PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
MINESTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

ECOLE NATIONALE POLYTECHNIQUE

ELECTRONICS ENGINEERING DEPARTMENT

IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR

ENGINEER'S DEGREE
(ELECTRONICS ENGINEERING)

Features extraction based on Schrödinger operator's spectrum for cognitive states classification

Mohamed MAOUI

Presented and defended publicly on 06/18/2018

Members of the Jury

President	Dr. Mourad Adnane	ENP
Supervisor	Dr. Taoues-Meriem Laleg Kirati	KAUST University
Co-supervisor	Pr. Larbes Cherif	ENP
Examiner	Mr. Mohamed Oussaid Taghi	ENP

ENP 2018

10, Avenue des Frères Oudek, Hassen Badi, BP. 182, 16200 El Harrach, Alger, Algérie

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Dedication

I would like to offer my work to my dear mother, who always helped me during my entire educational pathway. A special dedication to my uncle Mohamed, and my aunts Ghania and Chafika, who always supported me in tough moments.

I would like to dedicate this work to my father, who passed away before witnessing this special day in my life.

I would like to mention my young sister Ines and my young brother Amine, and all my friends who have been present for me to support me and motivate me, especially Nassim, Mehdi, Amine Anes, Ghouthi, El Kindi, Abderrahmane, Anis and all my friends at Polytech and KAUST.

I would like to dedicate my work to everyone who believes in my skills and potential. Finally, I dedicate this work to everyone who knew me and believed in me, all my friends and professors without forgetting anyone of them.

Sincerely,

Mohamed

Acknowledgement

I would like to offer my sincere gratitude to my supervisor Pr. Taous Meriem Laleg Kirati, who always helped me to understand the scope of any research I used tackle, with a great kindness. I would like to thank her for giving me the chance to engage in a cutting edge research, by housing me in her research group last summer at KAUST University. Being a visiting student in EMAN group at KAUST University contributed to improving my analytical and research skills, as well as my personality. It was truly a life changing experience for me.

I would like also to thank all EMAN group's collaborators as well, I especially name Fahad Albalawi, a Postdoc in professor Laleg group for his availability to answer any question I had regarding machine learning.

I would like also to thank my co-advisor and my professor at Ecole Nationale Polytechnique Pr. Larbes Cherif for his availability and for his help. The great advice he offered me, have dramatically helped me to learn great deal while completing my project. I am honored to say he is one of my best teachers and was a very good advisor also.

I would like to thank the committee members for reviewing my thesis and for their valuable and insightful comments.

Mohamed MAOUI

Algiers-2018

Abstract

ملخص:

إن تدريب خوارزميات التعلم الآلي لتصنيف الحالات المعرفية هو بمثابة تحدي يواجهه العديد من الباحثين في مجال الطب الحيوي في يومنا هذا، نظرا للفوائد الطبية العديدة التي يتمتع بها هذا النوع من الأبحاث، في فهم العديد من الأمراض العصبية. لهذه الأسباب، فانه من المهم امداد هذه المصنفات بخصائص عالية الجودة تسمح لنا بتحقيق تصنيف عالي للحالات العقلية. نقترح في هذا العمل، طريقة جديدة لتحليل الإشارات، لاستخراج خصائص مناطق معينة من الدماغ، يتم تنشيط هذه المناطق بواسطة حالتين عقليتين، ومن صرف أشخاص مختلفة. نستكشف من خلال النتائج فعالية التقنية وجوانبها الأساسية.

الكلمات الدالة: المصنفات, خصائص, الحالات العقلية.

Résumé :

L'entrainement d'algorithmes de l'apprentissage automatique pour classifier les états cognitifs est un défis auquel de nombreux chercheurs en biomédical sont confrontés de nos jours, pour les nombreux avantages en médicine que ce type de recherche a, dans la compréhension de nombreuses maladies neurodégénératives. Pour cela, il est important d'alimenter ces classificateurs avec des caractéristiques de haute qualité nous permettant d'obtenir des performances de classification élevées des états cognitifs. Nous proposons dans ce travail, une nouvelle modalité d'analyse du signal, pour extraire des caractéristiques de certaines régions cérébrales spécifiques dont les activations sont déclenchées par deux états mentaux, réalisés sur différents sujets. Nous explorons l'efficacité de la technique et de ses aspects fondamentaux.

Mots clés: Classificateurs, caractéristiques, états cognitifs.

Abstract:

Training machine learning algorithms to classify cognitive states is a challenge that many biomedical researchers are dealing with nowadays, for the numerous medical advantages that this kind of research has in understanding many neurodegenerative diseases. However, it is important to feed these classifiers with high-quality features allowing us to obtain high classification performance of cognitive states. We propose in this work, a new signal analysis modality to extract features from some specific brain regions whose activations are triggered by two mental states, performed by different subjects. We explore the efficiency of the technique and its fundamental aspects.

Key words: classifiers, features, cognitive states.

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Acronyms

AI: Artificial Intelligence.
AP: Action Potential.
ATP: The Adenosine Triphosphate.
BOLD: Blood Oxygen Level Dependent.
CBV: Cerebral Blood Volume.
CBF: Cerebral Blood Flow.
Dhb: Deoxy-Hemoglobin.
DWT: Discreet Wavelet Transform.
EPSP: Excitatory Postsynaptic Potential.
fMRI: Functional Magnetic Resonance Imaging.
IPSP: Inhibitory Postsynaptic Potential.
KNN: K- Nearest Neighbor.
LCD: Linear Discrimination Classifier.
LFP: Local Field Potential.
MSE: Mean Squared Error.
MLP: Multilayer Perceptron.
MRI: Magnetic Resonance Spectroscopy.
NB: Naïve Bayes.
PSNR: Peak signal-to-Noise Ratio.
PSD: Power Spectral Density.
PS: Picture Sentence.
PSP: Postsynaptic Potential.
ROA: Region of Activation.
SCSA: Semi Classical Signal Analysis.
SP: Sentence Picture.
SVM: Support Vector Machine.

INTRODUCTION

The study of the brain functions has received a tremendous boost in recent years from the advent of fMRI, a brain imaging method that dramatically improves our ability to observe neural brain activity in human subjects [1]. One approach, for understanding human brain functioning is to analyze the changes in the brain activity while performing cognitive tasks, to identify which regions of the brain are activated when a human performs a particular cognitive function (eg, reading sentences, watching TV).

Nowadays, artificial intelligence (AI) is making a revolution in the world and is making impact in different fields. Researchers in the biomedical field, are more and more interested in exploiting the huge fortune that AI provides which consists of the different algorithms that allow to better investigate one of the most complicated and mysterious organs in the human body which is the brain, to improve the quality of health in the world.

In cognitive science, researchers attribute great attention to the problem of classification in machine learning. Classification assigns an entity to a category on the basis of feature values encoded from a stimulus [2]. Feature selection methods are vital to reducing the dimensionality of the data. The obtained brain images from fMRI experiment are used by machine learning techniques to design decoders or sensors for the classification of brain states.

One of the challenges in the problem of classification or categorization that AI researchers are facing now is how to choose the best features to fuel machine learning algorithms in a particular way that gives an efficiency in obtaining high classification accuracy and a much reduced computational time.

Laleg and al [3] have recently developed a new semi classical signal/image analysis method called SCSA. The technique was mainly inspired from quantum physics and it provides an adaptive signal/image reconstruction approach, where the signal/image is decomposed into signal/image dependent functions. These functions are the L2-normalized squared eigenfunctions associated to the discrete spectrum of a Schrödinger operator, where the signal/image to be processed is considered as a potential of the operator.

The aim of this research is to explore the efficiency of using the SCSA modality to reconstruct signals fMRI signals, in order to select relevant features to feed machine learning algorithm for cognitive states classification. Our collaborators put high ambitions on the SCSA for obtaining promising results to compete with other feature extractions techniques that have already been presented in the literature for cognitive science purposes.

Chapter 1

Functional magnetic resonance imaging overview

1.1. Introduction

The brain is the most mysterious and complicated organ in the human buddy. Understanding its composition and how brain cells interact with each other to achieve a particular function is a challenge.

In this chapter, we start by presenting the anatomy of the brain and the different processes behind its activity. Next, we present an overview of the imaging modalities, with emphasis on fMRI modality, we describe its advantages and the key concepts behind its applications in biology and medicine.

The last part is completely devoted to fMRI data processing.

1.2. Brain anatomy

1.2.1. Brain Composition

Protected within the skull, the brain is an amazing organ that controls all functions of the body, interprets information from the outside world. Intelligence, creativity, emotion, and memory are a few of the many things governed by the brain. It is made up of more than 100 billion nerves that communicate in trillions of connections called synapses. The brain is composed of three parts: the cerebrum, the cerebellum, and the brainstem, their location is shown in the following figure (1.1):

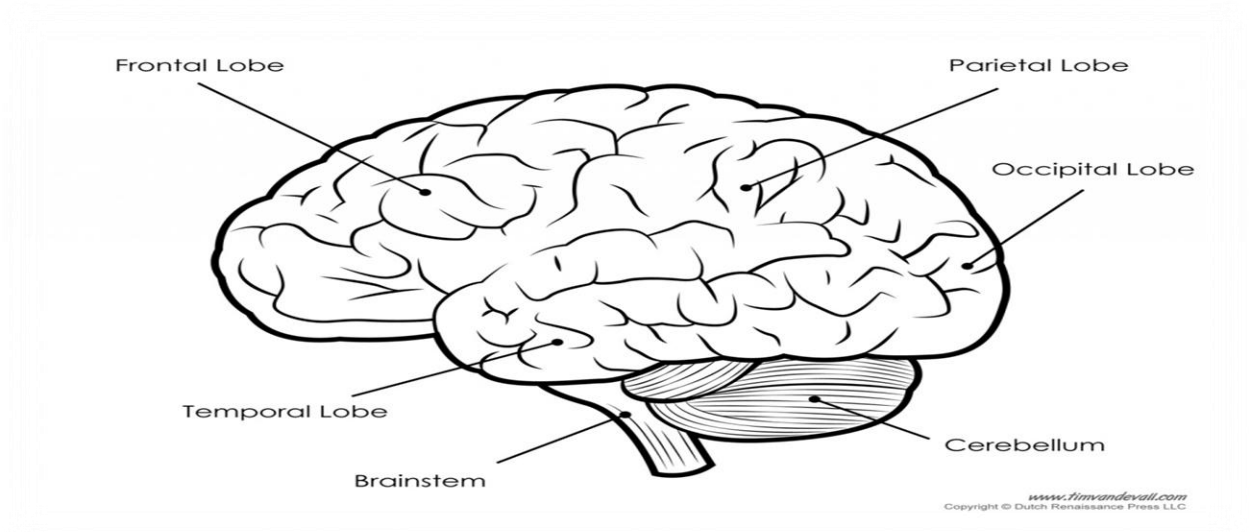

Figure 1.1: Brain composition [4]

Cerebrum

It's the largest part of the brain and is composed of right and left hemispheres. It performs higher functions like interpreting touch, vision and hearing, as well as speech, reasoning, emotions, learning, and fine control of movement. The brain has two cerebral hemispheres (half of the brain). Scientists identify four major lobes on the surface of each one. Each hemisphere(figure1.2) takes care of one side of the body, but the controls are crossed: the right hemisphere takes care of the left side, and vice versa these parts are: Frontal lobe, parietal lobes, temporal lobes and occipital lobes.

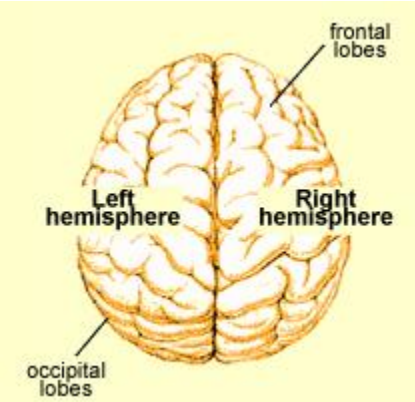

Figure 1.2: The hemispheres of the cerebrum part of the human brain [5]

Cerebellum

It is at the base and the back of the brain and is located under the cerebrum, its function is to coordinate muscle movements, maintain posture, and balance.

Brainstem

It is between the spinal cord and the rest of the brain. Includes the midbrain, pons, and medulla. It acts as a relay center connecting the cerebrum and cerebellum to the spinal cord. The brainstem performs many automatic functions such as breathing, heart rate, body temperature, wake and sleep cycles, digestion, sneezing, coughing vomiting and swallowing. Ten of the twelve cranial nerves originate in the brainstem. The following table summarizes the detailed composition of each part of the brain:

Tab. 1.1- Detailed composition of each part of the human brain

Cerebrum	Cerebellum	Brain Stem
• Frontal Lobe • Parietal Lobe • Occipital Lobe • Temporal Lobe	• Thalamus • Hypothalamus • Amygdala • Hippocampus	• Midbrain • Pons • Amygdala • Medulla Oblongta

1.2.2. Controlling the human body using the cranial nerves

The brain receives information through our five senses: sight, smell, touch, taste, and hearing- often many at one time. It assembles the messages in a way that has meaning for us, and can store that information in our memory. The brain controls the function of many organs within our body, and determines how we respond to stressful situations. In general, the brain communicates with the body through the spinal cord and twelve pairs or cranial nerves (figure 1.3).

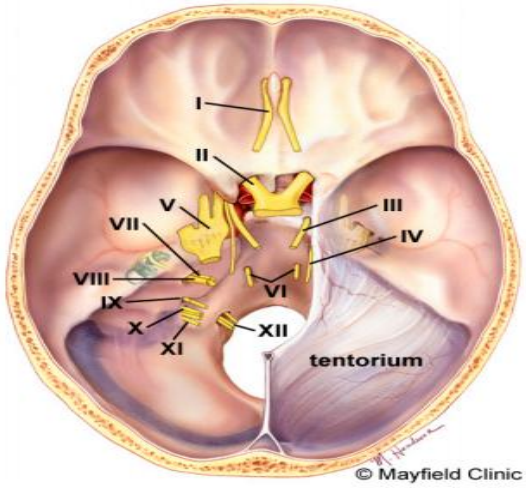

Figure 1.3: The cranial nerves of the human brain [6]

The table below shows the function of each nerve:

Tab. 1.2 - Associated functions of each cranial nerve [6]

No.	Name	Function
I	olfactory	smell
II	optic	sight
III	oculomotor	moves eye, pupil
IV	trochlear	moves eye
V	trigeminal	face sensation
VI	abducens	moves eye
VII	facial	moves face, salivate
VIII	vestibulocochlear	hearing & balance
IX	glossopharyngeal	taste, swallow
X	vagus	heart rate, digestion
XI	accessory	moves head
XII	hypoglossal	moves tongue

1.2.3 Brain activity

There are three types of brain activities:

1. **Neural activity**

Manifested by electrochemical signal conduction between brain cells.

2. **Metabolic activity**

Represented by energy production and consumption processes.

3. **Vascular activity**

This brain activity describes the cerebral blood flow and perfusion.

These brain activities are related to each other, we will describe each brain activity separately, and provide the relation between these activities.

Neural activity

Neuronal anatomy

We begin by describing the smallest unit of functional activity in the brain which is the neuron. The human brain contains around 100 billion neurons. The structure of each neuron is illustrated in figure 1.4. The main parts of the neuron are:

- Dendrites: Receiving end of neuron, receives and integrates input signals from other neurons.
- Soma: Provide metabolic and structural support for the neuron.
- Axon: Transmitting end of the neuron, signals elicited via action potentials to one or more neurons.
- Synapse: Specialized junction between dendrite and axon trough which information is transferred.

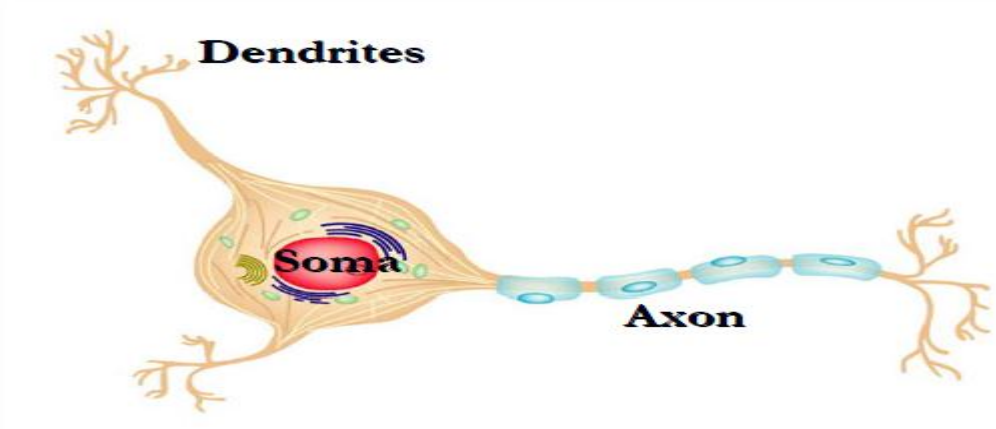

Figure 1.4: Neuronal anatomy [7]

Neural activity typically originates from groups of interconnected neurons communicating via electrical pulses using two important processes:

1. **Integrative processes**

Integration is the summation of the thousands of PSPs: EPSPs (depolarizations) and IPSPs (hyperpolarizations) received by dendrites, from all incoming axons, it provides a total voltage as an output.

2. **Signaling processes**

Integration lead to signaling and if the resultant voltage is beyond a threshold, an axon potential or a new action potential is elicited to continue signaling and sent down axon.

Information processing is thus the combination of neuronal integrative and signaling roles, as the following figure shows:

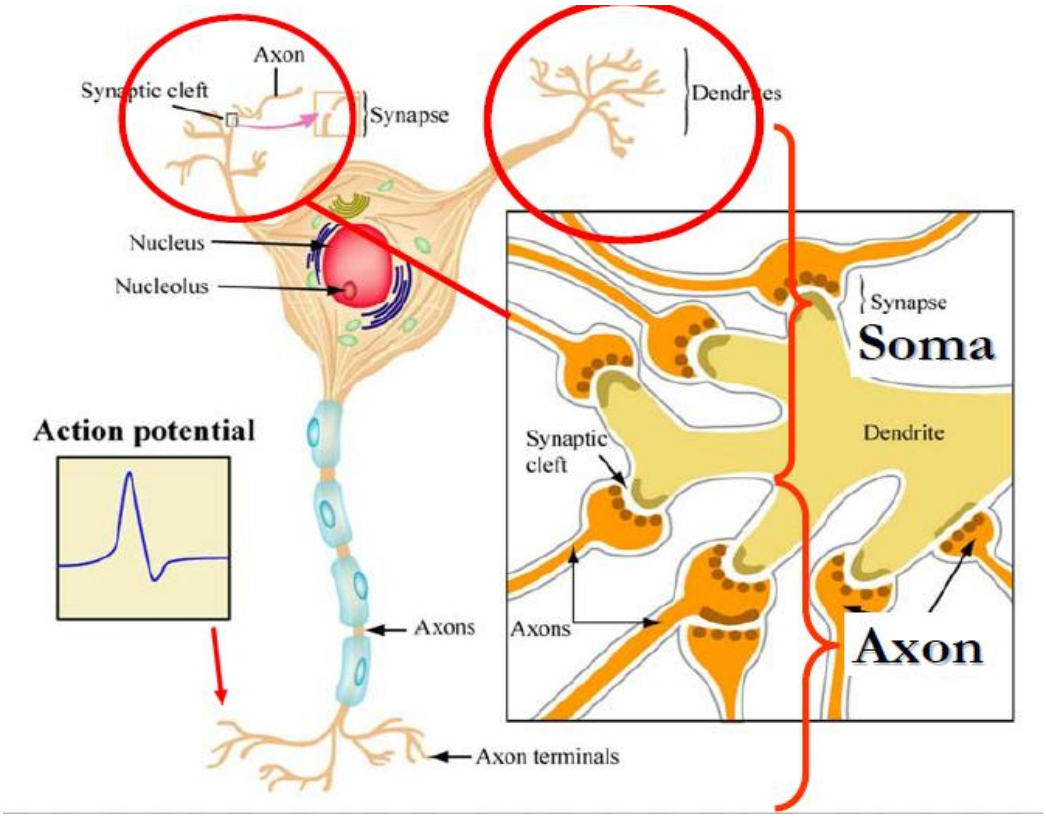

Figure 1.5 Integrative and signaling processes of a neuron [7]

Metabolic activity

Postsynaptic potential (EPSPs, IPSPs) and action potential AP generation depend on electrochemical gradients, ion flow, and neurotransmitter release. As signaling proceeds, the driving force behind their generation is lost, as ion and neurotransmitter stores are depleted.

For neural signaling to continue, ion concentrations and electrochemical gradients must be re-established. These processes require energy; the primary source of free energy in the brain is ATP.

The ATP generation

The process of producing ATP in the brain goes through the following steps:

Glycolysis:

- Consume glucose
- Produces 2 ATP, Acetyl CoA if O_2 and lactate if no O_2

TCA cycle/Ox Phos:

- Consumes O2
- Produces Co2, water and lots of ATP

Aerobic respiration:

- Require oxygen, produces 34 ATP, slow process
- Byproducts are CO_2 and H_2O

Anaerobic respiration:

- Doesn't require oxygen, produces only 2 ATP, but very fast process
- Lactate is major byproduct

The different processes are illustrated in the following figure (1.6):

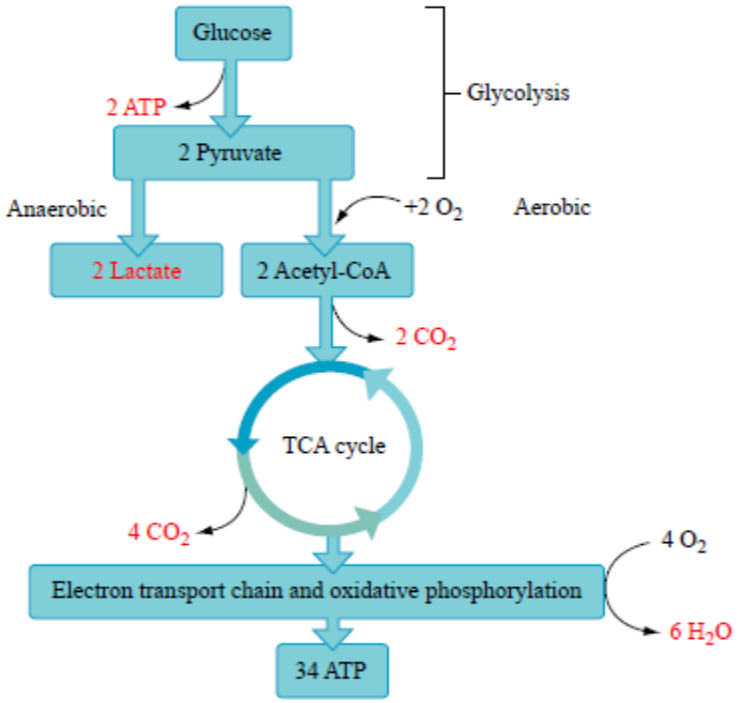

Figure 1.6: Metabolic processes leading to ATP production [7]

Vascular activity

The blood flow is defined by:

$$\text{Flow}=\frac{volume}{time} \qquad (1.1)$$

We define the transit time (τ) by

$$\tau=\frac{CBV}{CBF} \qquad (1.2)$$

Which is the time it takes for blood to cross vascular region and where: CBV and CBF are independent physiological parameters.

The mean transit time, gives information about the blood flow to some particular brain tissues:

- Increasing flow (CBF increases), decrease transit time, since velocity of the particles increases. As a consequence there would be a decreased oxygen delivery to tissue.
- Increasing volume increases transit time. (CBV increases).
- Increased mean transit can indicate regions with delayed blood flow.

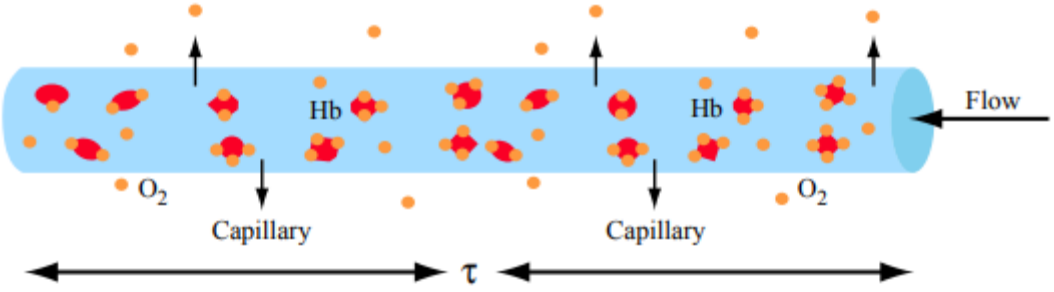

Figure 1.7: Blood flow across a vein section [7]

Relation between the different brain activations

When a brain activation is generated due to a cognitive task. There are some particular physiological changes that occur in the brain. The following table groups these changes:

Tab. 1.3- Physiological changes in the brain due to a presence of a cognitive task

Neuronal Changes	Metabolic Changes	Vascular Changes
AP spiking activity, LFP	Glucose metabolism (CMRGluc) Oxygen metabolism (CMRO2)	CBF, Transit time CBV

These interactions are illustrated in figure 1.8:

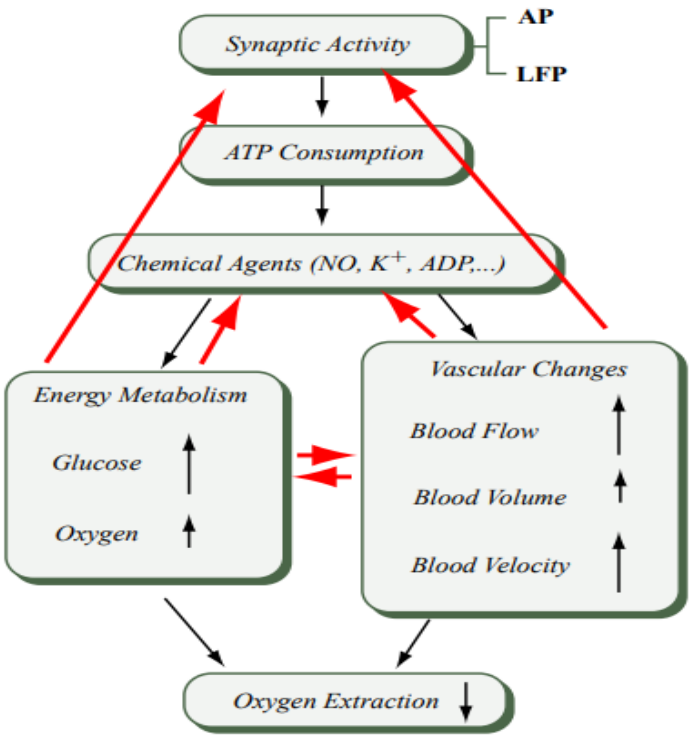

Figure 1.8: Relation between the different types of brain activities [7]

1.3 Neuro Imaging techniques

Neuro Imaging includes the use of various techniques to either directly or indirectly image the structure, function or the pharmacology of the brain, it falls into two categories:

- Structural imaging, which deals with the structure of the brain and the diagnosis of intracranial disease (such as tumor), and injury for example.
- Functional imaging, which is used to diagnose metabolic diseases on a finer scale (such as Alzheimer's disease) and also for neurological and cognitive psychology research and building brain-computer interfaces.

1.3.1 Magnetic Resonance Imaging (MRI)

MRI is a screening and diagnostic test that allow researchers to collect many image types, both anatomical images ('structural' MRI) and images that are related to the dynamic brain activity changes ('functional' MRI). In our project, we mainly concern with functional imaging (fMRI)

Mechanism of Magnetic Resonance Imaging (MRI)

The technique uses radio signals produced by protons inside atoms that are found in water and fat molecules in the body. In brief, applying strong magnetic fields to the body changes the alignment of the poles of the hydrogen protons in the body's tissues, causing the protons to give out radio

signals that can be detected by the MRI machine, which we call ” resonance phenomena ”. The radio signals given by the hydrogen protons will be used to construct an image of the tissues inside the body.

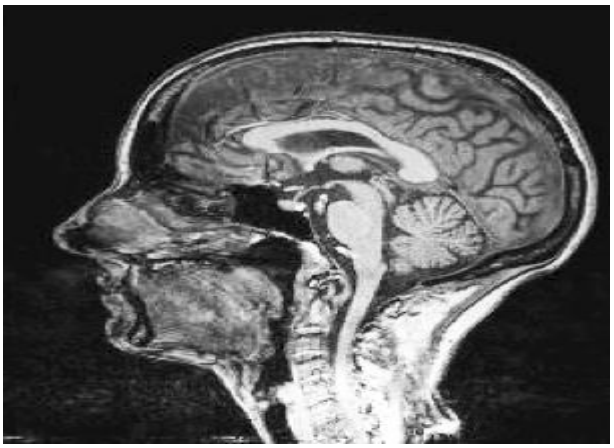

Figure 1.9: Brain image obtained using MRI technique [8]

MRI technique can be summarized in the following steps:

- Placing an object/subject in a big magnet
- Applying radio waves
- Measuring emitted radio waves

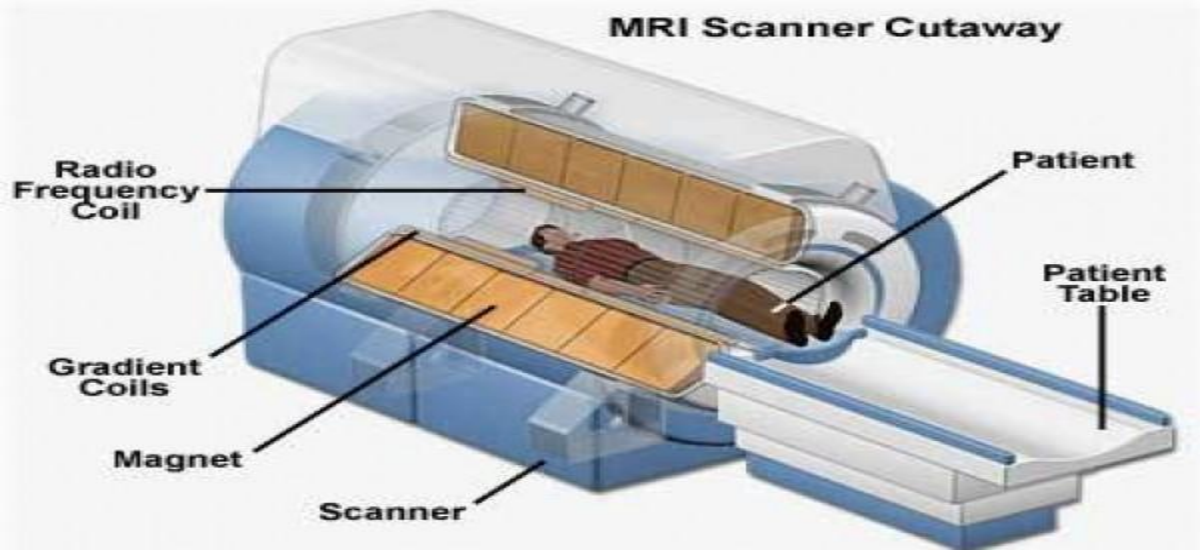

Figure 1.10: MRI scanner [9]

After presenting the mechanism of brain tissue imaging using MRI, we move now and introduce the Functional Magnetic Resonance Imaging technique, we go in-depth in explaining all the key concepts that are related to it, because we base all our results on exploiting the fMRI data.

1.3.2 Functional Magnetic Resonance Imaging (fMRI)

It's an imaging technique that measures changes in brain activity over time that is resulted from information processing of neurons throughout the brain (figure 1.11).

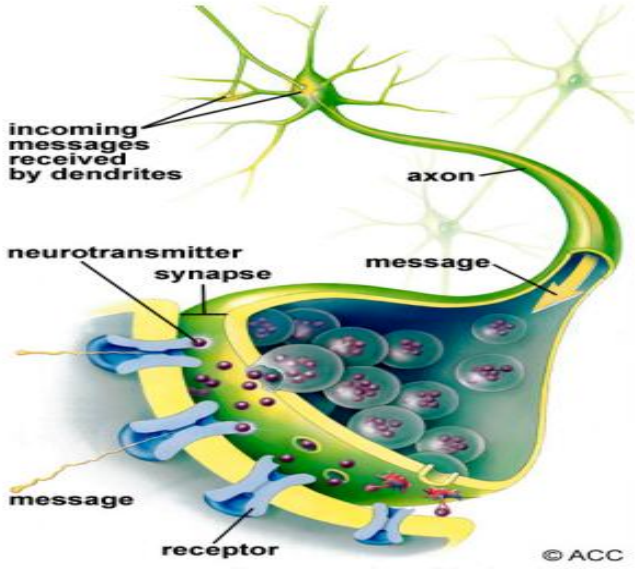

Figure 1.11: Information processed by neural cell [10]

fMRI detects variation in the cerebral blood flow, in other words, When blood flow to a particular brain region is increased, it suggests brain activity in this area has increased. Thus, fMRI can allow investigators to see what areas of the brain are active when an individual engages in a particular task, and explore those area using different computer science approaches, as we will see in the next chapters.

fMRI is the most widely used technique for investigating the living, functioning human brain as people perform tasks and experience mental states.[10] It is a noninvasive technique, and there is also no known side effects for being scanned several times with fMRI, and scans are now performed on both children and adults.

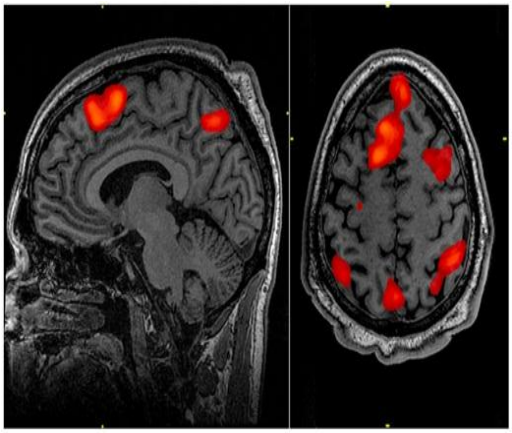

Figure 1.12: Activated regions associated to a particular cognitive task [11]

During the course of a fMRI experiment, a series of brain images are acquired, often while the subject performs a task set, which include viewing, hearing, feeling or smelling for example, these are the stimulus to use in a fMRI experiment, lying in the scanner without doing anything is called the resting-state fMRI.

On the cellular level, it is important to know that oxygen is delivered to neurons by hemoglobin in capillary red blood cells. When neuronal activity increases there is an increased demand for oxygen and the local response is an increase in blood flow to regions of increased neural activity (figure 1.13).

Hemoglobin is diamagnetic when oxygenated but paramagnetic when deoxygenated. This difference in magnetic properties leads to small differences in the MR signal of blood depending on the degree of oxygenation. Since blood oxygenation varies according to the levels of neural activity these differences can be used to detect brain activity[12]. This form of MRI is known as blood oxygenation level dependent (BOLD) imaging that will be discussed later in the chapter. BOLD imaging is the main method that is used to observe different areas of the brain or other organs, which are found to be active at any given time.

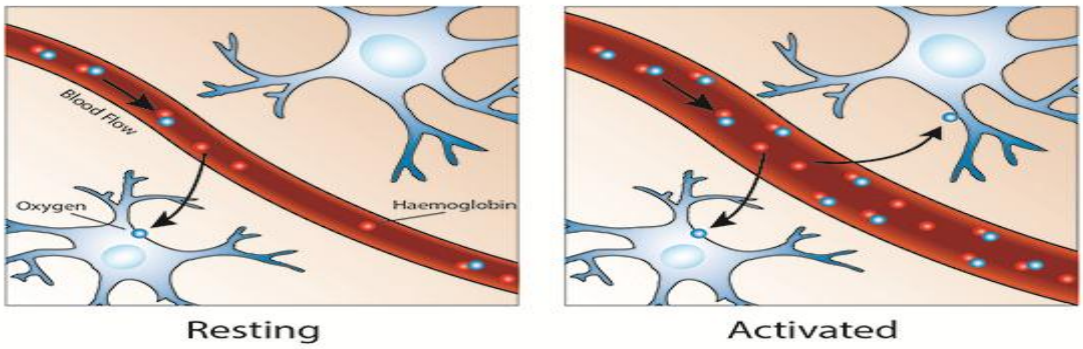

Figure 1.13: Degree of oxygenation according to the blood flow [12]

1.3.3 The BOLD signal

The BOLD response does not instantaneously follow neural activity, and occurs with delay and dispersion since the BOLD response arises primarily from a CBF response [7], it typically referred to as the "hemodynamic response" The modulation of blood flow leads to the fMRI signal (figure 1.14).The BOLD phenomenon is basis of contrast for nearly all fMRI experiments

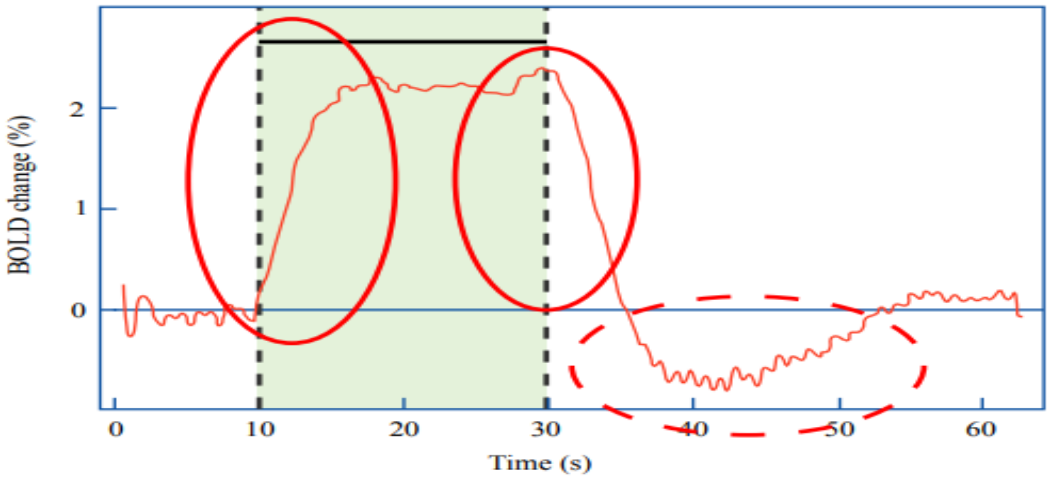

Figure 1.14: The BOLD signal [7]

Increased blood flow flushes out dHb, causes an increase in BOLD signal during activation (figure 1.15)

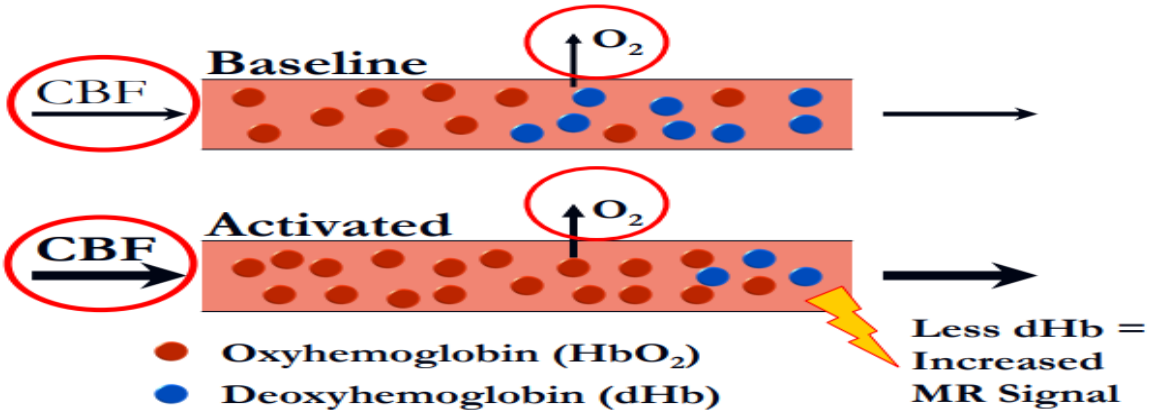

Figure 1.15: Metabolic changes related to an increase in BOLD signal [7]

fMRI experiment involves using a long duration visual stimulus (60 s), i.e. the "on" period Interleaved with long Interleaved with long "off" periods (60 s). Even earliest study revealed some characteristic features of the BOLD response: BOLD effect does not instantaneously follow stimulus, there is a delay after stimulus onset and offset.

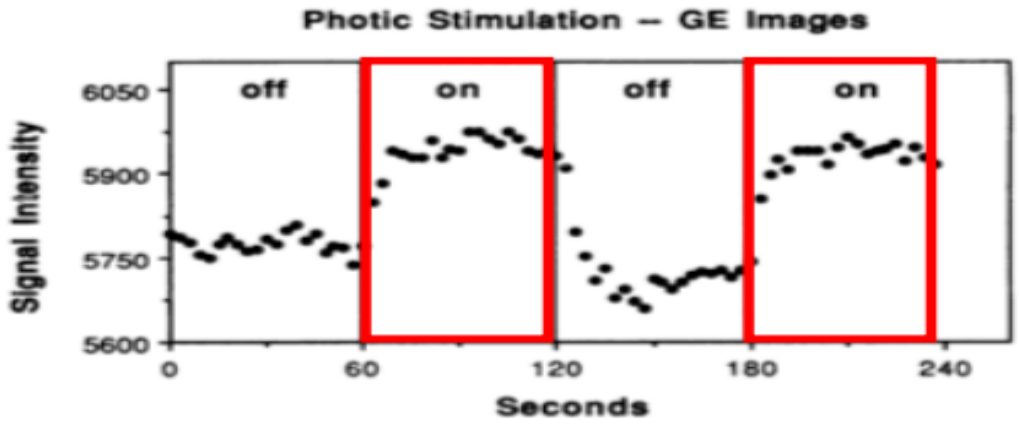

Figure 1.16: BOLD signal variation over an fMRI experiment [7]

ON→ Brain region is activated (presence of stimulus).

OFF→Brain region is deactivated (absence of stimulus).

In the next part, ware going to talk about the different steps that leading to processing and exploiting the fMRI data.

1.4 Processing and analysis stages of fMRI data

The following flowchart (figure 1.17) shows the basic data processing and analysis steps of fMRI data):

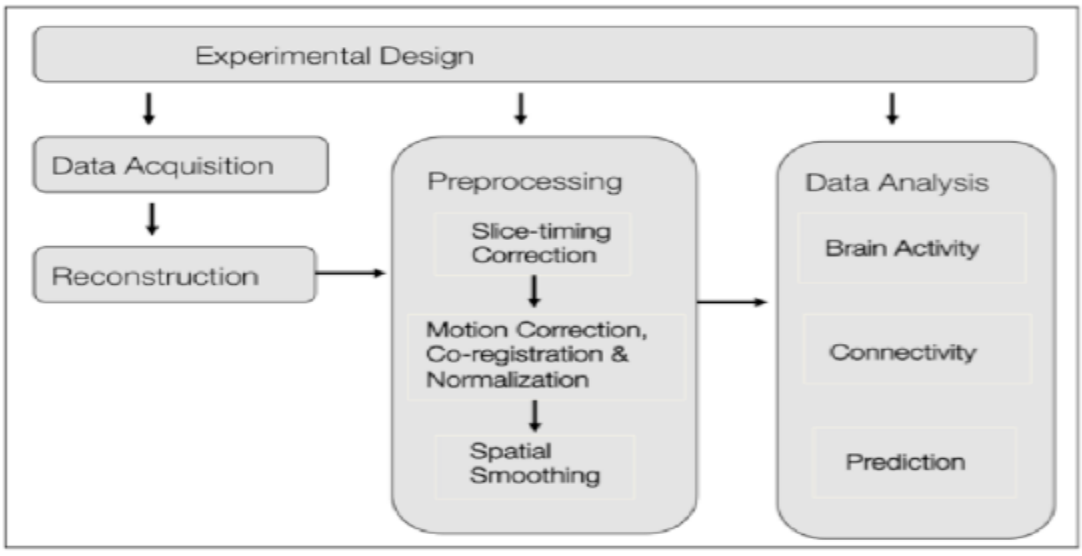

Figure 1.17: Block diagram for fMRI data processing [13]

Our main work consists of analysis fMRI data and prediction.

An fMRI experiment starts with the experiment design, which is the most crucial factor in determining how well the experiment will go. Data acquisition from the experiment, is the next

step, which will be followed by reconstructing the data and obtaining images. Before going to applying statistical tools, we perform a series of processing steps, such as:

- Anatomical alignment of the various types of images (coregistration).
- Timing issues.
- Head movement (motion correction).

And other related corrections. After performing the previous corrections, the images become ready for statistical analysis after processing. Statistical analysis include:

- Test an outcome brain activity related to a task.
- Assess functional activity.
- Develop multivariate models designed to correlate optimally with experimental variables or outcomes.

Acquisition of fMRI data

Data are sampled within small cubic volumes called "voxels", or 3D pexels. The voxel sizes depends on the thickness of the slice and related parameters. In-plane resolution and slice thickness determines voxels sizes. Researchers desire isotropic voxels, which have the same dimensions on all sides, a typical side of a voxel is 3x3x3mm voxels, this is close to optimal for many purposes when using a 3- Tesla scanner[13].

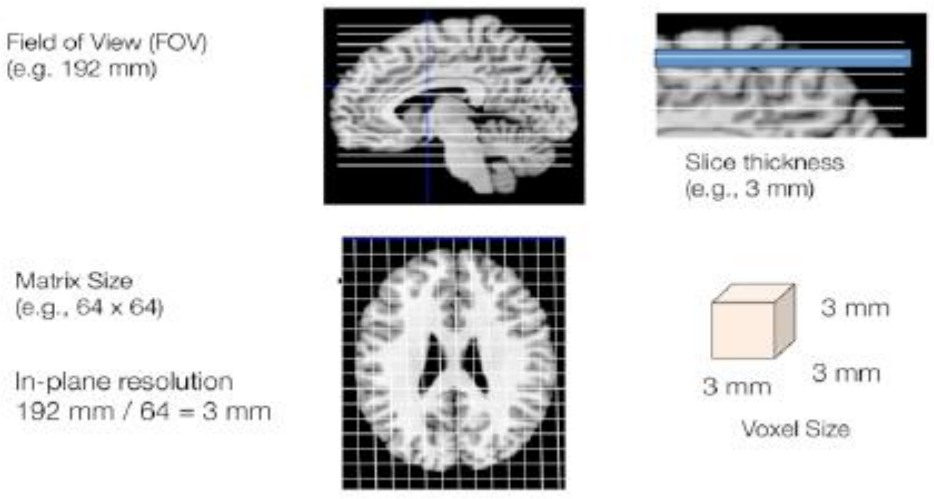

Figure 1.18: fMRI data structure [13]

Designing an fMRI study requires a series of tradeoff given the particular study. One fundamental tradeoff is between the spatial and temporal resolution, we can either collect data with high spatial resolution, or collect data fast, but we can't do both. This a technological constraint.

Image orientation and dimensions

It is important to understand and interpret which part of the brain one is viewing requires some practice. It is typical to show neuroimaging results on anatomical brain slices. Each of the three dimensions of the brain space has a special name:

- The left to right dimension is the X direction in standard brain coordinate space.
- The back to front dimension is the Y dimension which ranges from posterior(caudal) at the brain's back to anterior(rostral) at the front.
- The bottom- to-top dimension is the Z dimension which ranges from inferior to superior locations.

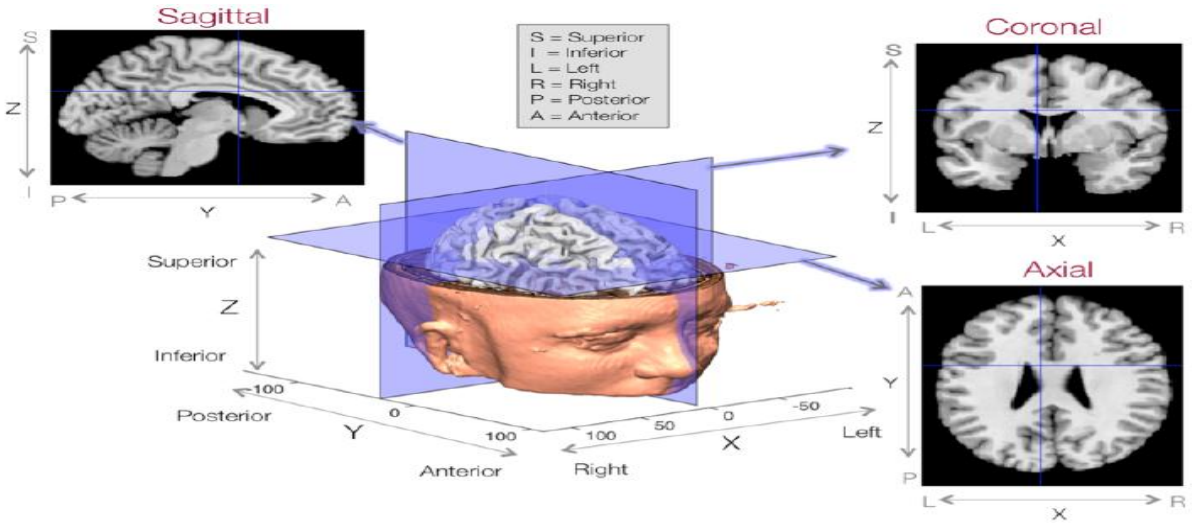

Figure 1.19: fMRI collected Image orientation [13]

Researchers typically report locations along these dimensions in [x,y,z] coordinate triplets with x,y, and z values indicating distance in millimeter units relative to a zero point. The [0 0 0] point, is by convention the anterior commissure[13], a small white-matter bundle, which connects the brain's two hemispheres, the following figure shows this point:

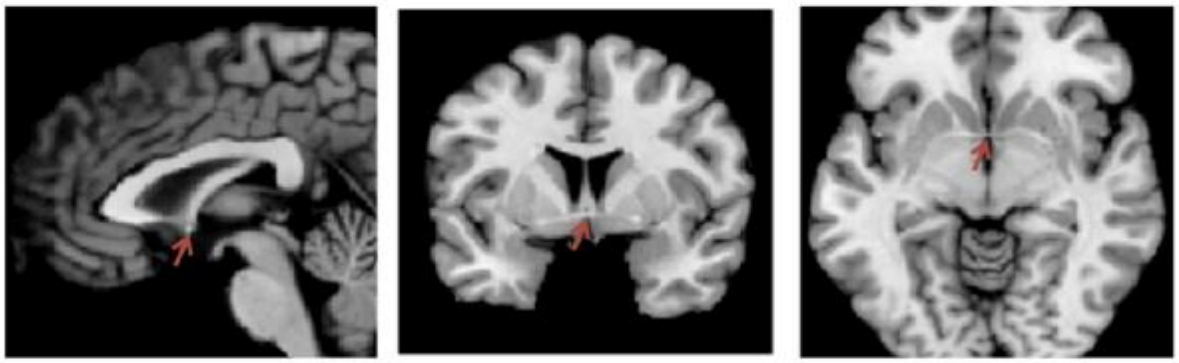

Figure 1.20: Position of the reference coordinate [0 0 0] [13]

1.4.1 fMRI time series

An fMRI dataset that is collected from one subject contains a time series of 3-D images, or "volumes". The volume covers the entire brain, but also can cover just one brain tissue section or slab, as we will see in the chapter 3.

The data of each volume are acquired slice by slice, after completing one volume, the scanner moves to the next image. As they are collected the data are sampled onto a rigid voxel grid.

The number of the voxels can be really huge that each 100.000 voxels per volume, this number mainly depends on the acquisition choice (the pulse sequence, the software that runs the RF antenna and other parameters.)[13].

Thus, fMRI data comprises hundreds to thousands of images in time series. As local regions's oxygen metabolism and blood flow change, researchers use variations in the measured signal to make inference about brain activity and connectivity between the neurons.

Researchers assess brain connectivity by examining associations in the fluctuations among voxels with or without task condition influence analyses.

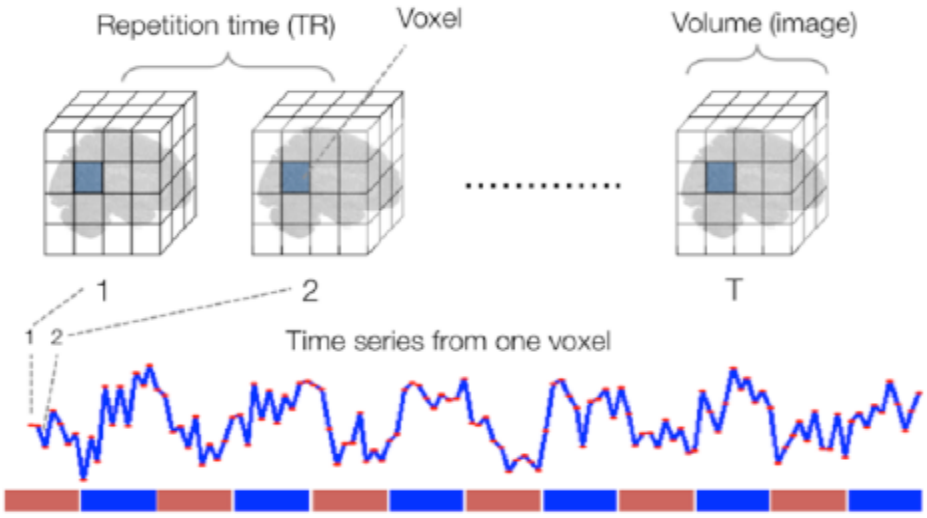

Figure 1.21: BOLD signal evolution in a particular voxel [13]

1.4.2 Statistical analysis

fMRI dataset contains a time series of each voxel's signal values, the idea is to study a particular voxel at a time. The data are quite noisy, so we use statistical analysis to determine whether a signal change is consistently associated with the particular task we are studying. We analyze closely the fMRI brain activity, by studying the BOLD signal. The signal model should show differences in the activity levels, between the rest period and the period during which the subject is under stimulus. Figure (1.22) shows a set for BOLD signals for some voxels in the cortex.

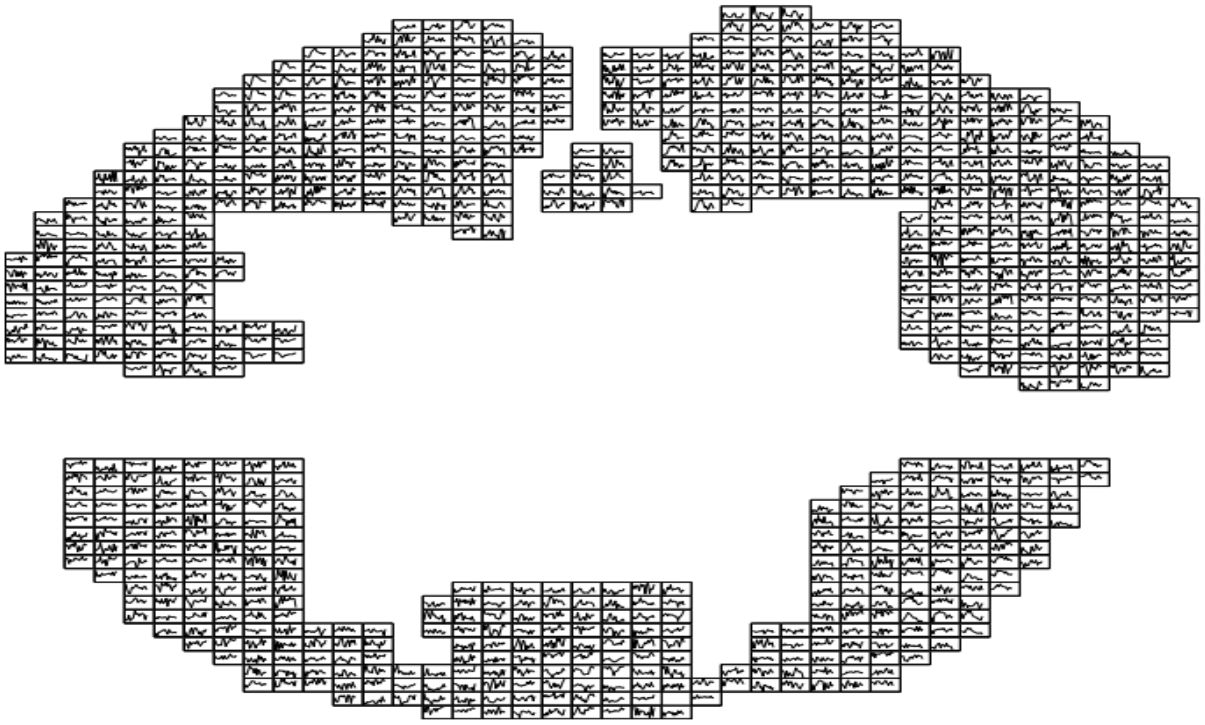

Figure 1.22: Typical fMRI data for a selected set of voxels in the cortex, from a two-dimensional image plane through the brain [1]

1.5 Conclusion

Through this first chapter we were able to learn about fMRI technique and how it is used for studying the brain activity, the latter is the most important factor to study when it comes to investigating the cognitive aspects of the brain. We will see in the next chapter, some of the most powerful concepts of artificial intelligence that will be used later to explore fMRI data for cognitive states differentiations.

Chapter 2

Artificial intelligence tools for brain investigation

2.1. Introduction

The beginning of this chapter consists in giving a clear description of the full process of cognitive states classification, followed by explaining the different machine learning approaches that are currently used for such application. We give special attention to the concept of features extraction and the several features extraction techniques that are mainly used in the literature by researchers.

A brief discussion of the different classification algorithms is also provided, with an emphasis on the selected classifier for our study.

2.2 Cognitive states classification stages

The general approach to tackle any cognitive science classification problem in machine learning is illustrated in the following figure:

Figure 2.1: Basic stages of cognitive states classification

Before presenting the different approaches that are used in brain states classification, we first start by providing some details about each stage of the classification process. Although all the approaches can be illustrated as figure 2.1 shows, some may differ in the way features are extracted from the fMRI data or in the choice of the classifier for example.

After collecting the fMRI data as we described in chapter1, the process of classification goes by the following steps:

1. Pre-Processing

Prior to analysis, fMRI data goes through a series of preprocessing steps, in order to remove different artifacts, and validating the model assumption. It's a common step in many pattern-based classification models.

2. Feature extraction

In machine learning and pattern recognition, a feature is an individual measurable property or characteristic of a phenomenon being observed [14].

Features extraction consists in creating new features as a function of other existing features. It looks for common and interesting features in the data that best fit the experimental design and the classification objective. Choosing informative and discriminating features is a crucial step for effective classification algorithms. In our study, the extracted features are the fMRI signal properties that allow to distinguish between different cognitive states.

Here we present the most important feature extraction modalities that are applied for solving signal processing research problems. These methods are the following:

- Mean: In this method we take the average value of the signal over the window as feature.

$$\text{Mean}=\frac{\sum X(t)}{n} \quad (2.1) \quad t=1\ldots n \quad (n: \text{total duration of the signal})$$

- Median: We compute the median signal value over the window.
  For a given sample X1, X2…..Xn, the median is either $\frac{n+1^{th}}{2}$ or $\frac{n}{2}$ (2.2)

- Variance: We compute the variance of the values of the signal over the windows.

  We have: $\sigma 2= E(X^2)- [E(X)]^2$ (2.3)

- Standard Deviation: By measuring the spreadness of the signal over the window.

We compute the square the variance using formula

- Root Mean Square: Here we use the quadratic mean value of the signal over the window.
- Averaged derivatives: By computing the mean value of the first order derivatives of the signal over the window.
- Spectral analysis techniques: A sort of feature extractions techniques that apply some transformations on the signal, in order to analyze its spectral components such as computing its Fourier transform and select some frequency bands as features or using the spectral density PSD for example. The Spectral Kurtosis, can also be used to provide a complementary useful information to the PSD about the spectral nature of an analyzed signal.
- Zero Crossing Rate: Features here are represented by the total number of times the signal changes from positive to negative or back or vice versa over the window
- Mean Crossing Rate: A feature in this method is represented by the total number of times the signal changes from below average to above average or vice versa normalized by the window length
- Spectral Entropy: This feature extraction technique consists of measuring the distribution of frequency components and use it as feature

3. Feature selection

As it's computationally infeasible to use all available features as input for the machine learning classifier, it is important to take a part of the features that have been already selected, based on the previous modalities that we described in the previous point, a new feature selection algorithm should search the best feature combinations within the set of features, the subset of the selected features should aim to reduce the classification error based on various criteria, for example, for a set of D features, the algorithm selects a subset of size $d < D$, which has the greatest potential to discriminate between classes, with high classification performance.

Features selection is an effective step in reducing dimensionality, removing irrelevant data, increasing learning performance and improving the output results and also reducing the computational cost. The feature selection techniques are divided into three types: wrappers, filters and Embedded. Here we provide a brief explanation of each feature selection method:

Wrapper methods

The wrapper approach are based on the classifier accuracy where the possible feature subsets is input to the model and the subset for which the model perform best is selected. The selection of a set of features is done using a search problem, where different combinations are prepared, evaluated and compared to other combinations. A predictive model allows us used to evaluate each obtained combination of features and assign a score based on the corresponded model accuracy. The scores are compared to each other, the combination representing the highest score is automatically selected.

Filter methods

Filter feature selection methods apply a statistical measure such as computing the mean, the variance and related statistical operators to assign a scoring to each feature. Afterwards, the features are ranked by the score and either selected to be kept or removed from the dataset depending on the obtained score.

Embedded methods

In this kind of method the variable selection happens in the process of training. Embedded methods learn which features best contribute to the accuracy of the model while the model is being created.

4. Learning and classification

The classifier is the machine learning algorithm that is going to perform the specific classification task we are looking for. The algorithm is chosen based on several factors.

The size of the data that we deal with, is an important parameter in deciding which classifier to choose. Besides, the approach the one adapt for the cognitive science study, contribute in choosing the best classifier. There are other aspects to take into consideration, but these are the main ones.

We will discuss later in this chapter some of the approach that are currently used for studying cognitive states.

Logistic Regression (Predictive Learning Model)

It is a statistical method for analyzing a data set in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable The goal of logistic regression is to find the best fitting model to describe the relationship between the dichotomous characteristic of interest and a set of independent variables.

Decision tree

Decision tree builds classification or regression models in the form of a tree structure. It breaks down a data set into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes. A decision node has two or more branches, it corresponds to the best predictor called root node. Decision trees can handle both categorical and numerical data.

Random Forest

Random forests is a method for classification that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification).

Nearest Neighbor

The k-nearest-neighbors algorithm takes a group of labelled points and uses them to learn how to label other points. To label a new point, it looks at the labelled points closest to that new point (those are its nearest neighbors), and has those neighbors vote, so whichever label the most of the neighbors have is the label for the new point (the "k" is the number of neighbors it checks).

This was an overview on some machine learning algorithms that are used for classification. Neural network algorithm and Naïve Bayes are also used for this task and will be discussed later in the chapter.

2.3 Machine learning approaches for cognitive state classification

There are several approaches in machine learning that are nowadays used by cognitive sciences researchers for brain states detection and classification, here we try to describe few of them and elaborate at the end on the approach that we used in our work..

2.3.1 Kernel based approach

This approach is mainly used for continuous brain states classification, in this approach the data consists of several fMRI images, each image consists of thousands of voxels that we described in the previous chapter. Kernel are essentially square, symmetric and positive definite matrices that try to encode similarities between each pair of images.

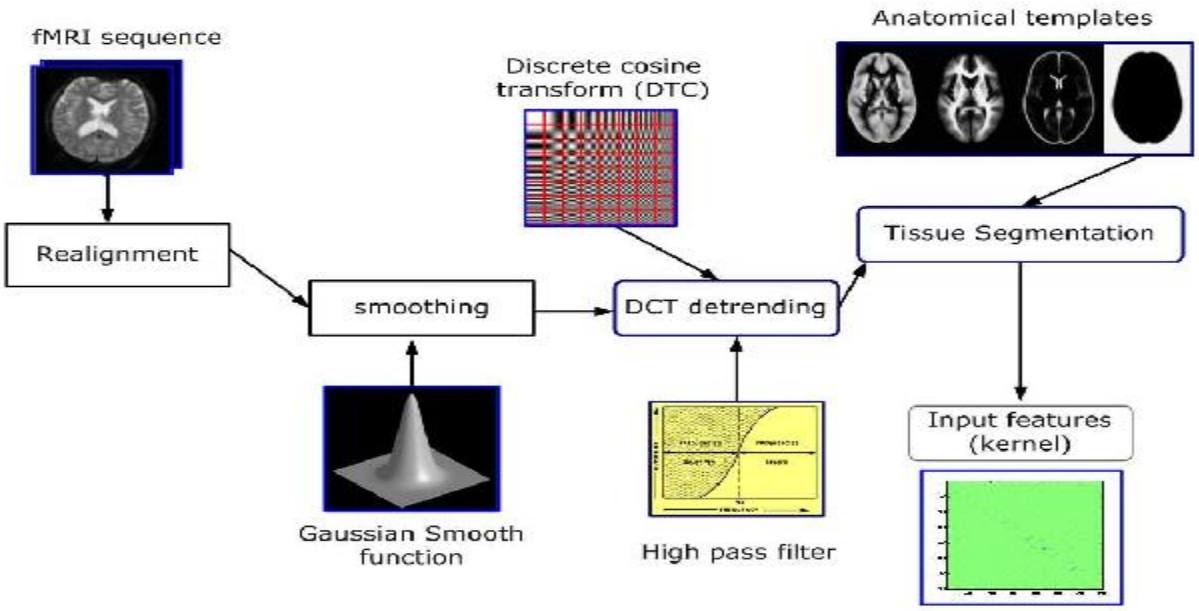

Figure 2.2: The pre-processing of the fMRI data. The black boxes are the key processing steps used in fMRI analysis, while the blue boxes are noise filter and hypothesis driven feature extraction technique [15]

2.3.2 Neural network approach

Neural network has been applied to a large spectrum of fMRI problems. The representative model for a neural network is shown in the following figure:

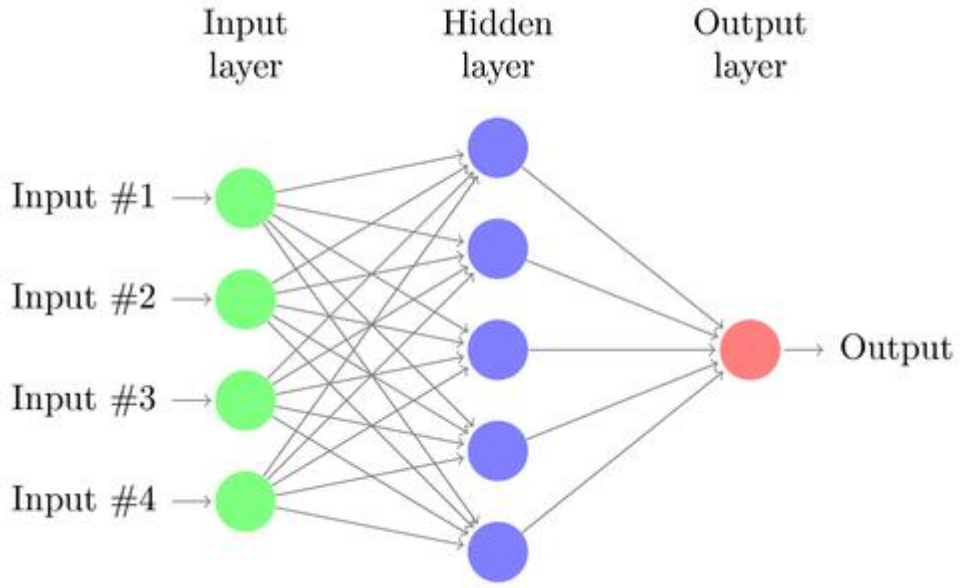

Figure 2.3: Representative model of a neural network [16].

The general components of a neural network are the following:

Input Nodes

Provide information from the fMRI data that has been collected to the network and are together referred to as the "Input Layer". There is no computation in this level.

Hidden Nodes

Perform computations and transfer information from the input nodes to the output nodes. A collection of hidden nodes forms a "Hidden Layer".

A simple neural network will only have a single input layer and a single output layer, as well as a broad neural architectures options. In fMRI data problems, we generally use an MLP Multi-Layer Perceptron MLP [20]. MLP has at least one hidden layer, the multiple number of hidden layers makes computational time shorter.

Output Nodes

The Output nodes are collectively referred to as the "Output Layer" and provides the results of the classification problem. We may have several outputs in case of several cognitive states.

Activation function

Or what we call the transfer function. It is used to determine the output of neural network like yes or no. It maps the resulting values in between 0 to 1 or -1 to 1..etc, and that depends on the type of the activation function. The Activation Functions can be basically divided into 2 types: Linear Activation Function and Non-linear Activation Functions.

Synaptic weights

Which refers to the strength or amplitude of a connection between two nodes. The learning process of the neural network algorithm consists of choosing the best values of these synaptic weights in order to get a neural network with the best performance.

2.3.3 Multiband Connectivity graph approach

It is a multi-band classification of connectivity graphs. The technique tries to identify the connections that are formed while performing the cognitive task, mainly these connections are most discriminative between brain states

The steps of this approaches are the following:

- Estimating connectivity at different temporal scales using the wavelet transform as a preprocessing step [21].
- Preparing classifier trained on functional connectivity graphs of a group of subjects to distinguish between brain states of an unseen subject.

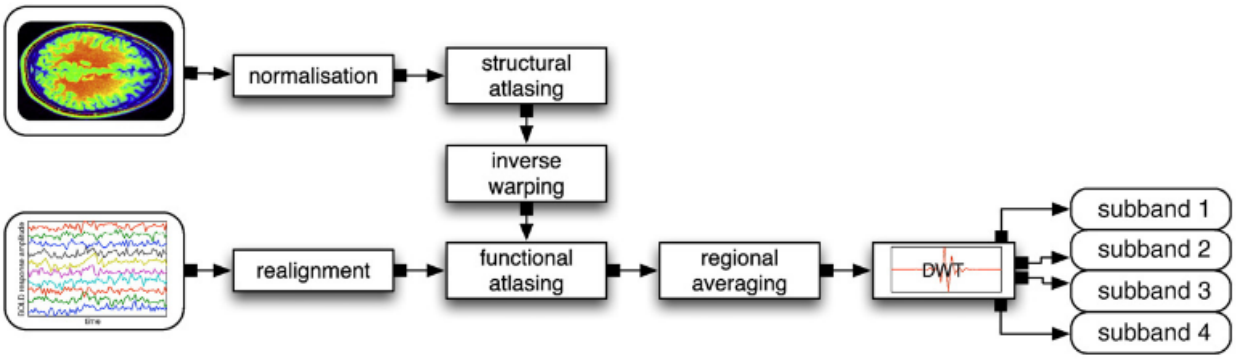

Figure 2.4: Flow chart of the preprocessing procedure. DWT stands for discrete wavelet transform [17]

A sample of a discriminative graph is shown in the following figure:

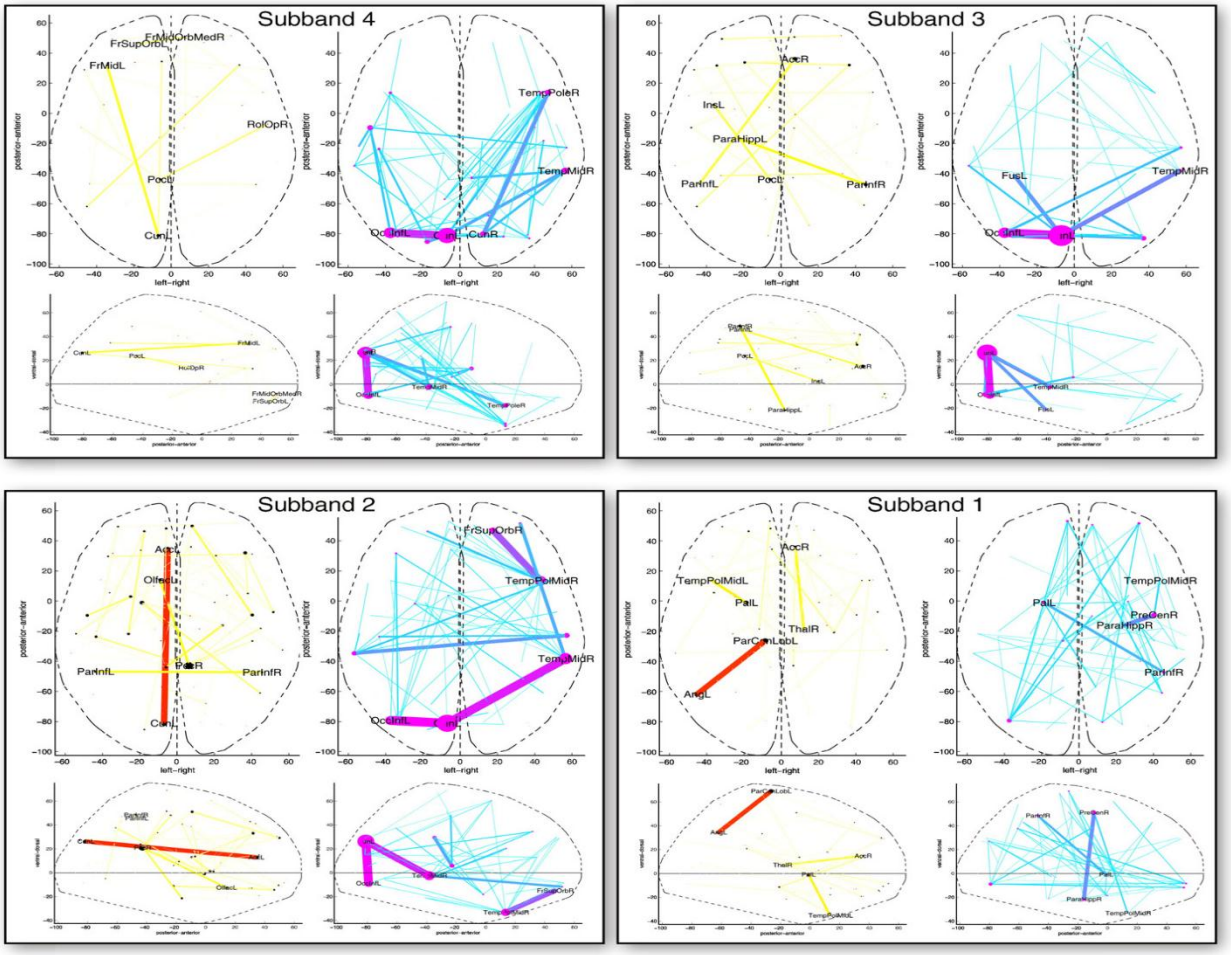

Figure 2.5: views of discriminative graphs. Connections with darker colors and thicker lines correspond to more discriminative ability [17]

2.3.4 Statistical approach

This kind of methods uses the statistical pattern recognition method for classification, and identification. In this report, we are going to adapt this type of approach in performing our cognitive states classification

The basic cognitive task in this kind of approaches includes the following:

1. Feature Extraction

Features here are selected based on computing statistical parameters such as the mean, the variance or other statistical operators.

2. Pattern Discovery

A detailed study of the data and the obtained features, allows us to understand the relation between the selected features.

3. Statistical Inference

We use statistical tools and other probabilistic theorems in order to get the key discriminator parameter for the classification task. Computing different probabilities based on the previous statistical features, in order to guess the right class of the cognitive state we are dealing with, is an example of a the best definition of the statistical inference step.

There are several machine learning algorithms that can be used for such supervised classification task. For such approach, one of the following algorithms can be used:

1. Naïve Bayes classifier (NB).
2. Support Vector Machine (SVM).
3. K- Nearest Neighbor (kNN).
4. Linear Discrimination classifier (LCD).

We chose in our work, the Naïve Bayes classifier, since we deal with reduced database and the algorithm has shown a great efficiency in applications that involve data with such dimension. In addition, the classifier is founded on statistical and mathematical tools that deal with features and perform the classification task.

It is important to understand how the Naïve Bayes classifier operators and the next point is devoted to that.

2.4 Naïve Bayes (NB) Classifier

Naïve Bayes classifier is an algorithm that is completely based on the theorem of Bayes with an assumption of independence among predictors, or between features. In other words, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature, even if these features depend on each other or upon the existence of the other features, all of these properties independently contribute to the probability and that is what we call the naïve assumption why. There are several advantages for the Naïve Bayes classifier, we list the following:

- Useful for very large datasets.
- Efficient for a reduced dataset.
- Easy model to build.
- Used for several applications such as real time Prediction and text classification/ Spam Filtering.
- Provides high performance even for complicated classification approach, such as multi-class prediction.
- It is easy and fast to predict the class of test data set
- It is easy and fast to predict the class of test data set

Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c) using Bayes theorem:

$$P(c|x) = \frac{P(\mathbf{X}|\boldsymbol{C})P(c)}{P(x)} \qquad (2.4)$$

Where,

- P(c|x) is what we call the posterior probability of class(c) given the features or the input we have inputs (x, features).
- P(c) is the prior probability of obtaining the specific class, for example in case of two cognitive states it is 0.5.
- P(x) is the prior probability of features, we generally don't take it into consideration when comparing between classes since it is used to normalize the results only, removing it, will not affect the final results.
- P(x|c) is the likelihood which is the probability of the features given class. Using the naïve assumption of the independence between features, the likelihood probability can be written as following:

$$P(x|c) = \mathrm{P}(x_1|c) * \mathrm{P}(x_2|c) * \mathrm{P}(x_3|c) * \mathrm{P}(x_4|c) * \dots\dots \mathrm{P}(x_n|c) * P(c) \qquad (2.5)$$

The class with the highest posterior probability is the outcome of prediction.

2.5 Conclusion

This chapter explained various machine learning for cognitive states classification. Additionally, we selected the most useful machine learning approach and the suitable classifier and its efficiency for our application.

In the next chapter, we are going to present the scope of our research, and how we are going to use the SCSA to extract relevant features for cognitive states classification.

Chapter 3

SCSA based features extraction

3.1. Introduction

The first part of this chapter is completely devoted to explaining the database that has been used for this project.

Another section, explains the method that we propose for our research. In this part of the chapter, we are going to attribute a particular attention to the SCSA, since our work is based on its application as a new feature extraction modality for mental states classification.

3.2 StarPlus database

3.2.1 Experience description

Times series data of the BOLD response were collected from a fraction of the brain that was imaged of 6 healthy subjects. The experiment consists of forty trial by subject, during each trial the subject was instructed to perform some cognitive tasks during a precise time intervals from the trial entire duration (Such as reading a particular sentence, or looking at a given picture).Whereas some other time intervals correspond to resting state, depending on the type of the stimulus, we differentiate between two type of trials SP and PS trials:

- SP trials: The sentence in this kind of the trials appears before the picture
- PS trials: In this case, the picture appears before the sentence.

The first 20 trials provide SP data, while the last 20 trials correspond to PS data. Every 0.5 seconds, a sample (an image or a snapshot) is captured. The timing within each trial is the following:

1. At the beginning of the trial, the subject was shown the first stimulus (Sentence in case of SP trial, or picture in case of PS trial), this step lasts 4 seconds.
2. The first stimulus is then removed and replaced by a blank screen (4 seconds).
3. The second stimulus appears and lasts a maximum of 4 seconds or until the subject presses the mouse.

Each subject was sequentially shown a picture and a sentence, and was told to press a button to determine if the picture correctly matched the sentence.

The picture were geometric arrangement of symbols such as: *,+ and/or $. The sentences were affirmative or negative descriptions such as “it is true that the plus is above the dollars” (affirmative) or “It is not true that the plus is above the dollars”.

Therefore, each trial lasts 27 seconds and provides 54 brain images. We summarize the experience in the following table:

Tab 3.1- Timing of the fMRI experiment

Type of the trial	Duration of each step	Numbre of images collected
SP/PS	4 secondes	1
SP/PS	4 secondes	9
SP/PS	4 secondes	17
SP/PS	15secondes	30

The data was marked with 25-30 anatomically regions of a fraction of the brain called the regions of activations (ROA), these regions are activated when the particular task, that was described in the experience performed by the subject.

The data consists of a set of trials, and all simulations in this research have been carried out in Matlab. Each .mat file contains the data of each subject that can be described with three variables:

3.2.2 Variable meta

This variable gives general information about the data, such as the morphology or the form of the imaged part, the coordination(x, y, z) of each voxel, the number of voxels in each region of activation, the name of the subjects are related information.

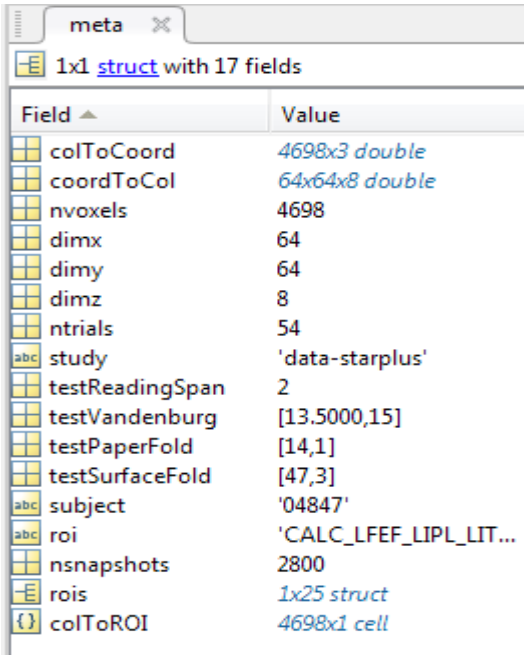

Figure 3.1: Meta variable structure

The most important fields are the following:

- meta.subject: gives the identifier (the number) of the subject taking the experience.
- meta.ntrials: gives the number of each trial in the whole dataset, in this case it is 54, since there are 14 trials that are not taken into consideration because they correspond to either noisy trials or resting trials.
- meta.nsnapshots: This field gives the number of snapshots within the trial.
- meta.nvoxels gives the number of voxels in each obtained image.
- meta.dimx (.dimz and .dim give similar information): This field gives the maximum x coordinate in the brain image, considering the minimum x coordinate is x=1.
- meta.colToCoord(v,:) gives the geometric coordinate (x,y,z) of the voxel number v.
- meta.coordToCol(x,y,z) This field gives the number voxel, whose coordinates are (x,y,z).
- meta.colToROI{v} gives the region of interest of the voxel Number v.

3.2.3 Variable info

It gives a description of each trial, details regarding the number of the trial, its type (SP or PS), the timing for the beginning and the end of each trial as well as the action made by the subject during the trial. The exact sentences and pictures are also presented, as well as the response time of each subject.

info

1x54 struct with 14 fields

Fields	len	mint	maxt	missing	nmissing	sentence	img
1	13	1	13	18x2 double	3	[]	[]
2	55	14	68	[7,52]	1	[]	[]
3	55	69	123	[]	0	'''It is true t...	'pad'
4	55	124	178	[]	0	'''It is not tr...	'das'
5	55	179	233	[3,34;4,34]	1	'''It is not tr...	'pas'
6	55	234	288	[]	0	'''It is true t...	'sad'
7	55	289	343	[]	0	''''''	''''''
8	55	344	398	[]	0	'''It is not tr...	'dap'
9	55	399	453	[]	0	'''It is true t...	'pas'
10	55	454	508	[]	0	'''It is true t...	'dap'
11	55	509	563	[]	0	'''It is not tr...	'sad'
12	55	564	618	[]	0	''''''	''''''

Figure 3.2: Info variable structure

The most relevant fields are the following:

- info.mint: gives the time of the first image in the interval
- info.maxt gives the time of the last image in the interval
- info.firstStimulus: This field contains either 'P' or 'S' indicating whether this trail was obtained during the PS session or SP session. The first 20 trials have firstStimulus='P', the remained have firstStimulus='S'(after picking out the noisy 14 trials)

- info.sentence gives the sentence presented during this trial. If none, the value is '' (the empty string).
- info.sentenceSym1: describes the first symbol mentioned in the picture
- info.sentenceSym2: describes the second symbol mentioned in the picture
- info.sentenceRel: describe the relation between the two symbols in the picture
- info.img: this field describes the image presented during this trial. For instance, 'sap' indicates that the 'start' is above the' picture' .The possible tokens are star (s), plus (p), and (d) dollar

3.2.4 Variable data

This variable contains the row data that we are going to explore during the project, the data is represented by the brain activation in each voxel over time for each trial. The following figure for example, shows the brain activations in 5 different voxels for trial number 3.The data for this particular trial, is structured as a group of 54 images (the case for each trial). The full obtained image is composed of the collection of all the brain activations in all voxels over time.

data | data{3, 1}

data{3, 1}

	1	2	3	4	5
1	-1.9499	-0.5248	-2.1763	6.2839	-3.7533
2	-0.0726	2.4680	1.9693	0.3211	-1.9515
3	-5.4259	-2.3075	2.1838	3.6508	-2.6478
4	-4.6432	-2.4682	0.6371	0.0495	0.4524
5	-2.1738	-5.1391	1.5710	-3.0700	-0.0178
6	-6.8689	-5.5188	2.4135	-2.3010	-3.4520
7	-1.3964	-4.9094	-1.4238	-4.5450	-2.5195
8	-6.0986	-1.2394	-2.4039	-4.7652	-1.8749
9	2.4433	1.9292	-0.2724	-1.7119	-0.4727
10	-1.5424	-0.4040	-0.3716	-0.0222	-1.4632
11	3.5486	-2.2296	2.1300	-0.3466	-1.2801
12	4.1894	1.1550	4.0997	3.5750	2.1008
13	2.3601	-1.5637	-1.2881	4.3391	-0.0544
14	5.6808	1.4922	1.8794	0.0216	-0.8715
15	5.4193	1.1647	1.7333	-1.5597	2.6369
16	3.8527	3.6715	3.4027	0.5709	2.4681

Figure 3.3: Data variable structure

The data structure is a [54x1] cell array, with one cell per 'trial' in the experiment. Each element in this cell array is an NxV array of observed fMRI activations with:

N: Number of the image

V: the activation at the particular voxel

3.3Regions of interests (RIOS) for Picture vs Sentence study

We aim to train a classifier to successfully distinguish between instantaneous cognitive states such as “the subject is reading a sentence” versus “the subject is looking at a picture”. We are interested in learning the mapping from the observed fMRI data to the subject’s instantaneous mental state, in other words, we are more interested in building a classifier that takes decisions based on fMRI data from a single time interval as we are going to see in our approach.

The task we are studying engages several brain regions, such as visual cortex for reading and seeing the sentence, intra parietal Sulcus for spatial visualization, motor cortex for pressing the button. The exact way in which the areas coordinate varies across subjects, based on their mental and verbal abilities.

In our experiment, different psychology researchers thought that there are 7 ROIS (CALC, LDLPFC, LIPL, LIPS, LT and LTRIA) that are most possibly involved in the tasks under study[1]. These regions contain a total of 1817 voxel. The following table summarizes the number of voxels in each region of interest:

Tab 3.2- Voxels number in each ROI

Region of interest	Number of voxels
CALC	318
LIPL	236
LT	305
LOPER	169
LIPS	236
LDLPFC	440
LTRIA	113

Here is an example of the variation of the brain activity of a particular voxel in LDLPFC and for the first trial. The results in figure are shown before normalization:

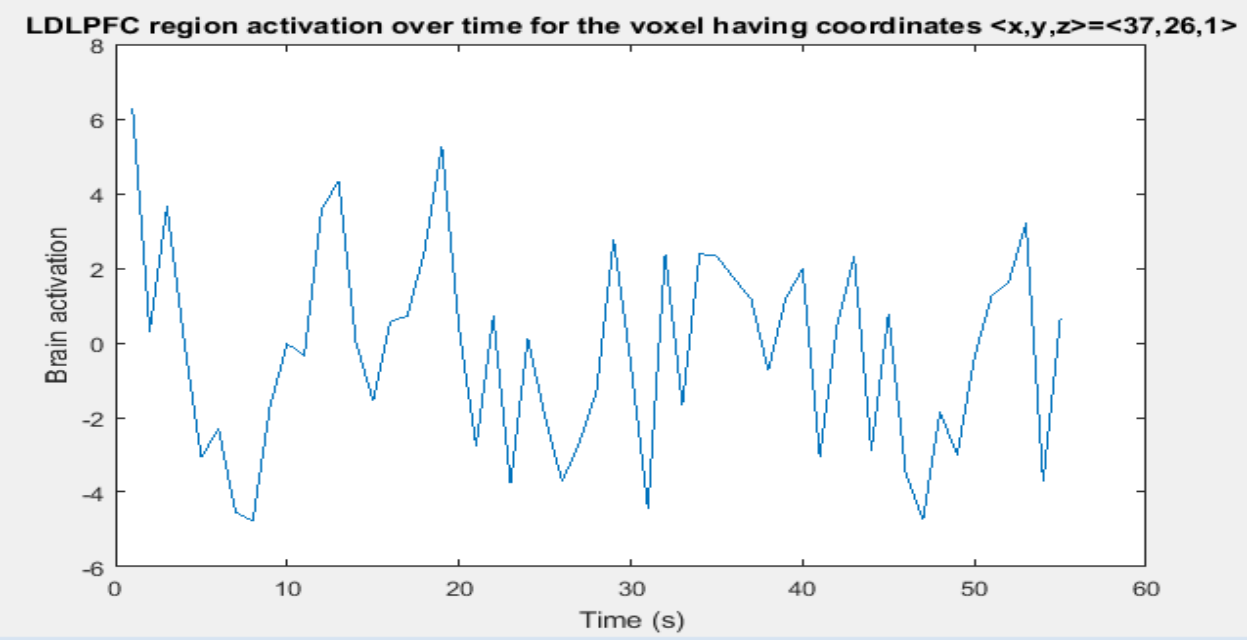

Figure 3.4: BOLD signal for a voxel situated in LDLPFC region

It is important to know that not all the voxels are active for a particular tasks. Therefore, it is very important to observe carefully the variation of the brain activities in several voxels within the brain regions. In addition, the brain activation can great vary from a voxel to another, even for the same cognitive task. Figure 3.5, shows the brain activation for another voxel from CALC region:

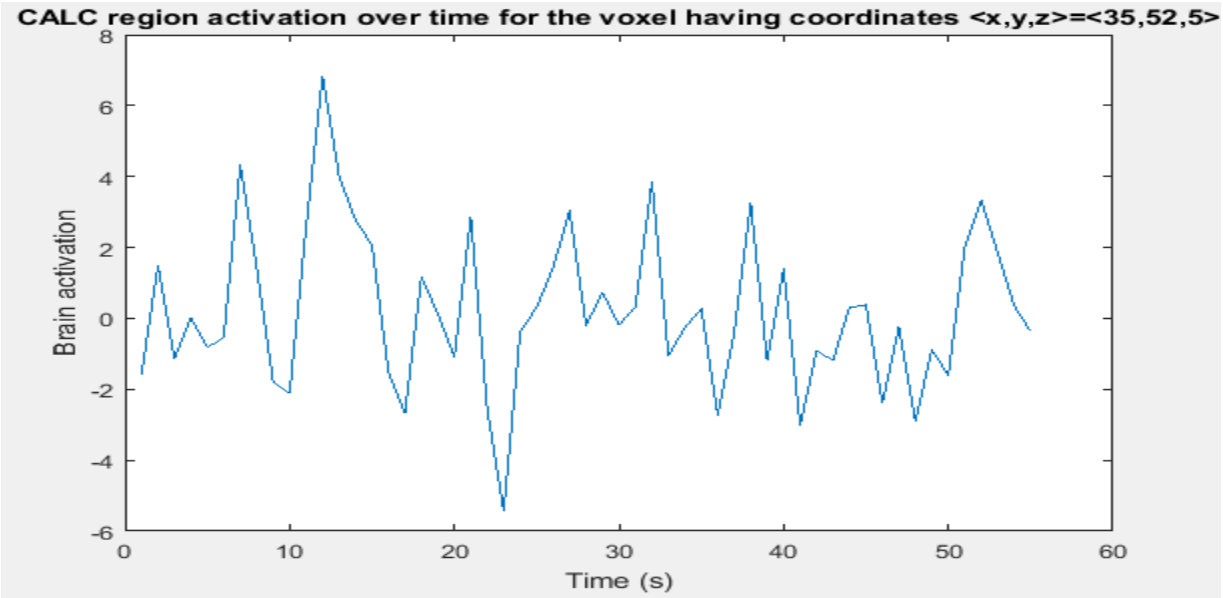

Figure 3.5: BOLD signal for a voxel situated in CALC

After we have defined the main objective of our work, we now go in depth in explaining the main contribution of our research. In this section, we are going to detail step by step the methodology of our work.

3.4 Approach

The classifier we are looking to train, should visually say whether the subject is viewing a picture or a sentence, based on the fMRI activations, more precisely, we are looking to perform the following application:

$$f_{subject}: \text{fMRI(t,t+8)} \rightarrow \{P,S\} \qquad (3.1)$$

fMRI(t,t+8) is the sequence of 16 observed fMRI images for a particular subject throughout the 8-second time interval. We only consider time intervals that align with the 8-second intervals during which the subject is viewing either a picture or a sentence.

As we stated in the experience description, snapshots or images were taken every 0.5 seconds. Subject in the experiment were instructed to rehearse the sentence in their mind until the picture is presented rather than trying to visualize the sentence immediately (case of SP data). While they were instructed to keep the picture in their mind until the sentence appears (case of PS data). Which means that even if the duration of the stimulus is 4 seconds, the generated brain activation lasts 8 seconds.

The proposed method is shown the following block diagram (figure 3.6):

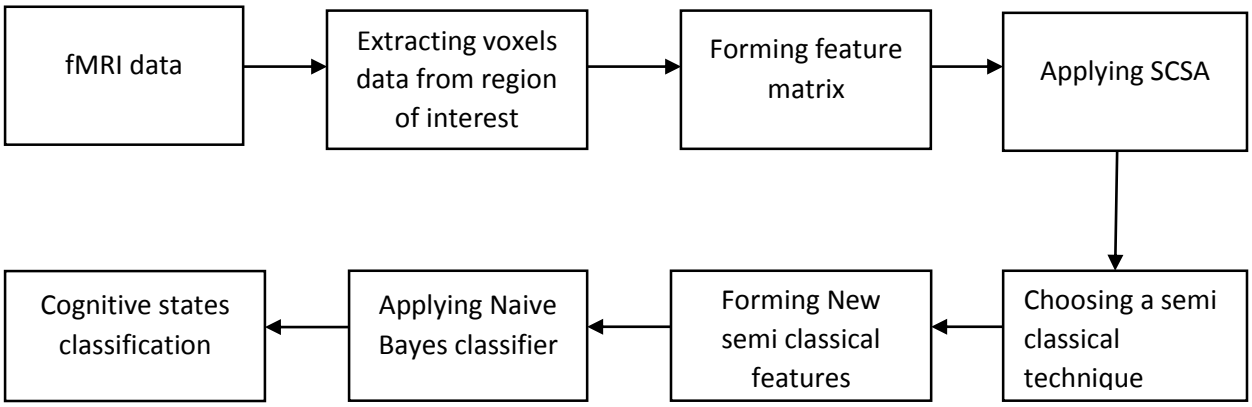

Figure 3.6: Block diagram of proposed method

fMRI data processing

We start by rescaling the data for each voxel, and for all trials, in order to give the same maximum and minimum for all brain activities, as a consequence, all brain activities values will be in [0,1] interval to have a mean of 0 and variance of 1, to ensure that there are no changes in the overall

"brightness" of the images. This step is achieved using a common technique in machine learning, which is the normalization. For every voxels the normalized values are computer using the following formula:

$$Y = \frac{X - minX}{\max X - \min X} \qquad (3.2)$$

Where Y is the new normalized brain activation value, and X is the old value of the brain activity.

Extraction of voxels data from regions of interests

Many techniques have been proposed for statistically analyzing fMRI data, and a variety of these are in general use [18].There are many ways to collect fMRI data from the voxels, however, it's important to choose the most informative voxels, or the most active voxels, the ones that can provide relevant information for the classification process. In order to select those voxels, we should use a t-test.

T-test shows the increasing or decreasing in the activation between two stimulus. For each voxel and for each stimulus, we compare the activity of the voxel during the stimulus X(X=P or S) versus the brain activity during the baseline (or the resting period) that we define.

Voxels are then selected by choosing for each stimulus the voxel with the largest t-statistic after ranking the voxels according to the obtained results.

During the serial t-test we compare the images acquired at each time point before, during and after the task with this baseline. Figure 3.7 illustrates the technique. For each time point following the stimulus, a mean and standard deviation image is constructed, as is a baseline mean and standard deviation image. Then a set of t-statistical parametric maps are formed by calculating, on a pixel by pixel basis, the t-score giving by the following equation:

$$T=\frac{\overline{X1}}{S_{a-b}} - \frac{\overline{X2}}{S_{a-b}} \qquad (3.3)$$

(3.3)

Where:

$$S_{a-b} = \sqrt{\frac{S_p^2}{n1} + \frac{S_p^2}{n2}} \qquad (3.4)$$

- S_p^2 is the pooled variance.
- $a = \overline{X1}$ and b= $\overline{X2}$
- n1 is the number of images acquired during the 'on' period of the task.
- n2 is the number of images acquired during the rest period.

$$S_p^2 = \frac{\sum(X1-\overline{X1})^2}{n1+n2-2} + \frac{\sum(X2-\overline{X2})^2}{n1+n2-2} \quad (3.5)$$

We compute the difference between mean image one and the mean baseline image, mean image two and baseline, and so on.

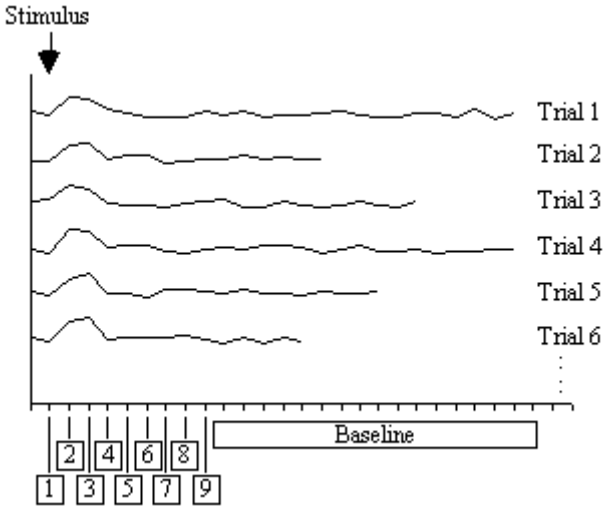

Figure 3.7: Results of the t-test [18]

Building the Feature Matrix

We start first by preparing our features. As we know, for each trial, the subject is going to view either a picture for 4 seconds in some time intervals (brain activation that lasts 8 seconds), or a sentence lasting 4 seconds (brain activation that lasts 8 seconds) as we previously mentioned. As a consequence, for each trial we select the brain activities that correspond to the variation of brain activities over time for either the sentence viewing task or picture viewing task. Hence, we get two signals for each trial.

Is it important to know that a full image at time t is formed by all the brain activations in all voxels at time t. In other words, the collection of all the brain activations forms the whole image at time t.

Each signal is represented by the values of each selected voxels for the 16 images and we concatenate them in order to form a feature vectors, so that n selected voxels produce a matrix of length 16 n.

Since we have 40 trials (SP+PS datasets), the maximum number of signals that we can have is 80.

This is a simple illustration for the feature matrix for one voxel n=1 and as a consequence, the dimension of the matrix is AxB, where:

A= Number of lines, which is equal to twice the number of trials, 80. Since for each trial, we select two signals, one signal that corresponds to the brain activations for the sentence viewing task, and one signal for the brain activations for the picture viewing task.

B= Number of column, which is equal to 16*n, where n is the number of voxels.

$$\begin{bmatrix} Brain\ activation\ for\ image\ 1\ (Trial\ 1) & \cdots & Brain\ activation\ for\ image\ 16\ (Trial\ 40) \\ \vdots & \ddots & \vdots \\ Brain\ activation\ for\ image\ 1\ (Trial\ 40) & \cdots & Brain\ activaation\ for\ image\ 16(Trial\ 40) \end{bmatrix} \quad (3.6)$$

Application of the SCSA

Definition

SCSA is a signal decomposition method that decomposes the signal to be analyzed into a set of squared eigenfunctions of the Schrödinger operator whose potential is considered to be the signal. Is it called SCSA as the Schrödinger operator depends on a semi classical parameter h.

Algorithm

The algorithm of the SCSA is the following:

- Considering first the signal as a potential of the Schrödinger operator

$$H_h(y)\psi(t) = -h^2\frac{d^2\psi(t)}{dt^2} - y(t)\psi(t), \quad \psi \in H^2(\mathbb{R}), \quad h > 0. \quad [3] \quad (3.7)$$

Where y is a real-valued function, we define H_h on a space β as follows:

$$\mathcal{B} = \left\{ y \in L_1^1(\mathbb{R}), \quad y(t) \geq 0, \quad \forall t \in \mathbb{R}, \quad \frac{\partial^m y}{\partial t^m} \in L^1(\mathbb{R}), \quad m = 1, 2 \right\} \text{[3] (3.8)}$$

L_1^1(R) is the Faddeev class:

$$L_1^1(\mathbb{R}) = \{V | \int_{-\infty}^{+\infty} |V(t)|(1 + |t|)dt < \infty\} \text{[3] (3.9)}$$

- Computing the negative eigenvalues and the associated L2- normalized eigenfunctions of the Schrödinger operator, by resolving the spectral problem, given by equation (3.7)
- Computing the approximated signal using the reconstruction formula (3.9):

$$y_h(t) = 4h \sum_{n=1}^{N_h} \kappa_{nh} \psi_{nh}^2(t), \qquad x \in \mathbb{R}. \qquad [3] \qquad (3.9)$$

- Looking for the best value of h that gives the best approximation of the real signal.

Figure 2.6 summarizes the previous steps of the algorithm,

Where: $(x = \frac{1}{h})$ (4.0)

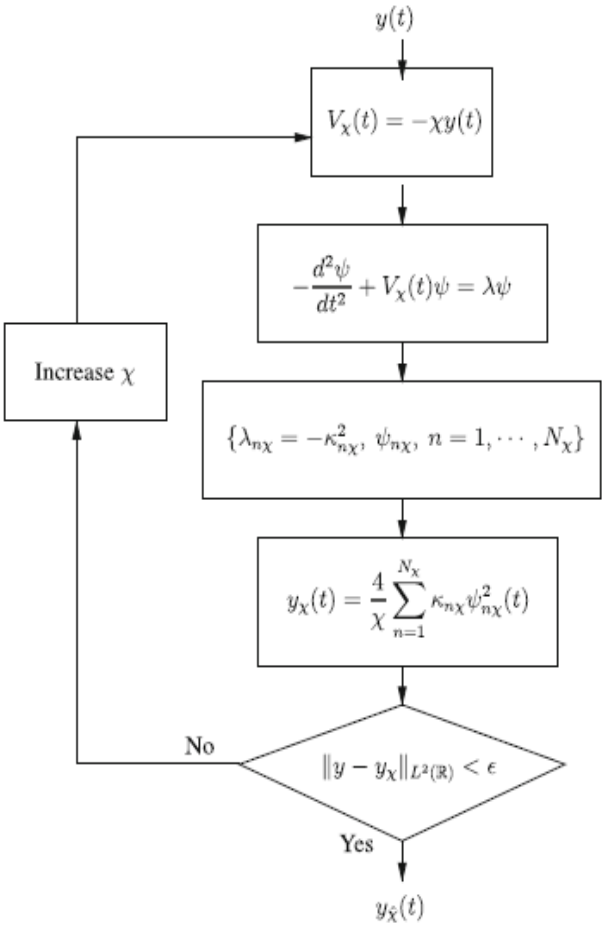

Figure 3.8: SCSA algorithm [3]

Properties

The SCSA has several properties, many of them are the results of different combinations of mathematical theorems and assumptions. Among these properties we list the following:

- The number of the negative eigenvalues is a decreasing function of the semi classical constant h (figure 3.9).

- The eigenfunctins associated to largest eigenvalues, are localized at the maximum peak of the signal and as the order of the eigenfunctions increases the oscillations increase and the amplitude decrease.
- The convergence property of the SCSA ensures a perfect reconstruction of the original signal, which means when (h→0), the reconstruction of the signal is exact.

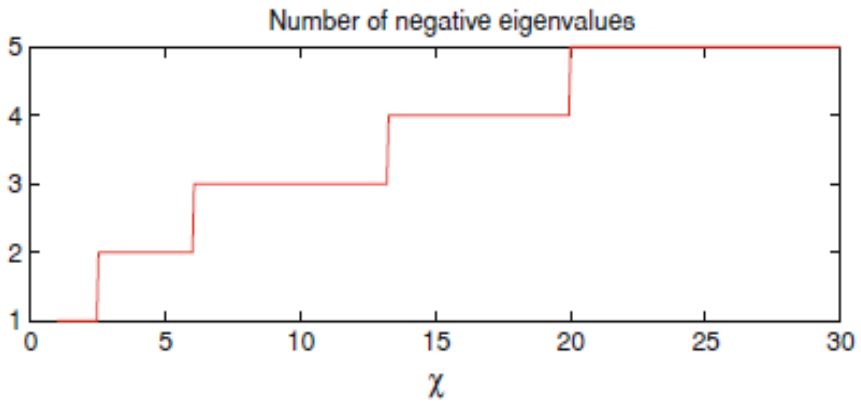

Figure 3.9: Evolution of the number of eigenvalues as function of the semi classical constant [3]

The SCSA method has proved to be very efficient in the analysis of pulse shaped signals [3]. For instance, interesting results have been obtained when applying the SCSA method to the analysis of arterial blood pressure signals [19]. Moreover, it has been shown that the SCSA has successfully been used for biomedical signals such as ABP waveform analysis [19] and it has been proved that the method can cope with noisy signals, such as MRS signals denoising [20] making this method a potential tool for denoising. The technique has also been extended to two dimensions for image analysis [21].

Because of these properties of the SCSA and the nature of fMRI signals, we decided to study the potential use of the SCSA as features extractions for mental states classification.

After forming the features matrix, we consider each signal separately. As a reminder, each signals represents the variation of brain activity for either the task viewing a picture or a sentence, each signal provides 16 fMRI data.

Now, for each signal we try to apply the SCSA to obtain a new reconstructed signal using the reconstruction formula (3.9). Since the signals are different the one to the others, because brain activity differ from a voxel to another and from a cognitive task to another, it is crucial to wisely choose the value of the parameter h, to obtain as much as possible a faithful reconstruction for each signal, so we will have several SCSA reconstructions. Figure (4.0) shows an example of reconstruction for the entire time course of a non-normalized voxel for the first trial.

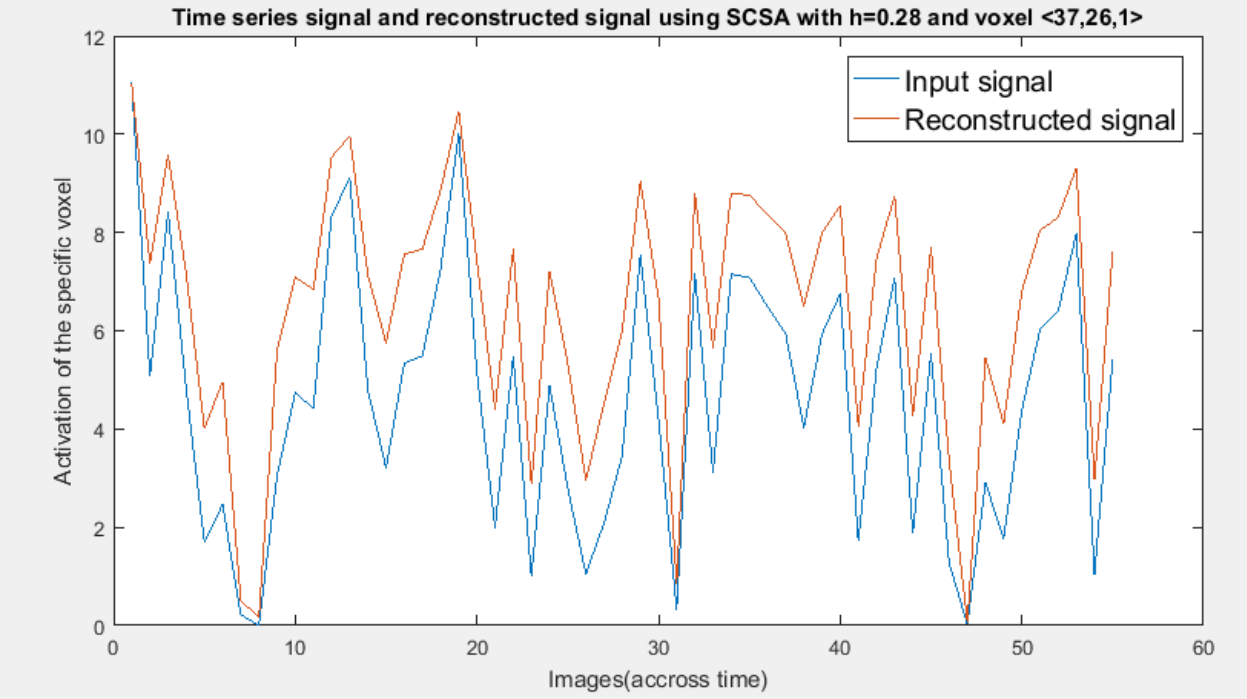

Figure 4.0: SCSA reconstruction for a particular voxel

In order to check if the chosen value of h for each signal is suitable, we use the following criteria, which is the peak signal-to-noise ratio (PSNR), which is defined by:

$$PSNR=10*\log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (4.1)$$

- *MAX* is the maximum possible pixel value of the image
- MSE is the mean squared error

PSNR measures the degree of correlation between different images, a reference image, which is our original fMRI signal and the reconstructed signal. For example if we compute it between two images, let's say the original signal and the reconstructed signal, the highest PSNR is the better the reconstruction is.

There is no unique value of h, we often get several values of h that provides us with a good PSNR value and as a consequence an interesting reconstruction. We developed an algorithm that automatically chooses the best value of h. The steps of the algorithm are the following:

- We consider each signal separately (one by one, until we manage to reconstruct the 80 signals).
- We choose an interval for the values of h, with a specific step. The semi classical constant h goes from [0.1 to 10] with a step of 1. This is a choice, several choices can be made, since the h is not unique for a particular signal. Sometimes, when we don't manage to get the value of h that gives the best reconstruction (high value of PSNR) we try to change the step of our search algorithm or we change the interval boundries, till we reach out target.

- We set a threshold for the value of PSNR (generally 15 dB or 20 dB)
- We compute the current value of PSNR for each h and we compare with the threshold, it we get higher PSNR then the algorithms stops the loop and take the best value of h, otherwise, it increases the step and continues looking for the right value.
- We repeat the process for every signal, until we get a new feature matrix that we call the reconstructed matrix.

The following table(Tab3.3), shows the values of h and the corresponding PSNR values for the some signals taken from LDLPFC region, more precisely those signals shows the evolution of the brain activity of the most active voxel in the region, chosen using the t-test.

Tab 3.3- SCSA reconstruction parameters

The number of signals	The h value	Nh	PSNR
1	0.460	8	25.3327
2	0.482	7	27.4711
3	0.200	15	16.5693
4	0.197	15	13.1382
5	0.294	12	25.9322
6	0.300	12	25.8797
7	0.180	16	14.6974
8	0.340	10	20.5337
9	0.400	9	22.8121
10	0.625	6	27.7934

Choosing a semi classical technique

After forming the reconstructed matrix, we try to take advantages of the results of the spectral resolution of the Schrödinger operator which are the eigenvalues and the corresponding eigenfunctions. In our research several approaches have been tested

Method1: Computing the Mean of eigenvalues

In this technique, for each reconstructed signal, we compute the mean of all the eigenvalues contributing to reconstructing the signal, depending on the averages obtained we will be able to separate between the cognitive states.

The average values will be replaced in the reconstructed matrix, and in this case we have done a transformation of the latter to a new matrix that we call SCSA matrix with a dimension of NxM.

- N: The number of signals 80
- M: The number of selected voxels,

In case we study the brain activations for one voxel, M=1 and we get a column vector instead of a matrix.

There will be what we call a threshold average, that we note "kscsa" that separates the two cognitive states. Signals having a mean of eigenvalues that is below kscsa will be classifier under the first cognitive task, while signals with an average that exceeds kcsa will be attributed to the second mental state.

Method2: Choosing the relevant eigenfunctions

In this method, we take the mean of some interesting eigenfunctions and we compute its sum. These eigenfunctions generally reflect some interesting characteristics about the original signal. We choose the first eigenfunction that generally contributes in reconstructing the highest peak of the original signal, and the three last eigenfunctions, these functions provide interesting information about specific details in the signal.

Cognitive tasks classification using Naïve Bayes

The features we get from applying the SCSA and choosing the semi classical feature technique, we use those features as the NB classifier input. The classifier differentiates between the two states based on the prior probability obtained.

We devote 80% of the signals to training the classifier (64 training example) and 20% for the testing (16 example). This choice is highly recommended in general in any machine learning classification problem. We measure at each time the performance of the classifier by computing the classification accuracy, which is defined by:

$$\text{Accuracy}=\frac{The\ number\ of\ correct\ predictions}{The\ total\ number\ of\ predications\ made}*100$$

3.5 Conclusion

Throughout this chapter, we treated the process of cognitive states classification, using the SCSA as feature extraction method. We have seen that there are several approaches to take advantage of the SCSA spectrum for investigating the activated brain regions due to the performed cognitive tasks.

In the next chapter we are going to present the obtained results and discuss several cases in our study.

Chapter4

Tests and results

4.1 Introduction

In this chapter we are going to present the results of the classification taking into consideration several factors, such as the selectivity of each region of interests and the number of voxels.

We start with investigating the contribution of each region of interest in the classification task, which will be followed by the study of the effect of the number of voxels that are involved on the classification performance, by choosing the most active voxels from each region of interests and apply the two semi classical techniques we described in the previous chapters.

In this last part of the chapter, we are going to adapt our classifier, so that it can be applied on different human subjects.

4.2 Selectivity of the brain regions

In this part, we try to test how informative is each region of interest among the 7 regions that were possibly involved in the picture versus sentence study. We are going to apply SCSA, and testing the performance of each semi classical method, that we described in the previous chapter.

We perform tests on one human subject (ID 04847). We test the performance classifier, using the most active voxel that was selected using the serial t-test that was explained in chapter2. Tab 4.1 and Tab 4.2 show the results of the test using the different semi classical methods of features extraction.

Tab 4.1- The results of the selectivity of each ROI for one human subject using the method of the mean of eigenvalues

The region	The accuracy
CALC	62.25
LDLPFC	43.75
LIPL	62.5
LIPS	43.75
LOPER	56.25
LT	75
LTRIA	56.25

The value of kscsa is equal to 1.31, which means all the testing signals having an average of eigenvalues that is below 1.31 were classified as picture viewing state, while the other signals were classified as sentence viewing state.

Tab 4.2- The results of the selectivity of each ROI for one human subject using the method of the relevant eigenfunctions

The region	The accuracy
CALC	62.5
LDLPFC	43.75
LIPL	56.25
LIPS	62.5
LOPER	68.75
LT	62.5
LTRIA	62.5

From comparing the results given by the two methods, we conclude that some regions of interests are not informative at all, such as LDLPFC, while some, provides very interesting classification accuracy, such as LT and LOPER.

We also notice that the method of the relevant eigenfunctions provides more interesting results comparing to the mean method, which indicates that the choice of the features in the second method was more efficient. The method of the relevant eigenfunctions takes into consideration some specific eigenfunctions that characterize carefully the shape of the brain activity, the last eigenfunctions provide information about the small details in the signal, which contribute in the differenciation tasks. In addition, and thanks to the first eigenfunction, we are able to detect the highest brain activity. These properties allows a better differentiation between the signals that corresponds to a picture viewing and the ones representing the sentence viewing task. On the other hand, computing the mean of all the eigenvalues may prevent the eigenvalues contributing to the reconstruction of the smallest peaks and the largest peaks of the signal from separating between the activation that is trigged by a sentence reaction from the one that is due to a picture viewing.

4.3 Influence of the number of regions of interests and number of human subjects

In this part, we are going to involve several regions of interests in our study, we form combinations of these regions (7 regions, 4 regions to 1 region). We try also to test the classification on different subjects following the same approach, we have been using

We first make the following combinations, based on the tests we obtained on the selectivity of each region of interest (Tab 4.1 and Tab 4.2)

- 7 ROIs: {’CALC’ ’LDLPFC’ ’LIPL’ ’LIPS’ ’LOPER’ ’LT’ ’LTRIA’}
- 4 ROIs: {’CALC’ ’LIPL’ ’LIPS’ ’LOPER’}

- 1 ROI: {‘ LT’}

The results of the classification using the two different semi classical methods are illustrated in Tab 4.3and Tab 4.4

Tab 4.3- Influence of the number of regions of interests and human subjects on the classification accuracy using the first semi classical method

The subject	7 ROIs	4 ROIS	1 ROI
04847	50	56.25	62.25
04799	62.5	62.5	72.5
05710	68.75	53.75	62.5
04820	75	62.5	62.50
05675	75	62.5	56.25
05680	62.25	50	43.75

Tab 4.4- Influence of the number of regions of interests and human subjects on the classification accuracy using the first semi classical method

The subject	7 ROIs	4 ROIS	1 ROI
04847	56.25	62.5	62.5
04799	62.5	68.75	62.5
05710	75	68.75	62.5
04820	62.5	50	43.75
05675	62.5	75	62.5
05680	62.5	62.5	50

4.4 Influence of the number of voxels on the classification

The previous tests were performed using only one active voxel. Now we try to increase the number of voxels involved in the study and repeat the test for each subject, taking only one region of interest, which is LT. The aim of this test is to know more about the effect of the voxels number on the classification task. We choose n=4(four voxels) the results for both semi classical techniques are shown in Tab 4.5 and Tab 4.6. We

Tab 4.5- Influence of number of voxels on the classification using the mean of eigenvalues method for n=4

The subject	1 ROI
04847	50
04799	56.25
05710	43.75
04820	37.5
05675	56.25
05680	75

Tab 4.6- Influence of number of voxels on the classification using the relevant eigenfunctions method for n=4

The subject	1 ROI
04847	50
04799	62.5
05710	50
04820	62.5
05675	68.75
05680	68.75

Now, we repeat the same test, using 20 voxels (n=20) and we notice the effect of the increasing number of voxels.

Tab 4.7- Influence of number of voxels on the classification using the mean of eigenvalues method for n=20

The subject	1 ROI
04847	62.5
04799	68.75
05710	31.25
04820	37.75
05675	50
05680	56.25

Tab 4.8- Influence of number of voxels on the classification using the relevant eigenfunctions method for n=20

The subject	1 ROI
04847	75
04799	75
05710	68.75
04820	43.75
05675	62.5
05680	50

We don’t notice an improvement in the classification results when we increased the number of voxels, this is probably due to the fact that some voxels are overlapped by other voxels that are more active.

4.5 Results across multiple subject

A key technical difficulty when combining data from multiple subjects is that different brains have physically different shapes, making it unclear how to align voxels across subjects (Figure 4.1). The figure shows that the location of voxels is different from a subject to another, for another cognitive task, which is the case for any other mental state. Several objects have their voxels activated in different regions even for a similar task.

In order to solve this issue, we abstracted the voxel activities for each subject. In particular, we. We then treated each of the regions of interests as a very large "supervoxel, In the tab 4.9 and 5.0 we show the result of the abstraction of one region of interest LT. We average all the brain activities in all regions of interests.

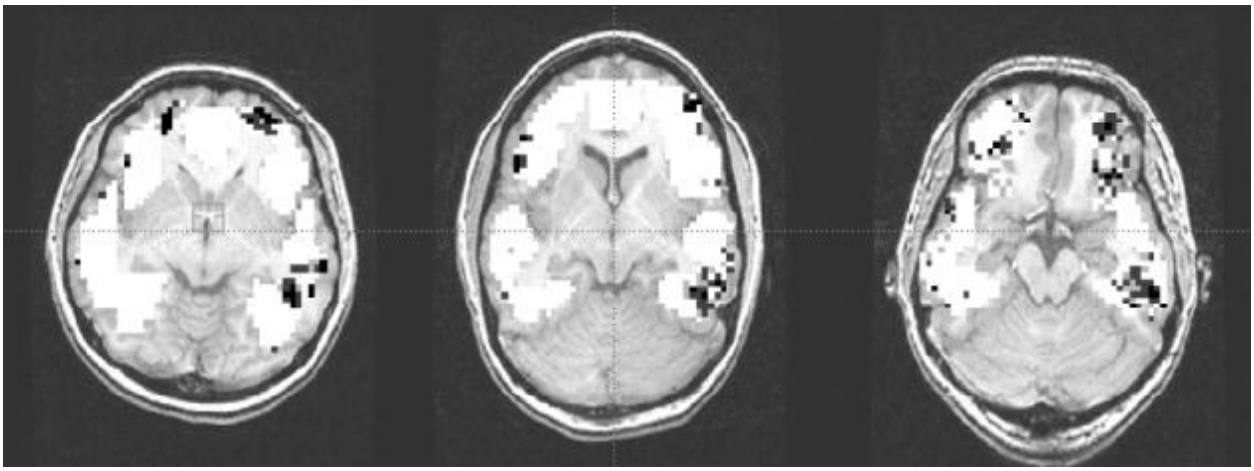

Figure 4.1: Plots show, for each of three human subjects, locations of voxels that best predict the semantic category of word read by the subject. Darkened voxels are those that produce the highest prediction accuracy; white voxels were also considered but were found to be less informative. Note the similar locations of predictive voxels across these three subjects [22]

Tab 4.9- Classification accuracy using a classifier for multiple subjects and the mean eigenvalues method.

The subject	1 ROI
04847	62.5
04799	56.25
05710	50
04820	50
05675	62.5
05680	68.75

Tab 5.0- Classification accuracy using a classifier for multiple subjects and the relevant eigenfunctions method

The subject	1 ROI

04847	62.5
04799	68.75
05710	68.75
04820	43.75
05675	62.5
05680	68.75

We have successfully trained a classifier,that works across subject, the second semi classical methods performs better than the first method, for this kind of classification.

4.6 Conclusion

In this chapter we presented the results of using the SCSA as feature extraction technique. We studied the accuracy of the our Naïve Bayes classifier based on different parameters such as the number of the regions of interests involved in the cognitive tasks, and the human subjects. We generalize our algorithm to several subjects, using the abstractions technique and the application of the SCSA remained satisfactory even in this case.

GENERAL CONCLUSION

Understanding the relation between the cognitive states and fMRI data, and developing machine learning tools that discover patterns in this data, to support probabilistic predictions in the human health is nowadays a very outstanding field that is facing several challenges. Understanding the key concepts behind this field and contributing to its research was the main objective of this project.

We began our work by doing an intensive literature review, and looking to the related works. We tried to understand the interdisciplinary of this kind of research, and reviewed the required skills in different areas such as computer science, electrical engineering and biology. Amongst the research that are conducted in mental states classification, the case of the instantaneous detection of the mental states was the one that attracted our attention the most for our project.

After that, we tried to propose a new feature extraction technique that is completely based on a signal decomposing technique, which is the SCSA that was described in detail in this report. We have seen that there are different ways to use the Schrodinger's spectrum in order to perform the classification task, and there is always a room for improvement.

We applied the SCSA to investigate the brain activations, corresponding to the picture versus sentence study. We tried to test the selectivity of each region of interest. We presented the results taking into consideration the influence of several parameters such as the number of the regions of interests that were possibly involved in the task, the number of activated voxels and other details.

Despite using the SCSA alone to extract features, the accuracy of our classifier is still interesting, but a variety of machine learning research is needed to extend these capabilities, since there is always a room for improvement. The technique may lead to an interesting impact, and would be of great use for research in cognitive science and in mental states diagnosis especially in patients with injury.

In many papers, researchers are trying to combine different techniques in order to extract features, which lead us more excited about the potential use of the SCSA with other techniques, mainly those of signal processing.

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