensations are known as stimuli (singular = stimulus).
2. Transmits information to the processing areas of the brain and spine
3. Processes the information in the brain and spine – Integration Function
4. Sends information to the muscles, glands, and organs so they can respond appropriately Motor Function. controls and coordinates all essential functions of the body including all other body systems allowing the body to maintain homeostasis or its delicate balance [13].

1.5. Biological neuron

Neurons, also known as nerve cells, send and receive signals from your brain. While neurons have a lot in common with other types of cells, they’re structurally and functionally unique.

At birth, the human brain consists of an estimated 100 billion neurons Trusted Source. Unlike other cells, neurons don't reproduce or regenerate. They aren't replaced once they die. [14].

1.5.1. Structure of a neuron

The nervous system contains more than 1000 billion of interconnected neurons. A neuron is a cell made up of a cell body and a nucleus. The cell body branches off to form what are called dendrites. These are sometimes very many, whether we are talking about dendritic hair or dendritic afforestation. It is through the dendrites that information is directed from the outside to the soma, the body of the nerve cell.

Then the information that is processed by the neuron travels along the (singular) axis to be transmitted to other neurons. Transmission between two neurons is not direct. There is an intercellular space of a few tens of angstroms (10-9 m) between an axon from the incoming neuron and the dendrites (called dendrites) of the outgoing neuron. The junction between two neurons is called a synapse [15].

Each neuron receives electrochemical inputs from other neurons at the dendrites. If the sum of these electrical inputs is sufficiently powerful to activate the neuron, it transmits an electrochemical signal along the axon, and passes this signal to the other neurons [16].

This figure, shows the shape of the neuron:

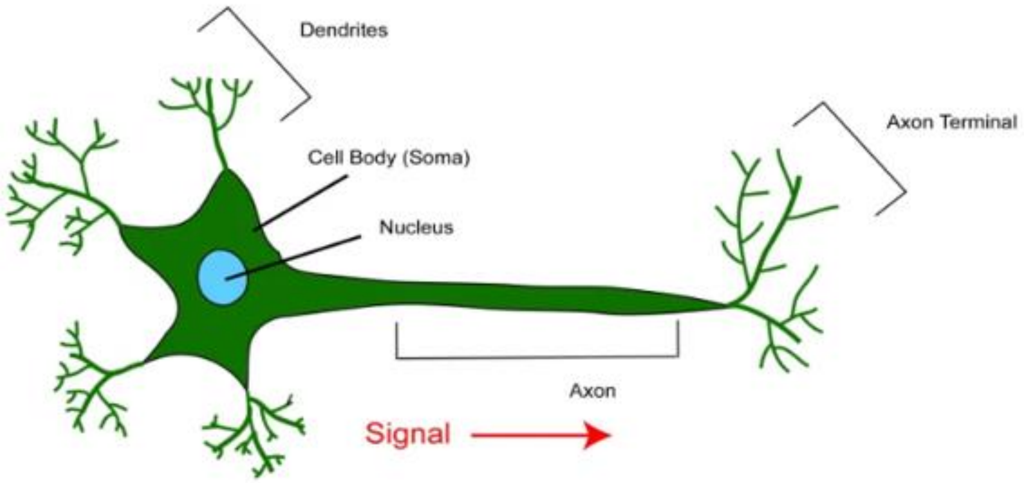


Figure 1.4 : Basic neuron structure.

1.5.2. Parts of a neuron:

We can divide the neuron into three main sections:

Dendrite: is similar to the structure of a large tree. The dendrites pick up signals sent to the neuron, they act as a sensor that receives signals from outside the world. And These tiny protrusions receive information from other neurons and transmit electrical stimulation to the soma.

Celle body (or soma): the cell body is the region of the neuron in which an electrical impulse is generated, are used for the reception of inputs from other neurons.

Axon: The axon is located at the end of the soma and controls the firing of the neuron. If the total strength of the signal exceeds the threshold limit of the axon, the structure will fire a signal (known as an action potential) down the axon., and transmit electrical impulses away from the cell body to other cells [17].

Synapse: a synapse is a specialized region where a nerve signal travels from one neuron to another. It is a communication site between two neurons.

1.6. Biological neural network

Humans Have Specialized Neuronal Connections, the myriad types of neurons and their specific synaptic connections include the basic components of neural circuits and networks, which are collectively referred to as the neural network. While the enormous complexity of the human neural network has become increasingly apparent over the past decade, largely due to advances in imaging technologies, our understanding of its organization and function at the level of long-range projections, local synaptic circuits, and intracellular signals remains very incomplete. Recent estimates indicate that there may be between several hundreds of trillions and more than one quadrillion synapses in the human central nervous system, with an average of 164 trillion synapses in the neocortex of an adult male. Moreover, cerebral white matter in young adults contains -149000-176000 km of myelinated axons, in principle, small changes in the connections of the neural network can lead to deep and specific functional changes [18].

A neural network is a dynamical system with one-way interconnections. It carries out processing by its response to inputs. The processing elements are nodes; the interconnects are directed links. Each processing element has a single output signal.

The neural system of the human body consists of three parts: receptors, a neural network, and effectors. The receptors receive the stimuli either internally or from the external world, then pass the information into the neurons in a form of electrical impulses. The neural network then processes the inputs then makes a proper decision of outputs. Finally, the effectors translate electrical impulses from the neural network into responses to the outside environment. Figure 1.5 shows the bidirectional communication between stages for feedback [19].

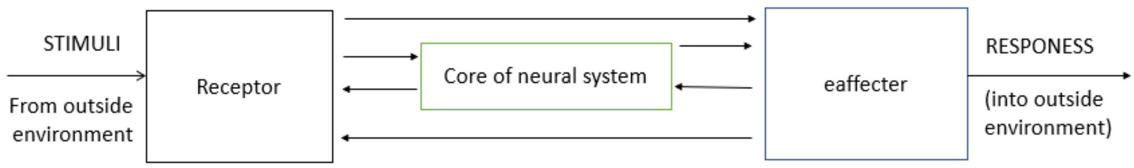


Figure1. 5 : Three Stages of Biological Neural System

1.7. Neural Communication

Neurotransmitters play an important role in neural communication. They are chemical messengers that carry messages between nerve cells (neurons) and other cells in your body, influencing everything from mood to involuntary movements. This process is generally referred to as neurotransmission or synaptic transmission [20].

1.7.1. A networked organization

Neurons are not independent of one another; Neurons create close connections and chains.

Neurons are excitable cells that receive and transmit electrochemical signals. The dendrites and the axon send these signals. As do wiring in an electrical circuit. The dendrites receive signals and transmit them to the axons. Each neuron can receive information from many other neurons and transmit it to many others, and we can count about 250,000 connections.

1.7.2. Transmission of information at synapses

The transfer of information from one neuron to another takes place at the synapse level. At this level, the membranes of neurons in communication are close to each other but separated by a synaptic space. The electrical signals cannot cross this space, the communication between two neurons takes place through the intermediary of chemicals called neurotransmitters. these substances differ according to the synapses; they are produced by the neuron which sends the message and recognized who receives it.

The connection in the chain of neurons is one-way. The nerve cell connects with various other neurons, and thus it constantly receives many chemical messages at the level of different synapses and takes them into account to develop. In turn, a new original nerve message will convey it, so the neuron is not a simple relay but a unit for processing information [21].

This figure represents how it starts of reception to neural transmission and integration by CNS, finally action by effectors

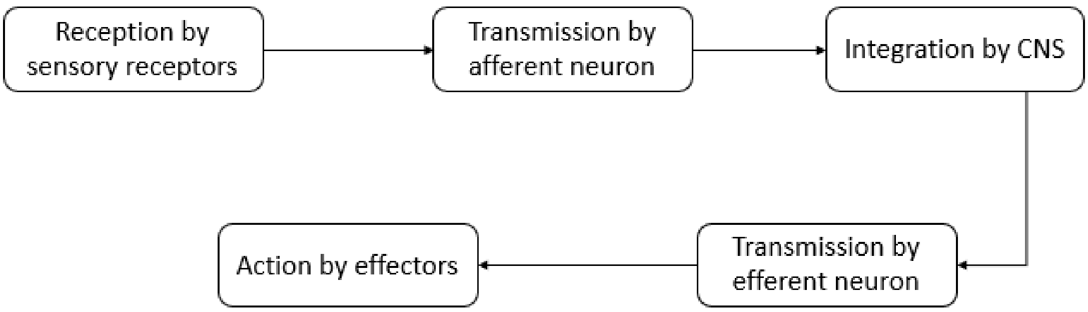


Figure 1.6 : The stages of information transfer from reception to implementation**.**

1.8. Conclusion

This chapter, presented an overview of people memo and tried to answer some of the problems that presented at the beginning. From an evolution in BCI's life historically, as well as how the brain signals work, and after that touched upon the evolution of the brain in biological terms of its components and regions. It also talked about the biological cell, its components, and how it works. the next chapter, we will be about the definition of the brain and device interface, as well as how to record and process signals.

Chapter II

Brain machine interface

2.1. Introduction

Brain–machine interfaces (BMIs) create closed-loop control systems that interact with the brain by recording and modulating neural activity and aim to restore lost function [22], most commonly motor function in paralyzed patients and creation of a direct communication channel between the brain and the device without the need to use external extremities such as muscles or another driving interface It could be a computer, wheelchair, robot, auxiliary, or alternative communication device [23],This technique makes it possible to exploit signals emitted from the brain during a specific activity in the form of brain waves. It was captured by an acquisition card and then processed, classified and finally translated as a control signal for the device.

This concept came to overcome the motor dysfunctions of the human body, after an Illness or functional deformation of a responsive organ, or after an accident of fracture of the spinal nerves, which leads to partial or complete paralysis. However, it is necessary for the brain's functions to remain healthy and for the person to be conscious.

This technology was previously aimed at those who have a functional dysfunction in one of the members, example: communication with the external environment (the medical field) [24], but now thanks to advances in technology, this interface can be used to operate several different tasks, example: the robot control arm, the wheelchair [25], (A simulation of controlling a wheelchair by using brain signals for paralyzed patients as the patient thinks about walking and moves wheelchair) , controlling drones, robotic arms [26], virtual avatars, video games. [27].

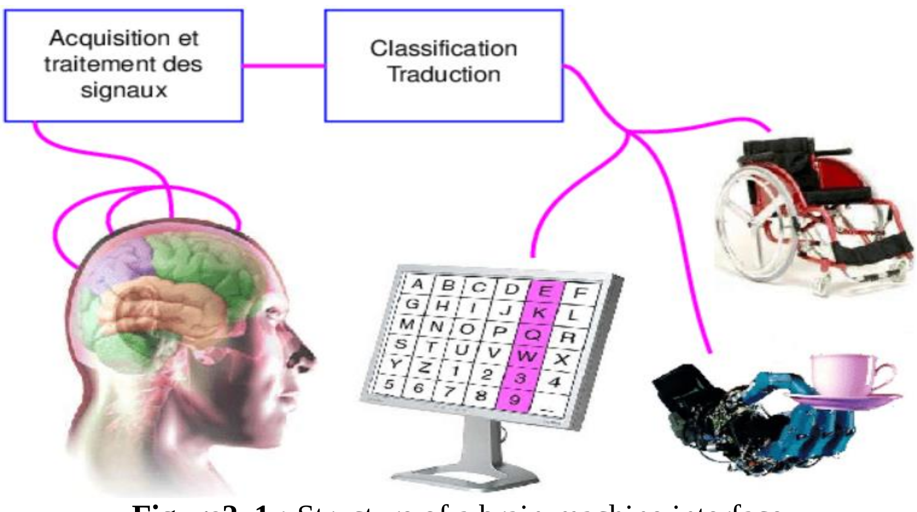


Figure2. 1 : Structure of a brain-machine interface

2.2. Brain signal recording of brain computer interface

A brain computer interface (BCI) is defined as a combination of hardware and software that enables external devices or even computers to be regulated by brain activity. Academia and industry have both been drawn to research in this field. The aim is to help people with serious disabilities enjoy as good a life as possible. Any of these disorders are known as neuromuscular diseases. The BCI system moves through several steps, including:

Pretreatment, extraction of characteristics, classification of signs, and ultimate control.

From the first chapter on brain signaling, it has have discovered that the brain interacts using impulses that are maximum or no electrical impulses as neurons obtain adequate input current via synaptic connections from other neurons.

It is not surprising, thus, that the first methods for monitoring brain function were based on the identification of variations in electrical potential in neurons (electrode-based intrusive techniques) or large numbers of neurons (non-invasive techniques such as EEG). New approaches also focused on indirect detection of neural activity by measuring changes in blood flow induced by increased regional nerve activity (fMRI) or by measuring subtle changes in the skull's magnetic field caused by neural activity (MEG). Some of these technologies that serve as input signal sources for BCIs are reviewed below [28].

2.2.1. Non-invasive

2.2.1.1. Electroencephalogram (EEG)

Although basics of the electroencephalogram (EEG) measurement in man have been the same since 1929, it was first made by Hans Berger, the technological developments give the opportunity to build much more sophisticated acquisition systems regarding clinical needs and scientific

researches. The human brain generates electrical signals called Electroencephalogram (EEG) signals which are related to body functions, these signals are roughly less than 100μV and 100 Hz and can be measured with electrodes placed on the scalp, noninvasively. EEG is a non-invasive method used to convert cerebral cortex activity into a usable electrical signal.

The EEG device is the electronic device that allows this signal to be recorded by the electrodes placed on the surface of the scalp that transmit this signal to an electronic card without modifying its nature, to give us electrical paths (Figure 2-2) . [29].

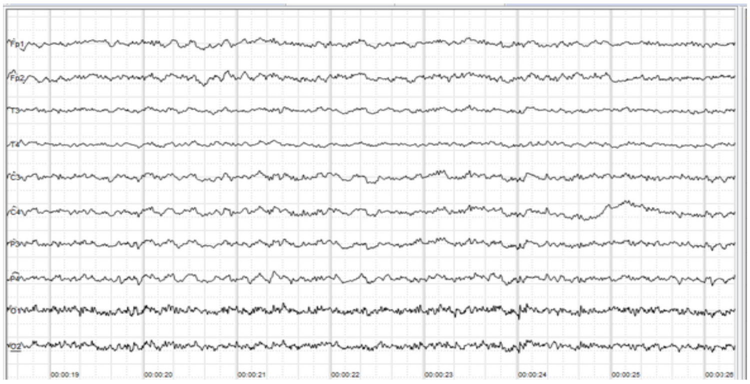


Figure2. 2 : EEG signal

The electrical activity is captured by electrodes placed at specific points on the scalp, where the strength of the brain's activity is multiplied by nearly a million times through an electronic system contained in the EEG. These electrical activities are documented in the form of waves of variable frequency on the device sheet, or it is possible that the data is stored immediately in the computer memory. During the examination, brain performance is tested during wake and sleep, as well as when the patient is activated by excess ventilation and lights flash.

The spatial resolution of the EEG is very low, and it is almost impossible to know the localized activities EEG. However, since EEG reflects the electrical activity of neurons, temporal resolution is very high. It is possible to follow the changes in brain activity in the order of several milliseconds. This is the biggest advantage of using EEG [30].

2.2.1.2. Magnetoencephalography (MEG)

Magnetoencephalography (MEG) tracks weak magnetic fields outside the human head, providing millisecond-accurate data on neural currents that facilitate the function of the human brain. The complementary methods of MEG and electroencephalography (EEG) are closely related and should be understood together wherever possible. This manuscript covers MEG's core physical and physiological concepts and addresses the key facets of state-of-the-art MEG data processing. Advice on best practices in patient planning is included, evaluation of triggers, compilation and analysis of MEG data, as well as regular clinical examinations for MEG interpretation.

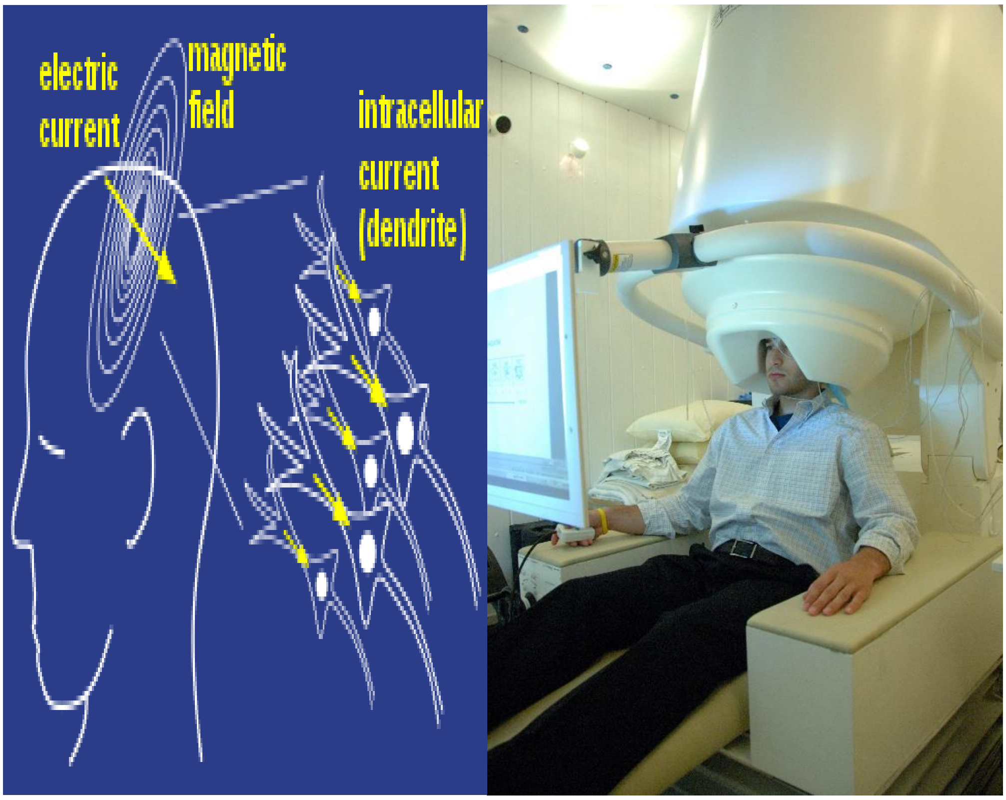
Around 200 whole-scalp MEG units, many of them located in clinical settings, were in use worldwide in 2017. However, there are still few therapeutic indications developed for MEG evaluations, mainly limited to the diagnosis of epilepsy and preoperative functional assessment of neurosurgical patients.

The vast ongoing fundamental MEG study demonstrates promise for the assessment of neurological and psychological syndromes, developmental disabilities, and post-stroke integrity of cortical brain networks. Basic and clinical science is now paving the way for a growing array of MEG clinicians to recognize new clinical applications. Abbreviations AEF, auditory evoked field; BOLD, oxygen-dependent blood level; CKC, corticokinematic coherence; CMC, coherence of cortex-muscle; DCM, complex causal modeling; EEG, electroencephalography; ECD, equal current dipole; ECoG, electrocorticograp; MNE, minimal standard estimate; MRI, magnetic resonance imaging; MUSIC, multiple signal classification; Electrical stimulation; ISI, interstimulus interval; MEG, magnetoencephalography. SEF, area evoked by somatosensory; SNR, signal-to-noise ratio; SQUID, Superconducting quantum interference device; SSS, separation of signal space; STN, subthalamic nucleus; TMS, magnetic transcranial stimulation; tSSS, separation of temporo-spatial signal space; VEF, field visually evoked Thus, MEG provides better spatial accuracy than EEG and is independent of the head geometry. In the other hand, MEG detectors are much more expensive than EEG systems, are cumbersome and non-portable, and require a magnetically shielded chamber to prevent interaction with external magnetic signals and the earth's gravitational field [31].

Using superconducting quantum interference instruments (SQUIDs), magnetic EEG (MEG) measures magnetic fields induced by electrical activity in the brain. A standard MEG configuration where a person sits in a chair and responds to on-screen stimulus by pressing buttons on a handheld device is depicted in (Figure 2.3).

Due to synaptic stimuli from other neurons, all MEG and EEG impulses emerge through the net result of ion currents streaming into the neuron dendrites.

As seen in Fig.2.3a, these currents (as dictated by Maxwell's equations) generate an orthogonal magnetic field. These current sources must have a common direction (otherwise they would be cancelled) in order to be observed by MEG, and hence the magnetic activity observed by MEG is assumed to be the product of the simultaneous activity of tens of thousands of pyramid neurons. The neocortex has a perpendicular orientation to the cortical floor. Since the orthogonal magnetic field is observed by MEG; It is only vulnerable to waves that incidentally flow through the scalp. Behavior from cortical sulcus (cortical surface grooves) rather than gyrus (cortical surface protrusions) is also preferentially measured as opposed to EEG, which is susceptible to both.



a **b**

Figure2. 3 : Magnetoencephalography (MEG)

Magnetoencephalography (MEG): (A) Schematic diagram illustrating the orthogonal magnetic field generated by currents in dendrites of similarly oriented cortical neurons. (B) Example MEG system [32].

2.2.1.3. Functional magnetic resonance imaging (fMRI)

Magnetic resonance imaging (MRI), particularly functional magnetic resonance imaging, has been used in a significant number of behavioral response research studies recently (fMRI).

Both of these experiments use level-dependent contrast imaging (BOLD-) for blood oxygenation, which includes mapping individual functioning brain areas through differences in blood oxygen. Differential fMRI has adequate spatial resolution to identify active brain regions and to delineate from visualized adjacent regions. A voxel that represents the activation region is commonly characterized as covering a couple of million neurons. Furthermore, the BOLD reaction is delayed from 1 to 2

It normally peaks at 5 s after stimulation, behind the stimuli before the vascular system responds. The control of the BOLD reaction can be decreased by continuing the same stimulation. After the activation fades, the thermal resistance time of a few seconds is always inadequate for BOLD photography, Depending on whether kinesthetic, auditory, or emotional are the activation mode.

The stimuli must be repeated several times to remove noise in the video. It only takes a few minutes to complete this process, and findings can then be compared across multiple individuals or animals. With respect to the above, in behavioral response research experiments using comparison fMRI, mice, goats, and monkeys were used. This method improved and thus improved the quality of the images produced by both spinning, pulse resonance and magnetic force increase.

The sensory portion of the brain, including the lateral geniculate bodies and the cortex, is one region of the brain that is common for fMRI mapping due to its relatively simple generation of stimuli. Our community has used a variety of distinct stimuli for both sensory and motor activations for fMRI mapping over the past 10 years, with some results. That include chewing and thumb resistance (in humans) and passive flexion of the elbow (in animals). Both motor and sensory functions, such as proprioception and movement, contribute to these various forms of stimulation. However, so far, only a small number of clinical trials have been reported on brain injury, Alzheimer's disease, and alcohol misuse using this tool.

The key benefit of fMRI is that spatial resolution is much higher, typically in the 1-3 mm range, than other non-invasive techniques such as EEG and MEG. The temporal resolution is, however, poor [33].

Figure2. 4 : fMRI recording of brain activity

fMRI machine with a subject whose brain is being scanned while performing an experiment. The subject is holding a button-press device for indicating choices or outputs [34].

2.2.1.4. Functional near-infrared (fNIR) imaging

Functional near-infrared (fNIR) imaging is a visual tool to measure changes in the level of blood oxygenation induced by elevated nerve activity in the brain. This form of picture detects the absorption, with and without oxygen, of near-infrared hemoglobin rays into the blood. Hence, it offers subtle insight into current brain activity in a similar manner to fMRI. It is less difficult than a functional MRI, but it is more noise-resistant and has poorer spatial resolution. Secure transportation, which involves well-functioning motor control operations, is an essential feature of everyday human life. The difficult relationship between the subcortical and cortical regions relies on human neuromotor regulation of everyday tasks such as walking. Technical advancements in neuroimaging systems make it possible to assess cortical activity during motor task execution. Functional -infrared spectroscopy (fNIRS) appears to be a promising tool for monitoring motor control processes in cortical regions in freely moving subjects.

To date, however, no uniform protocol has been developed with regard to the implementation and data processing of fNIRS signals that limits comparability between studies. This systematic analysis was therefore aimed at summarizing current implementation and data processing information in fNIRS studies concerned with gait or postural activities. From the original return of 1,420 papers, fifty-six papers were checked and information on the methods, data analysis, and findings was abstracted. Guidelines are identifyed for planning and discussing fNIRS studies based on our results. In kinesiology, future perspectives for calculating Functional near-infrared spectroscopy (fNIRS) signals are explored.

Functional infrared imaging is limited in nature to determine the behavior of neurons near the skull, opposed to functional magnetic resonance imaging, which can image deep regions of the brain. In the other hand, entities are not passed about, unlike practical magnetic resonance imaging, so they do not break within the MRI machine. Since near-infrared imaging is based on optical rather than electrical calculations, it is not vulnerable to muscle anomalies (compared to EEG). It is therefore much less costly and as compact as an EEG than a practical MRI [35].

2.2.2. Invasive

Techniques that cause individual neurons in the brain to be registered are usually invasive, that is, they require a type of operation in which a part of the skull is removed, an electrode or implant is inserted in the brain, and the part of the skull removed is then replaced. Usually, invasive recordings are taken from species including monkeys and rodents. The recording itself is not unpleasant because there are no internal mechanisms for pain in the brain, but the process of surgery and healing will induce pain and include risks such as infection. The monitoring technique can be performed on both anesthetized and awake animals, but the animal is usually limited to reducing objects arising from large movements in the case of awake recordings. Invasive recordings for humans are only recorded in hospital settings, such as during brain surgery or where patients are checked for irregular brain function (such as seizures) prior to surgery. In the case of such species, the time span available for documenting can varies from weeks and months to years (e.g., Monkeys) for a few days or minutes in a clinical setting in the case of humans. A major benefit of invasive recordings is that they allow the millisecond time scale to record action potential (the recognized output signals of neurons). This compares with non-invasive methods that measure indirect correlates of Neural activities that occur at a coarser time scale (hundreds of milliseconds), such as blood flow. The technology of electrodes is the basis of intrusive recording of both humans and animals [36].

2.2.2.1. Electrocorticography (ECoG)

Electrocorticography (ECoG) is a technique that involves placing electrodes to catch brain impulses on the brain's surface. The procedure involves making a surgical incision through the skull to inject the electrodes into the brain surface (Figure 2.5).

ECoG is typically done only in outpatient environments, such as monitoring in-hospital seizure activity in epilepsy patients. Usually, a grid or strip of m??n electrodes is inserted, where the values of m and n vary between 1 and 8. ECoG electrodes are normally 2-5 mm in diameter and carbon, silver, or gold alloy may be tipped. The distance between grid electrodes is usually 10 mm to 1 cm. The electrodes are fairly flexible to accommodate everyday tasks in the brain. Compared to single-cell electrodes or multielectrode arrays, ECoG electrodes can record the electrical variations caused by the coherent activity of large neuron populations (several tens of thousands). While ECoG electrodes do not specifically measure spikes, it is believed that the signal observed is directly related to the cortical neuron dendrites' input currents, especially in the upper layers of the cortical neurons. Cerebral cortex; ECoG has recently received interest from the BCI community as a partly invasive alternative between invasive multielectrode arrays and noninvasive EEG. Unlike multielectrode arrays, certain types of ECoG do not pass the blood-brain barrier, and are thus safer than arrays implanted inside the brain. ECoG electrodes may also be less likely to wear out, compared to brain penetrating electrodes that suffer from glial accumulation and scar tissue formation over time. The spatial precision of ECoG is higher than that of non-invasive techniques such as EEG, since the neuronal activity is similar to that (tenths of millimeters vs. centimeters),
Wider spectral bandwidth (0-200 Hz vs. 0-40 Hz), larger amplitude (50-100 μV vs. tens of μV), and considerably lower susceptibility to objects such as the operation of muscles and natural noise.

The drawbacks of ECoG include: Currently: (1) it can be used only in surgical settings. (2) it is possible to record only areas of the brain that are surgically essential, and (3) interference can occur due to patient-related drugs or disorders, such as seizures [37].

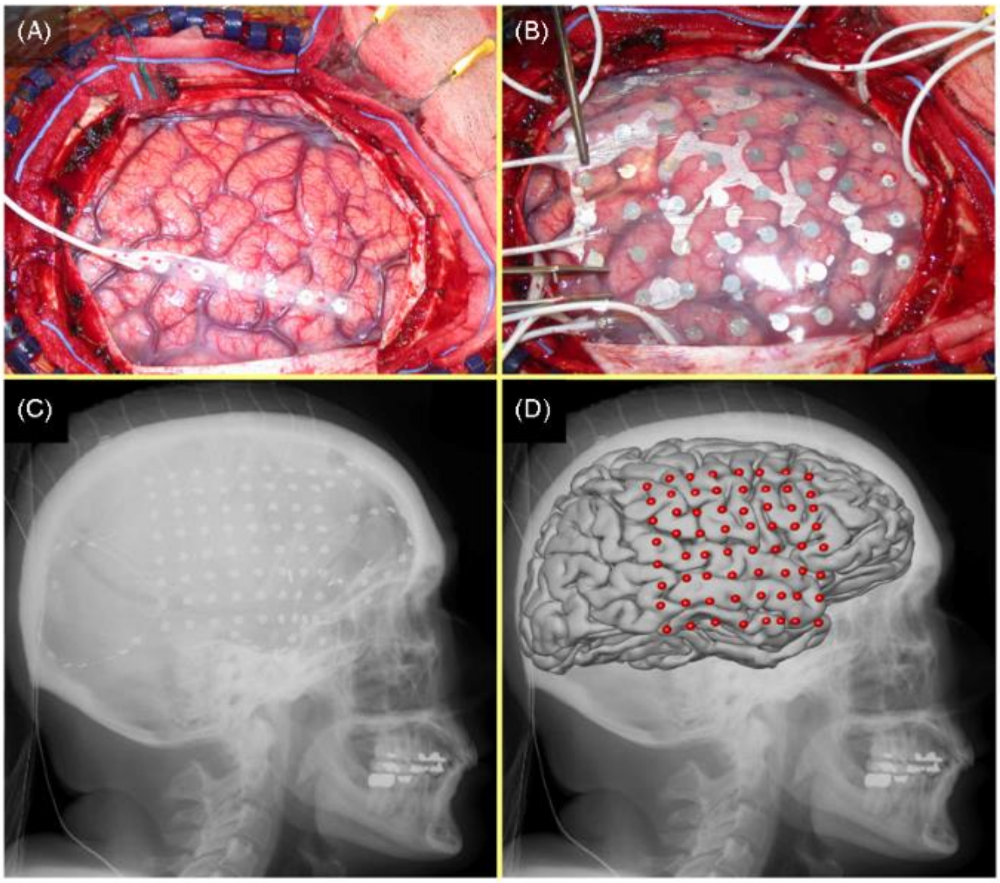


Figure2. 5 : ECoG in a human

(A) and (B) Implantation of an ECoG array. The brain is surgically exposed (A), and an electrode array (B) is placed under the dura onto the brain surface. The electrodes are 2 mm in diameter and separated from each other by 1 cm. (C) X-ray image of the skull showing the location of the electrode array. (D) Electrode positions shown on a standardized brain template [38].

2.3. BMI architecture

The interface of the brain machine consists of six sections:

2.3.1. Signal acquisition

The brain signal can be measured in two different ways: non-invasive or invasive. The non-invasive method is better, but the signals recorded in this way contain less information. Unfortunately, the invasive method of acquisition is difficult because it requires surgical intervention. This part is used to convert the brain signals into electrical signals by electrodes and responsible for recording brain activities using various types of sensors. After amplification and digitization

2.3.2. Pre-processing

The goal of signal processing is to increase the signal ratio and eliminate artefacts. In the case of an EGG, it’s usually started by applying a time filter to remove frequencies that are of no interest and which mainly contain interference from the environment (resulting in the 220-volt current used to power the devices, for example, large manufactures at 50 Hz), so physiological activities can be distinguished. Then a spatial filter can be applyed to increase the spatial resolution of the EEG.

2.3.3. Feature extraction

The feature extractor converts processed signals into values that correspond to the underlying neural mechanism. These features are used by BMI to control the output device.

2.3.4. Classification

In this step, the parameters extracted from the brain signal are used to determine the subject's mental state. This classification can be used offline to learn the system or online to run the application in real-time. This part is responsible for identifying the intention of the user from the extracted features [39].

2.3.5. Output device (Command)

This part is responsible for converting the classification result into understandable commands for devices connected to the brain interface. The output device can be a computer, a wheelchair, or an automatic arm.

2.3.6. Feedback

Feedback is the last component of the BCI series, a closed-loop system that makes feedback to the user, allowing the user to know how to interact in real-time, which is generally visible but can be auditory or somatosensory. [40].

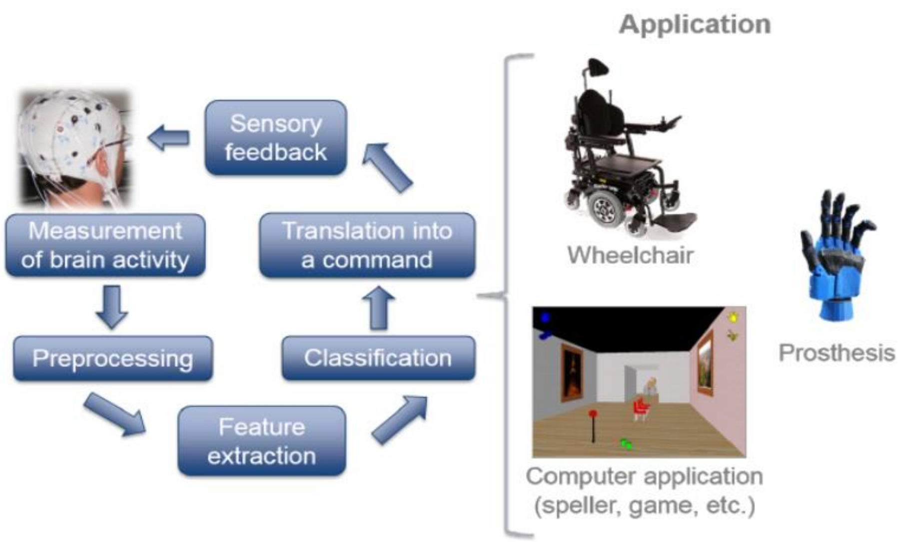


Figure2. 6 : General architecture of brain-computer interface

2.4. Pre-processing

Preprocessing is necessary for most BCI systems because an effective preprocessing method improves the signal-to-noise ratio and spatial resolution, which improves the performance of BCIs.

Preprocessing It includes the preparation of the EEG recordings. It is an important stage that decides the filtering, segmentation and detrending methods used to prepare the EEG data for further stages. Filtering and segmentation are used to identify and maximize the information over a certain time.

The pre-processing step has two main purposes, namely the elimination of artefacts and the improvement of the signal to noise ratio of the signals. In the case of EEG signals recorded on the scalp, the artefacts come from electrical potential parasites generated by activities of the individual other than those aimed at controlling the interface: muscle movements, electromyogram:(EMG), electrocardiogram (ECG), or electrooculogram (EOG), eyelid blinking [41], etc.... The signals are also marred by noise resulting from the superposition of electric fields.

The brain activity extracted from the EEG end .and is usually in the range of 0.2-40 Hz [42], so filtering reduces the noise. The band-pass filter is usually made at the electrical mains frequency. After filtering, the segmentation of EEG data is performed. This involves splitting the continuous EEG signal into time-locked windows, which usually overlap, or are locked to a stimulus (in the case of synchronous BCIs [43] ,because it is not spontaneous recording of brain activity).

Spatial and temporal filtering are common preprocessing methods used in most BCIs. These methods are described in more detail in the following:

2.4.1. Spatial and Temporal Filters

The electrical signals to the brain, are very weak compared to other bio signals, such as muscle activity or electrocardiogram. They lie in the range of 1–100 µV. For this reason, sensitive amplifiers are used to record EEG.

There are four main types of filters used:

1. High pass: filters that allow only frequencies above the required limit to pass. [44].
2. Low pass: filters that allow only frequencies below the required limit to pass.
3. Band pass: Allows only the required frequency band to pass.
4. Band stop (time filters): restricting a specific frequency range, the frequency-filter can be a time constant, which gives the allowable time for recording a signal.

2.4.1.1. Temporal filters

Temporal filters are used to restrict the analysis to frequency bands in which useful neurophysiological signals are located, i.e., BCI based on sensorimotor rhythms generally band-pass filter the data in the 8-30 Hz frequency band, as this band contains both the (α), and (β) rhythms, i.e., the sensorimotor rhythms. They are also used to remove other artefacts such as electrode polarization and power mains noise. This type of filtering is generally achieved using Discrete Fourier Transform (DFT) or using Finite Impulse Response (FIR) or Infinite Impulse Response (IIR) filters [45].

A signal in frequency field by Direct Fourier Transform (DFT) filtering can be visualized, to see a signal as a sum of oscillations at different frequencies f, which can be used to calculate power spectrum (or power spectral density), whose main disadvantage is the lack of time domain information [46], Thus, the DFT S (f) of a signal s(n), which is composed of N samples, as shown in the following equation (1):

$$S(f) = \sum_{n=0}^{N-1} s(n) e^{\frac{-2i\pi f n}{N}} \qquad (1)$$

Filtering a signal using DFT simply consists of removing all coefficients of the DFT which do not correspond to targeted frequencies, and then to transform the signal back into the time domain, by using the inverse DFT, as shown in the following equation (2):

$$S(n) = \frac{1}{N} \sum_{k=0}^{N-1} S(k) e^{\frac{2i\pi k n}{N}} \qquad (2)$$

DFT filtering can be used online and in real-time, thanks to the efficient and popular DFT implementation known as the Fast Fourier Transform (FFT) [47]. Filters can be further optimized to reduce complexity.

FFT coefficients can also be classified directly, without converting them back to the time domain.

FIR filters are linear filters which make use of the(M) last samples of a raw signal s(n) to determine the filtered signal $\hat{s}(n)$, as shown in the following equation (3):

$$\hat{s}(n) = \sum_{k=0}^{M} a_k s(n-k) \qquad (3)$$

a_k are the filter coefficients. Their values depend on the desired filter.FIR filters are known to have excellent performances in the frequency domain.

As FIR filters, IIR filters are linear filters. On the other hand, IIR filters are recursive filters, which means that, in addition to the M last samples, they make use of the outputs of the P last filtering, as shown in the following equation (4):

$$\hat{s}(n) = \sum_{k=0}^{M} a_k s(n-k) + \sum_{k=1}^{P} b_k \hat{s}(n-k) \qquad (4)$$

IIR filters can perform filtering with a much smaller number of coefficients than FIR filters [47].

2.4.1.2. Spatial filters

After channel selection, the EEG is decomposed to a series of frequency-time components which cover different time and frequency ranges at local scale. The decomposition is achieved by first filtering the EEG to basic frequency-bands and then dividing signals of each frequency-band into basic time segments [48], Efficient signal processing algorithm is crucial for implementing practical BCIs. The most important criterion for a ‘good’ algorithm is whether it can detect different mental tasks in real-time with high accuracy. To this end, the spatial filtering technique has been a key research topic [49] [50].

Spatial filters are used to extract localized information with a good signal to noise ratio, they filter are created by selecting electrodes when using a BCI based on hand motor imagery, the neurophysiological signals of interest are localized over the motor or sensorimotor cortex areas. Thus, the main interest is to focus on electrodes C3 and C4, which are located over the left and right motor cortex respectively (see Figure 2.7).

above the scalp, which are known to have relevant brain signals in the current paradigm. Other electrodes are not of interest.

The electrodes O1 and O2, which are located above the visible areas. Electrodes over the eyes, such as Fp1 and Fp2 are commonly used to reject blinking artefacts

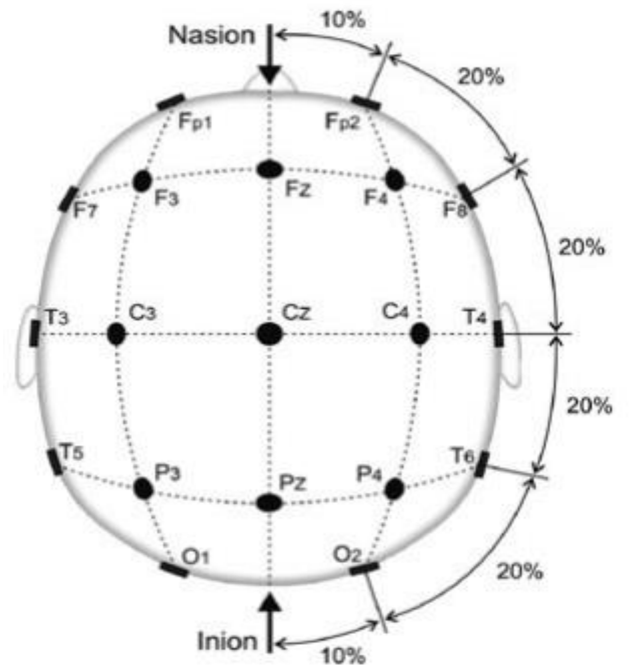


Figure2. 7 : The location of the electrodes C3, C4, O1, O2.

C3 and C4, which are located over the left and right motor cortex respectively, O1 and O2, which are located above the visible areas. Electrodes over the eyes, such as Fp1 and Fp2 are commonly used to reject blinking artefacts.

Other simple and popular spatial filters are the Common Average Reference (CAR) and the Surface Laplacian (SL) filters [51].

These two filters(SL) (CAR) [52],make it possible to reduce background activity. The CAR filter is obtained by equation (5):

$$\hat{V}_i = V_i - \frac{1}{N_e}\sum_{j=0}^{N_e} V_j \qquad (5)$$

where $\hat{V}_i$ and Vi are the ith electrode potential, after and before filtering respectively, and Ne is the number of electrodes used. Thus, with the CAR filter, each electrode is re-referenced according to the average potential over all electrodes. The SL filter can be obtained by equation [53] (6):

$$\hat{V}_i = V_i - \frac{1}{4}\sum_{j\in\Omega_i^4} V_j \qquad (6)$$

where Ω_i^4 is the set of the 4 neighbouring electrodes of electrode i. Thus, this filter (SL) emphasizes localized activity and can reduce diffuse spatial activity. It is represented graphically in Figure 2.8:

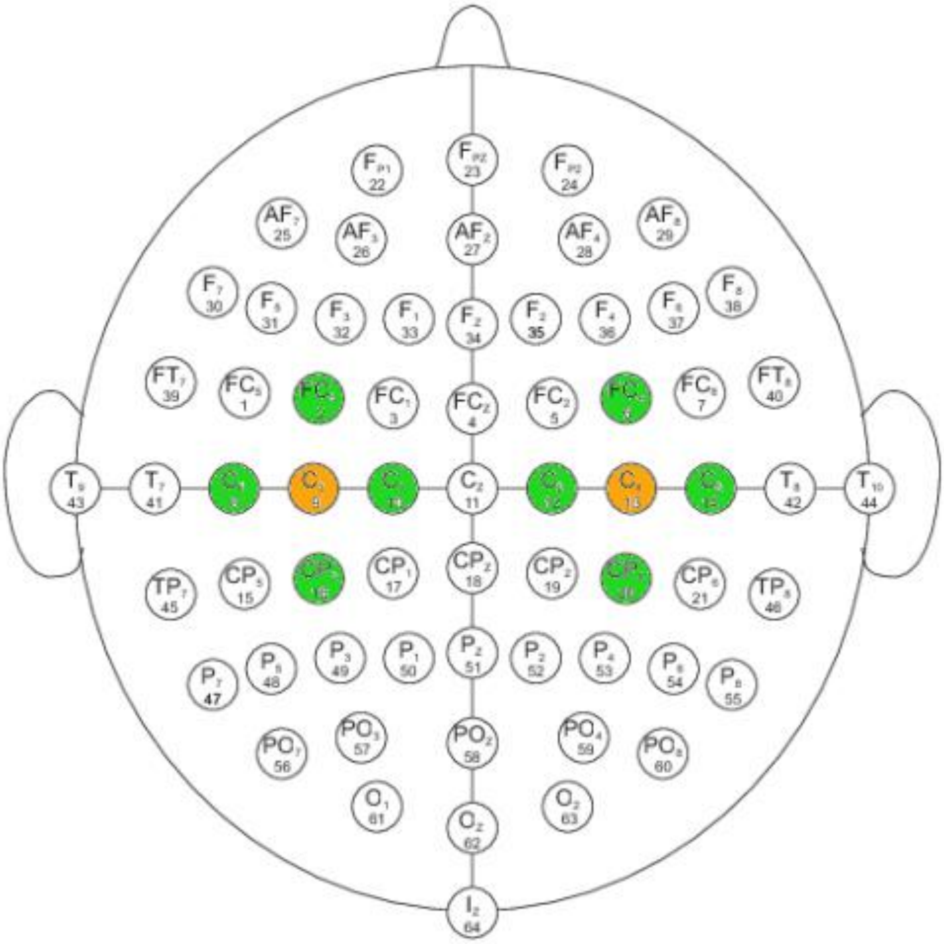


Figure2. 8 : Ω_i^4 is the set of the 4 neighbouring electrodes of electrode i.

2.5. Spike sorting

The continuous recording of thousands of neurons has made large-scale and high-density extracellular recording systems feasible.

The mechanism by which each sensed spike is allocated to its originating neuron is usually referred to as spike sorting. For traditional extracellular recordings, spike sorting is a tractable issue since it is usually performed separately for each recording channel. In this case, it is predicted that only a limited number of neurons can contribute to the signal on each Channel, which makes it possible to use reliable, though more expensive algorithms in terms of computation. In addition, most current spike sorting algorithms do contain an aspect of human interaction to modify or optimize the effects of sorting. The advancements in MEAs, however, have made the production of stable and efficient algorithms mandatory, primarily to address the difficulties added due to the number and spatial resolution of the electrodes, which are discussed in detail in the next section.

A description of the measures required from raw data to achieve sorted spikes. This chapter's overview is as follows. A summary of all the problems resulting from the use of MEAs is included in the first phase. First, a summary of strategies available to overcome these issues and a description of the benefits and disadvantages of each one follows. The key message of this section is not that there is a strategy that stands out from the others, but that there are many approaches of distinct sophistication.

It depends on the specifications of the experiments and their appropriateness [54].

2.6. Data Representation

2.6.1. Sampling a Signal

The most popular method for converting a continuous signal into a discrete signal (Fig.2.9). is made by equidistant sampling (see Fig.2.9Fig.2.10). The values in the continuous signal are read at periodic sample intervals nT (see Fig.2.11), where $n \in Z$. The distance T between two samples is called the sampling interval, and the exchanged quantity is called the sampling frequency. Equidimensional sampling can be mathematically expressed by Nyquist theorem:

$$fs \geq 2f_0 \tag{7}$$

where fs: is the samples frequency. The samples frequency should be two times higher than the highest f0 frequency component of the given signal, to not lose the required frequencies in the continuous signal.

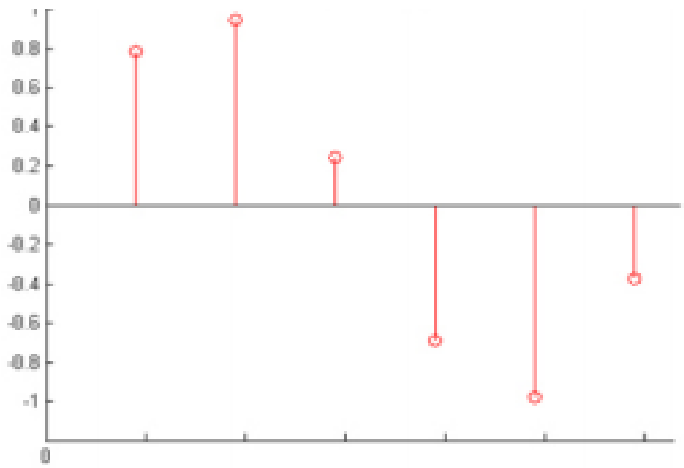


Figure2. 9 : The sampling Continuous Signal into a Discrete

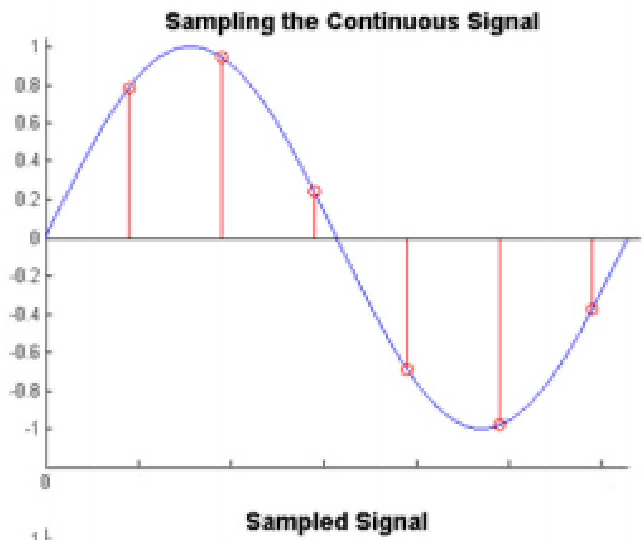


Figure2. 10 : The sampling Continuous Signal.

2.6.2. Representing Data

When talking about speed and computers it is important to work with data representations (numbers) given by the power of two.

Instead of sampling with 35Hz, 32Hz should be used and 256Hz instead of 260Hz.

foundation of the computer has to be considered. All computers work with binary numbers system, which means working with ones and zeros. There are several benefits working with numbers perfectly suited for the computer [55].

2.7. Conclusion

In this chapter, been touched about brain signal recording methods. The structure of the brain and computer interface were also discussed. Then we went deeper into the pre-processing part. including temporal filtering and spatial filtering. And finally, talked about data representation. (application). The medical and non-medical filed, for example.

Chapter III application of BCI

3.1. Introduction

In this chapter, will explore a range of applications of the BCI concept. With it, we review what we talked about in the last two chapters, ranging from the components of the cell to how the brain functions, how the signal develops, and how it relates to different types of BCI. This results in the different applications that we see in life, including medical devices and non-medical devices, all of these devices seek to facilitate life for humans and among these medical applications that we study in this chapter are sensory restoration as well as a wheelchair that is controlled by the brain before exploring applications in the fields of Others, such as entertainment, automatic control and games [56].

3.2. medical application

The field of communication between the brain and the computer arose to help the disabled and the paralyzed. So, we find that most of the main applications of BCI indicators so far have been in medical technology, especially the recovery of sensory and motor functions [57].

3.2.1. Sensory Restoration

Tactile feeling and proprioception involve accurate and effective movement of objects with one's hands. Cutaneous anesthesia lowers accuracy and the ability to differentiate conformity with artifacts . Function loss and somatosensation after amputation of the upper extremity (UE) can be catastrophic. Advanced UE prostheses begin to grow to imitate the work of anthropomorphic paws. Even if they accomplish the ideal mechanical approximation of the normal human hand, their work and use would be substantially restricted by the lack of successful somatosensory feedback.

Methods of sensory replacement seek to compensate for missing somatosensory information. Tension in body-powered prostheses harness cabling provides indirect sensory input that is associated with the stress applied by the terminal system. It is the indirect sensory connection to the terminal system for many amputees that makes the body-powered prosthesis a more appealing prosthetic alternative than a myoelectric prosthesis. Sensory replacement of vibratory tactors for myoelectric prostheses provides details about the position of the prosthetic hand or the pressure applied. In and outside of the laboratory, these boost regulations. However, sensory replacement, possibly owing to the perceptual strain of modal and spatial perception, is not generally accepted.

Via electrodes inserted in or near the remaining sensory nerves in the limb, electrical stimulation will evoke feeling that is thought to be situated on the missing side, providing a more normal tactile and proprioceptive input approximation. In small, isolated regions of the hand, electrical stimulation induces naturalistic stimuli that can be accurately scaled to perceived intensity. Naturalistic feeling put on the perceived hand may be more intuitive than sensory replacement, since it is more spatially and modally congruent, offering less preparation with greater practical benefits. Furthermore, naturalistic sensation may increase the embodiment of the prosthesis, thereby minimizing abandonment of the prosthesis. Technical functions that directly rely on or integrate with sensory input must be done with the prosthesis to assess the effect of sensation on prosthesis functionality. The standardized functional tests available for upper limb prostheses, however, were not designed to determine the effect of sensation . Item recognition exercises are conducted in the normal hand to assess sensory capacities and hand activity in people with carpal tunnel syndrome, neuropathy, or surgery for nerve repair. In these object discrimination tests with a natural hand, individuals are expected to decide object type, object size, or object texture. Although it is possible to distinguish objects that vary in size or texture using vision alone, assessing the conformity of an object involves physical input and awareness of the forward control model during object deformation. In addition to tactile input during manipulation of the object, assessment of object shape and size relies on knowledge of the hand location (i.e. proprioceptive information). Tasks of object discrimination indicate how well sensory input is perceived and used and are also insightful measures to determine the interpretability and utility of sensory input in UE prostheses.

The ability for sensory reconstruction to increase target recognition has been demonstrated through prior research. In this study, we tested the ability of amputees to conduct a battery of target recognition tasks with stimulus generated by peripheral nerve stimulation using their prostheses. This analysis had two aims. First, to investigate the degree to which multiple types of stimulus generated by extraneous stimuli (i.e. tactile vs. proprioceptive) could enhance target recognition with a prosthesis. And second, to determine the capacity of this research battery to catch the effect on practical and psychological effects of the revived sensation. Upper limb amputees implanted with extraneural cuff electrodes are the subjects of this study. We stimulated the nerve through these electrodes to provide input on fingertip pressure and aperture of the hand. In this research, participants used their own prosthetic hand with externally mounted electrodes, their own prosthetist-fit plug, and their own myoelectric control device. These settings were selected because we wanted to replicate as appropriate as possible conditions for the use of prosthesis, so that our results could be relevant to understanding the potential rehabilitation effect of artificial sensory input generated by neural stimulation. Our theory is that when they obtained knowledge about both fingertip pressure and hand aperture, subjects will perform best, instead of just no stimulation-elicited feedback or only one type of stimulation-elicited feedback [58].

3.2.2. Rehabilitation

A transdisciplinary, integrated approach to the conceptualization and management of sickness and disability is an important aspect of effective surgical recovery and, in many cases, certification for accreditation from state agencies such as the Joint Commission and the Accreditation of Recovery Facilities Commission (CARF). Medical neuropsychologists are one of the essential positions in these transdisciplinary teams. In the field of perception, neuropsychological experience is extremely beneficial in conceptualizing the skill of the patient, promoting goal-planning activities through therapeutic feedback and detailed test outcomes, transforming impairments into useful functional guidelines, adjusting treatments, and delivering patient/family and employee education.

Cognitive therapy has long become part of the variety of programs provided by clinical neuropsychologists, and neuropsychologists can also often perform rehabilitative efforts beyond the traditional inpatient environment, when mobile and touchscreen technology are widely used for cognitive disability care and reimbursement.

It will be helpful to characterize the forms and contexts in which these two clinical specialties overlap, as therapeutic psychology and neuropsychology continue to evolve in the United States. This present brief study aimed to complete two key objectives:

-(a) to include preliminary statistics on the demographics of neuropsychologists providing recovery services throughout the United States.

-(b) to describe the rehabilitation services offered by neuropsychologists in the United States, in particular what kinds of care (i.e. person, community, or mixed), tools of technology used Ultimately, such data may prove valuable to encourage more focused clinical surveys of neuropsychologists conducting recovery and offer a foundation for educating our patients and their families/caregivers, as well as other clinicians with whom neuropsychologists interface, about this particular expertise and ability set. For the purposes of compensation and clinical advocacy, such details may also be valuable [59].

3.3. Nonmedical Application

There was a terrible rise in those non-medical applications of BCI technology. Most of these applications are driven by commercial factors such as the ability to create a new interface for games and entertainment. Most of these applications are still in their infancy and are being investigated in research laboratories, but some have been applied to real-world problems such as image sorting and lie detection [60].

3.3.1 Lie Detection and Applications in Law

Latest developments in the use of the brain's functional magnetic resonance imaging (fMRI) to test deceit and distinguish lying and revealing the truth have produced hope of a breakthrough in the quest for lie detecting strategies based on technology. Attempts to incorporate fMRI lie detection evidence in courts by private companies have caused remarks and opposition on both legal and science grounds without a sufficient generation of new research results to answer those issues.

The susceptibility of the latest technologies to countermeasures, its external validity and precision, and the specificity of the observed fMRI patterns to deception are significant unanswered questions. Our analysis indicates that while these are important, the crucial knot of law and science that must be untangled in order to enable further translational advancement is the determination of the technology's "error rates" as specified by the admissibility criteria of Daubert. This decision not only requires the accuracy of the experiments for each subject, but also their predictive power in the specific community. The article attempts to clarify the main distinction between small-scale laboratory testing projects and carefully monitored clinical trials for the interdisciplinary audience. We stress that such trials are crucial to the authenticity of evidence. Expert evidence that a given witness is lying in answer to a given question remains a dangerous jump from current data before such trials. The financing of clinical trials of fMRI-based lie detecting technologies is not a trivial endeavor, considering the multidisciplinary scope of the study and the variety of special interests involved. We recommend a public funding project leading to a peer-reviewed translational research program on brain deception processes with a particular focus on multicenter clinical trials of fMRI-based lie detection, in view of its potential relevance to society and the fields of law and medicine. As stated in the National Research Council of the National Academies' report (NRC Report), Improving Forensic Science in the United States: A Way Ahead, the risks of admitting unproven empirical findings in courts are well known (2009). The study criticizes multiple aspects of forensic science, such as similarities of handwriting and fingerprints, arson and bitemark evidence, and notes the link between unproven forensic science and wrongful conviction "A disturbing number of wrongful convictions, some for capital crimes, and serious limitations in some of the forensic science approaches commonly used in the United States have been uncovered by DNA analysis" (NRC Report, 2009, p. 42). Nevertheless, courts fail to accept different forms of evidence from forensic science, sometimes dismissing its reported limitations. Scientific proof, once accepted, appears to become ingrained and impossible to remove later on. We think this study should persuade the legal profession to require a proper scientific framework for the emerging field of forensic neuroimaging, including fMRI-based lie detecting, before being admitted to court [61].

3.3.2 Monitored Vigilance

Among the important applications, BCIs monitor human alertness while performing critical but monotonous tasks such as driving or security monitoring. We also know about major disasters that occur every year by drivers who are very tired, drowsy or even sleepy at the wheel. But such incidents can be prevented by monitoring brain signals for any fluctuations from alertness to distraction or lack of alertness. Or it is possible to detect drowsiness or sleep by observing the closing of the eyelid, and this discovery comes too late to prevent an accident. Researchers have often sought to find links between decreased attention and alertness in brain signals, especially EEG. It has been known for some time that an increase in energy in some frequency ranges (e.g., alpha, 8-13 Hz) in the EEG is associated with decreased focus, or as measured by higher error rates in detection tasks.

However, assessing the perceived risk of a single driver is extremely difficult. Therefore, it is imperative to develop a quantitative and objective mechanism for assessing the driver's perceived risks, so that these risks can be compared with the risks of the actual work environment to identify mismatches. Current studies rely on questionnaires to assess unsafe driver behaviors and attention / alertness levels from a behavioral psychology perspective, therefore, it is imperative to develop an objective and quantitative approach that can monitor and measure a driver's perceived attention / alertness levels. The results of this approach can help improve field monitoring, safety management and training programs. To fill this research gap [62].

3.3.3 Teaching and Learning

Education authorities are increasingly motivated to create and implement experimental curricula to uncover student misunderstandings and initiate curriculum reforms that integrate new technologies, educational approaches, and interdisciplinary insights. The literature on students' conceptual understanding of biology has increased dramatically since 2010, helping to develop new curricula based on what the student needs to understand in order to develop it.

An authentic conceptual understanding. In light of this, conceptual understanding requires the ability to create a network of knowledge, ideally in an interdisciplinary perspective, to impart and apply this knowledge in a variety of contexts [63].

Several research studies on conceptual understanding aim to diagnose misconceptions.

Misconceptions were defined as persistent naive or incomplete interpretations of scientific concepts shared by many students . Often misconceptions are not recognized and persist during teaching if not addressed.

Often misconceptions are not easily detected by the usual meta-assessments that are made in academic institutions, because the majority of these assessments are built to assess retention of factual knowledge and thus measure memorization and attention capacity. Thus, these assessments seldom address true theoretical understanding. Instructional strategies that address misconceptions or prior knowledge are essential for optimal learning and to help students gain an understanding closer to specialized thinking [64].

Concept inventories are usually multiple-choice questionnaires based on student thinking, that is, distractions (wrong answers) correspond to common and persistent misconceptions that many students share. Developing inventories of concepts / tests is a challenging process as large numbers of students must collect verbal or written answers to questions dealing with different concepts in biology to develop distractors that represent the student.

Thinking. However, the time and costs of preparing these surveys are important.

For the current project, the Biological Concepts Tool (BCI) was chosen because it covers a wide range of concepts frequently taught in undergraduate biology courses [65] [66].

3.3.4 Security, Identification and Authentication

For many years, authentication technology has played an important role in terms of data security. The process of validation is determining whether someone or something, who or what is advertising itself. Biometric authentication is the most secure method that we use today.

Besides all the great advantages of modern biometrics methods, they still have some weaknesses and issues that brainwave authentication can cover. Brain-based authentication has become very popular in a researcher's work recently. Brainwave could be the most secure biometric authentication, as it does not have some of the issues and flaws, that other biometric technologies have. In terms of safety, brainwaves can have a higher level of safety as they cannot be replicated and the ID pattern is changeable. There are several research experiments that have used electroencephalography (EEG) to test brain waves for validation purposes using the brain-computer interface (BCI). Every BCI has three important parts including signal acquisition, feature extraction, and classification. This process will be different with regard to the main goal of using human brain waves. For example, using BCI for authentication purposes requires specific methods of the three main parts of the BCI process. Each part can have a huge impact on the results, and there is a multitude of research that has been used differently signal acquisition methods, feature extraction and classification techniques. According to the weakness of human brains, which is a type of electromagnetic wave, and the devices that we use to record them at the time of writing this paper, we need to use special techniques to record signals for any specific purposes to achieve the best results. This paper introduces a new mind wave acquisition strategy specifically dedicated to brain-based authentication and authentication by anticipating the ability to remember the image, through which, users can log their brain ID in the database, authorize themselves and pass the authentication safety using a unique visual style in their minds. The researchers used many different patterns including relaxation, muscle movement, visualization, breathing and sport activity, rapid serial visual representation (RSVP), passing on thoughts and many more. Mental imagery and imaging pattern using a signal acquisition strategy could be the most secure brain identifier type [67].

3.3.5 Gaming and Entertainment

The main purpose of the brain-computer interface technology (BCI) is to provide a neural alternative / an enhanced communication pathway between the human brain and the computer to allow people with severe disabilities and neurological conditions to communicate and interact with the outside world without the need to use the peripheral nerves and muscles. Through several years of joint efforts, various types of terminal device control models using BCI technologies, for example, event-related P300, and sensors tunes, presented and categorized in great detail. These models have been used to control different types of organisms to perform different functions, for example, controlling computer mice, wheelchairs, mechanical arms, and artificial nerves. Notably, the incorporation of BCIs into games is an important step in facilitating the transformation of BCI technologies from laboratory conditions to practical applications. For the disabled, especially paralyzed patients, BCI can act as a tool to restore function to enable them to play games, and disabled people may be interested in such games because games are excellent sources of entertainment in daily life. For healthy individuals, BCI-controlled games may be a unique and attractive opportunity to play games using thought rather than physical movements. In addition, the non-disabled user can also use BCIs as a possible alternative input strategy or as a sufficient complement to existing input devices, for example, a mouse, keyboards or touch screens while playing the game. In terms of models used in games. Animation is the most popular. For example, based on the well-known old video game and has built a BCI prototype from a video game called Brain Invaders, which made use of the whimsical P300 model; Parafita et al. (Parafita et al., 2013) developed a spacecraft game controlled by low-frequency stimuli SSVEPs to avoid obstacles in the space path, and it used similar methods (The Maze Chumerin et al., 2013). Indeed, previous studies have mainly focused on the use of single BCI models in BCI games. These control strategies still need some improvement for use in this easy-to-use BCI in children's games. For example, visual evoked potentials (VEPs), for example P300 and SSVEP, use flash stimuli to evoke user intentions. Systems that use these models are interactive BCIs. To create orders, users of interactive BCIs need to stare at visual stimuli. In general, interactive BCIs have advantages, such as small training actions, multiple control commands, and high rating accuracy, etc. However, these types of BCIs may cause visual fatigue during long gaming sessions. In addition, these models also do not apply to a user with photosensitive epilepsy (Marshall, Coyle, Wilson, & Callaghan, 2013). Another common type of BCI is the active BCI, such as MI. One of the advantages of this model is that it is autonomous speed control strategy. However, active BCIs are restricted by the number of commands, as a conventional two-class MI can only output two commands (left-hand and right-handed). To increase the number of MI orders, some researchers have investigated testing MIs based on different parts of the body, such as limbs, feet, elbows, shoulders, and tongues (Bhattacharyya, Konar, and Tibarewala, 2014). However,

These methods reduce the accuracy of classification and make mastering the control system more difficult. Some researchers have integrated MI sequences to encode various additional commands, but this procedure adds to the length of time required to output a command (Yue et al., 2012) and, therefore, may not be an ideal way to increase command dimensions. In recent years, so-called hybrid BCI indicators have attracted attention because these models can provide new directions for improving the performance of different BCI systems. Traditionally, BCI hybrids refer to systems that combine two or more variants of BCI models (Allison et al., 2012; Allison et al., 2010). Applications, such as Speller (Allison et al., 2010; Yin et al., 2014) and The wheelchair (Li, Pan, Wang, & Yu, 2013) has introduced hybrid BCI indicators to improve performance, such as accuracy and connection rate, or to achieve complex controls. However, the use of such mixed BCIs in play has not been thoroughly investigated. In some papers, researchers have combined BCIs with other devices or interfaces, such as a joystick and keyboard (Muhl et al., 2010) to improve the performance of BCIs in video games. Moreover, they implemented and tested hybrid BCIs along with keyboard, alpha rhythm, and SSVEP in a simple video game called "Bacteria Hunt". They focused their study on investigating the effect of positive versus negative neurofeedback on subjects' relaxation states and how well they used different BCI models together, rather than improving performance online and playing BCI games. She introduced a multifunctional hybrid BCI system that combined electroencephalogram (EEG) (MI) rhythms with SSVEP signals and implemented the system to verify her performance in a video game called Super Street Fighter. Focus primarily on the ability to perform complex procedures and how to enhance the control performance that needs to be added.

Tetris was chosen as a control objective to demonstrate the viability of playing with the hybrid model.

Here, MI is used to create two commands, which are used to move the bricks (left hand move, right hand move). At the same time, people need to stare at the flickering stimuli to enable detection of SSVEP 8.5 Hz events when they want to spin the bricks. Hence, this form represents a relatively natural way to play Tetris.

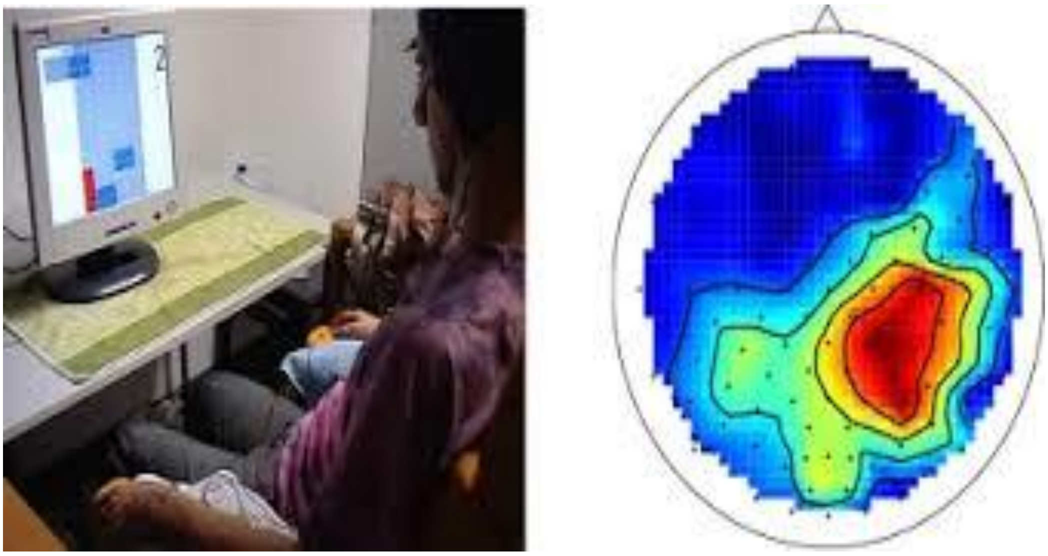


Figure 3. 1 : EEG BCI for the game of Tetris

Left: User playing the BCI- controlled Tetris game. Left- or right- hand motor imagery is used to move a falling piece to the left or right respectively, mental rotation to rotate it clockwise and foot motor imagery to let it drop. Right: Cortical activation map when the subject engages in mental rotation to rotate a Tetris piece [68].

3.5. Conclusion

With the different BCI applications that we have reviewed in this chapter, we see that it is our imagination that has tied us in terms of developing new ways to harness the power of BCIs. But the credit for this is due in many ways to the mechanics provided by medical applications such as the development of implants for the deaf (cochlear implant), paralysis-nerve prostheses (such as Brain Gate implant), and electrical stimuli to treat symptoms of debilitating motor diseases such as Parkinson's (deep brain stimulation or DBS). Faster computers and cheaper non-invasive EEG and fNIR registration systems have opened the door to many non-medical applications for able-bodied individuals, ranging from BCIs for security, education, and games or cognitive enhancement, but with the proliferation of BCI applications makes It is also necessary to address the many ethical and moral issues resulting from these subversive techniques.

Conclusion

Conclusion

Without using the brain's normal excretory pathways to the peripheral nerves and muscles, BCI helps a person to interact with or influence the outside world. Messages and instructions are conveyed by electrical phenomena such as mediated EEG characteristics or cortical neuron activation rather than muscle contractions. The mechanism of BCI relies on the involvement of two adaptive operators, the user, who must establish a near relation between his or her purpose and these phenomena, and BCI, who must convert phenomena into system commands that satisfy the intent of the user.

Future success relies on an interest in a variety of critical variables. These include: recognizing that the growth of BCI is a multidisciplinary issue, including neuroscience, psychology, engineering, mathematics, computer science, and clinical rehabilitation. Identification of signaling characteristics, whether evoked potentials, unconscious patterns, or neuronal firing frequencies, on which consumers are most likely to monitor; to what degree this monitor can be independent of the behavior in the traditional motor output and sensory input channels; to what degree this control depends on natural brain function; to decide the best methods of extraction of characteristic.

And to compensate for the partial deficit through surgery or the like, from what has been in seen in the previous chapters of a brain problem, the leads to paralysis in certain parts, or a loss of what the normal person has.

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