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Design of a digital FIR filter with minimum delay for BCI applications

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Acronyms

BCI Brain-computer interface

FIR Finite impulse response

IIR Infinite impulse response

EEG Electroencephalography

FFT Fast Fourier transform

SMR Sensorimotor rhythm

MRD Movement-related desynchronization

ERD Event-related desynchronization

PET Positron emission tomography

fMRI Functiional magnetic resonance imaging

MEG MagnetoencephaloGraphy

SNR Signal-to-noise ratio

VEP Visual evoked potential

SCP Slow cortical potential

CNS Central nervous system

NFB Neuro-feedback

Preface

The neuromuscular disorders are a topic that nowadays shakes a lot of sensibility in the scientific community and among common people, since the amount of people suffering this kind of problems has been considerably increased. In fact amyotrophic lateral sclerosis, brainstem stroke and spinal cord injury, are the frequent causes of disability all around the world and lead up to 600 million people to permanent neurological impairments [4]. The main question is that motor impairment associated with this kind of deseases seriously compromise the quality of ordinary life of these patients. Therefore, in order to restore motor functions severals rehabilitative treatments have been experimented. The most traditional approach includes: passive facilitation, promotion of alternative movements, aerobic exercises, constraint-induced movement therapy or bilateral arm-training. However with the recent technological advancements, the idea of an alternative rehabilitative strategy based on neuroplasticity arose: it is the so called Brain-Computer Interface (BCI). This platform employs neurophysiological signals originated in the brain to operate external devices: this kind of technology thus provides severly impaired people a new non-muscular channel for sending messages and commands to the external world. A first attempt to use BCI technology in the clinical context as a tool of neurological rehabilitation of motor paralysis was proposed in 1973 by J.Vidal in patients affected by tetraparesis. Then, many other studies were carried on and led to significant improvement of motor fuctions.

Nowadays research on BCI is a wide and various scenary, but this thesis work focuses on a reality close to Padua, that is the S. Camillo Hospital Foundation I.R.C.C.S. in Lido of Venice. There a BCI system for the recovery of motor functions in mild impaired stroke survivors has been implemented. In particuar, a closed-loop structure involving the subject's brain, his/her upeer limb and a

robotic arm controlled by a computer exploits the neuroplasticity property of the brain with the rehabilitative goal to associate new healthy neural paths to a more and more precise movement of the impaired upper limb. With a suitable BCI training - where a force is continuously provided to the subject through the robotic arm as a feedback of his/her neural activity - the patient learns to control his/her neurophysiological signals and, consequently, improves his/her motor abilities. However, the effectiveness of the force feedback strictly requires real-time operations. In order to reach this condition a reliable EEG signal processing is needed. Thus, the aim of this thesis work is designing a digital filter which allows to instantaneously process the neurophysiological data and, in particular, identifies the spontaneous energy decrease of the frequency bands related to the movement of the limb - the so-called *sensorimotor rhythms*.
The present thesis is structured as follows:

Chapter 1: Firstly, some basic concepts about humann brain are reported; then the origin and the current state-of-the-art of the BCI research is described with special mention for its applications for the rehabilitation filed. The chapter concludes with some perspective of the BCI future developments and its potentialities.

Chapter 2: In this section the BCI system implemented at San Camillo Hospital (Venice) is considered. Its advantages and innovative aspects are brought out along with some criticisms, e.g. the real-time requirement, that should be improved in order to make it a reliable and effective recovery platform.

Chapter 3: This chapter introduces the actual subject of this work: a real *filter* to be implemented in the San Camillo's BCI system. Its general time and frequency properties are defined, and its ideal model, which acts as a reference for the real one in this project is presented. Besides that, the most common filter design techniques are briefly explained.

Chapter 4: In this last chapter the simulations performed in MATLAB environment are described in detail, along with the strategies adopted to choose the most suitable digital filter for this BCI applications. Finally, the outcomes obtained on simulate EEG signal are presented, along with the strategies that in future could be adopted to continue the project.

Chapter 1

The Brain-Computer Interface

The acronym BCI - which stands for Brain Computer Interface - appeared for the first time in 1973, as the name of a project conducted at the University of California in Los Angeles [5]. That project layed its foundations on the evidence that EEG waves contain usable information of conscious and unconscious experiences. Indeed, important discoveries and insights had been collected about neural signals since the latest 20s. In particular, human cerebral signals recorded on the scalp were recognized as sustained fluctuations of the electrical potential correlated with variations in the upper layers of the brain cortex below the scalp surface. It was also noted that these signals structure could be modeled as a stochastic time series with small amplitudes (up to few tens of microvolts) and a considerable amount of very low frequencies (below 1 Hz) that "appear" and "disappear" somewhat randomly in time. Besides, signals collected on two or more electrodes exhibited changing levels of correlation, due either to physical proximity or to actual coordination between different cortical sites. In this sustained "ongoing" electrical activity, short-lasting (from 0.5 to 2 seconds) distinctive waveforms were also identified as *evoked* responses to stimuly externally received by the subject.
Enthusistic about the recent achievements in the EEG and neurophysiological field, in 1973, *Jacques J. Vidal* wrote: ”Can these observable brain signals be put to work as carriers of information in man-computer communication or for the purpose of controlling such an external apparatus as prosthetic devices?”[5]. That is considered the first basic idea of BCI and Vidal is all over the world recognised as

the father of these systems. In fact, the BCI project carried on in Los Angeles was the first successfully attempt to evaluate the feasibility and reliability of operating a man-computer dialogue by means of brain signals.

The success of the project is probably due to Vidal's foresight that despite of the rudimentary tools and incomplete knowledge about human brain available at the beginning of the Seventies, foresaw the future applications of this interface, and elevated computers to genuine prosthetic extensions of the brain. Then, considerable advances in neurophysiology, in signal analysis techniques and in computer science would be required to further approach that dreamer goal that nowasdays, years after Vidal's first words, remains far away from an actual daily life reality.

1.1 The human brain

Physiology and anatomy of the human brain are far to be completely explained, although significant progresses were made. One of the most important step in the neuroscience history was the invention of the electroencephalography in the latest 20s. The first registration of the human cerebral activity was performed by the German physiologist and psychiatrist Hans Berger in 1929: with the experiment he demonstrated the possibility of recording brain waves from the intact skull. Since then, an enormous amount of neural data has been investigated: the scalp-recorded brain signals showed a great deal of variability, reflecting the huge number of parameters that can influence their behaviour. Moreover, Berger's discovery encouraged the development of brain study. Lots of hospitals, laboratories and Universities had started to deeply investigate brain properties thanks to EEG and other devices. Although the great effort most of the cerebral complexity remains unclear and still fascinates researchers all over the world.

In the followings basic concepts of neurophysiology and neuroanatomy will be provided. It is well-known that human Central Nervous System (CNS) is constituted by brain and spinal cord. Brain, in particular, is shielded by two more layers that are the skull and the scalp. Then, from an anatomical point of view brain is made by three main parts, partially illustrated in Figure 1.1: cerebrum, cerebellum, and brain stem [10]. Each of these can be hierarchically subdivided into many regions, either according to the anatomical structure of the neural networks within

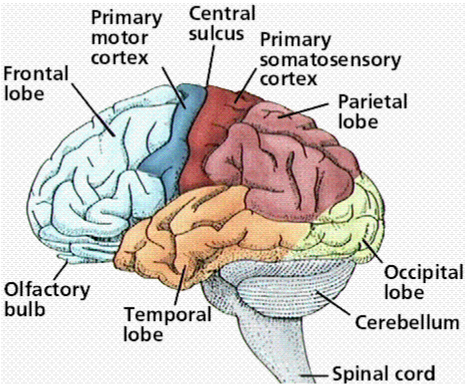

Figure 1.1: The principle brain regions.

it, or according to the function performed by them. Specifically, *cerebrum* consists of both left and right lobes with highly convoluted surface layers called cerebral cortex. The latter includes regions for movement initiation, conscious awareness of sensation, complex analysis, and expression of emotions and behaviour. *Cerebellum* coordinates voluntary movements of muscles and maintains balance. Finally, the *brain stem* controls involuntary functions such as respiration, heart regulation, biorhythms, and neurohormone and hormone sections.

But the very basic computational unit of the nervous system is the nerve cell or neuron. As shown in Figure 1.2, neuron is formed by dendrites (inputs), a cell body and an axon(output). Each neuron receives inputs from other neurons. Once the overall input to the specific neuron exceeds a critical level, the neuron *discharges a spike* - an electrical pulse that travels from the body, down the axon, to the next neurons or other receptors.

Receptors are, indeed, cells able to transmit information over long distances, across

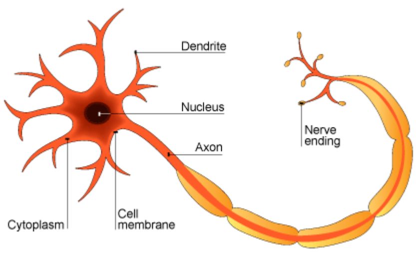

Figure 1.2: The nerve cell structure.

a dense net: each neuron is connected to approximately 10,000 other neurons, mostly through dendritic connections. The junction between axons and dendrites, or dendrites and dendrites of cells is called *synapse*, and the brain activities are mainly related to the synaptic currents. Thanks to this effective and exceptionally dense net of connection, brain can perform parallel computations in an extremelly efficient way. Moreover, it has already been demonstrated that when a disease partially damages brain, the latter can learn to use new resources to cope with the impairment: this amazing brain property is generally called *neuroplasticity*. advancements in the understanding of these neural capabilities and the advent of powerful low-cost computer equipments, made the Vidal's project an actual reality: electroencephalographic or other electrophysiological measures of brain activity can, nowadays, provide a new non-muscular reliable channel for sending messages and commands to the external world: thus, the Brain-Computer Interface era was begun.

Since Vidal's epoch, BCI technology has attracted increasing interests from the scientific community and has extended its potentials in several contexts. In fact, it is well-known that a lot of different disorders can disrupt the neuromuscular human system e.g. amyotrophic lateral sclerosis, brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis and numerous other diseases. Brain-Computer Interfaces can indeed provide beneficial effects against all these kinds of patologies. In particular, stroke is the third leading cause of death worldwide, and the 60% survivors remains with severe impairments that heavily compromise their ordinary life. It has been estimated that about 600 million people all around the world suffer from these deficits. An increasing number of neurological patients due to the general ageing of the global population has strongly driven the medical research on the way of alternative and more reliable rehabilitation methods as BCI has promised to be.

1.2 State of the art in BCI

Generally speaking, a BCI is a system by which an impaired individual can send responses and commands without using the usual communication channels, i.e. peripheral nerves and muscles: then, BCI represents an alternative method for acting on the world [3]. Several kinds of BCIs have already ben implemented all over the world in the last decades, therefore some distinctions are needed.

1.2.1 Dependent or independent BCIs

The first main distinction that can be highlighted is about the difference between dependent and independent BCIs [3]. The following exampe should clarify both the two definitions.

Consider a BCI system that allows the user to select one letter at time from a matrix of them to form words and sentences.

If the signal that controls the BCI is the gaze direction detected from the EEG traces, the BCI is defined as *dependent*, since it is dependent on a residual muscular ability to move eyes. On the contrary, if intention to choose a letter within the matrix is identified by an EEG, a MEG or another device the BCI is named *independent*.

1.2.2 Synchronous or asynchronous BCI

BCIs can be differentiated also by means of their switching on and off mechanism: if, on one hand, the BCI can be switched on and off by the user autonomously, i.e without any external intervention by the technical staff or the core assistant, the system is said to be *asynchronous*.

Otherwise, as in the most cases, the user can only control the BCI operations when the platform has been previously started. In these cases the BCI is named *synchronous*.

1.2.3 Invasive or non-invasive BCI

The third main distinction that can be made to classify the BCIs takes into account the method to record the cerebral activity of the subject operating the BCI.

In the USA, research is focused on *invasive* techniques to extract the cerebral information: electrodes are usually implanted over the cortex and the so-called electrocorticogram (ECoG) is used to provide control for the BCI. Besides that,

microarray of electrodes or micro-electrodes grids are usually employed to record local field potentials (LFPs) and neural spikes from the different parts inside brain. However, in the rest of the world, many other *non-invasive* techniques are successfully adopted: cerebral activity is, then, recorded outside brain, over or surrounding the scalp. Electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) are the most popular techniques employed in Europe and, particularly, in Italy.
A more detailed description of these methodologies is provided in the following.

1. *Electroencephalography and magnetoencephalography*
   Since 1929 when Berger observed the activity of different neural populations with an ancient analog EEG, investigations and therapies involved the use of this device to assess the patient's status on improvements after particular treatments.
   EEG is able to record cerebral changes in the range of milliseconds but has the considerable drawback of a very poor spatial resolution.

   To cope with these disadvantages, the MEG device is sometimes used as a complementary or alternative method. However MEG is employed almost exclusive in medical research because of its enormous costs of maintenance without an actual outperformance of the EEG. EEG remains, then, the most common tool in the clinical practise as weel as in most BCI research.
   However it has to be mentioned that both these techniques suffer from high susceptibility from external and other artefactual physiological interferences. This consequently, means that a consistent and reliable signal processing is needed to recover the useful physiological information from the background noise.

2. *Positron emission tomography*
   It is a nuclear medical imaging technique where a chemical compound labeled with a short-lived positron-emitting radionuclide of carbon, oxygen, nitrogen, or fluorine is injected into the body of the patient and the activity of such a radiopharmaceutical element is quantitatively measured throughout the target organs. This analysis returns a three-dimensional picture of functional

processes ongoing in the body.

3. *Functional magnetic resonance imaging*
   The basic principle that fMRI exploits is that when an area of the brain is working to perform a specific activity it needs for a larger amount of oxygen and this, consequently, means an increased blood flow in the active area is registered.
   fMRI then detects these changes in blood oxygenation and flow level in correspondence to some activities performed by the subject under evaluation. Analysis of the functional magnetic resonance tests produces statistical maps that show brain areas most likely involved in such activities.

   Therefore, a variety of techniques can be employed to monitor the brain activity, but the most suitable device in BCI applications, in terms of costs and equipments, means to be the EEG.

1.2.4 EEG based BCIs

As just exposed, for its properties the EEG signal offers the possibility of a new non-muscular communication and control channel, a practical BCI. In this script is considered and analyzed this kind of BCI, however despite the common method of signal-acquisition, it will be necessary to make further classifications.

Introduction to EEG

First of all the EEG deserves to be described more in detail. An EEG signal is a measure of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. When neurons are activated the synaptic currents generates a magnetic field measurable by electromyogram (EMG) and secondary electrical field over the scalp measurable by EEG systems. Notice that the skull attenuates the signal, and there is an additional component of noise generated either within the brain, or over the scalp. Therefore, only large populations of active neurons can generate enough potential to be recordable using the scalp electrodes, and this signal once received is amplified.
Since the brain is a surprisingly complex organ, constantly changing, and able to

manage many human functions, thus is natural to expect to find this plurality also in the EEG signals. Infact, there are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies are called:

- Delta (δ):
  These waves lie within the range of 0.5-4 Hz and are primarily associated with deep sleep.

- Theta (θ):
  Such waves lie within the range of 4 - 7.5 Hz and are associated with access to unconscious material, creative inspiration and deep medidation.

- Alpha (α):
  These waves mainly appear in the parietal and occipital lobes of the brain. In the frequency domain these waves lie within the range of 8 - 13 Hz and often appear as sinusoidal shaped. This rhythm is believed to indicate a relaxed state without any concentration.

- Beta (β):
  These waves describe the brain activity in the range of 14 - 26Hz, and they are associated with active thinking and active attention. Besides that, they can be recorded over the frontal and central brain regions.

- Gamma (γ):
  This frequency band includes all the frequencies above 30Hz. Their amplitudes are very low and their occurence is rare, in fact their presence could confirm certain diseases - these frequencies are mainly located in the frontocentral area.

All the above waveforms, measured on the scalp, show amplitude values in the range 10-100μV and they are only the main types of rhythm, however is often difficult to understand and detect them, in fact it is possible to identify many other brain waves.
For example the μ - rhythm is related to α in terms of amplitude and frequency. However they are associated to different brain activities: μ denotes motor activities

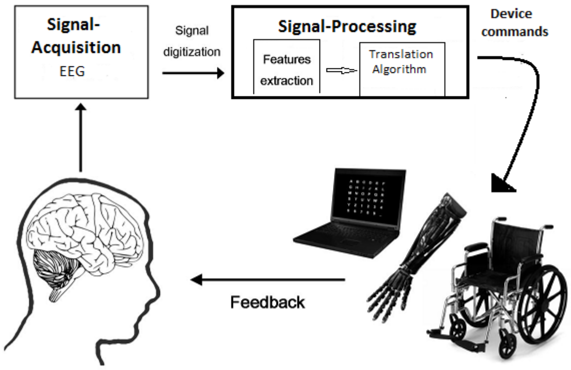

Figure 1.3: The basic design of any EEG based Brain-Computer Interface.

and is strongly recorded over the motor cortex; thus physical and imaginary movements can be investigated through the analysis of these rhythms. Indeed it is well-known from literature that during planning and execution of movement these waves are blocked: that is the so called *Movement Related Desynchronization* (MRD) phenomenon [2]. Which appeared in the brain's area contralateral to the imagined or performed movement, this phenomenon is exploited in some BCI's systems.

Since here has been spoken of EEG signal, however it is only the first step of the BCI structure which is called *signal acquisition*. After this latter, follow the *signal processing* and lastly the *output device* which actualizes the user's intent. Thus as any other BCI system, also the EEG-based BCI could be easily summed up by a blocks structure, Figure 1.3. The main operations that respectively compete to each block, are here below presented.

Signal acquisition

In the EEG -based BCIs, input signals come from an EEG device that records cerebral activity in the scalp of the subject. Recent digital EEG systems consist of a number of dedicate electrodes followed by a set of differential amplifiers (one for each channel) and filters. Besides that, to analyse EEG signals and process them in real time to provide the subject of a feedback is also necessary to digitize them. Thus, at this step of the BCI scheme the input is acquired by the recording

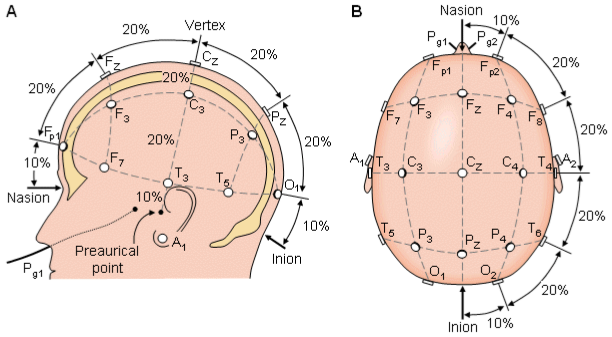

Figure 1.4: The standard International 10-20 electrodes setup.

electrodes, preprocessed, amplified and digitized.
The type and montage of the recording electrodes and their proper function are crucial for acquiring high-quality data. The International Federation of Societies for Electroencephalography and Clinical Neurophysiology recommends the usage of a standard called *10-20* defined with 21 electrodes. Usually the earlobe electrodes often identified as A1 or A2, respectively are used as reference electrodes[10]. In accordance with the International System, the 21 electrodes are arranged in five lines, and the EEG cap has two pivot points that are useful during preparation of an EEG recording: they are called *Inion* and *Nasion*. As pointedly shown in Figure 1.4, the Inion point is the prominence at the base of the occipital bone, while the Nasion is the top seam line of the nose. Each electrode is reffered with a letter indicating the lobe wich it belongs and a number from 1 to 21. Odd number mean position on the left hemisphere; on the other hand electrodes with even number lay on the right hemisphere. In case that more channels are needed, an extension of the conventional system can be operated: new electrodes can be placed in between the above 21 electrodes evenly separated from those already present. However, in BCI research applications often need a small number of electrodes decoding activity of the movement-related regions. Once located the sensors, the electrical potential difference between any electrode and the reference (A1 or A2) can be measured. It has to be noted that sensors are closely spaced: this means that they are highly correlated to each other.
For this reason the main problem is to separate the signals which carry information from the background in EEG - generally defined as *noise*, infact EEG is a highly

sensitive recording device so many other electrical internal and external signals can intefere with it causing disastrous artefacts. Thus signals need to be preprocessed. Eye-blinking, muscles movement, sweat and heartbeat are examples of physiological artefacts. Then other external disturbances generated by surrounding devices and environment can compromise EEG recordings. These disturbances can be removed through filtering operations and using suitable algorithms.
Once the brain-activity information is acquired, the signal digitalization process has to be performed. Since useful cerebral activity is mostly contained in a frequency range between 0 and 100Hz the Nyquist criterion for correctly sampling on analog signal establishes to choose a sampling frequency equal or higher than 200Hz.
In some applications where a higher resolution is required sampling frequencies of up to 2000 samples/s should be used. As the quantization resolution regards, a minimum of 16 bits is required to mantained the signal characteristics and, consequently, their diagnostic information.

Signal processing: features extraction

Once received the digitized signal, is necessary to extracts the signal features that encode the patient's messages or commands. A BCI can perform both time and frequency domain analysis. In general, the signal features extrapolated reflect brain events like the firing of a specific cortical neuron or the synchronized and rhythmic synaptic activation in sensorimotor cortex that produces a μ - rhythm. The knowledge of location, size, and function of the cortical area generating a rhythm or an evoked potential can indicate how it should be recorded, and how users might best learn to control its amplitude.

Signal processing: Translation Algorithm

In this step the signal features, previously extracted, are translated through algorithms into device commands-orders that carry out the user's intent. Whatever is the precise algorithm, it changes indipendent variables (signal features) into dependent variables (device control commands)[3]. The effective algorithms have 3 levels of adaptation to each user.
First, when a new patient beginns a BCI traetment, the algorithm adapts to that

user's signal features. For example, if the signal feature is the μ-rhythm amplitude, the algorithm should adjusts to the subject's range of μ-rhythm amplitudes. However, this first level of adaptation alone isn't enough, because the BCI would adjusts to the user only initially and never again, thus this is working-well only if the user's perfomance is very stable. Therefore is essential a second level of adaptation which consists of periodic online adjustments to reduce the impact of spontaneous variations, and to match as closely as possible the user's range of signal features values to the available range of device command values. Finally, the third level of adaptation exploits plasticity and adaptive capacities of the brain. Indeed, when an electrophysiological signal becomes an output that carries the user's intent to the outside world, it involves the adaptive capacities of the brain. As like in brain conventional neuromuscular communication, BCI signal will be affected by the device commands. Thus the wish is that the brain will modify signal features in order to improve BCI operations. For example, if the features are still μ-rhythm amplitudes, the correlation between that amplitude and the user's intent will hopefully increase during the treatment. An algorithm that uses this latter level of adaptation could recognize this user's improvement, and repay him/her with faster communication. It could be easily understood how important, and at the same time, hardly designed is this third level of adaptation, since it involves the interaction of two adaptive controllers: user's brain and the BCI system.

The output device

Commonly the output device is a computer screen, and the output is the selection of targets, letters or icons appearing on it. Some BCIs also provide additional output, for example the movement of a cursor towards an item previously selected, in this case the output represents the feedback that the brain uses to maintain and improve the accuracy of communication. The acquisition of the EEG signal has also been used successfully, although on simple routes, such as control of a wheelchair. Besides that, some BCI's experiments are also testing the control of a neuroprosthesis, in this case the user's own hand represents the output device.

Signal's features

Above has been pointed out the benefits of using EEG records and the general structure of such a BCI system. Although in the worldwide overview exist defferent schools. Thus present-day BCIs fall into 4 groups based on the electrophysiological signals they use.

- *Visual evoked potentials* (VEP)
  A first one group can be identified as that led by Jacques Vidal. In the course of his work, he developed a system that satidfied the current definition of a dependent BCI. This platform used the VEP recorded from the scalp over visual cortex to determine the direction of eye gaze, and thus to determine the direction in which the user wished to move a cursor. Thus VEP-based communication systems depend on the user's ability to control gaze direction.

- *Slow cortical potentials*
  Among the lowes frequency features of the brain-activity recorded EEG there are slow voltage changes generated in cortex. These potentials swing are noticed in time-intervals of 0.5-10 s and are called slow cortical potentials (SCPs). These potentials either can be positive or negative, in the first case they are associated with reduced cortical activation, while the negatives correspond to movement and other function involving cortical activation. These studies have been conducted for longer than 30 years by Niels Birbaumer and his colleagues, who have verified that people can learn to control SCPs and thereby control movement of an object on a computer screen. In this treatment, EEG is recorded from electrodes at the vertex referred to linked mastoids.

- *P300 evoked potentials*
  From brain's studies is known that particularly significant auditory, visual or somatosensory stimuli tipically evoke in the EEG over parietal cortex a positive peak at about 300 ms. Farwell and Donchin have used this "P300" in a BCI, where the user faces a matrix of letters whose rows and column at constant time intervals flash. The subject makes a selection by counting how many times the row or column containing the desidered choiche flashes.

The current P300-based BCI have a communication rate of one word per minute, but further improvements are possible. The advantage of such a BCI system lies in the fact that it requires no initial user training, indeed P300 is a typical and spontaneous brain response.

- *μ and β rythms from sensorimotor cortex*
  In awake people, motor cortical area often displays 8-12Hz EEG activity when it is not engaged in brain activity, this idle state is called μ-rhythm and is associated, as already mentioned, to the motor cortex. Some analyses have induced the discovery that μ-rhythm comprises a variety of different 8-12Hz waves, and are also associated with 18-26Hz β-rhythm. Therefore, several factors have suggested that these waveforms could be good for EEG-based BCIs, because they are associated with cortical areas connected to the brain's normal motor output channels. In particular, Gert Pfurtscheller [2] has noticed that movement or preparation to it is typically accompanied by a decrease in μ and β rythms, which starts in the contralateral brain hemisphere to the movement. Hence, this phenomenon already nominated in this script, have been called "event/movement-related desynchronization". While its opposite rhythm increase is called "event-related synchronization". Thus, Wolpaw, McFarland in the NY state and on the other hand Pfurtscheller in Graz have implemented BCI systems that employed these latter brain features. In their treatments through several repeated exercises, people with or without motor disabilities learn to control μ or β rythms amplitude and generally use that control to move a cursor to targets on a computer screen.

1.2.5 The main BCI's centers

For its particularly innovative idea the Brain-Computer Interface soon has been spread all around the world. Thus can be individuated several research areas, some of which has been already mentioned above.

1. The Berlin BCI (BBCI) group, which operates since 2000, whose main focus is reducing the intersubject variability of BCI [10].

2. The Wadsworth BCI research headed by Wolpaw and McFarland, as already said, uses mainly the ERD phenomenon of the μ-rhythm.

3. The Graz (Austria) BCI group is led by G.Pfurtscheller, their reasearch object are μ or β rythms amplitude

4. The San Camillo Hospital in Venice and Santa Lucia Hospital in Rome are the two major Italian BCI's centres, the first one collaborates with N. Birbaumer and whose experiments are exposed in Chapter 2.

1.3 BCI in future

BCI has been rapidly growing during the last three decades, and consequently non-muscular commuication and control is no longer merely speculation. The direct communication from the brain to the external world is possible and can serve useful purposes, in particular here has been viewed the motor rehabilition problem. Present BCIs in their best moments reach 25 bits/min. Thus the future progress of the BCI technology will depend on how much information transfer rate can be increased. The development is still in its beginning stages, and is not clear how far this project can go. However it is clear that the development depends on some crucial questions: BCI independence from the normal muscular communication channels, signal acquisition methods, chosen signal features, feature extraction techniques, translation algorithms, and output devices. Besides that, an other desidered aim is the portability of the system. For BCI technology based on wearable or epidermal EEG sensor systems, to become as useful for everyday activity as a note-book is today, technological breakthroughs will be required. Some such improvements may be enabled by Moore's law that should continue to allow extended scaling up in terms of amount of information integrated and the amount of offline and online computation performed [**?**].

Moreover has been seen that feedback plays an important role in learning to control human brain signals, and is of primary importance in re-stablishing the demaged sensorimotor loop. In effect, the brain's normal neuromuscular output channels depend for their successful operation on feedback, when this latter is absent from the start, motor skills do not develop properly; and when it is lost later on, skills deteriorate. Thus, a BCI system must provide feedback and must interact in a productive fashion with the adaptations the brain makes in response to that feedback. Moreover, successful BCI operation requires that the user develop and maintain a new skill, that consists of proper control of specific electrophysiological signals, and it also demands that the BCI translates that control into output that realizes the subject's intent. However a complete feedback system requires more effort and research to be undertaken. In addition, computationally efficient algorithms have to be developed in order to cope with the real-time applications. Finally, in order to reach a BCI system that could seroiusly promote motor learning of stroke patients, independently from the level of subject disabilities, it must be adapted to the real-time necessities.

Chapter 2

BCI at San Camillo Hospital

The *San Camillo Hospital Fundation*, which operates in Venice (Italy), since 1994 has been recognised by the Veneto region as Regional Specialised Hospital in neuro-rehabilitation. Thus this Hospital has become a reference point for patients, and their families, affected by brain and spinal cord injuries, stroke, multiple sclerosis, Parkinson's disease and so on. On March 2005, the San Camillo Hospital received the qualification IRCCS (Istituto di Ricovero e Cura a Carattere Scientifico). Besides, from more than 20 years the San Camillo Hospital conducts an extensive scientific research recognized by the Italian Ministry of Health. And in several of its researches, the Hospital takes advantage of a dense net of relationships and co-operations with important national and international institutes.

In particular, since some years ago, an alternative strategy to restore the motor functions from stroke has been attempted: the BCI system. In this experiment, the San Camillo Hospital has addressed the Department of Informtion Engineering (DEI) of the University of Padua, for an engineering support. Thus after seeing the entire BCI system, in the present chapter we focus our attention on the current platform used at the San Camillo Hospital. In this cooperation between Hospital and University a EEG-based Brain Computer Interface (BCI) has been used, in particular has been experimented a non-invasive, closed-loop circuit system between brain activity of the sensorimotor contralateral area of a stroke patient and a proprioceptive contingent feedback, in order to promote the reconstruction of the disrupted sensorimotor rhythm (SMR) loop. It should be specified that

this BCI system has been applied to patients with mild hemiplegia that are able to begin the asked movement autonomously and then the robot assistance helps them in completing the task or in moving on a more accurate trajectory. Anyway preliminary promising kinematic and neurophysiological outcomes supported the hypothesis that a contingent force feedback can improve motor functions.
In this chapter the importance of a contingent feedback, but also important attentions that must be taken into account for the system efficiency are highlighted.

2.1 Methodology

As just explained above, the goal of this study is to verify the importance of a contingent force feedback in a BCI scheme.
The experiment consists in a treatment which lasts approximately three weeks and is structured as described below:

- *The initial screening evaluation*:
  during this phase the subject does not receive any force feedback, instead he only undergoes a series of physiotherapic tests in order to know his clinical condition. In particular, it is well-known that during a movement, or even an imaginary one the spectral power in the sensorimotor area of the contralateral hemisphere in the μ and β bands – (8,12) Hz and (13,20) Hz, significatively decreases into respect to the rest condition. This phenomenon is called movement-related-desynchronization (MRD), and as it can be expected its frequency range and spatial localization is subjective, so it could vary individually. For this reason a screening session is needed: it allows to identify the scalp region and the range in which the MRD is stronger.

- *Six BCI training sessions*:
  each session is constituted by three runs per arm and during each of them the patient is asked to perform eighty times a standard center-out reaching task, that consists in reaching one-out-of-four cardinal points grasping the end-effector of a robotic device. The path that has to be covered is 18 cm long and a cursor on a screen in front of the subject represents the position

of the end-effector, thus providing a visual feedback of the trial course.
For convenience each trial is subdivided in 7 time-intervals:

- Pre-trigger: this is an initial window of 500 ms during which the subject is at rest;
- Post-trigger: this interval is activated after the appearance on a screen of the target cardinal point to reach. For simplicity it is further decomposed in 3 phases, lasting 500 ms each, and during this interval the subject has to wait in the starting position until an auditory signal is delivered.
- Reaction-time: after the above mentioned auditory sound, the patient is allowed to move but his/her reaction is not instantaneous; on the contrary it takes a little time to start the movement, usually about 400 ms. Indeed this time is needed firstly for the sound to be perceived by the patient and processed by the auditory human system, secondly the output motor command to be defined by the brain and transmitted to the muscles.
- Movement: the patient moves his/her arm towards the target. A movement is correctly performed if the subject reaches the target within a time interval between 500 and 740 ms. Otherwise, it is considered too slow or too fast and a different visual feedback on the screen is provided to the patient.
- Return: finally, the patient is asked to return to the initial position and relax before starting the next trial.

During the training just described, if the trauma is, for example, localized in the right hemisphere then produces effects of hemiplegia on the left arm, thus Cp2 and P4 electrodes shown in Fig. 2.1 has been selected for the injured arm and the symmetric locations Cp1 and P3 are chosen for the healthy one. These choices justify the fact that we are looking for the MRD in the hemisphere contralateral to the moving arm. Regarding the frequency bin was adopted the band detected during the initial evaluation, usually it is between (11-14)Hz.

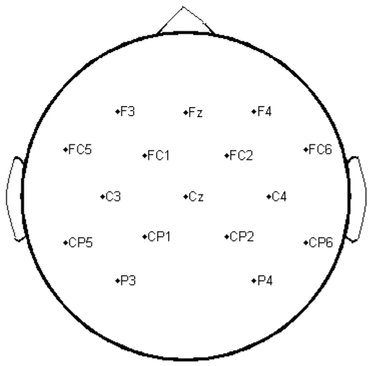

Figure 2.1: EEG sensors lacation

- *End test evaluation*:
  it takes place after the previous treatment of two weeks and as during the screening session, the patient does not receive any force feedback.

2.2 The system

Similarly to the general BCI scheme viewed in Chapter 1, the system layout adopted during the experiment is constituted by three main blocks: the acquisition unit, the signal processor module and the feedback one. It constitutes a closed-loop. Below, each block will be described in detail.

1. Acquisition unit:
   This block includes an electroencephalographic cap provided with 29 recording Ag/AgCl electrodes in a modified 10-10 system arrangement, and a 16 channels g.TEC amplifier g.USBamp. Thus are available only 16 out of 29 sensors, and are placed on the sensorimotor area, e.g. primary motor cortex, primary somatosensory cortex and the associative somatosensory cortex, as shown in figure 2.1. Each of these sensors is referred to the right-side ear lobe, whereas a site between P3 and P4 has been chosen as ground.
   Signals from the 16 sources are digitized with a 512 Hz of sampling rate and a 24 bit of resolution. Then a digital signal processor (DSP) applies a band pass filter between 0.1 and 60 Hz and a notch filter at 50 Hz to the data.

Finally, the amplifier sent the digitized EEG signal via USB connection to the processing unit.

2. Signal processing unit:
   This is the heart of the system. A standard pc processes the signals by means of BCI2000, a worldwide spread software implemented by Shalk in 2004 [7]. As already anticipated, this unit has an important role: it has to continuously quantify the MRD during the movement, that is the spectral power decrease in the selected (11,14)Hz band of the chosen two electrodes. These two spectral estimations are combined to a final value, called neuro-feedback (NFB). The latter can be viewed as a measure of the MRD phenomenon: the larger the NFB, the stronger the MRD and, so, the stronger the assistive force feedback provided to the patient. Finally, an UDP communication protocol controls the transmission of the NFB quantity to the next module.

3. Feedback unit:
   At this phase the NFB value coming from the previous block and updated every 16ms is transformed into a force level with a maximum of 6N. This contingent assistive target-directed force is provided to the subject during the trial. By means of a robotic arm device - PHANTOM, Premium 3.0/6 DOF Sensable Technologies. Actually, the feedback is delivered only if the current NFB value exceedes a minimum threshold in order to ensure an effective MRD-BCI control, helping the patient to accomplish the task. Thus, one can easily imagine how the system forms a closed-loop.
   On its turn, the feedback block is continuosly sending the task execution status to the signal processing unit that could compare the EEG recordings with the movement course. This inter-communication forms the afore mentioned BCI closed-loop and it is necessary, to effectively control the BCI system, and facilitate the following offline analysis during which the neurophysiological data are correlated with the kinematic behaviour.

Thus, as said at the beginning of this session, is evident that the entire circuit system constitutes a closed-loop between BCI and patient, however this leads the closing of another loop much more important but not visually perceptible. Indeed,

through the contingent feedback the sensorimotor loop compromised after the stroke, is closed artificially.
The robotic arm device, headed by the feedback-unit, provides a force to the patient and this impulse is sensed by the afferent pathways of the arm. Afferent neurons are fibers that carry nerve impulses from receptors or sense organs towards the central nervous system, in this case the sensorimotor perception is transferred to the contralateral hemisphere of the brain, the injured one. So communication has been restored, and has taken the form of a closed loop, as it should be under normal conditions.

2.3 Outcomes analysis

As has been explained at the end of 2.2 by the co-operation of the various system's blocks are made available neurophysiological and kinematic data. Comparing these outcomes of the final session into respect to the screening one, are quantified the improvements of the patient after the BCI treatment.

The Phantom device could record the knob real-time trajectory and instantenous speed through a sampling rate of 100 Hz, and other kinematic parameters as trial duration, mean speed and displacement from an ideal straight path. All these measures give different information, but equally important like: motor behaviour that is how many times the subject successfully completes the task, the rough arm control during the task course and finally improvements in the finer control and accuracy of the movement. These outcomes are computed all over the 240 trials of a session (80 trials each of three runs per arm).
Comparing these data is evident that the number of correct trials is significantly higher at the final session than at the initial screening test for both the affected and healthy arm. If at the beginning patient moved too slowly, with the training motion ability becomes faster and the subject spends shorter time to reach the target, thus the number of slow trials decreases.

Therefore, we have seen as such a BCI depends on the μ-rhythm. From the study on the brain activity it is well known that movement preparation and even its imagination are accompanied by that phenomenon already mentioned which is the MRD of the μ-wave, and this is noted especially in the contralateral sensorimotor

cortex. It should be observed that higher is the difference of the μ-rhythm between the movement and the rest period, stronger will be the desynchronization.
From outcomes it can be seen that a marked focalization in the ipsilesional part of the scalp arises. This fact agrees with the hypothesis that the ipsilesional part of the scalp is involved in neuroplasticity activities that lead brain to modify its functions, restore damaged paths or find alternative ways to re-stablish previous communications. The BCI traetment should exploit at its best the brain neuroplasticity, therefore through several repeated exercises the MRD could be voluntarily monitored, and the brain region near the stroke learns to control the movement. This approach is called operant conditioning.

In conclusion, the core idea of the BCI application presented in this chapter is to exploit μ oscillations to control an haptic device that acts in its turn as an input for the subject performing the task shaping a closed-loop scheme.
The neurophysiological data affirm the amplitude modulation of the μ-rhythm that acts as a carrier signal, like in the AM radio communication with the difference that here the information carried is about brain activity. The latter however can be modified with time and with respect to a lot of internal and external different causes.
This makes the MRD identification an issue, however the alghorithms used since here return a not too precise characterisation of the phenomenon, which needs to be better isolated from the typical EEG artefacts. This goal has been reached off-line, but the desidered aim is a reliable real-time filtering algorithm, in order to discard noise contributions in real-time.

Chapter 3

Design of a real filter

After seeing in Chapter 2 how works the BCI's system at San Camillo Hospital and the important results provided by a contingent force feedback, comes the real aim of this script.
Outcomes obtained by various experiments clearly show that the closed-loop scheme is significantly better if compared with previous BCI applications realized as open-loop circuit. However this approach introduces some problems and complicates the operation of the signal processing: in order to give a contingent feedback, which closes the sensorimotor loop damaged by the stroke injury and enhances the neuroplasticity of the brain, this force must be given in real-time that means before the movement, because only in this manner the patient can assimilate the correct action.
In defining the meaning of real-time we can be a little bit flexible, the important matter is giving the force before the movement, that is during the reaction-time which, as has been explained in 2.1, is subjective, yet it can be approximately set equal to 500 ms.

Besides, as already highlighted the signal process is not commonplace, during this stage are carried out several operations: the BCI platform receives the EEG signal previously digitized and here is applied a filter within a frequency band, where it is believed that MRD is present, then should be calculated the energy value and the corresponding brain area has to be located. Whenever actually there is the MRD phenomenon in the desidered brain area the patient would receive a

positive feedback, elsewhere - although it has not be tested yet - a negative one, but in both cases timely to the action. Thus each one of these operations must be done in time.
In addition the use of the filter makes the situation more delicate, in fact as well known the ideal filter isn't achievable, hence must be utilized a real filter which approximates how much better the ideal one, however introducing delay and distortion.

Thus, in this chapter firstly are described the parameters which characterize each filter, secondly is discussed the implementation of a digital filter in software.

3.1 Filter specifications

In electronics, telecommunications, computer science and all those disciplines that deal with signals, in a variety of applications it is of interest to change the relative amplitudes of the frequency components in signal, or perhaps eliminate some frequency components entirely, a process referred to as *filtering* [11]. In our case are considered filters designed to pass some frequencies essentially undistorted, and significantly attenuate or eliminate others, these are called *frequency-selective filters*. Furthermore, depending on the nature of the frequencies that need to be passed, is possible to identify some basic types of filter. For example, a *lowpass filter* is a filter that passes low frequencies, those around $\omega = 0$, and attenuates higher frequencies. A *highpass filter* is a filter that passes high frequencies and attenuates or rejects low ones. Finally, a *bandpass filter* - which is designed in this thesis-work - is a filter that passes a band of frequencies and attenuates frequencies both higher and lower than those in the band that is passed. And in each case, ω_c, the *cutoff frequency* is the frequency defining the boundaries between frequencies that are passed and frequencies that are rejected. Practically, a filter is an element that receives a signal *x(t)* as input, and return *y(t)*, a filtered version of the first one. Consequently, filtering can be accomplished through the use of LTI systems, for this reason a filter in time domain is characterized by its impulse response, often denoted *h[k]*, it is a measurement of how a filter will respond to the delta function, and its length is specified by N, the filter order. But the filter behaviour is mostly observed in frequency domain, thus an important parameter is the frequency response H(ω), obtained by the Fourier's transform of h[k]. Now is necessary to make an other distinction, the LTI system at issue can be described by differential or difference equations. In the first case the filter is said to be *analog*, which is a system operating on continuous-time analog signals. However, reminding the context in which we are working on, as saw in 2.2 the EEG signal, before being filtered, has been digitized, for this reason we need a digital filter, which performs its operations on a sampled, discrete-time signal.

3.2 The ideal digital filter

Fist of all, will be considered the ideal model in order to highlight the important properties in which we are interested.
Since it is believed that the MRD phenomenon of the μ and β waves may occur approximately around the value of 12Hz, therefore for an initial analysis we concentrate our attention on a frequency window sufficiently wide, set equal to [8-18]Hz,. The ideal digital filter has to pass signal components of this frequency interval without any distortion, thus - as shown in Fig. 3.1 - should have a frequency response that values one at these frequencies and zero at all other frequencies. As known the range of frequencies where the frequency response takes the value of one - that is (8,18)Hz - is called *passband*, therefore 10Hz is the *bandwidth* and the range of frequencies where the frequency response is equal to zero is called *stopband* of the filter. Besides, the digital filters have a periodic spectrum with a period equal to the sampling frequency Fs. Also, in the presence of a real signal in time the frequency response exhibits hermitian symmetry. Due to the periodicity of the signal in the frequency domain the hermitian symmetry translates in a hermitian symmetry between sample at frequency f0 and the corresponding negative frequency located at Fs-f0, that means this samples are complex conjugates, but have the same amplitude's value. For the case under study where we are designing a bandpass filter in the band (8,18) Hz the hermitian symmetry is for the samples at the frequency range (504-494) Hz. Specifically, if we consider a time interval 1 second long, we have 512 samples in the time domain. If we compute the signal in the frequency domain by FFT the 512 frequency samples numbered from 0 to 511 represents the spectrum samples at a frequency equal to the index number.

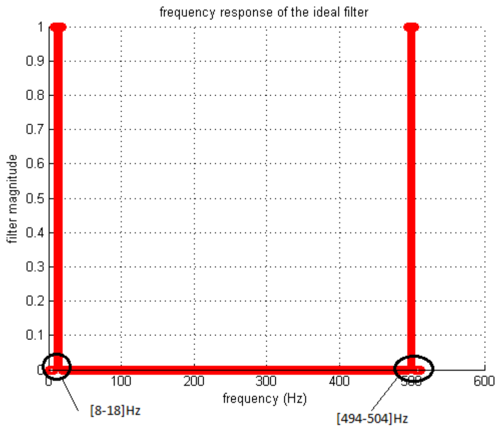

Figure 3.1: Ideal filter's frequency response

So, the ideal filter has zero values in the range [0-7], [19-493], [505-511], while it assumes the value 1 in the remaining samples, specifically for the samples [8-18] and [494-504]. As we will see, this ideal filter is quite useful in describing idealized system configurations, but it isn't realizable in practice and must be approximated.

3.3 A real digital filter

In 3.2 has been stated the desired characteristics, however such an ideal band-pass filter cannot be generated in practice, first of all because the corresponding impulse response is a *sinc* signal multiplied by a *cosine* function, that is not absolutely summable, and hence, the transfer function is not BIBO stable, then must also be noted that such an impulse response is not causal and is of doubly infinite length [9]. Thus the ideal filter with ideal features of Figure 3.1 cannot be realized by an LTI filter with a transfer function of finite order. Consequently, for practical purposes the ideal frequency response specifications are relaxed and is adopted a scheme of tolerance by including a transition band between the passband and the stopband to permit the magnitude response to decay gradually from its maximum value in the passband to the zero value in the stopband. Infact is sufficient to ensure that outside the specified frequency range the signal energy is arbitrarily small. Moreover, the magnitude response is allowed to vary by a specified amount both in the passband and the stopband.

3.3.1 Correspondence between frequency 'f' and angular frequency 'ω'

Since here with the term 'frequency' have been meant two different size: in 3.1 defining the lowpass, highpass and bandpass filters has been discussed their frequency behaviour respect to 'ω', instead in 3.2 'f', the size measured in Hz, has been interpreted as frequency. To avoid misunderstandings it is necessary to make some clarifications. During the MATLAB simulations and filter designing, as frequncy has been considered the quantity indicated with *f*, because the EEG machines as any other device measure the frequency in Hz. In this sense has been defined the frequency samples of the filter, the bandwidth 8-18Hz, the sampling frequency equal to 512Hz and so on. However commonly filter's parameter, algorithms and Fourier's transform formulas are expressed as function of ω known as angular frequency and measured in rad/s. These two sizes are related by the formula:

$$\omega = 2\pi * fT \tag{3.1}$$

At the frequency value $f_0 = \frac{1}{T}$ the angular frequency ω assumes the value 2π rad/s, thus it is defined in intervals whose length values 2π - the simplest one is [0,2π] - and outside this interval, in accordance to the periodicity property, the trend would be analogous. Therefore the frequency axis, previously defined in [0,512]Hz, will be described in [0,2π] in function of ω. The axis is still divided in 512 samples, with the difference that now the space among each other values $\frac{2\pi}{N}$, where 2π is the new length and N=512 the total frequency's samples. In this manner the real sample at 256Hz now corresponds to π, and as like the samples at 0Hz and 512Hz, for periodicity, were equal, now this equivalence is between 0 and 2π. However, for convenience, the interval 2π long considered is the range [-π, π], the same used in the next integrals.
Reminding the periodicity and Hermitian symmetry, can be deduced the follow correspondences:

- for the positive frequencies, f $\in$ [0,256]Hz $\Rightarrow \omega \in$ [0,π];

- for the the negative frequencies located in [257,511]Hz

$$\Rightarrow \omega \in [(-\pi + \frac{2\pi}{N}), (\frac{-2\pi}{N})];$$

Notice that in the above interval the extremes are included, thus the first interval has 257 samples, while the second one 255, a total of 512 samples as desidered. Similarly, also the filter's parameters can be expressed in the angular frequency domain, that is:

- the bandwidth primarily define as the frequency range [8,18]Hz becomes

$$\Big[8\Big(\frac{2\pi}{N}\Big), 18\Big(\frac{2\pi}{N}\Big)\Big] rad/s$$

- on the other hand the negative frequencies [494,504]Hz correspond to

$$\Big[\frac{(494-N)2\pi}{N}, \frac{(504-N)2\pi}{N}\Big] rad/s$$

Once specified these relations, can be introduced some important measures and formulas conventionally expressed in ω. Referring to Figure 3.2, important parameters are band edge frequencies ω_{sl}, ω_{pl}, ω_{pu} and ω_{su}, passband [ω_{pl}-ω_{pu}], transition bands $\Delta\omega_L$= ω_{pl} - ω_{sl} and $\Delta\omega_U$= ω_{pu} - ω_{su}, stopband, cutoff frequencies ω_{cl} and ω_{cu}, passband ripple (or deviation) δ_p and stopband ripple δ_s. Notice that for ideal (desired) filter, the passband frequency magnitude is normalized to 1 while the stopband to 0, and the frequency response of the designed filter oscillates between the high amplitude of 1 or the low amplitude of 0.

Digital filters studied in this chapter are specific causal and discret-time LTI systems. However the causality, synonym of feasibility, has important implications on behavior in frequency of the filter, that are here below discussed briefly:

- The frequency response cannot be zero except in a finite set of points;

- The amplitude of the frequency response, as shown in Figure 3.2, cannot be constant on a finite band, band-pass and stop-band show oscillations that cannot be eliminated - this is the Gibbs phenomenon which will be later explained.

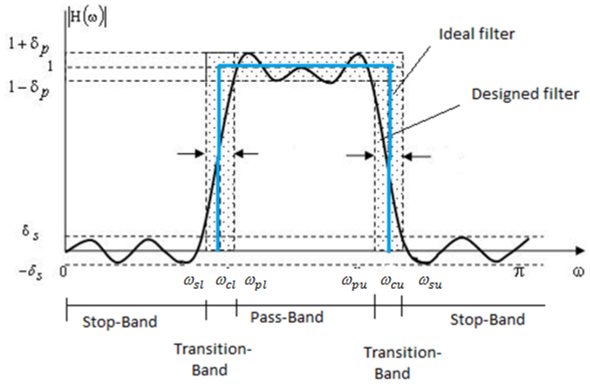

Figure 3.2: Relations among the frequency responses of an ideal band-pass filter and the designed filter.

Therefore, any digital filter that will be here considered is a particular LTI causal discrete-time system, however it could be differentiated by its impulse response length, since there are two main categories:

- **IIR filters**: belong to this group all systems having an *infinite impulse response* h[n]. For a causal IIR discrete-time system with a causal input x[n], the convolution sum can be expressed in the form:

$$y[n] = \sum_{k=0}^{n} x[k]h[n-k] \tag{3.2}$$

- **FIR filters**: if the impulse response h[n] is of finite length, that is, h[n]=0 for n<N_1 and n>N_2 , with $N_1 < N_2$
then it is known as a *finite impulse response* (FIR) discrete-time system. In this case the convolution sum is expressed as finite sum:

$$y[n] = \sum_{k=N1}^{N2} h[k]x[n-k] \tag{3.3}$$

This latter will be the type of filter used in all the next simulations, in fact the FIR filter will be more preferable than the IIR one, for two its properties:

1. A FIR filter is always causal and stable;

this can be noted observing its transfer function:

$$H(z) = \sum_{n=0}^{N} h[n]z^{-n} \tag{3.4}$$

It is a polynomial in z^{-1}, of degree N, with a unique pole in z=0, that is inside the unit circle.

2. A FIR filter could have a linear-phase design, this is ensured by the following condition:

$$h[n] = \pm h[N-n] \tag{3.5}$$

Comes now the real design of the digital filter, apropos exist several approaches that can be used, however the aim of this script is not that of displaying the different techniques, but rather attempt to identify a filter actually achievable, and in some sense - that will be clarified later - as close as possible to the ideal one in order to use it in the operations of signal processing for the BCI.
Therefore below will be given only a brief explanation of the various design methods, for more detailed information the reader is referred to [9].

3.3.2 FIR filter design based on windowed Fourier Series

Let $H_d(e^{j\omega})$ denote the desidered frequency response function. Since $H_d(e^{j\omega})$ is a periodic function of ω with period 2π, it can be expressed as a Fourier series,

$$H_d(e^{j\omega}) = \sum_{n=-\infty}^{\infty} h_d[n]e^{-j\omega n} \tag{3.6}$$

where the Fourier coefficients h_d[n]are the corresponding impulse response samples. However the desidered frequency response has sharp transitions between bands, and the the corresponding impulse response sequence h_d[n] is of infinite length and noncausal.

- **Least Integral-Squared Error Design** :
  In this case the objective is to find a finite-duration impulse response sequence h_t [n] of length 2M +1 whose DTFT $H_t(e^{j\omega})$ approximates the desidered

DTFT $H_d(e^{j\omega})$ in some sense. Actually the used approximation criterion is to minimize the integral-squared error:

$$\Phi = \frac{1}{2\pi}\int_{-\pi}^{\pi} |H_t(e^{j\omega}) - H_d(e^{j\omega})|^2 d\omega \tag{3.7}$$

where

$$H_t(e^{j\omega}) = \sum_{n=-M}^{M} h_t[n]e^{-j\omega n} \tag{3.8}$$

Using the Parseval's relation it could be rewritten as:

$$\Phi = \sum_{n=-\infty}^{\infty} |h_t[n] - h_d[n]|^2 \tag{3.9}$$

from this latter is clear that the integral-squared error is minimum when h_t[n]= h_d[n] for -M $\leq$ n $\leq$ M, in practice the best approximation in the mean-square error is obtained by truncation.
Defining the *rectangular window* $rett_M$(n) as:

$$rett_M = \begin{cases} 1, & \text{se } |n| \leq M, \\ 0, & \text{elsewhwere} \end{cases}$$

we have $h_t[n] = h_d[n] * rett_M(n)$, that is h_t[n] is obtained multiplying the desidered impulse response h_d[n], that we would approximate, by the rectangular window $rett_M$(n) just defined. However h_t[n] isn't causal, hence can be derived a causal FIR filter with an impulse response h[n] simply by delaying h_t[n] by M samples: h[n] = h_t[n-M].
Yet the causal filter obtained by such a sudden cutoff of the impulse response coefficients of the ideal filter causes some undesired effects, indeed exhibits an oscillatory behaviour in its magnitude response, this is well-known as *Gibbs phenomenon* . The reason can be explained examininig the windowing process in the frequency domain, where from the convolution theorem the expression $h_t[n] = h_d[n] * rett_M(n)$ becomes:

$$H_t(e^{j\omega}) = \frac{1}{2\pi}\int_{-\pi}^{\pi} H_d(e^{j\omega})\Psi(e^{j(\omega-\varphi)})d\varphi \tag{3.10}$$

Ψ stands for the frequency response of the rectangular window $rett_M$(n), and is defined as follow:

$$\Psi(e^{j\omega}) = \sum_{n=-M}^{M} e^{-j\omega n} = \frac{sin([2M+1]\omega/2)}{sin(\omega/2)}. \tag{3.11}$$

This response consists of a main lobe and many sidelobes, thus is an oscillatory signal and when is convolved, as indicated in 3.10, with the ideal response $H_d(e^{j\omega})$ will result a response $H_t(e^{j\omega})$ having a non-zero transition width and ripples in both the passband and stopband, this is the fact to which has been alluded at the beginning, and illustrated in Figure 3.2.

From 3.10 can be observed that if $\Psi(e^{j\omega})$ is a very narrow pulse centered at ω=0, that means a delta function, the interesting result of the convolution operation is $H_t(e^{j\omega}) = H_d(e^{j\omega})$, this is ideally our aim. On the grounds that the main lobe of Ψ is characterized by its width $\frac{4\pi}{2M+1}$, this will be narrow as an impulse function if M $\to \infty$, in other word this implies that the length 2M + 1 of the $rett_M$(n) window should be very large. On the other hand, the length or order 2M + 1 of the filter h_t[n], and hence that of $rett_M$(n), should be as small as possible in order to make the computational complexity of the filtering processes easier. Thus we have found two important but contradictory requirements, that must be taken into account during the designing evaluations.

In conclusion the presence of the oscillatory behaviour in the Fourier transform of a truncated Fourier series representation is due to two reasons:

1. The impulse response of an ideal filter is infinitely long and not absolutely summable, and consequently the filter is unstable;
2. The rectangular window has an abrupt transition to zero.

- **Fixed Window Functions:**
  When we simulate $H_t(e^{j\omega})$ using Maltlab sofware, with N = 2M +1 in the

hundreds we still see the non-zero transition width and ripples due to the Gibbs phenomenon. An infinitely long windows is not practical, so the idea is to look for finite duration windows which perform better than the rectangular. Infact the oscillatory phenomenon can be reduced, but not eliminated, by using a window that tapers smoothly to zero or by providing a smooth transition from the passband to the stopband. In literature there are many windows proposed, however there are four commonly used tapered windows - the same that have been used in this work - of length N = 2M + 1 listed here below:

- **Bartlett** window $w[n] = 1 - \frac{|n|}{M+1}$, $-M \leq n \leq M$
- **Hann** window $w[n] = \frac{1}{2}[1 + cos(\frac{2\pi n}{2M+1})]$, $-M \leq n \leq M$
- **Hamming** window $w[n] = 0.54 + 0.46cos(\frac{2\pi n}{2M+1})$, $-M \leq n \leq M$
- **Blackman** window $w[n] = 0.42 + 0.5cos(\frac{2\pi n}{2M+1}) + 0.08cos(\frac{4\pi n}{2M+1})$, $-M \leq n \leq M$

In Fig. 3.3 can be observed a comparison between these latter and the rectangular one. Could be noticed a common property, all the windows mentioned are symmetric about the mid-point $n = \frac{N-1}{2}$, these when combined with the symmetry or antisymmetry of the filter's impulse response will make the corresponding designed filter linear phase. As seen for the rectangular window, to ensure a fast transition from the passband to the stopband, the window should have a very small main lobe width, but as N increases also the sidelobes amplitudes rise. Contrariwise, to reduce the passband and stopband ripple δ, the area under the sidelobes should be very small, therefore the two conditions cannot occur togheter. Anyway, the maximum amplitude of the oscillations created by the rectangular window is substantially greater than those generated from others windows, then can be noted an improvement.

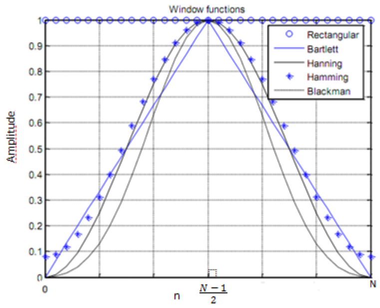

Figure 3.3: A comparison between the most used windows

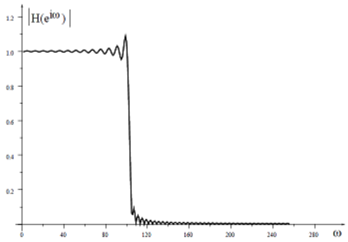

Figure 3.4: An example of low-pass filter designed through windowing

3.3.3 Design of Equiripple Linear-phase FIR Filters

As seen, the previuos method based on window creates some oscillations, which can be attenuated but not eliminated, in particular can be observed a peak in correspondence of the cutoff and bandstop frequencies, as shown in Figure 3.4. Thus the idea is attempt to lower the maximum oscillations amplitude, in order to spread this ripples all over the pass-band and stop-band. This is the optimization technique for the design of FIR filters, which try to minimize iteratively an error measure that is a function of the difference between the desired frequency response D($e^{j\omega}$)and the frequency response H($e^{j\omega}$) of the filter being designed. The weighted error function is given by

$$\varepsilon(\omega) = W(\omega)[H(\omega) - D(\omega)], \tag{3.12}$$

where W(ω) is a positive weighting function. This approach attempt iteratively to adjust the coefficients of the amplitude response H(ω), until the peak absolute value of ε is minimized. The linear-phase FIR filter obtained in this way is usually called the equiripple FIR filter, since after ε has been minimized, the weighted error function exhibits an equiripple behavior in the frequency range of interest. In literarute exists several algorithms dealing the problem, however these will be neglected .

Concluding, these are the FIR filters that are evaluated in Chapter 4. The design of these objects using a peculiar MATLAB's toolbox has been realized. And keeping in mind the purpose of the project, namely design a real filter in order to measure the energy of EEG signals, the performance of each real filter, comparing it with the ideal one, has been tested. Despite the different techniques adopted, there are obviously common features: all of them are pass-band filters in the range (8-18)Hz as set in 3.2, for each one a transition band of 0.5 Hz has been accepted, and regarding their order N it can be initially assumed equal to 200.

Chapter 4

Matlab Simulation

Here, the work that has been performed in MATLAB is explained in detail: simulations, counts and consequently from the outcomes, comparisons and considerations. Everything in order to achieve the best solution to our problem has been done: verify the presence and effects of de-synchronization phenomenon - remind it is a decrease of the energy - in the μ-rhythm recorded by the EEG. In fact, in conditions under which we have at our disposal the recordings of the EEG signals, obtained by asking the patient to perform exercises, i.e. the movement of an arm, filtering this recorded signal by an ideal pass-band filter (such as that described in 3.2), is possible to measure its energy over a fixed time window, thus verifying the actual presence of the MRD phenomenon.
Herein the same energy analysis using a real digital filter is repeated, notice that - as explained in Chapter 3 - the real filter introduces distortion and especially delay, this is the aspect in which we are most interested, since we would like to give the patient a real-time feedback.

4.1 Construction of the signal

First of all is necessary to describe the signal, which is the real subject of the work, because is on this latter that the various filters have been tested.
To verify the efficiency of the filter it has been considered appropriate to generate a synthetic signal, that means it has length, energy values and other parameters

established and eventually modified in the course of the analysis by us, this obviously using a signal actually recorded would not have been possible. This synthetic signal should simulate the information acquired from the EEG records, and when it arrives at the processing stage it has already been digitized, therefore has been considered a sampled sequence s[n]. The sampling frequency has been set equal to 512 Hz - that means there are 512 samples per second - and for convenience in carrying out the calculations and in using the FFT algorithm, the length of s[n] has been put equal to a power of 2, and precisely 2^{14} that is 16384 N_{FFT} samples. In 2.1 has been viewed that an experiment session is constituted by eigthy trials, here for our considerations has been created a short sequence of only 3 trials. The trials corresponds to the EEG signal recorded during an exercise, thus it carries the real information; each trial for convenience is subdivided by us in 7 phases and these by one or more markers, m_i which as reference points are used, are identified. Furthermore, as known from neurological studies and as already explained, during the imagination and execution of the task in the brain occurs an energy decrease, the so called MRD phenomenon that we should identify through the filter, so in the construction of the artificial signal this spontaneous neural phenomenon has been taken into account, trying to simulate it. Here below are listed the intervals that compose a single trial.

1. **Pre-Trigger**:
   It has a fixed length of 256 samples and its marker is called m_1;

2. **Post-Trigger 1**:
   This has the same fixed length of 256 samples, is distinguished by m_2, and at this point begins the de-synchronization, thus the values of these samples are multiplied by a coefficient equal to 0.9;

3. **Post-trigger 2**:
   It is constituted by 256 samples, marked by m_3 and has a coefficient equal to 0.7;

4. **Post-trigger 3**:
   It has a length analog to 2) and 3), is marked by m_4 and has a coefficient equal to 0.66;

5. **Reaction-time**:
   This interval clearly is subjective, thus a variable length in the range of [200,500] samples has been set, and marked by m_5. Here the patient is preparing him/her-self for the asking task, therefore in the sensorimotor brain area the energy continues to decrease and there is an even more low coefficient, equal to 0.64;

6. **Movement**:
   Also this phase is individual, its length can vary between [500-1000] samples, differently from the other blocks, this has two markers, m_6 at the beginning of the interval, and m_7 is set 256 samples farther, and all the block is multiplied by 0.62;

7. **Return** :
   This period could be constituted by 1000 or 1500 samples and is marked by m_8. Here the subject returns to the idle state, thus the MRD phenomenon finishes.

This structure has been applied three times - one for each trial. It is the core of the signal, but at the beginning a sequence of 10 blocks each containing 256 samples - totaling 2560 starting points - has been introduced as illustrated in Figure 4.1. This latter correspond to an initial condition of rest of the patient, so hasn't any useful information, however these samples in the signal processing operation result helpful, because allow the real filter to deplete its transitory phase, infact now the impulse response will have the main lobe, due to the causality, no longer centered around the 0 but shifted slightly later. However, if the order N of the filter initially set equal to 200, were to be increased may would be necessary to lengthen this initial phase.
In order to simulate as closely as possible the uncertainty of the EEG signal, the total sequence - 2560 starting samples plus the 3 trials - has been defined as a white Gaussian process, that is a particular random process. A generic random process is a function of two variables

$$x : \mathbb{Z} \times \Omega \mapsto \mathbb{R} \tag{4.1}$$

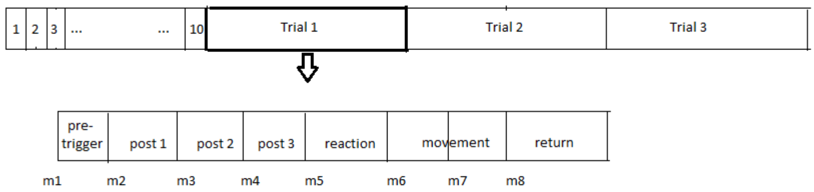

Figure 4.1: The structure of the synthetic signal: at the beginning there are 10 blocks of 256 samples each one, then there is a sequence of 3 *trials* each one done up of seven phases idicated by one or more markers m_i.

where $\mathbb{Z}$ is the temporal domain of the discrete-time process, Ω is the sample space of some probability space. If we fix $\omega = \omega_0$, the process is indicated as x(nT), with n $\in \mathbb{Z}$, and is called a *realization* of x. An important class is that of Gaussian processes. Recalling that a single random gaussian variable $x \sim$ N(μ , σ^2) is characterized by its probability density function:

$$p_X(a) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(a-\mu)^2}{2\sigma^2}} \tag{4.2}$$

More generally, N random variables forms the random vector $\mathbf{X} = [x_1, x_2, ..., x_N]^T$ and are said to be jointly gaussian if their joint pdf is as follows:

$$p_{\mathbf{X}}(\mathbf{a}) = \frac{1}{\sqrt{2^N \pi^N det k_X}} e^{-\dfrac{1}{2}(a-\mu_X)^T k_X^{-1}(a-\mu_X)} \tag{4.3}$$

where $\mu_X = E(X) = (E(x_1), E(x_2), .., E(x_n))^T$ is the mean vector and $k_X = E((X - \mu_X)(X - \mu_X)^T)$ is the covariance matrix. Thus, a random process is said to be Gaussian if, casually selected N signal's samples these are N random variables jointly Gaussian, that is their pdf is defined by expression 4.3, and the amplitude of each sample is indipendent from the previous values, that is the process is memoryless. Besides that, each one of these Guassian variables x is normalized, namely has mean, $m_X = 0$, and variance $\sigma^2 = 1$, thus from the definition of statistical power and variance follows that M_x=1 .

- Statistical power of x: M_x= E[$|x^2|$]

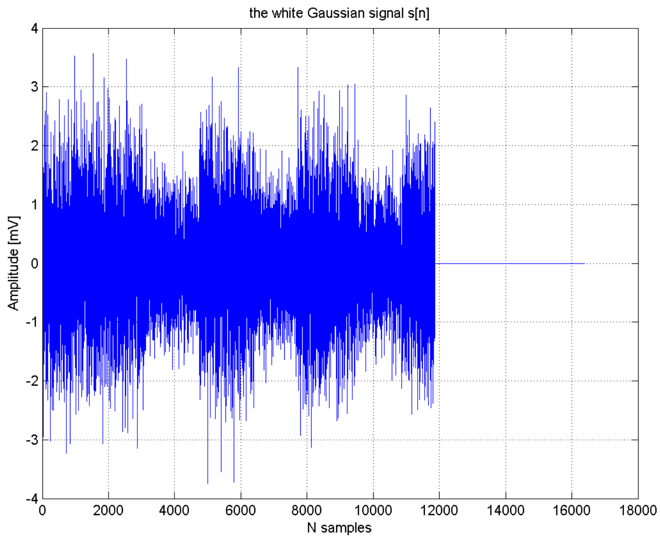

Figure 4.2: The signal s[n] which simulates the EEG records, it is a realization of the random process

- Variance of x : $\sigma_x^2 = \mathrm{E}[(x-m)^2]$

Then the statistical power of the entire sequence is still equal to one. Therefore, having seen the independence among signal samples, we can also deduce their incorrelation, that is:

$$r_X(\tau) = E[x(t)x(t-\tau)] = 0, \forall \tau \neq 0 \tag{4.4}$$

from this latter follows that the autocorrelation function can be expressed as

$$r_X(\tau) = a\delta(\tau), \tag{4.5}$$

with a > 0. Then the power spectral density *S(f)* of the signal, defined as the Fourier Transform of $r_X(\tau)$, from the well-known properties of δ function turns out to be a constant.
This implies that *S(f)* will be constant at all frequencies, and is the reason why the signal is defined white. Lastly, after this sequence a series of zeros up to reach a total length of 16384 samples has been queued - obtaining the signal in Fig. 4.2 - the reason of this operation is avoiding the *Aliasing* phenomenon in the frequency

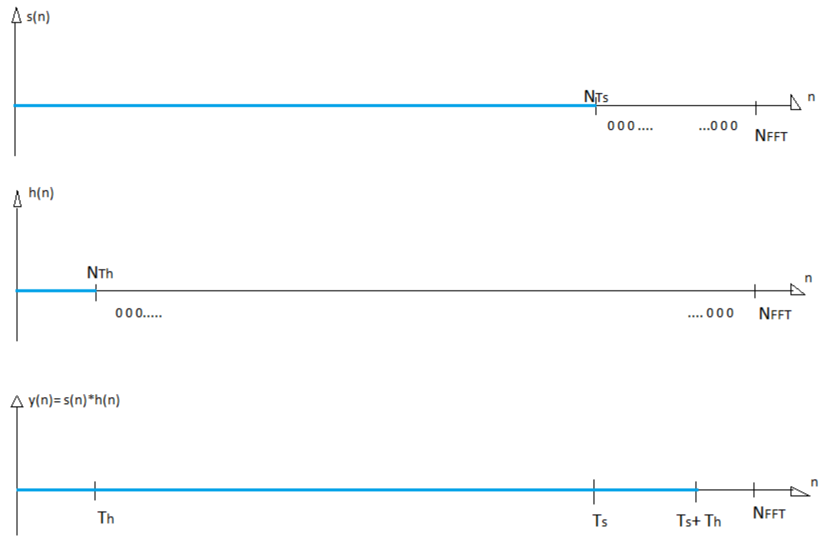

Figure 4.3: The respective lengths of the signal s[n], the generic impulse response h[n] and the output signal y[n] obtained from the convolution sum of the previouses.

domain.

The reason of the initial 2560 samples, and the final sequence of zeros can be clearly understood refering to Figure 4.3. As already exposed, for convenience in using the FFT algorithm, the length of s[n] has been set equal to a power of 2, and precisely it values 16384, thus N_{FFT}=16384. The generic impulse response h[n] has a length equal to N +1, where N is the filter's order. However in order to carry out correctly the convolution sum with s[n], h[n] has been viewed as a vector 16384 samples long, with N +1 initial samples, and filled up with a sequence of zeros. Notice that the condition

$$N_{T_s} + N_{T_h} < N_{FFT}$$

allows to avoid the undesidered *Aliasing* phenomenon, which otherwise would lead to the overlapping of the various replicas of the spectrum. Moreover, from the Figure 4.3 can be seen that y[n] length is equal to

$$N_{T_s} + N_{T_h},$$

but outside the central sequence of amplitude $T_s - T_h$, there are two subsequences both N_{T_h} samples long. These latter sequences correspond to an initial and final transitory phase due to the filter. For this reason is necessary to introduce the initial sequence of 2560 samples, because this let the filter to complete its transitory phase.

4.2 Filtering

Once the signal has been built, on this latter is possible to test the ideal filter and the FIR filters designed using the MATLAB toolbox. The FIR filters that has been decided to design and compare are: the least-squared designed filter, the equiripple filter, Bartlett window, Hamming window, Hann window, Blackman window and the Rectangular window. Whole these filters in MATLAB are called *dfilt* objects. Recalling that in the designing phase of these objects have been set:

1. The filter order N, equal to 200;
2. The sampling frequency equal to 512Hz;
3. *Fc1* the first cut-off frequency at 8Hz, and the second one *Fc2* equal to 18Hz;
4. Finally, a transition band of 0,5Hz.

Entering all these parameters, MATLAB returns us the respective impulse response coefficients, that is the samples of *h(n)*.

To proceed in the evaluation of the filter there are different philosophies.
A first one approach consists in considering the impulse responses:

- $h_I(t)$, the ideal impulse response whose energy is E_{h_I};
- $h(t)$, the impulse response of a generic FIR filter, with energy equal to E_h.

Defining the residual error as:

$$e(t_0) = E_{h_I}(t) - E_h(t + t_0), \tag{4.6}$$

where t_0 indicates the amount of which has been delayed the real filter respect to the ideal one. With the least squared estimation could be identify the value of t_0 that minimizes the error just defined. And the result will be two impulse responses

very similar in terms of waveforms.
Alternatively, since we are designing a filter to evaluate the energy values, and the input signal is a random process we could check whether may be possible to find some regularity. Therefore the optimal filter is selected according to the similarity of the energies in output. This second method, is a post-processing evaluation, and omits certain smallness in the structure of the filter, however, in our case may be a valid procedure.

4.2.1 Energy evaluations

All the next considerations will be done on the energy values, which is an important measure of the EEG signal.
Initially has been considered the signal s[n] just described in 4.1, and in order to have a greater knowledge on the behavior of the signal energy, has been chosen to calculate this parameter over 256 samples. Performing this calculation, the energy has been defined as the sum of the squares, that is:

$$E = \sum_{i=1}^{256} x_i^2. \tag{4.7}$$

Besides that, the entire sequence has been subdivided into 34 slots - 10 for the initial sequence, and 8 for each trial - each of them is identified by a point m_i that marks the beginning. The count has been performed more times, moving the markers, m_i, each time 8 samples further, to better understand the effects of de-synchronization along the signal.
Knowing that the energy can be described by an exponential random variable, has been found that its mean value m_T over 256 samples is equal to 0.5, then the corresponding variance σ^2 is $\frac{1}{32}$, and the outcomes obtained confirm these values.

All these calculations has been repeated for the signal filtered by the ideal filter, and the various FIR filters constructed. Practically, has been determined the energy of the filtered signal on sequences of 256 samples, and beginning in points identified by $m_i + \Delta$, where $\Delta = h \times 8$ and $h = 0, 1, 2, ..., 128$.
It has been decided to proceed by steps of 8, as it is not too great but not too small, and suitable for a first evaluation, if during the analysis we would have access to

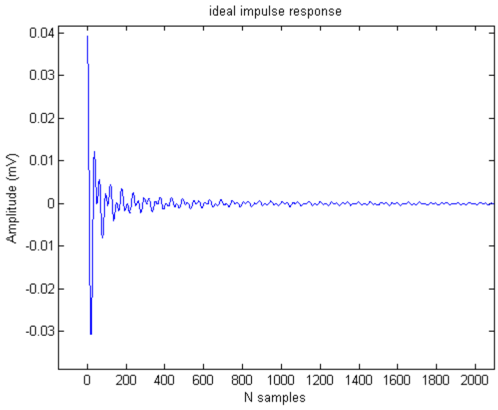

Figure 4.4: The first samples of the ideal impulse response

more data, then will be possible to apply a more meticulous finding. Goal lies in identifying the optimal value for Δ, and what means optimal will be explained later.

First of all have been considered the outcomes obtained using the ideal filter, with delay set equal to 0, that is the ideal output as it appears after filtering operations, without applying any further delay. At this step have been calculated the ratio between the energies of the trials's slots, E_{Tk} with $1 \leq \text{k} \leq 24$, and the energy in the third one block E_3, this provides 24 values - 8 for each trial. Therefore, the energies E_{Tk} namely have been normalized respect to E_3, this operation attempts to stabilize the random process. The choice to take E_3 as a reference parameter is made according to the length of the ideal impulse response, this latter is *sinc*cos* function and making a zoom on the initial part, in Figure 4.4 it can be seen that the impulse decays after about 500 samples, then in order to have a fine evaluation of the energy we should wait until the third block of 256 samples.
Thus we have these 24 values :

$$\frac{E_{T1}}{E_3}, \frac{E_{T2}}{E_3}, \frac{E_{T3}}{E_3}, ..., \frac{E_{T24}}{E_3} \tag{4.8}$$

Therefore, considering the real filters these operations have been repeated, with the difference that here have been applied a delay. Indeed, it is known that a real filter introduces a proper delay - since its impulse response isn't centered arround the 0 - and considering the output obtained, in the energy calculation an additional delay has been introduced, that is the initial points m_i have been translated to samples multiple of 8 gradually larger. The idea is to iterate this operation for each FIR filter and delay, in order to find that value of Δ which makes the output energy much more similar to that obtained by the ideal filter. Notice that, since the evaluations are made on the filtered sequence it is a post-processing approach.

As optimization criterion has been used the least-squared estimation, considering as residual error the amount:

$$e_{k,h} = (\frac{E_{T_k}, h}{E_3, h}) - (\frac{E_{T_k}}{E_3}) \tag{4.9}$$

where, $1 \leq k \leq 24$ indicates the slot and h stands for the delay value applied to the FIR filter. Thus, the aim is search such a value of Δ, or rather h at which the mean squared error is minimal, that is:

$$h^* = argmin \sum_{k=0}^{24} \frac{(e_{k,h})^2}{24} \tag{4.10}$$

This will be more clear with an example.
For a generic FIR filter, setting the delay equal to h, the 24 ratios are:

$$\frac{E_{T1,h}}{E_{3,h}}, \frac{E_{T2,h}}{E_{3,h}}, \frac{E_{T3,h}}{E_{3,h}}, ..., \frac{E_{T24,h}}{E_{3,h}} \tag{4.11}$$

Now is possible to relate the two sequences of values, by the mean-squared-error definition follows:

$$\frac{(\frac{E_{T1,h}}{E_{3,h}} - \frac{E_{T1}}{E_3})^2 + (\frac{E_{T2,h}}{E_{3,h}} - \frac{E_{T2}}{E_3})^2 + ... + (\frac{E_{T24,h}}{E_{3,h}} - \frac{E_{T24}}{E_3})^2}{24} \tag{4.12}$$

The smaller the value obtained, better the real filter approximates the ideal one in terms of output's energy. This considerations should be executed for each delay's value, thus is possible to find the least one error, which ideally should tend to zero. Once determined, for each filter, the optimal value of h, the filter's performance could be studied and compared through the SNR evaluation. As known, SNR stands for Signal-to-Noise-Ratio, infact this parameter compares the level of a desired signal to the level of background noise. In our case, the energy of the output obtained through the ideal filter stands for the useful signal, whereas the minimal mean-squared-error represents the noise, or better distortion.

$$SNR = \frac{E_{y_ideal}}{\sum_{k=0}^{24} \frac{(e_{k,h^*})^2}{24}} \tag{4.13}$$

4.2.2 Outcomes analysis

Since the synthetic signal s[n], as the potential EEG signal, is a random process the obtained results obviously aren't ever the same, however through several filtering operations some results can be observed.
As above exposed our optimization criterion is the mean-squared error, clearly we are interested in the minimum value of this error, and consequently in the corresponding delay Δ. Observing various simulations, this delay's values in most cases is located around the peak of the main lobe of the filter's impulse response, or it is spaced of few samples from this point - it was an expected result. Since the peak corresponds to the 100th sample, then the designed filter introduces a delay approximately equal to 200ms, and regarding our application, it could be acceptable.
An other investigation is based on the SNR ratio, as known, the higher the SNR value, more negligible is the distortion, and consequently the correspondent FIR filter is approaching well the ideal one in terms of energy. By this latter parameter we can be satisfied because its value is approximately 10^3 or equivalently 30dB. Notice that the two parameters, namely the optimal delay Δ and the maximum SNR ratio, sometimes aren't correlated, thus comparing the various filters a trade-off of these two measures should be taken into account. Reminding that, the analysis just explained has been executed shifting the markers point m_i at samples multiple of 8 even more higher, actually the error identified as minimum might be only a relative minimum value, then the search could be refined. In practice, once determined the minimum value of the error, and the corresponding delay Δ, the energy evaluation on the fixed windows of 256 samples has been perfomed again,

but the research has been focused around Δ, that is considering the previouses 7, and nexts 7 samples. Therefore, proceeding sample by sample the minimum absolute error for the corresponding real filter has been found.

Rather than, setting the filter order N equal to 50, obviously it introduces a lower delay, but on the other hand has been observed that the SNR ratio decreases - it stands in the hundreds - thus it does not appears as a better choice. Even though would be necessary more measurements, some constants outcomes can be observed: among the designed real filters, the major SNR ratio usually is reached by the least-squared designed FIR filter, the equiripple or eventually by the Rectangular window. This latter, in Chapter 3 has been discarded because of the Gibbs phenomenon, instead regarding our problem it seems to be a good possibility, but to confirm this hypothesis further and more sophisticated analyses are neeeded.

Chapter 5

Conclusions

Since the beginning of this thesis-work, the primary importance of a contingent-feedback in closed-loop BCI system has been highlighted. In fact, it constitutes an input for the impaired subject, in this manner he/she could maintain and improve the communication. Thus it is an attempt to reconstruct the disrupted SMR loop, in fact in normal condition means the body and the senses the brain would independently provide such a feedback. Actually a child, since the most banal action, learns receiving a feedback response about the status of the action in progress. However this physiological and spontaneous brain activity, in an artificial way, will not be as easily implemented.
Along the chapters of this thesis-work have been exposed the delicate operation of the EEG signal processing, which consists of several steps: the extraction of signal features which encode the patient's message, the identification of location, size and function of the brain area generating the signal feature, and finally through algorithms the translation of the encode brain message into device-commands; this latter constitutes for the patient a form of feedback response. These whole procedures must be done in time to allow the subject learning the correct action. Thus, even if in different ways, any BCI system should cope with the real-time issue.

The present thesis-work focused on the San Camillo's Brain-Computer interface, described in detail in chapter 2. In this case, acting in real time means: detect the MRD phenomenon on the controlateral hemisphere, calculate the corresponding

contingent force feedback and provide it at the beginning of the movement phase. We have at our disposal about 500ms. Confident results has been reached off-line, but the desidered aim is a reliable real-time filtering algorithm, in order to discard noise-contribution in real-time, during the BCI's treatment. Therefore, the present thesis-work with its aim of designing a real digital filter with the features descibed in chapters 3 and 4, is a first attempt to solve the question of the real-time.
However from the obtained results emerges that the project hasn't reached the aim yet, and we are only at the beginning step, in fact it isn't able to determine exactly the most suitable filter. Firstly, this limit can be explained by the fact that the signal s[n] is too brief, in effect in order to be able to get a statistic would be needed more trials. The research may proceed using different approaches and tools, which due to time constraints here have not been tested, but examples of different and possible future strategies are:

1. The energies E_{Tk} could be normalized respect to the mean value of the energies in the first 10 blocks, rather than to E_3;

2. Alternatively, the normalization could be executed previously, that is the energy of the signal filtered by the real FIRs can be normalized respect to the energy of the ideal output;

3. Finally, could be used a completely different approach based on the impulse response, rather than on the filtered signal. This method has been already mentioned in chapter 4, it attempts to find a simalirity in terms of waveforms; it might be stronger, that is if this latter idea should work well then it also implies the efficiency of the method in this thesis-work presented.

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