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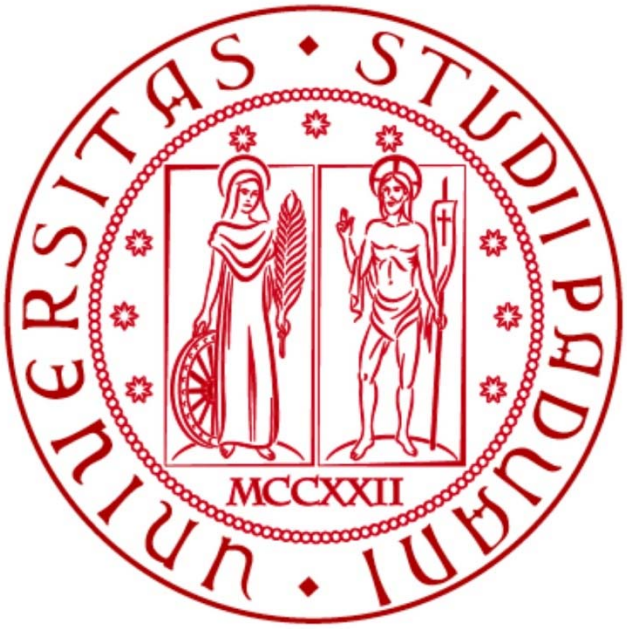

A Brain–Computer Interface based on Colour Dependent Visual Attention

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Abstract

In this thesis we designed a specific visual protocol for a new application in the brain-computer interface field. We evaluated how coloured stimuli affect brain activity in healthy subjects, and performed different analysis in order to highlight the possibility of using coloured stimuli as an input for a brain-computer interface system. We developed a specific visual protocol in order to classify two distinct phases in brain activity related to colour perception. In the first phase we evaluated the characteristic evoked potential derived from the appearance of a coloured rectangular element, while in the second phase we classified the differences in colour perception after the evoked potential phase, during the sustained attention analysis.

Chapter 1:
Brain-Computer Interface systems and their applications

1.1 General aspects of Brain-Computer Interface systems

A brain-computer interface (BCI) system links brain activity to a computer, which elaborates information deriving from brain signals and translates them into outputs that allow the final user to communicate and control external devices, without the participation of peripheral nerves and muscles [1]. BCI outputs can also be used as an input for software applications, and these outputs can be effectively used to provide options for communication and control for people affected by neuromuscular disorders such as amyotrophic lateral sclerosis (ALS), brainstem stroke, cerebral palsy or spinal cord injury. A BCI system replaces nerves, muscles and the movements they produce with hardware and software, that measure brain signals and translate them into actions [2].

There are several applications of BCI systems. In order to make easier the decision of determining the value of a BCI system for different subjects, Wolpaw et al. [3], suggested that BCI users could be categorized by the extent of their disability. According to this study, BCI potential users can be grouped in three different groups: 1) people who have no useful remaining neuromuscular control (totally locked-in), 2) people who have only a very limited capacity of movement, for example eye movement or a slight muscle twitch, and 3) people who still retain substantial neuromuscular control and can use conventional muscle-based assistive communication technologies.

The BCI research field includes different applications. For example one of its aims is to help patients in rehabilitation in order to restore the normal and conventional movements and actions or another purpose of

BCI research is to enable the end-users to convey their wishes to caregivers. To do so, BCI systems use processing programs or other software and, furthermore, use output information to control robotic arms or neuroprosthesis [4]. The basic requirement for a BCI system application is that the subject has to see and understand what the caregiver has implemented in real-time, in order to provide an effective control. This idea is strictly inside the concept of the closed loop.

1.2 Brain-Computer Interface closed loop schematization

The success of a BCI application depends on the interaction between two adaptive controllers: the user, whose brain signals encode the intent, and the BCI, which translates these signals into output. In order to be effective, a BCI system might provide a real-time feedback to the subject. The interaction between the user and the system should be adaptive to provide the desired results for the user [5]. In *Figure 1* it is reported a schematic view of a BCI closed loop. *Panel A* reports the firsts elements of the loop, which are the subject and the signal acquisition of brain activity. *Panel B* reports the feature extraction and the related feature classification. *Panel C* illustrates the continuous feedback that has to be provided to the user in order to close the loop, and an example of robotic device that acts as end effector. In **Section 1.3**, we will discuss further about each element inside the BCI loop.

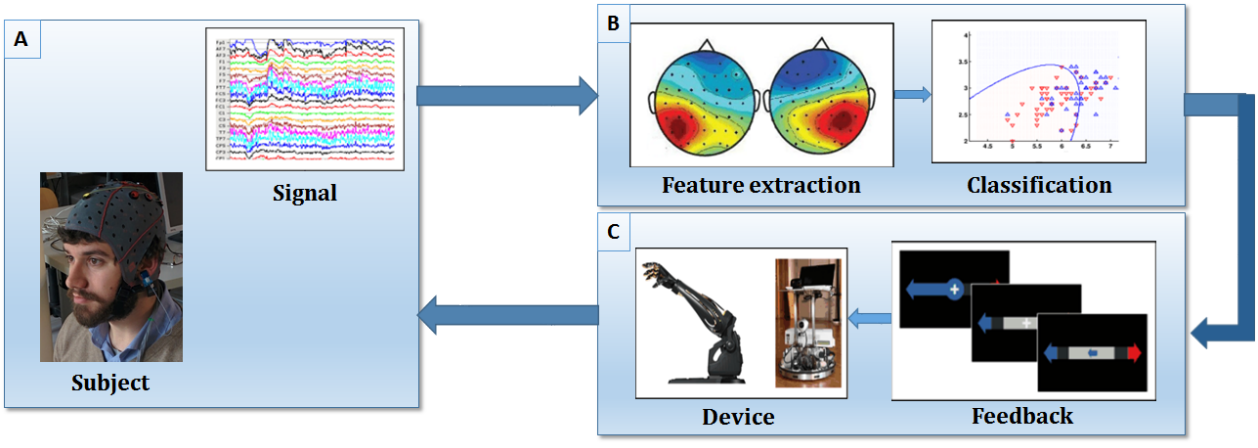

Figure 1 BCI schematic feedback loop. Panel A: subject, signal acquisition. Panel B: feature extraction, classification. Panel C: continuous feedback, external device.

Any BCI system consists of four essential elements. The first one is the signal acquisition: the record of brain activity can be based on several different typologies of brain signal acquisitions. The second element comprehends the feature extraction and selection: in this step there are assorted characteristics that are extracted from the acquired signal; according to the specific BCI application, there are different features that can be used, for example a selected feature can be signal amplitude or the power of the transformed signal in the frequency domain. The third element involves the feature classification in which the significant features are labelled and listed, and then utilized to provide a signal that will be used as an input for the consequent fourth phase. The fourth element utilizes the output signals from the third phase to control an external device [1].

The presence of a visual representation of the given command is important. This representation can be shown on a screen at first, and then it can be linked to the movement of a robotic arm. Feedback is necessary to effectively utilize a BCI system not only to correct any mislead command, but also to realize that each given command is correct in each particular situation. For these reasons, each BCI system needs to provide a real-time feedback to the user.

Control and communication in BCI applications are interactive processes. Controlling brain actuated devices is not an easy task. In real environment each obstacle, each movement leads to a complex situation. A series of high–level commands is given to a semi–autonomous system, which continuously maps few of these into continuous movements.

This concept can be easily understood figuring a horse carriage: the conductor constantly gives commands using bridles to the horses, which act to fulfil the given task. The interaction with the environment is a specific duty of the horses, the conductor has to interact with them only if the task has been correctly or incorrectly completed [1].

1.3 Brain-Computer Interface Operation

In the following sections we will introduce and specify the characteristics of each element inside the BCI loop, starting from signal acquisition and moving towards the last elements that are the continuous feedback and the device control.

1.3.1 Signal acquisition

One of the initial steps for developing a BCI system relies on the acquisition technique. Signal acquisition is the measurement of neurophysiological state of the brain. In BCI applications, the recording interface tracks neural information related to a person's intent, which is embedded in the ongoing brain activity. Basically there are two macro-distinctions in acquisition techniques for gathering brain signals: invasive and non-invasive.

- ***Invasive acquisition techniques*** use micro unit array (MUA). The invasive electrocorticographic (ECoG) technique contemplates the use of sub-cortical electrodes, implanted surgically directly onto the brain surface. The result is that all signals have a higher signal-to-noise ratio (SNR). This means that the spatial resolution is very high but, on the other hand, the usability is extremely low because of the surgical implantation. Several applications of BCI based on invasive acquisition techniques have been developed. For example, in one of Miller's studies [6], ECoG arrays were placed on the sub-temporal cortical surface of seven epilepsy patients. In one of his works, Miller analysed the decoding perception from electrical potentials measured from the human brain surface. Moreover, the high spatial resolution achieved using these systems allow to provide a fine control in most cases. For example, in a study conducted on primates, it has been possible to develop a very sensitive online BCI application based on motor imagery. A monkey, with ECoG electrodes, utilized a BCI system to feed itself using a robotic arm as end-effector, [7]. Figure 2 illustrates an invasive electrode deposition.

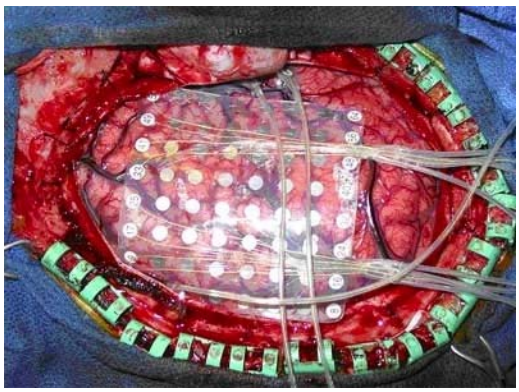

Figure 2 Surgical electrode implantation[1]

[1] *Edited from http://news.discovery.com/tech/flexible-brain-implant-could-treat-epilepsy-111115.htm*

- ***Non-invasive acquisition techniques*** use several different systems, according to the specific physic phenomenon used to record brain signals:
    - Electroencephalographic (EEG) acquisition is based on the electrical activity of a population of neurons. The acquisition involves the presence of surface electrodes, which are positioned on the scalp of the subject, (Figure 3). This means that the spatial resolution is lower than invasive acquisition techniques, because each electrode records and mediates electrical activity of a certain population of neurons. On the other hand surface electrodes are completely non–invasive and this kind of acquisition involves a high usability [8].

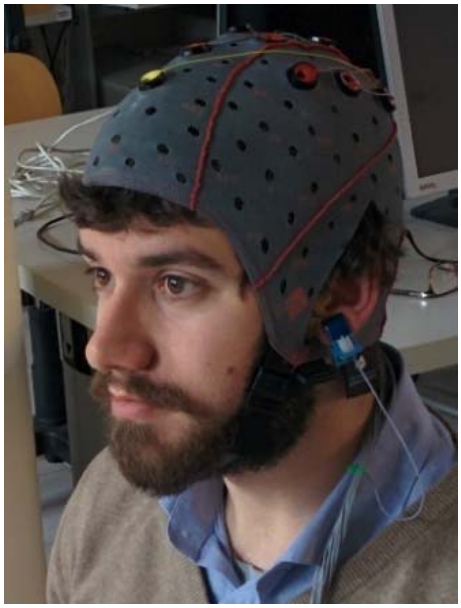

Figure 3 Non-invasive EEG electrode headset

    - Magneto-encephalographic (MEG) acquisition is based on the recording of magnetic fields generated by electrical currents occurring in the brain, using extremely sensitive magnetometers. Arrays of superconducting quantum interference devices (SQUIDs) are currently the most common used magnetometers [9]. Its strengths consist in independence of head geometry, compared to EEG, use of non-ionizing radiation, as opposed to PET and high temporal resolution, as opposed to fMRI. The application of this particular acquisition technique has been successfully utilized in BCI applications [10], (Figure 4).

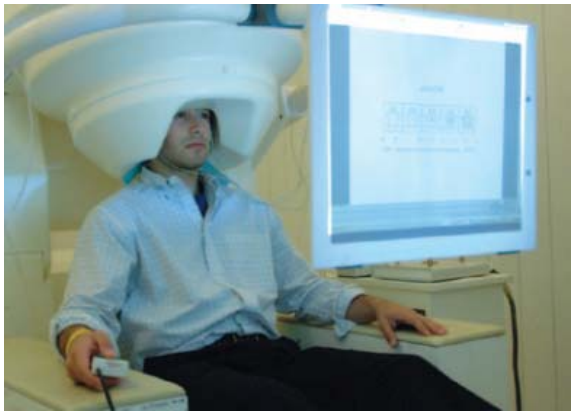

Figure 4 Patient in MEG scanner [2]

- Near-infrared spectroscopy (NIRS) signal acquisition is based on the near-infrared region of the electromagnetic spectrum. This technique is not particularly sensitive but it does not need probing bulk material with little or any sample preparation. The instrumentation is similar to interferometers and the signal can be measured either in reflection or transmission [11, 12], (Figure 5). NIRS signal acquisition allows to gather physiological information based on brain activity and on blood flow, combining information derived from electrical activity and reflection waves obtained by the interferometers [13].

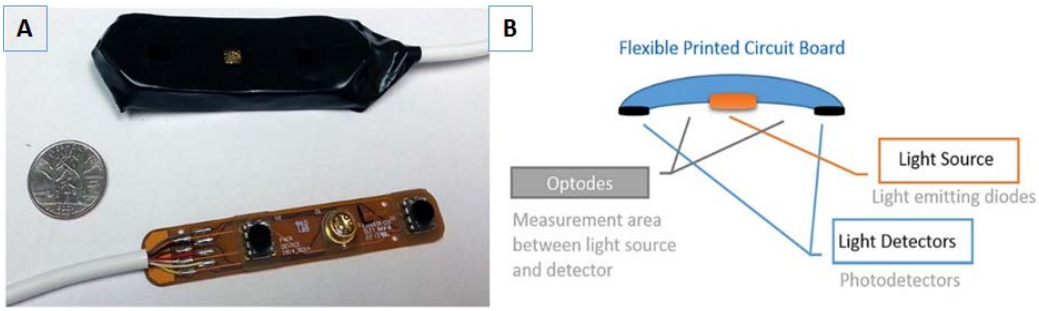

Figure 5 NIRS equipment* [3]*: panel A reports an image of the equipment usually utilized for NIRS application, panel B shows a schematic representation of the functioning of NIRS technology

[2] *Edited from http://www.nimh.nih.gov/health/publications/neuroimaging-and-mental-illness-a-window-into-the-brain/neuroimaging-faq_58327.pdf*

[3] *Edited from https://www.researchgate.net/figure/273063367_fig3_Figure-6-Miniaturized-and-scalable-fNIRS-sensor-pad-with-2-optodes-can-be-integrated*

- Functional magnetic resonance imaging (fMRI) signal acquisition is a functional neuroimaging using magnetic resonance imaging (MRI) technology. This technique relies on the fact that blood flow and neuronal activation are coupled [14]. A specific brain activation can be measured and can be presented graphically, using a contrast medium, by colour-coding the strength of activation inside the region of interest [15], (Figure 6).

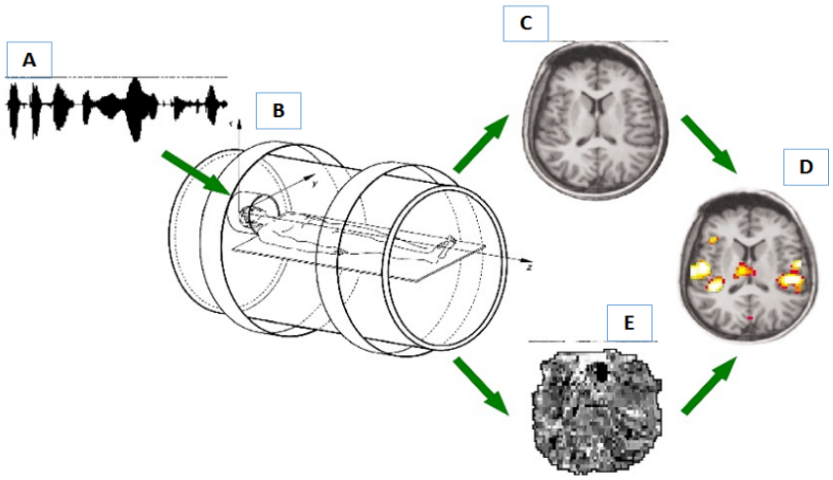

Figure 6 fMRI equipment and output imaging [4]: panel A reports a sample signal acquisition using fMRI and panel B shows a schematic illustration of an fMRI. Panel C illustrates a sample brain imaging before the contrast medium and in panel D the same representation after the injection of the medium. Panel E reports the digital discretization derived from the previous steps.

1.3.2 Feature extraction and selection

BCIs utilize a heterogeneous set of signals as an input. These input structures need to be limited in number, in order to focus the analysis solely on significant features. The nature of the specific analysis has direct applications in feature selection. This is why it is necessary to extract specific characteristics that can highlight the inter-signal differences. A feature is a specific characteristic that explains the evolution of the signal. The information is structured in features. The features can rely on different domains, such as temporal, spatial, frequency, or a combination of the aforementioned.

For example, time domain features can be extracted from several different characteristics of the time domain signal, such as signal peak time or peak value in μV. The second step involves the feature extraction

[4] *Edited from http:/www.anc.ed.ac.uk/CFIS/projects/prosody/material/fMRI.htm*

and the consequent feature selection. It is necessary to extract specific signal features that encode the user's intent, and these extracted features should have a strong correlation with the user's intent. The following phase contemplates the feature selection within the extracted features, in order to select the most significant features to characterize the differences between each one.

1.3.3 Classification

The third step involves the classification of each feature in order to provide a discrete group of tasks for the device that will actuate the command. The extracted features are listed and labelled according to the specific application, which can rely on the time or frequency domain, as anticipated before. The classification involves only the significant features. Within the selected features, only a restricted number of them is statistically different from the others and these features are useful to characterize the differences between brain activities related to different tasks.

1.3.4 Device control

The fourth step involves the final operation aimed to operate with an external device. As anticipated before, the output can be used to operate a spelling program on a computer screen through letter selection [16], to move a cursor on a screen [17], to drive a wheelchair or other assistive devices [18] [19], or even to be able to move a paralyzed arm through a neuroprosthesis [20].

1.4 Brain-Computer Interfaces based on EEG signals

In our analysis we utilized the EEG signal acquisition, because in this thesis we mainly focused on brain activity related to attentive tasks. This particular acquisition technique is well adaptable for research applications. Non-invasiveness and high temporal resolution are two of the most important aspects for the signal acquisition for our BCI system that will be introduced and described in the following sections. A brief descriptions of the typologies of signals that we utilized in this analysis is reported in Appendix.

1.4.1 State of the art of EEG-based BCI systems

The EEG provides one of the most applicable technique of brain signal acquisition. While MEG and fMRI require complex devices to perform a brain signal acquisition, an electroencephalograph requires lesser equipment in order to complete a single acquisition. ECoG technique too requires structures and even a surgical team to perform the surgical implantation. On the other hand, EEG acquisition is simple and does not require particular structures or items.

Electroencephalography signals, which are recorded from the scalp, provide high temporal resolution, although low spatial resolution. The spatial resolution is low because each electrode records and mediates electrical activity of a certain population of neurons.

On the other hand, temporal resolution is essential in order to transfer a series of information in reasonable time. Subjects expect any reaction from any command he/she sent to his/her body. This is why in BCI applications computer elaboration of each task ought to be similar in time reaction, especially when the end effector is mechanical.

Although EEG signals are affected by a low spatial resolution, the high usability and temporal resolution has made electroencephalographic acquisition one of the most used techniques for brain signal acquisition in BCI applications, [21].

1.4.2 Brain-Computer Interface typologies

As anticipated in the previous **Section 1.3.2**, BCI systems can find different applications, according to the specific purposes. One of the possible distinctions between different typologies of BCI systems involves the typology of the task that the user is asked to perform according to a specific stimulus. In BCI applications the term stimulus refers to an external event that affects brain activity.

For example, a stimulus could be an auditory stimulation that influences and perturbs the subject's state of rest. A flashing light or even a simple shaped object displayed on a screen, or even a more complex object can be used as a visual stimulus during an experiment. A BCI system that records the characteristic brain reaction due to an external stimulation is defined as passive or semi-passive. In other applications, the patient has to mentally focus on a determined task. In these BCI systems the subject has to perform a self-paced task in an active way. For example a motor imagery task could be to imagine to move one of his arms. In these typologies the patient is completely active, because the end-user is actually having an active role inside the BCI system.

One of the differences between this system and the previous one lies in the fact that during motor imagery tasks, the user is acting to generate a specific reaction, on the other hand during external stimulations the subject is not acting but simply spectating.

According to the nature of the stimulus, several BCI systems were developed. The first example is called SSVEP–BCI, a BCI system based on steady–state visual evoked potentials (SSVEP). The subject has to focus on a flickering object at a certain frequency of flashing. According to the flickering frequency, a strong brain activity lies at this particular frequency.

Several studies showed that there is a strong frequency representation in brain activity, situated in the frequency range of the stimulus [22, 23]. An example of result representation is shown in Figure 7.

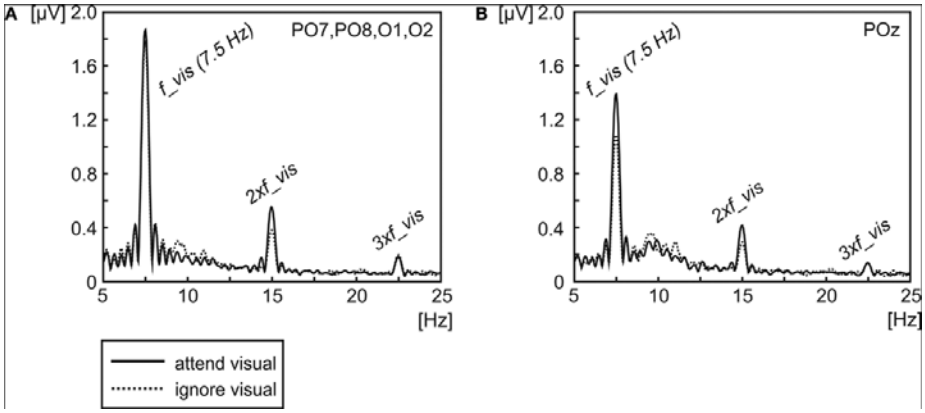

Figure 7 Schematic illustration of the signal amplitude of the SSVEP (at 7.5 Hz) and its 2nd and 3rd harmonics (at 15 Hz and 22.5 Hz) [34]

A second example of BCI system utilizes P300 evoked potentials as an input. This typology of BCI uses an external stimulus to evoke brain activity in the subject. The cognitive process is based on the paradigm: target vs. no-target. Whether a no-target stimulus takes place, brain activity does not show significant differences from the basal oscillatory resting trend. Whether a target stimulus occurs, brain activity presents a typical peak after $150 - 350\,ms$. Figure 8 is presents a sample illustration of the typical P300-BCI based results. A P300-BCI visual protocol contemplates a series of no-target stimuli, randomly alternated by target stimuli in lesser number. Technically, the target stimuli are defined as rare stimuli.

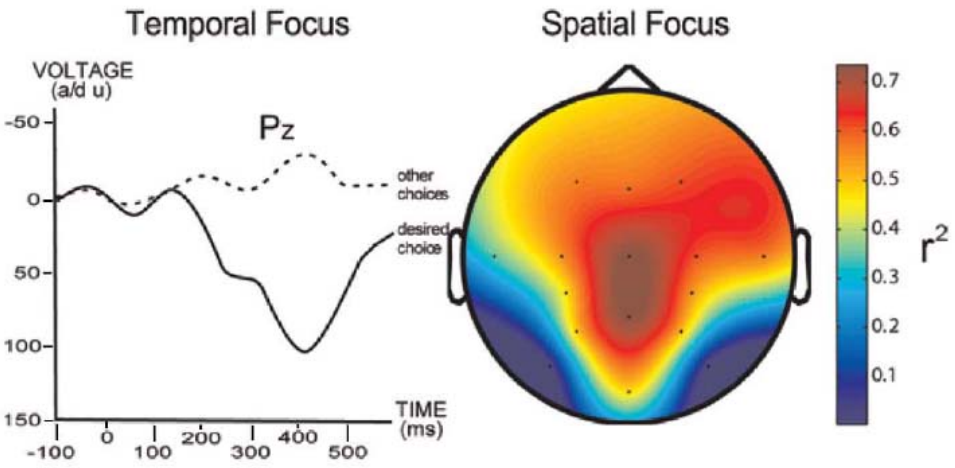

Figure 8 Sample of P300-BCI results. The representation includes a temporal focus, which illustrates the voltage amplitude averaged on all trials distinguished in target and non-target trials. The second panel shows the spatial relevance in terms of r^2 in a color scale starting from blue and moving towards red for higher relevance zones [1]

The third example is called SMR–BCI, a BCI system based on sensory-motor rhythms (SMR). This particular typology of BCI system relies on the fact that motor tasks and motor imagery tasks activate the same brain regions, in almost the same way. The motor imagery task performed by the subject produces a (de)synchronization of the motor cortex at $8 - 12\ Hz$.

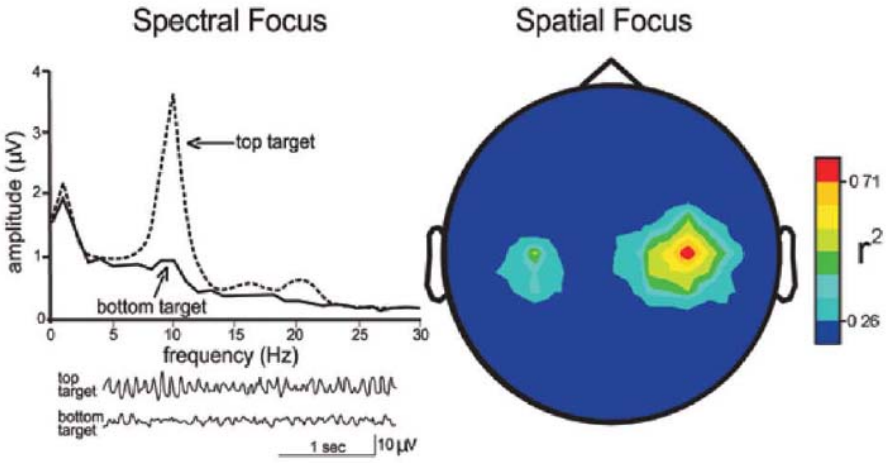

Figure 9 Sample of (de) synchronization during SMR tasks. The representation illustrates the spectral focus, related to the de-synchronization due to the motor imagery task. In the frequency domain this involves an increase at the alpha band (around 10 Hz). In the second panel it is shown the relevance in terms of r^2 [1]

A computer is able to classify the patient's thoughts in order to move a robotic device [24]. This BCI typology is completely voluntary and presents a self–paced modulation on the sensory–motor cortex. The representation is in frequency, temporal and spatial domain (Figure 9). While the patient is thinking at a determined direction (i.e. motor imagery), the computer task is to control the robotic device according to the patient's brain activity.

1.5 Current trends in BCI development

In nowadays application of BCI systems, several differences can be found, starting from the signal acquisition and ending to the specific application in which the BCI system needs to fit in the best way according to the analysis object. Brain activity is connected to every different external stimulation and even to voluntary modulation in the case of self-paced tasks.

The present thesis project was developed at IAS Lab[5] at the Department of Information engineering, where different BCI systems have been recently reviewed and produced, [25, 26]. In this thesis, we developed a BCI system application to evaluate brain activity connected to colour perception, in order to classify posteriorly what colour has been seen by the subject. Colour perception is an important aspect that influences visual perception in our everyday life. This is why we analysed the possibility of introduce a novel BCI system using different colours as an input for a BCI application.

[5] IAS Lab website: *robotics.dei.unipd.it/*

Chapter 2:
A novel Brain-Computer Interface based on colour perception

Colour is one of the most interesting aspects of visual perception. Each visual information is perceived at the beginning, thanks to the visual system which comprehends eyes, retina, optical nerves, and then it is transferred toward the cortex of the occipital lobe.

Since humans are able to distinguish between different colours, we can formulate the hypothesis that the different colour perception could be found also in differences in brain activity. In this chapter we will introduce the basic aspects related to colour perception.

2.1 Colour perception

Colour vision is the ability of an organism or machine to distinguish objects based on the wavelengths (or frequencies) of the light they reflect, emit, or transmit.

Colours can be measured and quantified in various ways; indeed, a person's perception of colours is a subjective process whereby the brain responds to the stimuli that are produced when incoming light reacts with the several types of cone cells in the eye. The brain region responsible for visual perception is situated in the visual cortex. A schematic representation is reported in Figure 10.

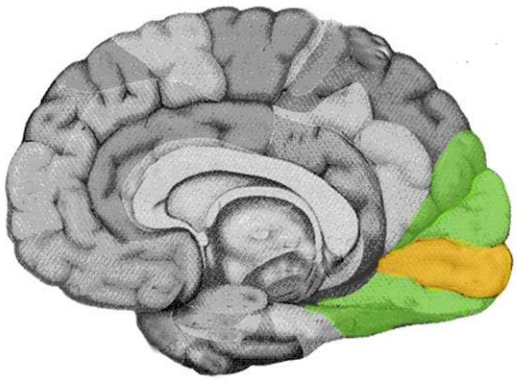

Figure 10 Schematic representation of human brain, at the back the occipital lobe is highlighted. The Primary Visual Cortex (V1) is highlighted in yellow, while the Dorsal and Ventral Stream is illustrated in light green [6]

Cones and rods decode visual information into electrical activity for the brain. The first ones are responsible for colour vision and the latter ones are responsible for light changing. Cones are less sensitive to light, rather than rods, but cone cells responds faster to visual stimuli than rod cells. This means that a substantial difference in these colours could be found also in early evoked potentials, as already demonstrated in early studies [27, 28, 29].

The ventral stream is associated with form recognition and object representation. This area is also linked with the storage of the long-term memory. The dorsal stream is associated with motion, object locations, control of arms and eyes, for example the saccade (a quick and simultaneous eye movement for scanning), [30, 31]. Colour perception is addressed in the primary visual cortex and the differences between colours are related to the different wavelengths of light that mark each colour. An illustrative model has been developed since the XVIII century, and it is called colour wheel.

A colour wheel is an abstract illustrative representation of the organization of colour hues, in a circular shape that shows the relationships between primary colours, secondary and so on. According to the colour wheel (Figure 11), yellow and green are positioned on the same side of the wheel, while magenta is positioned at the opposite.

[6] Edited from http://www.neuroscientificallychallenged.com/glossary/visual-cortex/

Moreover, yellow and green colours used in this experiment had a similar luminance, while magenta was darker. Leaving aside colour wheel theories, physiologically our ocular receptors reacts differently depending on certain visual stimuli.

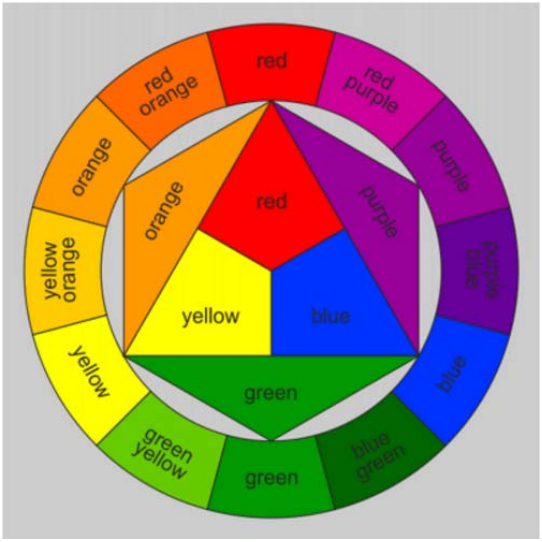

Figure 11 Colour Wheel [7]

2.2 BCI systems based on coloured stimuli

Colour is a fundamental aspect of perception and could be used as an input for BCIs. Some studies analysed the effect of different colours in brain activity. Increased beta and decreased alpha power were observed when the subjects were exposed to blue and red light than to dark stimuli, [32].

These studies reported that the alpha and beta powers were larger for red stimuli rather than blue stimuli. All considerations were made analysing the statistical signal differences between different coloured flashing stimuli. These results led to confirm that different brainwave frequencies can be utilized to highlight the statistical differences found in coloured inputs, even analysing brain activity related to the perception of a coloured stimulation.

In another study, a game has been developed to test whether these statistical differences were relevant enough for online BCI application, [33]. This game was based on an arithmetic choice question, in which a

[7] Edited from http://www.artyfactory.com/color_theory/color_terms_1.htm

BCI was implemented to decode users' attention to the colour stimulus and determine their intended choice.

The possibility of using our colour perception in order to classify correctly the difference in colours, thanks to the difference in brain activity, has been analysed and led to important results and considerations, [32, 33]. These considerations allowed us to introduce another brick to this new field of analysis in BCI applications: the possibility of using our colour perception as an input for a BCI system, with the difference that we utilized a non-flashing stimulation but the sustained attention to a coloured element. Furthermore, we utilized two different aspects related to colour perception. The first is linked to the evoked potentials triggered by the appearance of a coloured element, while the second is the self-paced attention to the colour that appeared.

2.3 A new BCI system

Conversely from SSVEP-BCI studies [32, 33], based on flashing coloured stimuli, in lots of situations we face non–flashing colours. This is why we wanted to analyse how static colour stimuli affected brain response. Our work concerned two different analysis: the characteristic evoked potential and the sustained attention to a coloured element.

In our study, we developed a BCI system based on colour-dependent visual attention. The main purpose of our work was to create a BCI system, able to recognize if a subject is focusing on a certain colour or on another one. This work, focused on designing a new experimental protocol, aimed to highlight two different reactions due to coloured stimuli.

We analysed the visual evoked potential, triggered by the appearance of a coloured rectangular element inside the subject's field of view. The display of each coloured rectangular element activates an evoked potential. Our work focused on classifying whether a colour belonged to one specific class or to another one.

Our analysis focused also on the second period, in which the evoked potential phase was assumable as accomplished. In this second period of each trial the rectangular element presented a constant speed, though different, in each trial. We defined this phase as sustained attention. We performed a frequency analysis with the purpose of discriminating our classes.

Unlike previous studies, our work combined two different typologies of analysis in order to better characterize how the comparison of a coloured element affects brain activity. To do so, we split our focus into two different time regions of the EEG signal: a first phase in which we analysed visual evoked potentials and a second phase in which we analysed the voluntary sustained attention to the coloured stimulus, with similarity to SMR-BCI voluntary motor imagery tasks.

2.4 Aim of the thesis and summary of contents

A few studies proved the existence of different neural correlations associated to colour perception in human brain [34, 35]. This phenomenon can be observed both in a change of the characteristic reaction due to the coloured stimulus, which is situated in earlier evoked potentials, and in a second phase of sustained attention [36, 37, 38].

In this last phase, the temporal evolution of the evoked potential has run out. Which means that the neural correlates mainly depend to the colour perception in the sustained attention phase.

This thesis combines two different perception aspects and two different potential inputs for a BCI system: the first phase, in which we analysed visual evoked potentials, is connected to the second phase. In the sustained attention phase we evaluated a voluntary task of attention, in a similar way respect to the usual analysis for motor imagery tasks in SMR-BCIs.

In chapter 3, we discuss the main purposes for this analysis, introducing a new brain-computer interface based on colour dependent visual attention. Then, the experimental design details are presented, aside with the participant characteristics, the experimental protocol submitted to all subjects and, finally, we report the data organisation after acquisition, then used for all analysis. At last we provide a description of the hypothesis utilized in this work.

In chapter 4, we present all methods used in this experiment, including the data processing procedures implemented in time and frequency domain. In chapter 5, we report the final results, obtained in time and frequency analysis. Deriving results are characterized to the purpose of better highlighting possible future applications and considerations. The last chapter comprehends the conclusions and future applications related to this thesis results. Finally we report the appendix for the neurophysiology of the EEG signals.

Chapter 3:
Experimental Design

3.1 Signal acquisition

Scalp EEG was recorded using a 16-channel electrode system developed by G-tech. This system included 1 electrode used as reference and positioned in the left ear, 1 electrode used as ground reference and 16 scalp electrodes. All 16 electrodes were sampled at 512 Hz, with a notch filter at 50 Hz to remove power supply interference. The electrode positioning was set in order to record electrical activity derived from the parieto-occipital lobe where visual perception is addressed, as described in the previous chapter.

According to international 10-20 configuration, the location of these electrodes was:

$Cz, CPz, CP1, CP2, CP3, CP4, Pz, P1, P2, P3, P4, POz, PO1, PO2, PO3, PO4.$

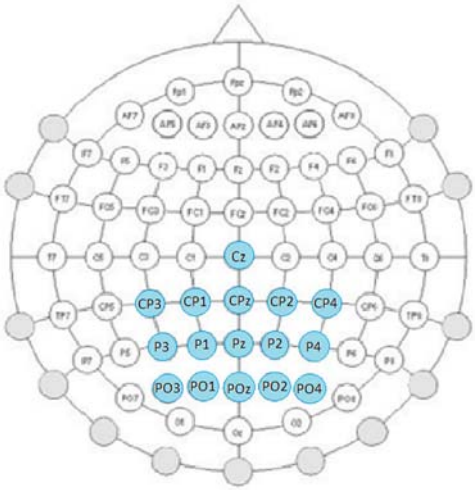

Figure 12 Scalp electrode positioning

The specific experimental set up is presented in Table 1. We utilized three classes, corresponding to the three different colours utilized in trials. For each class we presented fifteen trials per class, for a total trials

per class of forty-five. The experiment consisted in four runs per session, with an overall trial number of one hundred and eighty trials.

Table 1 Experimental information

Classes	3
Trials per class	15
Trials per run	45
Runs per session	4
Total trial number	180

3.2 Participants

Ten healthy volunteers (25,9 $\pm$ 1,79 years old, 3 females, $[s1 - s10]$) with normal or corrected normal vision participated in this study. Moreover, no subject was affected by colour blindness which was a basic requirement for a colour based analysis.

3.3 Visual paradigm

During this experiment, a volunteer sat comfortably on a chair, which was positioned $0.5\,m$ in front of a $21 - inch$ LCD monitor. At the beginning, on black background, a white square frame was presented. In the centre of this frame was positioned a fixation point, represented by a cross symbol, draw in white. Then, a series of coloured rectangles appeared one by one after a random time of waiting. To avoid brain habituation phenomenon, each rectangle speed was randomized. All rectangles appeared on the right of the subject, moving right to the left. A trial example is illustrated in Figure 13. All subjects were instructed to focus their attention to the fixation point and the subjects' task was to click in appearance and in disappearance instants of a coloured rectangle. Once the coloured rectangle appeared inside the square frame, the subjects had to concentrate to the specific colour displayed in that trial. A few tips were given to all subjects to better understand this request. A first way to focus at a certain colour was to associate this colour to a specific object that represented, for the subject, the best match with that colour. For example, for a yellow rectangle one could associate the sun, a lemon, a banana and so on. Another way was to mentally fill a wall with the specific colour that appeared during that trial. After a test run, all subjects were asked to choose a way to fulfil the

mental task of focusing to the colour and to keep using it during the experiment.

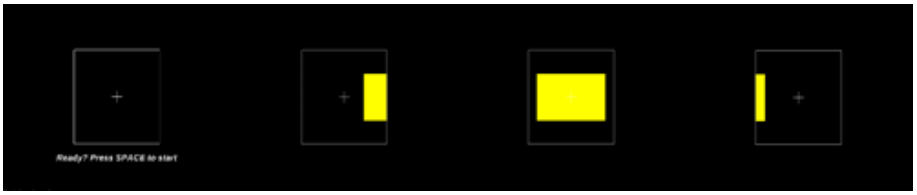

Figure 13 Trial example. Left to right: initial trial square with black background and the fixation point drawn in white, appearance of the coloured element, sustained attention phase in which the element is flowing right to left, disappearance of the element.

This visual protocol was developed specifically for this experiment in C++ code. Trial average duration, i.e. the time duration between the appearance and disappearance of the coloured rectangle, was set to be averagely around 3 s for all trials, ($[3000 \pm 53{,}46]\ ms$). The sequence comprehends the initial time instant at $t = 0s$, after an initial waiting time around $1\ s$ there is the trial start the duration of which is approximately around $3\ s$. Then, according to the specific rectangle speed of that particular trial, there is a consequent waiting time in order to keep the trial duration averagely around $5\ s$, ($[5000 \pm 91{,}23]\ ms$). Figure 14 illustrates the schematic execution of one trial.

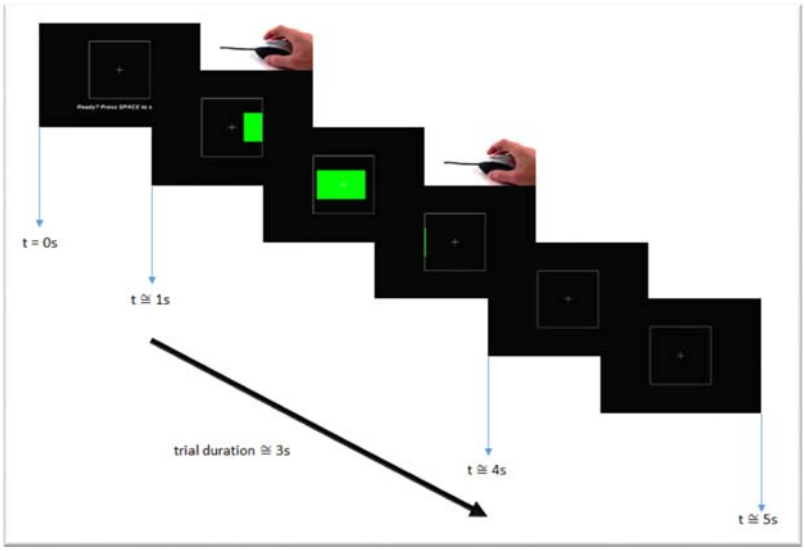

Figure 14 Sample trial sequence. The first step corresponds to the trial start, then after t=1s there is the appearance instant of the coloured element. Each element flowed right to left for approximately 3s. At t=4s each element exited the white frame, then we presented only the black background and the white frame for a waiting time around 1s. The two mouse images recall that in the appearance and disappearance instants the subject had to click with a mouse.

Chapter 4:
Data Processing

4.1 Time domain analysis

4.1.1 Pre-processing

In the time domain analysis we selected a time window of 1000 ms, after the appearance instant of the coloured element (i.e. trial start), in order to evaluate the early evoked potentials due to the appearance of the coloured rectangle.

All data were sampled at 512 Hz and then filtered with a 4^{th} order Butterworth pass-band filter at 1–50 Hz. Consequently, a common average reference (CAR) spatial filtering was applied to all data. CAR spatial filtering technique is based on scaling all data with the common average, computed on all channels.

The common average is obtained mediating all electrode signals and this particular spatial filter utilize all headset electrodes. A representative image of the CAR spatial filtering technique is reported in Figure 15.

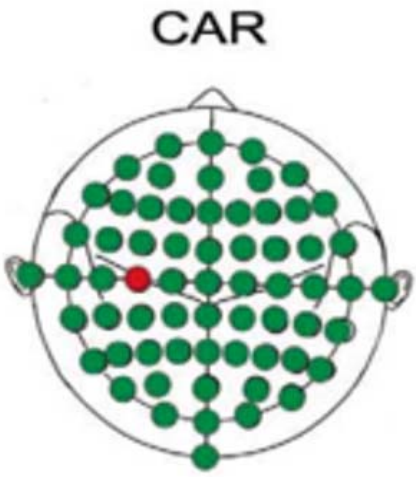

Figure 15 Common Average Reference Spatial Filtering

Fault trials were excluded before spatial filtering. Fault trial selection was based on a basic check, comparing the single trial with an amplitude set to 100 μV. Trials that presented a signal amplitude over this threshold were rejected.

4.1.2 Feature extraction and selection

We selected four most significant parameters directly from the filtered EEG signals, within $[0 - 1]$ s:

- Peak-Value (PV): this parameter evaluated the highest EEG amplitude of the positive peak during the evoked potential phase.
- Peak-Time (PT): this parameter evaluated the time delay between the initial trial time and the time instant in which was positioned the Peak-Value.
- Sum-Value (SV): this parameter evaluated a simple numerical integration of the signal, based on the sum of the EEG signals calculated on all time samples.
- Energy (E): this parameter evaluated the signal energy, computed on all time samples, using a simple numerical integration, based on the sum of the EEG power signals calculated on all time samples.

Starting from this configuration, we utilized these parameters to perform the feature selection. This step is essential, because the number of significant features is always a sub-set of all extracted features. For example in this case, the total number of extracted features was 64, resulting from four parameters per sixteen channels. The use of the total number of features would lead to implement an over fitting classifier that hardly would be useful for the testing phase. In addition, feature selection allows to identify only the discriminative features (task-related). To do so, we used task-related observations to build discriminative metrics that was used as basis to the next analysis. To perform the feature selection, we utilized the canonical variate analysis (CVA), [39]. Given the feature matrix F, defined as [observations x features], the CVA projects all data on a canonical space of dimension k-1, where k is the class cardinality. At this point the Discriminant Power (DP) is computed for each feature:

$$DP_e = \left(\sum_{u=1}^{k-1} \gamma_u t_{eu}^2 \; / \; \sum_{e=1}^{c} \sum_{u=1}^{k-1} \gamma_u t_{eu}^2 \right) \cdot 100$$

According to DP results, we can select the most discriminative features. Figure 16 illustrates an example of the computing of feature selection in this analysis, for subject s1. The result of CVA gives a 2-D map of the statistic relevance of each feature compared to the others. In the x-axis we report the parameters, while in the y-axis the different channels of the EEG headset.

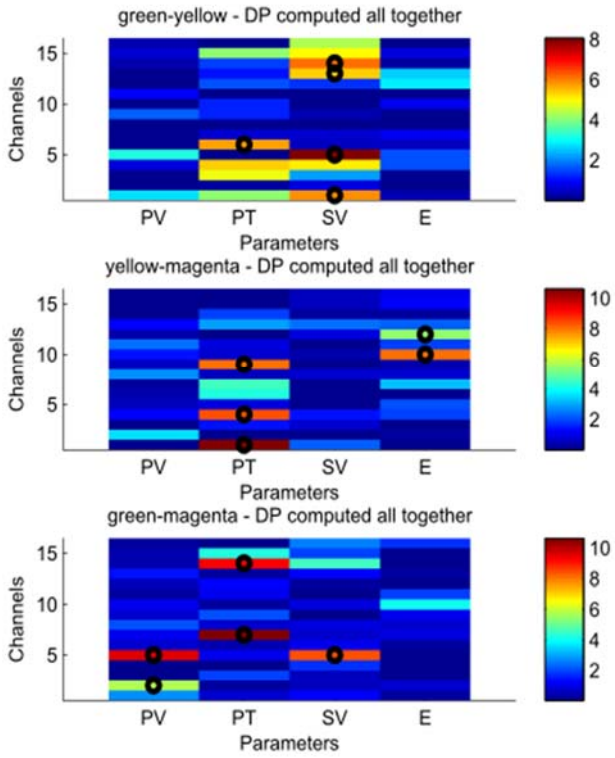

Figure 16 CVA/DP example for subject: s1. Legend: PV = peak value; PT = peak time; SV = sum value; E = energy.

These three panels (Figure 16) represent the results derived from the CVA analysis. On the x-axis we report the four parameters utilized for feature extraction, while on the y-axis the 16 channels utilized. The black circles represent the selected features according to the statistical differences highlighted by the CVA method. The colour bar on the right is related to the discriminant power computed using the CVA. The lowest values are represented in blue and gradually towards the red scale the highest values.

4.1.3 Classification

According to CVA results we classified all data verifying whether a single trial was classified correctly or not, and we computed a basic overall accuracy for all colour couples, Green vs. Yellow, Yellow vs. Magenta and Green vs. Magenta. The overall accuracy for each colour couple was based on the count of correct labelled trials by the classifier on the whole number of trials for that colour couple. The classification accuracy (ACC) was computed following a confusion matrix C, where its elements c_{ij} indicate how many samples of class i have been predicted as class j. The accuracy can be derived thanks to the following equation, where N represents the number of trials and M is the number of classes ($M = 2$).

$$ACC = \frac{\sum_{i=1}^{M} c_{ii}}{N}$$

4.2 Frequency domain analysis

4.2.1 Pre-processing

In the second phase, as anticipated before, we evaluated the voluntary attention to the coloured stimulus. We called this second time phase as sustained attention phase. Assuming at first that all evoked potentials were accomplished, it is reasonable to think that during this phase the only contribution to EEG signals is due to the colour attention from the subject.

The pre-processing procedure involved at first a spatial filtering of all data using a Laplacian spatial filter. This spatial filter involves a local approach of filtering. The Laplacian spatial filter procedure utilizes the neighbour electrodes to operate the filtering. Figure 17 illustrate one step of the Laplacian filtering.

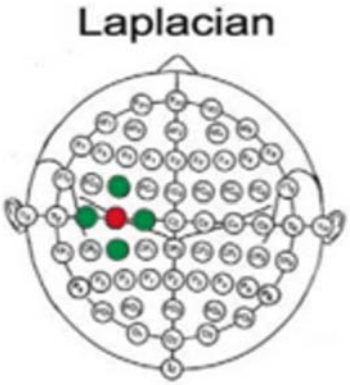

Figure 17 Laplacian spatial filtering. In red is represented the filter output channel and in green the neighbour channels utilized to compute the spatial local filtering

We selected from filtered data, a series of time windows in which we computed the power spectral densities (PSD) using the Welch's method. The time window duration was set at 1 s, while the step for overlapping was set at 32 samples, corresponding to 0.0625 s. The significant frequencies for our analysis lied within $[4 - 48]\ Hz$. Conventionally, all frequencies were gathered with a resolution of 2 Hz.

The significant time region was within $[1.2 - 3]s$. Selecting this time period, we were relatively sure not to consider the evoked potential regions, due to the appearance and disappearance of the coloured rectangle elements. Then we concatenated all PSD windows.

At this point we selected all PSD windows related to trial start events. Figure 18 reports an example of PSD signal for subject $s2$. Each frame illustrates the average PSD signal, mediated on all trials for each channel.

At this point, we selected a baseline period of one second before the starting trial event in order to compute the event-related (de)synchronization (ERD/ERS) of the signal. This step is usually performed in SMR-BCI pre-processing [40]. The computation of the ERD/ERS of the signals is reported in the following formula:

$$ERD/ERS(f, c, w) = \frac{PSD(f, c, w) - PSD_{baseline}(f, c)}{PSD_{baseline}(f, c)}$$

Where the three parameters are f frequency, c channels and w windows respectively. Figure 19 illustrates an ERD/ERS computation example for subject $s2$.

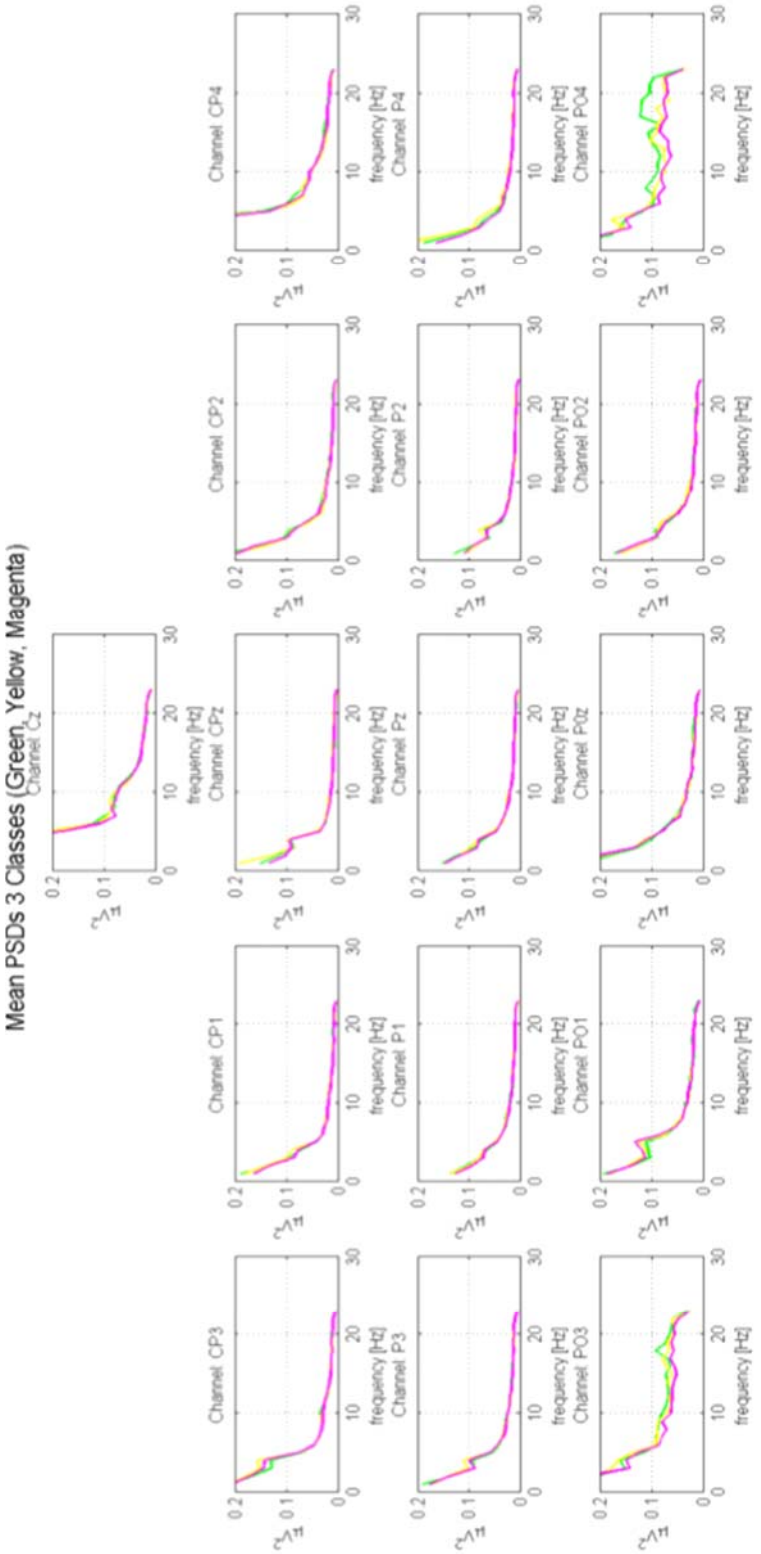

Figure 18 Mean PSD signals on all trials, example with subject s2

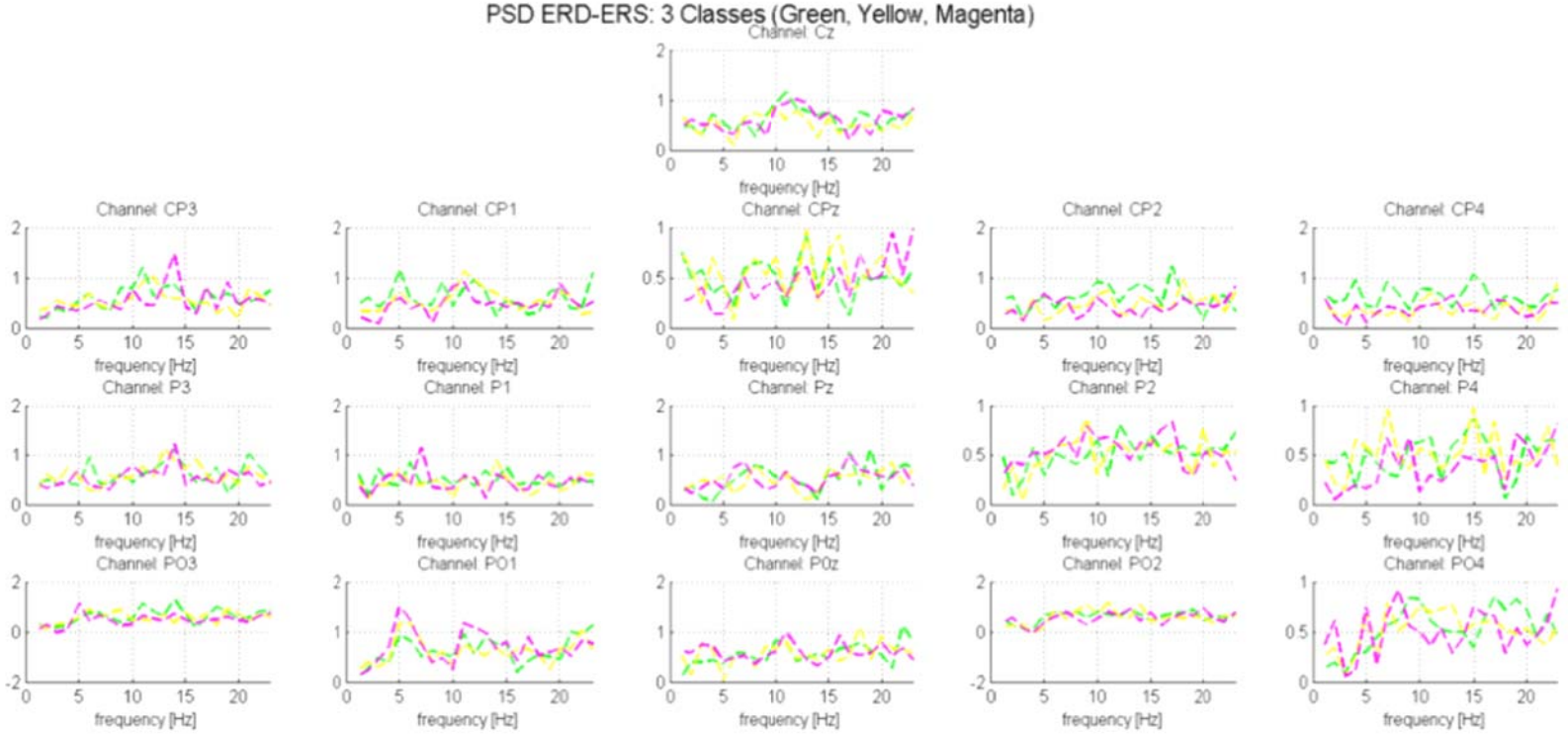

Figure 19 Mean PSD ERD/ERS signals on all trials, example with subject s2

4.2.2 Feature extraction and selection

We extracted each feature according to the correspondence between the time instant of trial start and the respective time window in which the PSD was computed. At this stage, the feature structure was a couple [frequency x channel], which means that we extracted the features inside the sustained attention period. Feature selection was computed via CVA, using as an input for the selection the ERD/ERS signal, which was obtained before. We set a minimum and a maximum number of selected features according to CVA results.

4.2.3 Classification

We developed a specific classifier based on a linear discriminant analysis, which explicitly attempts to model the differences between the two classes of data. Then we utilized a Bayesian approach to prior information. We used the posterior probabilities, derived from the first time analysis, as priors to the frequency testing classification.

At this final step, we computed an overall accuracy estimation, using different basic accuracy computation techniques. We utilized a counting of correct labelled trials compared to all trials, the integration of the posterior probabilities, the mean value of post probabilities, the last probability derived from probability accumulation framework analysis and the maximum value derived from the probability accumulation framework analysis.

The accumulation framework technique operates an exponential smoothing, based on the following formulation:

$$D(t) = D(t-1) \cdot \alpha + D(t) \cdot (1-\alpha)$$

This formula recursively utilizes the precedent value for the computation of the following step, weighting it in different ways. The weight is represented by the parameter α: using $\alpha = 0$, the weight of the precedent step is nullified, using $\alpha = 1$, the weight of the actual step is nullified and the precedent step completely influences the actual step. Varying this parameter it is possible to enhance the level of smoothing.

This technique is called exponential smoothing. It is a recursive technique that allows to perform a smoothing filtering to data, acting like a low-pass filter to remove high frequency noise [41].

Chapter 5:
Results

In this chapter we present the results of this thesis. The chapter is composed of two different domain results related to the two different analysis that have been conducted. The first sub-chapter deals with the time analysis results, in which we evaluated the effects of the colour stimulus in regards to the early evoked potentials. In the second sub-chapter we discuss the results obtained from the sustained attention phase.

5.1 Time domain analysis results

The time domain analysis highlighted the presence of an early evoked potential component in all subjects. An example is shown in Figure 20 for subject s2. The utilized colours are reported in this illustration, according to the three classes used in this experiment. In green we reported the average values related to green trials for each channel. In yellow we reported the average values related to yellow trials for each channel. In magenta we reported the average values related to magenta trials for each channel.

A few different aspects characterized EEG signals, according to the presentation of a specific type of colour. For example, there's a difference both in amplitude and in delay time between the three classes of the positive peak of the evoked potential.

By visual inspection these differences are not easy to be detected. In the parieto-occipital channels we highlighted the presence of the visual evoked potential related to the coloured stimuli, while in channel *Cz* we highlighted the presence of a P300 component.

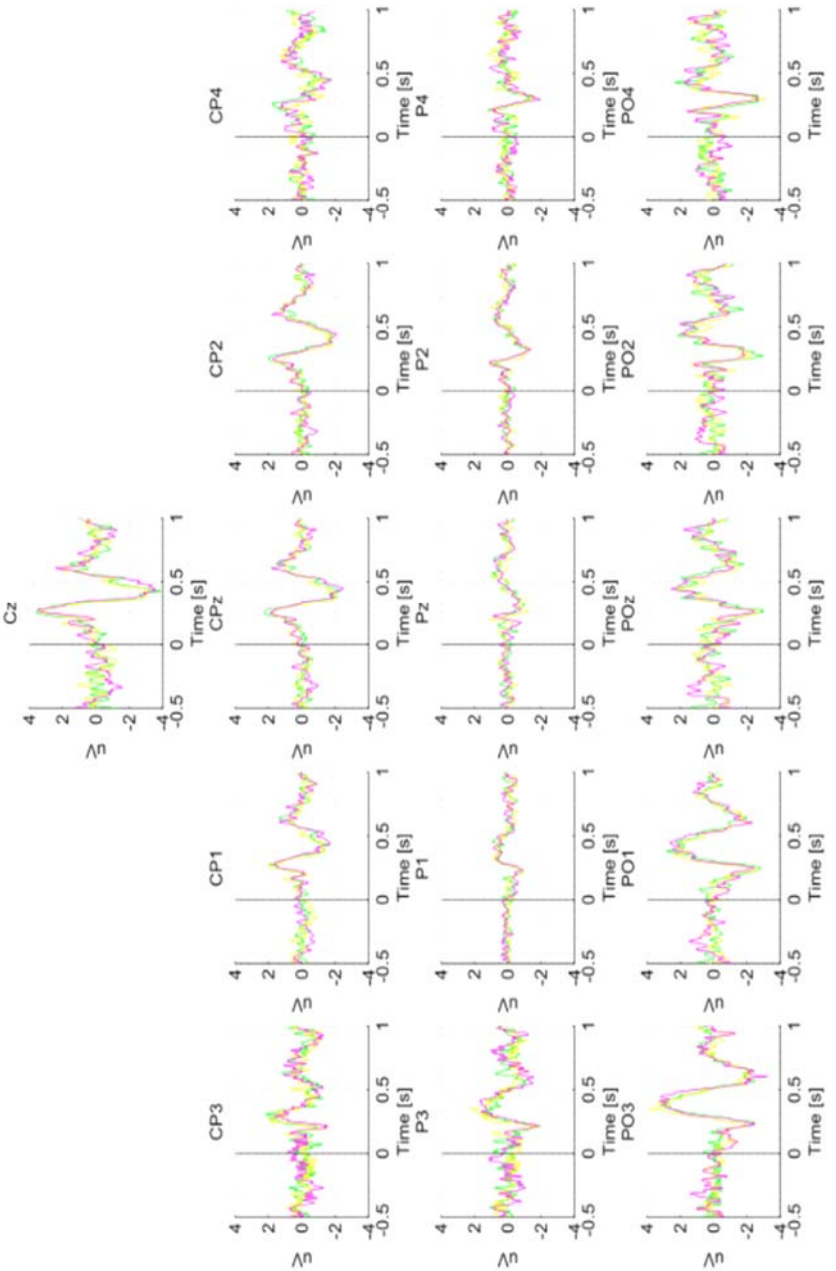

Figure 20 Mean EEG signals on all trials, example with subject s2

Anyway, the presence of these differences is perceptible when observed focusing on a single channel, in Figure 21 we report an example of a single channel (*PO3*) EEG signal mediated on all trials for subject s2.

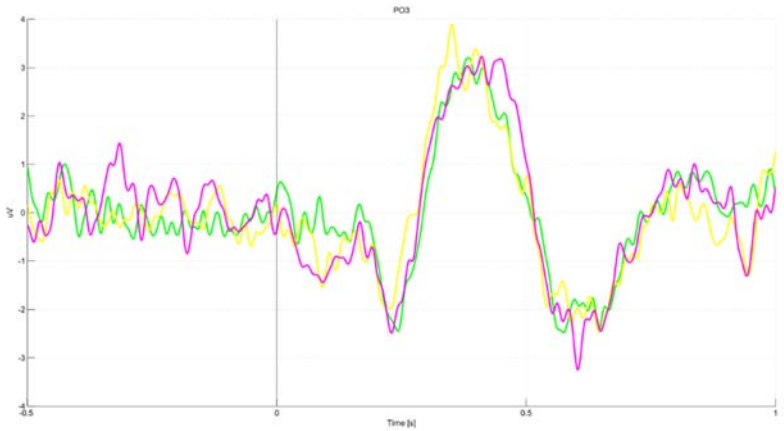

Figure 21 Time differences, subject s2, channel PO3. The three different colours represent the three different classes of colours utilized in the protocol: green for green trials, yellow for yellow trials and magenta for magenta trials.

In the testing phase we evaluated four different parameters, in order to perform the feature selection and feature extraction. These parameters were Peak-value (PV), Peak-time (PT), Sum-value (SV) and Energy (E).

During the testing phase, we evaluated the different contributes derived from each parameter in different configurations:

- Using all four parameters
- Using three parameters, commuting the excluded one
- Using one parameter at the time.

For each of these configurations we calculated an overall accuracy of classification using a feature number within [1-10].

In order to better evaluate what was the best parameter configuration, we tested all configurations. Table 2 represents the results that brought us to utilize the four parameter configuration. In the x-axis we can find the different configurations: using all four parameters, excluding one parameter at the time and using all parameters separately.

Excluding one parameter at the time did not bring any significant improvement and the contribution of each single parameter configuration was definitely worst in terms of overall accuracy.

We present the results for subject s6 as an example, for each couple of classes and for all configurations. Those results are divided by the colour comparisons, Green vs. Yellow, Yellow vs. Magenta and Green vs. Magenta. We used the information derived from time analysis to provide an accurate feature selection.

The Table consists in three sub-tables, the first one reports the results for the comparison between the Green vs. the Yellow class (G vs. Y), the second for Yellow vs. Magenta (Y vs. M), and finally the third between the Green vs. Magenta class (G vs. M).

The colour scale in the Table 2 assigns the green colour to the best performance percentage value inside the whole set and the red colour to the worst performance inside the whole set.

Table 2 Accuracy time results,

G vs. Y = Green vs. Yellow class,
Y vs. M = Yellow vs. Magenta class,
G vs. M = Green vs. Magenta class.

G vs. Y	PV PT SV E	PT SV E	PV SV E	PV PT E	PV PT SV	PV	PT	SV	E
1	62,2%	62,2%	62,2%	58,9%	62,2%	58,9%	58,9%	62,2%	54,4%
2	62,2%	61,1%	62,2%	61,1%	62,2%	61,1%	54,4%	56,7%	58,9%
3	61,1%	55,6%	61,1%	62,2%	61,1%	57,8%	53,3%	54,4%	56,7%
4	63,3%	55,6%	63,3%	60,0%	58,9%	56,7%	55,6%	54,4%	53,3%
5	62,2%	55,6%	62,2%	58,9%	63,3%	57,8%	54,4%	58,9%	63,3%
6	64,4%	58,9%	64,4%	58,9%	61,1%	64,4%	53,3%	57,8%	62,2%
7	66,7%	66,7%	66,7%	60,0%	60,0%	62,2%	50,0%	56,7%	60,0%
8	63,3%	66,7%	62,2%	55,6%	62,2%	58,9%	50,0%	57,8%	53,3%
9	63,3%	70,0%	65,6%	57,8%	60,0%	56,7%	50,0%	58,9%	50,0%
10	65,6%	67,8%	67,8%	60,0%	62,2%	54,4%	46,7%	55,6%	57,8%
Y vs. M	PV PT SV E	PT SV E	PV SV E	PV PT E	PV PT SV	PV	PT	SV	E
1	63,3%	63,3%	60,0%	63,3%	63,3%	55,6%	63,3%	60,0%	56,7%
2	61,1%	61,1%	62,2%	64,4%	61,1%	53,3%	61,1%	62,2%	56,7%
3	64,4%	64,4%	62,2%	58,9%	64,4%	55,6%	61,1%	61,1%	57,8%
4	61,1%	63,3%	58,9%	65,6%	61,1%	51,1%	61,1%	58,9%	50,0%
5	62,2%	60,0%	55,6%	63,3%	62,2%	53,3%	58,9%	56,7%	56,7%
6	63,3%	58,9%	56,7%	63,3%	62,2%	52,2%	57,8%	53,3%	53,3%
7	63,3%	62,2%	58,9%	63,3%	61,1%	52,2%	57,8%	51,1%	54,4%
8	62,2%	61,1%	55,6%	63,3%	58,9%	50,0%	60,0%	50,0%	53,3%
9	57,8%	60,0%	54,4%	61,1%	56,7%	52,2%	56,7%	52,2%	51,1%
10	63,3%	62,2%	53,3%	58,9%	58,9%	47,8%	58,9%	51,1%	53,3%
G vs. M	PV PT SV E	PT SV E	PV SV E	PV PT E	PV PT SV	PV	PT	SV	E
1	67,8%	67,8%	67,8%	62,2%	67,8%	60,0%	62,2%	67,8%	63,3%
2	67,8%	67,8%	70,0%	66,7%	67,8%	58,9%	66,7%	70,0%	61,1%
3	64,4%	64,4%	65,6%	62,2%	64,4%	54,4%	62,2%	70,0%	60,0%
4	68,9%	68,9%	64,4%	60,0%	68,9%	64,4%	60,0%	65,6%	60,0%
5	67,8%	67,8%	61,1%	58,9%	67,8%	60,0%	58,9%	61,1%	52,2%
6	65,6%	65,6%	57,8%	65,6%	65,6%	58,9%	63,3%	57,8%	51,1%
7	63,3%	63,3%	57,8%	63,3%	63,3%	58,9%	62,2%	58,9%	51,1%
8	72,2%	72,2%	63,3%	63,3%	67,8%	57,8%	63,3%	54,4%	50,0%
9	71,1%	71,1%	61,1%	64,4%	62,2%	56,7%	62,2%	58,9%	54,4%
10	68,9%	66,7%	58,9%	64,4%	63,3%	57,8%	61,1%	57,8%	52,2%

After the preliminary considerations explained above, we selected a coherent number of features according to the best accuracy results in the first configuration. In Figure 22 we reported the accuracy results for all subjects, in the best configuration selecting the subject-specific number of features. For all subjects, the accuracies computed reached an average of 64.6% for the Green vs. Yellow couple, 64.2% for the Yellow vs. Magenta couple and 65.9% for the last Green vs. Magenta couple.

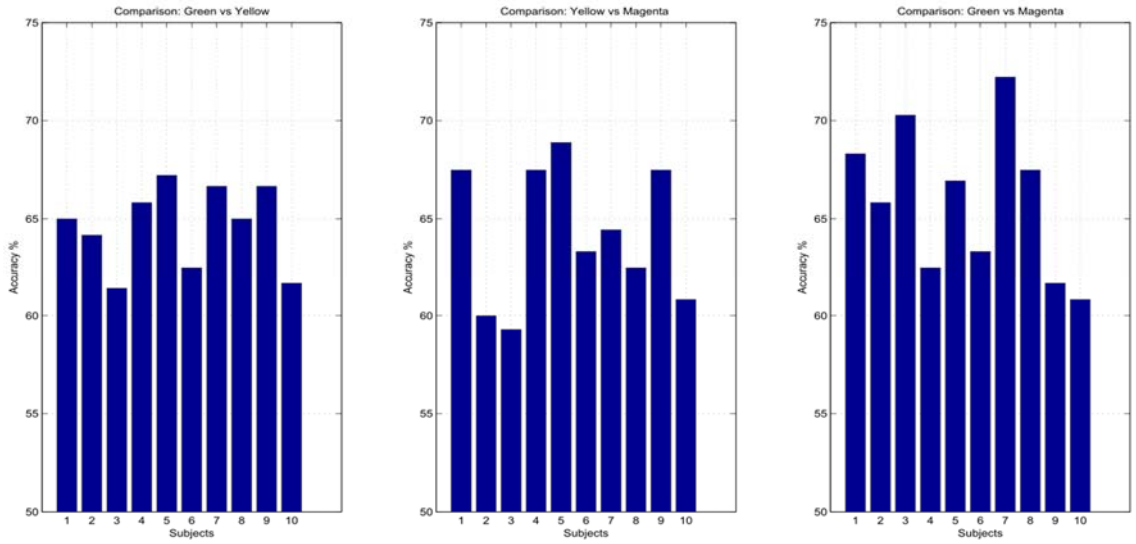

Figure 22 Accuracy time analysis results, racy time analysis results:
1^{st} panel: comparison between Green and Yellow classes;
2^{nd} panel: comparison between Yellow and Magenta classes;
3^{rd} panel: comparison between Green and Magenta classes;

It is noteworthy that these overall accuracies were computed gathering basic information from the EEG signals. The inter-subject variability in terms of colour perception is noticeable, but an interesting aspect that emerged from these results is that each subject, on average, reacted differently comparing the different colour couple presented during the experiment.

We found that on average each subject presented two comparison classes that were classified better than the third one. Anyway, average results confirm that all overall accuracies live stably over 60% of accuracy, in most cases over 65% and reaching accuracy peaks over 70%.

According to these results, we utilized the best configuration for each subject to improve the specific results in the following sustained attention phase. We extracted the posterior-probabilities gathered using the best configuration as priors for the frequency analysis.

5.2 Frequency domain analysis results

As anticipated before, we utilized a Bayesian approach to the frequency analysis in the sustained attention phase. In addition, we selected three different time instants to better evaluate how the sustained attention evolved during the second phase of the trial. We kept a one-second window, in which we analysed the PSD, varying the starting position of the window. In details:

PeriodStart = 10	PeriodStart = 15	PeriodStart = 20
$[0.625 - 1.625]s$	$[0.9375 - 1.9375]s$	$[1.25 - 2.25]\ s$

Figure 23 reports, for each subject, the overall accuracy grouped by colour and plotting the differences in the three different PeriodStarts.

A preliminary consideration is that all accuracies have been enhanced at least by a 5%, while for some subjects these accuracies improved to a further 10%, respect to the time analysis results. This means that for some subjects (s 1-6 and s9), the final overall accuracy lies within 70% and 75%.

This representation illustrates that each subject reacts differently to each colour and the sustained attention brain activity varies during the second trial period. Some subjects focus better during the beginning of the sustained attention phase, while others focus better after a few time instants.

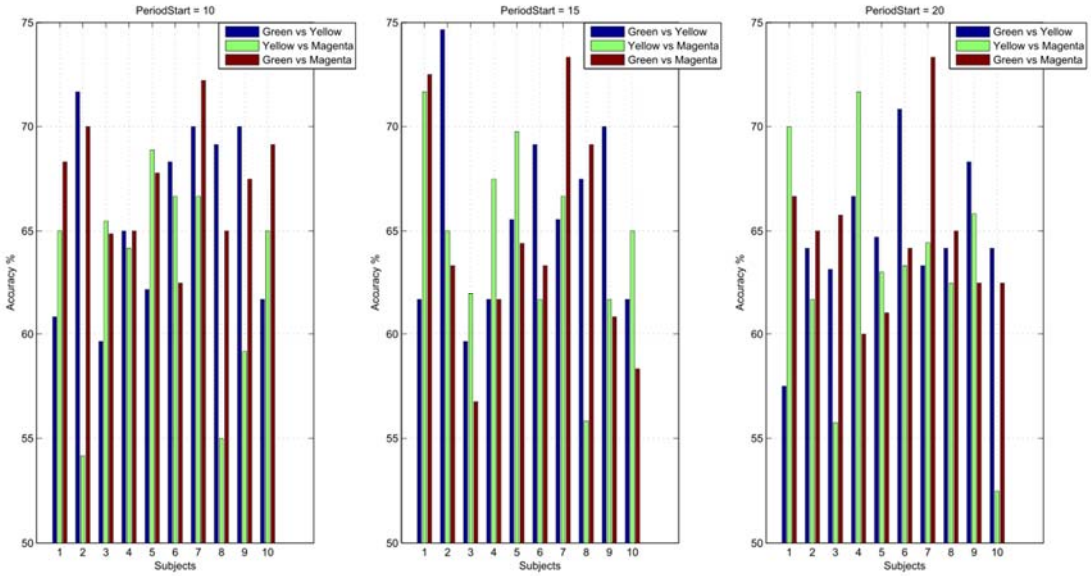

Figure 23 Frequency analysis results;
1^{st} panel: PeriodStart = 0.625 s, all class couples;
2^{nd} panel: PeriodStart = 0.9375 s, all class couples;
3^{rd} panel: PeriodStart = 1.25 s, all class couples;

Figure 24 reports the average values, calculated on all subjects for each period and for each colour couple. These average values are grouped by each time section for the signal and in each bin are presented the mean values for each colour, including the standard deviations.

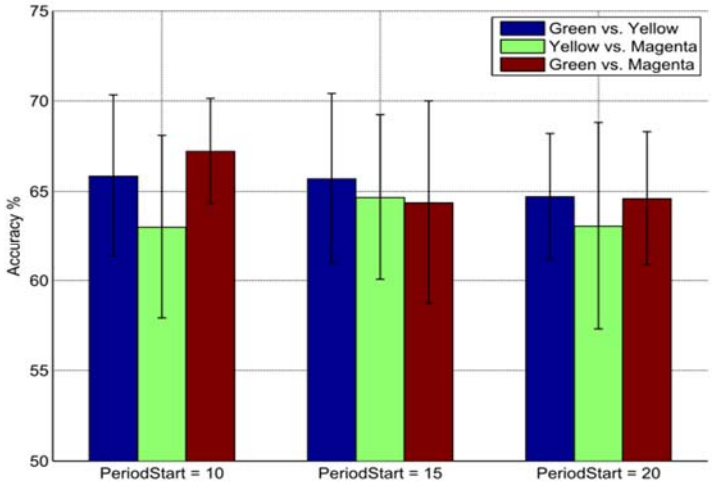

Figure 24 Frequency analysis results, mean accuracy results. In blue is reported the average accuracy value, mediated on all subjects, for the couple G vs. Y, while in light green is reported the mean accuracy value for the couple Y vs. M, and finally in red for the couple G vs. M. Each bin comprehends the specific deviation standard values for that couple.

Figure 25 reports the accuracy trend, respect to the starting position of the sustained attention period. It contains three frames, each frame presents the accuracy results for each colour couple. For each subject, in each bin there are the three accuracy results derived from the three different PeriodStarts. This Figure illustrates the time evolution of classification accuracy, varying the selected window for frequency analysis in the sustained attention period.

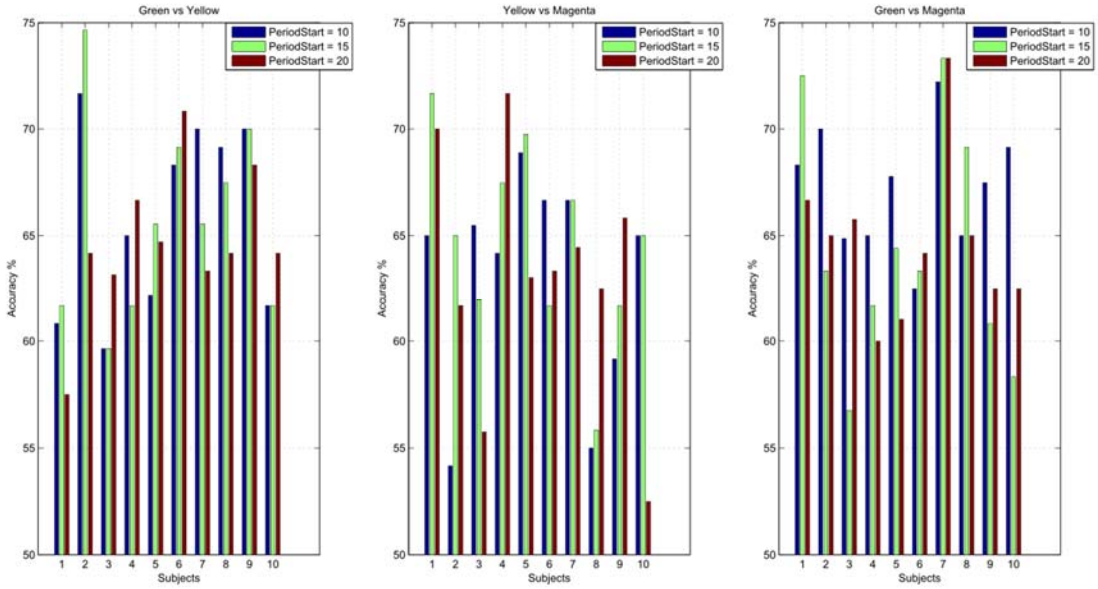

Figure 25 Frequency analysis results;
1^{st} panel: comparison between Green and Yellow classes;
2^{nd} panel: comparison between Yellow and Magenta classes;
3^{rd} panel: comparison between Green and Magenta classes;

5.3 Discussions

In order to be able to estimate the reliability of a new method, it is necessary to follow some standard signal processing stages. One of these standards is the use of a cross-validation statistic when presenting offline classification results. [42]

Related to this observation, the meaningful way to present classification accuracies is to couple these results with the number of trials on which the computations are based. In the article presented by Müller-Putz et al [43], they showed the theoretical confidence limits of a chance result for a 2-class BCI system. Using a number of trials of 120, the confidence

limits of a chance result with a 2-class paradigm are within 60% and 65%.

Our results are positioned above these guide lines. In fact, in Figure 32 we reported the average accuracy results mediated on all subjects and on all analysed period of sustained attention, with an accuracy within 63% and 65%. In our analysis we utilized 60 trials per class, for a total number of trials of 180. Having a 2-way classifier, we used 120 trials per couple of classes.

Chapter 6: Conclusions

6.1 Summary of the work

The aim of this work was to develop a novel BCI system, which utilized as an input brain activity signals related to colour perception in a non-flashing stimulation, utilizing two different aspects: the visual evoked potential and the self-paced visual sustained attention to the coloured stimulation.

Our work focused on two different aspects of colour perception in healthy subjects. The first aspect is related to the visual evoked potential triggered by a coloured stimulus. This aspect was confirmed by the results and verified the first hypothesis, which means that a specific colour stimulus evokes a specific brain reaction situated in the early evoked potential components, as described in literature in different articles [32, 33].

Our results show that there is a statistical difference in the three colours utilized in this experiment: Green, Yellow and Magenta. We obtained an average accuracy of 65% mediating on all subjects, with peaks around 70%. Another important aspect is that we highlighted the intra-subject difference, in regards to the specific colour perception. Each subject reacts differently when we present a specific coloured stimulus and his reaction presents specific characteristic that allow to discriminate what colour the subject has just seen.

The second aspect is related to the sustained attention phase. After the conclusion of the evoked potential phase, the focusing of each subject on a specific colour can effectively be used as an input for a BCI system, at least for offline classification. Using prior information derived from the time analysis, we verified the second hypothesis which is related to the presence of significant differences in a self-paced task of attention to a coloured stimulation.

Especially for the couples Green vs. Yellow and Green vs. Magenta, we obtained an average accuracy of 65% non-distinguishing between

different periods during the sustained attention phase and mediating on all subjects, but differentiating our focus on different sections of the sustained attention phase, we evaluated several overall accuracies, for each period, around and above 70%.

The possibility of classifying correctly which colour stimulus occurred is strictly connected to the presence of neural correlates, depending to the specific colour stimulus. Leaving aside inter-subject differences, our results show that, during the sustained attention phase, a frequency analysis can lead to a correct classification with peaks around 75% and averagely around 68%.

In this analysis we evaluated overall accuracies by testing the colour perception reaction in a set of ten subjects. Further applications of this methodology should utilize a more numerous number of subjects, in order to evaluate a more solid population trend for a BCI system based on colour dependent visual attention. In addition, our results showed the possibility of using this BCI system for online applications.

We believe that using a 64-channel headset or a headset with a higher number of external electrodes would lead to more accurate results.

6.2 Further considerations

In order to evaluate the possibility of classification starting from biological signals, an offline approach may be an easier way to better understand whether a signal type could be used as an input for a BCI system or not. Although offline results may help to provide a path towards online application for BCI systems, if offline analysis won't lead to promising results then it would not be necessary to investigate furthermore with an online analysis.

This experiment evaluated principally how a colour stimulus affects brain activity, not only in the evoked potential phase, but also during the sustained attention phase.

The importance of this offline analysis lies in the different approach between precedent studies. The combination of evoked potential analysis and the voluntary attention tasks is one of the most interesting aspects of this analysis. In addition the use of basic and standard evaluation methods during the analysis can lead to further and more complex classifications of this particular phenomenon.

Furthermore, this experiment could be performed eventually also by subjects affected by epilepsy, while a SSVEP-BCI could not be applicable to these subjects without any precautions. Whether a subject, affected by epilepsy, performs a series of trials in a SSVEP-BCI application, the possibility of an epilepsy attack are not so remote. Which means that the application of a SSVEP protocol should be performed foreseeing the necessity of a medical structure in the case of an epileptic subject. On the other hand, our visual paradigm can be performed by any kind of subjects and it does not need particular specimens to be performed.

6.3 Future applications

This project started in parallel with the Cybathlon Project, a championship for robot-assisted parathletes that will take place in October, 8th, 2016 in Zurich. In particular, IAS Lab will participate as a Team Leader of WHi Team (wearable hybrid interface). This BCI race involves three possible commands and the functioning is based on the SMR-BCI. These three different classes are presented to the parathletes thanks to different colours inside the run itself. These colours are green, yellow and magenta. This is why we utilized the same three colours in our BCI colour-dependent visual attention system.

The stand-alone application of a colour-based BCI is not yet applicable in real life situations, but the most interesting application can be found in a synergy context. Several BCI systems find their place in BCI applications as a parallel tool for other more tried out BCI systems; in these cases it has been coined the term “Hybrid-BCI” [44, 45].

Colour dependent BCI systems could work aside with other BCI systems in order to parallel improve results. This Hybrid-BCI system could be composed by a colour dependent BCI and a motor imagery BCI. For example, in the Cybathlon Project, mentioned in the previous chapters, a colour recognition could improve the MI results in classification, as an additional accuracy check even in real time applications.

Several future applications can be imagined for the use of this technique. This BCI system could be a tool not only in the field of disability, but also for healthy subjects. Nowadays several technologies have been introduced inside vehicles [46], for example parking sensors, emergency obstacle breaking systems, and so on. An online colour based BCI system could be a powerful addition for better recognizing what is happening in the outside environment.

Other possible applications could be in the world of entertainment. Always working aside with other systems, a colour based BCI system could provide a further choice during gaming experiences, for example shooting in a shooting game or could provide effectively a higher control for sport gaming.

One of the most important concepts that this thesis highlighted is that it is really possible to utilize the subject's colour perception, in order to say what colour has been seen by the subject. In addition, the voluntary self-paced task of focus at a colour provides a quite consistent signal that can be used as an input for a BCI system and this result can be precursive for an online application.

Appendix

Neurophysiology of the EEG signal

1 Neurons

All brain activity and all typologies of communication between our brain and the rest of our body relies on neuron cells. A neuron is an electrically excitable cell that transfers information through electrical and chemical signals [1]. Figure A1 reports a schematic representation of a neuron.

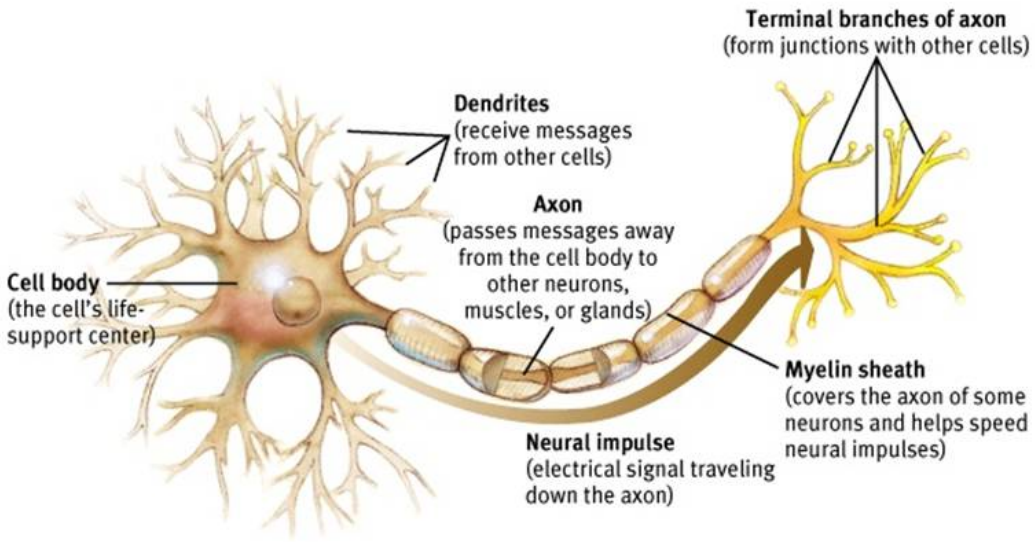

Figure A1 Schematic representation of a neuron[8]

A neuron consists of a cell body, called soma, dendrites, and an axon. The seconds are the branched projections of the neural cell; their function is

[8] *Edited from http://www.appsychology.com/Book/Biological/neuroscience.htm*

to provide linkage between other neurons or even between other kinds of cells, for example muscular cells.

These cell protrusions act to propagate the electrochemical stimulation received from other neural cells to the cell body. The signal is then transferred to the axon. Its role typically is to conduct all electrical impulses away from the cell body [2] towards another receiving cell.

Brain cells are electrically excitable, as mentioned before, and changes in the cross-membrane voltage over a certain threshold can trigger the generation of an action potential. This signal travels rapidly along the cell's axon and then activates synaptic connections with other cells. In Figure A2 we reported the principal schematic representations for neuron signal transmission, with emphasis on electrical impulses and on neurotransmitter molecule mechanism for the propagation of the action potentials.

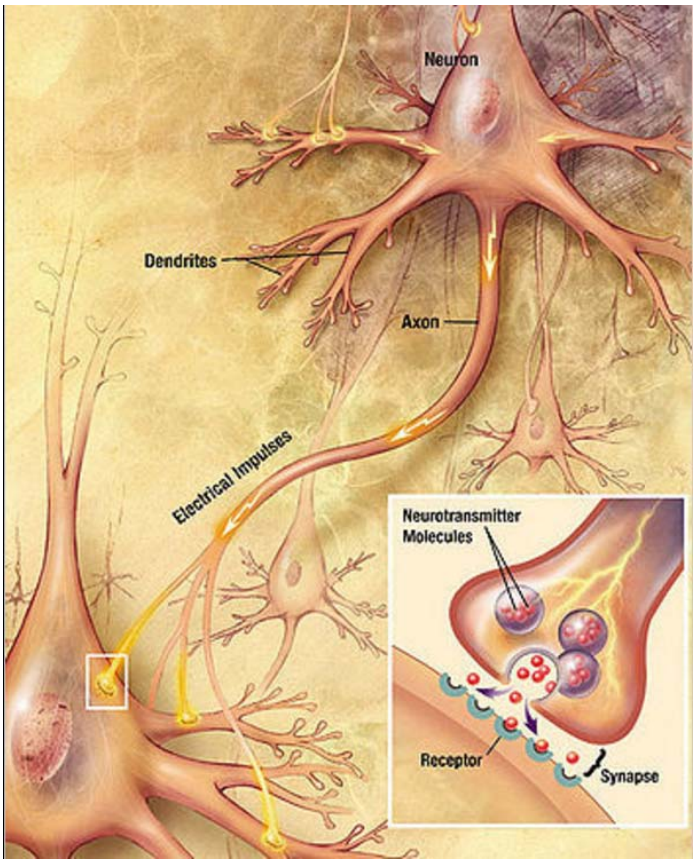

Figure A2 Schematic representation of a signal propagation between neurons[9]

[9] *Edited from https://www.nia.nih.gov/alzheimers/publication/alzheimers-disease-unraveling-mystery/preface*

Signal transmission occurs via synapses. The transmission of information is conveyed thanks to action potentials. An action potential is a short-lasting event in which the electrical potential of the cell membrane rapidly rises and falls, following a consistent pattern of trajectory [3].

2 EEG signals

EEG signals consist in the recording of variations and fluctuations of electric potentials, gathered from the scalp in a non-invasive way. The EEG signals reflect the real-time mass action of neural networks from a certain neuron population [4]. The possibility of recording in a real-time way brain activity has been determining to extend the knowledge about brain perception and even human emotions. This is why they provide a direct window onto human brain functioning [5, 6]. On the other hand, recording the electrical activity of a population of neurons in a specific brain region cannot provide an accurate measure. The direct consequence is the low spatial resolution, but this cons is not a strict limitation. Time resolution is far more important to effectively understand the functioning of brain in most of cases. Figure A3 illustrates an example of an EEG acquisition.

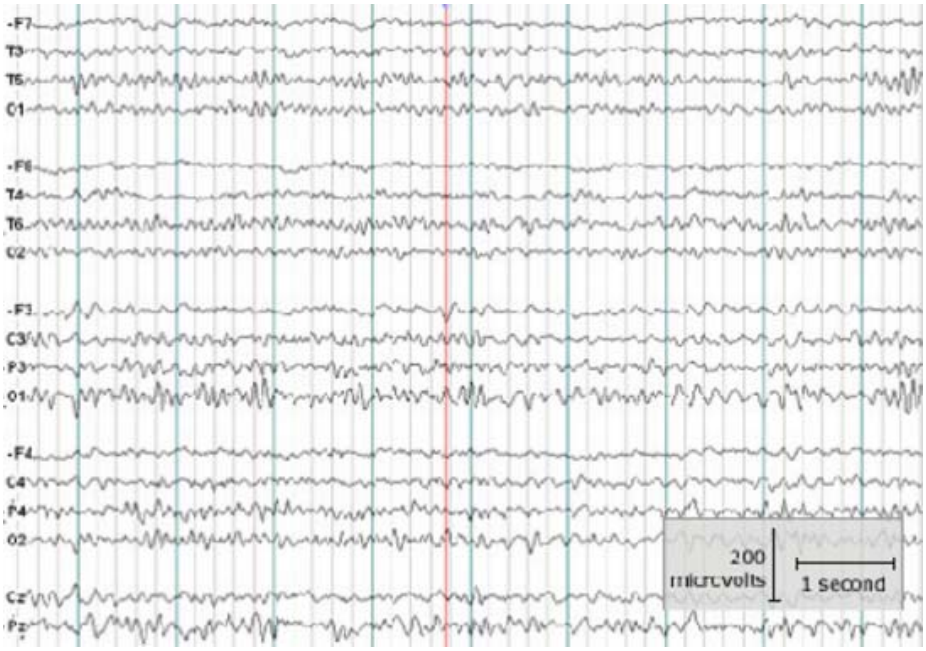

Figure A3 Sample EEG signals[10]

[10] *Edited from http://www.brainfactor.it/?p=1852*

External events stimulate our brain in different ways, according to the typology of the stimulation. Whether these stimulations are sensed, they provoke different electrical activities in different brain regions. In most cases, an external sensorial stimulation can be auditory or visual.

For example, the visual presentation of a particular object can evoke a particular brain activity or even an auditory presentation of a certain sound can induce in the subject a peculiar reaction, reflected in the brain activity. The particular structure of functioning of brain signal transmission, directly implicates that brain activity has a characteristic oscillatory trend, which is composed by different wave signals.

3 Brain rhythms

Neural oscillations are divided in different waves according to the specific frequency of oscillation. In human brain, there are four principal brain rhythms that are easily identifiable: *delta, theta, alpha* and *beta* rhythms.

The first neural oscillations are called *delta waves.* A delta wave is a high amplitude brain wave with a frequency of oscillation between [0– 4] Hz. They are usually associated with the deep stage 3 of NREM sleep, also known as slow-wave sleep (SWS), and aid in characterizing the depth of sleep. Figure A4 illustrates a typical trend for a delta wave rhythm.

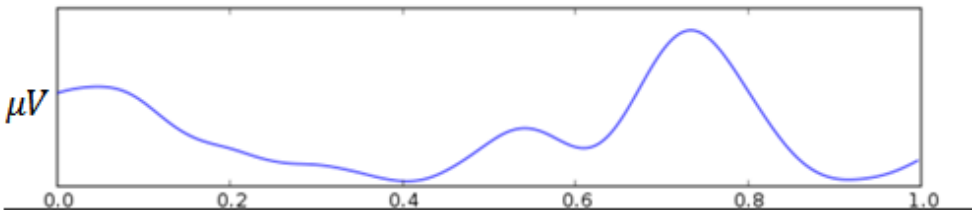

Figure A4 Delta wave [4]

The second neural oscillations are called *theta waves.* Their frequency band is situated within [4– 7] Hz. Theta waves are mainly present in childhood at the age of 1 up to 6 years and their presence is constantly reducing with the age. In adults they can be recorded principally during the asleep phase and in the rapid eye movement (REM) phase. In Figure A5 we can see an example of a theta wave.

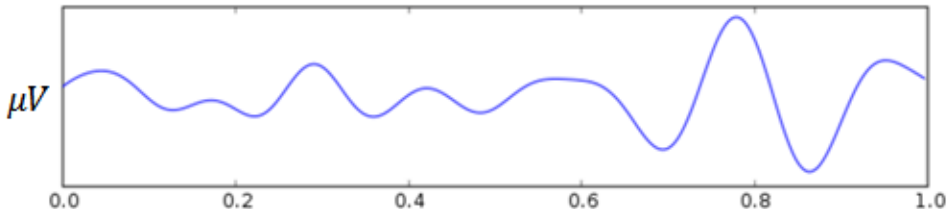

Figure A5 Theta wave [A4]

The third neural oscillations are called *alpha waves.* These oscillations have a frequency range of oscillation within $[7{,}5 - 12{,}5]\ Hz$. An example is reported in Figure A6.

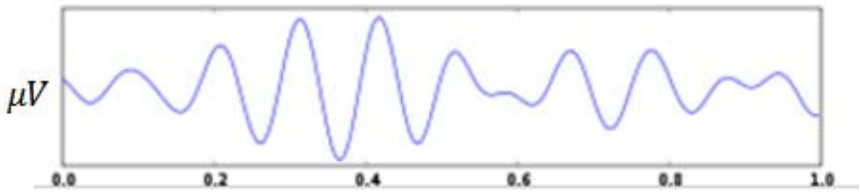

Figure A6 Alpha wave [4]

Alpha waves predominantly originate from the occipital lobe during wakeful relaxation with closed eyes. Occipital alpha waves during periods of eyes closed are the strongest EEG brain signals in amplitude [7].

The fourth neural oscillation are called *beta waves.* With the term beta wave it is designated the usual frequency range of human brain activity. The frequency band lies within $[12{,}5 - 30]\ Hz$. An example is reported in Figure A7.

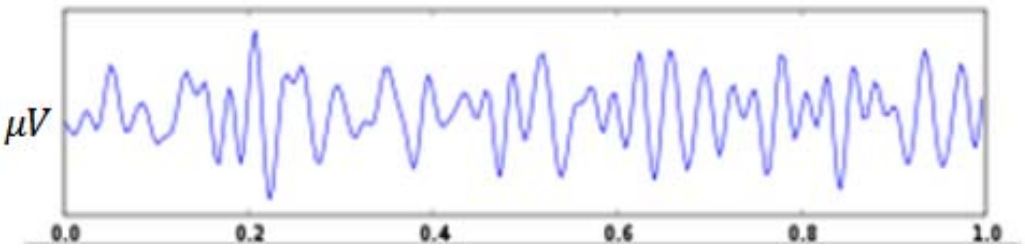

Figure A7 Beta wave [4]

Increasing amplitude in beta activity is associated with a strengthening of sensory feedback in static motor control, while it is reduced in movement changes [8].

The perception of an external stimulation is connected to a specific reaction that is reflected in a modification in brain activity. According to the typology of the external stimulation, specific neuron populations gain a synchronous electrical polarization, which is reflected in a signal amplitude increase [9]. This category of signals is called sensory evoked potentials.

4 Evoked potentials

An evoked potential can be described as an electrical potential of the brain, due to the presentation of an external stimulation. There are three typologies of sensory evoked potentials in clinical use: auditory, somatosensory and visual evoked potentials.

As anticipate in **Section 2**, it is the external stimulation that evokes a characteristic brainwave in the subject. This typology of evoked potentials is defined as event-related potentials (ERP), [10, 11].

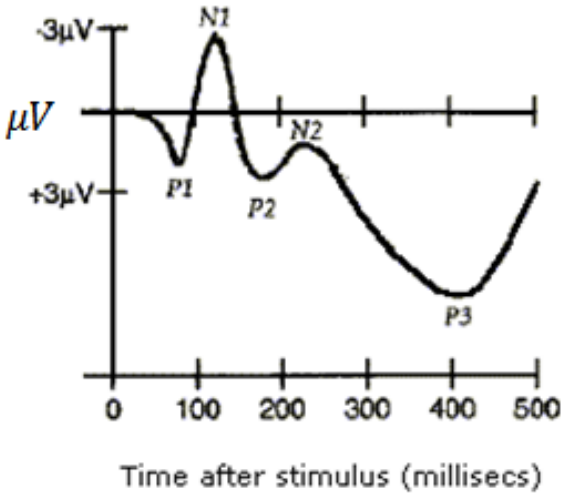

Figure A8 Schematic representation of ERP components [11]: this illustration of a typical event-related potential highlights the principal components related to visual evoked potential.

[11] *Edited from http://www.intechopen.com/books/advances-in-clinical-neurophysiology/the-neurocognitive-networks-of-the-executive-functions*

An ERP comprehends several components, distinguished by shape and time appearance according to the stimulus. Figure A8 illustrates the principal ERP components, associated to visual perception.

Typically, the components are labelled with two elements: the first letter indicates the positive or negative trend that the component has (in amplitude [μV]), while the second element is a number and it indicates either the hierarchical appearance, in terms of time, of the wave (i.e. P1, P2, N2 and so on) or the time instant where it usually reaches an amplitude peak (i.e. P300 components have a peak around 300 ms).

We report a brief schematic list of the principal ERP components involved in visual perception.

- The P1, also called the P100, is the first ERP positive-ongoing component and it usually peaks around 100 ms. This component is related to the processing of visual stimuli.
- The N1, also called the N100, component is the first negative-ongoing component and it is usually elicited by visual stimuli.
- The P2, also called P200, component is the second positive-ongoing wave evoked by the stimulus. Typically it is elicited as part of the normal response to a certain visual stimulation and has been studied in relation to attention, language and memory.
- The N2, also called N200, is a negative-ongoing wave that peaks $200 - 350\ ms$ after the stimulus appearance. It fluctuates in relation of cognitive processing and is known as one of the most direct measures of covert mental operations.
- The P3, also called P300, wave is a component elicited during the process of decision making and its occurrence is involved in the evaluation and categorization of the stimulus. This component trend has a positive peak at roughly around 300 ms.

ERPs components are connected to all different responses that our brain activates after a specific stimulus. What brings together all ERP components is that all ERPs represent the synchronous activity from neuron populations in a certain region [12].

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