Electroencephalogram Signal Analysis

Electroencephalogram Signal Analysis:

Epileptic Cerebral Activity Localization and Implementation

Edited by

Salah Hamdi

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FOREWORD

The electroencephalogram (EEG), which records electrical activity in the brain, is quickly becoming a standard tool for studying human brain functioning and diagnosing different mental and neurological illnesses. In fact, the analysis of EEG data has been identified as the most prevalent technique to the challenge of obtaining knowledge on brain dynamics. Data analytics, machine learning, and artificial intelligence (AI), as well as biomedical engineering, are examples of computational, mathematical, and engineering domains that are fast evolving. A thorough, accessible, and research-informed book on current breakthroughs in biological signal processing is long needed.

EEG Signal Analysis: Epileptic Cerebral Activity Localization and Parallel Implementation, edited by a team of scholars with expertise in the field of medicine, computer science, electronics and quantitative methods satisfy this requirement by reporting on the most recent breakthroughs in EEG signal analysis.

Dr. Salah Hamdi received his PhD in 2016, and has been at the Laboratory of Technology and Medical Imaging at the Faculty of Medicine of Monastir, University of Monastir since 2009. Currently, he is Principal Professor Emeritus at the Higher Institute of Finance and taxation of Sousse. One of his main areas of research is that of computer science, AI and signal analysis.

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The edited EEG Signal Modeling and Classification: Epileptic Cerebral Activity Localization and Parallel Implementation collection is structured in five chapters. The first chapter is devoted to providing a full overview and a comprehensive introduction of EEG signal processing methods. The second one deals with neural methods to EEG signal classification. The book explains how machine learning may be used for locating epileptic brain activity in the third part. The fourth chapter explains a parallel implementation for EEG artifact elimination. Finally, the book uses VAR models to investigate correlation and causation between EEG signals.

The book provides an extensive and modern assessment of advancements in this fast-moving topic for academic scholars and practitioners. The book provides a multidisciplinary update on biological signal methodologies and applications with contributors from diverse fields of research. We need to process biological signals more than ever with the health and medical concerns facing the rising and aging population of the planet.

This edited collection is a contemporary and great resource for students and researchers that deal with a range of data, data and signal processing techniques. The collection is highly suitable for undergraduates and graduate students.

CHAPTER 1

PREFACE

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The progress of digital electronics and computer technologies is sweeping through all areas of daily life, especially the biomedical field. In this context, an important artificial vision peculiarity should be noted. In fact, more and more importance is being given to the exploitation of visual information. To ensure reliable treatment of the human health condition, the development of an intelligent environment for analyzing physiological signals will be a primary goal for many clinicians.

In medical signal processing, doctors generally establish their diagnosis by mentally inferring the dynamic behavior of the organ (brain, heart, etc.), from temporal plots of its electrical activities. This process requires a great deal of experience. It is difficult, subjective and not very precise. Automated tools are now asserting themselves as a major new medical technology aimed at performing real-time processing of the traces of physiological signals, more particularly electroencephalogram (EEG) signals and carrying out monitoring over long periods of time.

Given the importance of the brain, several medical imaging techniques today allow precise access to the anatomy of the brain as well as to brain activity. Among these techniques are Positron Emission Tomography (PET), Mono-Photon Emission Tomography (TEMP-SPECT), Functional Magnetic Resonance Imaging (fMRI), Magnetic Resonance Imaging (MRI), Electroencephalography (EEG) and Magnetoencephalography (MEG)).

A priori, the EEG technique is of great interest since it gives good temporal resolution at the scale of these processes. The Technologies and

Medical Imaging Laboratory (LTIM) of the Faculty of Medicine of Monastir has enough scientific and clinical skills in processing and analyzing physiological signals, particularly EEG.

Through this book, we were interested in different applications of processing and analysis of EEG signals based on advanced intelligent methodologies in the field of signal processing. Three application objectives were carried out. The first objective was to contribute to the field of EEG signal preprocessing through developing tools for filtering EEG signals by integrating automated methods in order to detect and remove the different types of artifacts. The methods proposed for the filtering allow to further refine the diagnosis by the efficiency and performance of suppressing noise embedded in EEG signals. In fact, an application of physiological EEG signals classification poses many problems because of the shape complexity and the variation in morphology of these signals, the presence of the artifacts and the complexity of reading the EEG signals. To remedy these problems, the use of intelligent techniques (neural networks and machine learning) represents a necessary step in the work of this book. However, the computational complexity of EEG signal analysis applications is incompatible with the use of sequential computations. Parallelism is one of the solutions that aims to speed up algorithms related to the processing of brain signals. The highly specialized parallel architecture optimized for intensive parallel computing justifies the choice of using GPU graphics processor. GPU cards also help reduce overall system consumption. The specifics of GPU computing are not just limited to the change of language. The way calculations are handled is different. Independent operations, whether sequential or parallel, occur very quickly and recursive calculations do not saturate the machines.

Chapter 1 of this book is a general introduction presenting the general book theme. Chapter 2 shows to reader what kind of relevant information can be extracted from EEG signals. The main sources of information are spectral information, which is used with band power characteristics, temporal information, typically represented as the amplitude of preprocessed EEG signals over time, and the spatial information, which can be exploited by focusing on certain sensors or by using spatial filters. Moreover we provide a comparative study between different kinds of methods: tempo-frequency, spatial and adaptive. An evaluation based on accuracy performance criteria is carried out.

In chapter 3, neuronal approaches and learning machines for EEG signal classification are presented. Several studies have been carried out, using artificial neural networks, to discriminate vigilance states in humans from electroencephalographic signals. Connectionist methods with supervised and unsupervised training have been used to discriminate the EEG signals characterizing the decrease in vigilance. Furthermore, an implementation of connectionist system onto hardware devices using have been realized.

Chapter 4 is a complement to the previous chapter. This chapter describes an intelligent system based on of Support Vector Machine (SVM). This system was able to detect epileptic seizures from electroencephalogram (EEG) signals. An implementation of the developed system was realized on a Graphics Processing Unit (GPU) by exploiting parallel computing. A parallel implementation of the proposed system was developed based on Graphics Processing Unit (GPU) using Compute Unified Device Architecture (CUDA) description.

In chapter 5, a parallel implementation for EEG artifact rejection was applied on the EFICA-DWT filtering method which combines the Efficient Fast Independent Component Analysis (EFICA) and Discrete Wavelet Transform (DWT) techniques. Three methods were developed based on GPU Matlab in order to optimise the EFICA-DWT execution time compared to a Central Processing Unit (CPU) implementation.

Chapter 6 presents an EEG signal modeling using VAR model by taking and analyzing measurements in large quantities of EEG and ECG signals. This chapter examines the cognitive and cardiovascular system function simultaneously to seek statistical causality between EEG and ECG signals.

CHAPTER 2

EEG SIGNAL PRE-PROCESSING METHODS

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Abstract: EEG signal recordings are always accompanied by interference and artifacts, requiring the addition of a filtering step which aims at keeping only useful information related to the movements of the lower and upper limbs. Since EEG signals have statistical properties dependent on time, frequency and space, the preprocessing phase incorporates frequency, time or spatial filtering techniques. In addition, given the large size of the EEG signals acquired as well as the presence of a strong information redundancy, it is necessary to use a second characteristic extraction stage making it possible to reduce the size of the signals while keeping the discriminative information. The extracted features are useful for classification.

Keywords: Nervous system, EEG signal, Brain Computer Interface, Filtering methods.

1. Introduction

The nervous system is the medium responsible for knowledge, reflection and action. As part of the analysis and interpretation of physiological processes, sophisticated devices have been created to record the response of neurons to different types of stimuli. Several non-invasive techniques have made it possible to study cognitive processes and pathological activities. Numerous studies have provided a better understanding of how the brain works and improved clinical diagnosis such as encephalography. The electroencephalogram (EEG) is a plot representing the potential difference between two electrodes placed on the scalp. This signal has become very widespread and can describe the activity of the brain and its changes during cognitive tasks in a clinical setting. Indeed, the EEG signal is used for the diagnosis and monitoring of many pathologies of the central nervous system such as epilepsy and sleep disorders.

However, Brain-Computer Interfaces (BCI) has demonstrated limits in performance, stability, robustness, and calibration time and noise sensitivity. Thus, several studies are considering developing robust EEG signal processing algorithms with short calibration times, in order to create practical BCIs, usable and useful outside of laboratories.

In this chapter, we will talk about the nervous system and the recordings of EEG signals using brain-computer interfaces. In addition a part is to describe the EEG signal and its characteristics. In addition, a large part is prepared to present the different techniques of temporal, frequency and spatial filtering of the EEG signal.

2. Nervous system

The nervous system is made up of the brain, the brainstem, the spinal cord, and the nerves that connect this system to the rest of the body. The brain is divided into sub areas responsible for different tasks: vision, touch, memory [9]. This information is transmitted from one neuron to another by action potentials. These action potentials will give rise to postsynaptic potentials, which in turn can lead to action potentials when a threshold is reached. The nerves enable the coordination between the different parts of the human body, as well as the reception of messages related to sensations. The nervous system is also the seat of cognition, that is to say the means to achieve knowledge [5]. The overall nervous system is shown in Figure 1. It can be divided into two parts:

- The central nervous system (CNS), which contains the spinal cord and brain.
- The peripheral nervous system (PNS), which contains the spinal nerves coming out of the spinal cord.

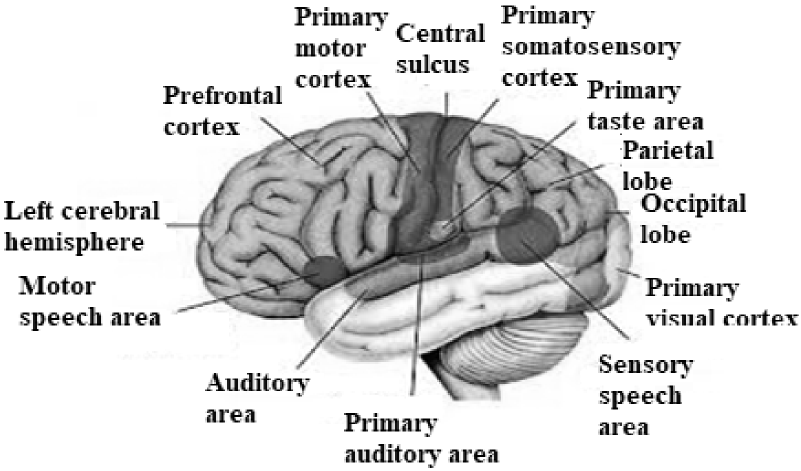

Figure 1: Nervous system

The brain is responsible for the connection between the external environment and the internal one in order to manage all human reactions. It is made up of three main parts:

- The brainstem
- The cerebellum
- The brain

The brainstem is an extension of the spinal cord made up of two types of nervous tissue: white matter at the periphery, and gray matter in the center, unlike the brain. Two types of information pass through the trunk and spinal cord, sensory and motor. The cerebellum is the part immediately below the brain and behind the brainstem. It manages nerve impulses and orders from the brain and changes them based on information from nerve endings distributed throughout the body. Thus, it controls muscle tone by sending regulatory signals to motor neurons in the brain and spinal cord. Damage to the cerebellum causes loss of muscle coordination and disrupts movement [6].

It is very difficult to attribute a given function to a limited part of the brain, because the processing of information takes place through interconnected regions. Primary areas receive information from higher areas that play a role in the perception of the outside world. However, there are dominant ones. The frontal lobe is heavily involved in cognitive tasks such as memory, reasoning, and associative conceptualization. The occipital lobe helps manage the processes of vision. The parietal lobe is involved in the analysis of touch. The temporal lobe is used to manage auditory and olfactory information. Each of the two hemispheres is divided into four lobes which are the frontal lobe located just behind the forehead, the temporal lobe located at the temples and below the frontal lobe, the parietal lobe located behind the frontal lobe and the occipital lobe, which is located at the rearmost part of the skull [7]. The cerebellum lies below the occipital and temporal lobes.

There are about eight billion neurons in the brain. Neurons are organized according to two scales:

- Global communication network that links the different cortical regions together.
- Local network in order to process information within the same structure.

Figure 2 shows the neuron as a cell that receives, propagates, and transmits the electrical signals constituting the nerve impulse [51]. These signals are transmitted from one cell to another through specialized contacts: the synapses. The neuron is characterized by a cell body that contains the nucleus and its genetic material.

Two types of extension start from the cell body:

- The dendrites, numerous and highly branched, which receive information and send it to the cell body.
- The axon which transmits signals to other neurons. A neuron can have thousands of synaptic contacts with other neurons.

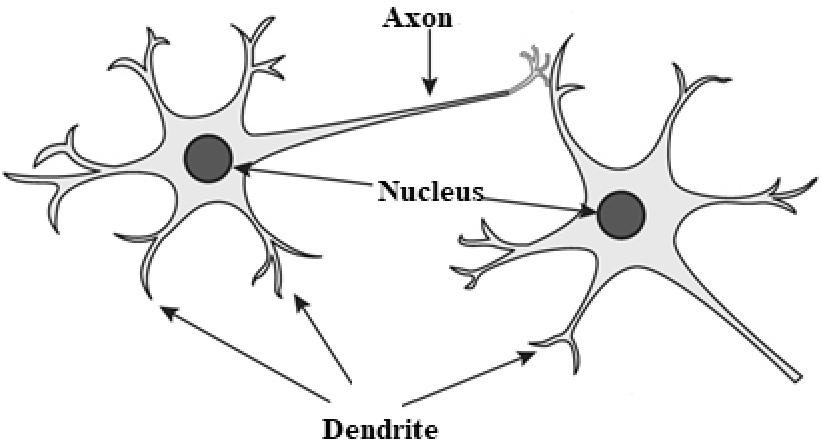

Figure 2: Neuron

The synapse represents a functional contact zone between two neurons, but also between a neuron and another cell [9]. In the case of neuronal synapses, this contact is made between a presynaptic neuron via the axon and a postsynaptic neuron. There are two types of synapses:

- Chemical synapses
- Electrical synapses

Chemical synapses are in the majority and characterized by the presence of a space between the presynaptic element and the postsynaptic element called the synaptic cleft. The electrical information is then transformed into chemical information through the release of neurotransmitters contained in the presynaptic vesicles.

Electrical synapses are communicating junctions where electrical information is transmitted directly without any chemical intermediary. Synaptic transmission is a polarized one-way transmission connecting the presynaptic element containing the neurotransmitter with the postsynaptic element where the neurotransmitter is located.

The arrival of action potentials in the presynaptic element results in calcium entry and fusion of synaptic vesicles with the plasma membrane. This fusion of the synaptic vesicles with the membrane exocytically releases the neurotransmitter into the synaptic cleft. The released neurotransmitters can attach to receptors located on the postsynaptic element. This binding causes ions to pass through the postsynaptic membrane through the opening of ion channels. When the membrane reaches a certain potential, an action potential is triggered. It is therefore the transformation of a chemical signal into an electrical signal.

3. EEG signal recording

EEG signals can be recorded using electrodes placed on the head or implanted directly into the skull to make an intra-cerebral recording. The electrodes are illustrated in Figure 3 and they require the use of gel. However, the gel can cause artifacts and takes some time to apply. Indeed, there are works carried out experiments using dry electrodes. The goal is to have a measurable EEG signal, since interactions between neurons give rise to ionic currents generating action potentials. Practically, ionic currents resulting from dendritic electrical activity represent the majority of the brain-derived EEG signal collected from the scalp.

Postsynaptic events are at the origin of EEG through their duration of a few tens of milliseconds while the action potential lasts only a few milliseconds.

The acquired EEG signals' amplitude is about 1 mv. In order to be able to detect them correctly by signal processing systems, these signals must be amplified before their digitization so that the variations of the voltages can be displayed in graphic form (paper or screen) or recorded in a readable manner in a standard format. This amplification uses a differential amplifier which measures and amplifies the difference in potentials between a pair of electrodes. Amplification is characterized by its amplification factor which can reach 106 according to cascade architecture of differential amplifiers. These are modeled by voltage generators which can thus adjust the Common-mode-rejection ratio: (CMRR) which exceeds 80 dB for modern acquisition systems. The potential difference causes a variation in the bandwidth of the recorded EEG signals exceeding the tolerated limits between 0 and 100 Hz.

Figure 3: EEG signal recording

There are two types of currents:

- Primary currents: these are generated at the level of a neuron.
- Secondary currents: they result from the synchronous superposition of the primary currents generated by pyramidal neurons parallel to each other and perpendicular to the surface of the cortex.

The factors that affect the EEG signal are:

- The distance between the recording electrodes and the source of the synaptic currents.
- The duration and number of synchronized synaptic potentials.

- The geometric orientation of neurons that generate extracellular electrical potentials.

The electrodes are used to collect the signal on the subject's scalp, and should not polarize. They are most often made of chlorinated silver and placed by a helmet surrounding the subject's head, or by fixation with a colloidal gel.

Currently, recent systems can achieve 128 or even 256 electrodes. An important factor to take into account is the proper spatial sampling of electrical potentials [8]. Previously, the electrodes were placed according to the international system '10-20 'based on 19 electrodes or '10 -10' based on 64 electrodes. Figure 4 shows the international '10-20' system.

An electrode is identified by a letter followed by a number. The letter specifies the region as follow:

- F: frontal
- T: temporal
- C: central
- P: parietal
- O: occipital

The numbers specify the hemisphere. Even numbers are for the right hemisphere and odd numbers are for the left hemisphere. The *z* letter refers to the electrodes placed on the center line.

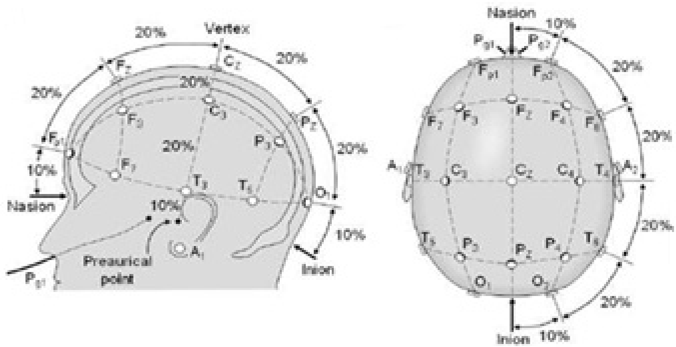

Figure 4: EEG Helmet and international 10-20 system

There are two main types of assembly:

- Bipolar assemblies: the activities obtained are the result of the subtraction of two consecutive electrodes, which cancels the effect of the recording reference on re-reading.
- Reference assemblies: electrical activity is recorded against an identical reference electrode for all channels.

Each of the recording methods has advantages and disadvantages. Indeed, the surface EEG has the advantage of a simple set-up and a global vision with high temporal precision.

However, the signals are disturbed by different types of artifacts which sometimes have very large amplitudes and can drown out actual brain activity. The sensitivity of recordings to temporal lobe activities is also an unresolved issue. Thus, the extraction of signals generated by an EEG stimulus often requires several iterations of stimuli in order to minimize noise.

For intra-cerebral recording, the depth electrodes are implanted directly into the skull during an operation under general anesthesia. This results in signals having a very good signal-to-noise ratio, while directly recording the cerebral structures therefore with very high spatial specificity.

4. Brain-computer interface

Brain-Computer Interfaces (BCIs) have demonstrated their enormous potential in many applications. However, they remain mainly prototypes, not yet used outside of laboratories. This is mainly due to their following limitations:

- Performance: the low classification precision obtained with BCIs makes them difficult to use or even simply useless compared to existing alternative interfaces
- Stability and robustness: the sensitivity of EEG signals to noise and their inherent non-stationary make performance already low and difficult to maintain over time.
- Time: the need to adapt the BCI to the EEG signals of each user makes their calibration times long.

Indeed, several studies are thinking of correcting these defects by designing robust EEG signal processing algorithms and with short calibration times, in order to create practical BCIs. The figure below shows the role of Brain Computer Interface to make EEG signals recording.

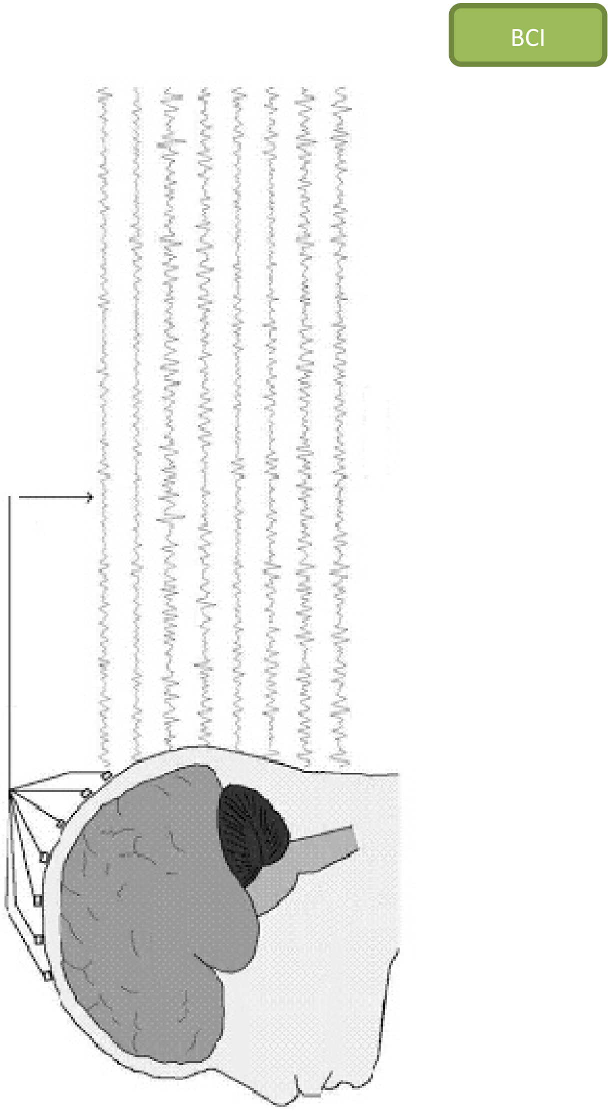

Figure 5: Brain Computer Interfaces and EEG signals recording

To this end, we explore robust spatial filters to make BCIs more precise, more resistant to noise and non-stationary. However, simply adding more sensors will not solve the performance issues. Indeed, using more sensors means extracting more features which further exposes the dimension curse. So adding sensors can even reduce performance especially if the number of available learning examples is too low. In order to efficiently operate multiple sensors, there are three main algorithms to reduce the dimension of the feature vector:

- Feature selection algorithms, which are methods for automatically selecting a relevant subset of features, among all the features initially extracted [26].
- Sensor selection algorithms, which are methods for automatically selecting a relevant subset of sensors, among all the available sensors.
- Spatial filtering algorithms, which are methods combining several sensors to form a new virtual sensor from which the characteristics will be extracted.

We will focus on spatial filtering, for which EEG and BCI specific algorithms have been applied. Feature selection is a set of general machine learning tools, not specific to EEG or BCI. As for the selection of sensors, the algorithms used are generally derived from the feature selection algorithm. [2, 48].

5. BCI design and EEG features extraction

In the design of BCIs, the processing of EEG signals often relies on machine learning techniques. This means that the classifier and characteristics are adjusted and optimized for each user, based on examples of that user's EEG signals. These EEG signals are called a learning set. Thanks to this training set, we will be able to calibrate a classifier so that it can recognize the class of different EEG signals.

Usually, features are grouped together in a vector called a “feature vector” [55]. A characteristic is a value describing a property of EEG signals, for example, the power of the EEG signal in the μ rhythm for electrode C3.

The illustrated Figure 6 depicts that, in order to identify the extracted features in EEG signals, powers are in a specific frequency band. The band powers are calculated in the μ (8-12 Hz) and β (16-24 Hz) frequency bands for the electrodes above the sensorimotor cortex. Some characteristics can be classified using a classifier such as Linear Discrimination Analysis (LDA).

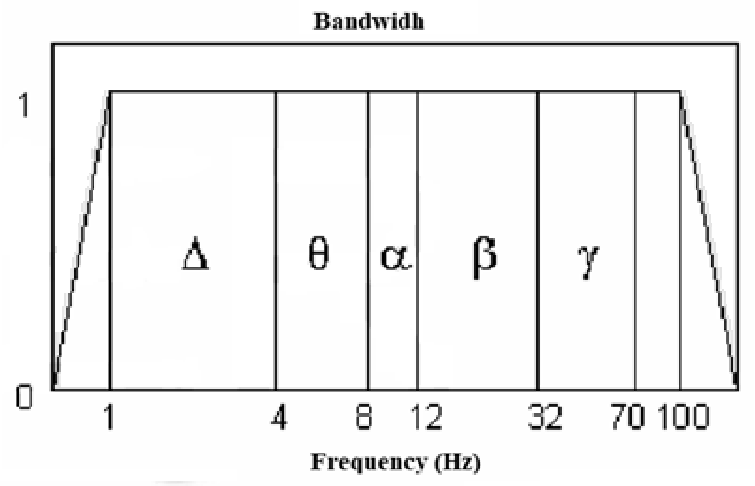

Figure 6: Frequency bands of EEG signal

Features can be optimized through examples of EEG signals by selecting the most relevant electrodes to recognize different mental states. Thus, designing a BCI using machine learning requires:

- Learning or training phase: which consists of acquiring learning EEG signals and optimizing the processing chain of EEG signals by adjusting the parameters of the characteristics and / or by training a classifier.
- Test phase: which consists of using the classifier and the obtained features during the learning phase to recognize the user's mental state from new EEG signals.

At the end of the learning phase, a classifier capable of learning from examples which class corresponds to which input characteristics, must be designed. Thanks to “curse-of-dimensionality”, the amount of examples needed increases exponentially with the dimension of the feature vector [44]. Studies even recommend using 5 to 10 times more training examples per class than the dimension of the feature vector.

For example, imagine we are using a common EEG system with 32 electrodes sampled at 250 Hz for a given mental task lasts 1 second.

We would therefore have a feature vector with a dimension of 8000 (32 times 250).

So this would require at least 8000 times 5 = 40000 learning examples per class.

Practically, you can't ask a user to do every mental task 40000 times! So we need a more compact representation.

To extract characteristics from signals, there are three main sources of information that can be used:

- Spatial information: which selects specific EEG electrodes or focuses more on certain sensors.
- Spectral information: which describes how the strength of the EEG signal in specific frequency bands varies.
- Time information: which describes how EEG signals vary over time.

In practice, it is necessary to use different sources of information. BCIs exploiting oscillatory EEG activity mainly use spatial and spectral information [22, 37, 42, 54]. These are BCIs using mental states giving rise to changes in the power of EEG signals in certain frequency bands.

In return, BCIs exploiting Evoked Potentials (PE) mainly use spatial and temporal information. Table 1 summarizes the main techniques for extracting the most used characteristics.

Table 1: Feature extraction methods

Author	Method	Complexity	Noise sensibility	Subject adaptation	Redundancy
Nicolas et al. [38]	Band-Power	+	+	+	-
Her et al. [27]	Power spectral density	+	+	+	-
Sun et al. [52]	Power spectral density	+	+	+	-
Pen et al. [41]	Autoregressive setting	-	-	-	+
Siu et al. [50]	Wavelet Transform	+	-	-	-

The band-power (BP) method applied a band-pass filter sized according to the active bands of the movements of the right or left hand Nicolas et al. [38]. The filtered samples endured multiplication and addition operations in order to generate the feature vector of the signal. This method is vulnerable to artifacts and its use requires the addition of a feature selection block in order to remove the redundancy. The redundancy is mainly due to the similarity of signals belonging to different classes. The number of features extracted by this technique is fixed by the number of channels of the recorded EEG signal. Thus, the use of a large number of channels makes the classification operation quite difficult and could seriously degrade the accuracy. In addition, this method requires precise localization of active bands which vary from subject to subject. It is for this reason that the application of this method requires an offline study to study the frequency variability for each subject. Power spectral density (PSD) method [27, 52] was used to extract feature by estimating the power of each frequency component present in the EEG signal ranging from 0 Hz up to the frequency corresponding to half the frequency sampling. There are a variety of PSD techniques such as: Yule-Walker PSD, Periodogram PSD, Short Fast Fourier Transform (SFFT), etc. The application of the DSP technique required the addition of a spectral analysis block to quantify the bands of active frequencies. Indeed, the useful frequency components are those which present an increase or a decrease in power compared to a reference period initiated just before the start of the movement. This technique also required the addition of a selection block for the most active channels since the number of features is related to the number of recording channels which is relatively large. The autoregressive method allows the trials to be divided into a set of time intervals in order to estimate, from each segment, the associated parameters (Pen et al.) [41]. This technique is sensitive to artifacts and is not satisfactory for the extraction of motor imagery signals. An optimization has thus been proposed aiming to build an adaptive autoregressive statistical model (ARA) which takes into account the temporal variations in the signal.

Siu et al. [50] presented a new hybrid approach based on the clustering technique and the Least Squares Support Vector Machine (LS-SVM) called CT-LS-SVM for the classification of EEG signals into two classes. The study aims to extract representative features from the original EEG data using the CT method, and then classify the EEG signals to two classes by the LS-SVM using these features as inputs. The experiments were performed on epileptic EEG data. The proposed approach achieves an average classification accuracy of 99.19% for EEG data from mental imaging tasks and 94.18% for epileptic EEG data.

6. Epileptic seizures

Epilepsy is one of the most common neurological disorders which is harmful to health [19]. The epilepsy disorder is mainly characterized by a perdurable predisposition to generate epileptic seizures and by the neuro-biologic, cognitive, psychological, and social consequences of this condition [3]. This disorder is characterized mainly by recurrent and unpredictable interruptions of normal brain function that are called epileptic seizures. An epileptic seizure is defined conceptually as a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain [10, 21]. Did you know, for example, that too many flashes and staring at your cell phone at night can also cause epilepsy?

The epilepsy disorder had become the second-highest incidence of cerebrovascular diseases where about 1% of the world's population suffer from epilepsy [52]. The epilepsy disorder affects all ages [49] wherein the USA, more than 500 thousand patients are older than 65 years and more than 300 thousand patients are younger than 14 years. Despite the introduction of new antiepileptic drugs in the last decades, one-third of people with epilepsy continue to have seizures despite treatment [32].

Epileptic seizures are often thought to have a well-defined onset time determined with EEG and or clinical signs (semiology). However, some persons suffering from epilepsy can sense the seizures coming before it is registered on the EEG (prodrome), indicating that physiological changes happen in the pre-ictal period before the seizures arise [29]. Figure 7 shows the relationship between epileptic seizure and EEG disorder.

In most cases, the EEG monitoring which presents the gold standard in neurology and for the clinical monitoring of seizures activities is usually unavailable [18]. Moreover, monitoring the seizures activity based on the use of the EEG signals is not always easy. Several disadvantages where the abrasive paste and the electrolyte get are sticky products make the hair scalp dirty and could be harmful. [33]. Further, the specialists are wasting time trying to reduce the impedance of the electrodes to an acceptable value where a countdown begins when gel dries causing the disappearing of the transductive properties [24].

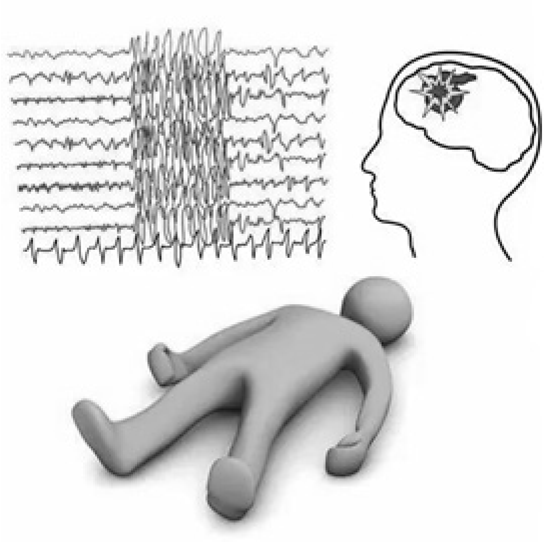

Figure 7: Epileptic seizures

The measured EEG signals are the result of noisy mixtures of signals from different regions of the brain. In other words, the EEG signal from the cortex diffuses as it passes through the skull or scalp and then arrives at the EEG sensors. Thus, the signal is found diffused and dispersed on several EEG sensors and need for filtering.

The author [20] shows the presence and severity of autonomic dysfunction in patients with epilepsy by assessing time and frequency. Other approaches proposed [23] are based on the use of linear HRV analysis to predict seizures. The approach consists in extracting the characteristics of the frequency domain and then in predicting the seizures. The characteristics of the frequency domain have been normalized because they are different from patient to patient.

In [40], the author used the Support Vector Machine (SVM) to predict the onset of the seizure based on the uninterrupted cross-validation (LOOCV) technique. The proposed approach achieved 91% sensitivity and an accuracy of 95.6%. Currently, recent works study the prediction of epileptic seizures using ECG signals. This will prove the strong dependence between EEG and ECG signals.

7. Alzheimer's disease

Alzheimer's disease (AD) is a neurodegenerative disease characterized by progressive dementia, for which no cure is known. This section reviews recent advances in the diagnosis of AD from EEG. Early detection of patients with AD can be achieved by analyzing their electroencephalography (EEG) signals, which show reduced complexity, disturbed synchrony and slowed rhythms. The first symptoms usually appear at the age of 50 for patients with Down syndrome. AD is usually diagnosed at the age of 52. The average age of death was 60 years. The time between the first symptoms of Alzheimer's disease and death is usually around 9 years. Three major effects of AD on EEG were observed:

- EEG slowing
- reduced complexity of EEG signals,
- disturbances in EEG synchronization.

The application of electroencephalographic techniques to the field of research on AD has remained somewhat in the shadow of the dramatic developments in imaging methods that have taken place in recent years. However, the techniques for collecting and analyzing EEG signals have also benefited from enormous technological advancements, and while EEG recording remains far from offering the same spatial precision as MRI, it has the advantage of a greater power of temporal resolution. It makes it possible to study phenomena on the scale of the millisecond. Studying the EEG signal can thus provide information that cannot be accessed by other methods. This is the case, in particular, if one is interested in the very early stages of the disease, when the brain tries to compensate for its first dysfunctions, before the neuronal losses are noticeable. Functional EEG recordings were repeatedly collected from participants in this study. The researchers analyze signals called “evoked potentials”. These are the special electrical waves that occur during brain stimulation. In this case it was a word memorization test. We can expect that, for "pre-Alzheimer's" subjects, a learning situation will require particular brain resources. Thus, in subjects at risk or progressing to the disease, it will be possible to look for changes in the electrical signals observed during a memory test, changes which could be the markers of the onset of the disease.

In recent years, few studies perform discriminant analysis using support vector machines (SVM), neural networks, etc. A variety of sophisticated computational approaches have been proposed to detect the subtle disturbances in the EEG of AD patients. Giulia et al. [25] applied a procedure that exploits EEG signal feature extraction and classification techniques to distinguish patients with AD from those affected by samples of mild cognitive impairment (MCI) and healthy controls (HC). The author applied both Fourier and wavelet transforms to AD, MCI and HC classes. By comparing the classification performance methods, it was found that wavelet analysis outperforms Fourier. Therefore, a combination with supervised methods for automatic classification of patients based on their EEG signals has been suggested to aid in the medical diagnosis of dementia.

Justin et al. [30] described method that attempt to detect EEG slowing. The author discussed several measures of EEG complexity and explains how these measures have been used to study fluctuations in EEG complexity in patients with AD. Next, various measures of EEG synchrony were considered in the context of the diagnosis of AD. Many studies confirm the great potential of EEG for the diagnosis of AD. However, many critical questions will need to be addressed before EEG can enter clinical practice for the diagnosis of AD.

Electroencephalogram (EEG) signals are often contaminated with various artifacts. These artifacts make subsequent EEG analyzes inaccurate and prevent practical use. Unfortunately, EEGs are susceptible to being contaminated simultaneously with various types of artifacts. This is the goal of the next section.

8. Physical signal filtering

Any physical signal coming from an electronic instrumentation can be represented as follows:

$$Signal = useful\,signal + Noise \qquad (1)$$

The purpose of a filter is to separate certain useful signals from other undesirable signals which are mixed with them. The production of a filter therefore requires knowledge of the spectrum of frequencies making up the useful signal. Noise suppression can be achieved using more sophisticated and complex techniques.

8.1 Ideal filter

An ideal filter is one that transmits the wanted signal without distortion or delay, while completely eliminating unwanted signals. For each filter,