# POLITECNICO DI TORINO

**Master's Degree in Biomedical Engineering**


**Master's Degree Thesis**

# Flashing checkerboard and attentional effort: SSVEPs signals analysis and adjustment of stimulation frequencies

**Supervisor:**

Prof. Luca Mesin

**Candidates:**

Giulia Macchia

Laura Rollo

**July 2021**

*Alla mia famiglia.*

# Abstract

Patients in the complete locked-in state (CLIS) are unable to interact with the reality around them and to manifest their condition, although they are aware of what is happening around them. Due to a complete interruption between the cortex neurons of the Central Nervous System and the motor neurons responsible for movement, the impulses from the brain cannot reach all the extremities involved in movement. The only technological support able to compensate for the lack of functionality of these neurons is the BCI.

Specifically, in SSVEP-based BCIs, the signal components that are derived in response to a visual stimulus are the SSVEPs, which can be recorded on the primary visual cortex with a non-invasive electroencephalogram (EEG). Most of the BCIs available on the market use the eye movement of LIS (Locked-In Syndrome) patients, but CLIS (Complete Locked-in Syndrome) patients are also unable to perform this type of movement: in order to investigate this aspect, the study carried out in this thesis is aimed precisely at patients who are in the latter stage of the disease.

In SSVEP-based BCIs, the type of visual stimulus administered influences both the goodness of the results and the stress caused to the patient. Using an effective but low-stress stimulus can improve the already problematic communication in such subjects: in this work, a type of visual stimulation that tries to satisfy this condition was tested.

A visual stimulus consisting of a checkerboard was designed to allow the subject to provide a binary response. It is made up of very small squares, close to each other, coloured with two different colours and in which each colour flashes at a certain frequency, whose values are within the alpha band of the EEG signal. In this way the patient, unable to move his eyes, has less difficulty in concentrating on one or the other colour, depending on the response he wants to give: he does not have to concentrate on the single square object, but on the whole colour associated with the response to be given. In addition, stimulation frequencies adapted to the subject were sought. These frequencies, which may vary from subject to subject,

elicit the best responses for the individual subject.

In order to explore all these aspects, a non-invasive EEG signal sampling system was used, allowing us to collect, on healthy subjects, the electroencephalographic signal during periods of visual stimulation at different frequencies and during periods of rest. During stimulation, particular strategies were used to reproduce the fixed gaze condition that characterises CLIS patients. Thus, offline signals were analysed and processing techniques were implemented in order to build an algorithm able to derive the best stimulation frequencies for each subject and to guarantee a binary response.

# Contents

# Introduction

This thesis work was developed with the aim of allowing communication possible for patients in complete locked-in state (CLIS). This is an objective already found in other works in the literature, but in this case the aim was to adapt the stimulation frequencies to the subject in order to make the detection of the SSVEP response more evident. In addition, attention was paid to the visual stimulus to be provided, so that the latter is as pleasant as possible. In this preliminary research, the study was carried out on 5 healthy subjects who were positioned in the best possible way to reproduce the condition of fixed gaze that characterises CLIS subjects.

First of all, attention was paid to the analysis and construction of the visual stimulus provided. Thanks to an analysis of the literature, it was possible to choose the most suitable colours and frequencies for this study, firstly excluding anything that was compatible with the onset of epileptic seizures. The advantages and disadvantages of studying high or low frequencies were then analysed and the final choice was made in the frequency range corresponding to the alpha band. In addition, in order to arrive at the final visual stimulus to be provided to the subject, different sizes and shapes of the components of the checkerboard were analysed, leading experimentally to the conclusion that the stimulation method described in this thesis is the one that brings the least fatigue and discomfort to the subject. This part of the work was described in Chapter 2 of this thesis, with particular reference to the technical part of the construction of the algorithm that led to the visual stimulus as described.

The signal to be studied was acquired on the basis of the experimental protocol, also described in Chapter 2: this protocol aims to meet the requirements of the study compatibly with the available instruments. In this case, particular reference was made to the construction of the classifier, which requires a certain number of observations in order to consider its classification reliable. Moreover, a compromise had to be reached regarding the exposure time of the subject to the visual stimulus provided: the latter should not be prolonged as this could lead to fatigue and/or adaptation, but at the same time it could not be excessively reduced to meet the

demands of the classifier. Once the experimental protocol was defined, the signal was processed and analysed as described in Chapter 3.

The signal analysis, which continues in Chapter 4, played an essential role in this work. In fact, feature extraction and classifier construction are what the algorithm's response was based on. Therefore, starting from what has already been proposed in the literature, different methods of extracting information from the signal have been studied and tested, focusing mainly on frequency analysis. Ultimately, the features extracted in this work are always in frequency, but they attempt to extract signal features by isolating the single frequency component of interest.

Finally, in order to have an overview of what this kind of study can bring, the analysis of the results constituted another fundamental point of this work. As this is a very broad and very open topic in the field of research, the methods of analysis and the analyses themselves described in Chapter 5 made it possible to make a contribution, albeit a small one, to the investigation in the field of SSVEPs and at the same time were confirmed by some results already present in the literature. For this reason, a mention was made in Chapter 6 of the possible future work that this research has elicited and that could not be completed.

# Chapter 1

# Neurophysiology, EEG signal and BCI SSVEP-based

## 1.1 Anatomy of the brain

The functioning of the human brain and brain activity are increasingly fields of research interest. In order to do this, it is necessary to outline the anatomy of the brain with particular reference to the functional areas of the brain.

Macroscopically, the brain and the spinal cord constitute the central nervous system (CNS). Both the brain and the spinal cord are immersed in a protective fluid, surrounded by membranes (the meninges) and further protected by an outer bone covering, which for the brain is the skull and for the spinal cord is the vertebral column.

The brain, starting from the bottom upwards, consists of the brainstem, the cerebellum and the forebrain (Figure 1.1).

**Brainstem.** The brainstem is the most caudal portion of the brain, connecting the forebrain and cerebellum with the spinal cord. It consists of three main regions: the midbrain, the pons and the medulla oblongata or bulb. The brainstem contains highly complex structures that perform and regulate innumerable functions, including involuntary functions controlled by the autonomic nervous system, such as cardiovascular function and digestion.

**Cerebellum.** The cerebellum is a bilateral and symmetrical structure with a ovoid shape divided into two hemispheres, it is located in the posterior cranial fossa hidden beneath the cerebral hemispheres. The basic functions of the cerebellum are to control motor activity and maintain balance, providing important feedback in motor coordination and eye movements.

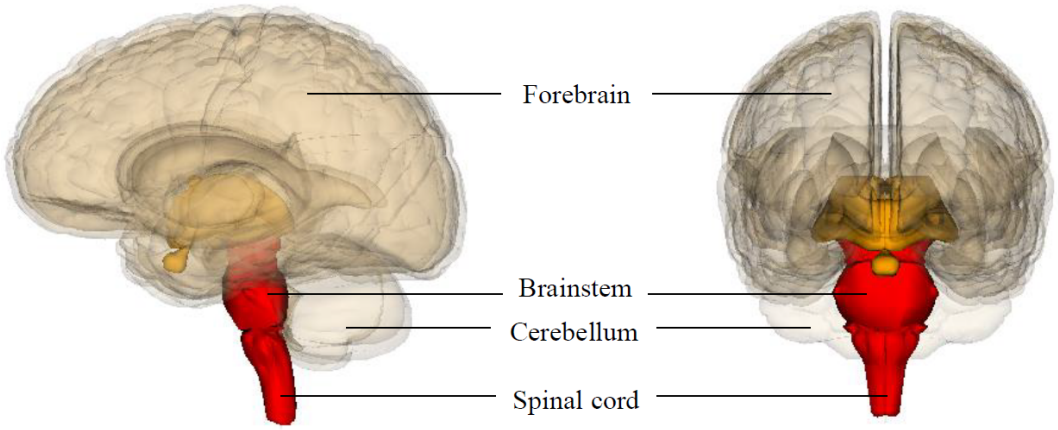



Figure 1.1: *Lateral and frontal view of the brain. The three components of the brain (forebrain, cerebellum and brainstem) and the spinal cord can be seen. In the frontal view (right) the two cerebral hemispheres can be seen.*

**Forebrain.** The forebrain consists of two cerebral hemispheres separated by a deep fissure in the sagittal direction and consists of the brain and the diencephalon.

The brain is a large C-shaped structure containing grey matter and white matter. The grey matter, rich in neurons, is the outermost part and it comprises the cerebral cortex and deep subcortical nuclei. The white matter is the innermost layer and it consists of nerve fibres.

The diencephalon includes the thalamus and the hypothalamus, two median structures located near the base of the forebrain, each of which contains multiple small nuclei.

### 1.1.1 Functional organisation of the cerebral cortex

The cerebral cortex is the outermost part of the brain. It is made up of a large number of circumvolutions that originate from *gyri* and *sulci*, which allow the large volume of grey matter to be contained within the skull. The cerebral cortex performs the highest and most evolved cerebral functions and in doing so acts as an integrating centre as it receives sensory signals, processes them and uses them to formulate thoughts and actions.

Each hemisphere consists of four main lobes: the frontal lobe, the parietal lobe, the temporal lobe and the occipital lobe. The cerebral lobes are defined both anatomically, as each is located in a specific part of the brain, and functionally. The cerebral lobes perform different functions, so the cortex can be subdivided into functional areas specialised in different brain functions, as shown in Figure 1.2. However, joint work is often required to properly integrate the information received, as the brain still functions as a unitary organ.

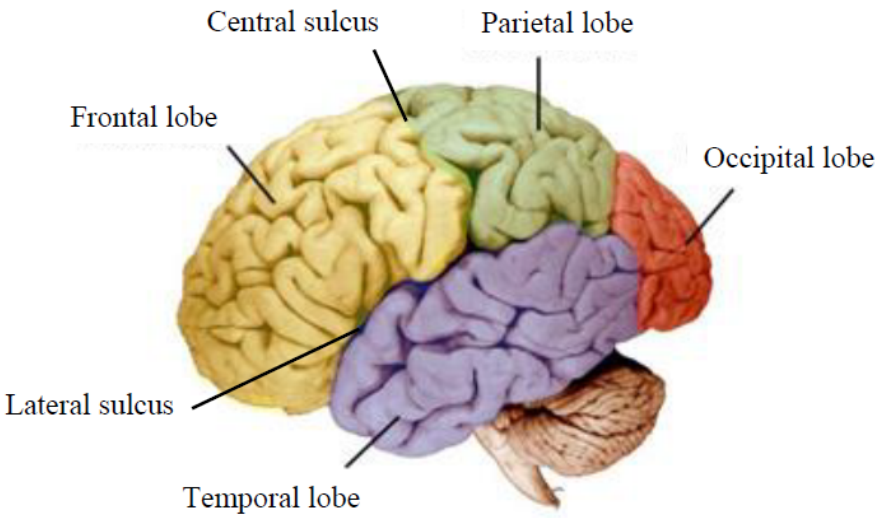



Figure 1.2: *The four lobes into which the cerebral hemispheres are divided, the lateral sulcus and the central sulcus are highlighted.*

**Frontal Lobe.** The frontal lobe is located in the anterior part of both hemispheres. The central sulcus separates it from the parietal lobe and the lateral sulcus separates it from the temporal lobe. Functions related to emotional regulation, planning, body movement, reasoning and problem solving occur in the frontal lobe. Language functions are also related to this lobe (Broca's area).

**Parietal lobe.** The parietal lobe is behind the frontal lobe, separated by the central sulcus. Areas of the parietal lobe are responsible for the integration of sensory information, including touch, temperature, pressure and pain. In addition, the parietal lobe is responsible for the interpretation of language, words, and spatial and visual perception.

**Temporal lobe.** The temporal lobe is separated from the frontal lobe by the lateral sulcus. In the temporal lobe is the area that receives auditory information from the ears and secondary areas and processes the information so that we understand what we hear. In addition, there is Wernicke's area, which deals with speech understanding. Finally, the medial temporal lobe (closest to the centre of the brain) contains the hippocampus, a region of the brain important for memory, learning and emotions.

**Occipital Lobe.** The occipital lobe forms the posterior part of the two hemispheres and is the main centre of visual processing in the brain, in fact it is also called the visual cortex. The primary visual cortex receives visual

information from the retina of the eyes. These impulses are transmitted via the optic nerve to various secondary visual processing areas, which interpret the depth, distance, position and identity of the objects seen.

Since the visual stimulus and its effects on the EEG are the central topic of our thesis, the occipital and parietal lobes were studied more closely.

## 1.2 Physiological bases of the neuron and communication in the CNS

The central nervous system (CNS) is composed of two main classes of cells: neurons and glial cells. The main characteristics of these two types of cells are described below.

### 1.2.1 Neuron

The neuron is the basic unit of the nervous system. It is able to react to stimuli and rapidly transmit the resulting excitation, influencing other neurons, muscle cells and glandular cells.

Considering a classification based on the direction of propagation of the action potential, it is possible to distinguish neurons in the following way:

- sensory or afferent neurons, which transfer information from receptors in the body to the central nervous system. They are characterised by long dendrites and short axons;
- motor or efferent neurons, which transmit information from the central nervous system to effectors (such as muscles or glands). They are made up of short dendrites and long axons;
- interneurons, which determine the connection of motor and sensory neurons with specific regions of the central nervous system. These neurons have short dendrites, but may have long or short axons.

Instead, from an anatomical point of view, the neuron consists essentially of three parts:

- a cell body or *soma*, the genomic and metabolic centre of the neuron;
- a single axon, capable of transmitting nerve impulses to its terminal branch. In particular, it is specialised for the transmission of coded information, such as *"all-or-none"* action potentials;

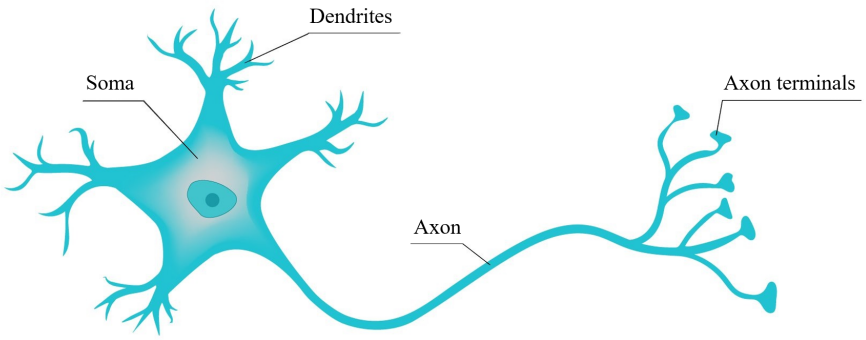



Figure 1.3: *Neuron representation.*

- a variable number of dendrites, to which the neural signals reach: they receive the information and transmit it to the soma.

Every nerve cell has a cell membrane, which acts as a sort of selective filter, very thin and made up of two layers of phospholipids. The cell membrane is characterised both by specific receptors for certain types of chemical substances and by specific channels for the passage of ions with positive ($Na^+$, $K^+$, $Ca^{2+}$) or negative ($Cl^-$) electrical charges. All channels can be opened or closed by specific biochemical changes in the membrane itself [14].

### 1.2.2 Glial cells

Glial cells, which are much more numerous than neurons, are present in various types and basically have a trophic and sustaining function in relation to neurons.

#### Classification of glial cells

As with neurons, glial cells can also be classified. Considering the CNS, it is possible to identify: astrocytes (astroglia), oligodendrocytes (oligodendroglia), microglia and ependymal cells. In particular, astroglia and oligodendroglia are called macroglia.
Glial cells are able to undergo mitosis throughout their lives and this distinguishes them from neurons, which are not able to divide mitotically. Furthermore, glial cells do not have synapses, are not capable of generating action potentials and, in general, are not directly involved in information processing [21].

#### Multiple roles of Glia

Considering the roles that glia play in the nervous system, it quickly becomes apparent that there are many. Some of the main roles played by most glial cells are highlighted here:

1. The glia allows the CNS to have structural support for neurons.
2. Some glial cells guide developing neurons to their proper destination and regulate the development and maintenance of synapses.
3. Glial cells release growth factors crucial to the development of the nervous system.
4. Astrocytes control the development of special capillaries that restrict the movement of certain molecules between the blood and the central nervous system. These capillaries are called the blood-brain barrier.
5. Some glial cells protect neurons from toxic substances, oxidative stress and remove cellular debris.

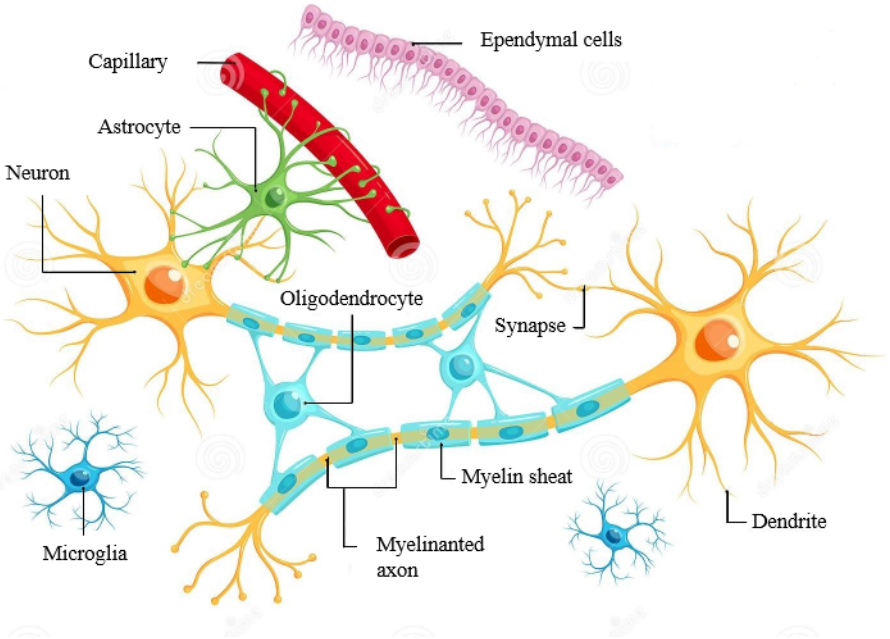



Figure 1.4: *Neurons and neuroglia representation.*

### 1.2.3 Synapse

All nerve cells are able to establish connections between neurons through synapses that can occur at the level of the cell body, dendrites and axon.

Synaptic transmission can be electrical or chemical:

- Electrical synapses enable messages to be transmitted between one neuron and another by means of gap junctions. They connect, in particular, the cell membranes of adjacent cells. In this way, an electrical signal, such as an action potential generated in one cell, can be propagated directly to an adjacent cell, thanks to the flow of ions through these junctions. This type of synapse allows rapid communication between adjacent neurons, synchronising their electrical activity. Indeed, if many cells are linked by electrical synapses, when the threshold necessary to generate an action potential is exceeded, then the entire group of electrically coupled neurons will discharge synchronously following the *all-or-none* principle.

- In the chemical synapse, a first neuron, called a presynaptic neuron, secretes a neurotransmitter into the extracellular space in response to an action potential arriving at its synaptic termination. The neurotransmitter, passing through the so-called synaptic cleft, then binds to a receptor on the cell membrane of a second cell, the postsynaptic

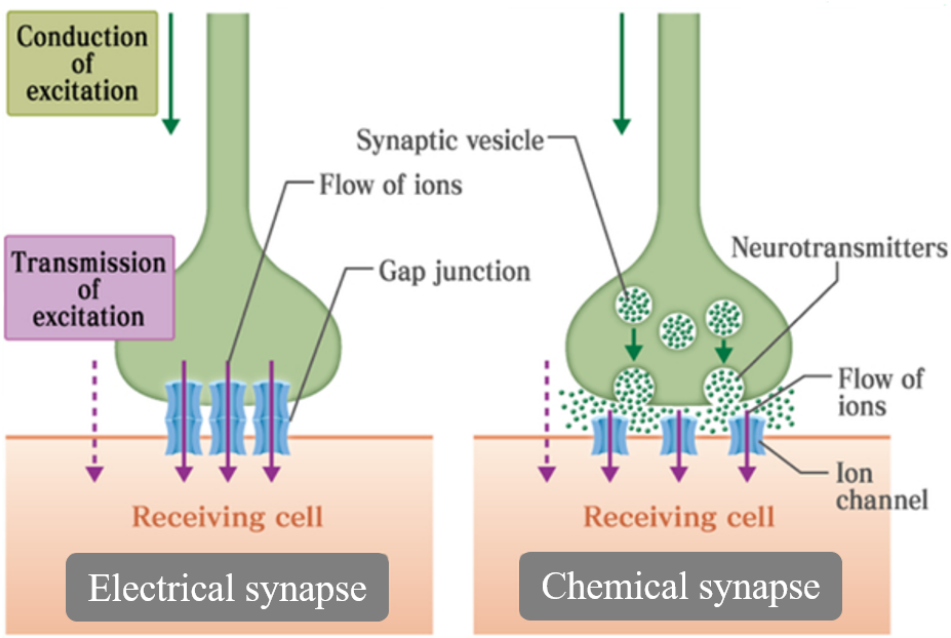



Figure 1.5: *Representation of electrical and chemical synapse, respectively.*

neuron, in such a way as to give rise to an electrical signal that may or may not lead to the generation of an action potential, depending on various circumstances. Any postsynaptic potentials generated may be excitatory (EPSP) or inhibitory (IPSP), depending on the neurotransmitter released. The time between the arrival of the action potential at the presynaptic terminal and the response at the postsynaptic level is 0.5-5 milliseconds. This interval is defined synaptic delay.

## 1.3 EEG

The normal functioning of the human brain generates electric and magnetic fields. These fields are the sum of the electrical signal generated by billions of neurons located in the cerebral cortex which, in response to stimuli, generate a measurable flow of ions [19].

The measurable electrical signal consists of:

1. spontaneous activity
2. evoked potentials
3. bioelectric events produced by individual neurons.

Spontaneous activity is continuously present in the brain. Evoked potentials, on the other hand, are components of the EEG signal that occur in response to an external stimulus.

Bioelectrical events caused by single neurons can be recorded using microelectrodes implanted directly into the cells of interest, but these are not the subject of interest in this thesis work as the invasive sampling technique is different from the one we use.

The EEG signal is an expression of spontaneous electrical activity in the cerebral cortex. Together with the spontaneous activity, evoked potentials are also recorded by EEG, but these signals are usually of small amplitude compared to the spontaneous activity, becoming comparable with the noise level and therefore not easily recorded. Therefore, trains of stimulation pulses are generally used to induce and analyse evoked potentials, in order to record multiple signals and average them, thus increasing the signal-to-noise ratio.

In most cases the EEG signal is mainly due to the effect of excitatory and inhibitory local postsynaptic potentials (PPS) in the cortical cells. The recorded potentials are a net potential difference between the measuring and reference electrode. If all the dendrites of cortical cells were randomly arranged in the cortex, the total current would be almost zero. However, pyramidal cells are oriented so that their dendrites are arranged parallel to each other. The change in potential of one part of the cell relative to another creates a field that imparts an extracellular current, so a potential difference is measurable at the surface. The PPS influences the signal at the surface according to its sign, as it can be excitatory (+) or inhibitory

(-), and its location relative to the sampling system.

Moreover, in the case of evoked potentials, due to the synchronous activity of groups of cells involved, the sum of these potentials can never tend to zero. All this leads to what we read in the EEG signal.

The detection of the EEG signal is called electroencephalography. It is a technique, invented by Hans Berger in 1929, that reads the electrical potential of the brain and measures it using an instrument called an electroencephalograph, as explained below.

In the case of electroencephalography, being a non-invasive technique, the electrical activity of the brain is measured by means of electrodes placed on the scalp, thus allowing both spontaneous activity and evoked potentials to be measured. As mentioned before, in more experimental cases it is also possible to measure brain activity more invasively using electrodes placed directly on the cerebral cortex, in which case the sampling technique is called electrocorticography.

With electroencephalography, a graphic representation of the voltage difference between two different brain positions over time is obtained. Therefore, the EEG signal generated by neurons in the brain and taken from the scalp depends on: the electrical conductive properties of the tissue placed between the electrical source and the recording electrode on the scalp, the conductive properties of the electrode itself and the position of the sampling electrodes [18].

### 1.3.1 Properties of the EEG signal

Although the EEG signal is studied as a random signal due to the fact that it is generated by the simultaneous activity of many neurons, variables can be examined for its classification and for the analysis of its characteristics.

**Frequency.** The frequency band of the EEG signal extends from about 1 to 50 Hz, although typically the greatest amount of information content extends down to 30 Hz (Figure 1.6).

**Amplitude.** The amplitude of the EEG signal is measured in volts (V). In humans, under normal conditions, the amplitude of potentials recorded on the scalp varies from 10 to 100 $\mu$V and is divided into low ($< 30$ $\mu$V), medium (30-70 $\mu$V) and high ($> 70$ $\mu$V). The amplitude of the EEG signal depends above all on the degree of synchrony with which the cortical

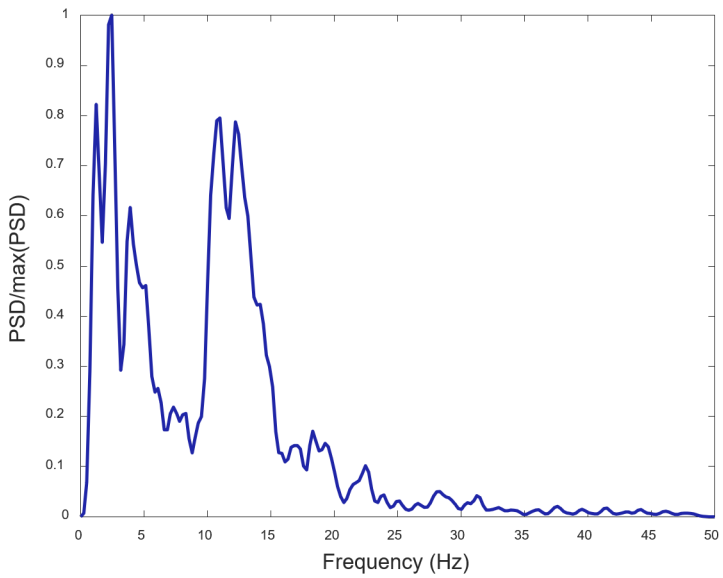



Figure 1.6: *Frequency spectrum of the EEG signal of a subject at rest with open eyes. For ease of visualisation, a filtered signal is shown with a high-pass filter at 1 Hz and a notch filter at 50 Hz.*

neurons interact. In fact, a synchronous excitation produces a signal of greater amplitude than an asynchronous excitation due to the temporal summation of the single electrical contributions. As explained below, high frequencies generally correspond to low amplitudes and vice versa.

**Morphology.** Morphology refers to the shape of the waveform. The shape of an EEG signal is determined by the frequencies, which combine to form the EEG wave, and consequently by the amplitudes. An EEG pattern can be:

- monomorphic, characterised by the regular sequence of potentials at the same frequency and amplitude, so a dominant activity can be identified;
- polymorphic, consisting of several frequencies that combine to form a complex waveform;
- sinusoidal, resembling sine waves. Monomorphic activity is usually sinusoidal;
- transient, isolated pattern distinctly different from background activity.

Morphology analysis is important when identifying epileptic waveforms for an adequate diagnosis of epilepsy in pathological subjects.

**Synchrony.** EEG signal synchrony refers to the simultaneous occurrence of even morphologically distinct events in different regions of the head or in both hemispheres.

**Periodicity.** Periodicity of the EEG signal refers to the appearance of an event over time, such as a particular EEG activity at more or less regular intervals.

**Topography.** The topography of the EEG signal relates to the spatial distribution of EEG activity on the surface of the skull or in the cerebral cortex, depending on where the source generation occurred.

### 1.3.2 Frequency bands

Electrical potential fluctuations can be characterised in terms of spectral content (EEG bands or rhythms) or time domain characteristics (Evoked and Event-related potentials).

In particular, frequency (in Hz) and consequently also amplitude (in V) are used to determine normal or abnormal rhythms [10]. It is important to understand the significance of frequency bands in various mental processes.

The EEG waveform is classified into five different frequency bands, so five rhythms can be identified: delta waves, theta waves, alpha waves, beta waves and gamma waves (Figure 1.7).

**Delta.** The delta band corresponds to the lowest frequencies (0.5-4 Hz). It is the rhythm normally present during deep, unconscious sleep, normal and dominant in children up to one year of age, but abnormal for adults who are awake.

**Theta.** The theta band comprises frequencies from 4 to 8 Hz and is classified as 'slow' activity. This rhythm is present during sleep, specifically reflecting the state between wakefulness and sleep and referring to the subconscious mind. It is therefore abnormal in awake adults, but is perfectly normal in children up to 13 years old.

**Alpha.** Alpha waves are those between 8 and 12 Hz. It is the main rhythm seen in normal, relaxed adults and therefore occurs when a person

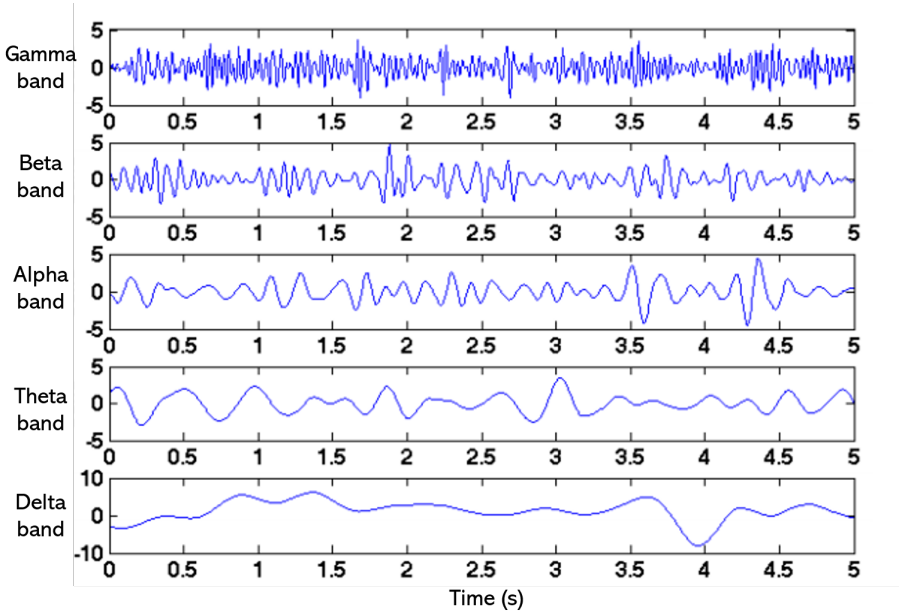



Figure 1.7: *Comparison of EEG frequency bands.*

is alert but not actively processing information. The alpha rhythm can be observed when the subject closes their eyes. Alpha waves are strongest on the occipital cortex, an area that receives visual information from the retina of the eyes, which is why the alpha rhythm is attenuated in the presence of a visual stimulus.

**Beta.** The beta band is between 12 and 30 Hz and is considered a 'fast' activity. It is generally considered a normal rhythm and is the dominant rhythm in those who have their eyes open, are alert, anxious, thinking during problem solving, decision making, processing information about the world around them.

**Gamma.** The gamma rhythm has a frequency greater than 30 Hz and is the one with the lowest amplitude. It is related to high cognitive processes in which the senses and memory are combined.

## 1.4 EEG recording and electrode placement

As mentioned above, as electroencephalography (EEG) is a non-invasive method of recording the electrical activity of the brain, it requires the use of electrodes placed on the scalp.

### 1.4.1 Surface recording electrodes

Bioelectrical activity is generated in or conducted through the tissues, and electrodes are the connecting system between the tissues and the EEG system.

Surface electrodes can be of various types and shapes, but they must be as stable as possible and resistant to external interference. They must allow the correct recording of signals between 0.5 and 70 Hz.

The type of metal from which the electrode is made can distort the EEG signal on the surface of the electrode. In particular, it is essential that all electrodes used at the same time are made of the same metal, that their surface is not contaminated and that they are therefore highly pure.

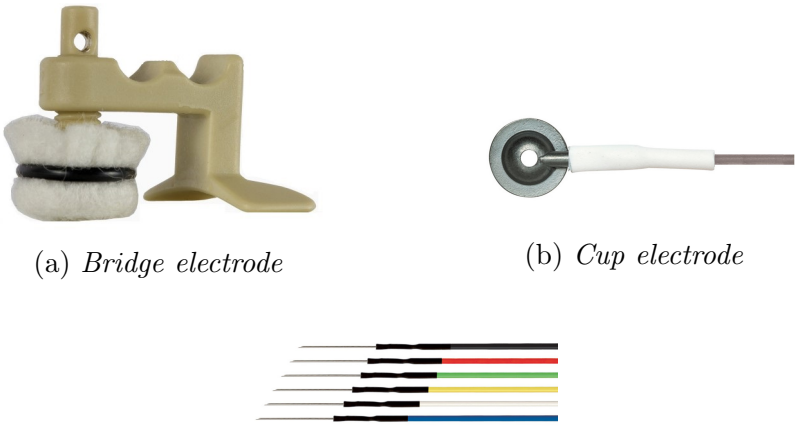
Silver electrodes are usually used for surface EEG recordings. These must be chlorinated to prevent polarisation, which is the main cause of signal distortion.

The types of electrodes used for standard recordings are:

- Bridge electrodes, consisting of a plate-shaped distal part covered with a cotton pad and an elongated, threaded proximal part into which the lead connectors are connected. The electrode is mounted on a plastic jumper. Such electrodes ensure reliable recordings and allow easy movement and repositioning, but the preparation does not remain stable for long periods [14].

- Cup electrodes, made of silver/silver chloride ($Ag/AgCl$) or tin, held to the skin by means of adhesive/conductive pastes and consisting of a discoidal plate with a diameter of 5-10 mm, slightly concave on the inside and with a small hole in the centre for inserting the conductive gel. The latter creates an optimal electrode-skin contact, thus favouring signal conduction and compensating for the effects of any movements, maintaining a constant adhesion between the electrode and the skin. Therefore, these types of electrodes favour more stable preparations over very long periods.

- Needle electrodes, with a stainless steel or platinum-iridium needle placed under the skin. They are useful for comatose patients or those with little or no pain response.



(a) *Bridge electrode*

(b) *Cup electrode*

(c) *Needle electrodes*

Figure 1.8: *Types of electrode*

**Headcaps for EEG**

These are caps made of elastic material on which the electrodes are fixedly positioned (pre-wired caps) or on which the electrodes can be precisely positioned according to the 10-20 system (e.g. neoprene caps).

The use of a headset to support the positioning of the electrodes is more covenient for the patient, but above all it allows many electrodes to be mounted quickly and guarantees good recording accuracy, especially in the case of prolonged monitoring or crises that trigger motor components, since, thanks to the headset, the electrodes are more difficult to move.

### 1.4.2 The International 10-20 Electrode Positioning System

The international 10-20 system developed by the *International Federation of Societies for EEG and Clinical Neurophysiology* (IFSECN) is considered for placing the electrodes on the scalp.

The invention of this system makes it possible to define the positioning of the electrodes on the scalp using well-defined anatomical reference points, making sure that the electrodes cover the entire head and identifying the positioning of each electrode taking into account the area below the brain, using letters and numbers to identify them. This makes communication much easier. In addition, the odd and even electrodes are positioned to the right and left of the skull respectively, while those in the centre are designated with "Z".

More specifically, to position the electrodes correctly on the scalp, ideal lines must be drawn from particular anatomical landmarks. These lines are

perpendicular to each other and are represented by [14]:

1. *Antero-posterior median line* joining the nasion to the inion, passing through the vertex. Across this line it is possible to identify 5 fixed points, named fronto-polar (Fpz), frontal (Fz), central (Cz), parietal (Pz) and occipital (Oz). Taking into account the total distance in centimetres between the nasion and the inion, the points Fpz and Oz are at 10% of this distance from the nasion and the inion respectively. The other points are at 20% of the distance between Fpz and Oz. Considering the theoretical arrangement, the Cz electrode should be in the centre of the line between nasion and inion.

2. *Lateral coronal line*, connecting the right and left preauricular points, passing through the central point at the apex. The temporal electrodes are located on this line. In particular, originating from the preauricular point, they are placed at 10% of the total distance, while the lateral central electrodes (C3 and C4) are situated at 20% from T3 and T4 and from Cz.

Considering these two lines, the positions of the remaining electrodes can be identified, resulting in 21 standard electrode positions, including the two reference electrodes A1 and A2 (Figure 1.9).

**10-10 system.** The 10-10 system is an extension of the 10-20 system proposed later, with extra electrodes placed at intermediate sites to those in the 10-20 system to allow for denser signal acquisition on the scalp.

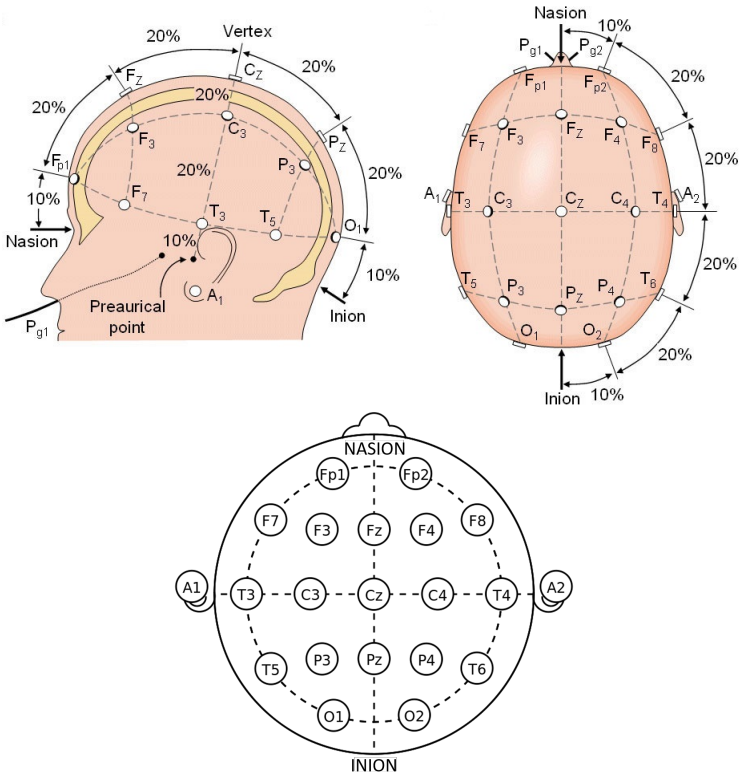



Figure 1.9: *Electrode positioning according to the 10-20 System.*

### 1.4.3 Montage

Two different electrodes are always considered when performing electrophysiological recordings. In order to position these electrodes, two standard leads can be used: bipolar or unipolar.

In the *unipolar* derivation, one electrode is placed in an active site, while the other (reference electrode) is placed in an electrically neutral site such as the mastoid, tip of the nose, chin or earlobe. Specifically, by taking a unipolar reading, the potential of each electrode can be measured with respect to the neutral electrode or with respect to the average of all electrodes, subtracting from each channel the average activity of each other lead [16].

In the *bipolar* derivation, on the other hand, both electrodes are placed on active sites in the area of interest and the signal detected corresponds to the difference between the activities of the two sites. In this way it is possible to know the potential gradient between two brain areas.

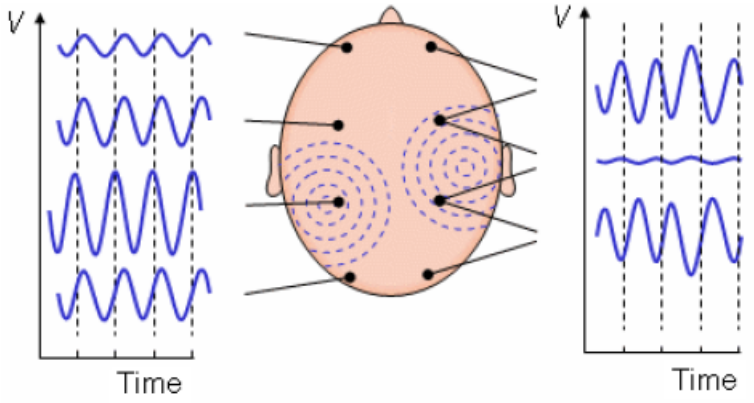



Figure 1.10: *Example of monopolar (left) and bipolar (right) derivation.*

## 1.5 Brain Computer Interface

A Brain Computer Interface, often referred to as a BCI, is a neural interface that, by means of electroencephalography (EEG), allows direct communication between the Central Nervous System and an external device. There are numerous methods of interfacing to enable this type of connection and behind this there are various purposes: from trying to reactivate sensemotor functions to describing cognitive networks.

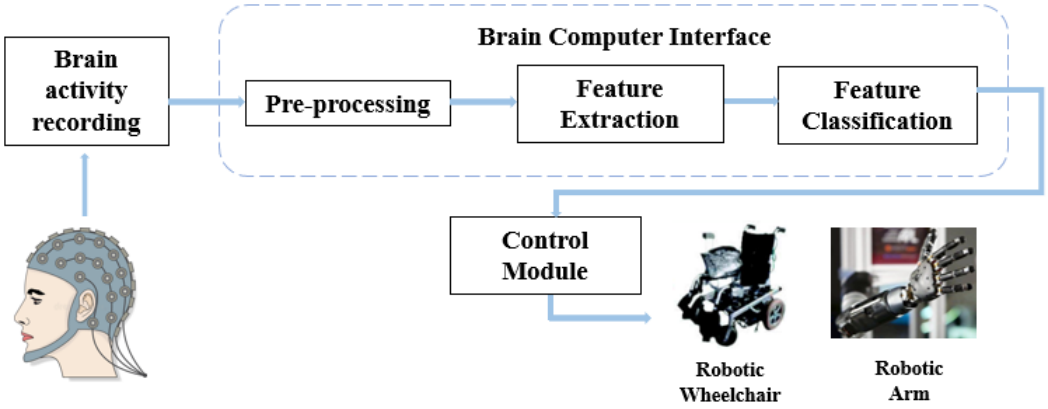



Figure 1.11: *Brain Computer Interface scheme*

Considering conceptually what is behind a BCI, it is possible to identify some main blocks:

- a signal acquisition block
- a conditioning block (in which the signal is processed and elaborated in order to extract instructions for the external device)
- a feedback block that provides to the subject a correspondence of the found mental state.

In particular, it is possible to differentiate systems as a function of signal acquisition techniques, according to processing algorithms, but also according to the type of feedback provided.

A point of fundamental importance concerns the invasiveness of the instrument used for signal acquisition. In fact, there are two types of BCI, namely invasive and non-invasive, which differ in the method of application.

For invasive BCIs, surgery is required to insert an electrode array subcutaneously: in this way, some brain functions are replaced. Therefore, the aim here is not to establish an interaction between the brain and the external device, but to intervene in an invasive way to remedy problems such as the presence of lesions in the brain or synaptic inactivations.

At an experimental level, for obvious reasons, non-invasive BCIs are much more studied, which, as mentioned above, use electroencephalography as a fairly safe technique for the patient, portable and with a good temporal resolution. Interfaces using EEG are called EEG-based BCIs.

Furthermore, non-invasive BCIs are currently used to support patients suffering from diseases affecting the nervous system, such as amyotrophic lateral sclerosis (ALS), in order to allow the control of support devices or to guarantee the patient an interaction with the outside world through eye movement, especially when voluntary movements start to be limited.

BCIs can be further subdivided according to the control signals extracted from the EEG tracing: the most common are VEPs (Visual Evoked Potentials) which are part of SEPs (Sensory Evoked Potentials), P300 evoked potentials, SCPs (Slow Cortical Potentials) and SMRs (Sensory Motor Rhythms).

### 1.5.1 SSVEP

SEPs are electrical potentials detectable by EEG analysis from the central nervous system. Unlike spontaneous potentials, which are measured without stimulation, SEPs occur following the presence of external stimuli; SEPs are a non-invasive means of assessing the somatosensory system. In contrast to Event Related Potentials (ERPs), SEPs are phased locked to the stimulus and can be interpreted as the reorganisation of spontaneous brain oscillations in response to stimuli.

Among SEP, visual evoked potentials (VEP) are of particular importance. VEPs are electrical potentials that can be recorded from the scalp at the visual cortex, then in the occipital region, by electroencephalography.

Steady State VEPs (SSVEPs) are part of VEPs. SSVEPs differ from *Transient VEPs* (TVEPs), which are also part of VEPs, in that TVEPs are generated in response to short visual stimuli, whereas SSVEPs are generated in response to trains of repeated stimuli. In practice, SSVEPs consist of repeated TVEPs that reach a "frequency stable state". In fact, for stimulation frequencies of less than 2 Hz one speaks of TVEPs, whereas to certainly have SSVEPs it is necessary to start with stimulation frequencies greater than 6 Hz.

SSVEPs contain stationary periodic oscillations and tend to resemble a sinusoid with a fundamental frequency equal to the stimulation frequency, so the amplitude distribution of the spectral content of these signals with characteristic peaks remains stable over time. For this reason, the detection

of SSVEPs is usually done through spectral analysis, e.g. by estimating the Power Spectral Density (PSD). Consequently, the most relevant and exploited feature of SSVEPs is to possess a spectrum with time-constant power peaks corresponding to the stimulus frequency and its harmonics (Figure 1.12).

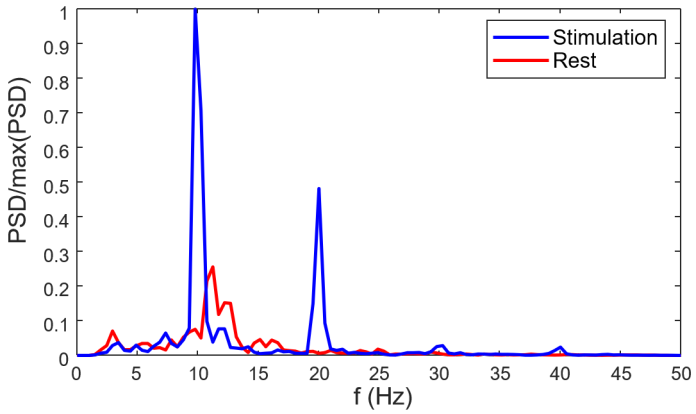



Figure 1.12: *From the blue trace it can be seen that the visual stimulus, flashing at 10 Hz, generated peaks in the PSD of the EEG signal corresponding to the stimulation frequency of 10 Hz and also its harmonics.*

Thus, the SSVEP response is characterised by an increase in the EEG signal at the same stimulation frequency. This characteristic, which is more evident if the signal is mediated on more than one trial, makes these evoked potentials very useful for engineering applications: they are much more immune than TVEPs to muscle artefacts, are better identifiable and have less intra-subject variance.

The most popular and effective system for generating SSVEP patterns is the use of constant frequency on/off stimulus patterns. As mentioned above, to talk about SSVEP, one must have a stimulus that flashes at a frequency of at least 6 Hz. The practical advantage of high-frequency stimulation mainly concerns visual comfort, an advantage to be taken into account especially when the practical application of SSVEPs is aimed at unhealthy patients with numerous physical and psychological problems. On the other hand, it is known that stimulations at lower frequencies are characterised by a larger response in the EEG signal than at higher frequencies, and therefore more easily detectable.

One characteristic of SSVEPs concerns the speed of wave propagation through the scalp. In particular, it has been shown that there is a progressive increase in speed as the oscillation frequency increases: alpha waves

travel at a higher speed than the slow sleep waves found in low frequencies [22].

Because of their high signal-to-noise ratio and robustness to artefacts, SSVEPs have proven useful in both research and clinical applications. In addition, SSVEPs can also be considered for diagnostic purposes, as they are useful for studying pathological brain dynamics of visual perception. SSVEPs are also used to assess seizure disorder and to study and monitor age-related and neurodegenerative disorders (such as Alzheimer's disease, Parkinson's disease, schizophrenia and others). Finally, SSVEPs are also widely used in brain-computer interfaces (BCIs) based on overt and covert attention [22]. The wide range of applications in research and clinical practice is justified by the safety, comfort and ease of use that SSVEPs provide.

### 1.5.2 BCI SSVEP-based

One method of performing a BCI using SSVEPs is to ask the subject to focus his or her gaze on a number of light stimuli, each flashing at different frequencies, thus allowing only the stimuli of interest to be selected.

In this way, the corresponding SSVEPs are produced, which can be analyzed in order to understand the frequency resulting from the EEG signal and evaluate the characteristics of the signal at the precise frequency of stimulation: the intent of the subject is thus captured, used to allow him to communicate or to control a device.

Figure 1.13: *Example of visual stimulation*

The advantages of implementing a BCI based on SSVEPs are many: first of all, since the SSVEP signal is frequency stable and has a much higher signal-to-noise ratio than other evoked potentials, it is easy to detect even in the absence of synchronization techniques with the stimulus. Moreover, thanks to SSVEPs, it is possible to select among several commands, which are perceived by the BCI in a more accurate and faster way than other types of connections.

Wanting to create a BCI that is as well adapted as possible to a particular problem of the subject, promising results could also be obtained through attentional effort, i.e. without the need to move the eyes. In this way, one would have a type of BCI that could be aimed at users with paralysis for whom vision is very reduced and eye mobility is severely impaired [24]. However, it is still necessary to have residual visual ability and to be able to concentrate fully to try to perceive the stimulus that will induce SSVEP.

What is usually used to induce SSVEPs are either LEDs, which require dedicated electronics, or cathode ray tube (CRT) monitors and LCD screens. The latter certainly allow to provide multiple types of stimuli and to interface more easily with a computer than using LEDs, but the available stimulation frequencies are limited by the refresh rate of the screen. To get around this constraint, special interpolation techniques are often considered, with which SSVEPs can be evoked at any frequency [1],[4].

In fact, as part of this thesis work, having used an LCD monitor, it was essential to rely on one of these techniques (discussed in the next chapters) in order to evaluate many more frequencies.

This need arises precisely from the fact that there is no ideal stimulation frequency, capable of evoking a greater response. In addition to the fact that there is variability between different subjects, what also greatly influences a response is the type of stimulus, how it is applied, color, duration of stimulation, etc. Having under control all these aspects and accurately structuring the entire process is essential to try to maximize performance.

# Chapter 2

# Materials and methods

## 2.1 Instrumentation employed

The instrumentation used in this study includes:

- a CE-certified EEG signal acquisition device (Enobio-8 - Neuroelectrics)
- a computer on which is installed the NIC2 software that manages the sampling of the EEG signal; it manages also the acquisition of this signal in Matlab and its subsequent processing
- Psychophysics Toolbox, a special toolbox designed for the design of visual stimulation by programming in a Matlab environment. In fact, it interfaces with Matlab allowing the provision of controlled visual stimuli
- an external LCD monitor with which visual stimuli were administered to the subject. The monitor used has a resolution of 1440 px x 900 px (42 cm x 26 cm) and a refresh rate of 60 Hz.

According to the classification of Council Directive 93/42/EEC for medical devices, Enobio-8 is a class IIa medical device. It is a wireless, portable electrophysiological sensor system for recording the electrical activity of the human brain with 8 channels, to be chosen according to the International System 10-10. It is designed to acquire, store, transmit and display electrophysiological signals. The system digitises the analogue EEG signals collected by an electrode headset, amplifies them and uses Bluetooth wireless connectivity to transmit the EEG data to a dedicated host computer with NIC2 software.

The cup electrodes, covered with a layer of Ag/AgCl and in which the electrically conductive gel is placed, are the part applied directly to the

subject's scalp. Two other electrodes, which are pre-gelled disposable electrode pads, are used as a reference and placed on the mastoid.

The Necbox is the core and control unit of Enobio. The Necbox is a battery-operated device that is attached to the neoprene cap and electrode cables. In turn, the electrodes are inserted into the electrode spaces of the cap according to the 10-10 system. The electrodes placed on the scalp are connected to the Necbox via a cable matrix. This cable matrix consists of 10 cables and contains 8 channels, numbered 1 to 8, for EEG monitoring, and two reference channels labelled CMS and DRL. This allows the channels to be freely assigned to any position in the skullcap.

Figure 2.1: *ENOBIO 8 headset and its wet electrodes used in this study.*

The application that allows the computer to interact with Neuroelectrics devices is called Neuroelectrics Instrument Controller (NIC), and is prepared for both wired and wireless connections, but in this study only a Bluetooth wireless connection was used. In addition, the second version of NIC, called NIC2, is used. NIC allows streaming of EEG data and real-time analysis with the Enobio device. NIC2 can also be controlled in real time by Matlab via TCP connection, as explained in Chapter 3.

| Specification | Value |
|---|---|
| Number of Channels | 8 Channels, flexible placement |
| Sampling rate | 500 SPS |
| Bandwidth | 0 to 125 Hz (DC coupled) |
| Resolution | 24 bits – 0,05 microvolt ($\mu$V) |
| Measurement Noise | $< 1$ $\mu$V RMS |
| Communication | Bluetooth 3.0 and 2.1 |
| Output | EDF+, ASCII, NEDF data files or TCP/IP raw data streaming |
| Battery | USB rechargeable system using Li-Ion battery |
| Dimensions | $89 \times 61.1 \times 23.8$ mm |
| Weight | 85 g |

Table 2.1: *Neuroelectrics Enobio 8 specifications.*

## 2.2 Study protocol

In this study, subjects were recruited according to the following criteria.

Inclusion criteria:

- Age between 18 and 80
- Healthy subjects with normal or corrected vision

Exclusion criteria:

- Presence of colour blindness to the colours used in the experiment (green and red)
- Presence of severe pathologies of the visual system
- History of neurological problems such as seizures or epileptic attacks

Therefore, although the study is aimed at CLIS patients, the trials were only conducted on healthy subjects, who tried to reproduce as best as possible the fixed gaze condition that characterises CLIS patients, as explained below.

**Enrolment procedure.** Subjects present in the area where the study was conducted, most likely Turin, were considered, respecting the inclusion and exclusion criteria mentioned above. Subjects were informed about the purpose and characteristics of the research and the processing of their personal data by means of the information sheets in the Appendix. These

documents were duly drafted and provided to the subject prior to submitting to the study, to ensure that the trial would be risk-free. At this point, subjects who made a free and informed decision to participate were enrolled.

In addition, during the course of the experiment they were guaranteed the possibility of abandoning or stopping the experiment at any time. For example, if they felt visually fatigued or if the entire experimental procedure caused them any form of discomfort. In this case, there would be no negative consequences for them and the data acquired would be deleted, excluding them from the study.

### 2.2.1 Description of the experimental phase

To achieve the objectives of the study, the experimental phase was organised as follows: the subject was initially submitted to the application of electrodes on the head, using the instrumentation present in Enobio-8, to acquire the EEG signal.

The installation phase involved the following steps:

1. The subject wore a headset pre-holed for electrode placement according to the international 10-10 system.

2. To position the electrodes of interest, first the hair was removed from the holes to ensure more direct contact with the scalp. Once the electrodes were positioned, the necessary amount of electro-conductive gel was inserted using a syringe provided by Setup Enobio to reduce the electrode-skin impedance.

3. After cleaning the skin of any impurities, 2 pre-gelled electrodes were applied to the mastoid bone, to which the reference channels were connected.

4. The cable to which all the electrodes was connected was in turn connected to the Enobio Neuroelectrics Control Box (Necbox), i.e. the heart of the Enobio system. In this way, the assembly phase could be considered complete and the subject was ready for sampling.

Once the assembly was completed, the sampling device (Enobio) was switched on, which interfaces with the PC via a special software (NIC2), allowing the transmission of data to the PC via Bluetooth connection. At this point, after several checks (as explained in detail in Chapter 3) the EEG signal starts to be recorded.

The experiment was carried out in a dark room: the subject was placed on a chair, in comfortable conditions, with an LCD monitor in front of him

so that his gaze was perpendicular to the surface and directed to the centre of the screen at a distance of 30-40 cm from it.

During the sampling and simultaneous recording of the EEG signal, the subject was subjected to visual stimulation phases provided by Psychophysics Toolbox, a special toolbox created for the design of visual stimulation by programming in Matlab.

The object of stimulation consisted of a square checkerboard drawn on the screen, with one side equal to the smallest dimension of the screen itself, whose targets were coloured in two different colours (red and green) in an alternating way. The red targets were drawn in such a way as to flash at a frequency that was always different from that of the green targets, but both according to a sinusoidal modulation, as explained in more detail in Psychophisics toolbox section.

The choice of colours was made taking into account the literature [9], [7]. During the stimulation phase, the squares of the entire checkerboard flashed as described above and the subject had to try to focus on one colour or the other, but without moving their eyes. For this reason, while the targets were flashing, there was a fixed white cross inside the central black square, to help the healthy subject keep their eyes fixed on it while trying to reproduce as best as possible the condition of a patient in CLIS.

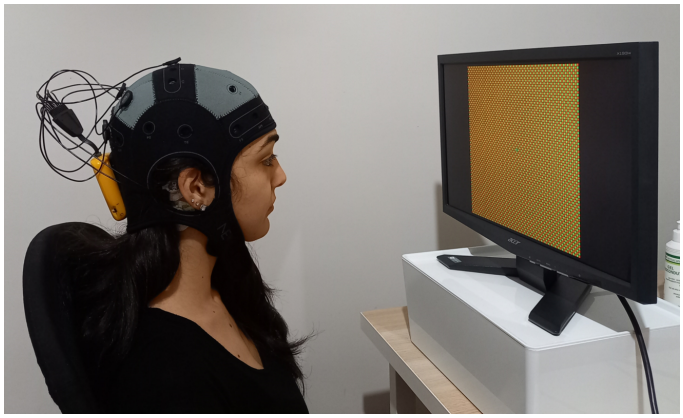


Figure 2.2: *Subject ready for visual stimulation and EEG signal collection.*

All the stimulation phases were always alternated with periods of rest, during which there was a still checkerboard drawn on the screen. In addition, the cross in the centre during this period became randomly red or green, depending on which colour the subject had to focus on in the seconds of stimulation immediately following.

The frequencies at which the squares flashed were in the following range:

8 Hz - 15 Hz, chosen on the basis of some evidence found in the literature [11], [8].

Each stimulation period lasted 5 seconds, alternating with a rest period of the same duration, for a total duration of each trial of a maximum of 20 minutes, according to the requirements of the study. Considering the need to perform several test tasks for each subject, a total time commitment for each was approximately 1 hours, ensuring the necessary rest of the subject between each test.

At the end of each trial, the recording of the EEG signal was stopped and saved in the *.easy* format, together with the *.info* file, potentially useful in the offline data processing phase.

Once the signals were obtained during the experiments, the most appropriate processing techniques were implemented with the support of the literature. An attempt was made to bring out the frequency component actually present during the stimulations and therefore to understand which colour the subject focused on.

## 2.3 Psychophisics toolbox

Visual stimuli were generated using the Psychophysics Toolbox Version 3 (PTB-3).

Psychophysics Toolbox is used for vision and neuroscience research, it is a software package that provides the control necessary for accurate stimulus visualisation, in fact it allows for the synthesis and display of accurately controlled visual and auditory stimuli. However, in this thesis work we only dealt with visual stimuli.

PTB-3 is a set of Matlab functions that interfaces between Matlab and computer hardware.

The routines underlying Psychtoolbox provide access to the display frame buffer and colour look-up table, allow synchronisation with vertical retrace, and support sub-millisecond times to allow precise stimulus display.

### 2.3.1 Visual stimulus provided

The visual stimulus provided in this work is a checkerboard.

In order to ensure that the checkerboard is fully represented, the technical characteristics described above of the external monitor used were taken into account.

The checkerboard, represented in Figure 2.3, consists of 73 x 73 squares, coloured alternately red and green. The central square of the checkerboard is black and contains a white cross: as mentioned above, this has been done in order to help the healthy subject to reproduce in the best possible way the condition of fixed gaze that characterises the sick subjects to whom the study is addressed. Each square has a side size of 10 px and a black border 1 px thick around it, so each square is 2 px away from those around it; the arms of the cross have a thickness of 2 px (Figure 2.4).

The black border was added because it was thought to help subjects focus on one colour or another, and indeed the experimenter confirmed that, in terms of successful concentration, it is better to have the coloured squares separated by the black border than when the coloured squares are attached to each other, probably because of the greater contrast created between the two colours.

Furthermore, on the basis of experimental tests carried out, it was seen that, again in terms of contrast between the coloured part on which the subject has to focus and everything else, using a square checkerboard is preferable to having a checkerboard that fills the whole screen, which is why one has the two black bands at the sides.

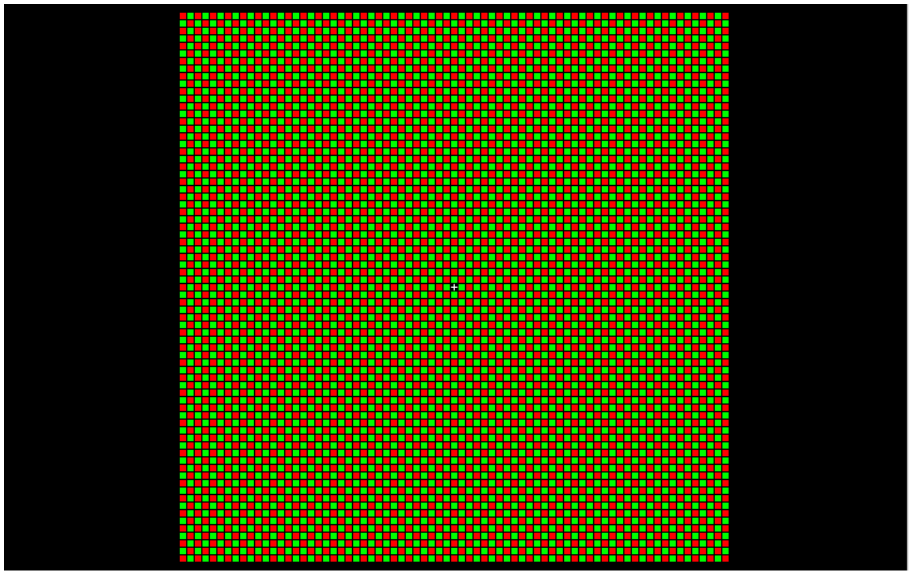


Figure 2.3: *Checkerboard when the stimulus is not flashing, but stationary, that is, during rest periods.*

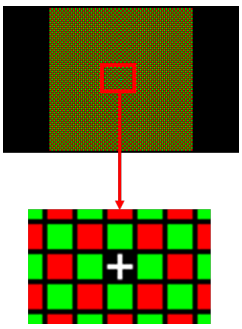


Figure 2.4: *A zoom of the central part of the checkerboard including the white cross is represented, useful to keep the eyes fixed during the stimulation phase.*

### 2.3.2 Checkerboard development

The checkerboard was constructed from the initialisation of the x and y coordinate grids of the squares constituting the checkerboard: each of these two grids had both sides of the number of squares to be represented (73 in this case), these x and y coordinates contained the positions of the centres of the 73 x 73 squares constituting the checkerboard. The centre of the grids was positioned at the origin of the screen axes, where the origin was considered to be in the pixel at the top left of the screen, as in the Figure 2.5.


Figure 2.5: *The arrows indicate the point from which we start counting the positions of the squares that are then represented. Each square is identified by the x and y coordinates that represent its centre.*

At this point, the checkerboard consisted of 73 x 73 squares of side 1 px centred in the origin of the axes (Figure 2.6).

To obtain the final positions of the squares that make up the checkerboard, the grids of x and y coordinates of the centres of the small squares have been moved to the centre of the screen and enlarged by the desired size (Figure 2.7), so as to obtain new x and y coordinates. These new x and y coordinates were still the coordinates of the centres of the squares

Figure 2.6: *The grid of squares in the top left-hand corner of the black screen is intended to be a representation of the checkerboard. The checkerboard used has many more squares than are represented, but for clarity of display a 7 x 7 grid has been represented and not a 73 x 73 grid.*

that made up the checkerboard, but they took into account the fact that each square had a side of 12 px and no longer 1 px.

Lastly, in order to have each square of the desired colour, the coordinates of the vertices of the squares have been calculated and not the coordinates of the centres of the individual squares, since this is what the Screen('FillRect') function uses.

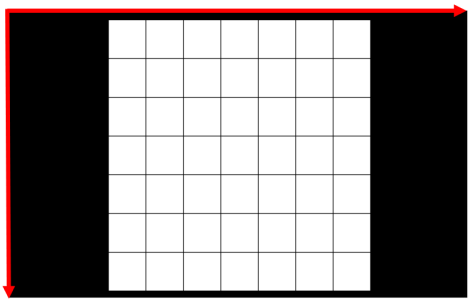


Figure 2.7: *Final checkerboard, centred in the centre of the screen and with squares of the desired size. As in the previous figure, the checkerboard used has many more squares than those represented, but for clarity of visualisation a 7 x 7 grid has been represented and not a 73 x 73 one.*

Each quadrant was then filled with its respective colour.

In the resting phase, the squares were alternately filled with red and green, 100 and 010 respectively, according to the RGB coding. The cross was overlaid on the central black square. In particular, in the resting phase it was randomly filled with the colour on which the subject should focus in the following stimulation phase (Figure 2.8).

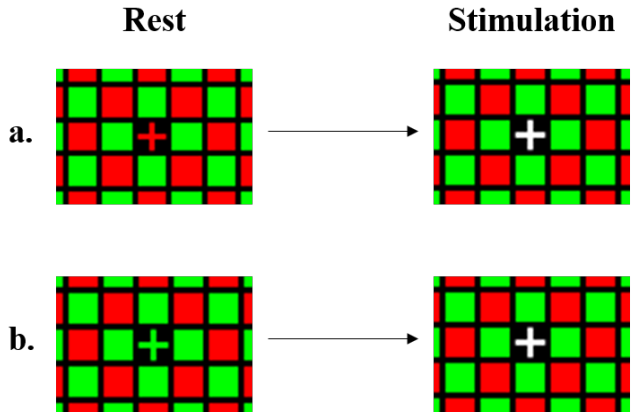



Figure 2.8: *In case (a) the red cross in the rest phase indicates that the subject should focus on the red in the next stimulation phase, during which the cross turns white. The same thing happens in case (b) but with green.*

In the stimulation phase, on the other hand, the squares had to flash at two different frequencies specific to each subject. In this phase the colour intensities changed from intense colour to black through a sinusoidal modulation at the chosen stimulation frequency. The central cross in the stimulation phase became white in order not to influence the subject's concentration on the particular colour.

As mentioned above, Psychtoolbox is able to support times of less than a millisecond. Nevertheless, it was necessary to take into account the technical characteristics of the monitor used to provide the visual stimulus, in particular the refresh rate of the monitor.

The refresh rate of a display, measured in Hz, is the number of frames that the device can display in one second, thus determining the maximum number of frames that can actually be seen in one second.

The external monitor used to provide stimulation via checkerboard has a refresh rate of 60 Hz. This means that the maximum representable frequencies were all those below 30 Hz, thus ensuring that the Nyquist criterion was respected.

In order to ensure that the number of stimulation frequencies was not limited by the monitor's refresh rate, it was decided to modulate the colour intensity by means of a certain waveform. Specifically, in this case the colour intensity was modulated by means of a sine wave at the desired stimulation frequency and sampled at a monitor refresh rate of 60 Hz, based on [5].

Instead, using a constant number of frames per cycle would have con-

strained the usable pacing frequencies. In fact, with a monitor with a refresh rate of 60 Hz, the representable frequencies could have been integer divisions of the monitor's refresh rate (e.g. in the vicinity of the alpha band 7.5 Hz, 10 Hz, 12 Hz, 15 Hz). In the extreme case of using a frequency of 30 Hz, in fact, the 60 frames in 1 s would have to represent alternately 0 and 1 to indicate 'black' and 'deep colour' respectively.

Modulating the intensity of the colour by means of a sine wave, it varies from 0 to 255, where 255 is the maximum colour intensity that in Matlab is associated with 1, depending on the chosen stimulation frequency: in 1 s there are 60 frames, each of these 60 frames varies in intensity depending on the amplitude of the sine wave associated with the stimulation frequency used.

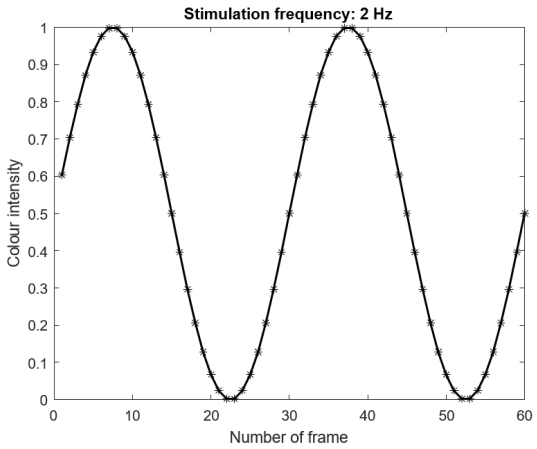



Figure 2.9: *On the x-axis, the time in frames is represeted: frames vary from 0 to 60 and, being the monitor refresh rate of 60 frames/s, it means that 1 s is reported on the abscissa axis. The y-axis shows the intensity of the colour, which varies from 0, corresponding to black, to 255, corresponding to full colour, red or green. The sine wave is sampled at the monitor's refresh rate (60 Hz). The crosses, i.e. the sampling points, are the intensity values of the squares that make up the checkerboard that vary over time.*

In the Figure 2.9 a stimulation frequency of 2 Hz is assumed. In fact, two periods of the sinusoid are represented corresponding to 60 frames, therefore to 1 s: at each frame the intensity of the colour varies from 0 to 255 and this is what has been displayed on the checkerboard.

During the stimulation phases, the red and green squares of the checkerboard modulated the intensity of the colour according to this principle at two different stimulation frequencies, chosen according to the analysis made and adapted to the subject.

It has been shown experimentally that this visual stimulus causes little strain on the subject, so this is a great advantage for the CLIS subjects at whom the study is directed, as we would like to make their unique way of communicating as stress-free as possible.

In fact, before reaching this conclusion, different types of stimuli in different shapes and sizes were constructed and experimentally tested. Initially, larger squares were tested for the checkerboard, but it was proven that having a very large target a few centimetres from the eyes is very tiring. In addition, too large squares led the healthy subject, who should have his gaze fixed on one point, to make a mistake: the large target placed close to the point where his gaze falls led him involuntarily to look away. On the other hand, the large target size led to very noticeable peaks in the PSD at the stimulation frequencies. In the end, the minimum size of the squares constituting the checkerboard was chosen, which still allowed to have evident peaks in the PSD, with the advantages of allowing the subject to concentrate on the set of smaller points without moving his gaze and not having such a tiring stimulus.

# Chapter 3

# Signal acquisition and pre-processing

## 3.1 Description of acquisitions

The EEG signal was collected by placing 7 wet-cup electrodes (Ag/AgCl) on the head. Each of them was connected to one of the 8 channels provided by the sampling system for EEG monitoring, according to the protocol shown in Figure 3.1.

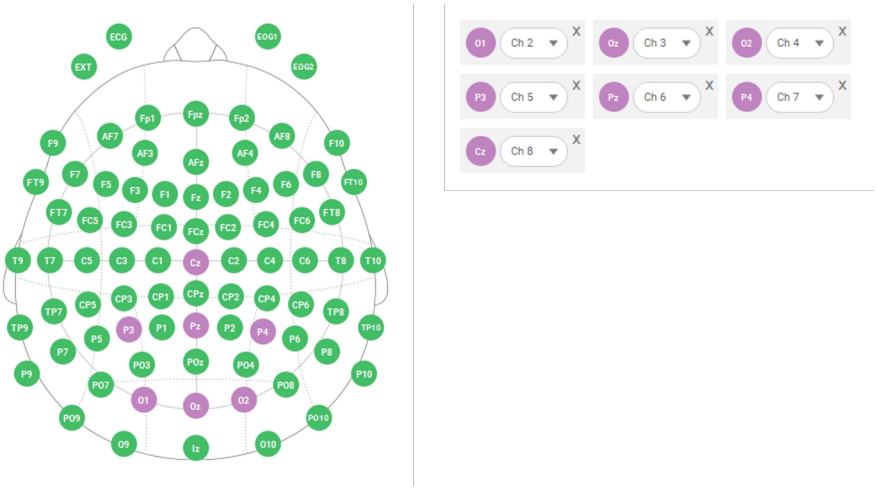



Figure 3.1: *Setting the channels used via the NIC2 software.*

Since it has been demonstrated that occipital and parietal areas are the most important contributors to SSVEP frequency recognition, electrodes were placed in O1, Oz, O2 and P3, Pz, P4 ([12], [3]). In the acquisition phase a monopolar sampling was carried out, but in the processing phase a referencing was performed for each of them with respect to Cz, therefore the signal at Cz position was also taken. Although Cz is in a position not

far from the explored region, it was chosen as the electrode to which to refer all the others because it is in any case outside the region in which the activity of interest is recorded.

The reason for this choice is linked to the intention of having less noisy signals: by referring all the signals to Cz we eliminate all the components not of interest and emphasise the components of interest present only in the occipital and parietal areas.

Once the protocol was defined, it was always checked before starting the recording that the quality of the signal in each channel was such as to guarantee a good recording. This was done both by visual inspection of the signals and by observing the colour code provided by the software for each EEG channel. The colour code is based on the quality index (QI) as shown in the Table 3.1.

| **Color** | **Quality Index (QI)** |
|---|---|
| Green | 0.0 - 0.5 |
| Orange | 0.5 - 0.8 |
| Red | 0.8 - 1 |

Table 3.1: *Colour code according to quality index.*

As described in the manual [17], IQ is calculated every 2 seconds, and depends on four parameters:

- Line Noise: power ($\mu V^2$) of the signal in the standard line noise frequency band (EU: 50±1 Hz; US: 60±1 Hz)
- Main noise: signal power of the standard EEG band (1–40Hz)
- Offset: mean value of the waveform
- Drift: the drift is measured but not included in the QI computation because it has a high inter-subject variability. A high drift does not imply bad signal

An example of recurring values when signals have a quality index corresponding to the colour green can be seen in Figure 3.2.

Another check done before starting to record the signal was to evaluate the difference between the signals with eyes open and eyes closed, since, in the latter case, if the signal is taken correctly, it is easy to visualise the presence of the alpha band (as can be seen in Figure 3.3).

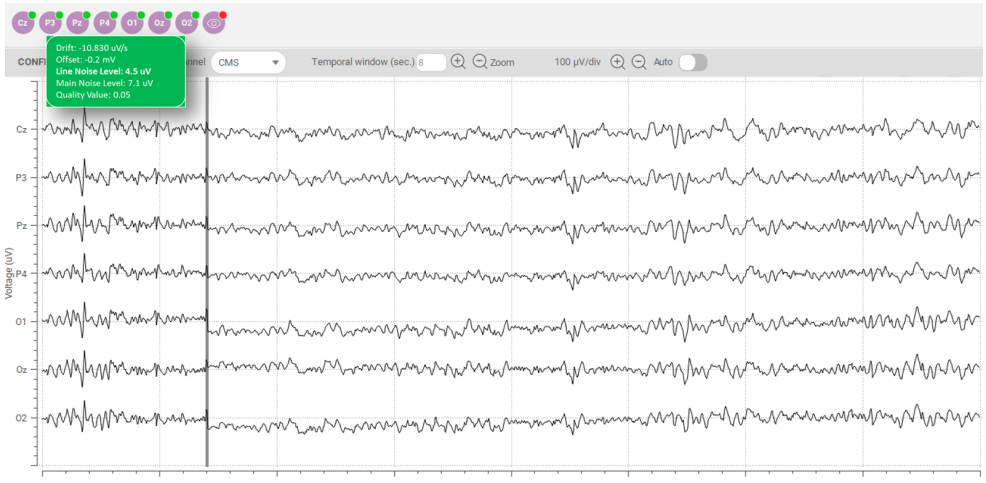



Figure 3.2: *Example of signals where the quality index is within the range to ensure a clean recording.*

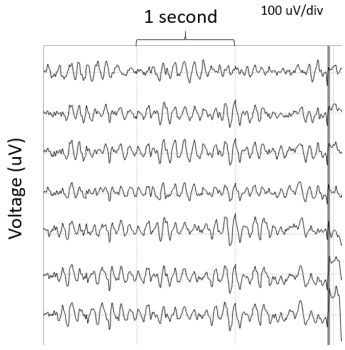



Figure 3.3: *When the subject closes their eyes, the presence of the alpha band can be visualised in the EEG signal. In fact, in this example case, it is possible to count in one second the presence of about 9/10 peaks.*

The recording was then started and, together with the signals from the various channels, the stimulation markers (identified by number 1) were also stored at the beginning of a period of visual stimulation. In order to execute everything in the most automated way possible and obtain a more precise sending of the marker than could be expected from an operator, the TCP-IP connection was used. In particular, by enabling this type of connection from the NIC2 software and disabling the option shown in the Figure 3.4, the NIC software worked as a server and Matlab was identified as a client.

Once this was defined and the TCP-IP connection created in Matlab as well, it was possible to obtain the *writing* of the marker on the NIC2 software directly from Matlab, almost in real time at the start of the stimulation provided with the Psychotoolbox. Thus, the signal stored at the end

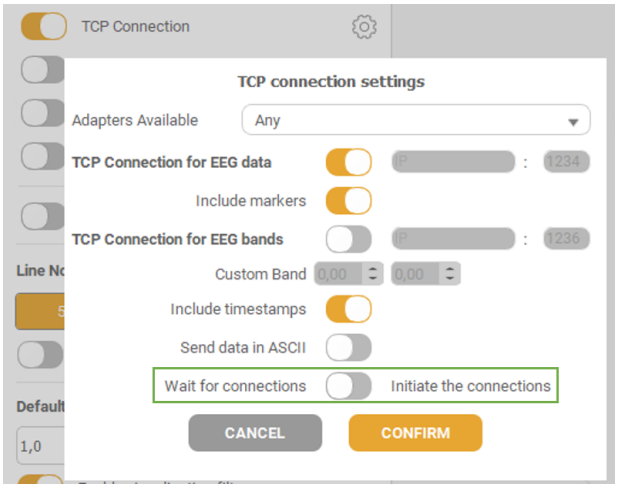



Figure 3.4: *Activation of the TCP-IP connection in the NIC software and setting up the NIC as a server.*

of the task contains markers of interest, which are useful during processing to separate rest periods from stimulation periods.

### 3.1.1 Frequency scanning

Two signals were recorded for each subject with the aim of obtaining the most suitable stimulation frequency pair for the subject.

Specifically, different pairs of stimulation frequencies (one frequency for red and one for green) were scanned during each of the two acquisitions. For each scanned frequency pair, 5 trials of visual stimulation in which the subject had to focus on the colour red and 5 trials of stimulation in which the subject had to focus on the colour green were carried out randomly.

Each frequency pair was analysed by extracting features (as explained in Chapter 4) from the pre-processed signal (in the way explained in the following section) and recorded during stimulation with these frequencies. The extracted features were then sent to the classifier, which returned a percentage of accuracy: at each scan, the best frequency pair was the one that returned the highest accuracy.

Some of the alpha-band frequencies were initially analysed: 8, 10, 12 and 15 Hz.

In the first scan (first recorded signal) a combination of these frequencies was considered, therefore the frequencies on which the first tests were carried out, which are the same for all subjects, were as follows (Table 3.2).

From the second scan onwards the tests could vary from subject to subject, in fact the procedure was as follows: the surroundings of the frequency

| **f_red** | 10 | **12** | 15 | 8 | 12 | 15 | 8 | 10 | 15 | 8 | 10 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **f_green** | 8 | **8** | 8 | 10 | 10 | 10 | 12 | 12 | 12 | 15 | 15 | 15 |

Table 3.2: *Frequency pairs analysed during the first scan.*

pair that had produced the best results in terms of accuracy in the first scan (e.g. 12 Hz and 8 Hz) were scanned and the surroundings of the best pair were inspected in steps of 1 Hz.

Example: In the first scan, the best frequency pair is f_red = 12 Hz and f_green = 8 Hz. The surroundings of these two numbers (11, 12, 13 Hz and 7, 8, 9 Hz) are analysed and the resulting vectors are combined (pairs already inspected in the previous scan are eliminated). Considering the example case, the combinations are (Table 3.3):

| **f_red** | 11 | 12 | **13** | 11 | ~~12~~ | 13 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|
| **f_green** | 7 | 7 | **7** | 8 | ~~8~~ | 8 | 9 | 9 | 9 |

Table 3.3: *Frequency pairs analysed during the second scan.*

From the Table 3.3, it can be concluded that the best frequency pair is, for example, 13 Hz for red and 7 Hz for green.

It was decided to proceed with two successive scans because analysing the whole range of frequencies of interest in fine steps from the beginning would have led to an excessively long exposure time of the subject to the visual stimulus. With the chosen mode, in fact, the time necessary to perform a single scan is already sufficiently high.

For example, to perform the first scan, where there are 12 combinations of frequency pairs to be analysed, it was necessary:

*10 s (5s rest + 5s stimulation) * 10 trials * 12 combinations of frequencies = 20 minutes*

In addition, the subject had time to relax between scans. While, following the same reasoning, the duration of the second scan was a maximum of 15 minutes (depending on whether there were pairs already explored or not).

A third scan (in steps of 0.6 Hz) was also explored in the study phase, but as no clear advantages were found in doing this and taking into account that the subject could become tired during the scans (although they may relax between scans), it was decided to stop at the second scan.

## 3.2 Pre-Processing

This section describes the steps involved in implementing the pre-processing techniques used to process the acquired signals, discussing and justifying the choices made.

### 3.2.1 Referencing and filtering

In order to analyze the EEG signals, before carrying out the actual processing, each channel was referred to the Cz electrode, also a signal electrode. In this way, the potential of one electrode is compared with that of another signal electrode placed on the head: we thus attempt to obtain signals that are less sensitive to diffuse noise and other types of artefacts, but more sensitive to localised brain activity [23].

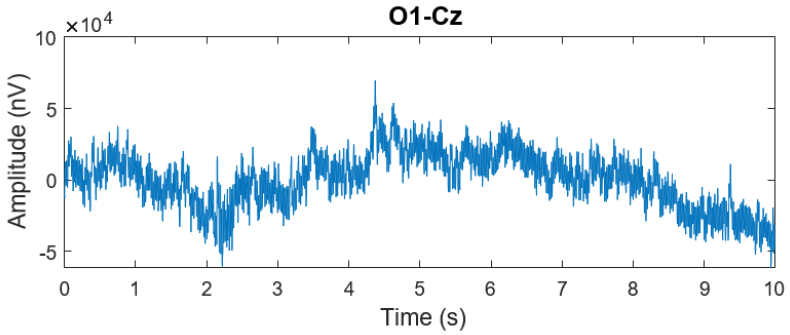



Figure 3.5: *Example of signal taken in resting conditions, with eyes open and referred to Cz. The average was subtracted only for the purpose of visualization.*

The first operation performed on the signals was digital filtering. In general, 2 filters were applied:

- High-pass filtering, useful for eliminating low-frequency noise components
- Recursive filter to remove mains interference at 50 Hz

In particular, high-pass filtering was performed by applying the *Butterworth* filter. This type of filter is part of the IIR (Infinite Impulse Response) family of filters and is of the ARMA (autoregressive, AR and moving average, MA) type, i.e. the filter transfer function $H(z)$ has both zeros (roots of the numerator) and poles (roots of the denominator), but the poles prevail since the filter has an infinite impulse response.

This is a filter that has an amplitude response that is maximally flat in the passband and overall monotonic. However, this smoothness results in a lower rolloff slope.

It was designed in Matlab via the *butter* function that returns the vectors of filter coefficients $a$ and $b$:

$$[b, a] = butter(4, 2/fN, 'high')$$

choosing an order of 4, which is reasonably lower than the number of samples in the sequence to be filtered, and a cut-off frequency of 2 Hz, which is a bit higher than necessary, but taking into account the $\alpha$-band as the band of interest. The cutoff frequency was normalized by the Nyquist frequency (named $fN$ and equal to the sampling frequency/2, with a sampling rate of 500 Hz).

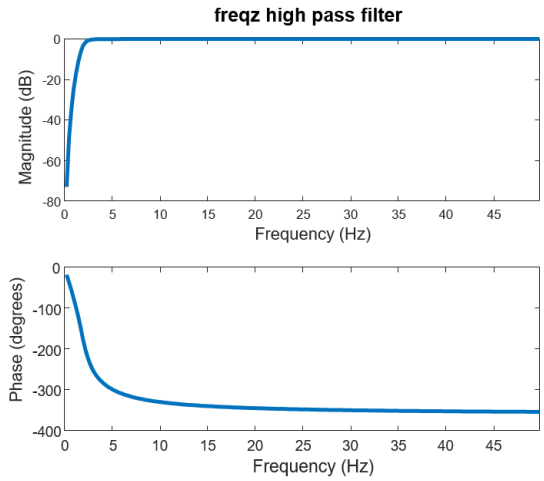



Figure 3.6: *Modulus and phase of the high pass filter frequency response.*

An IIR filter was chosen because, compared to FIR filters (with Finite Impulse Response), it meets given specifications with a lower order and this is considered an important aspect, since a lower order gives rise to a lower transient. However, IIR filters have a non-linear phase and therefore introduce a phase distortion: having a distortion in the passband causes a morphological variation of the signal in the time domain, so it is important to compensate the introduced phase distortion. It is possible to achieve this through the technique of anti-cusal filtering with zero phase rotation.

In fact, the coefficients of the filter $a$ and $b$ are passed to the Matlab function *filtfilt* which filters the signal by performing the filtering twice, both in forward and reverse directions: after filtering the data in the forward direction, *filtfilt* reverses the filtered sequence and passes it through the filter again. As a result we have zero phase distortion, i.e. anti-causal filtering that allows the signal to be undistorted.

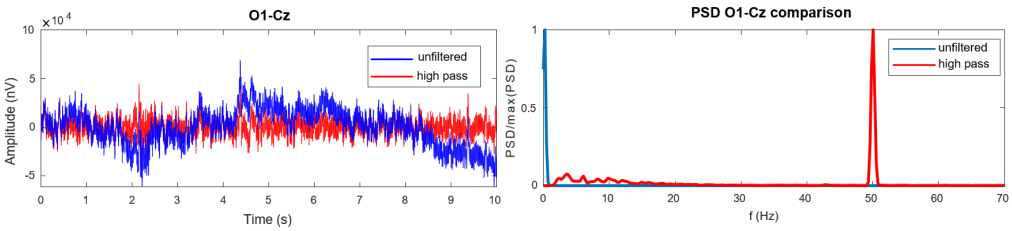



Figure 3.7: *Example of high-pass filtered signal and PSD.*

In order to remove the line interference at 50 Hz, a recursive ARMA-type band-rejecting filter was designed, centred at a frequency of 50 Hz, with an attenuation of 0.01 at this frequency and with a bandwidth between one root and the other of 2.

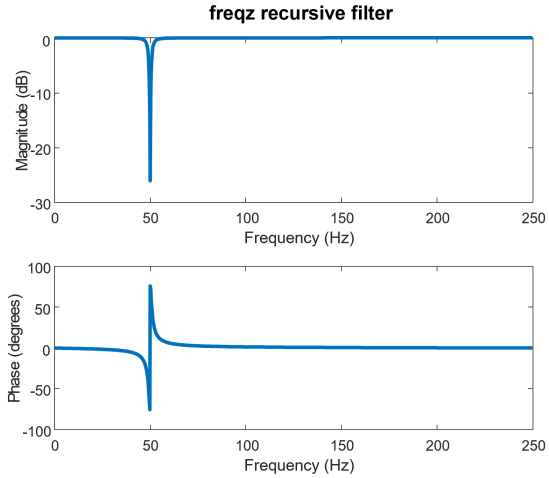



Figure 3.8: *Modulus and phase of frequency response of ARMA recursive filter centred at 50 Hz.*

Since this is also an ARMA-type filter, once the filter coefficients were obtained, filtering was carried out by means of the *filtfilt* function. In this way the 50 Hz component was attenuated, as can be seen in Figure 3.9.

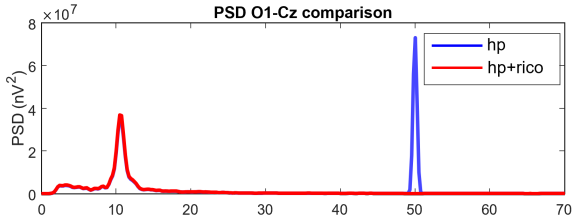



Figure 3.9: *PSD comparison of an example signal (taken in resting conditions, with eyes closed) with and without recursive filter.*

## 3.3 Spectral analysis of EEG signal

Brain activity, hence the EEG signal, shows continuous oscillations modulated in amplitude and frequency. For this reason, the analysis of the EEG signal and its parameters generally occurs in the frequency domain [23]. The digital EEG signal is converted from the time domain to the frequency domain and Fourier (or spectral) analysis is the most common method for this conversion and forms the basis of many advanced methods.

The classical algorithm to perform the spectral analysis is based on the estimation of the Fourier transform of the signal, in particular the direct method to estimate the PSD is based on the periodogram [15].

The Fourier transform expresses any arbitrary time series as a sum of sine waves with different frequencies and phases. This makes it possible to break down the signal into individual sine-wave components and assess how much each frequency is present in the signal. The set of frequency-dependent values (frequency components), whether continuous or discrete, is called the amplitude or power spectrum (understood as amplitude squared).

The EEG is classified as a stochastic and stationary signal for short intervals, which immediately posed problems in the application of Fourier analysis to it, since the latter, in theory, can only be correctly applied to deterministic signals or stationary or at least 'slowly' varying stochastic processes. The limit of non-stationarity has been overcome by subdividing the EEG signal into many sub-intervals (typically 1-2 s), which are assumed to be stationary. The analysis of the locally stationary EEG signal requires a trade-off between temporal and frequency resolution, as one can only be improved at the expense of the other. The trade-off is expressed by the choice of the length of the stationarity interval. The size of this time window (or epoch) is an important factor as it determines the lowest frequency that can be detected by mathematical analysis.

In this thesis work, Welch's method for calculating PSD was chosen, based on averaging of windowed and overlapped periodograms. By choosing different windowing and averaging approaches, these compromises can be adopted according to the case at hand.

Welch's method calculates a periodogram for each signal epoch considered, but this epoch is windowed (in our case a *hamming* window was chosen) in order to reduce band polarisation. The windowing, however, causes loss of information. The periodograms of each segment are then averaged to produce the power spectral density estimate and this has the

advantage of reducing the variance estimate. However, the averaging effect leads to a reduction in overall spectral resolution.

The PSD represents the frequency spectrum of a digital signal with a frequency resolution equal to the sampling frequency divided by the number of points in the DFT, called NFFT. The number NFFT is a scalar that can be chosen by considering that

- must be at least greater than or equal to the length of the signal epoch
- preferably a power of 2 for computational efficiency [23].

By not taking a signal epoch whose length in samples is a power of 2, zero padding is done. Zero padding is used to slightly increase the length of a block of data, in this case with the aim of obtaining a length of data corresponding to a power of 2, so this leads to increasing the size of the transformation but without introducing new information to the signal. Zero padding does not actually increase the spectral resolution because no additional information is added to the signal in the calculation, but the spectrum is only interpolated more finely. This could lead to the disadvantage of having artificial ripples around the peaks of the spectrum, a problem that is mitigated by adding a window and thus reducing the ripples in the spectrum [23].

As you can see, depending on what one has and what one needs to achieve, the best compromises with reference to the case at hand have to be adopted.

In this case, if we want to be able to discriminate frequencies 1 Hz apart, it is necessary to have a frequency resolution of at least 0.5 Hz. This leads to working on signal epochs of 2 s, a length in which the stationarity of the signal can still be considered valid.

An additional, but only apparent, improvement that can be made concerns the number of points on which to represent the power spectrum: if a number of points greater than the number of points corresponding to the selected time window is chosen, it is as if the frequency resolution were improved, but only apparently. In fact, no additional information is added, but again the spectrum is simply interpolated in a finer way. For example, choosing an apparent frequency resolution corresponding to half of the theoretical resolution means that one wants to reconstruct the power spectrum on a number of points that is double the number of points corresponding to the theoretical frequency resolution: this means that a fictitious point is added between one point and another of the original spectrum, i.e. the result of the interpolation of the two real points.

So this allows to obtain a finer resolution, but only apparently.

Although it was essential to take the above aspects into account, the PSD was a very useful tool in the signal processing phase, especially in the first visual inspection phase, when it was necessary to check for the presence of peaks at the stimulation frequencies.
In fact, before designing the checkerboard to deliver the stimulation, for study purposes only, a single coloured square (of the size of the order of hundreds of pixels and positioned in the centre of the screen) was used to stimulate. In particular, to be confident that stimulation was being delivered, the PSD was displayed, comparing the rest period with the stimulation period and checking for the presence of the expected peaks in the stimulation period (see Figure 1.12).

In addition, many of the changes made to the checkerboard before deciding on its final version were mostly made on the basis of the evidence found with the PSD. For example, the target size of the checkerboard was set at 10 pixels, as larger sizes not only caused more visual fatigue but also made it impossible to observe the peaks in the power spectral density at the concentration frequency and its harmonics. For us, this indicated that larger targets were less likely to allow the subject to concentrate and thus be effectively stimulated.

Figure 3.10 shows the power spectral density of the signals from each of the 6 channels in a stimulation condition consistent with the study protocol used.

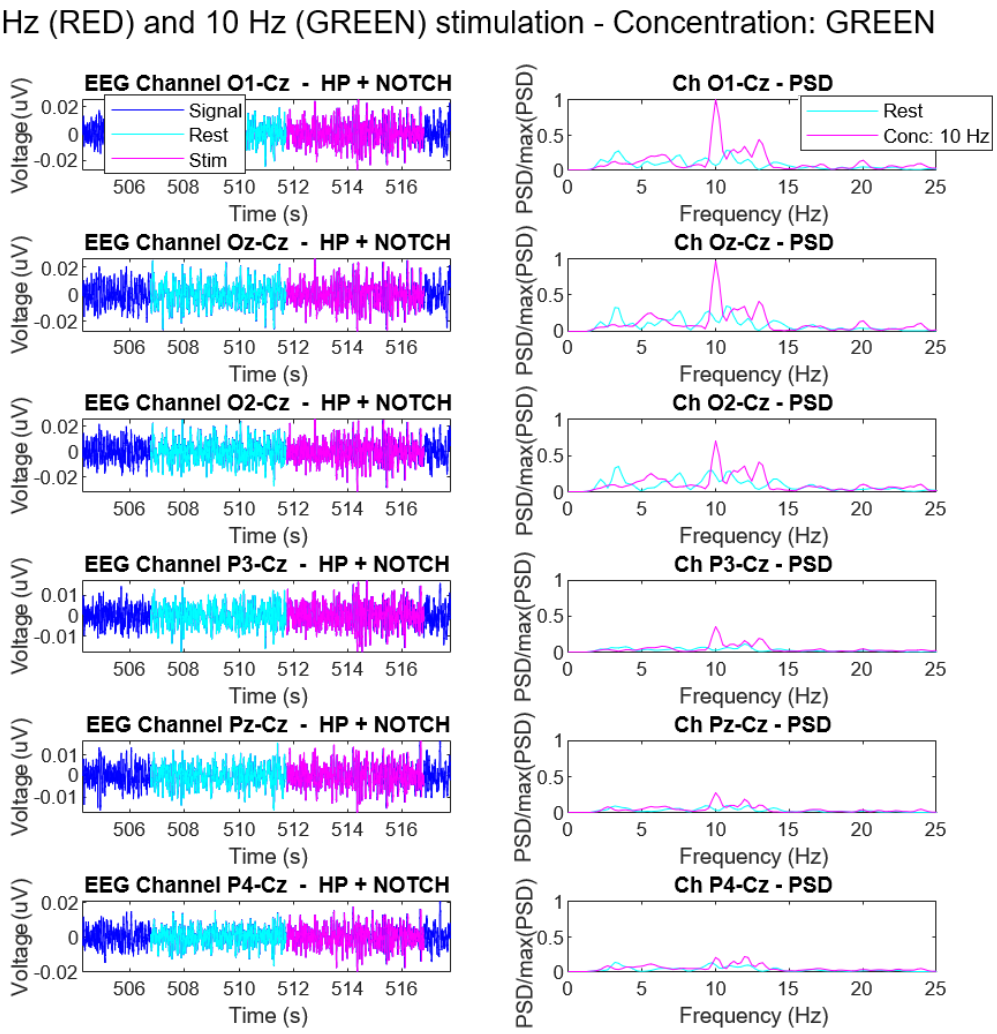



Figure 3.10: *Visualization of the rest and stimulation periods of the signals in the various channels (left) and representation of the respective power spectral densities (right), calculated using Welch's method with a Hamming window, a frequency resolution of 0.5 Hz, an overlap of 50% and a number of points (NFFT) of 2048.*

# Chapter 4

# Algorithms used to process the EEG signal

The purpose of signal processing is to extract information from the signal itself, typically in terms of classes. Such classes may represent mental states, subject responses or more or less physiological conditions of the human brain.

This information translation needs two main steps: feature extraction and classification [13].

## 4.1 Features extraction

Feature extraction is done with the aim of reducing the dimensionality of the raw data, from which more informative and manageable information is extracted for processing. This leads to reduce the cost of resources required to describe a large number of raw data, while still maintaining an accurate and complete description of the original dataset. Specifically, in reducing dimensionality one wants to extract the relevant information to describe mental states, while eliminating noise and irrelevant information. The extracted features are collected in a vector called features vector.

The features extracted in this work are features that concern the frequency domain because what we want to discriminate are precisely the frequencies of stimulation on which the subject focuses. However, of these features we look in some way at their reconstruction in time, so the information in time is not completely left out.

### 4.1.1 Amplitude estimation of the sinusoidal component in SSVEP

A technique designed in an attempt to detect the presence of response to visual stimuli is described below: it tests whether or not there are amplitude changes (of the signal reconstructed using this technique) in correspondence with attentional effort.

As already discussed in the first chapter, when there is an SSVEP response at a certain frequency, it is as if there were stationary periodic oscillations, which tend to resemble a sinusoid with a fundamental frequency equal to the stimulation frequency. For this reason, the aim of the technique is to extract the sinusoidal component from the signal at the stimulation frequency and observe that its amplitude actually increases, a sign that the subject has been stimulated at that frequency.

First of all, the reference signals, i.e. a sine and a cosine, were constructed so that their sum took into account both the modulus and the phase of the sine wave to be found in the input signal.

Next, the sinusoidal component was extracted from the signal under analysis (these operations were carried out on the entire matrix containing the signals of all the channels studied).

The steps taken were:

- removal of the analysed frequency component from the signal by recursive filtering;
- isolation of the part of the signal containing only the searched frequency component;
- calculation of the delay between the latter and the original signal;
- delay compensation: having noise greatly reduces performance;
- calculation of the cross-correlation, using the *conv2* function in Matlab, between the signal containing only the searched frequency component and the reference signal (for both sine and cosine);
- estimating the modulus of the calculated components

In order to have a smoother amplitude trend, a moving average with a two-second window was applied.

The technique was implemented for both frequencies with which the subject is stimulated using the checkerboard. However, in correspondence with the colour on which the subject focuses, a corresponding increase in the estimated amplitude should be observed, meaning that a sinusoidal component has been found in the EEG signal at that frequency. On the other hand, the reconstruction of the amplitude at the other stimulation

frequency (representing the other colour of the checkerboard) should not show an increasing trend, indicating that, since the subject did not focus on that colour, that frequency component is not present in the EEG signal.

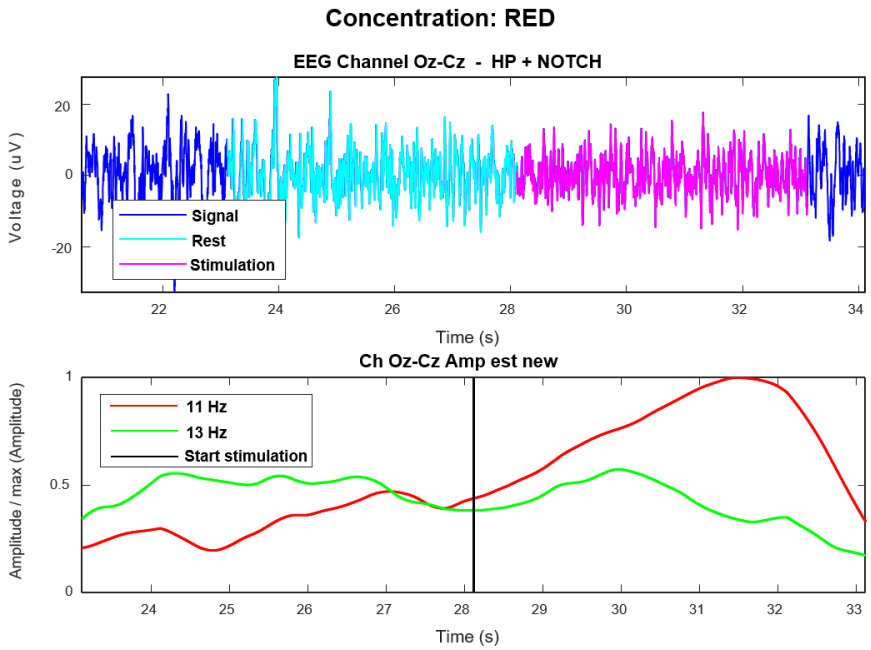



Figure 4.1: *Amplitude estimation at both stimulation frequencies: as the subject focuses on red, there is an increase in the amplitude of the sinusoidal component extracted at 11 Hz.*

The amplitude estimated by this technique was used as a useful feature to classify the subject's response following stimulation with the checkerboard. In particular, the mean value and standard deviation of the reconstructed amplitude are used as features.

**Mean Value.** The average value of the reconstructed amplitude in the first 3 s following the start of stimulation is calculated. This value was considered an important indicator because it was noted that the reconstructed amplitude increases for the colour on which the subject concentrates, while for the other colour on which the subject does not concentrate it remains almost constant, as can be seen from the Figure 4.2. This occurs, however, especially in the first seconds following the start of stimulation, for which only 3 of the 5 seconds of the stimulation period are considered.

This value is calculated both for the reconstruction with the two fundamental stimulation frequencies and with the first harmonics of the two

stimulation frequencies, therefore both for the red colour and for the green colour: at this point we obtain 4 features that will be part of the final feature vector.

**Standard deviation.** From the analysis of the graphs and from the theoretical reflections made, another indicator found to be useful is the standard deviation of the curve representing the reconstructed amplitude at the frequencies of interest. In particular, of the amplitude reconstructed at the two frequencies of interest and their first harmonics, the moving average was made and from this time-averaged reconstruction the standard deviation at the stimulation frequency and the first harmonic of both red and green was calculated.

As it can be seen from Figure 4.2, the standard deviation for the curve corresponding to the colour on which the subject focuses is clearly different from that of the trend corresponding to the colour on which the subject does not focus.

This indicator also yields four features which, when added to the previous features, make the feature vector comprise a total of 8 features.

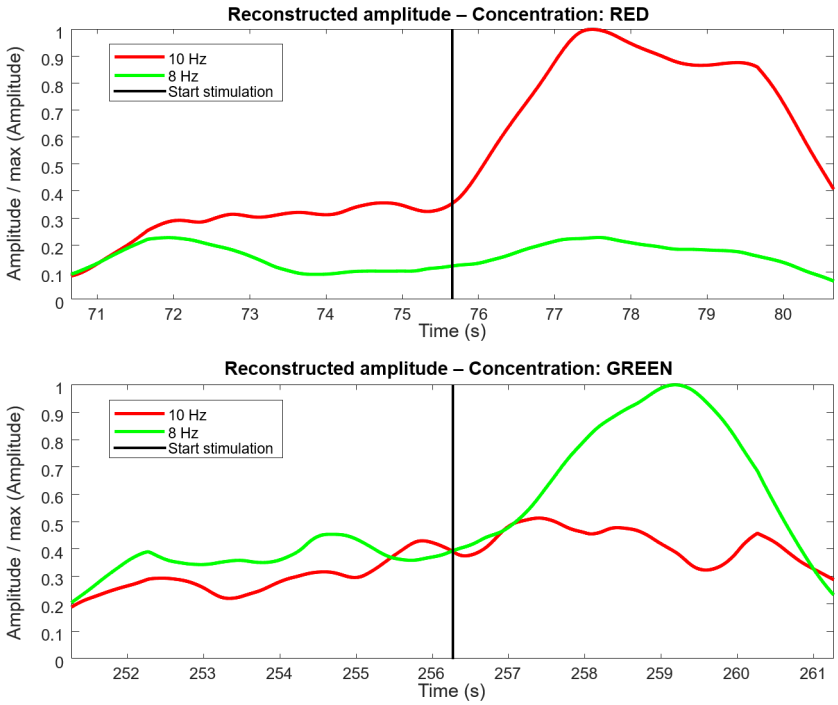



Figure 4.2: *Example of amplitude reconstruction at the green and red stimulation frequencies. In this example, the amplitude reconstructions at the first harmonics of the two stimulation frequencies have not been shown, but the result is similar. In both graphs shown, the first 5 s correspond to the resting phase preceding the stimulation phase (5 s following the vertical black line). It can be seen that the curve corresponding to the colour on which the subject concentrates in the stimulation phase increases immediately after the start of stimulation, while the other curve remains more or less constant. The mean value and standard deviation of these curves have been calculated because they are representative of the trend of the curve on the colour of concentration.*

### 4.1.2 Feature matrix organization

The feature vector, therefore composed of 8 features, was calculated for each observation. The feature matrix was then composed of N rows and M columns, where N is the number of observations and M is the number of features, 8 in our case.

With regard to the number of observations to be considered, it was necessary to assess:

- the time of execution of the test to which the subject is exposed,
- the number of observations needed by the classifier to be able to train.

The higher the number of observations given to the classifier, the better the classifier is able to train. But having a high number of observations means submitting the subject performing the task to an excessively prolonged visual stimulation. Therefore it was decided to have the subject perform 10 trials for each construction of the classifier, each trial lasting 10 s (5 s of rest and 5 s of stimulation), for a total of 100 s for each construction of the classifier, i.e. for each subtask. The time then becomes longer as the total task can also include 12 subtasks having to scan different frequencies as explained above, for a total of 20 min (maximum time for which the subject is subjected to the visual stimulus in a continuous manner).

However, even considering 10 trials, these were not enough to build a stable classifier, so it was decided to use all the electrodes available to have more observations. The work was set up in such a way as to have 6 signals taken from 6 different points on the scalp: 3 occipital electrodes and 3 parietal electrodes. The 6 signals taken at each trial were considered as single observations, for a total of 60 observations in each subprobe on which the classifier is built.

The disadvantage of this approach is that for each trial 6 observations are sent to the classifier as if they were taken from the same point on the scalp, however this is not exactly the case because the 6 observations come from almost the same region but not exactly from the same point on the skin. However, the fact of having a classifier that is not able to discriminate from where on the scalp the single observation comes from has the advantage of having a classifier that is insensitive to small movements of the electrodes on the skin. In fact, it has been verified that moving the cap with the electrodes, repeating the assembly and carrying out the tests several times always gives the same results.

### Feature matrix normalization

Once the feature matrix is complete, before it is used to construct the classifier, it is normalised.

Some machine learning algorithms do not work well without normalization, which is an essential step because the features may be different in nature, have different meanings and therefore the range of data values may vary widely between features. Since many classification methods are based on the concept of distance, features with a wide range of values may prevail over others. Therefore, it is always good to perform the normalization of the feature matrix in order to have all features distributed in the same range of values.

There are several methods to perform the matrix normalization. In this case, the *min-max scaling method* has been chosen. This is the simplest method and consists of returning all the values in the interval [0, 1] according to the formula:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{4.1}$$

where $x$ is the original value and $x'$ is the normalized value.

## 4.2 Classification

In order to extract information from the signal, after the feature extraction step, it is necessary to perform classification.

The classification consists in assigning a class to a set of features (vector of features) extracted from the signal, in fact this step is also called "features translation" [13]. The class corresponds to the mental state that one wants to identify, which in our case identifies the concentration on one of the two colours of the checkerboard, associated to a positive (in the case of green) or negative (in the case of red) response.

In this work, the Support Vector Machine (SVM) was chosen as the classification method, as it is very suitable for solving binary classification problems such as the one under consideration.

### 4.2.1 Support Vector Machines

SVMs (Support Vector Machines) are part of the supervised machine learning algorithms used for classification in artificial intelligence [6]. In particular, the SVM algorithm achieves maximum effectiveness in binary classification problems.

In this case, we have to deal with a classifier that differentiates the two classes by means of an optimal hyper plane, which maximises the margin between the two classes themselves [20].

The basic concepts behind the operation of an SVM are as follows:

- Hyperplane or linear decision boundary. If only 2 spatial dimensions (x and y) are considered, it is represented by a line separating and classifying a set of data. In the case of 3 dimensions, it is represented by a plane; if more than 3 dimensions are considered, it is generically called a hyperplane.
- Support vector. These are the points closest to the hyperplane and depend on the data set being analysed. If they are removed or modified, they change the position of the dividing hyperplane.
- Margin. It is the distance between the support vectors of two different classes closest to the hyperplane. At half of this distance, the hyperplane or line is drawn, depending on the dimensions considered.

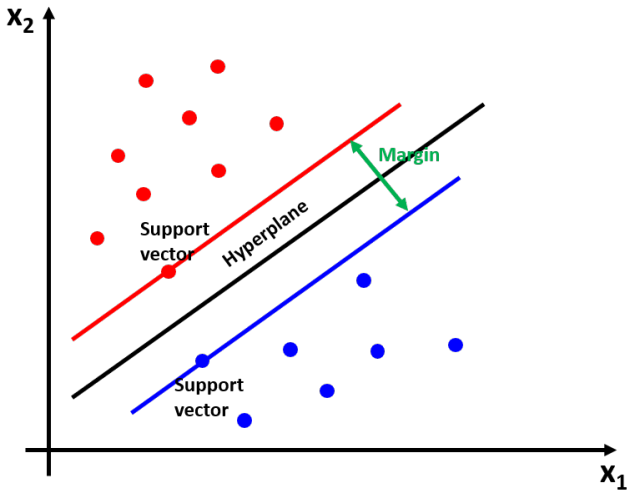



Figure 4.3: *Main elements of a Support Vector Machine.*

Already on the basis of the above observations, it is possible to understand how the main objective of an SVM is to identify the hyperplane that best divides the support vectors into classes. When it is easy to divide

the two classes, we are referring to a linearly separable hyperplane, i.e. a decision boundary that divides the values of one class from the other (e.g. a line when dealing with 2 dimensions).

It is possible that more than one hyperplane exists: in that case the algorithm looks for the one that has the highest margin with the support vectors, in order to improve the accuracy of the model.

In reality, the problem is to find out which of the infinite number of lines is the optimal one, i.e. capable of creating the minimum classification error on a new observation. What is desired is that the data points are as far away from the hyperplane as possible, while remaining on the exact side (Figure 4.4). When new test data are then provided, the model decides which class to assign according to the identified linearly separable hyperplane.

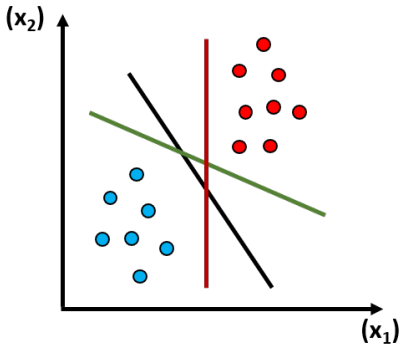



Figure 4.4: *Possible linearly separable hyperplanes, which can be assimilated to straight lines (red, green and black lines) when considering 2 dimensions.*

Considered in mathematical terms, an optimal hyperplane can be defined as a multidimensional scalar product in compact form:

$$\vec{w}\vec{x} + w_0 = 0 \tag{4.2}$$

where $\vec{w}$ is the weight vector, $\vec{x}$ is the input feature vector and $w_0$ is the bias.

Considering that we have 2 dimensions, we obtain the following form:

$$w_0 + w_1 x_1 + w_2 x_2 = 0 \tag{4.3}$$

where, the points that lie above the hyperplane and represent a class, satisfy the following condition:

$$w_0 + w_1 x_1 + w_2 x_2 > 0 \tag{4.4}$$

while every point that lies below the hyperplane belongs to the other class, satisfying the condition

$$w_0 + w_1 x_1 + w_2 x_2 < 0 \tag{4.5}$$

If class margin limits are also included in these conditions, the coefficients or weights $w_1$ and $w_2$ can be adjusted in the following form:

$$\begin{cases} w_0 + w_1 x_1 + w_2 x_2 \geq 1 & \text{if } y = +1 \\ w_0 + w_1 x_1 + w_2 x_2 \leq -1 & \text{if } y = -1 \end{cases} \tag{4.6}$$

where y is the class label that can take on a positive (+1) or negative (-1) value. The latter represent precisely the boundaries of the margin and the support vectors are precisely the training data that fall on these boundaries.

As described above, the vector of weights is $w$ and its length is represented by the norm $||w||$, so we can say that the size of the maximum margin is:

$$\frac{1}{|w|} + \frac{1}{|w|} = \frac{2}{|w|} \tag{4.7}$$

then minimising the weight vector $w$, it is possible to find the maximum margin that constitutes the optimal hyperplane. This problem could be solved by the method of Lagrange multipliers and the Karush-Kuhn-Tucker conditions.

SVM algorithms use a set of mathematical functions called kernels. What a kernel does is to transform the input data into the required form if a linearly separable hyperplane cannot be found.

The kernels are usually linear, resulting in a linear classifier, but there are also non-linear kernels from which non-linear classifiers are derived.

The most common kernel types are:

- linear
- polynomial
- RBF (Radial Basis Function) or also called Gaussian kernel

A linear kernel has been used in this work because it is a binary classification.

In general, an SVM classifier has the advantage of using support vectors, which makes it efficient in terms of memory. However, a problem with SVMs and all non-parametric techniques is the lack of transparency of the results. However, the interpretation of results can be facilitated by graphical visualisation techniques.

### 4.2.2 SVM construction

As explained above, a percentage of correct classification is derived for every 60 observations, until one is obtained for each analysed frequency pair.

The construction of each classifier consists of a training phase and a testing phase. In this case, however, cross-validation by means of the k-fold method is applied every time a classification takes place (every 60 observations).

First of all, during each training phase a set of data, called training set, is used to train the SVM supervised system. The training set consists of a set of feature vectors with an associated response or classification. In this phase the algorithm learns, based on the answer or classification, which features discriminate the elements belonging to the different classes.

In order to create the training set, 80% of the data from the entire dataset was chosen randomly. In particular, 80% is made up of half of the data corresponding to the "red" class and half of the data corresponding to the "green" class in order to have a balanced training set. Having a different number of data for the classes could make the learning process biased, as the model tends to focus on the prevailing class and ignore rare events, so it is important to have a balanced training set in order to give the classifier a chance to train well for both classes.

Furthermore, in order to apply cross-validation during the classification of each frequency pair, a number of folds equal to 5 was set, since we wanted to obtain a division of the dataset into training set and test set of 80% and 20% respectively. Therefore, having a dataset composed of 60 observations, the dataset was divided into 5 groups of 12 items each (corresponding to 20% of 60, in particular, in order to have balanced classes, as explained above, 6 items belonging to the red class and 6 items belonging to the green class are always considered).

Using k-fold cross-validation, it was ensured that, in an iterative manner, each of the 5 groups was used once as a test set and 4 more times as a training set (see Figure 4.5). In this way, it is ensured that each fold is used for both training and testing: thus, the whole dataset is tested and for each classification a final confusion matrix is obtained which is the sum of the 5 classifications obtained during cross-validation.

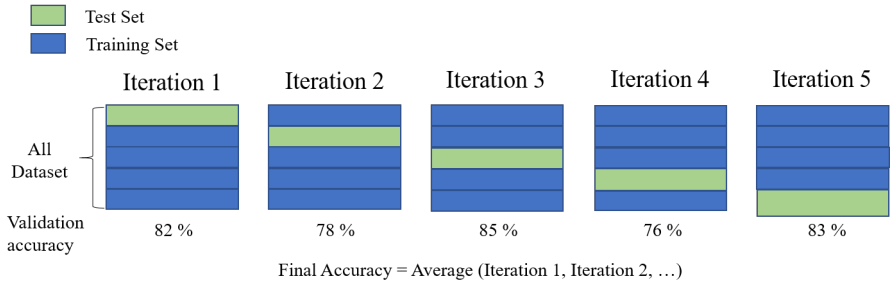



Figure 4.5: *In order to classify the features of a frequency pair, k-fold cross validation is applied. For each frequency pair we have a dataset consisting of 60 observations. A number of folds equal to 5 was used, dividing the 60 observations into 5 groups of 12 items. Each group serves once as a test set and 4 times as a training set, iteratively, for a total of 5 iterations. The total accuracy will be given by the average of the accuracies obtained in each iteration, as for the example accuracy values shown in the figure.*

Each time cross-validation was applied, the training of each classifier was performed in Matlab using the function *fitcsvm*, which requires as input the training set, the vector of classes corresponding to the data used as training set and the use of a linear kernel for binary classification. The output of this function is a trained SVM classification model.

For each training phase carried out, the test phase was always performed. In this phase, the data set that had not been used for training, called the test set, is always used to assess the correctness of the algorithm on new data and to verify the absence of overfitting.

The test phase was carried out using the *predict* function of Matlab, which requests as input the trained model, the data set to be tested and returns a vector of predicted classes corresponding to the data used as the test set.

The vector of predicted classes obtained is compared with the vector of real classes of the same dataset in order to evaluate the percentage of correct answers out of the totality of answers given by the classifier. Having applied a cross-validation method, all this is repeated for a number of times equal to the number of folds chosen until the final classification is obtained for each pair of frequencies. From this, the percentage of accuracy is obtained, which gives information on the goodness of the classification itself.

# Chapter 5

# Results and Discussions

## 5.1 Results

The data were taken from 5 voluntary subjects. Each subject performed 2 trials in a row, interspersed with the rest required by the subject and related to the two frequency scans explained in Chapter 3. A feature matrix was derived from each trial and used in the classifier to classify the subject's response in each trial into the two classes "red" and "green".

The classifier uses k-fold cross-validation which makes the estimation of the ability of the machine learning model less biased and less optimistic than a simple division of the dataset into training sets and test sets could do. What is obtained from the classification and what is examined in this paper is the total confusion matrix, given by the sum of the individual confusion matrices related to the classification of a single fold.

The confusion matrix is used to understand the performance of a predictive classification model in order to determine how accurate and effective this model is. Several indicators can be derived from the confusion matrix, but first of all it is worth explaining how it is constructed (Table 5.1). In this work we are dealing with a binary classification as we have to classify two classes "red" and "green". Remember that the test subject has to give binary answers of the type "yes" or "no", so the class "red" is associated with a negative answer, while the class "green" is associated with a positive answer. Consequently, the confusion matrix is a 2x2 matrix in which the predictions are represented by the columns (called "predicted classes") and the actual state is represented by the rows (called "real classes").

The intersection of true and predicted values of the confusion matrix is best understood by associating the following terms, adapted to this case:

- true red (TR): these are the cases where a negative response was

| | | **Predicted** | |
|---|---|---|---|
| | | Class RED | Class GREEN |
| **Real** | Class RED | TR | FG |
| | Class GREEN | FR | TG |

Table 5.1: *Confusion matrix structure.*

predicted and the subject was really focused on the colour red,

- true green (TG): these are the cases in which a positive response was predicted and the subject was really focused on the colour green,
- false red (FR): these are the cases in which a negative answer was expected, but in reality the subject was focused on the green colour, therefore he wanted to answer "yes",
- false green (FG): these are the cases in which a positive answer was expected, but in reality the subject was focused on the colour red, therefore he wanted to answer "no".

In each frequency scan performed, the confusion matrix is examined, but in particular what is evaluated in order to proceed with the tests is the accuracy. Accuracy is the most widely used metric and is calculated from the following formula:

$$Accuracy(\%) = \frac{TR + TG}{TR + FG + FR + TG} * 100 \tag{5.1}$$

This indicator measures the percentage of correct predictions out of the total number of observations and is the inverse of the error rate. Accuracy is the indicator that most generally evaluates the performance of the algorithm, it does not evaluate the goodness of classification of a single class, as do the other indicators mentioned below, so it was chosen as a yardstick in order to choose the most suitable pair of stimulation frequencies for each subject.

Below are the tables with the accuracy results for each frequency pair examined for each subject (Table 5.2, Table 5.3, Table 5.4, Table 5.5, Table 5.6). In the frequency column, the first frequency shown is always the one corresponding to the colour red, while the second frequency is always the one corresponding to the colour green.

As it can be seen from the tables, the first scan (table (a) for each subject) includes the same frequencies for each subject. However, each subject showed a different percentage of accuracy for each frequency pair analysed,

| Frequencies (Hz) | Accuracy |
|---|---|
| 10 - 8 | 65,00% |
| 12 - 8 | 53,33% |
| 15 - 8 | 55,00% |
| 8 - 10 | **80,00%** |
| 12 - 10 | 65,00% |
| 15 - 10 | 33,33% |
| 8 - 12 | 55,00% |
| 10 - 12 | 75,00% |
| 15 - 12 | 61,67% |
| 8 - 15 | 55,00% |
| 10 - 15 | 50,00% |
| 12 - 15 | 75,00% |

(a) *First frequency scan*

| Frequencies (Hz) | Accuracy |
|---|---|
| 7 - 9 | 66,67% |
| 8 - 9 | 60,00% |
| 7 - 10 | 61,67% |
| ~~8~~ - ~~10~~ | - |
| 9 - 10 | 68,33% |
| 7 - 11 | 60,00% |
| 8 - 11 | 70,00% |
| 9 - 11 | **81,67%** |

(b) *Second frequency scan*

Table 5.2: *Subject 1*

| Frequencies (Hz) | Accuracy |
|---|---|
| 10 - 8 | 71,67% |
| 12 - 8 | 63,33% |
| 15 - 8 | 53,33% |
| 8 - 10 | 75,00% |
| 12 - 10 | **83,33%** |
| 15 - 10 | 55,00% |
| 8 - 12 | 71,67% |
| 10 - 12 | 68,33% |
| 15 - 12 | 68,33% |
| 8 - 15 | 61,67% |
| 10 - 15 | 55,00% |
| 12 - 15 | 73,33% |

(a) *First frequency scan*

| Frequencies (Hz) | Accuracy |
|---|---|
| 11 - 9 | 75,00% |
| 12 - 9 | 66,67% |
| 13 - 9 | 78,33% |
| 11 - 10 | 68,33% |
| ~~12~~ - ~~10~~ | - |
| 13 - 10 | 66,67% |
| 12 - 11 | 76,67% |
| 13 - 11 | 45,00% |

(b) *Second frequency scan*

Table 5.3: *Subject 2*

so the second scan continues following these results: the frequency pair with the highest percentage of accuracy is considered and its surroundings are examined in steps of 1 Hz.

Let's take subject 1 as an example: the highest percentage of accuracy occurred for the frequency pair 8 Hz - 10 Hz. Then in the second scan we proceeded by examining the surroundings of these two numbers: the second scan includes the frequencies that are a combination of the vec-

| Frequencies (Hz) | Accuracy |
|---|---|
| 10 - 8 | 45,00% |
| 12 - 8 | 61,67% |
| 15 - 8 | 60,00% |
| 8 - 10 | 48,33% |
| 12 - 10 | 63,33% |
| 15 - 10 | 56,67% |
| 8 - 12 | 71,67% |
| 10 - 12 | 63,33% |
| 15 - 12 | 56,67% |
| 8 - 15 | **76,67%** |
| 10 - 15 | 53,33% |
| 12 - 15 | 60,00% |

(a) *First frequency scan*

| Frequencies (Hz) | Accuracy |
|---|---|
| 7 - 14 | 65,00% |
| 8 - 14 | 55,00% |
| 9 - 14 | 56,67% |
| 7 - 15 | 75,00% |
| ~~8~~ - ~~15~~ | - |
| 9 - 15 | 73,33% |
| 7 - 16 | 58,33% |
| 8 - 16 | 48,33 |
| 9 - 16 | **81,67%** |

(b) *Second frequency scan*

Table 5.4: *Subject 3*

| Frequencies (Hz) | Accuracy |
|---|---|
| 10 - 8 | 65,00% |
| 12 - 8 | **71,67%** |
| 15 - 8 | 51,67% |
| 8 - 10 | 63,33% |
| 12 - 10 | 58,33% |
| 15 - 10 | 63,33% |
| 8 - 12 | 58,33% |
| 10 - 12 | 61,67% |
| 15 - 12 | 35,00% |
| 8 - 15 | 56,67% |
| 10 - 15 | 51,67% |
| 12 - 15 | 55,00% |

(a) *First frequency scan*

| Frequencies (Hz) | Accuracy |
|---|---|
| 11 - 7 | **85,00%** |
| 12 - 7 | 58,33% |
| 13 - 7 | 80,00% |
| 11 - 8 | 76,67% |
| ~~12~~ - ~~8~~ | - |
| 13 - 8 | 75,00% |
| 11 - 9 | 70,00% |
| 12 - 9 | 63,33% |
| 13 - 9 | 58,33% |

(b) *Second frequency scan*

Table 5.5: *Subject 4*

tors [7, 8, 9] (around 8 Hz) and [9, 10, 11] (around 10 Hz). Among these combinations is the combination 8 Hz - 10 Hz which has already been examined in the previous scan, so in this second scan it is not examined again.

If in the second scan no frequency pair produces greater results than in the first scan, the best pair from the first scan is chosen as the final best pair. This is the case for subject 2 (Table 5.3): the best accuracy percentage in the first scan was achieved with the 12 Hz - 10 Hz pair, but

| Frequencies (Hz) | Accuracy |
|---|---|
| 10 - 8 | 51,67% |
| 12 - 8 | **75,00%** |
| 15 - 8 | 56,67% |
| 8 - 10 | 58,33% |
| 12 - 10 | 60,00% |
| 15 - 10 | 56,67% |
| 8 - 12 | 55,00% |
| 10 - 12 | 61,67% |
| 15 - 12 | 65,00% |
| 8 - 15 | 66,67% |
| 10 - 15 | 58,33% |
| 12 - 15 | 53,33% |

(a) *First frequency scan*

| Frequencies (Hz) | Accuracy |
|---|---|
| 11 - 7 | 63,33% |
| 12 - 7 | 40,00% |
| 13 - 7 | 55,00% |
| 11 - 8 | 56,67% |
| ~~12~~ - ~~8~~ | - |
| 13 - 8 | 65,00% |
| 11 - 9 | 53,33% |
| 12 - 9 | 55,00% |
| 13 - 9 | **78,33%** |

(b) *Second frequency scan*

Table 5.6: *Subject 5*

in the second scan no other frequency pair was able to generate better results. Therefore for subject 2 the best frequency pair remains 12 Hz - 10 Hz.

In the Figure 5.1 the best accuracies for each subject are represented: they are all around 80% for an average accuracy between subjects of 82%. For each subject the standard deviation is also represented, calculated on the 5 accuracy values returned by the k-fold cross-validation of each subject.

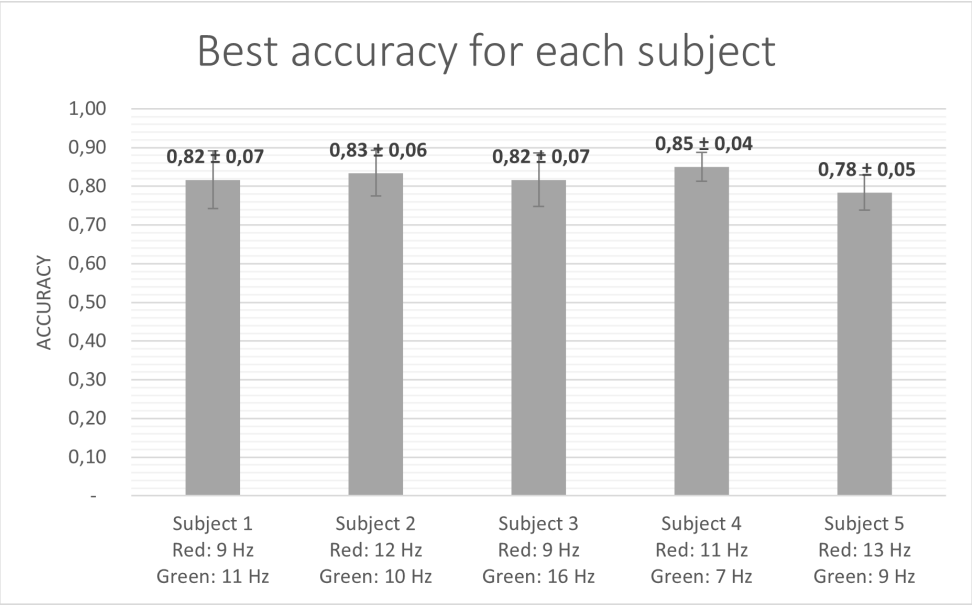



Figure 5.1: *The best accuracies for each subject are represented in a range [0, 1]. For each subject, the frequency pair that produced the best accuracy and the best accuracy, average of the 5 k-fold cross-validation accuracies, is shown. In addition, the standard deviation, also obtained from the 5 k-fold cross-validation accuracy values, is shown for each subject.*

### 5.1.1 Use of Cross Validation for Multiple Iterations

The k-fold cross-validation method was performed each time that 60 observations were to be classified, i.e. for the classification of features related to the same frequency pair. As mentioned earlier, this is done to get an unbiased estimate of the algorithm's performance on unseen data, thus making sure that iteratively the whole dataset was tested.

However, the cross-validation algorithm may produce different results since, although a fixed number of folds is used here, the algorithm uses randomness to split the data into the k folds.

Thus, in order to understand how robust the algorithm is on the dataset and, in particular, to make sure that indeed the performance with the best frequency pair is superior to that obtained with the comparison pair, cross-validation was performed several times for both pairs, considering a number of iterations equal to 10.

Furthermore, at this stage, in addition to the accuracy value, other useful indicators were calculated at each iteration in order to evaluate the performance of the algorithm with the best frequency pair and the com-

parison pair.

In particular, the following parameters were calculated from the confusion matrixes obtained for each iteration relating to the two frequency pairs:

1. Sensitivity: indicated by the ratio of all times the prediction with the frequency used for the colour green is exact (TG) divided by the sum of true green and false red, i.e. all times the prediction should have been exact, i.e. the subject actually answered "yes". Taking into account the confusion matrix explained above, this indicator was calculated according to the formula:

$$Sensitivity(\%) = \frac{TG}{TG + FR} * 100 \tag{5.2}$$

2. Specificity: indicated by the ratio between all the times the prediction with the frequency used for the colour red is correct (TR) divided by the sum of true red and false green, i.e. divided by all the times the prediction should have been red, i.e. the subject actually answered "no". This indicator was calculated as follows:

$$Specificity(\%) = \frac{TR}{TR + FG} * 100 \tag{5.3}$$

3. Positive Predicted Value (PPV): expresses a measure of how much on average the classification results in the answer "yes". In particular, it is a parameter that relates how much the algorithm says that the subject answered "yes" (and had to answer "yes"), related to all the times the algorithm says "yes". This is a parameter related to sensitivity, but it is not the same thing since it also counts how many times the algorithm said "yes", possibly making a mistake.

$$PPV(\%) = \frac{TG}{TG + FG} * 100 \tag{5.4}$$

4. Negative Predictive Value (NPV): expresses the ratio of the number of times the algorithm correctly says that the subject has answered "no", compared to all the times the algorithm says "no", possibly making mistakes.

$$NPV(\%) = \frac{TR}{TR + FR} * 100 \tag{5.5}$$

All these values were expressed as percentages. In this way it is also possible to make an evaluation by "class", distinguishing the performance of

the algorithm in recognising the subject's "yes" and "no" answers. Among the various indicators available to assess performance within a binary classification, these four were chosen, in addition to accuracy, as each of them provides different information on each class. Moreover, they can be said to be two by two complementary (sensitivity is complementary to positive predicted value and specificity is complementary to negative predicted value).

In all cases, if for both frequency pairs these indicators assume a high value, it means that the algorithm works well (i.e. recognises the subject's response) regardless of the frequency pair used. On the other hand, if these indicators assume higher values when considering the pair optimised for the subject, it means that for that subject there is a pair of frequencies more "suitable" for him/her that makes the algorithm able to correctly recognise his/her responses. This is probably because the subject is able to concentrate better when that frequency pair is used for him, making his responses more reproducible and repeatable for the algorithm.

### 5.1.2 Statistical evidences

For each calculated indicator (accuracy, sensitivity, specificity, PPV and NPV) during the 10 iterations, 10 values for the subject-adapted frequency pair and 10 values for the comparison pair were obtained.

At this point, a statistical significance test was used to compare the performance of the algorithm for one frequency pair and the other, in order to understand whether there was a statistically significant difference between the two groups of 10 values of each indicator (relating respectively one to the adjusted frequency pair and the other to the comparison frequency pair).

As no firm assumptions could be made about the normality of the distribution of values, a non-parametric test was considered, namely, the Wilcoxon rank sum test. It was carried out using the *ranksum* function of Matlab. The type of test set is the right-tail hypothesis test, i.e. the alternative hypothesis states that the median of the sample data x is greater than the median of the sample data y, against the null hypothesis that it is not.

At this point, for each indicator considered, the 10 values for the best frequency pair were given as the first input (x) and the 10 values for the comparison frequency pair as the second input (y). The $\alpha$ significance level was set at 5%.

The boxplots representing the distributions, for each subject, for each indicator are shown below: in particular, the distributions obtained for the best frequency pair and for the pair of comparison frequencies (always 15 Hz for the red colour and 10 Hz for the green colour) are always compared. Each distribution is represented by 10 elements, i.e. the values obtained from the 10 repetitions of the k-fold cross-validation.
In the title of each figure we highlight all the p-values obtained from the Wilcoxon statistical test that are less than or equal to 0.05, i.e. those for which it is possible to accept the alternative hypothesis that the median of the observations for the best pair is greater than that for the observations of the comparison pair.

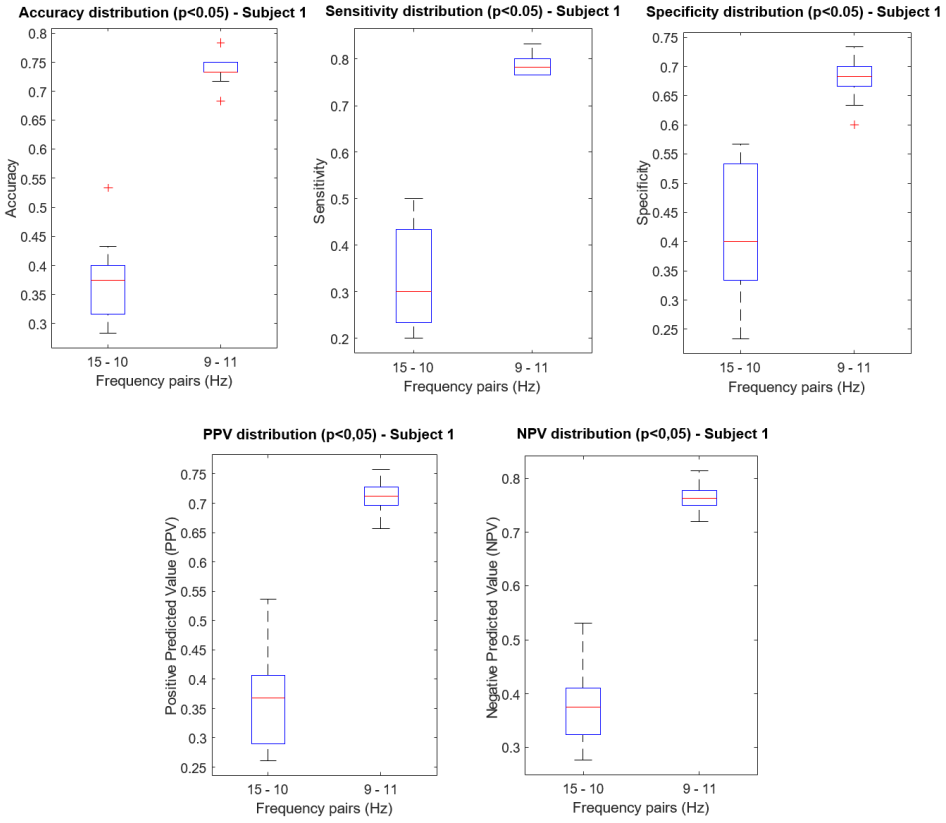



Figure 5.2: *Subject 1: 9 Hz (associated with the red colour) and 11 Hz (associated with the green colour) is the best frequency pair. For all indicators, p-values of less than 0.05 were always found, so the alternative hypothesis is always verified.*

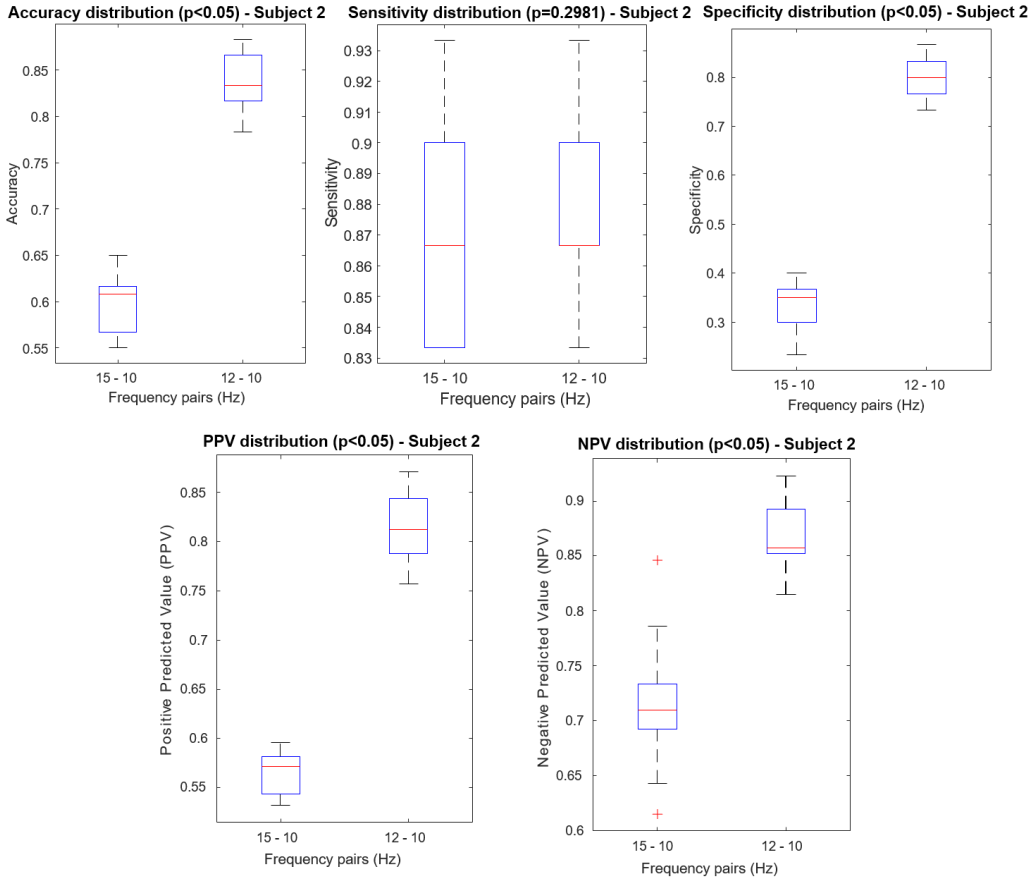



Figure 5.3: *Subject 2: 12 Hz (associated with the red colour) and 10 Hz (associated with the green colour) is the best frequency pair. Only for the sensitivity indicator was a p-value greater than 0.05 found, so it was not possible to reject the null hypothesis; on the other hand, p-values of less than 0.05 were always found for all the other indicators, so the alternative hypothesis was accepted.*

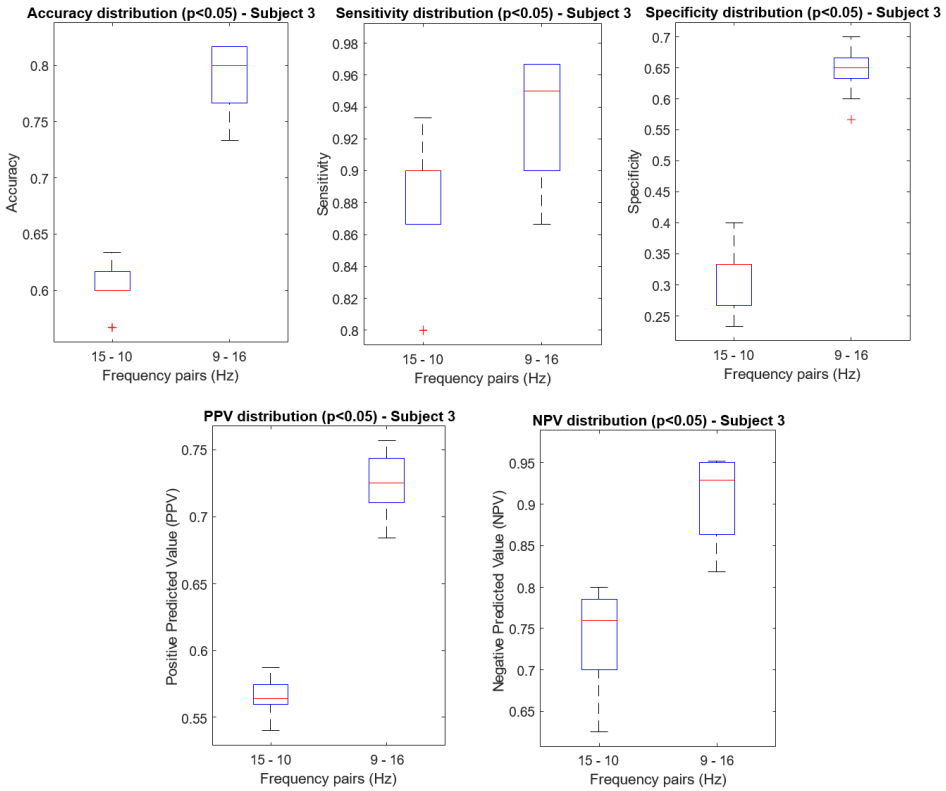



Figure 5.4: *Subject 3: 9 Hz (associated with the red colour) and 16 Hz (associated with the green colour) is the best frequency pair. For all indicators, p-values of less than 0.05 were always found, so the alternative hypothesis is always verified.*

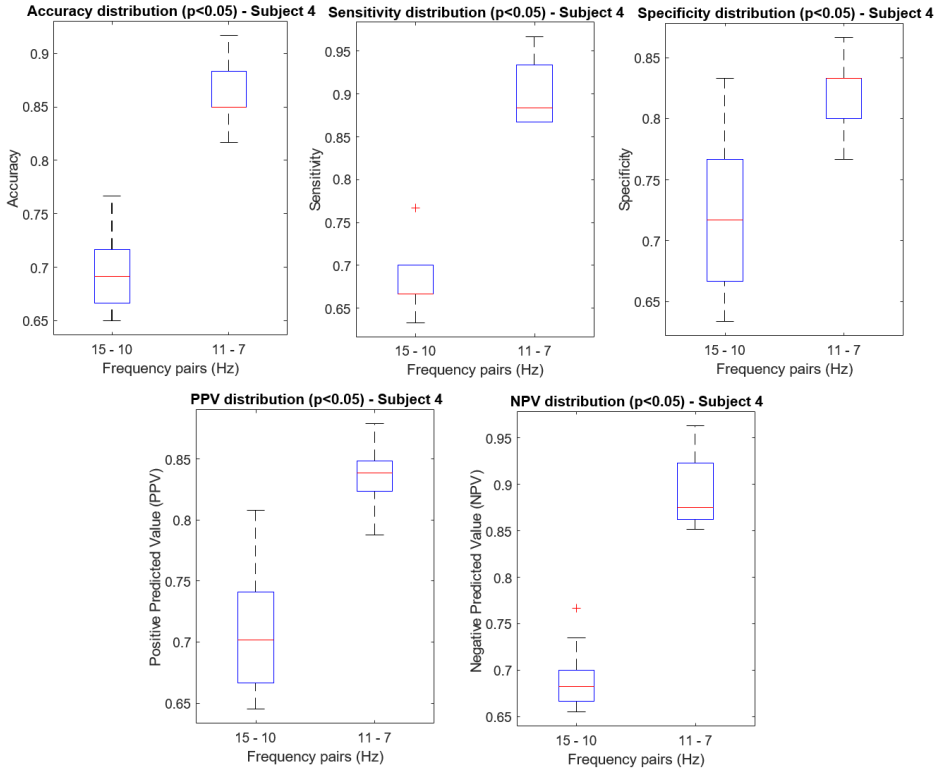



Figure 5.5: *Subject 4: 11 Hz (associated with the red colour) and 7 Hz (associated with the green colour) is the best frequency pair. For all indicators, p-values of less than 0.05 were always found, so the alternative hypothesis is always verified.*

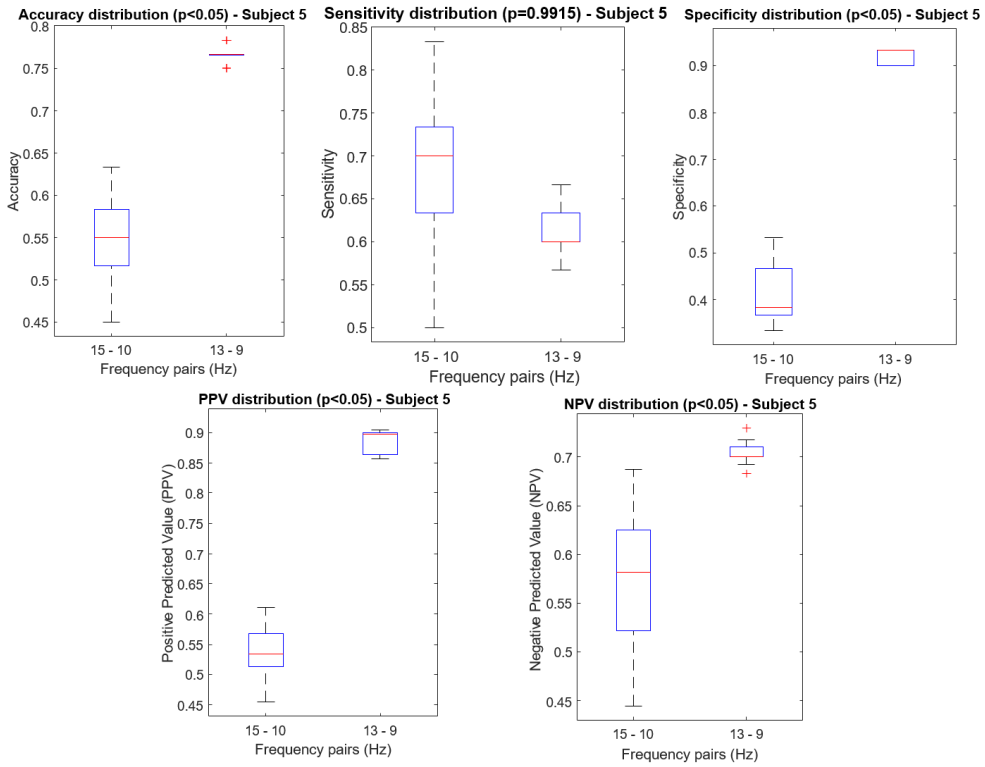



Figure 5.6: *Subject 5: 13 Hz (associated with the red colour) and 9 Hz (associated with the green colour) is the best frequency pair. Only for the sensitivity indicator was a p-value greater than 0.05 found, so it was not possible to reject the null hypothesis; on the other hand, p-values of less than 0.05 were always found for all the other indicators, so the alternative hypothesis was accepted.*

## 5.2 Discussion of results

In the context of the discussion of the results obtained, it is important to pay attention first of all to the parameters that were chosen to evaluate the performance achieved.

The first analyses were carried out on the basis of accuracy alone: the choice was dictated by the fact that, among the indicators that can be extracted from the confusion matrix, it is the one that most generally evaluates the performance of the algorithm without making a distinction between classes, as happens with the other indicators analysed later. In the context of this work, it is not so important to preserve the goodness of the positive or negative classification, but in general one wants a good classification on both classes, therefore it was chosen to evaluate the performance based on accuracy.

Looking at the accuracy values for each subject, it can be seen that, although performing the same task and under the same conditions, the accuracy percentages differ greatly depending on the pair of stimulation frequencies used. Often for the single subject only one pair of stimulation frequencies returns a percentage of about 80%, while the others are very different from this value. This is evident from the tables relating to subjects 1 (Table 5.2) and 5 (Table 5.6). This is also obtained for the other 3 subjects, but with a slightly smaller gap from the other pairs of stimulation frequencies. In particular for the subject 2 (Table 5.3) also the couple 13 Hz - 9 Hz returns a percentage of accuracy which is not low, but in any case lower than the one chosen as the best, for the subject 3 (Table 5.4) this happens with the couple 8 Hz - 15 Hz, for the subject 4 (Table 5.5) with the couple 13 Hz - 7 Hz.

Overall, it can be seen from Figure 5.1 that the best average accuracy across all subjects is 82%. The same figure also shows the standard deviation, calculated on the 5 accuracy values returned by the k-fold cross-validation: the lowest standard deviation was found for subject 4, however the values obtained for the other subjects are more or less similar to each other, thus obtaining an average standard deviation over the 5 subjects of 6%.

After testing the hypothesis of having different best stimulation frequencies from subject to subject, we tried to understand the cause of this characteristic by observing the PSD. The hypothesis was to have a peak in the alpha band different between subjects and close to at least one of the 2 stimulation frequencies constituting the best stimulation pair. The

PSD of all the channels of the signal taken in the rest period were observed in order to avoid peaks at the stimulation frequencies (present precisely in the stimulation phase), but no useful information was obtained to support this hypothesis.

As it can be seen from Figure 5.7, in which for simplicity the PSD of the Oz channel only has been represented, the peak of the alpha band, highlighted by the black asterisk, does not have an evident relationship from a visual inspection with the best stimulation frequencies for the individual subject. However, the cause of this result may simply be that each subject is able to concentrate better at certain frequencies, which vary from subject to subject, without this necessarily being related to the peak of the PSD in the alpha band.

However, after choosing the best stimulation frequency pair on the basis of accuracy alone, it was deemed appropriate to evaluate other indicators as well. These indicators were always extracted from the confusion matrix, but allow for an indication of the goodness of classification for each class. This was done with the intention of confirming what was previously tested with only one indicator. The new metrics used are sensitivity, specificity, PPV and NPV: as we will see below, almost all of these indicators calculated and compared between the best stimulation frequency pair and the comparison pair confirmed that there is a lower performance using the stimulation pair not adapted to the subject.

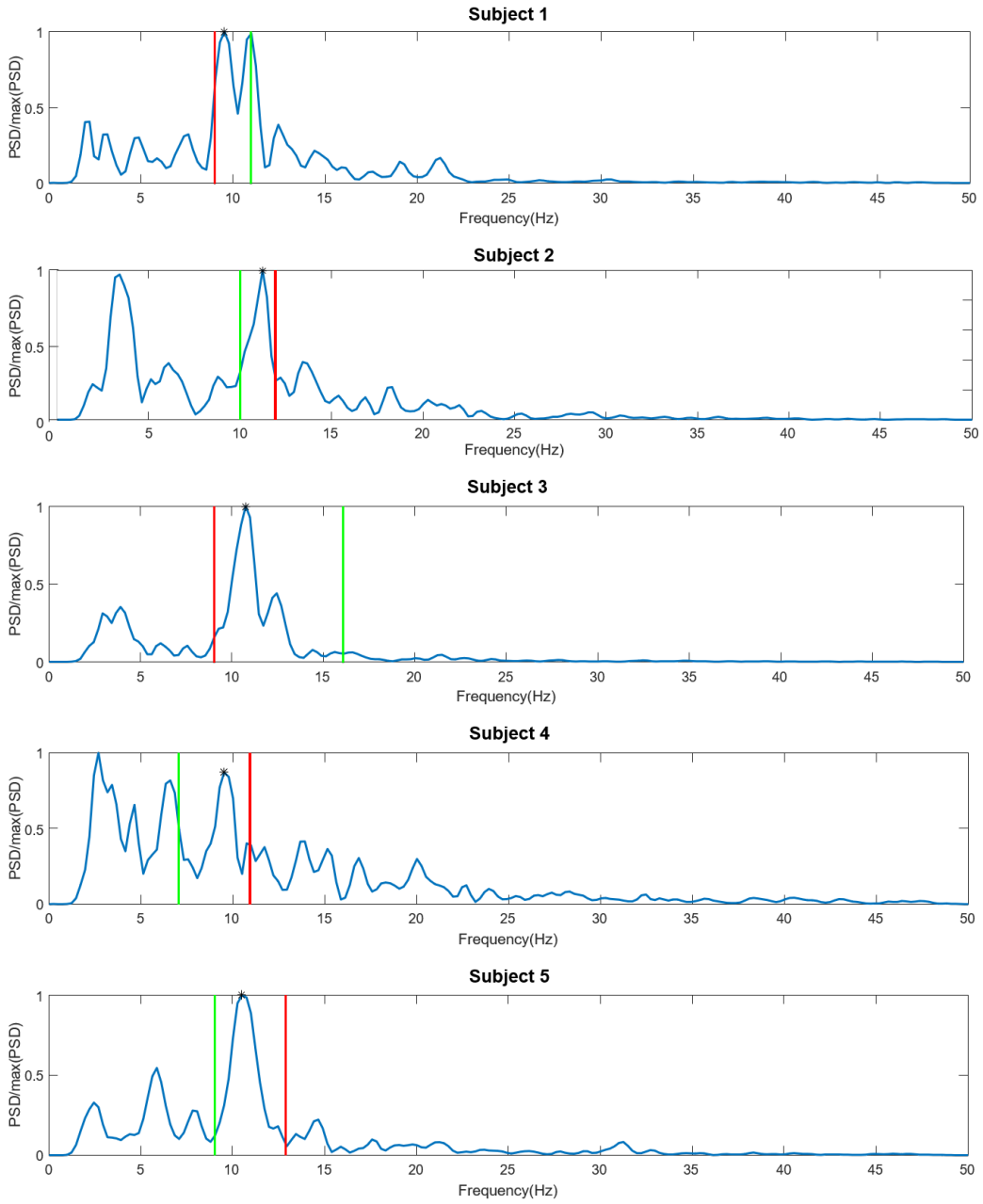



Figure 5.7: *In blue, the PSD of the Oz channel normalised to its maximum is represented. The signal on which the PSD is carried out relates only to the resting phase, therefore without any stimulation frequency in progress. The green and red stimulation frequencies are shown in green and red respectively. They have been represented in an attempt to find a relationship between them and the peak of the PSD in alpha band, highlighted by a black asterisk. This representation was made for all the subjects under analysis in this work.*

Specifically, analysing the results obtained from the 10 repetitions of the k-fold cross-validation method, the following observations can be made for each subject:

- Subject 1: In general, with reference to Figure 5.2, it can be said that for all indicators the distributions (between 25th and 75th percentile) for the best frequency pair are more concentrated around the median than for the comparison pair. Moreover, the values found in the distributions of the best pair are always larger than in the distributions of the comparison pair. These results could indicate that there is effectively a pair of frequencies that allows the entire algorithm to understand what response the subject is giving. In particular, having high sensitivity and high PPV values means not only that the algorithm actually recognised many times when the subject answered 'yes' (high sensitivity), but also managed to predict the 'yes' answers without making too many mistakes (high PPV). The same reasoning could be made for the "no" answers, considering the high values of both specificity and NPV.

- Subject 2: In this case, however, referring to Figure 5.3, we cannot say that the distributions (between 25th and 75th percentile) for the best frequency pair are always more concentrated around the median than what happens for the comparison pair (as in the case of the PPV). The positive predictive value is an indicator that assesses performance by class: in this case, it is precisely the "green" class, associated with the 10 Hz frequency, which here coincides with the same value present in the comparison pair. Therefore, this behaviour could be related to this aspect. However, as the median reaches a higher value, it could be said that by using the best pair the algorithm still predicted the answer "yes" with a smaller error than by using the comparison pair. On the basis of similar reasoning, observations can be made about what happens with the sensitivity indicator. This is again an indicator that assesses the performance of the algorithm on the green class: for the comparison pair and the best pair the medians reach equal values (in both the frequency associated with green is 10 Hz). In fact, Wilcoxon's statistical test returns a p-value$>$0.05, which then leads to accepting the null hypothesis. This means that the two pairs have the same ability to classify green out of the total number of real green classes. On the other hand, the other indicators (specificity and NPV) confirm that, for the best pair, the frequency associated with red allows the algorithm to recognise "no" answers better than the comparison frequency.

- Subject 3: Looking at Figure 5.4 it is possible to make the same considerations found for subject 1, except that in this case it is not

possible to say that the distributions of the indicators (between 25th and 75th percentile) relative to the best pair are more concentrated around the median than those of the comparison pair. Here, there is much more variability (except for the case of the specificity indicator). However, there is always a statistically significant difference between assessments made on the best frequency pair and those made on the comparison pair. In particular, the medians of the best frequency pair are always higher. Therefore, with the best frequency pair there is a better classification both globally and on the classes. As for subject 1, this could mean that there is effectively a frequency pair that allows the whole algorithm to better understand which response the subject has given.

- Subject 4: From Figure 5.5 we can state that, also for subject 4, the same considerations found for subject 1 are valid, although, as for subject 3, the distributions of the indicators (between 25th and 75th percentile) relative to the best pair are not always more concentrated around the median than those of the comparison pair (sensitivity case and NPV). Again, there is always a statistically significant difference between the indicator ratings of the best and comparison pairs. Therefore, the same conclusion can be reached as for subjects 1 and 3.

- Subject 5: In this case (see Figure 5.6), as in subject 1, the distributions (between 25th and 75th percentiles) of all the indicators for the best frequency pair are more concentrated around the median than for the comparison pair. In addition, the Wilcoxon statistical test almost always tests the alternative hypothesis that the median of the distributions of the best frequency pair is higher than those of the comparison pair. This cannot be said for the sensitivity indicator (as was the case for subject 2), in fact the alternative hypothesis is rejected: the median of the right-hand distribution is not higher than that of the left-hand distribution. This is probably because the best frequency associated with green is in any case very close to the comparison frequency, also associated with green. Therefore, the indicator that evaluates the performance of the algorithm on the green class (sensitivity) reaches a higher value for the pair of comparison frequencies, and therefore, for the same total of "yes" answers given by the subject, the algorithm detected more when the frequency associated to green was equal to 10 Hz. In contrast, this cannot be said for the complementary PPV indicator, which still evaluates the performance of the algorithm on the green class but with respect to the total predicted greens. The fact that for the best frequency pair this indicator has a higher median of the distribution means that the

algorithm predicted few "false green" and thus, in the case of the sensitivity indicator, the number of "false red" was higher. Out of the total number of classes, these situations still resulted in a higher total accuracy for the best frequency pair and above all, a very narrow distribution around the median.

# Chapter 6

# Conclusions and future work

## 6.1 Conclusions

From the analysis and processing of the EEG signal taken, it was possible to explore some of the applications of SSVEPs in the field of Brain Computer Interfaces.

At the moment, however, our algorithm was only an exploratory study carried out offline, in fact it was only a small step towards what could become a BCI for a CLIS patient, implemented online.
By the way, our preliminary results are confirmed by the literature in this area.

Part of our work was, first of all, to understand all the technical aspects that have allowed to interface in real time the device of collection of the EEG signal with the toolbox used for visual stimulation. It was ensured that when stimulation was completed, the recorded EEG signal had automatically (without operator intervention during stimulation) the markers indicating the beginning of each period of visual stimulation, in order to facilitate the processing of the signal itself.

Then, in view of a future online implementation, after having taken and subjected the EEG signal to a basic processing, the processing and classification algorithms used allowed us to understand that, indeed, for each subject there is a pair of stimulation frequencies "more suitable", with which he is able to concentrate better. Therefore, such a pair would allow the algorithm itself to better detect his SSVEP response.

In particular, the use of a processing technique able to estimate the amplitude of the sinusoidal component present in the SSVEP response was what allowed us in a certain way to isolate precisely the components of in-

terest to allow the algorithm to identify the response. Indeed, in the power spectral density (usually used for SSVEP analysis) the expected peaks were often hidden by all the other frequency components, so it was not always easy to get evidence of the presence of stimulation, although it was very useful in the study phase.

Another important aspect, which we took into account during the design of the stimulation checkerboard, was to understand how to make it as stress-free as possible for the subject. In fact, before arriving at our final version described in the thesis, we experimentally tried to change the size and shape of the checkerboard and came to the conclusion that square targets of just a few pixels, as well as giving the subject an overview of the colour on which to concentrate, also caused less visual fatigue.

From the final results obtained over several classification iterations, we observed that for the best frequency pairs of each subject the performance was superior, both in terms of accuracy and in terms of classification for each class, except for those cases where there was no statistically significant difference for the reasons explained in the discussion of the results.

In conclusion, having carried out the study on 5 subjects, certainly did not give us the opportunity to make many evaluations, but it did allow us to observe that even on 5 people the most suitable pairs of stimulation frequencies are very different from each other. Therefore, it is clear that there is a lot of variability from subject to subject although the results we have reached for all subjects are very comparable, confirming the fact that by adapting the stimulation frequencies we can obtain superior performances of the algorithm.

## 6.2 Future work

In this thesis work, the focus has been on adapting the algorithm to the subject in terms of stimulation frequencies that can more easily detect the SSVEP response.

A limitation of this work may be due to the training time required by the subject. Certainly the first possible improvement concerns the online implementation of this work. Communication between NIC and Matlab is possible and has already been explored as part of this work. A possible online implementation would imply changing the setting of the work, such as the features extracted from the signal used by the classifier: one should test features that, sent to and with the classifier, are able to give a reliable

response within a short time of the visual stimulus provided. The features used in this work do not exclude this possibility, but their effectiveness in an application of the online work has not been tested. The online implementation would reduce the time in which the subject is subjected to the visual stimulus and would allow to obtain a response in a much shorter time than that obtained in the case of offline analysis of the signal previously taken.

Having a response almost in real time, or at least in a short time, would also open up the possibility of providing feedback to the subject. It is known that feedback improves the performance of a BCI and, in particular visual feedback, plays a key role in learning a BCI [2]. Providing feedback, in fact, closes the cycle of a BCI that starts from the production of the brain signal, goes through the learning of the feedback and comes back again to the production of a new brain signal based on the received feedback. This allows the user to identify and adapt strategies to voluntarily modify his activity according to the instructions given to him and according to what he wants to communicate.

Again with the aim of reducing the training time for each subject, another method of classification could be used which allows a reliable response to be obtained even on a smaller number of observations than the one used here: in this way the number of trials required for training is reduced and consequently the time the subject is exposed to the visual stimulus is reduced.

In addition, in order to facilitate the assembly of the instrumentation necessary for the collection of the EEG signal on CLIS subjects, a further advantage could be the reduction of the electrodes to be used. In this case 6 channels were used because these were necessary, as the work was set up, for the construction of the classifier. It could happen that, by choosing a classifier that is more stable even on a few observations, the number of electrodes can be reduced, facilitating the assembly and reducing the time needed for the latter. Furthermore, reducing the number of electrodes used would have an advantage in terms of the computational cost of the data processing algorithm and in economic terms due to the reduction of the material and tools used.

Finally, improving or combining together several analysis techniques increases the computational cost of the algorithm, but may have the advantage of better performance in terms of the percentage of answers provided correctly out of the total number of answers given by the subject.

# Ringraziamenti

Alla fine di questo lungo e intenso percorso di studi, cogliamo l'occasione per ringraziare coloro che ci sono stati vicini in questi anni.

Innanzitutto, ringraziamo vivamente il Prof. Luca Mesin per tutti i suoi preziosi consigli, i suggerimenti e il supporto datoci durante il lavoro di tesi. Grazie per la costante disponibilità, per aver creduto in noi e per averci dato l'opportunità di svolgere tutto questo.

Un grande ringraziamento va all'Ing. Orazio Arcidiacono per averci scrupolosamente seguito e supportato in questi mesi. Collaborare e confrontarci durante l'attività di tesi ci ha dato la possibilità di imparare davvero tanto.

Un ringraziamento speciale ai nostri genitori. Grazie per averci sostenuto in ogni momento, per aver sempre creduto in noi e per averci permesso di realizzare tutto questo.

A tutti i nostri amici, agli amici di una vita e a quelli che Torino ci ha dato la fortuna di conoscere: grazie per esserci stati sempre vicini in questi anni, sia fisicamente sia a chilometri di distanza. Grazie per tutte le emozioni e i bei momenti vissuti insieme.

# Appendix A

# Information sheet and Informed consent form

Politecnico di Torino

**FOGLIO INFORMATIVO**

***PROTOCOLLO DI STUDIO***

***ANALISI DI SEGNALE EEG PER LO STUDIO DI SSVEP***

Gentile interessato/a,
intendiamo proporle di partecipare ad una ricerca e, al fine di informarla circa lo scopo e le caratteristiche della ricerca stessa affinché lei possa decidere in modo consapevole e libero se partecipare, la invitiamo a leggere attentamente quanto riportato di seguito. I ricercatori coinvolti in questo progetto sono a disposizione per rispondere alle sue eventuali domande.

| | |
|---|---|
| Responsabile scientifico dello studio | Luca Mesin<br>luca.mesin@polito.it |

1. **Qual è lo scopo di questo studio?**

Lo scopo dello studio è quello di valutare se sia possibile ottenere, tramite opportune stimolazioni di tipo visivo e contemporaneo prelievo di segnale EEG, delle risposte a domande di natura binaria poste al soggetto in analisi.

2. **Come si svolgerà lo studio?**

**Le fasi di preparazione e le attività sperimentali che verranno proposte e messe in atto sui partecipanti per svolgere lo studio sono articolate nel modo descritto di seguito.**

Il soggetto verrà inizialmente sottoposto al montaggio degli elettrodi sul capo, necessari per il prelievo del segnale EEG, utilizzando la strumentazione presente in Enobio-8 – Neuroelectrics (opportuno strumento utilizzato per il prelievo di segnale EEG, avente marcatura CE).

La fase di montaggio prevederà i seguenti passi:

1. Verrà predisposta al soggetto una cuffia pre-forata per il posizionamento degli elettrodi secondo il sistema internazionale 10-10;
2. Per effettuare il posizionamento degli elettrodi di interesse, innanzitutto si procederà scostando i capelli in corrispondenza dei fori, in modo da garantire un contatto più diretto con il cuoio capelluto.
   Una volta posizionati gli elettrodi, tramite siringa opportunamente fornita dal Setup Enobio, verrà inserita la quantità di gel elettro-conduttivo utile per ridurre l'impedenza elettrodo-cute.

Politecnico di Torino

Gli elettrodi posizionati sono 7 e si tratta di elettrodi a coppetta (tipologia di elettrodi adatti al prelievo di segnale elettroencefalografico). Ciascuno di essi viene collegato ad uno degli 8 canali predisposti dal sistema di prelievo EEG.

3. Dopo aver ripulito la cute da eventuali impurità della pelle, verranno applicati 2 elettrodi pregellati in corrispondenza dell'osso mastoide, ai quali verranno collegati i canali di riferimento.
4. Il cavo cui sono collegati tutti gli elettrodi sarà a sua volta collegato ad Enobio Neuroelectrics Control Box (Necbox), cioè il nucleo del sistema Enobio.

A questo punto, la fase di montaggio può ritenersi conclusa ed il soggetto è pronto per il prelievo.

Terminato il montaggio, verrà attivato il dispositivo di prelievo (Enobio) che si interfaccerà con il pc tramite opportuno software, il quale permetterà la trasmissione dei dati allo stesso per mezzo di connessione Bluetooth. A questo punto sarà possibile avviare la registrazione del segnale EEG.

L'esperimento si svolgerà in una stanza buia: in particolare, il soggetto sarà posizionato su di una sedia, in condizioni confortevoli e gli verrà posto di fronte un monitor, in modo che lo sguardo sia in direzione perpendicolare alla superficie dello schermo e ad una distanza di 30-40 cm dallo stesso.
Durante il prelievo e la contemporanea registrazione del segnale EEG il soggetto sarà sottoposto a delle fasi stimolazione visiva fornite mediante Psychophysics Toolbox, apposito toolbox nato per la progettazione di stimolazioni visive tramite programmazione in ambiente Matlab.

L'oggetto della stimolazione consiste in una scacchiera quadrata disegnata sullo schermo, i cui target sono colorati di due colori diversi (rosso e verde) in maniera alternata. I target di colore rosso saranno progettati in modo da lampeggiare ad una frequenza sempre diversa da quella dei target di colore verde, ma entrambi secondo una modulazione di tipo sinusoidale. Le frequenze con cui lampeggeranno i quadrati saranno comprese nel seguente intervallo 8 Hz – 15 Hz. Sia la scelta delle frequenze che quella dei colori sono state effettuate tenendo conto di quanto riportato in letteratura.

Alla fine della prova la registrazione del segnale EEG sarà interrotta e salvata nel formato opportuno per analizzare successivamente il segnale; sarà conservato anche il file contenente informazioni di natura tecnica del segnale, potenzialmente utile nella fase di elaborazione offline.

## 3. <u>Per quale ragione le proponiamo di partecipare?</u>

Pur avendo come obiettivo ultimo di questa ricerca quello di permettere ai pazienti CLIS (Complete Locked-in Syndrome) di comunicare, è richiesta la partecipazione di soggetti sani in quanto è molto difficile reclutare un gran numero di pazienti CLIS solo per condurre questo studio preliminare. Si tratta di pazienti che si trovano in uno stato di locked-in totale (CLIS), cioè non sono in grado di interagire con la realtà che li circonda e sono incapaci di manifestare la loro condizione, pur essendo coscienti di ciò che accade intorno.
Inoltre, si vorrebbe evitare di interferire negativamente sulla condizione già problematica di tali pazienti, al solo fine di raccogliere dati utili per questa ricerca. Per tale motivo è richiesta la

Politecnico di Torino

partecipazione di soggetti sani che cercheranno di riprodurre la condizione di "sguardo fisso" che caratterizza i pazienti CLIS, poiché sono impossibilitati anche al movimento oculare. Tutto ciò al fine di garantire che i risultati possano essere in futuro adattati in qualche modo a questi ultimi.

**4. Lei è obbligato/a a partecipare allo studio?**

*La sua partecipazione è completamente libera, il rifiuto di partecipare non comporterà alcuna conseguenza negativa. Inoltre, se dovesse cambiare idea e volesse ritirarsi dallo studio, in qualsiasi momento sarà libero/a di farlo senza dover fornire alcuna spiegazione.*

*In caso di ritiro, potrà scegliere se intende revocare il trattamento fin dall'inizio della sua partecipazione allo Studio, chiedendone la cancellazione totale e in tal caso i suoi dati personali precedentemente raccolti saranno cancellati, mentre le registrazioni effettuate ed i dati derivati saranno conservati in forma totalmente anonima, ovvero acconsentire a che i dati già raccolti e conservati fino alla revoca o al ritiro dallo Studio/ricerca possano essere ancora utilizzati*.

**5. Quali sono i passaggi necessari per partecipare allo studio?**

*La partecipazione allo studio avviene previa dettagliata informazione sulle caratteristiche, sui rischi e benefici derivanti dallo stesso. Al termine della fase informativa lei potrà acconsentire alla partecipazione allo studio firmando il modulo di consenso informato. Solo dopo che avrà espresso per iscritto il suo consenso, potrà attivamente partecipare allo studio proposto*.

**6. Che cosa le verrà chiesto di fare?**

L'esperimento vero e proprio consiste nel sottoporsi a stimolazioni visive.

In particolare, viene mandata a video una scacchiera e durante il periodo di stimolazione i quadrati rossi e verdi della scacchiera lampeggeranno a frequenze diverse tra loro, come riportato più nel dettaglio nel punto 2.

Ciò che verrà richiesto sarà tentare di concentrarsi su di un colore o sull'altro, cercando però di mantenere lo sguardo fisso verso il centro della scacchiera (indentificato per mezzo di una croce bianca al centro di un quadrato nero), senza quindi focalizzare lo sguardo propriamente sui colori rosso o verde dei quadrati. Il motivo di tale richiesta proviene dalla ragione spiegata nel punto 3.

Per ciascuna prova verrà segnalato, nella fase di riposo precedente, su quale colore concentrarsi. Questo verrò fatto colorando la croce su cui è diretto lo sguardo del colore su cui il soggetto deve concentrarsi nella fase di stimolazione (in cui la croce ritornerà ad essere bianca).

Ciascuna prova sarà organizzata in più trial di stimolazioni vere e proprie. Ogni trial sarà della durata di 5 secondi, intervallato da un periodo di riposo della stessa durata, per una durata complessiva di ogni prova di un massimo 20 minuti, in base alle esigenze dettate dallo studio in corso. Però, considerando la necessità di dover fare più prove per ciascun soggetto e per garantire l'opportuno riposo tra una prova e l'altra, è stato stimato un tempo totale di impegno per ciascuno pari a circa 2 ore. Salvo problematiche di tipo tecnico, le prove per ogni soggetto saranno effettuate in un'unica sessione sperimentale.

Politecnico di Torino

**7. Quali sono i possibili rischi ed i disagi dello studio?**

Non è previsto alcun rischio o pericolo derivante dalla partecipazione allo studio.
Il soggetto potrebbe eventualmente trovarsi in uno stato di disagio fisico dovuto alla necessità di mantenersi in posizione ferma e seduto per un massimo di 20 minuti.
Un altro possibile disagio fisico potrebbe essere dovuto allo stimolo luminoso che verrà somministrato, ma tale stimolo verrà interrotto nell'arco di 5 secondi per un periodo di riposo di altrettanti secondi, per un totale, al massimo, di 20 minuti.
Per mitigare questi disagi ogni sessione di 20 minuti è seguita da una sessione di riposo in cui il soggetto può rilassarsi e riposarsi, fino a quando non si sentirà pronto per una nuova sessione di prove.

**8. Quali sono i possibili benefici derivanti dallo studio?**

I benefici derivanti dalla partecipazione allo studio riguardano, in generale, il vantaggio dell'aumentata conoscenza che questo studio porta alla ricerca scientifica e, in particolare, per i pazienti in stato di CLIS, il giovamento di una possibile comunicazione normalmente compromessa.

**9. Come viene garantita la riservatezza e sicurezza delle informazioni/dati/campioni?**[1]

*Lo sperimentatore le chiederà di fornire i seguenti dati personali: segnale EEG (non associato al suo nome e cognome) e l'eventuale presenza di patologie neurologiche pregresse che la escluderanno dallo studio. Le chiediamo questi dati perché sono strettamente necessari alla corretta esecuzione del test e alla successiva elaborazione dei dati.*

*Queste informazioni, così come i dati che emergeranno nel corso della ricerca, sono importanti per il corretto svolgimento dello studio. La liceità del trattamento e la riservatezza di tutte le informazioni sarà garantita secondo la normativa vigente (Regolamento europeo UE 2016/679 concernente la tutela delle persone fisiche con riguardo al trattamento dei dati personali e la libertà di circolazione di tali dati - https://www.garanteprivacy.it/regolamentoue).*

**10. Altre informazioni importanti**

L'originale del Consenso informato scritto da lei firmato verrà conservato dal responsabile del presente studio, mentre lei hai diritto a riceverne una copia.

Durante lo studio, lei potrà chiedere qualsiasi informazione al Responsabile dello studio ai seguenti contatti:

Giulia Macchia: s263231@studenti.polito.it
Laura Rollo: s265636@studenti.polito.it

La ringraziamo per la disponibilità

Politecnico di Torino

**DICHIARAZIONE DEL RESPONSABILE DELLO STUDIO**

Dichiaro di aver fornito alla/al partecipante informazioni complete e spiegazioni dettagliate circa la natura, le finalità, le procedure e la durata di questo progetto di ricerca. Dichiaro, inoltre, di aver fornito alla/al partecipante il foglio informativo.

FIRMA DEL RESPONSABILE DELLO STUDIO

Data

Nome del Responsabile dello studio (*in stampatello*)

Politecnico di Torino

**ESPRESSIONE DI CONSENSO INFORMATO**

Io sottoscritto/a _____

**DICHIARO**

- di aver ricevuto spiegazioni esaurienti in merito alla richiesta di partecipazione allo studio sperimentale in oggetto e sufficienti informazioni riguardo ai rischi e ai benefici implicati nello studio, secondo quanto riportato nel foglio informativo qui allegato.
- di aver potuto discutere tali spiegazioni, di aver potuto porre tutte le domande che ho ritenuto necessarie e di aver ricevuto in merito risposte soddisfacenti;
- di essere stato, inoltre, informato del mio diritto di ritirarmi in qualsiasi momento dalla ricerca stessa.

Alla luce delle informazioni che mi sono state fornite, pertanto:

| | | | | |
|---|---|---|---|---|
| ☐ | ACCONSENTO | ☐ | NON ACCONSENTO | a partecipare allo studio |
| ☐ | ACCONSENTO | ☐ | NON ACCONSENTO | ad essere informata/o su eventuali risultati utili alla mia persona derivanti dallo studio stesso[2] |

LUOGO DATA

FIRMA DEL PARTECIPANTE

[2] previsione riferita alla ricerca medica, biomedica ed epidemiologica così come previsto dall'art. 8, comma 4 delle "Regole deontologiche per trattamenti a fini statistici o di ricerca scientifica"

Politecnico di Torino

In caso lo studio preveda il trattamento dei dati personali

**BOZZA DI INFORMATIVA AI SENSI DELL'ART. 13 DEL REGOLAMENTO GENERALE SULLA PROTEZIONE DEI DATI UE 679/2016 PER LA PARTECIPAZIONE ALLO STUDIO "ANALISI DI EEG PER LO STUDIO DI SSVEP"**

Gentile interessato/a,
ti abbiamo già fornito nel modulo di foglio informativo da te sottoscritto le indicazioni riguardanti la ricerca in oggetto, nel seguito ti forniamo alcune ulteriori informazioni riguardanti il trattamento dei tuoi dati personali ricordandoti che i ricercatori coinvolti in questo progetto sono a disposizione per rispondere alle sue domande.

| | |
|---|---|
| **Titolare del trattamento dei dati** | |
| Politecnico di Torino<br>in persona del legale rappresentante<br>Rettore *pro tempore*<br>Prof. Guido SARACCO | Dati di contatto:<br>PEC: politecnicoditorino@pec.polito.it<br>Per informazioni e chiarimenti: privacy@polito.it |
| Contitolare del trattamento dei dati<br>(*eventuale*) ex art.28 GDPR | |
| | |
| Responsabile del trattamento dei dati<br>(*eventuale*) ex art.28 GDPR | |
| **Data Protection Officer di Ateneo** | Dati di contatto:<br>avv. Nicoletta Roz Gastaldi<br>PEC: dpo@pec.polito.it<br>Mail: dpo@polito.it |
| **Responsabile scientifico dello studio** | Luca Mesin |

Politecnico di Torino

In caso lo studio preveda il trattamento dei dati personali

1. **Quali sono i principi, la finalità e la base giuridica del trattamento**

Nel rispetto dei principi di liceità, correttezza, trasparenza, adeguatezza, pertinenza e necessità di cui all'art. 5, paragrafo 1, del GDPR, il Politecnico di Torino, in qualità di Titolare, provvederà al trattamento dei suoi dati personali ai sensi dell'art. 6, paragrafo 1, lettera e) ["*il trattamento è necessario per l'esecuzione di un compito di interesse pubblico o connesso all'esercizio di pubblici poteri di cui è investito il titolare*"] nonché in accordo con le disposizioni del Codice Privacy (D.lgs. 196/2003) nel perseguimento delle finalità istituzionali connesse al progresso nella ricerca scientifica come disciplinato e previsto dallo Statuto di Ateneo.

2. **Quale tipologia di dato viene trattato e quali misure di sicurezza vengono garantite?**

*Lo sperimentatore le chiederà di fornire i seguenti dati personali: segnale EEG (non associato al suo nome e cognome) e l'eventuale presenza di patologie neurologiche pregresse che la escluderanno dallo studio.*
*Le chiediamo questi dati perché sono* ***strettamente*** *necessari alla corretta esecuzione della ricerca e alla successiva elaborazione dei dati.*
*I suoi dati saranno trattati all'interno dell'Università, sotto la responsabilità del Titolare, da soggetti adeguatamente istruiti ai sensi dell'art. 29 del GDPR, coinvolti nelle funzioni necessarie allo svolgimento delle specifiche finalità indicate: ricercatori e soggetti coinvolti nel progetto di ricerca.*

3. **Come saranno usati i suoi dati personali?**

*Nel corso dello studio, i dati utili ai fini dello stesso saranno raccolti e conservati in forma anonimizzata (il suo nome e cognome non verranno associati al segnale EEG prelevato e alle informazioni su eventuali patologie neurologiche pregresse).*
*Al termine dello studio, i risultati del progetto potranno essere presentati alla comunità scientifica, a congresso, sotto forma di pubblicazione su rivista scientifica o in altre forme. In tali occasioni i dati saranno presentati in forma aggregata e anonima. Ciò significa che dai dati presentati non si potrà in alcun modo risalire ai dati né all'identità del singolo partecipante.*

4. **È previsto il trasferimento in un paese terzo?**

***Non è previsto*** *il trasferimento dei dati in territori extra-UE o ad organizzazioni internazionali. In caso di necessità connessa alla finalità che le abbiamo dichiarato nella presente informativa, prima di procedere al trasferimento le forniremo una informativa specifica e, qualora per il Paese di destinazione non sia stata emanata una decisione di adeguatezza, oppure non siano disponibili adeguate garanzie di protezione, le verrà richiesto il consenso per procedere al trasferimento.*

Politecnico di Torino

In caso lo studio preveda il trattamento dei dati personali

5. **Che ne sarà dei suoi dati alla fine della ricerca?**

*Al termine della ricerca i suoi dati saranno conservati per un periodo di 1 anno e verranno conservati su un server non collegato in rete e saranno protetti da ideone misure di sicurezza.*
*Qualora i dati siano anonimizzati ovvero non ci sarà modo di risalire dai dati salvati alla sua persona potranno essere oggetto di successive elaborazioni e mantenuti per un periodo ulteriore di 1 anno.*

6. **I suoi dati potranno essere ceduti a terzi?**

*I dati raccolti saranno utilizzati ai fini di questa ricerca o per ricerche successive nell'ambito del gruppo di ricerca. In ogni caso non potranno essere ceduti a terzi se non in forma completamente anonimizzata e solo al termine della ricerca stessa.*

7. **Come sono conferiti i tuoi dati personali?**

*Il conferimento dei tuoi dati è facoltativo, cioè non discende da un obbligo normativo, ma è necessario per la realizzazione del presente studio. Il mancato conferimento dei dati per tali finalità avrà come unica conseguenza l'impossibilità di partecipare allo stesso.*

8. **È previsto un processo decisionale automatizzato?**[1]

*Il trattamento non comporta l'attivazione di un processo decisionale automatizzato (compresa la profilazione).*

9. **Quali sono i tuoi diritti?**

*In qualità di interessato hai diritto di chiedere al Titolare del trattamento, conformemente agli artt. 15 e ss. del GDPR,*

- *l'accesso ai tuoi dati personali ed a tutte le informazioni di cui all'art. 15 del GDPR;*
- *la rettifica dei tuoi dati personali inesatti e l'integrazione di quelli incompleti;*
- *la cancellazione dei tuoi dati, fatta eccezione per quelli contenuti in atti che devono essere obbligatoriamente conservati dall'Ateneo, e salvo che sussista un motivo legittimo prevalente per procedere al trattamento;*
- *la limitazione del trattamento nelle ipotesi di cui all'art. 18 del GDPR.*

*Hai, altresì, il diritto:*

- *di opporti al trattamento dei dati personali,*
- *di revocare il consenso eventualmente prestato, senza con ciò pregiudicare la liceità del trattamento basata sul consenso prestato prima della revoca;*

*Se desideri esercitare qualsiasi dei tuoi diritti, puoi rivolgerti al Titolare del trattamento.*

[1] **N.B.:** se la ricerca preveda un processo decisionale automatizzato si ricorda che è necessario procedere alla valutazione di impatto (DPIA, art. 35 GDPR) come in tutti i casi in cui il trattamento presenti un rischio elevato per i diritti e le libertà delle persone fisiche per l'uso di nuove tecnologie, considerati la natura, l'oggetto, il contesto e le finalità del trattamento. In tali casi è necessario informare il DPO.

Politecnico di Torino

In caso lo studio preveda il trattamento dei dati personali

**Reclamo**

*Hai il diritto di rivolgerti al Garante per la protezione dei dati personali secondo le modalità indicate al seguente link: https://www.garanteprivacy.it/web/guest/home/docweb/-/docweb-display/docweb/4535524 oppure all'Autorità Garante dello Stato dell'UE in cui risiedi abitualmente o lavori, oppure del luogo ove si è verificata la presunta violazione in relazione a un trattamento che consideri non conforme.*
*Altresì, puoi di adire le opportune sedi giudiziarie come previsto dall'art. 79 del GDPR.*

La presente informativa è aggiornata al 4.05.2021

# Bibliography


[1] Søren K Andersen and Matthias M Müller. Driving steady-state visual evoked potentials at arbitrary frequencies using temporal interpolation of stimulus presentation. *BMC neuroscience*, 16(1):1–10, 2015.

[2] Álvaro Barbero and Moritz Grosse-Wentrup. Biased feedback in brain-computer interfaces. *Journal of neuroengineering and rehabilitation*, 7(1):1–4, 2010.

[3] Guangyu Bin, Xiaorong Gao, Zheng Yan, Bo Hong, and Shangkai Gao. An online multi-channel ssvep-based brain–computer interface using a canonical correlation analysis method. *Journal of neural engineering*, 6(4):046002, 2009.

[4] Xiaogang Chen, Yijun Wang, Masaki Nakanishi, Tzyy-Ping Jung, and Xiaorong Gao. Hybrid frequency and phase coding for a high-speed ssvep-based bci speller. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 3993–3996. IEEE, 2014.

[5] Xiaogang Chen, Yijun Wang, Masaki Nakanishi, Tzyy-Ping Jung, and Xiaorong Gao. Hybrid frequency and phase coding for a high-speed ssvep-based bci speller. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 3993–3996. IEEE, 2014.

[6] Mike X Cohen. *MATLAB for brain and cognitive scientists*. MIT Press, 2017.

[7] Panisa Dechwechprasit, Montri Phothisonothai, and Suchada Tantisatirapong. Time-frequency analysis of red-green visual flickers based on steady-state visual evoked potential recording. In *2016 9th Biomedical Engineering International Conference (BMEiCON)*, pages 1–4. IEEE, 2016.

[8] Hung-Luen Jian and Kea-Tiong Tang. Improving classification accuracy of ssvep based bci using rbf svm with signal quality evaluation.

In *2014 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, pages 302–306. IEEE, 2014.

[9] Peter K Kaiser. Physiological response to color: A critical review. *Color research & application*, 9(1):29–36, 1984.

[10] J. Satheesh Kumar and P. Bhuvaneswari. Analysis of electroencephalography (eeg) signals and its categorization–a study. *Procedia Engineering*, 38:2525–2536, 2012. INTERNATIONAL CONFERENCE ON MODELLING OPTIMIZATION AND COMPUTING.

[11] Damien Lesenfants, Dina Habbal, Z Lugo, M Lebeau, Petar Horki, E Amico, Christoph Pokorny, F Gomez, A Soddu, Gernot Müller-Putz, et al. An independent ssvep-based brain–computer interface in locked-in syndrome. *Journal of neural engineering*, 11(3):035002, 2014.

[12] Zhonglin Lin, Changshui Zhang, Wei Wu, and Xiaorong Gao. Frequency recognition based on canonical correlation analysis for ssvep-based bcis. *IEEE transactions on biomedical engineering*, 53(12):2610–2614, 2006.

[13] Fabien Lotte. A tutorial on eeg signal-processing techniques for mental-state recognition in brain–computer interfaces. *Guide to brain-computer music interfacing*, pages 133–161, 2014.

[14] Oriano Mecarelli. *Manuale teorico pratico di elettroencefalografia*. Wolters Kluwer Health, 2009.

[15] L. Mesin. *Introduction to biomedical signal processing*. ilmiolibro self publishing, 2017.

[16] L. Mesin. *Neuromuscular System Engineering*. ilmiolibro self publishing, 2019.

[17] Neuroelectrics. *Neuroelectrics User Manual - Part 3. NIC2 -*. Neuroelectrics, 2019.

[18] Piotr Olejniczak. Neurophysiologic basis of eeg. *Journal of clinical neurophysiology*, 23(3):186–189, 2006.

[19] RB Paranjape, J Mahovsky, L Benedicenti, and Z Koles. The electroencephalogram as a biometric. In *Canadian Conference on Electrical and Computer Engineering 2001. Conference Proceedings (Cat. No. 01TH8555)*, volume 2, pages 1363–1366. IEEE, 2001.

[20] Rajesh Singla and BA Haseena. Comparison of ssvep signal classification techniques using svm and ann models for bci applications. *International Journal of Information and Electronics Engineering*, 4(1):6, 2014.

[21] Norman L Strominger, Robert J Demarest, and Lois B Laemle. *Noback's human nervous system: structure and function*. Springer Science & Business Media, 2012.

[22] Tsvetomira Tsoneva, Gary Garcia-Molina, and Peter Desain. Ssvep phase synchronies and propagation during repetitive visual stimulation at high frequencies. *Scientific reports*, 11(1):1–13, 2021.

[23] Jonathan Wolpaw and Elizabeth Winter Wolpaw. *Brain-computer interfaces: principles and practice*. OUP USA, 2012.

[24] Dan Zhang, Alexander Maye, Xiaorong Gao, Bo Hong, Andreas K Engel, and Shangkai Gao. An independent brain-computer interface using covert non-spatial visual selective attention. *Journal of neural engineering*, 7(1):016010, 2010.